TugaTAC Broker: A Fuzzy Logic Adaptive Reasoning Agent for Energy Trading

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Abstract. Smart Grid trends and technologies are changing the way energy is generated, consumed and distributed. With the increasing spread of renewable power generators, new market strategies are needed in order to guarantee a more sustainable participation and less dependency of bulk generation. In PowerTAC (Power Trading Agent Competition), different software agents compete in a simulated energy market. Impersonating broker companies, the agents must evaluate how factors such as the weather, market prices and customer's hourly energy demand or production may influence their strategies to offer more attractive tariff contracts and make higher profits. In this paper we present TugaTAC Broker, a PowerTAC agent that uses a fuzzy logic mechanism to analyse and create tariffs based on the production and demand in its portfolio of customers. Fuzzy sets can be easily reconfigured in order to adapt agents' goals or to create different agents with the same approach. To validate and compare the performance of TugaTAC, we have run a local version of the PowerTAC competition. The experiments comprise TugaTAC competing against other simple agents and a more realistic configuration, with instances of the winners of previous editions of the competition. Preliminary results show that our approach is able to manage imbalances and win the competition in the simple case. In a more competitive setting, TugaTAC shows a promising dynamic: it remains winning the competition during some time, but succumbs to more sophisticated profit strategies. TugaTAC allows the study of the interest on buying or selling energy in the creation of new tariffs, based on conceptual values and relying less on numerical values, as in traditional approaches. We envisage to refine TugaTAC strategies by enabling a more sophisticated market dynamics sensitiveness providing a more competitive behaviour.

Keywords: PowerTAC, Energy Trading Agents, Smart Electricity Market, Smart Grids, Fuzzy Logic, Power Tariffs

1 Introduction

The management of energy consumption and production is not only a customer concern, but however, a new trend characterised by the wide presence of distributed renewable energy generators in low voltage grids. This factor is imposing new challenges for main energy generation and distribution companies. In this new scenario companies are not able anymore to predict energy demand, given the limited visibility (small and distributed generator units are unknown), production volatility (weather uncertainty affects renewable energy generation) and consumption flexibility (caused by smart grid and home automation technologies that can control and shift loads to improve customer efficiency).

All these characteristics increase the difficulty for generation companies and distribution utilities to keep the stability and quality of electrical distribution systems. In this sense, centralised control strategies used by supplier companies are not suitable to handle the intermittent energy production regarding the large number of small size distributed renewable sources installed along grid elements.

Electricity markets at retail level can help to address grid energy generation and load balance challenges, providing economical incentives for customers to control and shift their loads and also to predict their consumption and production in advance of energy purchase [1]. As a result of liberalisation programs, electricity markets were already introduced in some countries, allowing market competition and network regulation through direct negotiation or auctions of energy for future periods [2]. Figure 1 shows the different layers of a smart grid [3], highlighting the market as an important part of the grid.

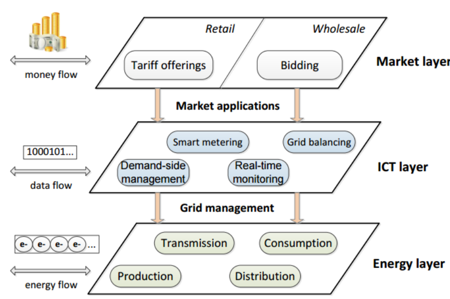


Fig. 1: Different layers of a Smart Grid [3]

In order to keep the inherent complexity of electricity market negotiation transparent for customers, there exist intermediary entities, usually called *brokers*. These trading agents are also responsible for providing and managing an internal market among customers that produce and consume energy. In an electricity market, brokers need intelligent strategies to define contract tariffs that will attract more customers than other competing brokers, and additionally make some profit from energy negotiation among retail and wholesale markets. Electricity market simulation frameworks comprise important tools to test and validate different approaches and algorithms for brokers in a simulated and controlled environment.

In this sense, this work presents an approach based on fuzzy logic to define competitive strategies for energy brokers in the market. The proposed approach was defined and tested on PowerTAC – our broker agent was developed to compete against others in this smart grid market simulation.

