Evolving Buyer’s Bidding Strategies Using Game-theoretic Co-Evolutionary Algorithm

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Abstract— This paper presents a co-evolutionary algorithm for evolving bidding strategies for buyers in a reconstructed pool-type electrical power market. A demand-driven algorithm which aims to closely follow the individual demands while maintaining low locational marginal price has been implemented and analyzed in detail based on simulation results under different market scenarios. The algorithm has been tested on a simulated power market with 7 buyers and 20 sellers in IEEE 14 bus network. The simulation results suggest that the proposed demand-driven co-evolutionary algorithm is an effective learning algorithm which helps the buyers optimize their bidding strategy. A novel hybrid algorithm which combines the demand-driven algorithm with a game-like decision making process has also been implemented to improve the performance of this algorithm.

I. INTRODUCTION

The worldwide deregulation of the traditionally monopolized and vertically integrated electric power industry in the last decade has lead to a competitive industry. The whole industry of generation, transmission and distribution, wholesale and retail has been unbundled into individual competing entities which need to adopt new efficient economic behaviours. The restructured market offers more opportunities as well as fierce competition among the various players [1].

The interconnectedness of the system through the transmission grid creates the necessity for organizations that can accommodate competition in services, generation, and contracting while preserving the reliability of the transmission system. There are many other different types of participants in an electrical power market, such as the generation companies, distribution companies, transmission companies, end consumers and other new players such as traders. Among these participants, the generation companies (sellers) and the distribution companies (buyers) are two groups of profit-driven players which are the most active in the market. Their behaviors and bidding strategies have been studied and analyzed by researchers through modeling and simulations, in the hope to understand more about the sophisticated market and thus gain more competitive advantages.

Agent-based modeling and simulation has been widely used by researchers, where each agent represents a market participant which is typically a software representation of a decision-making unit. Each agent has its own traits, decision-making rules and limited scope of knowledge about the market and other participants [2, 3]. Many researchers have also focused on incorporating computational intelligence algorithms to simulate a much simpler version of multi-agent electrical power market system and learn some specific attributes or characteristics of the electric power market. Research on multi-agent power market system is still a new area, hence there are still many attributes of the market waiting to be studied. Among which, market participants (agents)’ strategic behavior is particularly significant in the context of competition since bidding strategies of the individual seller or buyer agents can greatly affect the free power exchange market.

Evolutionary algorithm (EA) has been one of the frequently used techniques. An evolutionary algorithm was used in [4] to make the agents human like with attributes such as bounded rationality and emotion. This model was further extended in [5] to incorporate possible physical constrains of the power transmission system. [6] proposed a co-evolutionary algorithm (co-EA) where each agent evolved seller’s bidding strategies based on individual objectives. An evolutionary algorithm was combined with fuzzy rule based algorithm in [7] in which fuzzy variables were used to handle bidding information. The algorithm proposed in [8] adopted Cournot game concepts where the agents compete to maximize their profits by identifying the Nash equilibrium optimum solution. Most of the work in this area has focused on the studying and analyzing strategic behaviors of the power suppliers (sellers) to maximize profit. However, there are actually only a few power suppliers in a city or even in a nation-wide electrical market. The behavior of power buyers is seldom considered although they outnumber the sellers. In [9] the focus was placed on evolutionary alliances building between the buyers, such that the buyers received their desired electric power while reducing their locational marginal prices (LMP).
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The focus of this paper is on learning algorithms to study the strategic behavior of buyers in a power market. A co-evolutionary algorithm has been proposed to evolve bidding strategies for individual buyers. The evolutionary process uncovers interesting agent behaviors and strategies for collaboration. The developed agent-based model uses PowerWorld simulator to incorporate the traditional physical system characteristics and constraints while evaluating individual agent’s behavior, actions and reactions on market dynamics. Simulation results on IEEE 14-bus system show that the evolutionary approach evolves mutually beneficial strategies that enhance the buyer’s profitability. A hybrid model of game theory and demand-driven co-evolutionary algorithm has also been implemented, where the buyers learn when to seek for cooperation based on their evaluation of self performance.

II. SIMULATION NETWORK

In this paper, the electrical power market simulated is a 24 hours-ahead market where sellers and buyers submit their bids for each hour of the next 24-hour scheduling to PX and ISO before the day starts. It is a PoolCo type system [1] where PX and ISO accept or reject the bids they receive and plan for dispatch schedule for the next day, upon taking into consideration of the bids submitted, transmission constraints and energy security factors. Uniform non-discriminatory pricing is adopted here instead of “pay-as-bid”, which means that all agents pay or get paid the locational marginal price (LMP) depending on their location. Each LMP reflects the incremental cost of dispatching the system to supply load at a given location, and is similar to the market clearing price (MCP) if no additional charge is needed to solve congestion in the system.

Both high inflow and low inflow scenarios are simulated and studied in this paper for all the algorithms discussed. Under the high inflow case, the inflows are generous where generation availability is much higher than total load. Whereas under the low inflow case, the generator capability is low (about a quarter of the full capacity) and there is great probability that some buyers may not be able to get the amount of energy they require. Several simulations using these broad scenarios were conducted to study the algorithm under different market conditions.

