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CrocodileAgent 2018: Robust Agent-based Mechanisms for Power Trading in Competitive Environments

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Abstract. Besides the smart grid, future sustainable energy systems will have to employ a smart market approach where consumers are able choose one of many different energy providers. The Power Trading Agent Competition (Power TAC) provides an open source, smart grid simulation platform where brokers compete in power brokerage. This paper presents CrocodileAgent, which competed in the Power TAC 2018 finals as a broker agent. The main focus in the design and development of CrocodileAgent 2018 was the creation of smart time-of-use tariffs to reduce peak-demand charges. CrocodileAgent 2018 was ranked third in Power TAC 2018 Finals, with a positive final profit and a positive result in each of three game types. In addition, CrocodileAgent 2018 had the highest percentage of "profitable games" (91%) from among all competing agents, the second highest level of "net profit per standard deviation" (0.48) and the third highest "net profit per subscriber" (79 monetary units).

Keywords: computer simulation, agent-based modelling, electricity trading, tariff design, Power TAC, CrocodileAgent

1. Introduction

Environmental challenges like pollution and CO2 emissions have recently become one of main drivers for innovations within the energy sector [9]. The common denominator for innovations is changes which make the world a better living place for current and future generations, and is a key concept behind sustainable development [28]. Given the importance that decision makers possess a holistic view when considering sustainability issues [27], the electricity market is a particularly relevant area of research as it directly deals with the triple bottom line, *i.e.*, social, environmental (or ecological) and financial aspects of the energy industry.

Evidently, the ever-increasing efforts to include renewable energy sources, such as wind turbines and solar systems, in the existing *energy layer* of a power system aim to address the *environmental part* of sustainability. Large-scale producers (*e.g.*, coal-based power plants), as well as small-time producers, also known as *prosumers* (*e.g.*, individual households with solar panels), end-consumers and energy brokers (*i.e.*, entities which essentially act as mediators between large-scale producers and end-consumers), are examples of highly heterogeneous *social* groups that exhibit potentially conflicting objectives. For example, producers often seek to maximize profit which in turn negatively affects the consumer objective of minimizing electricity costs. In order for stakeholders to work in such progressively complex market environments, the *smart grid* is seen as an essential technical solution because it allows entities to connect and exchange information by implementing the *ICT layer* within the power system as well as enabling a two-way flow of electricity [12].

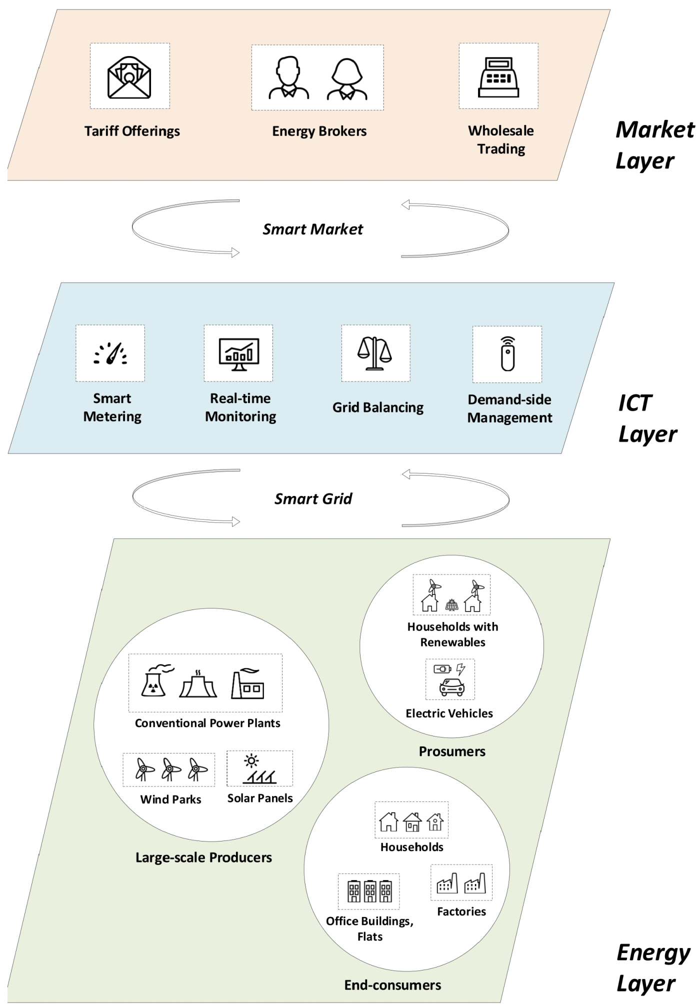

Fig. 1. A multi-layered concept of the next-generation power system (adapted from [2]).

However, as seen in Figure 1, it is evident that the smart grid is only a *technical foundation* for the next-generation power systems. In order to have a truly sustainable energy system of the future, one needs to *design*, *evaluate* and *implement* the *market layer* which ultimately provides added value for both market participants and end-consumers [2]. For example, until recently, end-consumers found themselves in highly-regulated environments and were tied to a single energy supplier, an approach that may not have been so market efficient. On contrary, with new functionalities now offered by smart grids (*e.g.* smart metering), end-consumers can receive and react to price signals from numerous energy suppliers, and thus have an active role in the newly-formed *smart market* [7].

Undoubtedly, designing this kind of market is not straightforward due to the need to overcome numerous inherent challenges. Perhaps the most intriguing challenge relates to system *complexity* which stems from complex interactions of heterogeneous entities. As opposed to other commodity markets (e.g., soft commodities like wheat, coffee and fruit), the electricity market is different due to certain intricacies related to electricity. That is, electricity must be used *instantly* when generated, meaning that *supply must match demand* exactly at any given time across the grid.

The scope of this work focuses on the trading mechanisms that a power broker usually utilizes on the electric power market in order to mediate electricity supply from producer to consumer. When it comes to brokering, a successful power broker is expected to maintain a profitable retail customer portfolio. To do so, a power broker is also required to have a compatible strategy on the wholesale market in order to meet customers' demand for energy. Since the electric power system is a critical resource for consumers, it is exceptionally important that the broker deploy mechanisms which have been *thoroughly tested* beforehand. Accordingly, researchers nowadays often resort to computer simulations that provide a highly-detailed computational model of the real-world system [1] [10]. Once the computational model is implemented, the entities within the model can be adjusted to evaluate and quantify the impact of certain interactions within the system in a risk-free environment. Hence, this paper follows the same principle by using an open source simulation platform called Power Trading Agent Competition (Power TAC) to evaluate robust trading mechanisms which are encoded within the agent-based [25] [6] power broker called CrocodileAgent. Within the scope of this work, *robustness* of trading mechanisms refers to the ability of a power broker to be competitive in the majority of scenarios regardless of the competition size. The result obtained from the annual Power TAC world competition 2018, *i.e.*, third place against 6 broker agents prepared by other research groups, demonstrates the applicability of the proposed trading mechanisms in competitive environments.

To summarize, the contribution of this paper comprises the following two parts: (i) design and implementation of robust agent-based mechanisms for power trading in next-generation power systems; and (ii) evaluation of the proposed mechanisms based on data from the Power TAC 2018 world competition.

