AgentUDE17: Imbalance Management of a Retailer Agent to Exploit Balancing Market Incentives in a Smart Grid Ecosystem

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Abstract. Electricity retailers suffer from the burden of financial challenges due to their balancing responsibility in the energy markets. They are penalized or rewarded by system operators, in the extent of their contribution or harm to the balancing process. In this paper, we present two novel algorithms, firstly to predict the demand of a mixed customer portfolio, secondly to bid strategically in the wholesale market, which exploits the inefficiencies between the wholesale and balancing markets. The algorithms were first deployed and tested in our winning broker agent (AgentUDE17), which competed in the Power Trading Agent Competition (Power TAC) 2017 Final. We analyze the tournament data, using several key performance indicators. Post tournament analysis shows that AgentUDE17 successfully managed its imbalance, even generating extra revenue within this process.

Keywords: broker, wholesale market, balancing market, trading.

1 Introduction

Energy transition policies have been changing the energy landscape. Intermediary power actors (hereinafter broker or retailer are used interchangeably) are the most vulnerable entities, as they keep the bridge in balance between customers and generators [8, 13]. This challenge is usually controlled by non-profit transmission operators, by means of penalizing or rewarding the broker imbalance. In future electricity grids, retailers may have more instruments (e.g. demand response) to benefit from the incentives. Basically, brokers can do this in two ways: The system operator is permitted to utilize a certain amount of capacity for up and down power regulations. Secondly, brokers directly generate imbalance to help the system operator [17]. This paper focuses on the latter.

In this work, we present two novel algorithms. The first algorithm solves the demand forecasting problem of a heterogeneous customer portfolio. The second algorithm manages the imbalance strategy of AgentUDE17, and in turn, it determines the wholesale

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market order price. The algorithm basically exploits the incentives, given by the balancing market. We deployed the algorithms in our winning broker agent AgentUDE17 and competed in Power TAC 2017 Final games. Results show that AgentUDE17 is a successful broker in many metrics, among its competitors.

The structure of the paper is organized as follows. Related work and the problem definition are explained in Section 2 and Section 3, respectively. The algorithms are detailed in Section 4. Afterwards, Section 5 describes the tournament data and the analysis process as well as a subsection, dedicated to the results. Finally, the paper is concluded in Section 6 with an outlook to our future work.

2 Related Work

This section details the relevant research of the concepts of this paper. We first introduce the existing works and potential challenges in the field of electricity demand forecasting. Then we will have a look at wholesale trading algorithms, implemented by other Power TAC developer teams.

Electricity demand forecasting has been studied by many researchers. In a survey, Taylor et al. [14] comprehensively review the seasonal autoregressive integrated moving average (SARIMA) methods to forecast time-series signals. Wang et al. [18] focus on the usage pattern of an individual customer and aggregate these patterns. Rubio et al. [12] implement a fuzzy logic trading mechanism whereas Hernandez-Leal et al. [4] introduce an opponent model, which explores and tracks the opponent actions. A winning broker agent Maxon16 [15] uses multiple linear regression models to predict the future demand. Another winning broker TacTex13 [16] predicts the future demand, using a locally weighted linear regression by means of estimating the changes in customer subscriptions. In our approach, we process the signal of the aggregate demand. Therefore, our algorithm can be applied to any kind of customer portfolio.

In the literature, strategic bidding has been mainly applied to the energy amount or the limit-price. Kuate et al. [7] use a reinforcement learning algorithm to put the strategy on the energy amount. Hoogland and Poutre [5] implement a heuristic algorithm, which determines the cheapest auction slots and increases the limit-price only for these auction slots. Urban and Conen [15] use a defensive strategy to buy the needed energy as early as possible, using multiple price levels. Urieli and Stone [16] uses an acyclic approach, in which a back-sweep operator finds a limit price using a balancing price and a probability function of limit-prices. Unlike other approaches, their method builds a bridge between the balancing market and the wholesale market for the first time. In this paper, we extend this approach, using more data from the balancing market.

3 Problem Definition and Motivation

Power TAC [6] is an open-source smart grid simulation framework, which simulates competitive electricity markets and state-of-the-art customer models [11] for a robust policy guidance on the operation and structure of markets. A Power TAC broker is challenged to increase its profit, attracting more customers and trading in the electricity markets on behalf of them. In this work, we exclude the retail market activities and focus on the wholesale and balancing market.

