AgentUDE17: A Genetic Algorithm to Optimize the Parameters of an Electricity Tariff in a Smart Grid Environment

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Abstract. Electricity retailers are the most vulnerable actors in the electricity grid since they are responsible for many financial challenges. As a business entity, electricity retailers aim to maximize their sales volume and minimize the procurement cost in a highly competitive environment. On the retail market side, they publish rich tariffs specifications, which resolves the needs of customers in time, energy, and financial domains. In the paper, we present an online genetic algorithm that optimizes the parameters of an electricity consumption tariff, such as unit retail price, periodic, sign-up, and early withdrawal penalty payments on the fly. Additionally, we use time-of-use (TOU) price scheme to reduce peak-demand charges. The algorithm was first deployed and tested in our winning broker agent (AgentUDE17), which competed in the Power Trading Agent Competition (Power TAC) 2017 Final games. In the paper, we first present the theoretical background and detail the concepts of the algorithm. Secondly, we comparatively analyze the tournament data. Post tournament analysis shows that AgentUDE17 successfully optimized its tariff parameters on the fly and significantly increased its utility. Additionally, it managed to reduce its peak-demand charges thanks to its adaptive TOU price schemes.

Keywords: autonomous agent, retail market, optimization, genetic algorithms.

1 Introduction

Energy transition policies have been challenging the intermediary power actors (hereinafter broker and retailer are used interchangeably) since they take the burden of increasing costs and penalties on the changing energy landscape [7]. The smart grid can help both customers and brokers for an effective management of resources in real-time [3]. In that sense, autonomous smart algorithms can be employed by these entities to make full use of available data. Before using such smart algorithms in the real-world, competitive agent-based simulations are needed to identify the destructive and unanticipated behaviors of the grid participants. We use Power Trading Agent Competition (Power TAC) to simulate an autonomous power trading agent (AgentUDE17). In the paper, we only focus on the retail trading problem of the broker.

Brokers must publish rich, flexible tariff specifications to meet the needs of most customers, such as electric vehicles, local producers, households, and industrial consumers. A wider set of tariff parameters (i.e. unit retail price, periodic, sign-up, early withdrawal penalty payments, and contract length) makes the tariff specification more flexible and attractive. However, in terms of finding the optimal parameter set, many machine learning algorithms fail to explore the full search space, and, in most cases, they find a local optimum instead of a global optimum. In the paper, we present a genetic algorithm to find a parameter set (hereinafter chromosome or individual), which maximizes the net profit over a period. Results show that AgentUDE17 managed to gain significant profit, despite a tough competition. Moreover, peak-demand charges are significantly reduced thanks its TOU price scheme. Note that the peak-demand charge refers to the amortized cost of infrastructure, which billed weekly to the brokers in the extent of energy usage in peak hours.

The structure of the paper is organized as follows. Related work is explained in Section 2. Game description and definitions are given in Section 3. Our genetic algorithm is detailed in Section 4. Afterwards, Section 5 describes the tournament data and the analysis process as well as a section, dedicated to the results. Finally, the paper is concluded in Section 6 with an outlook to our future work.

2 Related Work

Many agent-based simulations exist to address the challenges in the smart grid applications (e.g. microgrids, demand response). In the field of competitive markets, Power TAC is one of the leading frameworks, which enables the competitive benchmarking in the smart grid [5].

Within the Power TAC framework, autonomous power trading has been studied by many research teams. Chowdhury et al. [2] use a Q-learning mechanism in the retail market, which rewards the gain or penalizes the loss in the profit. Given a state, their broker acts by incrementing, decrementing or keeping the tariff price. A winner broker Maxon16 [10] uses a TOU price scheme and determines the tariff rates using a Hill Climbing Algorithm. Another winner broker TacTex13 [11] uses a lookahead policy, which estimates the long-term utilities of candidate actions, and, in turn, reduces the complexity of searching in a high dimensional state-action space. Hoogland and Poutré [4] use a heuristic algorithm to determine the tariff price based on competitors' tariff prices. Wang et al. [12] use three independent SARSA processes to determine the tariff prices for 3 customer groups. Like in [10], the algorithm finds the optimal price by means changing the tariff price. Rúbio et al. [9] use a fuzzy logic algorithm based on their customer portfolio. They claim that the algorithm allows adaptive configurations, given a complex parameter set in the environment.