The rest of the paper follows a specific structure. Section 2 presents the Power TAC simulation platform and its simulation scenario which resembles the real-world next-generation power system. Section 3 presents the proposed trading mechanisms by explaining the key design choices for the CrocodileAgent 2018 broker agent. Section 4 analyses and evaluates the CrocodileAgent 2018 using data generated from the Power TAC 2018 world competition. Section 5 concludes the paper and presents directions for future work.

2. Power Trading Agent Competition

2.1. Simulation Platform

The Power Trading Agent Competition (Power TAC) started as a collaboration between six European and North American universities. The goal was to create an open-source, competitive simulation that models a "liberalized" retail electric power market, where competing business entities offer energy services to customers through tariff contracts, and must then serve those customers by trading in a wholesale market [15] [13]. An attempt was made to introduce this kind of liberalized electric power market in California in 2000, eventually resulting in a major energy crisis [31], and leading to the conclusion that additional research and simulation was necessary in determining the regulatory framework for such a market where Power TAC, as a computational model of the electricity market, is an efficient way of achieving that in terms of time and costs.

Power TAC requires that competing teams establish trading agents or "brokers" that aggregate supply and demand in order to earn a profit. Brokers may buy and sell energy through contracts with retail customers and by trading in a wholesale market modelled after the European and North American wholesale energy markets. In the customer (tariff) market, brokers offer tariff contracts to a population of customers which may include fixed or variable prices for both consumption and production of energy, incentives for energy conservation, sign-up bonuses or early-withdrawal penalties. The wholesale market enables brokers to buy and sell energy for future delivery while the balancing market is responsible for real-time balancing of supply and demand on the distribution grid.

The initial version of the Power TAC platform was released in 2011. Power TAC is designed as an annual tournament with the first competition held in 2013. Usually, 6 to 11 participants from universities and research centres around the world compete in the tournament. In this tournament environment, simulations are run with different numbers and combinations of broker agents, and the most profitable agent over a range of scenarios is the winner [14]. After the tournament, participants typically present and discuss their work on relevant conferences and publish scientific papers [5]. Teams are encouraged to release their agent code, so that all teams can experiment with a range of different agent behaviours, thus improving their agent designs for the following year. Each year, the scenario is updated with new challenges, tuning market designs and adding a new level of realism. Changes in the 2018 scenario were focused on stability, simplifying interaction with the balancing market, and on encouraging more vigorous competition [15].

2.2. Brokers

In Power TAC, brokers are trading agents competing against each other to maximize their profits. In each time slot (one-hour simulated time period), a broker can offer or modify tariffs on the *tariff market*, submit a balancing order on the *balancing market* as well as submit asks and bids on the *wholesale market* to sell or procure energy for future time slots. The simulation server simulates *large-scale producers*, *prosumers* and *end-consumers* and their communication with corresponding markets, exposing only those markets to the energy brokers as shown in Figure 2. Brokers get weather forecast information, wholesale market clearing data, tariff transactions, portfolio supply and demand, including market and cash position from the simulation server each time slot. Apart from trading in markets, broker should balance its overall supply and demand, as any surplus or deficit of energy will be covered by the distribution utility at a very unfavourable price. A broker balances its portfolio by acquiring producers and consumers that balance each other in real time, by acquiring storage capacity, controllable consumption and production capacity that is used as needed, and by trading future contracts on the wholesale market. Given that consumer consumption of electricity and production of energy from renewable sources is a variable factor, brokers need to have methods for forecasting energy consumption and production as precisely as possible in order to provide consumers with the required amount of energy and balance supply and demand. To provide further insight into a broker's main responsibilities and best strategies, this paper will next review literature on the most successful brokers that competed in Power TAC, i.e., TacTex, cwiBroker and AgentUDE.

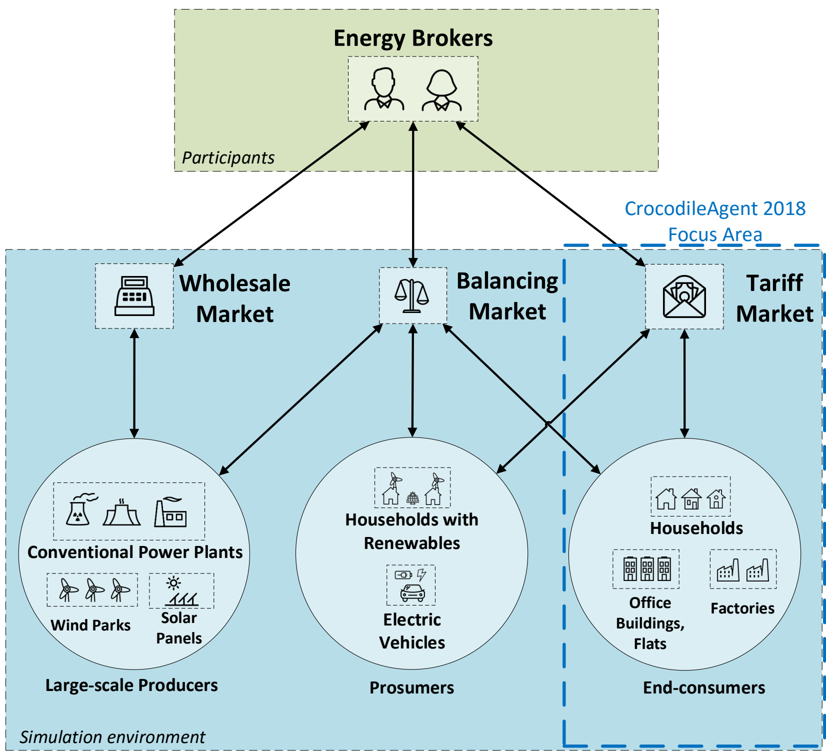

Fig. 2. Relations between Power TAC brokers and the simulation environment; the focus of CrocodileAgent 2018 was on designing and implementing successful tariff market mechanisms

TacTex was the champion in the 2013 inaugural competition [29]. It operates simultaneously in multiple markets and aims to increase the cash amount in its bank account which is treated as its utility measure. It maximizes its utility by simultaneously optimizing energy-selling prices, total energy demand from its customers and energy procurement costs. The wholesale market bidding strategy of the TacTex 2013 broker is to collect market data and estimate market demand in order to minimize energy procurement costs. Its estimates improved during the game as more and more data was collected using an online reinforcement learning algorithm, optimization and adaptation of the bidding strategy to the specific market conditions in the game. Given the predicted energy demand and cost, TacTex in 2013 optimized future demands and selling-prices in the tariff market. Furthermore, the broker performed best in games with a small number of competitors, winning 6 out of 6 two player games and 15 out of 16 four player games.

The second-placed broker in the 2013 and 2014 Power TAC finals was cwiBroker [18]. The competitor cwiBroker endeavoured to balance its demand and supply by estimating the production and consumption of each type of customer. In the tariff market, its strategy varies depended on the type of game. If it was a duopoly game, the broker was initially competitive and then, after obtaining a reasonable number of customers, it copied its competitor's tariff price. In games with three or more players, the broker was more competitive by devising a set of tariffs, estimating the amount of profit achieved using a particular tariff and publishing the most profitable tariff. The wholesale bidding strategy used by cwiBroker was to buy energy at bargain prices in the first auction for each timeslot and then sell the surplus in later auctions at higher price. The competitor cwiBroker performed best in games with a high number of players, winning all seven player games.

