Multi-Agent Systems and Virtual Producers in Electronic Marketplaces

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Abstract. This paper presents an agent-based simulator designed for analyzing agent market strategies based on a complete understanding of buyer and seller behaviours, preference models and pricing algorithms, considering user risk preferences. The system includes agents that are capable of improving their performance with their own experience, by adapting to the market conditions. In the simulated market agents interact in several different ways and may joint together to form coalitions. In this paper we address multi-agent coalitions to analyse Distributed Generation in Electricity Markets.

1 INTRODUCTION

Market players and regulators are very interested in foreseeing market behaviour: regulators to test rules before they are implemented and detect market inefficiencies that should not encourage strategic behaviours that might reduce market performance; market players to understand market behaviour and operate in order to maximize profits. Simulation and Artificial Intelligence techniques may be very helpful under this context.

Multi-agent based simulation is particularly well fitted to analyze dynamic and adaptive systems with complex interactions among constituents [1]. Unlike traditional tools, agent based simulation does not postulate a single decision maker with a single objective for the entire system. Rather, agents, representing the different independent entities in electronic markets, are allowed to establish their own objectives and decision rules. Moreover, as the simulation progresses, agents can adapt their strategies, based on the success or failure of previous efforts.

We present a multi-agent market simulator designed for analyzing agent market strategies based on a complete understanding of buyer and seller behaviours, preference models and pricing algorithms, considering user risk preferences. Each market participant has its own business objectives, and decision model. The results of the negotiations between agents are analyzed by data mining algorithms in order to extract knowledge that gives agents feedback to improve their strategies. The extracted knowledge will be used to set up probable scenarios, analyzed by means of simulation and game theory decision criteria.

We intend to apply this platform to different market types, taking into account some previous work of our research group, where two different simulation platforms have already been developed, namely ISEM – Intelligent System for Electronic MarketPlaces [2], and MASCEM – Multi-Agent Simulator for Competitive Electricity Markets[3].

ISEM focuses specially on markets with finite time horizon. This simulator was selected as a worldwide case study in simulation of negotiation agents [4], while MASCEM focus particularly on market mechanisms usually found in liberalized electricity markets and was selected as a worldwide case study of agents technology applied to markets [5].

Our proposal is a Market Simulator that will act as a kind of What-if tool, trying to analyze what may occur if some decision is taken. However, some additional intelligence need to be placed in the system, otherwise we will have a kind of combinatorial explosion, since many scenarios need to be analyzed. Moreover, the Market Simulator will be used as the engine of a Market Participant (Seller or Client) in order to suggest him/her about the actions to have in the market.

Entities from real markets can use our tool to test several different negotiation mechanisms, different behaviours, strategies and risk preferences, and to analyze the future market evolution and other entities expected reactions. Our tool may also be used to understand the implications of agents' coalitions on markets.

Electricity Markets are an important area of application of our research. In this paper we present our developments in studying the increase in Distributed Generation, and its market influence, by means of agents' coalitions.

In a general way the formation of coalition can be seen as an enterprise example of the constitution of a social net, where the several elements of this net establish negotiation processes in order that a formal structure, with the capacity to supply goods and services to the society, can emerge. Each element of the coalition is not able to supply the services and goods with the desirable amount and quality, but the coalition presents itself as a credible structure to the eyes of the potentials consumers, that is, the structure (coalition) thus created worth more than the sum of its parts.

This article illustrates the constitution of coalitions for an important problem, subject to enormous transformations and with clear social and strategically impact: the establishment of electric energy supply contracts through competitive markets.

The rest of the paper is organized as follows: section 2 outlines the multi-agent model; section 3 addresses the negotiation mechanisms; section 4 explains the use of data mining in the scope of our tool; section 5 addresses agents strategic behaviour; and section 6 explores agents coalition to represent virtual power producers in the study of distributed generation penetration on electricity markets.

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2 MULTI-AGENT MODEL

Our Simulator facilitates agent meeting and matching, besides supporting the negotiation model. In order to have results and feedback to improve the negotiation models and consequently the behaviour of user agents, we simulate a series of negotiation periods, $D = \{1,2,...,n\}$, where each one is composed by a fixed interval of time $T = \{0,1,...,m\}$. Furthermore, each agent has a deadline $D_{max}^{Agt} \in D$ to achieve its business objectives. At a particular negotiation period, each agent has an objective that specifies its intention to buy or sell a particular good or service and on what conditions.