All approaches above fail to explore the full search space, which means that their algorithms focus on a small portion of the retail trading problem. In the best case, these algorithms end up with a local optimum in the search space. We aim to find a point near global optimum, taking all important tariff parameters into account. For sure, too many parameters result in a huge search space. Therefore, we use a genetic algorithm to overcome this problem. Genetic algorithms (GA) are used in many optimization problems where the problem cannot be solved easily due to the number of parameters and constraints added to the objective function [6]. Autonomous power trading is one of those applications that GA can conveniently be applied.

3 Game Description and Definitions

Power TAC [5] is an open-source simulation framework, which simulates competitive electricity markets for a robust policy guidance on the operation and structure of markets. A Power TAC broker is challenged to increase its profit by competing against other brokers and trading in the following energy markets:

- *Wholesale market* is a multi-channel spot market where buyers and sellers place their buy and sell orders for the next 24 delivery hours to match the customer demand. These auctions independently run in parallel and form a periodic double auction.
- *Balancing market* is operated by a distribution utility (DU) which ensures that the system is balanced and financially settled in real-time. DU may reward or penalize the brokers in the extent of their contribution or harm to the balancing process.
- *Retail Market* is the marketplace where brokers publish tariff specifications to attract customers. Customers are small and medium-sized consumers, producers and prosumers, and they may pick any tariff based on their economic preferences.

In Power TAC, time proceeds as a discrete time block, called time slot. A Power TAC game takes up to a random time slot count, starting from one, where the first 360 time slots are dedicated for a bootstrap period and the proceeding time slots for the competition. A tournament consists of multiple games, which are categorized in different game sizes, e.g. 3-player, 5-player, and 8-player games. Theoretically, each game is independently played. However, brokers can pass data from one game to another.

In a game, AgentUDE17 has only one active consumption tariff. Whenever a modification is needed during the optimization process, it supersedes the tariff with a new specification. In the paper, we will denote a tariff specification as $\tau = \langle p_{avg}, \grave{p}, bp, ewp, cl \rangle$. The parameters are now defined in detail:

- Tariff rates $\{p_1, p_2, \ldots, p_R\}$ (€/kWh): Unit cost of customer consumption. We use a single average rate p_{avg} to denote all rates (see Formula 2). Details to create a TOU scheme is detailed at the end of the next section.
- Periodic payment $\grave{p}$ (€): Daily payment (mandatory) from customers.
- Sign-up bonus bp (€): It is paid unconditionally by broker to subscribed customer.
- Early withdrawal penalty ewp (€): It is charged to customers, if they leave the tariff earlier than specified in the contract length.
- Contract length cl (in time slot, $cl \in N$): Minimum period in which the customer should stay in the tariff. If a customer subscribes to a tariff at time slot t and later withdraws it before time slot $cl + t$, then the customer pays a penalty (ewp).

Brokers may publish, revoke or modify tariffs anytime during the competition. In contrast to the new tariff publication, any modification on the tariff voids the early withdrawal penalty and contract length for existing customers. At any time slot, the tariff is published in the retail market, in the form of $\langle\{p_1, p_2, \dots, p_R\}, \grave{p}, bp, ewp, cl\rangle$ and become available to subscriptions. Hereinafter, we call this tuple as a chromosome and individual interchangeably, which is denoted by C.

Definition 1. (Fitness Function) *Let C be a chromosome of an active tariff, between time slots t and $t+\delta$. Then the **fitness function** $f(C)$ returns a fitness value f_C, which is the total profit of the chromosome over a period. The function is defined as $\sum_t^{t+\delta} R_t - M_t$, where R_t is the net revenue (including $\grave{p}, bp, ewp$ and peak-demand charges) from the customers and M_t is the total of wholesale market commitments.*

In the fitness function, we excluded all other costs, such as metering fee, imbalance cost, tariff publication and revocation fees, since these variables may slightly change during the game and challenge the algorithm.