AgentUDE was the winner of the 2014 [22] [20] and 2017 [23] [24] Power TAC finals and was ranked among the top 4 in 2015 and 2016. It stores historical data in a local repository which was subsequently evaluated using the wholesale and tariff module while creating future values for the retail and wholesale markets. In the wholesale market, AgentUDE predicts market trends regardless of weather conditions by tracking historical market data [21]. In the tariff market, it deploys an aggressive tariff strategy. The broker endeavors to offer the cheapest tariff, thus provoking other brokers to publish cheaper tariffs and triggering tariff penalties which translated into profit. The change in the 2015 Power TAC specification which added peak-demand charges for brokers whose customers spend the largest amount of energy in peak times required a change in broker behavior. To reduce peak-demand charges, AgentUDE used a time-of-use tariff price scheme with different rates depending on the time of day and day of week to encourage customers to avoid consumption during peak hours.

Previously mentioned brokers were designed with the aim to participate in the Power TAC world competition. However, Power TAC as a platform can also be used in a so-called *research mode* in which researchers are able to conduct *in vitro* experiments for exploring various research questions related to the next-generation power system. One such a research example is the work by Rubio el al. [26]. Concretely, the authors used fuzzy models to develop the so-called TugaTAC broker agent. The key mechanism is based around on updating tariffs using a conceptual model for agent's interest on selling or buying energy. Based on the input the broker receives from the environment, the fuzzy model helps the broker in improving tariffs with the aim to attract the best profile of clients. The proposed mechanism is benchmarked against the default broker and several brokers from the Power TAC 2014 competition. The same evaluation approach was used by Wang et al. for the sake of testing mechanisms implemented within the GongBroker agent [30]. Such a broker utilizes a hybrid-learning approach which includes a data-driven method for predicting short-term customer demand, a Markov Decision Process (MDP) for activities on the wholesale market and reinforcement learning for activities on the retail market. The use of MDP in wholesale activities was also investigated by Kuate et al [17] within the AstonTAC broker agent. It is important to notice that our work is different than previously mentioned brokers in terms of the focus area, *i.e.*, improvements on the retail market activities based on the idea of avoiding peak-demand charges. Furthermore, one can conclude that our work has a stronger validation due to the fact the analysis was performed based on data from the latest Power TAC 2018 world competition.

Considering the approaches used by the above-mentioned broker agents, it is evident that Power TAC is the community-driven simulation platform evolving after each annual cycle [16]. Once the game specification is updated, broker agents need to make careful adjustment to stay competitive in new tournaments. Furthermore, given the complexity of the simulation platform, successful research teams often opt to specialize their broker for a certain trading task. For example, instead of developing an all-around broker, research teams might only focus on developing solutions aimed at retail consumption customers. Finally, judging from the results of the previous annual competitions, it becomes evident that different broker teams were successful in different years. This suggests that broker teams who fail to devise innovate designs for each annual competition are likely to be less competitive and underperform. For example, the CrocodileAgent broker [19] [3], after initially obtaining encouraging results, including fourth and third places in the 2013 and 2014 tournaments, experienced a gradual decline in performance before eventually dropping to last place in the 2017 tournament. The next section explains how the latest iteration of the CrocodileAgent broker, CrocodileAgent 2018, succeeded in significantly improving its competitiveness by focusing on innovations in tariff structure pricing with the specific aim of stabilizing unwanted risk exposure and negative fees.

3. Power Broker Design: CrocodileAgent

In general, broker agent actions in Power TAC can be summarized by three key interactions that occur in the following sequence: (i) publishing tariffs on the retail market to attract customers at an attractive consumer price point; (ii) purchasing energy at a competitive price for future time-slots to satisfy customer energy demand; and (iii) balancing energy supply-demand for each time slot to reduce over- or under-purchasing of electric energy. Given that the broker is a software product, organizers of the Power TAC provide dummy agent code in the Java programming language which is then used by research teams to code their brokers.

The key principle behind the CrocodileAgent broker is a modular design to facilitate integration of newly-developed mechanisms for power trading. That being said, broker functionalities are categorized into three sections: (i) wholesale market operations; (ii) retail market operations; and (iii) internal portfolio tracking that enables the agent to successfully participate in both the wholesale and retail market. Figure 3 showcases a modular approach used in the CrocodileAgent design and implementation. The *Wholesale Manager* module is responsible for activities in the wholesale market. The main goal of the module is to implement the efficient purchase of energy with respect to the price of power because the arrangement enables the broker to earn potentially significant profits. However, to make the appropriate trades on the wholesale market, the module requires the information on demand for power from retail customers. To enable such an information, the *Portfolio Manager* module is used to actively track customer behaviour of all subscribed customers. In the retail market, the main objective is to have the most efficient resale of inventory, while taking into account prices from the wholesale market as well as demand for power from retail consumers. Operations in the wholesale and retail markets are highly interconnected. The behavior of CrocodileAgent 2018 regarding retail activities is encoded in the following modules: *Tariff Manager* is used to evaluate a tariff price, based on input from the wholesale market; *Smart Tariff Creator* is used to create tariffs based on multiple options (*e.g.,* tariff types and special conditions such as early withdrawal fees); and *Tariff Rate Creator* is used to create individual tariff rates which depend on the desired margin effects that each tariff is expected to exhibit.

3.1. Data-driven Strategic Planning

Given that agent trading within the Power TAC framework is characterized by competitive game interactions, the assumptions and initial approach can be modelled using *game theory* and *financial economics* based on participant interactions and profit opportunities.

Power TAC trading interactions simulate an environment using several players (brokers). The assumption is rational behavior by brokers endeavouring to maximize their individual profit. It is worth pointing out that the rules of Power TAC forbid any kind of *collusion* and that all competition information is publicly available to the agents. Hence, one can use the *Efficient Market Hypothesis (EMH)* to assume that the power brokerage

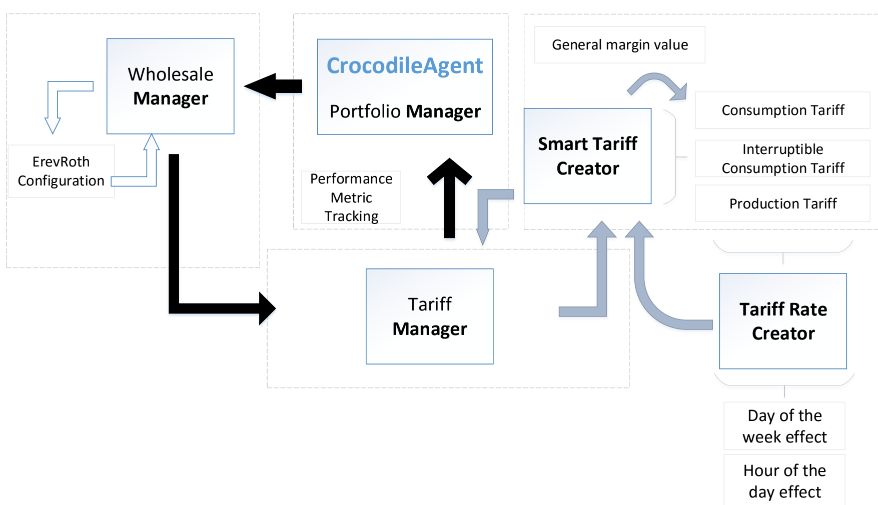

Fig. 3. Interactions among CrocodileAgent modules for wholesale and retail operations

market should be efficient or weakly efficient, creating a stable equilibrium where the profits of individual agents converges towards zero or into negative territory in a competitive environment. The EMH direct implies the impossibility of "earning profit" consistently on a risk-adjusted basis given that market prices in both the retail and wholesale sectors should incorporate all available information [11].