The available agents can establish their own objectives and decision rules. Moreover, they can adapt their strategies as the simulation progresses on the basis of previous effort's successes or failures. The simulator probes the conditions and the effects of market rules, by simulating the participant's strategic behaviour.

The simulator was developed based on "A Model for Developing a MarketPlace with Software Agents (MoDeMA)" [4]. The following steps compose MoDeMA::

- Marketplace model definition, that permits doing transactions according to the Consumer Buying Behaviour Model;
- Identification of the different participants, and the possible interactions between them;
- Ontology specification, that identifies and represents items on transaction;
- Agents architecture specification, and information flows between each agents module;
- Knowledge Acquisition, defining the process that guarantees the agent the knowledge to act on pursuit of its role;
- Negotiation Model, defining the negotiation mechanisms to be used;
- Negotiation Protocol, specification of each negotiation mechanism rules;
- Negotiation Strategies, specification and development of several negotiation strategies;
- Knowledge Discovery, identification and gathering of market knowledge to support agents' strategic behaviour.

Multi-agent model includes a market administrator, buyers, sellers, traders and a market operator.

The market administrator agent has two main functions: coordinator and knowledge provider. On one hand it coordinates the simulated market and ensures that it functions correctly, according to market mechanisms and established rules. On the other hand, it plays the role of "power" agent, since it has access to market knowledge, which contains information about the organisational and operational rules of the market, as well as information about all different running agents, their capabilities and historical information. The market previsions and agent behaviour models are obtained through data mining algorithms, using data resulting from agent negotiations that support agents' market strategies.

Since we intend to cover several negotiation mechanisms, our model also includes a market operator agent, responsible to support negotiations based on an auction mechanism.

Seller and buyer agents are the two key players in the market, so we devote special attention to them, particularly to their business objectives and strategies to reach them. In order to be competitive in today's economic markets, buyer and seller agents need not only to be efficient in their business field, but also to be able to quickly react and adapt to new environments as well as to interact with other available entities. The control architecture adopted for the design of those agents meet these requirements, having a similar structure but with a kind of symmetrical behaviour (due to their antagonistic business objectives).

3 NEGOTIATION MECHANISMS

As a decision support tool, our simulator includes several types of negotiation mechanisms to let the user test them and learn the best way to negotiate in each one. So, we include bilateral contracts and a Pool, centralized mechanism based on an auction, and regulated by a market operator. Both types of negotiation may exist at the same time: Mixed Market. These implies each agent must decide whether to, and how to, participate in each market type.

Let $Agtb$ denote the buyer agent, $Agts$ the seller agent and let $[Pi_{\min}, Pi_{\max}]$ denote the range of values for price that are acceptable for agents.

A seller agent has the range $[Psi_{\min}, Psi_{\max}]$, which denotes the scale of values that are comprised of the minimum value that the seller is disposed to sell to the optimal value.

A buyer agent has the range $[Pbi_{\min}, Pbi_{\max}]$, which denotes the scale of values that are comprised of the optimal value to buy to the maximum value.

3.1 Bilateral Contracts

In bilateral contracting buyer agents are looking for sellers that can provide them the desired products at the best price. We adopt what is basically an alternating protocol [6].

Negotiation starts when a buyer agent sends a request for proposal. In response, a seller agent analyses its own capabilities, current availability, and past experiences and formulates a proposal.

Sellers can formulate two kinds of proposals: a proposal for the product requested; or a proposal for a related product, according to the buyer preference model.

$PPg_{i\,Agts \to Agtb}^{DT}$ represents the proposal offered by the seller agent $Agts$ to the buyer agent $Agtb$ at time T, at the negotiation period D for a specific product.

The buyer agent evaluates the proposals received with an algorithm that calculates the utility for each one, U_{PPgi}^{Agtb}; if the value of U_{PPgi}^{Agtb} for $PPg_{i\,Agts \to Agtb}^{DT}$ at time T is greater than the value of the counter-proposal that the buyer agent will formulate for the next time T, in the same negotiation period D, then the buyer agent accepts the offer and negotiation ends successfully in an agreement; otherwise a counter-proposal $CPg_{i\,Agtb \to Agts}^{DT}$ is made by the buyer agent to the next time T.