The wholesale market is a multi-channel spot market where buyers and sellers place orders in the wholesale market for future time slots. These auctions independently run in parallel and form an individual periodic double auction. Brokers ought to predict future aggregate demand $\{\widetilde{D}_{t+1}, \widetilde{D}_{t+2}, \dots, \widetilde{D}_{t+24}\}$ in MWh, and match it in the wholesale market to close the imbalance gap.

Balancing market is operated by a distribution utility (DU) which ensures that the system is balanced and financially settled in the current time slot t. It may penalize the broker in the extent of the gap between the actual net demand D_t in MWh, and wholesale market commitments $\sum_{o=t-1}^{t-24} ca_t^o$, where o is order time slot for the market clearing amount ca (MWh). Therefore, we can formalize the imbalance amount in the formula below:

$$I_t = D_t - \sum_{o=t-1}^{t-24} ca_t^o \tag{1}$$

At current time slot t, brokers receive a bunch of information, e.g. market clearing prices $cp_t, cp_{t+1}, \dots, cp_{t+23}$ (€/MWh) and clearing amounts $ca_t, ca_{t+1}, \dots, ca_{t+23}$ for delivery hours $\{t, t+1, \dots, t+23\}$ as well as balancing unit cost bp_t (€/MWh), and imbalance amount I_t (MWh) for the current time slot. Therefore, brokers pay $I_t bp_t$ € as an imbalance penalty to the DU. After all, the objective function can be formalized as follows:

$$min \sum_{t=1}^{T} \left(\sum_{o=t-1}^{t-24} ca_t^o cp_t^o \right) + I_t bp_t \tag{2}$$

where T is a time horizon and the formula represents the cost function. In the formula, broker can only determine the price and energy amount to be submitted to the wholesale market. In the paper, we offer a solution to solve two problems, which determines the energy amount (i.e. demand prediction) and limit-price (i.e. strategic pricing), to be placed in the wholesale market.

3.1 Demand Volatility

Brokers require a robust demand prediction algorithm to avoid cautionary imbalance penalties. However, thanks to the integration of new customer types (e.g. roof-top solar panels), the prediction accuracy tends to be driven by the power type and customer capabilities. Electric vehicles and storage customers are capable of demand response and they may react to prices or power regulations in an unpredictable way.

3.2 Incentives and Penalties in the Balancing Process

In Power TAC environment, the DU implements an incentive-based balancing mechanism [9]. Brokers are awarded (or penalized) in the extent of their contribution to the balancing problem. From the broker's perspective, the balancing price bp_t at current time slot is determined depending on the broker imbalance and system imbalance. System imbalance refers to total of broker imbalances $I_t^{sys} = \sum_i I_t^{B_i}$ (MWh), where B_i is the i-th broker. System and broker imbalance amount can be in positive or negative magnitude. At current timeslot t:

1. If the system and the broker B_i have identical imbalance signs (e.g. $I_t^{sys} < 0$ and $I_t^{B_i} < 0$), then the broker usually pays a penalty, since it is one of the reasons of the system imbalance. Imbalance payments fund the contributing brokers (2) and ancillary services.
2. If the system and the broker B_i have different imbalance signs (e.g. $I_t^{sys} < 0$ and $I_t^{B_i} > 0$), then the broker is paid, due to its contribution to the balancing process. The payment is financed by the brokers in (1).

Fig. 1 shows the hourly balancing prices for the scenarios above. As seen, balancing unit prices dramatically differs in peak and off-peak hours.

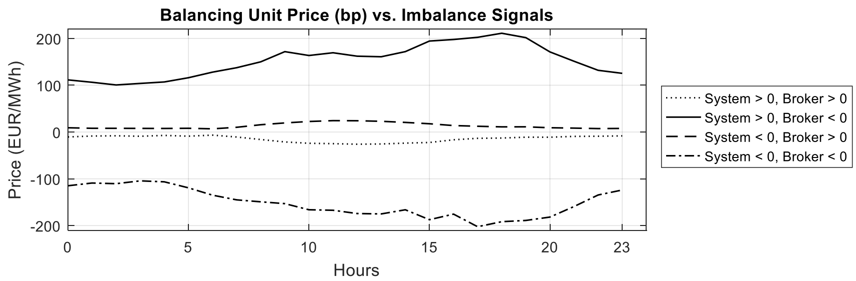

Figure. 1. Hourly average balancing prices (bp) in four scenarios. A negative price refers to the payment from broker to DU. Broker is represented by AgentUDE.