To establish novel trading mechanisms, an extensive post-mortem analysis of CrocodileAgent performance was conducted based on data from the previous world competition (*i.e.*, Power TAC 2017). In general, organizers of the Power TAC world competition record the following data which can be used for elaborate analysis:

– *aggregated per-tournament data* reports the financial balance of each broker and determines the winner of the tournament;
– *aggregated per-game data* reports the financial balance of each broker for a game; and
– *raw per-game data* allows for detailed inspection of a particular game.

For reference, Table 1 summarizes the results of Power TAC 2017. Performance from that year was used to initially target CrocodileAgent behavioral changes.

Table 1. Power TAC 2017 final results (in Mln "monetary units" and normalized)

	Profit by game size (in Mln)				*Z-score by game size*			
Broker	**7 brokers**	**4 brokers**	**2 brokers**	**Total**	**7 brokers**	**4 brokers**	**2 brokers**	**Total**
AgentUDE	-7.37	5.12	66.79	*64.53*	0.54	1.22	1.83	*3.58*
fimtac	-4.23	-7.61	0.07	*-11.77*	0.58	1.10	1.17	*2.85*
SPOT	-12.75	-11.21	0.06	*-23.90*	0.47	1.07	1.17	*2.70*
VidyutVanika	-9.33	-69.92	-36.93	*-116.18*	0.51	0.54	0.80	*1.85*
ewiBroker	-37.44	-32.98	-40.54	*-110.96*	0.14	0.87	0.76	*1.77*
COLDPower17	-25.30	-63.44	-55.28	*-144.02*	0.30	0.60	0.62	*1.52*
maxon17	-41.48	-158.20	-110.94	*-310.62*	0.08	-0.26	0.07	*-0.11*
CrocodileAgent	-241.96	-310.75	-176.95	*-729.65*	-2.61	-1.63	-0.58	*-4.82*

A highly competitive environment is evident due to small profits achieved in Power TAC 2017. The majority of brokers achieved a negative profit and loss (PnL) irrespective to the game size, implying that retail energy brokerage is effectively efficient (see Table 1). After taking a closer look at the reasons for sub-optimal performance in 2017 (*i.e.*, CrocodileAgent was ranked last), the conclusion is that CrocodileAgent 2017 was too aggressive on the retail market which ultimately resulted in high costs on the balancing market. The reasonable solution to this detrimental behaviour is to design a more *defensive approach* in an attempt to preserve capital and minimize risk exposure both on the wholesale as well as retail market. In practical terms, the key mechanism behind the risk aversion strategy for purchasing and selling energy lies in prudent markup pricing for both trading markets.

When it comes to modeling brokerage interaction, the primary goal for CrocodileAgent 2018 was to correctly *price in* the risk exposure from its actively participation in the wholesale and retail markets. Adverse risk exposure consists of direct costs (*e.g.*, electric energy purchasing price) and indirect costs (*e.g.*, inventory imbalance), hence the main target actions on the market are twofold: (i) *tariff publishing* needs to implement markup for pricing exposure to potential customer actions; and (ii) *wholesale purchasing* needs to be performed at an adequate price point to minimize negative exposure on the balancing market.

Given general strategy of CrocodileAgent, the implemented margin change needs to be sufficient to cover the mentioned costs using the following equation for achieving a return in a specific time slot:

$$r_t = profit_R + profit_W - cost_t \tag{1}$$

where r_t is the net return in time slot t, $profit_R$ is the profit from the retail market, $profit_W$ is profit on the wholesale market and $cost_T$ includes total time slot fees and costs from brokerage operations.

If we assume that profit is achieved directly through brokerage operations, net return can be summarized using a more detailed formula:

$$r_t = quantity_t * price_W * margin_R - cost_t \tag{2}$$

where $margin_R$ is the mean margin across mean energy quantity $quantity_t$ bought at the wholesale price $price_W$ and reduced by the total time slot fees and cost from brokerage operations $cost_t$.

The main hidden cost in Power TAC trading that may impose an *unexpected cost* for the broker are stochastic events resulting from indirect or direct broker actions on the retail market. These costs may occur if a broker fails to purchase an adequate amount of energy. In that case, as a negative consequence, the distribution utility steps in at the specific time slot to provide the required energy. In doing so, the distribution utility also penalizes the broker for failing to maintain the energy balance. Also, the broker may face severe losses in the form of transmission capacity fees for energy transmission when exposed to the grid capacity utilization event. Since the Power TAC scenario considers a broker's contribution to the overall grid load peak by looking into the broker's peak exposure (*i.e.*, broker's contribution to peak demand) and average grid load, each broker is taxed for the maximal grid load proportional to the broker's contribution to peak demand events [15].

The initial analysis of historic Power TAC logs and experimentation with CrocodileAgent has shown that the transmission capacity cost was several orders of magnitude higher than the expected gain. Furthermore, data from experimental simulations and the Power TAC 2017 world competition confirmed two findings. First, it was discovered that the margin for attracting customers in Power TAC is generally low due to competition. Furthermore, as the number of brokers increases, the average tariff margin decreases, and it approaches zero or even a negative value of having a chance to attract customers. Second, simulations have confirmed that penalized costs imposed on Power TAC agents were primarily driven from capacity fees and distribution fees. This conclusion is valid for Power TAC 2018 as well, as is evident in Figure 4 and which presents the cost breakdown for the Power TAC 2018 competition.

The tendency of setting attractive rates for customers is heavily mitigated by the fact that the stochastic nature of the electric peak grid cost provides a heavy bias towards losses in a competitive environment. To mitigate this effect, our approach included in the CrocodileAgent 2018 design was to offer tariffs which amplified margins during hours where the probability of peak energy exposure was the highest.

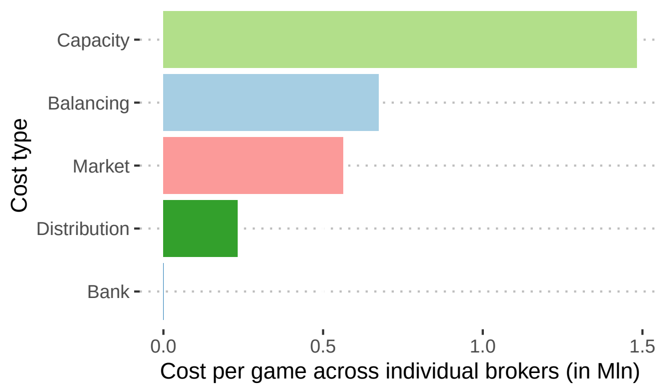

Fig. 4. Breakdown of average broker costs in a Power TAC 2018 game

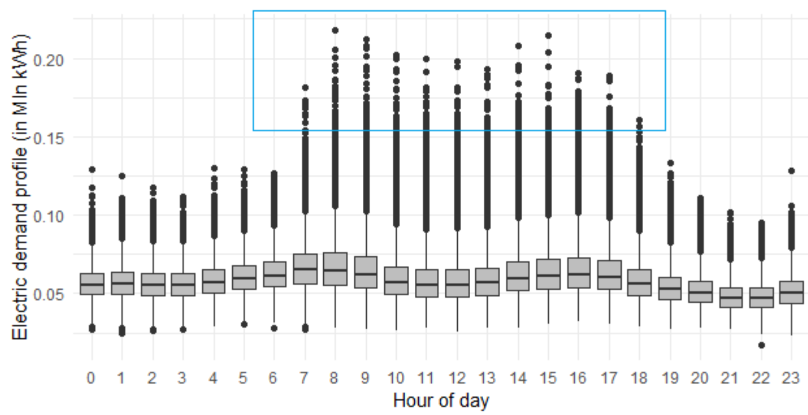

Fig. 5. Box-plot of Power TAC 2018 average in-game electric net demand per hour of day showing that the peak demand occurs usually between the hours 7 am and 6 pm