The seller agent will accept a buyer counter-proposal if the value of U_{CPgi}^{Agts} is greater than the value of the counter-proposal that the seller agent will formulate for the next timeT; otherwise the seller agent rejects the counter-proposal.

On the basis of the bilateral agreements made among market players and lessons learned from previous bid rounds, both agents revise their strategies for the next negotiation rounds and update their individual knowledge module.

3.2 Pool

In our simulator, agents also have the possibility of negotiating through a Pool, which is a centralized mechanism that functions according to an auction mechanism, and is regulated by a market operator. We have two different auction mechanisms: a double and a single uniform auction.

The process starts at the market operator, who sends a request for participation. The *call_for_participation* message triggers the negotiation process and is delivered to all agents in the simulated market. If the agent is interested, or capable, of participating in the Pool, it will formulate a bid and send it to the market operator, specifying for each requested parameter the value of its proposal.

The process of formulating bids, by buyer and seller agents, is related to agent strategies, addressed in detail in section 6. The market operator evaluates all the received bids, analyses them through the pool auction mechanism, defines the market price and accepted bids. Then a *reply_bid* message is sent to all pool participants, specifying the settled market price and if the bid was or not accepted and why.

3.3 Mixed Markets

The Mixed model combines features of Pools and Bilateral Contracts. In this model, a Pool isn't mandatory, and customers can either negotiate an agreement directly with sellers, at the pool market price or both. Agents must decide whether to try or not the Pool, whether to keep bilateral negotiations simultaneously with Pool negotiations or just after Pool results if bids were not accepted. For that agents use their past experiences, market knowledge and agents own negotiation strategies to support their decisions.

4 DATA MINING SUPPORT

The market previsions and agent behaviour models are obtained through data mining algorithms, using data resulting from agent negotiations that support agents' market strategies. In practice, usually, after a confidential negotiation period, the market administrator agent discloses information about past transactions and agents' characteristics (if possible); all agent interactions are logged at a transaction level of detail, which provide a rich source of business insight that can help to customise the business offerings to the needs of the individual buyers. With this functionality it is possible to discover sub-groups that behave independently and associations between products. For that, our market simulator uses clustering, classification and association operations.

To carry out the clustering operation a Two-Step clustering algorithm [7] is used to target buyers with similar characteristics in the same agent group. Then, to obtain more relevant information that describes the consumption patterns of each cluster population, a rule-based modelling technique, using C5.0 classification algorithm, an evolution of C4.5 algorithm [8], is used to analyse those clusters and to obtain descriptions based on a set of attributes, collected in the individual agents' knowledge module. These models are transferred to the market administrator agent and offer a set of market information, such as: preferred sellers; preferred marks; favourite products and reference prices, which support the process of agents' strategy implementation.

To discover associations between buyer details and purchases, data from multiple agent negotiations are manipulated to create "basket" records showing product purchases. This permits the observation of the behaviour of each buyer agent. This data is combined and manipulated by the "Apriori algorithm" [9], to discover associations between buyer details and purchases. The best association rules, those with a strong support and confidence, are extracted and transferred to the market administrator agent. With this kind of knowledge it is possible to provide insight into the sellers' agents about the profiles of buyer agents with certain purchase propensities, showing associations between products, prices, style, etc.

After these operations, to get confident data, agents can request the services provided by the market administrator agent, in order to support their strategic behaviour. Only players with more sophisticated behaviour will take advantage of this new knowledge; since the user can determine which seller agents have access to this facility. The user can also determine if the agents' information will be private or public; public information is available to market analysis with the data mining functionality. However the market can get knowledge about an agents' behaviour even if they are set as a private information agent. This situation occurs, by the simple fact of being on the market.

5 STRATEGIC BEHAVIORS

5.1 Bilateral Contracts

Agents use four time-dependent strategies to change their price during a negotiation period: Determined, Anxious, Moderate and Gluttonous, these strategies depending on both the point in time when the agent starts to modify the price and the amount it changes.