The paper is organised as follows. Section 2 gives an overview of the challenges on the Electricity Markets area and related work regarding the PowerTAC competition. Section 3 presents our strategies aiming to create a competitive broker agent named TugaTAC and Section 4 describes the results obtained from running the competition scenario, comparing our model with other approaches. We conclude the paper in Section 5 pointing the advantages of using fuzzy logic in the tariff creation process and looking for improvements in future works.

2 Electricity Markets and Power Trading Agent Competition

Electricity markets comprise commercial environments where electricity is negotiated (bought, sold and traded) by several entities such as generator companies, retailers, intermediary utilities, households, small and medium enterprises, electric vehicles owners and others. Energy is negotiated for different time slots and intervals, ranging from few minutes to months ahead. Considering the agreements, it can be negotiated through directly purchase transactions, auctions, or tariff contracts. Usually electricity market are separated in the wholesale electricity market, where retailers and intermediaries negotiate large amounts of energy (MWh) with big distribution entities, such as generation companies or power plants, and the retail electricity market, where small and medium customers negotiate small quantities of energy (kWh) with retailers.

The market Operator or Regulator is the entity which act independently of the market and has the function of manage transactions and maintain generation and load balance. It is responsible to appropriately charge buyers and sellers for their negotiations and also imbalances. The retail market dynamics directly influence the wholesale market and vice-versa, since retailers define their prices based on their customer portfolio and wholesale market price, while wholesale market define their prices based on supply and demand principles. These features create dynamic environments with high financial risks that have been leveraged by the advent of smart grid and the use of all kinds of smart appliances and metering enabled by customers, which are interested in better control and shift loads that can optimise their consumption.

Creating intelligent autonomous systems to safely and effectively operate in such environments requires tests and validation of the employed strategies and algorithms, before deploying them in real world scenarios. In this sense, there exist electricity market simulation frameworks, such as the PowerTAC [4]. The PowerTAC employs many robust models based on real historical data to simulate the wholesale market, the regulated distribution utility, and the customer population. The wholesale market models follow the existing rules on actual wholesale markets. Several models are used to simulate different kinds of customers such as, households, electric vehicles, and a variety of commercial and industrial entities, many of them including energy production capabilities (solar panels and wind turbines). The regulated distribution utility uses a market-based mechanism for balancing the energy supply and demand.

2.1 PowerTAC broker agents

PowerTAC also comprises an electricity market competition[1], where different teams are challenged to develop fully autonomous broker agents to operate between wholesale and retail market. In order to simulate a more realistic environment, the simulation is subject to different constraints, such as fees for publication and withdrawal energy contracts, for energy distribution and also for imbalances [5]. The broker agents act as self-interested companies, aiming to make high profits from the aggregation of supply and demand of small and medium distributed customers (producers and consumers). In the real world, brokers could be represented by energy retailers, commercial or municipal utilities, or energy cooperatives [6].

As retailers, brokers need to define profitable tariff contracts to achieve bigger market share. Thus, brokers indirectly compete in the energy market by offering specific tariffs contracts for each kind of customers (production, consumption, storage) and specific type of energy source (solar, wind, thermal, etc.). Moreover, brokers should try to reach a balanced portfolio, i.e. trying to keep the amount of energy produced by customers close to the demanded energy, in order to reduce the dependency from wholesale-coming energy. The tariff contracts have many features that broker agents could define to make them more attractive for individual customers, including fixed or dynamic price for kWh along the day, incentives for energy saving, bonus for sign-up, early withdrawal penalties, and monthly distribution fees.

In order to define profitable and competitive tariffs, brokers could analyse information from different sources, such as customers, wholesale market and even weather. With such information they need to be able to predict the total customers' production and consumption, leading to the necessary actions to keep the balance between supply and demand, achieved through the creation of tariffs that attract specific type of customers for complement the differences between production and consumption.