Experimentation confirmed two major areas that may affect a broker with the highest peak exposure (see Figure 5): (i) the early morning period when people are going to work; and (ii) the afternoon period when people are returning from work. Additionally, sporadic capacity events were identified for the midday peak period (*e.g.*, air-condition period during summer). In CrocodileAgent 2018, we divided the necessary margin hikes (*i.e.*, margin increases) during those periods into internal "medium" and "high" coefficients depending on the peak exposure. By design, this provides a twofold utility for the broker: (i) it hikes the tariff price necessary to cover the expected average exposure to potential losses; and (ii) it discourages consumers from using power during those periods in order to minimize penalization costs for the broker.

Peak exposure is penalized on a weekly basis by pricing the top energy peaks which were above peak threshold (*i.e.*, dynamically calculated value based on mean and standard deviation of the net demand from the previous time slots). Figure 6 shows a load curve

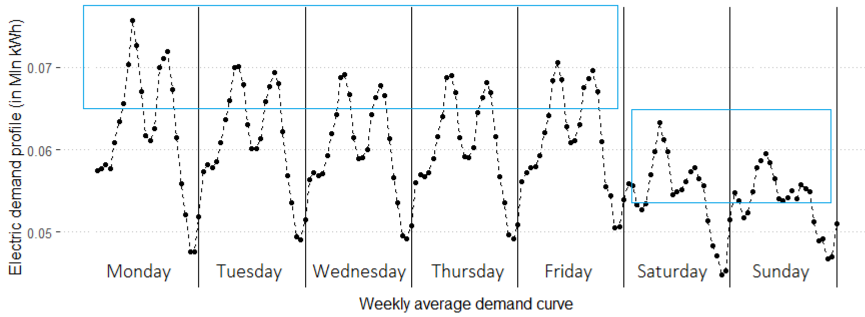

Fig. 6. Characteristic Power TAC 2018 load curve showing the lower peak average energy demand during the weekend (compared to working days)

for a typical week generated by consumers in Power TAC. Since working days usually consumer higher amounts of energy, peak exposure is primarily dictated by a probability distribution heavily favoring Monday to Friday. In contrast, exposure on the weekend follows a comparatively lower energy load and, consequently, the probability of a lower peak cost exposure.

3.2. Retail Mechanisms

Retail mechanisms at the disposal of the Power TAC agents revolve around tariff broadcasting and managing customer portfolios. Obviously, a profitable tariff design, a crucial prerequisite for an agent's competitiveness, is based on evaluation of a customer's tariff expense throughout the subscription lifetime. Power TAC models customers realistically whereby it evaluates all competing tariffs and generally subscribes to the most favorable tariff (one that has the highest profitability or lower cost for the customer). It is worth pointing out that customers are based on a logic choice model augmented with a stochastic (random) parameter for tariff assessment. Nevertheless, the parameter proved to be non-significant in the tariff assessment across the customer portfolio given that the random effect (*i.e.*, client irrationality) during the tariff assessment phase is evenly distributed across competing tariffs. Hence, generally speaking, no broker has an effective advantage over this process [15].

CrocodileAgent 2018 uses three types of tariffs for the retail market: *Consumption Tariff* is a general-purpose consumption tariff for broad retail customers; *Interruptible Consumption Tariff* is a consumption tariff that can curtail the electric load for a desired proportion of the client power usage and shift a clients energy load to other time slots; and *Production Tariff* is a tariff which enables the purchasing of energy on the retail market from producers such as solar homes.

Taking into account the above-mentioned tariffs, an agent's responsibility is to find a profitable solution to the brokerage problem of selling and buying energy. The following mechanisms were used to optimize the broker's performance on the retail market:

– *Time of use effect*: a rate which is directly tied to the hour of the day to which it applies. It provides an opportunity to have higher or lower prices during the day in order to effectively exercise tiered pricing on the consumer tariffs.

- *Weekday / weekend rate effect*: an effect that explicitly governs the intra-week behavior and adjusts the tariff price by tiers.
- *Signup payment value*: a positive payment value for the customer as a bonus for signing up to the tariff.
- *Minimal subscription duration value*: the minimum subscription length duration that governs the early withdrawal penalty trigger.
- *Early withdrawal penalty*: a penalty for withdrawal during the lockup period. This modifies a customer switching options in order to penalize customers from exploiting the sign-up payment opportunity and turning to a more favorable tariff.

In addition to the above-mentioned factors, two additional risk pricing values in tariff creation have been used as a floating component (corrective mechanism for tariff price modification) in defining the rate of the tariff:

- *Margin impact coefficient* (Ci): a coefficient used to update different rates with a desired margin hike to adjust for potential transmission load exposure and risk exposure.
- *Margin coefficient corrections* (Cc): a discounting factor used to attract customers by lowering impact coefficients.

CrocodileAgent 2018 corrects the tariff price according to the following equation:

$$TF = Price * (1 + margin_R) * Ci/Cc \tag{3}$$

where TF is the tariff price structure, $Price$ is an average wholesale price, $margin_R$ is a general margin set by the broker and Ci and Cc are the above-mentioned coefficients calculated separately for a different hour of the day or day of the week. The calculation of Ci and Cc is based on an extensive set of experimental simulations with publicly available brokers from the Power TAC 2017 world competition.

3.3. Wholesale Mechanisms

Even though the focus of CrocodileAgent 2018 is on the retail market, taking into account the wholesale market for procurement of required energy remains is important. In general, the agent estimates the subscription count and energy demand for future time slots and uses bidding strategies to place orders for estimated energy while endeavouring to minimize negative effects from the balancing market.

Implementation of bidding strategies relies on the Erev-Roth reinforced learning method for finding the optimal strategy for minimizing the above-mentioned cost function [4]. The main sub-module consists of (i) *bidding strategies module*, (ii) *reward module* and (iii) *weighted randomizer* module. The optimization cycle follows a pattern where bidding strategies are chosen based on the reward module, while their probability of selection is dictated by a weighted randomizer from the probability distribution.

Since brokers can trade up to 24 hours in advance (*i.e.*, power trading in the Power TAC simulation framework operates as a day-ahead market), the wholesale mechanism is modified to trade up to 24 times for the desired time-slot until the time-slot effectively starts. This enables CrocodileAgent to track progress of numerous wholesale trades as well as to bid for every time slot while continuously updating its reward function. It is worth mentioning that the initialization parameters of CrocodileAgent (*e.g.* learning parameters for Erev-Roth and margin impact coefficient) are empirically derived and calibrated from an extensive set of experimental simulations publicly available to brokers at the Power TAC 2017 world competition.

