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Metalearning to support competitive electricity market players' strategic bidding

Tiago Pinto[a,*], Tiago M. Sousa[a], Hugo Morais[b], Isabel Praça[a], Zita Vale[a]

[a] GECAD - Knowledge Engineering and Decision Support Research Centre - Polytechnic of Porto (IPP), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal

[b] AUTomation and Control Group–Technical University of Denmark (DTU), Richard Petersens Plads, Building 326, 118, 2800 Kgs. Lyngby, Denmark

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ABSTRACT

Electricity markets are becoming more competitive, to some extent due to the increasing number of players that have moved from other sectors to the power industry. This is essentially resulting from incentives provided to distributed generation. Relevant changes in this domain are still occurring, such as the extension of national and regional markets to continental scales. Decision support tools have thereby become essential to help electricity market players in their negotiation process. This paper presents a metalearner to support electricity market players in bidding definition. The proposed metalearner uses a dynamic artificial neural network to create its own output, taking advantage on several learning algorithms already implemented in ALBidS (Adaptive Learning strategic Bidding System). The proposed metalearner considers different weights for each strategy, based on their individual performance. The metalearner's performance is analysed in scenarios based on real electricity markets data using MASCEM (Multi-Agent Simulator for Competitive Electricity Markets). Results show that the proposed metalearner is able to provide higher profits to market players when compared to other current methodologies and that results improve over time, as consequence of its learning process.

1. Introduction

Electricity markets (EM) have been introduced in several countries in the early 1980s, and the worldwide spread has reached its peak during the 1990s. Since then, regulator entities have done several reforms in order to guarantee the market competition and transparency [1]. The majority of European countries have already joined together into common market operators, resulting in joint regional EM composed of several countries. Additionally, in early 2015, several of these European EM have been coupled in a common market platform, operating on a day-ahead basis [2].

EM are environments with significant dynamic characteristics due to their restructuring [3]. This process was conducted with the purpose of increasing the competition in this sector, leading to a decrease in energy prices. In the future, EM prices are expected to be more volatile, depending on the renewable based generation, especially wind and solar [4]. The complexity in EM operation also suffered an exponential increase, bringing new challenges to players' participation [5]. In order to overcome these challenges, it became essential for the market entities to fully understand the principles of EM, and how to evaluate their investments in such a competitive environment. The need for understanding those mechanisms and how the involved players' interaction affects the outcomes of EM contributed to increase the use of simulation tools. Multi-agent based software is particularly well fitted to analyze dynamic and adaptive systems with complex interactions among its constituents [6–9]. Several EM simulators have been developed, allowing the study of different EM types and models. Relevant examples in this context are: AMES Wholesale Power Market Test Bed [6], EMCAS—Electricity Market Complex Adaptive System [7], or GAPEX—Genoa Artificial Power-Exchange [9].

Although the existing simulators include some machine learning capabilities, the decision support that is provided is not yet adequately explored. In order to overcome this gap, MASCEM (Multi-Agent System for Competitive Energy Markets) [8,10] has been developed. MASCEM supports EM simulation, considering an extensive set of different market models, and including all the most important entities that take part in such transactions. The decision support of EM players is performed through ALBidS (Adaptive Learning strategic Biding System) [11] which considers several

* Corresponding author. Tel.: +351 22 8340500; fax: +351 22 8321159.
E-mail address: tmcfp@isep.ipp.pt (T. Pinto).
URL: http://www.gecad.isep.ipp.pt (T. Pinto).

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different approaches to analyse market data and to define adequate action profiles for market players.

It is in the decision support field that this paper gives its main contribution. Using the outputs of ALBidS' strategies (bid prices), a new methodology is proposed, which creates a new strategic proposal, by combining the existent ones using the metalearning concept [12]. The proposed approach is defined as a metalearner since it uses meta-data related to the performance confidence values that each strategy is obtaining, in order to define the weights with whom each strategy affects the metalearner's output, thus improving the performance of existing learning algorithms. The combination of meta-data (bid prices resulting from the other strategies outputs and confidence values of each of the strategies) is done using a dynamic artificial neural network (ANN). This way the metalearner is able to adapt its results, giving higher influence to the results of the best strategies, while lowering the contribution of the strategies which are presenting worst results.

After this introduction, an overview of MASCEM and ALBidS is presented in Section 2. Section 3 describes the proposed ANN-based metalearner. In Section 4, simulation results using the proposed approach, considering real EM data are presented. Finally, Section 5 presents the main conclusions and contributions of this work.