Although time-dependent strategies are simple to understand and implement [10], they are very important since they allow the simulation of important issues such as: emotional aspects and different risk behaviours. For example, an agent that gains utility, with the time, and has the incentive to reach a late agreement (within the remaining time until the end of a negotiation period) is considered a strong or patient player; an agent that loses utility with time and that tries to reach an early agreement is considered a weak or impatient player.

5.2 Behavior-dependent Strategies

In this work, we have also used the time-dependent strategies, based on the model proposed by S. Fatima [11], to model different attitudes towards time, during a negotiation period.

Agents use behaviour-dependent strategies to adjust parameters for the next negotiation period according to the results obtained in the previous ones. Buyers and seller agents develop their behaviour and strategies based on a combination of public information, available through requesting from market administrator services; and private information, available only to the specific agent at their individual knowledge module.

For Pool Negotiations we define two different behaviour-dependent strategies: one called Composed Goal Directed (CGD) and another called Adapted Derivative Following (ADF). The CGD strategy is based on two consecutive objectives, the first one is selling (or buying) all the available (or needed) units, and then increase the profit (reduce the payoff). The ADF strategy is based on the Derivative Following strategy proposed by Greenwald [12]. The ADF strategy adjusts its price by looking at the amount of revenue earned in the previous period as a result of the previous period's price change. If the last period's price change produced more revenue per good than the previous period, then the strategy makes a similar change in price. If the previous change produced less revenue per good, then the strategy makes an opposite price change.

For Bilateral Contracts Negotiations we also have several behaviour-dependent strategies. Buyer agents can use two complementary behaviour-dependent strategies: the Modified Goal Directed for Buyers (MGDB) and the Fragmented Demand (FD). The MGDB strategy is an adaptation of CGD for bilateral contracts. The FD strategy, adjusts the demand per day by attempting to reach the goal of buying its entire needs by the last day of the market, and not before, this strategy paces its purchases over the market, with the goal of buying all the units needed but with less costs. Seller agents can also choose from two different behaviour-dependent strategies: the Modified Goal Directed for Sellers (MGDS), that adjusts its price by attempting to reach the goal of selling the entire inventory by the last day of the market, by lowering prices when sales in the previous day are low and raising prices when the sales are high; and the Derivative Following (DF) strategy weighted by Seller Satisfaction (DFWS) or by the Previewed Demand for a specific product (DFWPD). The DFWS/PD is based on the ADF behaviour weighted by the referred issues. Seller agents can obtain these values through requesting for market administrator agent support.

6 AGENTS COALITIONS MODELLING VIRTUAL POWER PRODUCERS

Coalition formation is the coming together of a number of distinct, autonomous agents that agree to coordinate and cooperate, acting as a coherent grouping, in the performance of a specific task. Such coalitions can improve the performance of the individual agents and/or the system as a whole. It is an important form of interaction in multi-agent systems.

It has been advocated in e-commerce (where buyers may pool their requirements in order to obtain bigger group discounts), in grid computing (where multi-institution virtual organizations are viewed as being central to coordinated resource sharing and problem solving), and in e-business (where agile groupings of agents need to be formed in order to satisfy particular market niches). In all of these cases, the formation of coalitions aims to increase the agents' abilities to satisfy goals and to maximize their individual or the system's outcomes.

Most work on coalition formation in multi-agent systems and game theory has focus on payoff distribution, where it is usually assumed that a coalition structure has been formed, and the question is then how to divide the payoff so that the coalition structure is stable. In this context, many solutions have been proposed based on different stability concepts. Transfer schemes have also been developed to transfer non-stable payoff distributions to stable ones (while keeping the coalition structure unchanged).

Research is giving attention to the coalition structure generation [13], [14]. The work of Shehory and Kraus [15] considers a somewhat broader environment, where the coalitions can be overlapped but the complexity is reduced by limiting the size of the coalitions.

Some other researchers address both coalition structure generation and payoff distribution in competitive environments. Ketchpel [16] presents a coalition formation method with cubic running time in the number of agents, but his method can neither guarantee a bound from the optimal nor stability. Shehory and Kraus's protocol guarantees that if the agents follow it, certain stability (kernel-stability) is met. In the same paper, they also present an alternative protocol that offers a weaker form of stability with polynomial running time. However, in both cases, no bound from the optimal is guaranteed.

More recent research in coalition formation area has also begun to pay attention to dynamic environments, where agents may enter or leave the coalition formation process and many uncertainties are present (e.g. the coalition value is not fixed, but it is context-based [17]).