An important study here regards the features brokers use to create tariffs. In simulation environments it is easy to analyse each factor's numbers and compose binary solutions like "If variable is greater than some value then do that". This approach limits brokers coverage creating crisp sets of possible actions. In real decision making scenarios, human brokers compose their solutions based on both numbers and conceptual analysis. Humans often interpret concepts such as "high", "low", or "interested", enabling a richer set of combination values for actions [7]. Analysing PowerTAC competition, many of these conceptual values could be combined to design a tariff generator mechanism.

[1] http://powertac.org/

2.2 Tariff Selection Problem

Since we are dealing with negotiations and contracts between customers and brokers, the most important problem is how to design competitive and interesting tariffs that provide the conditions required by customers and yet, be profitable to brokers [4]. Customers want to select the best tariff based on their self interest, which is determined by its customer's model. For example, some customers prefer tariffs with time-of-use price while others could prefer fixed prices, and so on.

Customers actively participate in the trading market by choosing new tariffs through periodic evaluation of offered tariffs. Nevertheless, the utility function used in customer models include an aversion of change and complexity that can retard the changing for better tariff offers [8]. Accordingly to the PowerTAC specification [9], customers in the competition are more opened to new opportunities at the beginning of the simulation, but later they do not evaluate new offers frequently. Instead, most of the time they consider it junk mail. They use a inertia model for the probability of not evaluating tariffs, calculated as I_a that depend on the number of tariff publication cycles (n) and a factor $I \in [0, 1]$ as seen in Equation 1.

$$I_a = (1 - 2^{-n})I \tag{1}$$

The key part of customer tariff evaluation is the calculation of the expected cost or gain over the lifetime of a contract relationship. Tariffs are compared using a utility value computed from the monetary implications and other aspects. Our intention is to find a good approach that can gain customers attention and also be useful to them. If no broker achieve this goal, customers will use default tariffs provided by the *default_ broker*, an agent that exists to assure that all customers will have at least one option. Hence, we are interested in the analysis of how customers evaluate tariffs.

In PowerTAC, the utility of a given tariff T_i is computed as a function of per-kWh payments pv_i, periodic payments pp_i, a one-time sign-up payment $psignup_i$, a potential one-time withdrawal payment $pwithdraw_i$ in case the customer withdraws its subscription before the tariff's contract minimum duration, and an inconvenience factor x_i to account for inconvenience of switching subscriptions, and of dealing with time-of-use or variable prices or capacity controls. The Equation 2 describes this utility.

$$u_i = f(pv_i, pp_i, psignup_i, pwithdraw_i, x_i) \tag{2}$$

On the other hand, the cost of using a default_broker tariff depends on the consumption amount $Ct_{default}$, the cost per-kWh $(Pv_{default})$ and the periodic payment $Pp_{default}$, as seen in Equation 3. More details about PowerTAC models can be found in [9].

$$cost_{default} = \sum_{t=0}^{d_e} (Ct_{default} * Pv_{default} + Pp_{default}) \tag{3}$$

Many PowerTAC related works address this problem differently. Reddy et. al [10] created a model to predict the attraction probability of a specific tariff, given the broker's portfolio. Liefers et. al [11] uses a Tit-For-Tat strategy, copying opponent's tariffs and then, improving them. The CrocodileAgent [12] in the other hand, uses market properties as scarcity, balance and oversupply to generate the most needed tariffs at a given time.

Although some of the related works on creating tariffs on PowerTAC retail market describe conceptual characteristics, such as scarcity, none of them consider modelling conceptual values in the calculations, just numerical values. We have seen that mapping the properties to values only helped competitors to interpret the market in a simplistic and rigid way. This motivates us to address the tariff generation problem with a different paradigm, the conceptual analysis. The goal is to create a tariff generator that could understand the linguistic concepts and help us to define tariffs which could improve customers utilities and gather the biggest market share.

3 TugaTAC Broker Agent

In this work, we propose some strategies for the development of PowerTAC broker agents based on fuzzy models. In the wide scope of power trading markets our efforts were focused in the retail market, specially on the module that generates competitive and profitable contract tariffs that should be attractive enough in order to allow the broker to increase its market share and portfolio balance. The proposed approach is called TugaTAC.