4 Imbalance Management

In AgentUDE17, we use truthful information (i.e. forecasted prices) for the energy amount. However, we do not use the forecasted prices directly since we put the strategy on the limit-price. In the next sections, we will explain how we create the demand predictions and strategic limit-prices.

4.1 Demand Prediction

As noted in Section 3.1, the accuracy of the demand prediction model is driven by the demand volatility. However, most brokers serve a wide variety of customer groups, which means producers, consumers, and prosumers are served in the same portfolio. To cope with that, we create two prediction models and a correlation coefficient to measure the demand volatility.

For low-volatile and periodic customer demands, we pick a seasonal autoregressive integrated moving average (SARIMA) model [2], $SARIMA(1,0,0)x(0,1,0)_{24}$. We can formalize it as follows:

$$\widetilde{D}_{t+n}^{lv} = (D_t - D_{t-24}) + D_{t-(24-n)} \quad (3)$$

Where $t+n$ is the n-th time slot after the current time slot t. For high-volatile customers, the model that we picked is a simple autoregressive model (AR), $AR(y)$. It can be formalized as:

$$\widetilde{D}_{t+n}^{hv} = \sum_{i=1}^{y} \omega_i D_{t-i} \quad (4)$$

Where $\sum_{i=1}^{p} \omega_i = 1$ and y is the number of autoregressive terms, experimentally set to 2. In the next step, we calculate a correlation coefficient to measure the volatility of the demand signal.

$$\rho_t = corr\left(\begin{pmatrix} D_{t-1} \\ D_{t-2} \\ \ldots \\ D_{t-24} \end{pmatrix}, \begin{pmatrix} \widetilde{D}_{t-25} \\ \widetilde{D}_{t-26} \\ \ldots \\ \widetilde{D}_{t-48} \end{pmatrix}\right) \quad (5)$$

Where $corr(a,b) = \frac{Cov(a,b)}{\sigma_a \sigma_b}$, which is known as Pearson product-moment correlation coefficient. We basically compare the actual demand vector of the most recent 24 hours and exponentially smoothed demand prediction vector of the previous day. In case of a spike in the actual demand, the coefficient converges to zero. Likewise, if the demand is periodic, the coefficient should be near one. We find the demand prediction using the formula below:

$$\widetilde{D}_{t+n} = \rho_t \widetilde{D}_{t+n}^{lv} + (1 - \rho_t) \widetilde{D}_{t+n}^{hv} \quad (6)$$

Subject to $\rho_t = 0$, if $\rho_t < 0$. Note that $\widetilde{D}_{t+n}$ is smoothed with its previous value, if exists. At the end, $\widetilde{D}_{t+n}$ poses for the predicted energy amount for the n-th time slot after current time slot t.

4.2 Strategic Price

In our strategic pricing algorithm, we use multiple balancing prices and forecasted market clearing prices to define the boundaries of the limit-price. The basic idea behind it is to increase the limit-price up to the balancing price, as the gap between the order and delivery hour closes. In our previous work, we explain how we forecast market clearing prices, using a dynamic programming approach [10]. In this work, we omit the details of the electricity price forecasting algorithm. Hereinafter, we denote forecasted market clearing prices as $\widetilde{cp}_{h''}^{h'}$, where h' and h'' are order and delivery hours, respectively.