Definition 2. (Assessment Period) *Let τ_{ude} be an active tariff, published at time slot t. Then, assessment period δ is the time slot gap between time slots t and $t+\delta$. At time slot $t+\delta$, the active tariff is replaced by another tariff, $\tau_{ude} \leftarrow \tau_{ude}^{t+\delta}$. The length of the period is proportional to the tariff publication fee and may take values as $\delta \in \{42, 84, 168\}$.*

Definition 3. (Population) *Population is a set of N individuals $\{C_t^1, C_t^2, \dots, C_t^N\}$ at time slot t, where the chromosomes (i.e. individuals) are ordered by their fitness values (i.e. $f_{C_t^1} \geq f_{C_t^2} \geq \dots \geq f_{C_t^N}$). The population represents the collection of published and assessed tariffs in the past. The first chromosome represents the healthiest individual, which literally means that it has the highest fitness value. If a new chromosome satisfies the condition, $f_{C_t^N} \leq f_{C_t^{new}}$, then it is replaced with the least successful individual C_t^N.*

Definition 4. (Bootstrap Data) *Bootstrap data (BD) is an initialization database, which contains the initial population and tariffs of competitors in the form of $\{C_{BD}^1, C_{BD}^2, \dots, C_{BD}^N, \tau_{B_1}, \tau_{B_2}, \dots, \tau_{B_i}\}$ where τ_{B_i} is the opening tariff specification of i-th broker in the game. This tariff specification reflects the most recent data.*

We use a 3-level decision tree to store multiple bootstrap data. Top level BD stores the data from all games. Second level BD's (i.e. children of the top-level BD) are grouped by the game sizes, e.g. 3-, 5- and 8-players. Level 3 consists of unique broker sets, given the number of competing brokers and game size. For example, 5 brokers yield 10 unique combinations of possible games in 3-player mode. At the beginning of a tournament, AgentUDE17 has only one top-level database (BD). However, AgentUDE17 always requests a BD on the third level. If it does not exist on the third level, it firstly checks whether a BD exists on the second-level. If it is found, it is copied to the third level. Otherwise, the top-level BD is copied to both second level and third levels. After each assessment period, BD is updated on the fly, as the broker explores new individuals between two consecutive assessment periods. This can be formalized as $BD \leftarrow \{C_t^1, C_t^2, \dots, C_t^N\}$. However, its parent and top-level databases are also affected from the update, so that their chromosome values are exponentially smoothed with empirically found weights 0.2 and 0.1, respectively. Likewise, competitors' opening tariffs are carried to the upper levels. The second and the top-level databases contain the most recent opening tariffs of all brokers in their sub-trees. This way, AgentUDE17 always gets the initial data about its competitors.

Definition 5. (Baseline Price) *Let τ_i be the i-th active tariff in the retail market at time slot* t*. Then the baseline price is* $p_{base} = \min_{\tau_i \epsilon \tau} p(\tau_i)$*, which literally means the cheapest active tariff in the market.*

However, the baseline price does not denote the lowest tariff price only, instead, $\grave{p}, bp, ewp$ and cl values of the respected tariff are also taken into consideration. We formalize the process using the formula (1):

$$p(\tau_i) = p_{avg}^{\tau_i} + \begin{cases} (\grave{p}^{\tau_i} - bp^{\tau_i})/\max(\delta_{day}, cl^{\tau_i}), & p_{avg}^{\tau_i} \leq \min_{\tau_k \epsilon \tau, k \neq i} p(\tau_k) \\ (\grave{p}^{\tau_i} - bp^{\tau_i} + ewp^{\tau_i})/\max(\delta_{day}, cl^{\tau_i}), & \text{else} \end{cases} \quad (1)$$

Where δ_{day} refers to the hours in a day (=24) and $p_{avg}^{\tau_i}$ is the weighted mean of all rates in the tariff.

$$p_{avg}^{\tau_i} = \sum_{r=1}^{R} p_r^{\tau_i} \omega_h \quad (2)$$

Where $\sum \omega_h = 1$ and h corresponds to the time interval in which the rate $p_r^{\tau_i}$ is active. The weight ω_h refers to the share of total distribution (grid wise) in the regarded interval. The impact of the bonus payment and early withdrawal penalty are projected to a single time slot and added to the average rate. If the average rate is the cheapest among all other tariffs, then we omit the impact of ewp from the formula. Note that the formula can only estimate the real baseline price. The real value of the tariff varies from customer to customer, depending on their economic preferences.