TugaTAC is a broker agent for negotiating energy in PowerTAC. TugaTAC's strategy consists of the adaptation and update of market tariffs using a conceptual model of agent's interest on selling or buying energy. Depending on the production and consumption quantities coming from customers subscribed to TugaTAC's tariffs (portfolio), a fuzzy model determines the broker intentions and what it needs to do in order to improve the tariffs and attract the best profile of clients (consumers or producers) that could help reducing imbalances.

Figure 2 shows a simplified scheme of the TugaTAC reasoning mechanism, in which the market prices are combined with the values of energy production and consumption from the broker's customer portfolio. The result is mapped to agent's *interest* on buying and selling energy. The agent uses the fuzzy inference to generate the interest values that will help to compose the new tariffs.

3.1 Fuzzy Conceptual Tariff Strategy for Retail Market

The reasoning mechanism described in Figure 2 is highly conceptual and connects numerical values to abstract interest values. Good models for this kind of relationship are fuzzy systems. Fuzzy is an alternative for the traditional binary logic in which variables can present more than two values (true or false), usually presenting a continuous ranging between 0 (completely false) to 1 (completely

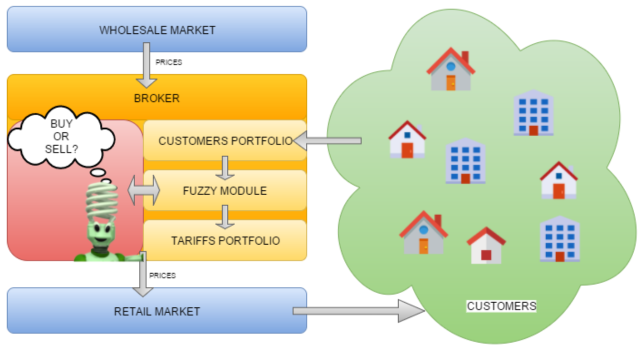


Fig. 2: TugaTAC tariff composition and interactions with the environment

true) [13]. In fuzzy logic a linguistic approach is used instead of a complex mathematical formulation, thus the variables are described using conceptual values, e.g. a temperature variable could be specified as "cold", "normal", and "hot".

Our proposed approach for defining tariff contracts is based on a fixed price tariff model, where customers pay the same price along the day for the kilowatt-hour. Therefore, this strategy only cares for the price value definition. For this, it considers the fluctuation of the wholesale market price, which varies along the day according to demand and production. This way the tariff price always needs to be above this price, otherwise the broker will lose money. Thus, we have defined two fuzzy models: one for selling energy and the other for buying, implemented and tested using the jFuzzyLogic API[2].

The fuzzy model representations are illustrated on Figure 3 for the *buy-interest* variable and Figure 4 for the *sell-interest* model. The *fuzzification* process establishes the correspondence between the input and output models. A set of IF-THEN fuzzy rules are defined in terms of the linguistic concepts defined. This is the biggest advantage of using fuzzy logic in our approach. Reconfiguring broker reactions to specific case scenarios, such as when the production is high or the consumption low, is as easy as changing some rules, as the ones observed in Algorithm 1.

Finally, in order to create the tariffs we used an approach similar to [12]. In initial rounds customers tend to be more open to new tariffs. Besides, it is in this period that most of the tariffs are published. Brokers try to gather the attention. Our TugaTAC broker takes advantage of this period using a Tit-For-Tat approach, copying competitor tariffs when a tariff for the same power type does not exist in TugaTAC's portfolio. If there is some similar tariff, we trigger the fuzzy model to calculate a new value for ours, in order to beat the conditions offered.