6.1 Virtual Power Producers

The aggregation of distributed generation plants gives place to the new concept of Virtual Power Producers (VPP). VPPs are multi-technology and multi-site heterogeneous entities, being relationships among aggregated producers and among VPPs and the remaining Electricity Market (EM) agents a key factor for their success. An aggregating strategy can enable owners of Distributed Generation to gain technical and commercial advantages, making profit of the specific advantages of a mix of several generation technologies and overcoming serious disadvantages of some technologies.

Any type of generation unit or load may be included: wind turbines, photovoltaic, mini turbines, micro-turbine, fuel cells, energy storage units, non-controllable loads, controllable loads etc. The typical size of single distributed energy resource units may range from a few kW to some MW.

In the scope of a VPP, aggregated producers (AP) can make sure their generators are optimally operated and that the power that is not consumed in their installation has good chances to be sold on the market. At the same time, VPPs will be able to commit to a more robust generation profile, raising the value of non-dispatchable generation technologies.

Under this context, VPPs can ensure secure, environmentally friendly generation and optimal management of heat, electricity and cold and optimal operation and maintenance of electrical equipment, including the sale of electricity to the EM. VPPs should adopt organization and management methodologies so that they can make distributed generation a really profitable activity.

VPPs must be flexible enough to use the advantages of its resources (e.g. market-based environmental value in the form of pollution and/or carbon credits, renewable energy credits) and overcoming their problems and limitations.

VPPs must identify the characteristics of each of the AP and try to optimize the selling activity so that each one delivers the biggest possible amount of energy. However, this is not simple due to uncertainty of generation associated with the technologies that depend from natural resources such as wind, sun, waves or water flows.

So, in order to have VPP able to coexist with other market agents, it is necessary that it gets profits and that has credibility in the EM. This context must be considered in VPPs organization and operation methodologies as their goal is to optimize their APs' profits in this market.

A successful achievement of VPPs' goals requires the use of a mix of adequate technologies for optimizing and supporting their activities. Under this scope agents and multi-agent systems are important technologies to adequately simulate EM behaviour and gather knowledge to provide decision-support to strategic behaviour. Taking into account the already described MASCEM characteristics, it can be a valuable framework to test VPP functioning under different market mechanisms and concerning different market strategic behaviour.

6. 2 VPP Coalition formation

From the point of view of the multi-agent system, VPP are seen as coalitions of agents, requiring specific procedures for coalition formation. Once a coalition is established, it can aggregate more agents or even discard some agents. This allows modelling all the decision making concerning VPP formation and also subsequent aggregation of more producers.

VPP needs to have an adequate knowledge of each potential aggregated producer characteristics. Some of the most important characteristics are:

- Nominal Power: the sum of nominal power installed in each producer;
- Available Power: the power a VPP can buy to the producer;
- Overload Power: some units may produce overload power for limited periods. The VPP may use this power in critical situations;
- Equipment characteristics: information concerning producers' equipment allows the VPP to know the power characteristic, reliability, maintenance periods, lifetime, relation with external factors, possible variations of the energy price in function of the cost of the primary resources, etc.
- Operating limits: for the units which are dependent from natural resources, it is possible that the primary resource must be below or above of equipment operating limits. This must be considered in risk analysis in the generation forecast. Usually when the resources forecast is near to the minimum machines operating limit the risk is small, but when they are near to the maximum limit the risk can be enormous;
- Grid connection characteristics: This is an important aspect if it is necessary to pay the losses in the lines; also the existence of two or more producers connected to the same electric substation should be considered; etc;
- Historical generation data: the availability of historic generation data can enable the VPP to get useful forecasting tools.

On one hand, each VPP classifies the producers according to several defined criteria. On the other hand, it establishes the goals of VPP formation or of VPP aggregation of more producers, according to its operating strategies and to its necessities at the moment. Aggregation proposals are then elaborated based on the resulting knowledge. Each producer decision of participating or not in VPP coalition is dependent on agents' market strategies and risk preference.

Once the VPP formation process finished, the VPP needs to coordinate its operation. The VPP must place bids in the market, considering the contracts with producers, the generation forecast, the reserves and its market strategy. According to its member generation capabilities and consumption needs, for a given period, the VPP agent will need to sell or buy electricity. VPP agents have the same market interface as Seller or Buyer agents.