Definition 6. (Bottom-line Price) *Let* τ *be a tariff candidate of AgentUDE17. Then the bottom-line price, denoted as* p_{bottom}*, must be less than the average rate, which satisfies the condition* $p_{bottom} < p_{avg}^{\tau}$*. Bottom-line price is obtained through estimating the wholesale market costs.*

After all, the bottom-line price determines the lower boundary of the average tariff price so that AgentUDE17 can safely optimize the tariff parameter set, instead of searching in the full search space.

4 Genetic-based Optimization

Genetic algorithms (GA) are used in many large optimization problems where the problem cannot be solved easily due to its large search space [6]. In this section, we detail how we applied GA to solve the retail trading problem on the fly.

As noted before, AgentUDE17 has only one active tariff, which is required by the algorithm due to trackability of the changes in the tariff specification. At the beginning of the games, AgentUDE17 always start with an offline data, called bootstrap data BD.

The bootstrap data initializes the variables that will create the initial tariff τ_{ude}. To do it, we copy individuals and initial tariffs of competitors from BD to the local repository:

$$C_t^1, C_t^2, \dots, C_t^N \leftarrow BD[C_{BD}^1, C_{BD}^2, \dots, C_{BD}^N] \tag{3}$$

$$\tau_1, \tau_2, \dots, \tau_i \leftarrow BD[\tau_{B_1}, \tau_{B_2}, \dots, \tau_{B_i}] \tag{4}$$

The individuals are sorted in a way that the healthiest individual is always placed at the first position whereas the weakest one is placed at the last position. Once the repositories are initialized with BD and after every assessment period, we decrease the fitness values of all individuals with a negative constant δ_{bias} to prevent the biased behavior. The biased behavior occurs when an individual has relatively high fitness value among others and its chromosomes are outdated due to a significant change in the economic environment. Therefore, we make sure that a new individual is added to the population, ranked in a top position. We define the bias constant as follows:

$$\delta_{bias} = -\left|f_{C_t^1} / \delta_{bias-cons}\right| \tag{5}$$

where $\delta_{bias-cons}$ is an experimentally determined integer. In addition to the competitors' tariffs (see Formula 2), new published tariffs are added to the tariff repository. Therefore, we calculate the baseline price before and after each assessment period:

$$p_{base} = \min_{i \neq ude} p(\tau_i) \tag{6}$$

where i is the number of active tariffs in the tariff repository. One cycle in GA is called a generation, and it consists of selection, crossover and mutation steps, as shown in Fig. 1. A new child is created just after the assessment period.

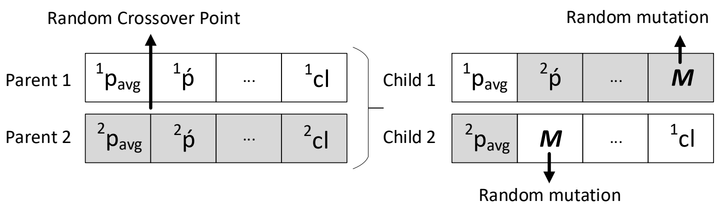

Fig. 1. Crossover and mutation steps in our genetic algorithm.

In the selection process, we only pick the first two individuals as new parents from the repository, which is called elitism. The reason behind it that tariff specifications can rapidly be outdated due to changing conditions either in the markets or in the retail policies of competitors. In the crossover process, we determine a random point between genes. As illustrated in Fig. 1, the genes on the left side are kept in child 1 and child 2, whereas the ones on the right side are appended to child 2 and child 1, respectively. The crossover process results in two new children. Afterwards, we randomly pick one of the children to apply the mutation process. The new chromosome is denoted as $C_{new} = \langle p_{avg}^{\tau_{ude}}, \grave{p}^{\tau_{ude}}, bp^{\tau_{ude}}, ewp^{\tau_{ude}}, cl^{\tau_{ude}} \rangle$.