[2] http://jfuzzylogic.sourceforge.net/

IF buy-production **IS** high **THEN** definitely-interested
IF buy-production **IS** high **AND** buy-consumption **IS** high **THEN** interested
IF buy-production **IS** low **AND** buy-consumption **IS** high **THEN** not-interested
IF buy-production **IS** medium **OR** buy-consumption **IS** high **THEN** not-interested
IF buy-production **IS** medium **AND** buy-consumption **IS** medium **THEN** interested

Algorithm 1: Fuzzy rule set example: *buy-interest* variable

The resulting value of the fuzzy represent a multiplying factor for the prices (per-kWh) called interest, which represent the interest value on performing that action, as $interest \in [0, 1]$. When the interest is high, then multiplication will make the prices rise, otherwise the price will decrease. The evaluation of the new price values are verified in two equations, one for buying (to producers, Equation 4) and other selling (to consumers, Equation 5).

$$buying : price_{new} = price_{last} - (price_{last} * buy_{interest}) \tag{4}$$

$$selling : price_{new} = price_{last} + (price_{last} * sell_{interest}) \tag{5}$$

3.2 Tariff Composition Mechanism

The tariff composition module is responsible for using the prices and interest values for creating and updating tariffs that will be proposed to the customers. We used a similar approach as in [12], our TugaTAC broker takes advantage of the customers openness on initial publication cycles, as explained in Section 2.2, using a Tit-For-Tat approach that copy available tariffs when a tariff for the same power type do not exist in our portfolio.

If there is some similar tariff, we trigger the fuzzy model to calculate new prices in order to beat competitors' conditions. This process repeats hourly for each kind of energy type, plus the generic *production*, *consumption*, *storage* types. Within this approach our broker covers more market possibilities for gathering customers and offering a wide range of tariffs.

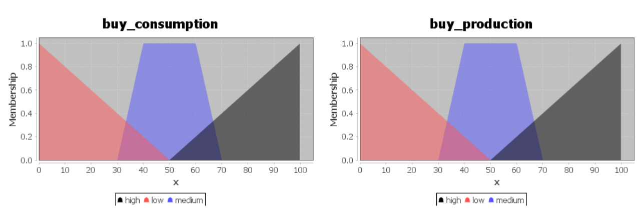


Fig. 3: Fuzzy input variable for model *buy-interest*

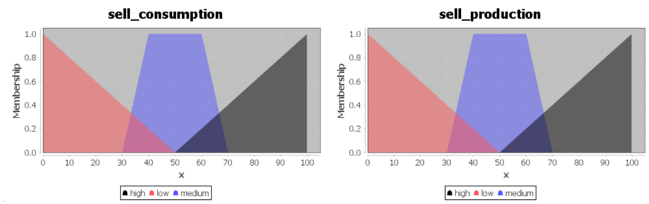


Fig. 4: Fuzzy input variable for model *sell-interest*

4 Evaluation

Realising experiments on a competition environment brings some challenges regarding the evaluation metrics and how to compare the performance of our broker. PowerTAC, as an open source distributed Multi-Agent System simulation platform, allows us to configure our own competition server and run the simulation: 1) competing against the default broker (intrinsic to the server) or 2) competing against other brokers that connect to our server. In this work we use the 2015 server and client versions of the PowerTAC framework.

The best way to evaluate the performance of our model would be facing well consolidated agents, the last years competition winners. If our broker presents good results in such scenarios, then it could be a good competitive broker for real tournaments. Since the binary code for the ultimate PowerTAC finalists are available online, we could run the simulation with this exciting environment. In fact, besides downloading the real PowerTAC competitors we instantiated another broker and called it ZucaTAC. ZucaTAC shares the same code of TugaTAC but has the fuzzy module disabled, updating the tariff prices with a random interest factor, useful for increasing the number of competitors without introducing other complex strategies as those presented by real competitor codes.

Being a preliminary work, our broker is not yet tuned in order to fairly compete with the big ones, which have very complex reasoning architectures and include many other factors to tariff creation. However, we wanted to check whether TugaTAC was able to win the competition in three evaluation experiments:

1. *Experiment 1 - 1 vs DF:* only one broker vs the default
2. *Experiment 2 - 2 vs DF:* 2 agents plus the default broker
3. *Experiment 3 - 3 or more:* 3 or more agents competing

These experiments consist on running one complete simulation competition tournament and evaluate the results. The winner of the competition is the broker agent with the highest total profit. Our validation metrics are: the energy traded both in wholesale market and retail market, and the total profit at the end of the game. We analyse each one of the experiments and their results regarding these metrics and the dynamics through the competition simulations.