As detailed in Section 3.2, balancing prices are the main driver of our strategic pricing algorithm. In Fig. 1, we identified four hourly balancing prices, bp_h^{++}, bp_h^{+-}, bp_h^{-+} and bp_h^{--}, where hour h is hour of day and it corresponds to time slot t as $h = t \,\%\, 24$. The first and second sign on the upper-right corner indicate the signs of the system imbalance I_t^{sys} and broker imbalance I_t^B, respectively. At current time slot t, AgentUDE updates only one of these variables with the balancing price bp_t, since the system and broker imbalances can be either positive or negative. For example, only bp_h^{+-} is updated, if the $I_t^{sys} > 0$ and $I_t^B < 0$ at time slot t. The updated balancing price is smoothed with its previous value at $t-1$, using an experimentally determined smoothing factor. At the beginning of games, initial values are needed for hourly balancing prices. Therefore, we assign the average balancing prices, shown in Fig. 1 as initial values.

As already mentioned, we use balancing prices to define the boundaries of the limit-prices at future time slots. To do that, we first reduce the number balancing price variables, and we obtain a new negative and positive balancing prices $\overrightarrow{bp}_{h''}^{-}$, $\overrightarrow{bp}_{h''}^{+}$, projected to a future delivery hour h''.

The system imbalance can accurately be predicted (whether positive or negative) for next few time slots. Therefore, we need a quadratic weight to mitigate the effect of rewarding balancing prices on a future time slot, when the time slot proximity δ increases. The proximity δ refers to distance in time slot between order hour h' and delivery hour h''.

$$\omega_{bp} = \left(\frac{\delta}{A}\right)^2 \tag{7}$$

Negative price $\overrightarrow{bp}_{h''}^{-}$ is used for bidding (e.g. buying energy) and defines the maximum limit-price in €/MWh that brokers pay.

$$\overrightarrow{bp}_{h''}^{-} = \begin{cases} bp_{h''}^{--}\omega_{bp} + bp_{h''}^{-+}(1-\omega_{bp}), & I_t^{sys} > 0 \\ bp_{h''}^{--}, & else \end{cases} \tag{8}$$

Same way, we obtain a new positive balancing price $\overrightarrow{bp}_{h''}^{+}$, which is used for asking (selling energy) and defines the minimum selling price:

$$\overrightarrow{bp}_{h''}^{+} = \begin{cases} bp_{h''}^{++}\omega_{bp} + bp_{h''}^{+-}(1-\omega_{bp}), & I_t^{sys} < 0 \\ bp_{h''}^{++}, & else \end{cases} \tag{9}$$

This way, rewarding balancing prices are weighted more when the gap (i.e. proximity δ) between the delivery hour and order hour is small.

We use forecasted prices to define the other side of the boundaries. However, we do not use them directly. Instead, we first create a mean $\mu_{h''}$ and standard deviation $\sigma_{h''}$ for a future delivery hour h'' as follows:

$$\mu_{h''} = \sum_{h'=1}^{A} \widetilde{cp}_{h''}^{h'} / A \qquad (10)$$

$$\sigma_{h''} = \sqrt{\sum_{h'=1}^{A} \left(\widetilde{cp}_{h''}^{h'} - \mu_{h''}\right)^2 / A} \qquad (11)$$

Where A is the number of opened auctions for a delivery hour, h' is the order hour. We set A as 24, which means that the first auction is enabled 24 hours before the delivery hour. For bidding, we use $(\mu_{h''} - \sigma_{h''} - \sigma_{h''})$ as the lowest limit-price, which determines the boundary along with Formula (10). Likewise, we use $(\mu_{h''} + \sigma_{h''} + \sigma_{h''})$ as the highest limit-price, which complements Formula (11).

After all, we defined the maximum and minimum limit-prices for the auction at delivery hour h''. We need another weight ω_s to determine the limit-price between the lowest and highest boundaries.

$$\omega_s = \left(\frac{\delta}{A}\right)^2 \qquad (12)$$

This weight simply mitigates the effect of balancing prices $\overrightarrow{bp}_{h''}^{-}$ and $\overrightarrow{bp}_{h''}^{+}$ on the limit-price of the delivery hour h''. After all, we define the limit-price as follows:

$$lp_{h''} = \begin{cases} (\mu_{h''} - \sigma_{h''} - \sigma_{h''})\omega_s + \overrightarrow{bp}_{h''}^{-}(1 - \omega_s), \; if \; buying \\ (\mu_{h''} + \sigma_{h''} + \sigma_{h''})\omega_s + \overrightarrow{bp}_{h''}^{+}(1 - \omega_s), \; else \end{cases} \qquad (13)$$

Limit price $lp_{h''}$ is submitted to the wholesale market along with a certain amount of energy, targeting a future delivery time slot. The amount is determined using the demand prediction algorithm, detail in Section 4.1. If the broker has already a market position for the regarded future time slot, then only the missing quantity is submitted.