$$C_{new} \leftarrow crossover(C_t^1, C_t^2) \tag{7}$$

Which is subject to (8) and (9):

$$p_{bottom} \leq p_{base} \tag{8}$$

$$p_{base}\left(1 - \varepsilon_p\right) \leq p_{avg}^{\tau_{ude}} \leq p_{base}\left(1 + \varepsilon_p\right) \tag{9}$$

where ε_p is a mutation constant and it determines the value range in which tariff prices can be defined. Therefore, if condition (9) is not satisfied, then $p_{avg}^{\tau_{ude}} = p_{base}$. Likewise, if condition (8) is not satisfied, then $p_{avg}^{\tau_{ude}} = p_{bottom}$. We apply a random mutation to all genes, subject to the constraints (8) and (9). We randomly define the new values, satisfying the following conditions:

$$p'^{\tau_{ude}}_{avg} \in [p_{avg}^{\tau_{ude}}\left(1 - \varepsilon_p\right), p_{avg}^{\tau_{ude}}\left(1 + \varepsilon_p\right)] \tag{10}$$

$$\grave{p}'^{\tau_{ude}} \in [\grave{p}^{\tau_{ude}}\left(1 - \varepsilon_p\right), \grave{p}^{\tau_{ude}}\left(1 + \varepsilon_p\right)] \tag{11}$$

$$bp'^{\tau_{ude}} \in \left\{bp^{\tau_{ude}} + \varepsilon_{bp\&ewp}, bp^{\tau_{ude}} - \varepsilon_{bp\&ewp}\right\} \tag{12}$$

$$ewp'^{\tau_{ude}} \in \left\{ewp^{\tau_{ude}} + \varepsilon_{bp\&ewp}, ewp^{\tau_{ude}} - \varepsilon_{bp\&ewp}\right\} \tag{13}$$

$$cl'^{\tau_{ude}} \in \{cl^{\tau_{ude}} + \varepsilon_{cl}, cl^{\tau_{ude}} - \varepsilon_{cl}\} \tag{14}$$

Where mutation constants $\varepsilon_{bp\&ewp}$ and ε_{cl} are used for bonus and penalty payments and contract length, respectively. Tariff prices in (10) and (11) use a multiplier to determine their new values whereas (12), (13) and (14) are defined, by means of incrementing and decrementing the original value. New values constitute the mutated child $C_{new}^{mutated} = \langle p'^{\tau_{ude}}_{avg}, \grave{p}'^{\tau_{ude}}, bp'^{\tau_{ude}}, ewp'^{\tau_{ude}}, cl'^{\tau_{ude}} \rangle$.

After all, the new mutated child is transformed into a tariff specification $\tau_{ude} \leftarrow C_{new}^{mutated}$ and submitted to the retail market as of current time slot t. It will remain active during a new assessment period, literally until time slot $t + \delta$. On the other side, the preceding active tariff $\tau_{ude}^{t-\delta}$, that is defined at time slot $t - \delta$ must assessed, using the fitness function. It is added to a position in the population, ranked by its fitness value. The assessment process is skipped at the beginning of games.

As mention before, we use a TOU price scheme in the tariff specifications and the unit consumption value p_{avg} only indicates the average price of the scheme. Therefore, we transform p_{avg} into a detailed TOU price scheme, using the wholesale market costs and grid-wide distribution data. Average market clearing price are denoted as cp_h^{wd} and cp_h^{we} separately for weekdays and weekends, where $h \in \{1,2,\ldots,23\}$. Likewise, average hourly distribution is denoted as D_h^{wd} and D_h^{we}. Note that the distribution data reflects the net distributed energy of all brokers, and customer-based production amount is substracted from the total consumption. Then we obtain two vectors, $(\omega_1^{wd}, \omega_2^{wd}, \ldots, \omega_{24}^{wd})$ and $(\omega_1^{we}, \omega_2^{we}, \ldots, \omega_{24}^{we})$, where $\omega_h = cp_h^{wd} D_h^{wd}$. Then we normalize these vectors, satisfying $\sum \omega_{24}^{we} = 24$ and $\sum \omega_{24}^{wd} = 24$. After all, we define the TOU rates for weekdays and weekends as follows:

$$\left\{p'^{\tau_{ude}}_{1}, p'^{\tau_{ude}}_{2}, \ldots, p'^{\tau_{ude}}_{R}\right\} \leftarrow \left\{p'^{\tau_{ude}}_{avg}\omega_1, p'^{\tau_{ude}}_{2}\omega_2, \ldots, p'^{\tau_{ude}}_{24}\omega_{24}\right\} \tag{15}$$

In a standard tariff of AgentUDE17, we define 48 rates, representing every hour on weekdays and weekends. The flowchart of the algorithm can be summarized in Fig. 2.