4.1 Experiment 1 - TugaTAC against the Default Broker

We ran the simplest test: competing against the default broker. As explained on Section 2, the default broker guarantees that customers will have at least one tariff option. In this case, if our broker wins against the default broker, it means that our strategy at least makes sense. If something is wrong, e.g., if the broker prices are not competitive, the results show a big deficit with the bank. In this experiment, we wanted to check whether TugaTAC could win.

Figure 5 presents the profit evolution during the simulation. TugaTAC agent won the competition with more than 2 million euros in cash, a significant difference in terms of profit. It seems that initially, the default broker has some advantage in the tariff publication period, being overcome in less than 10 hours. The default broker seems to gather customers attention in the moment our tariffs are being adjusted. Although TugaTAC overpasses its income, we will try to reduce this time in future versions.

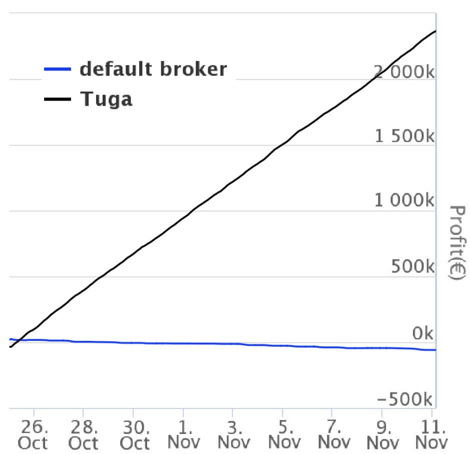


Fig. 5: Experiment 1 - Profit results

In Table 1 we see the ranking results of the simulation. The energy traded with wholesale and retail markets are described on the respective columns and represent the total amount of traded energy through the competition in each market in order to supply the customers with the needed energy. The negative values represent energy sold. Although the default broker had not traded any energy, it made some profit because initial customers paid fees when they changed to TugaTAC tariffs.

TugaTAC ends the game with 95% of the clients subscribed to its tariffs while the default broker only gathered 5% of the clients. This distribution of customers in the simulation corroborates that TugaTAC is suitable for the competition.

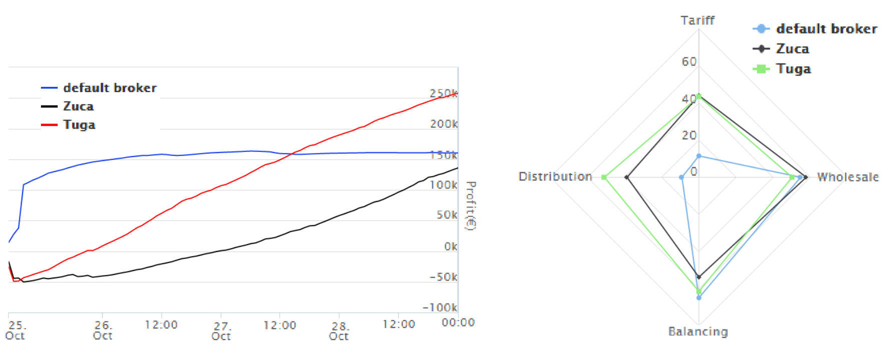
Table 1: Experiment 1 - Results of the simplistic competition scenario

Broker Agent	**Wholesale trades**	**Retail trades**	**Profit**
TugaTAC	23 MWh	-47575 kWh	2364911 €
default-broker	0 MWh	0 kWh	59019 €

4.2 Experiment 2 - 2 brokers against the Default Broker

Results from Experiment 1 show that TugaTAC seems to be a good broker, taking a big part of the market share and winning the competition against the default broker. However, the results of the first experiment do not give us much information about how good our fuzzy model performed. In Section 2 we have seen that in the formula of the cost, customers have a penalty when subscribing to default broker tariffs. This could be a reason why TugaTAC gathered so many subscriptions and won the competition in Experiment 1.