4. Evidence from a World Competition: Power Trading Agent Competition 2018

4.1. Competition Setup

As already mentioned, Power TAC is a community-driven project that keeps evolving after each competition cycle on a yearly basis. That said, the organizers of the Power TAC 2018 world competition have introduced several changes in comparison to previous iterations. Apart from many minor updates, the key changes in Power TAC 2018 aim to increase software reliability, simplify interactions within the balancing market as and encourage a higher level of competition [15].

Competition rules specify that each research team needs to prepare a software agent based on the provided Java-based dummy agent, which then acts as a competitive broker within the Power TAC simulation scenario. Furthermore, during the competition, each research team is expected to run two instances of the same agent so that the organizers can schedule multiple independent games which can be played simultaneously in order to reduce time. The main idea behind multiple independent games is to run different scenarios according to the plentiful game initialization parameters, including game size (*i.e.*, number of competing brokers in a particular game), random seed number (*i.e.*, to influence stochastic elements in the game), initialization parameters for customers (*e.g.*, number of consumers), weather (*e.g.*, input data for weather reports), and the wholesale market (*e.g.*, input data for wholesale prices). The main objective of this arrangement is to expose the brokers to various simulations scenarios which in turn has two important implications:

- research teams are discouraged to fine-tune their brokers for a specific default game scenario, instead, they need to come up with *trading mechanisms which can perform in different contexts*; and
- the data produced during the world competition is particularly valuable for *evaluating trading mechanisms as it enhances generalizability of the research results*.

Obviously, one can conclude that Power TAC, when used in a world competition setting, is a reasonably complex distributed system which assumes the active involvement of many stakeholders, including *organizers* who supervise the competition, a *technical crew* for maintaining hardware infrastructure where Power TAC simulation servers are deployed, and *research teams* who need to monitor their brokers in order to secure a reliable connection with remote Power TAC simulation servers. To make sure competition is credible and complies with the rules, the organizers of Power TAC 2018 allowed research teams to test their brokers before the start of competition during two trials which took place in May 2018 and June 2018. After the trials, the qualifying round took place in June 2018. All broker agents that performed to the rules during the qualifying round were allowed to enter the finals which took place from 16 to 27 July 2018. All analyses presented in the next subsections are based on data from the Power TAC 2018 finals.

4.2. Competitors

The entry list in the 2018 competition included the following broker agents from seven international research teams:

– **AgentUDE**, Universitaet Duisburg-Essen / DAWIS (*Germany*);
– **Bunnie**, Nanyang Technological University (*Singapore*);
– **COLDPower18**, INAOE/CICESE-UT3 (*Mexico*);
– **CrocodileAgent**, University of Zagreb (*Croatia*);
– **EWIIS3**, University of Cologne (*Germany*);
– **SPOT**, University of Texas at El Paso (*Texas, USA*); and
– **VidyutVanika**, IIIT Hyderabad (Machine Learning Lab) and TCS (*India*).

The following three different game types were used in the Power TAC 2018 finals: (i) two-broker games where a broker is competing against another broker; (ii) four-broker games where a broker is competing against three other brokers; and (iii) seven-broker games where all of the above-mentioned brokers compete in the same game.

The CrocodileAgent performance in Power TAC 2018 finals was extensively assessed from a total of 324 games with the following breakdown:

– 84 instances of 2-broker games (24 games with CrocodileAgent participating)
– 140 instances of 4-broker games (80 games with CrocodileAgent participating)
– 100 instances of 7-broker games (all 100 with CrocodileAgent participating)

Table 2 shows the final results. It is evident that CrocodileAgent in Power TAC 2018 secured a respectable third place with a positive final PnL in the total result and a positive individual result in each of the three game types.

Table 2. Power TAC 2018 final results (in Mln and normalized)

	Profit by game size (in Mln)				*Z-score by game size*			
Broker	**7 brokers**	**4 brokers**	**2 brokers**	**Total**	**7 brokers**	**4 brokers**	**2 brokers**	**Total**
AgentUDE	49.96	62.14	134.91	*247.01*	1.09	0.63	1.57	*3.29*
VidyutVanika	48.20	101.94	47.54	*197.68*	1.06	1.06	0.34	*2.45*
CrocodileAgent	27.66	45.44	62.88	*135.98*	0.65	0.45	0.55	*1.65*
SPOT	-6.98	32.98	49.18	*75.19*	-0.04	0.32	0.36	*0.64*
COLDPower18	2.06	10.29	0.52	*12.88*	0.14	0.08	-0.33	*-0.11*
Bunnie	-67.98	-25.05	-19.60	*-112.63*	-1.25	-0.30	-0.61	*-2.16*
EWIIS3	-87.27	-206.96	-109.80	*-404.03*	-1.64	-2.25	-1.88	*-5.77*

4.3. Game Size Sensitivity Analysis

The most favorable game type for CrocodileAgent 2018 were the “2-broker games”, where the agent went head to head against other brokers. It is worth pointing out that other game sizes were also ranked favorably by CrocodileAgent 2018 and were generally within the similar competitive advantage area. This leads to the conclusion that the performance of CrocodileAgent 2018 was balanced across all game sizes.

Figure 7 shows that profit distribution in “2-broker games” generally follows a two-mode distribution. Most of the time there was a small positive advantage within games, whereas a larger advantage was found in a smaller number of games. Detailed inspection of Power TAC 2018 data suggests that the large advantage primarily came from games where CrocodileAgent 2018 has played against COLDPower18 and EWIIS3 brokers.

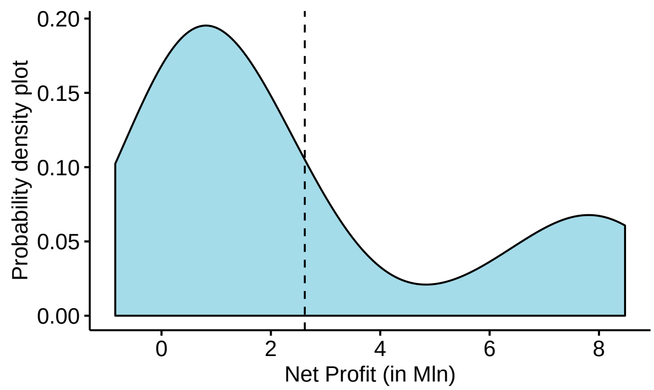

Fig. 7. Profit distribution for CrocodileAgent 2018 in “2-broker games” (with dotted mean of 2.62 Mln “monetary units”)

Table 3 shows CrocodileAgent broker’s performance relative to other brokers in Power TAC 2018. The relative performance was measured as a difference between final profit results for “2-broker games”. Although both brokers could have finished positive, the one that had the highest score had the positive relative difference and vice versa. Evidence suggests that CrocodileAgent 2018 exhibited better performance relative to most of the competing brokers (*i.e.*, COLDPower18, EWIIS3, SPOT [8] and Bunnie).