5 Results and Discussions

As mentioned earlier, we deployed the presented approaches in our winning broker agent AgentUDE17. Therefore, we will analyze the tournament data (Power TAC 2017 Final) due to lack of possibility to prepare controlled experiments. In the analysis, we will show how presented algorithms affected the profitability against other brokers.

5.1 Tournament Data & Analysis Process

Power TAC 2017 Finals were played in June 2017 immediately after two trial tournaments and a qualification round. Eight brokers competed in 284 games, in the size of 3-, 5- and 8-player games. The finalist brokers were: AgentUDE [10], COLDPower17, CrocodileAgent [1], SPOT [3], VidyutVanika, ewiBroker, fimtac, and maxon17. According to the official tournament results[1], published on Power TAC website, AgentUDE, fimtac, and SPOT took the first, second and third position, respectively. After a game successfully completed, a state log file is created which contains financial and energy transactions. We transform this raw data into a relational database model. All relevant outputs were processed in MATLAB R2016b and the results are valid for Power TAC release 1.4.3.

5.2 Results

In this section, we evaluate the performance of the approaches. Note that the results do not include all the tournament data due to high computational complexity. We randomly picked 8-player games #56, #57, #58, 5-player games #93, #134, #164, and 3-player games #205, #225, #238, #240 from the Power TAC 2017 Final games, in which AgentUDE involved. All the results reflect the average of these 10 games.

We measure the performance of our demand forecasting algorithm with an error function, which is the rate of forecasted demand to actual demand. Fig. 2 illustrates the demand prediction error by time slot proximity. Fig. 3 and Fig. 4 summarize the wholesale market performance of AgentUDE.

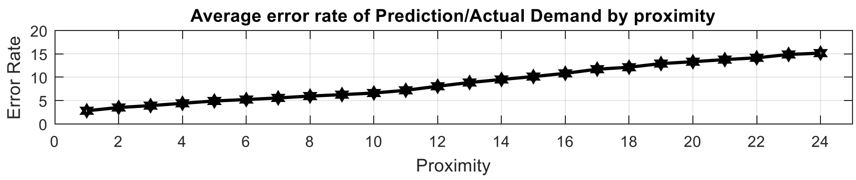

Figure. 2. Demand prediction error rate by proximity, having consumers, producers, and electric vehicle customers in the portfolio.

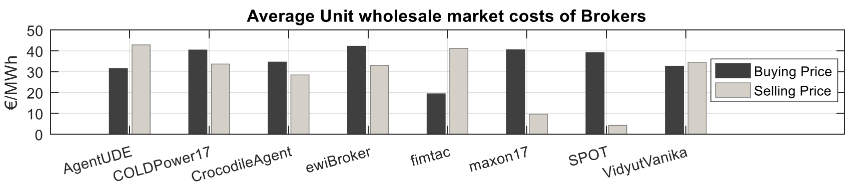

Figure. 3. Average unit costs of brokers in the wholesale market.

[1] cf. at http://powertac.org/node/96, accessed 03.10.2017.

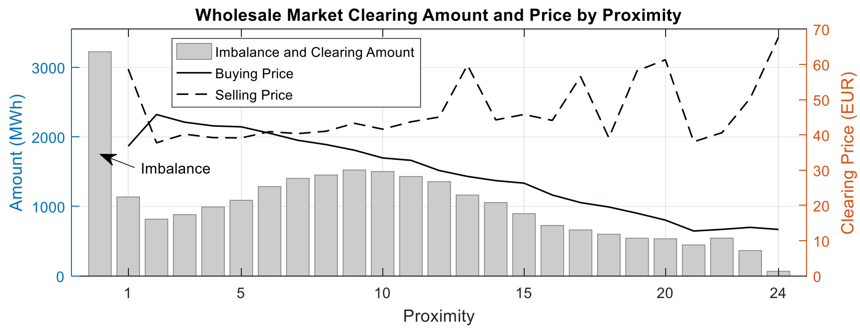

Figure. 4. Wholesale market clearing amount and average clearing prices of AgentUDE in a game (by proximity). The first column in the bar indicates the total imbalance amount.