The second step for validating our proposal is to compare TugaTAC fuzzy mechanism to another broker, similar in complexity. For that, we ran the competition introducing also ZucaTAC. Figure 6a shows the profit dynamics throughout the game. It seems that in a more competitive scenario, TugaTAC slowly increases its participation on the market, trying to adjust the needs on buying and selling energy.



(a) (b)

Fig. 6: Experiment 2 - Profit (a) and balance (b) competition dynamics

TugaTAC broker achieved the right number of customers it needed to become more independent from the wholesale market, achieving good results in terms of profit. The cumulative balance chart in Figure 6b corroborates with this assumption, by showing a more squared shape in TugaTAC's balance, which means more equilibrium on the energy management.

Finally, Figure 7 shows the trading prices on this simulation. It is easy to see that the fuzzy model guaranteed a good adjustment on competitiveness.

TugaTAC was able to negotiate less energy with a better relation of customers prices when compared to the prices paid on wholesale.

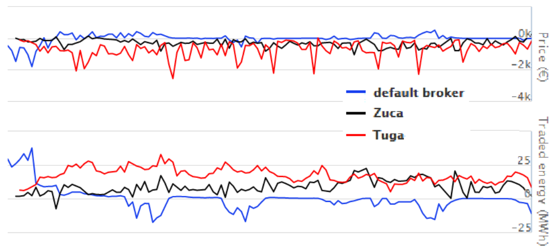


Fig. 7: Experiment 2 - Evolution of price dynamics

In fact, TugaTAC has demonstrated to be good competing with other agents. The experiments shown that the profit margin is very similar to the values achieved on real tournaments of the competition [3].

4.3 Experiment 3 - 3 or more agents

In a software competition things can change drastically from year to year. We want to compare our approach with the most advanced broker available. Nothing better than competing with the current champion, which serves as a benchmark. We have downloaded AgentUDE broker, the winner of the 2014 competition. The test scenario consisted in putting three agents to compete: In one side, ZucaTAC, with its simple mimic mechanism for tariffs generation. In the middle, TugaTAC, our novice competitor with its powerful fuzzy adjustment system. And, in the other side, AgentUDE.

Developed by University of Duisburg-Essen, AgentUDE's strategy relies on contract withdraw fees. The broker publishes highly competitive tariffs with big penalties for the customers that may want to change to other brokers. In fact, this broker takes advantage of competitors that change their prices based only on the market price. When the competitors drop prices to gather more customers, AgentUDE charges, with high fees, the customers that want to move on, violating the contract.

In Figure 8 we can clearly observe through the evolution of the game that AgentUDE had a flawless victory against our TugaTAC. We observe the impact of dropping prices directly related to the profit drop. When the price drop occurs, the other brokers seem to lose their customers and their money. We highlight AgentUDE stayed in owe a long time, having negative profits. In some way, this could represent that our TugaTAC resisted well to competitor's attacks.

Another interesting behaviour was noticed when comparing the tariff evolution dynamics. AgentUDE not only recovered from the owe, but yet gained much

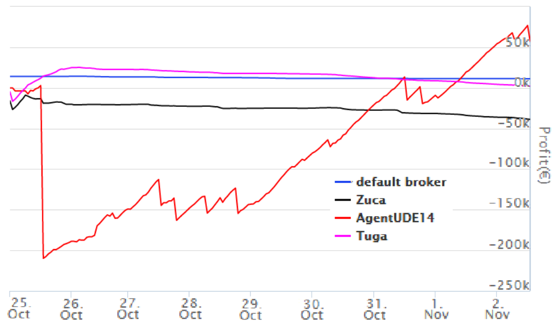


Fig. 8: Experiment 3 - AgentUDE vs TugaTAC

of the market share that TugaTAC owned, as seen in Figure 9. With the greatest market share assured, it increased tariff prices and got the revenue recovered.