2. MASCEM and ALBidS

2.1. MASCEM simulator

MASCEM [8,10] is a modelling and simulation tool with the purpose of studying complex restructured EM operation. MASCEM models the complex dynamic market players, including their interactions and medium/long-term gathering of data and experiences. The main goal of MASCEM is to simulate as many market models and player types as possible, so it can reproduce, in a realistic way, the operation of real EM. This enables it to be used as a simulation and decision-support tool for short/medium term purposes but also as a tool to support long-term decisions, such as those taken by regulators. Unlike traditional tools, MASCEM does not postulate a single decision maker with a single objective for the entire system. Rather, it allows agents representing the different independent entities in EM to establish their own objectives and decision rules. Moreover, as the simulation progresses, agents can adapt their strategies based on previous successes or failures. MASCEM's key players reflect actual entities from real markets and provide a means for aggregating consumers and producers.

MASCEM includes several negotiation mechanisms usually found in electricity markets, being able to simulate pool markets, bilateral contracts, balancing markets, forward markets, and ancillary services. The different market types offer players the chance to approach market negotiations strategically, taking advantage of the several opportunities that arise at each time. The need for adequate decision support to the strategic behaviour of negotiating market players must be addressed by means of intelligent approaches that can take the most advantage out of the surrounding environment and context. Metalearners have an important role, as they use meta-data to improve the performance of existing learning algorithms. Using meta-data derived from other learning algorithms, a metalearner creates flexibility in solving different kinds of learning problems [12], especially when dealing with dynamic environments with a large associated uncertainty, such as EM.

The need for this type of decision support extends, not only to the requirement of maximizing players' gain from market participation (maximization of profits or minimization of costs), but also to the improvement of several other essential features of intelligent agents, such as [13]: (i) the capability of interacting and reacting on the same environment as other intelligent agents, (ii) social abilities that allow the interaction with other agents, (iii) autonomy to enable agents deciding and controlling their own actions, (iv) learning abilities, to allow an agent to change its behaviour based on prior experience, and (v) flexibility, so that agents' tasks do not need to be pre-determined, rather adapted according to previous events and to current context of the environment.

With the purpose of providing decision support to market players, ALBidS has been developed and integrated with MASCEM [11], and has been improved by integrating the metalearner proposed in this paper.

2.2. ALBidS decision support system

ALBidS integrates several strategies, taking advantage of each one in different contexts. The algorithms are placed below the main reinforcement learning algorithm (RLA), which allows that in each moment and circumstance the technique that presents the best results for the current scenario is chosen as the system's response [11]. ALBidS is implemented as a multi-agent system itself, where each method is implemented in an individual agent.

The diversity of algorithms that are used by ALBidS bring out the need for the development of a mechanism that is able to manage the balance between the Efficiency and Effectiveness (2E) of the system. This mechanism provides the means for the system to adapt its execution time to the purpose of the simulation, i.e., if the expected results from ALBidS are as best as it is able to achieve, or, on the other hand, if the main requirement is for the system to be executed rapidly. The 2E management mechanism decides which methods are used at each moment; depending on their performance in terms of efficiency and effectiveness. In this way certain strategies can be excluded when they are not fulfilling ALBidS' requirements. Strategies are also manipulated internally, so that they adapt their individual results quality/execution time balance to each simulation's needs.

A highly dynamic environment such as the EM forces players to be equipped with tools that allow them to react to diverse negotiation circumstances. The existence of a variety of different strategies grants ALBidS the capability of always being prepared for the diversity of situations that a market player may encounter during market negotiations. The different natures of the considered strategies offer coverage over a diversity of areas, guaranteeing a high probability that there is always one strategy suited for each different context. The considered strategies are [11]: Based on statistical approaches; Composed Goal Directed; Adapted Derivative-Following [14]; Market Price Following; Dynamic Feed Forward ANN [15]; Adaptation of the AMES bidding strategy [6]; Simulated Annealing-Q-Learning [16]; Game Theory [17]; Economic Analysis [18]; Determinism Theory [19]; and Error Theory.

The main RLA, which is responsible for choosing among the various strategic alternatives, presents a distinct set of statistics for each context. This means that an algorithm that may be presenting good results for a certain context may possibly never be chosen as the answer for a distinct context [11]. ALBidS provides three alternative reinforcement learning algorithms, namely: (i) a simple reinforcement learning algorithm that updates strategies' confidence values according to the absolute value of the difference between the prediction and the real value; (ii) the revised Roth–Erev reinforcement learning algorithm [6], which besides the features of the previous algorithm, also includes a weight value for the definition of the importance of past experiences; and (iii) learning algorithm based on the Bayes theorem of probability [20], which updates the values through the propagation of the probability of each algorithm being successful given its past performance.