However, as VPPs are themselves a set of other agents, there are some preliminary steps to define its bids. Firstly, all the capacity available from the different aggregated distributed energy resources must be gathered to establish the electricity amount to trade on the market. The different generation costs must be analyzed to define the interval for envisaged proposals. This means VPP agents have a utility function that aggregates all the involved units' characteristics. The analysis of the aggregated producers' proposals will be done according to each unit capabilities and costs.

After the market session, the VPP agent undertakes an internal dispatch, analyzing and adjusting its generation and reserve to maximize profits. VPP informs the aggregated producers about their dispatch. Finally, in function of the generation, the used and unused reserve of each producer and the established contracts of the VPP fulfilment, the VPP determines the producers' remuneration. The Introduction of VPP models in the simulator required to rethink the multi-agent architecture, namely in what concerns agent communication [18]. Figure 1 illustrates the simulator negotiation framework allowing for VPPs.

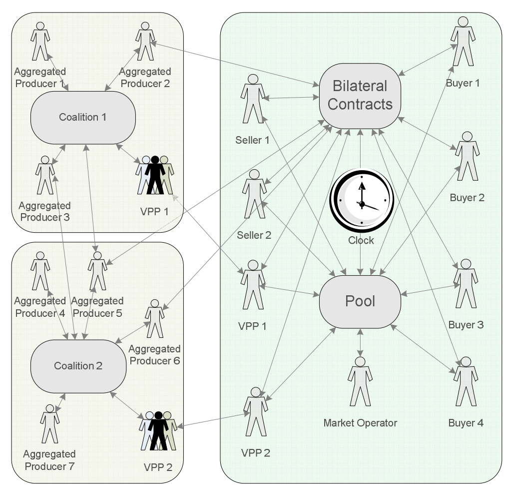

Figure 1. Negotiation framework regarding VPPs

Considering each VPP as a multi-agent system allows an interesting approach from both the performance and the conceptual point of view. In order to develop a computational implementation of this conceptual architecture, each VPP has to have its own facilitator. This means that each VPP has now its own facilitator that allows it to communicate with all the producers that are part of this coalition or intend to join it, independently from the rest of the simulation.

6. 3 VPP Case Study

In fact, our simulator is already being used to study several scenarios from real electricity markets, namely from real data obtained from OMEL, the Spanish Electricity Market. The data was analyzed by means of statistical and data mining techniques in order to have an illustrative scenario although with a limited number of agents. In this example we have a scenario with 7 buyers, 5 sellers, and 2 VPPs. Concerning VPPs, there is a VPP with 3 aggregated producers, all of which have wind farms; and another with 4 aggregated producers (1 photovoltaic plant, 1 wind farm, 1 co-generation and 1 mini-hydro). Figure 2 illustrates market transactions by agent.

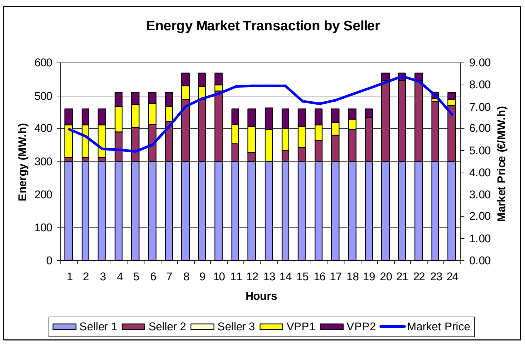

Figure 2 Energy market transactions by seller

Market results showed a coherent behaviour which gives us confidence on using our simulator to test several VPP configurations under different scenarios in order to draw conclusions about VPP advantages and drawbacks for the involved agents and for the market.

7 CONCLUSIONS

In the near future, agent market strategies will be a common competitive manoeuvre for electronic markets. Market participant's strategic behaviour is very significant in the context of competition. In addition, the availability of new market knowledge obtained with data mining algorithms is vital for supporting marketing and sales. Also important is the development of agent-based tools that will help in understanding what kinds of electronic market strategies are appropriate. Agent coalitions is an important issue that can also be analysed by means of our tool. This is already being important to study and obtain conclusions about distributed generation penetration into electricity markets.

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