Table 2 shows the result of the competition in terms of each broker's accumulated profit. TugaTAC is second after AgentUDE, with a profit of 11311€. AgentUDE made approximately 600% more profit with 70490€. ZucaTAC appears third, without having much presence in this game, only 2790€ explained by its simplicity and not adaptive tariff prices. Last is the default broker, with only 59€. It is interesting to see that in more complex scenarios the default broker loses expressiveness also. Although AgentUDE achieved the highest score, we fear that its strategy is not a fair comparison for our preliminary work on TugaTAC. AgentUDE takes advantage of price dropping and our broker is not sensitive to this kind of strategy. We highlight here that our fuzzy approach makes the agent much more self-interested than needed. Trying to reduce imbalance should be combined with other strategies to get better results.

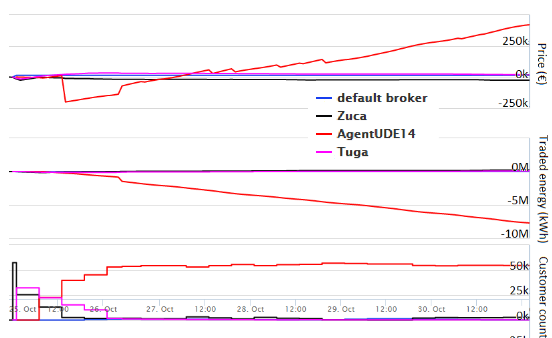


Fig. 9: Experiment 3 - Tariff analysis: price, energy and customers count

Table 2: Experiment 3 - Results of the realistic competition scenario

Broker Agent	**Wholesale trades**	**Retail trades**	**Profit**
AgentUDE14	42 MWh	-47793 kWh	70497 €
TugaTAC	31 MWh	-27485 kWh	11311 €
ZucaTAC	4 MWh	2246 kWh	2790 €
default-broker	0 MWh	0 kWh	59 €

It is clear that AgentUDE outperforms TugaTAC in terms of profit and energy traded amount. AgentUDE is a very consolidated broker, with many optimisations, using more competition information to compose the tariffs. We already expected that our simple tariff generation mechanism could be insufficient to defeat more complex broker strategies. Current work in TugaTAC consist in analysing and considering other sources to enhance its ability to manage market information as weather forecast to predict production, learning other players' strategies or optimising its participation on the wholesale part. As a preliminary work, we know that TugaTAC agent lacks some implementation in these aspects and we envisage to present an improved version in future works.

5 Conclusions and Future Work

This work outlines how fuzzy systems can be employed for composing tariff contracts in the electricity retail market of the PowerTAC. The inherent features of fuzzy models enable a more conceptual interpretation of the market information, without requiring a complex modelling of mathematical formulation specific to each case. This enables market experts and others with domain knowledge to define and map suitable tariff contract policies. The PowerTAC framework demonstrated to be a powerful simulation engine for the development and test of new strategies for electricity market, an essential task to address some of the issues and challenges that will enable and leverage the adoption of smart grid technologies.

Our experiments shown that TugaTAC is not the most optimised broker for trading energy at lower prices in the smart grid market but it is still highly competitive. When compared to the 2014 champion of the PowerTAC competition, our broker's fuzzy strategy showed great potential leading the competition in market share and profit for a long time, just losing in the end affected to the drop-pricing fee penalisation approach of AgentUDE. As a preliminary work we observe that the models proposed in TugaTAC are promising, but need to be refined. TugaTAC is not very sensitive to other competitors' strategies and should be extended integrating more market information such as consumption and production forecasts in order to improve profits. A balanced participation is a very good goal for agents in this scenario, where self-interest determines the competition and learning mechanisms will also be considered to improve agent's decisions. As future work we envisage to extensively test and tune the proposed fuzzy models with other consolidated brokers and try to find the more optimised fuzzy sets for the interest on negotiation. Finally, we plan to define and apply our fuzzy models to support trading in the wholesale market.

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