To analyze the balancing market performance, we use several benchmarks:

- Cumulative Imbalance/Distribution Ratio $\gamma_{I/D}$: We use this benchmark to measure the imbalance ratio of brokers. We obtain the ratio, using the formula $\sum_{t=1}^{T}|I_t|/D_t$, where T is the length of a game.
- Cumulative Penalty γ_P (€): Per game cumulative penalty refers to imbalance payments from broker to the distribution utility. Positive value refers to credits which means that the broker is paid for its imbalance. We obtain it, using $\sum_{t=1}^{T} I_t bp_t$.
- Cumulative Actual Balancing Cost γ_{AC} (€): In addition to the imbalance penalty, actual cost includes neglected procurement cost. We pick the average unit wholesale market costs (AMC) from the Fig. 3. We obtain it, using $\sum_{t=1}^{T} I_t bp_t - I_t AMC$.
- Overall Unit Balancing Cost $\gamma_{AC/D}$ (€): We obtain this benchmark when γ_{AC} is divided by broker's distribution amount. Therefore, we formalize it as $\sum_{t=1}^{T} (I_t bp_t - I_t AMC)/D_t$.

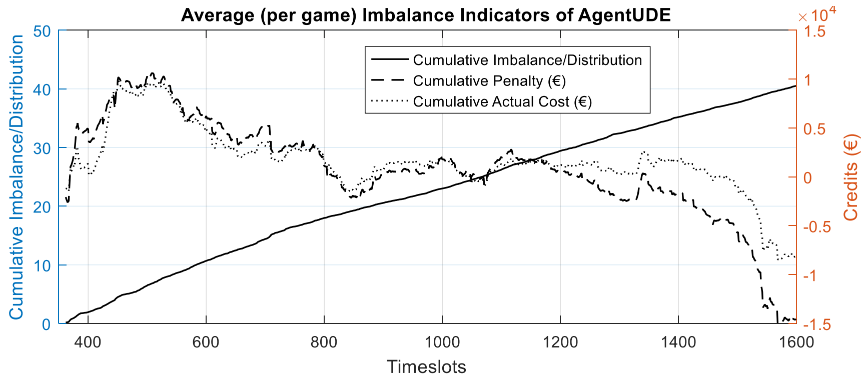

Figure. 5. Average per game imbalance/distribution ratio, cumulative penalty and the actual cost of AgentUDE over time slots.

In addition to the details of AgentUDE, shown in Fig. 5, following table compares the benchmarks of brokers.

Table 1. Comparison of benchmarks of brokers. Values indicate the average per-game totals.

Broker	$\sum D$	$\sum I$	$\gamma_{I/D}$	γ_P	γ_{AC}	$\gamma_{AC/D}$
AgentUDE	9,058	2,948	**27554**	-14,529	-8,010	**-0.89**
fimtac	8	349	3336	-43,087	-29,106	-3,611
SPOT	197	373	7373	55	-8,922	-45
ewiBroker	5,299	2,903	69	-249,346	-216,076	-40
VidyutVanika	6,950	9,084	181	-162,119	-432,389	-62
COLDPower17	5,382	4,591	886	-282,451	-205,578	-38
maxon17	12,969	2868	28	-235,071	-229,863	-17
CrocodileAgent	30,270	3,846	15	-68,735	-166,021	-5