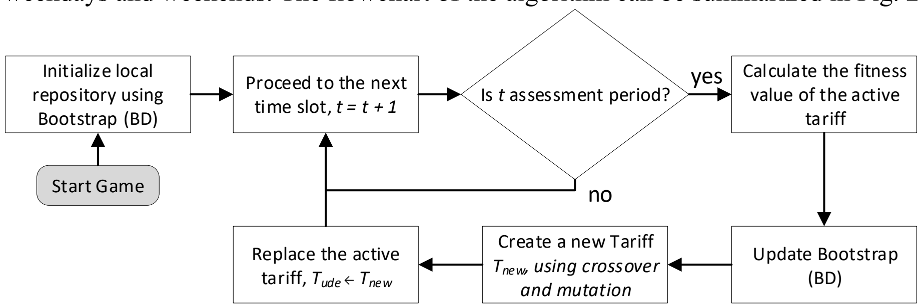

Fig. 2. Flowchart of the proposed algorithm.

5 Results and Discussion

We deployed the presented approaches in our winning broker AgentUDE17 that was extensively challenged in the Power Trading Agent Competition 2017 Final. Therefore, we will analyze the tournament data to validate our approach (proof of concept).

5.1 Tournament Data & Analysis Process

The Power TAC 2017 final games were played in June 2017 immediately after two trial tournaments and a qualification round. Eight brokers competed in 284 games. From those games, 60 were played in 8-player mode whereas 112 games were played in both 5-player and 3-player modes. The brokers in the finals were: AgentUDE17 [8], COLDPower17, CrocodileAgent [1], SPOT [2], VidyutVanika, ewiBroker, fimtac, maxon17 [10]. AgentUDE won the tournament using the methods in this paper.

After a game is successfully completed, a state log file is created that contains all financial and energy transactions. All relevant outputs were processed in MATLAB R2016b and are valid for Power TAC version 1.4.3.

5.2 Results

In this section, we evaluate the performance of the algorithm, based on tournament data. We included all the games from the Power TAC 2017 Final tournament, in which AgentUDE17 is involved. Out of 172 games in total, 60 games were in 8-player, 70 games were in 5-player and 42 games were played as 3-player games.

In the tournament, we optimized the tariff parameters based on a single active tariff. Therefore, our algorithm needs to publish and revoke tariffs after short intervals to measure the fitness value of the tariff. Fig. 3 shows the cost of running the algorithm.

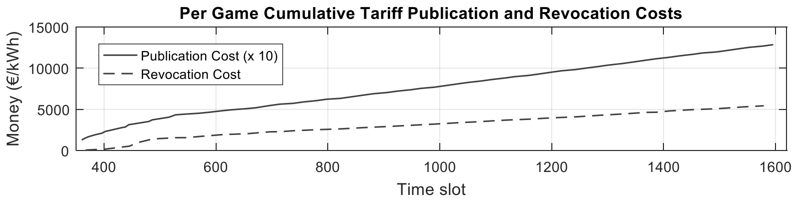

Fig. 3. Per game cumulative sum of tariff publication and revocation fees.

As mentioned earlier, we use a TOU price scheme in the tariffs for a few reasons. Firstly, we reduce the peak-demand charges. Peak-demand charges may be extremely high during the peak hours and may result in a huge loss in the broker's bank account. We use high rates for peak hours and low rates for off-peak hours to solve this problem. Therefore, we encourage our customers to avoid consumptions during peak hours.

As seen in Fig. 4, AgentUDE17 motivated its customers to shift (i.e. valley filling) their loads to the preceding or proceeding time slots. The same figure (right panel) compares the peak-demand charge rates of the brokers.