Table 3. CrocodileAgent 2018 broker’s relative performance in Power TAC 2018 (in Mln “monetary units”)

Agent Name	*Total difference (aggregate for all games)*	*Average difference (per game)*
COLDPower18	29.62	7.40
EWIIS3	27.11	6.78
SPOT	18.96	4.74
Bunnie	4.17	1.04
VidyutVanika	-6.04	-1.51
AgentUDE	-8.18	-2.05

Figure 8 shows the profit distribution for “4-broker games”. What is noticeable is that this distribution is heavily centered around the mean value indicating a constant advantage over other games. This observation is also supported by the fact that the agent achieved a positive profit in 69 out of 80 four broker games (approx. 86 percent of games played).

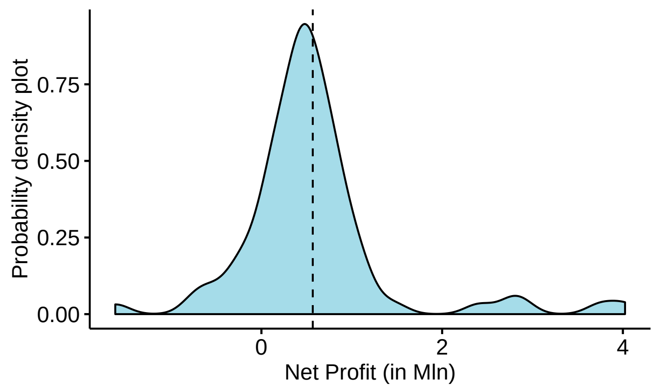

Fig. 8. Profit distribution for CrocodileAgent 2018 in “4-broker games” (with a dotted mean of 0.57 Mln “monetary units”)

The “7-broker game” is perhaps the most relevant type of game as it reveals how an agent preforms in a highly competitive and heterogeneous environment with the most varied broker strategies. Figure 9 shows that the profit distribution is positive but significantly lower when compared to “2-player games” and “4-player games”. Next, Figure 10 shows the probability for probability-probability (P-P) plot of profits as well as suggests that the profit distribution may follow a theoretical normal distribution. The mean profit as an adequate measure of broker’s competitive advantage can be confirmed by testing the distribution to perform like a normal distribution around its average. Therefore, a one-sample Kolmogorov-Smirnov test was used (p-value: 0.3669; alternative hypothesis: two-sided) which confirmed the assumptions given that there was were not enough evidence to reject the null hypothesis.

Even though the broker exhibited small profits, it is worth mentioning that the profitability rate (*i.e.*, the ratio between profitable games and all games) was 95 percent. This observation supports the objective of designing a robust agent that protects against high losses and, at the same time, is able to achieve a positive profit in the majority of the games.

4.4. Benchmarking Against Competitors

In this section we present a benchmark analysis of all competing brokers using several key performance indicators: (i) *subscriber count* to assess the attractiveness of tariffs; (ii) *net profit per subscriber* to quantify the financial performance of tariffs; (iii) *capacity and balancing cost* to analyze the proposed mechanisms in terms of peak exposure; (iv) *total cost per subscriber* to get a sense of the customer portfolio quality; (v) *information ratio* to assess broker’s profitability while taking into account profit variability across the games; (vi) *profitability rate* to give an indication as to whether the mechanisms are robust

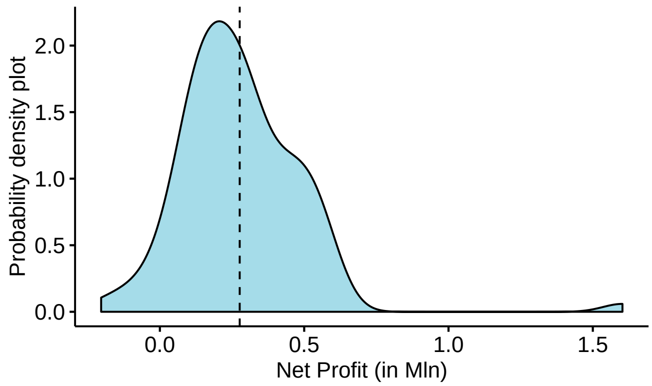

Fig. 9. Distribution of profit for CrocodileAgent 2018 in "7-broker games" (with dotted mean of 0.28 Mln "monetary units")

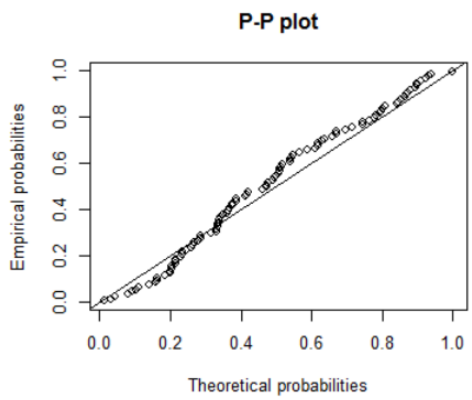

Fig. 10. Probability-probability (P-P) plot of CrocodileAgent performance in 7-broker games vs theoretical normal distribution

with respect to different scenarios; and (vii) *performance bubble chart* to link profitability rate with the final normalized scores.

Subscriber count Figure 11 reveals that CrocodileAgent 2018 had a generally low average subscription count when placed against multiple brokers and indicating it had a pricey tariff structure. The CrocodileAgent 2018 had a relatively higher average subscription amount in "2-broker games" but it was still below the top three brokers according to this KPI. These results validate the tariff mechanisms given that it supports the objective of having a defensive broker on the market.

Net profit per subscriber We calculate the net profit per subscriber as the ratio between the net profit and the average subscriber number per time slot for any given time. To reduce

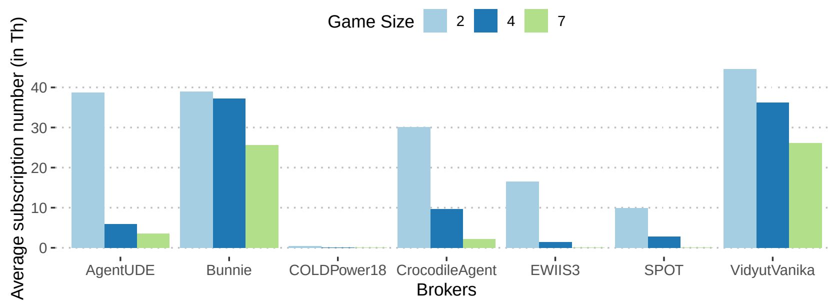

Fig. 11. Power TAC 2018 Finals: average subscription count for individual competing broker per specific game type

the impact of outliers and other situations which are not related to retail tariff subscription (*e.g.,* positive results from a wholesale price differential, huge monetary amounts due to random chance but where the broker had no additional subscribers etc.), we filter out games where the broker had less than 10 subscribers on average. Table 4 shows that CrocodileAgent 2018 had a medium level of profit per subscriber, indicating that it had the ability to extract a "sufficient" income for profitable brokerage operations (statistics for agent COLDPower18 is not shown in the table as it had less than 10 subscribers on average per time slot in each of the games in which it participated).

Table 4. Net profit per subscriber in the Power TAC 2018 Finals competition

Broker	*Net profit per subscriber (in "monetary units")*
SPOT	166
AgentUDE	140
CrocodileAgent	79
VidyutVanika	30
Bunnie	-18
EWIIS3	-767

Capacity and balancing cost Figure 12 shows that CrocodileAgent 2018 was able to reduce the peak exposure and minimize the unwanted negative cost to the level of a profitable brokerage. Balancing costs in comparison to other brokers were on the higher side, indicating a potential for improvement in future work.