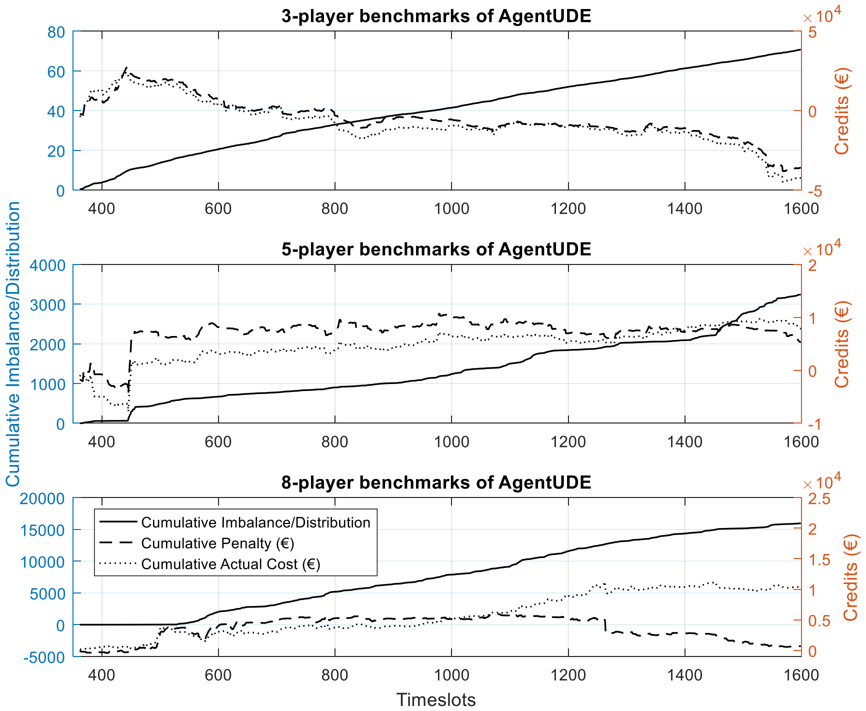

Figure. 6. Benchmarks of AgentUDE by game size.

As seen in Table 1, $\gamma_{I/D}$ performance of AgentUDE is the highest among other brokers. However, it has the lowest cumulative actual cost γ_{AC}. We use overall unit balancing cost $\gamma_{AC/D}$ to see the real performance, dividing the actual cost to the distribution volume. For this benchmark, the result is more significant, as AgentUDE has the lowest $\gamma_{AC/D}$ ratio among other brokers.

Now, we focus on AgentUDE and see how game size (i.e. number of players) affect the overall unit balancing cost. Fig. 6 illustrates the benchmarks by game size. As clearly seen, AgentUDE significantly performs better in games where a higher number of brokers compete. The reason behind this picture is that the system imbalance at a time is defined as the sum of participants' imbalances (see Formula 1). Therefore, a broker, e.g. in a 3-player game, may easily lead the system imbalance. Table 2 summaries the performances of the benchmarks. In 8-player games, AgentUDE created the highest imbalance/distribution rate with the lowest penalty payments.

Table 2. Benchmarks of AgentUDE in different game sizes.

Broker	$\sum D$	$\sum I$	$\gamma_{I/D}$	γ_P	γ_{AC}	$\gamma_{AC/D}$
3-player	21,725	4,899	70	-42,280	-35,849	-1.65
5-player	500	1,538	3,241	5,434	7,933	15.9
8-player	559	1,242	15,946	697	10,520	18.8

6 Conclusion and Future Work

In this paper, we presented a novel approach to minimize the energy procurement cost of our winning broker AgentUDE. To do that, we first implemented multiple linear regression methods to forecast future customer demands, which uses a correlation coefficient to weight the regression models. The coefficient basically measures the stationarity of the aggregate demand. Therefore, it determines the weight of short-term and long-term regression model on the fly. Secondly, we implemented a strategic wholesale bidding algorithm, which transforms forecasted prices into strategic prices depending on the system and broker imbalance. Basically, AgentUDE leaves intentional imbalance, when the distribution utility rewards the imbalance.

Results show that AgentUDE has the lowest imbalance cost (even negative) and the highest imbalance amount among other brokers. After all, AgentUDE legally exploits the balancing market, which means that all parties, contributed to the balancing problem are satisfied. The algorithm in the paper may not be applied to real-world power systems in some regions due to the limited market operations. However, it is fairly transferable to the future energy markets once electricity grids hopefully digest the smart grid programs, such as demand response and distributed generation.

Broker agents trade in a highly dynamic environment. This means that they deal with a huge number of variables on the go. 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 in such dynamic environments. As a part of this project, we plan to replace the strategic bidding algorithm in the paper with an evolutionary bidding mechanism since we think that autonomous traders (not limited to power traders) needs an advanced self-evaluation structure to fully explore the search space and adapt themselves quickly.

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