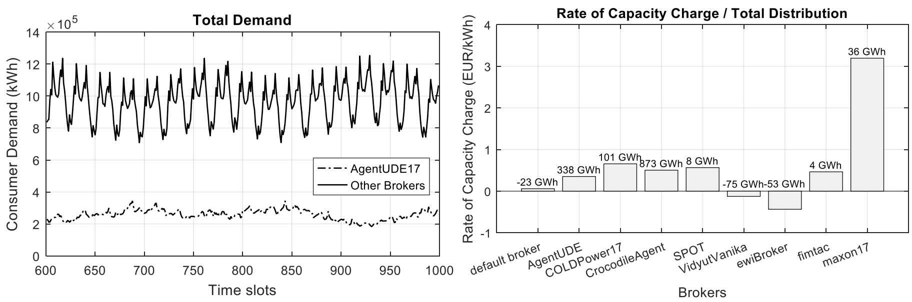

Fig. 4. Left panel indicates the total demand of AgentUDE17 and the total demand of other brokers. A TOU price scheme drives the motivation of customer demand. Right panel shows the rate of total peak-demand charges to total distribution. Annotations refer to total distribution in GWh. Negative distribution refers to local production, which is subject to production tariffs.

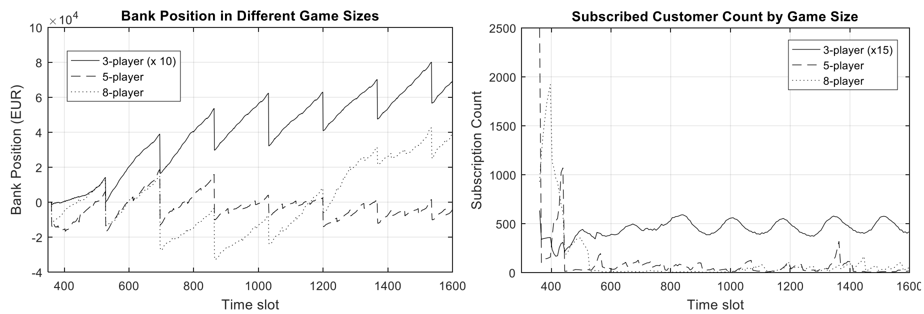

Fig. 5. Left panel indicates the average cash position of AgentUDE17 in different game sizes. Sharp declines in the bank position refer to peak-demand charges, paid once a week (168 time slots). Right panel shows the number of subscribed customers to the AgentUDE17 tariffs. The count for the 3-player games is 15 times higher than the indicated.

Fig.5 illustrates the average cash position of AgentUDE17 in 3-, 5- and 8-player modes. In 5- and 8-player games, AgentUDE17 managed to minimize its peak-demand charges and increase its profit steady. Especially, in 5- and 8-player games, AgentUDE17 could not attract many customers, due to limited profitability space. Adding the tariff publication and revocation fee (see Fig. 3) on top of average cash positions, AgentUDE17 managed to stay on the profitable side.

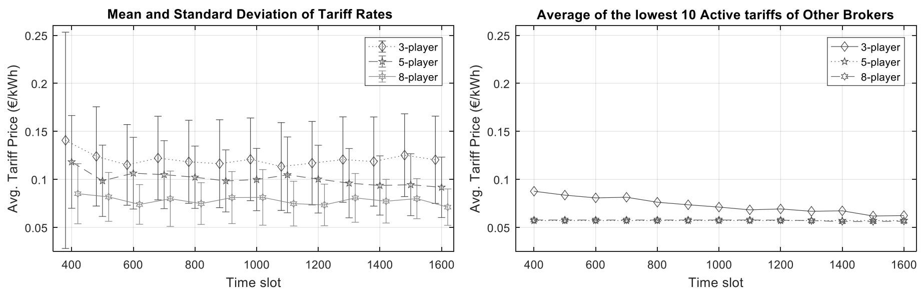

Fig. 6. Left panel illustrates the mean and standard deviation of tariff rates in short intervals. Right panel indicates the average of the lowest 10 active consumption tariffs of the competitors.

Fig. 6 illustrates the mean and standard deviation of tariff rates in AgentUDE17 tariffs (left panel) and average tariff price of the lowest 10 tariffs of competitors (right panel). On the left panel, the standard deviation and the mean are inversely proportional to the game size. The reason is that 8-player games are repeated with the same brokers.

Fig. 7 illustrates the mean and standard deviation of periodic payment (left panel) and the cumulative sum of periodic payment by game size (right panel). In 5- and 8-player games, we see a steady increase in the value of the periodic payment. The reason behind it that AgentUDE17 attracts few customers in 5- and 8-player games due to the tough competition. The level of the competition is relatively lower in 3-player games. Especially, in 8-player games, the periodic payment is optimized in a larger search space. Due to the number of customer count in 3-player games, it provided the highest earnings, as shown in the right panel.