Total costs per subscriber Figure 13 shows that only two brokers (*i.e.,* EWIIS3 and SPOT) were effectively heavily penalized when they had subscribers and the rest, including CrocodileAgent 2018, were able to keep cost per subscribers at a relatively lower level.

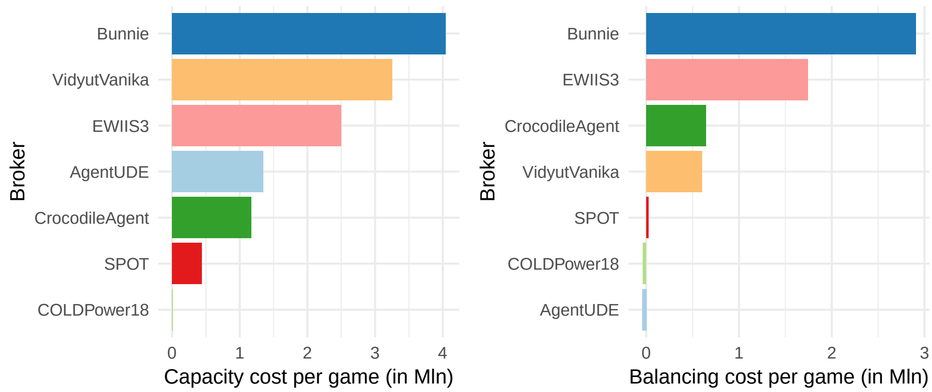

Fig. 12. Power TAC 2018 Finals: average capacity and balancing cost for individual competing brokers (in Mln "monetary units")

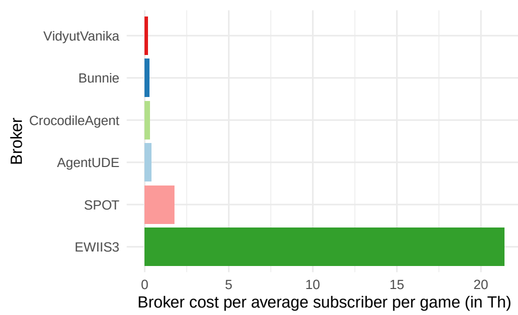

Fig. 13. Power TAC 2018 Finals: total costs per subscriber across all games by competing broker (in Th "monetary units")

Information ratio Broker information ratio is defined as the average net profit divided by the standard deviation of net profit. The significance of this KPI is that it creates a relationship between the net profit of individual brokers and the variability of that net profit. It shows us which brokers perform better per unit of risk (standard deviation). Figure 14 shows that the highest "risk adjusted" returns were realized by VidyutVanika on a 0.79 per game basis. CrocodileAgent 2018 was second with an information ratio value of 0.48 and AgentUDE was third with 0.45.

Profitability rate The broker profitability rate is defined as the ratio between the number of games a broker finished with a positive net amount and the total number of games in which the broker participated. Figure 15 shows that CrocodileAgent 2018 had the highest profitability rate of 91% across all games. This suggests that CrocodileAgent 2018 is a stable agent for power brokerage that would achieve a profit in the majority of market situations.

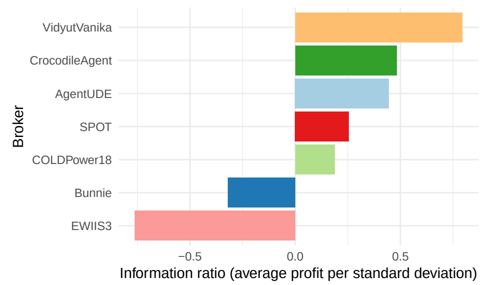

Fig. 14. Power TAC 2018 Finals: competing brokers' information ratio levels

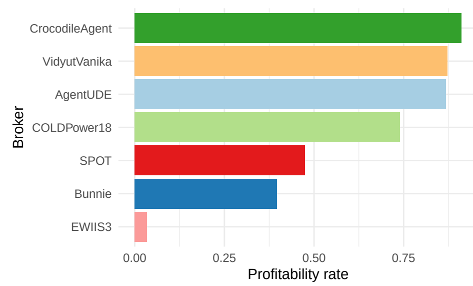

Fig. 15. Power TAC 2018 Finals: profitability rate in all simulated games by competing broker

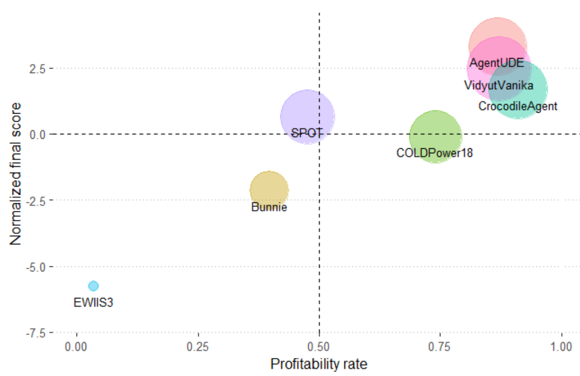

Fig. 16. Power TAC 2018: summarized performance bubble chart

Performance bubble chart The bubble chart in Figure 16 shows broker position based on the profitability rate (x-axis), a normalized final score (y-axis) and the information ratio (bubble size). The chart shows that three brokers: AgentUDE, VidyutVanika and CrocodileAgent performed similarly while EWIIS3 was the biggest outlier in terms of performance with a sizable negative performance. This also correspondents to the final rankings of agents, where AgentUDE, VidyutVanika and CrocodileAgent took podium places while EWIIS3 was ranked last in the finals.

5. Conclusion

Sustainable energy systems of the future will not only include advanced infrastructure but also innovative markets. The Power Trading Agent Competition is a competitive simulation platform which models energy markets. The scope of this paper required designing and implementing the proposed trading mechanisms using a software agent called CrocodileAgent 2018. To perform a proper analysis, the mechanisms were put to test in the Power TAC 2018 world competition against six research teams from Germany, Singapore, Mexico, Texas and India. In particular, a detailed inspection of data from the Power TAC 2018 finals showed that tiered margin weighting was adequate to create a stable and well-rounded robust solution for the broker agent problem of buying and selling electricity al in a competitive environment. Intra-day seasonal components were identified as the primary driver of risk exposure to potential negative costs stemming from peak charges and were consistent on a week-to-week basis. Analysis of customer demand exposure and power grid load were suitable for creating a “profitable structure” for the broker agent. Moreover, it effectively minimized the downside risk of extreme losses and maximized the positive upside in the retail market. The robustness and consistency of CrocodileAgent 2018 was evident through its profitable performance in almost all games throughout the competition. The third place in the Power TAC 2018 world competition, along with the highest profitability rate of 91%, suggests that the broker agent presented in this paper is a profitable framework to build-upon for future competitions.

In future work which will be aimed at designing and implementing CrocodileAgent 2019, the focus will be on improving the retail trading mechanisms, such as lowering average balancing cost, and designing new solutions to tackle complexities of the wholesale trading aspect in the Power TAC environment. Therefore, apart from using the well-established offline learning mechanisms, future work will seek to design and implement new mechanisms which are based on online learning mechanisms.

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