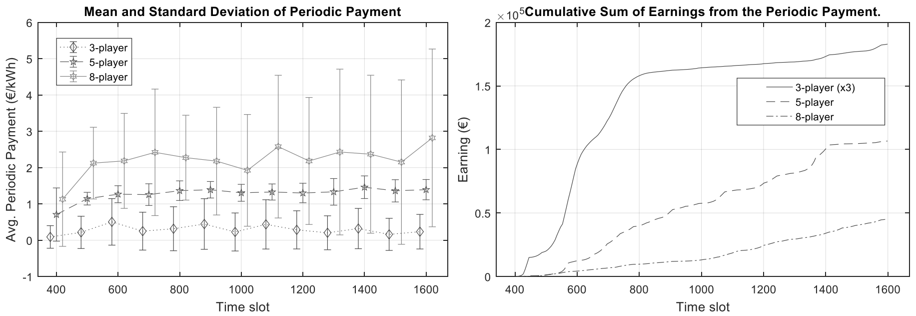

Fig. 7. Left panel shows the mean and standard deviation of periodic payments. Right panel illustrates the per game earnings of AgentUDE17 from the periodic payment.

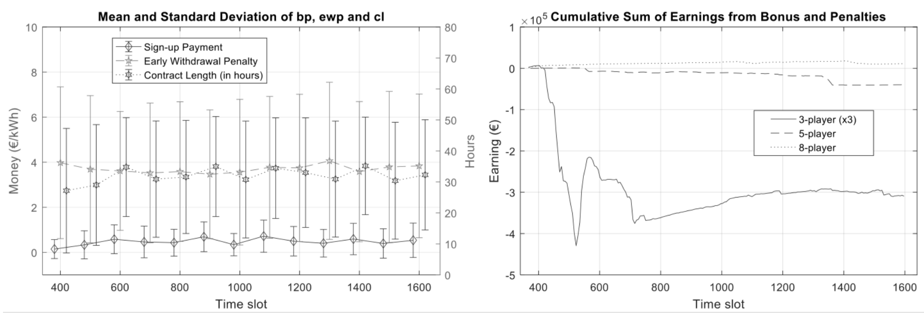

Fig. 8. Left panel illustrates the mean and standard deviation of tariff fees and contract length. Right panel shows the cumulative earnings from the tariff bonus and penalties.

Fig. 8 illustrates the mean and standard deviation for the bonus payment, early withdrawal penalty, and contract length as well as the cumulative sum of earnings, collected from these payments. As seen in the right panel, AgentUDE17 paid the most amount of money in 3-player games. AgentUDE17 gained some profit in 8-player games.

6 Conclusion and Future Work

In this paper, we presented a genetic algorithm to optimize the tariff parameters of an electricity tariff on the fly. The broker always starts with an offline data, called bootstrap database, which is picked from a decision tree structure. In the bootstrap data, we basically keep the most recent knowledge of the broker as well as competitive tariffs of other brokers. During a game, the algorithm periodically produces a set of parameters. The broker modifies the active tariff, replacing its parameters with the new ones. However, the algorithm selects the parameter values after many evolutionary processes so that it maximizes the profitability in long term.

We employed the algorithm in our winning broker agent AgentUDE17. We investigated the Power TAC 2017 Final tournament, analyzing its game logs files. Results show that AgentUDE17 succeeded to be on the profitable side, despite a tough competition, especially in 8-player games. Besides, it managed to minimize its peak-demand charges by means of using TOU price schemes.

Broker agents trade in a highly dynamic environment. This means that they deal with a huge number of variables on the fly. Many of them fail in terms of finding the global optimum, despite using advanced machine learning algorithms. In AgentUDE17, we used a genetic algorithm (GA) in the retail market and realized that GA fits extremely well to such dynamic environments. As a part of this project, we plan to implement an evolutionary bidding mechanism on the wholesale market since we think that autonomous traders (not limited to power traders) need an advanced self-evaluation structure to fully explore the search space and adapt themselves to new market conditions.

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