PowerWorld® simulator is used in this paper to aid the simulation of multi-agent electric power system in order to achieve a higher level of market reality. PowerWorld does not only provide validity check for the test system, it also performs the functions of PX and ISO, by taking care of the scheduling and dispatching of electric power according to bids submitted by generators (sellers) and distributor (buyers). The optimal Power Flow Tool (OPF) minimizes the objective function while taking into consideration various limits and constraints on capacities of the generators/loads and line limits.

The IEEE 14 Bus network with 20 buyers and 7 sellers (Fig 1) has been built in PowerWorld simulator. The network has sellers and buyers with different attributes to introduce variety to the system and also make the simulations closer to the real world situation.

![Fig. 1. IEEE 14 Bus Layout at PowerWorld](image)

The market simulated is assumed to be young and selfish initially. The agents lack experience (reliable data or traditional models) and act independently for their own good without taking into consideration the behavior of other agents in the system. Therefore every agent starts with randomly assigned initial bidding strategies, but learns and becomes more tactful as the algorithm progresses.

The focus of this paper is on the strategic behavior of the buyers in the electrical power market, therefore the behaviors of the sellers are less important in this paper and assumed to be more or less consistent. This means, the evolutionary algorithms simulated are only applied to the buyers’ bids, while the sellers’ bids do not go through evolution. Instead, seller’s bids only go through a random minor adjustments for every generation. In this paper, though transmission limit is enforced, the main objective in this paper is on strategies that help reduce the MCP instead of on solving the congestion problem.

III. CO-EVOLUTIONARY ALGORITHM FOR EVOLVING BUYERS’ BIDDING STRATEGIES

The proposed method uses a co-evolutionary algorithm to evolve cooperative strategies in a multi-agent framework. In this co-evolutionary algorithm (co-EA), each buyer agent undergoes a separate evolutionary process within its own population pool. Each chromosome is a concrete bidding strategy (or bid), which is made of six (quantity, price) pairs. The population size for each evolutionary process is 24, which represent the hourly bids in the previous 24 hours for each individual buyer. There are altogether 20 such evolutionary processes going on in each generation since 20 buyers are involved. Since the load demand on weekends and public holidays is very different than on weekdays, these days are treated separately to evolve biddings strategies for these days. Elitism is used such that the worst one of the 24 evolved strategies is replaced by the best one from the
previous generation. Tournament selection is adopted for selecting parent individuals. The overall probability of crossover between two parent bids is 0.5.

The fitness of the bidding strategies is calculated based on the difference between power received and the actual power demand on the previous day. The smaller the difference, the fitter the bidding strategy. Equation (1) illustrates the fitness function for this “Demand-driven” co-EA.

Mutation is implemented in the form of a correction component where all the bids are corrected with a user specified mutation probability. The percentage and direction of correction is totally based on the relationship between the power received in the previous round and its demand. Equation (1) shows the mutation function described above.

\[
\text{Target} = \text{GAMMA} \times \frac{1.2 \times \text{PowerDemand} - \text{PowerReceived}}{1.2 \times \text{PowerDemand}}
\]

\[
\text{Percent} = \frac{\text{Target} \times 1.2 \times \text{PowerDemand} - \text{PowerReceived}}{\text{Target} \times 1.2 \times \text{PowerDemand}}
\]

For all bid prices,

\[
\text{new}_\text{bidprice} = \frac{100 + \text{percent}}{100} \times \text{old}_\text{bidprice}
\]

Where \( \text{GAMMA} = 0.2, \text{DELTA} = 5 \)

IV. SIMULATIONS RESULTS

The algorithms presented above were tested under several high inflow and low inflow scenarios. The proposed “demand-driven” algorithm is compared against another co-evolutionary algorithm in which the buyers always try to get as much power as possible while trying to pay low locational marginal price (LMP). The objective function takes in these two factors into consideration, which means the bidding strategies which lead to higher power received and less LMP paid are considered to be fitter than others. However, getting higher power is normally associated with bidding higher and thus likely paying higher price, thus the evolutionary process needs to strive for a good balance and find the optimal bidding strategies which satisfy both. Equation (2) illustrates the fitness function for “greedy” co-EA.

\[
\text{Greedy Fitness} = \frac{\text{Power Received}}{\text{Capacity}} \times 30 - \text{LMP}
\]

The simulation results of 4 different cases have been presented. Case 1) and 2) show the performance of buyers when all 20 of them adopt either one of the co-evolutionary algorithm. In this, buyers with same capacity are positioned opposite to each other on the same bus. Since half of the buyers adopt one algorithm while their respective identical opponents adopt another algorithm, the purpose is to find out which will eventually win the battle. Therefore in case 3) 10 buyers adopting demand-driven algorithm has been made to compete with 10 opponents who adopt the greedy algorithm in the same market. In this paper, the results are shown only for two buyer agents (buyer 17, 18). The performance of the other buyer agents shows similar trend.

1) Uniform “Greedy” strategy

Under the first simulation scenario, where the available supply exceeds the actual demand, the buyer agents managed to obtain high power. However, the second objective of less LMP is not fully met. Instead, the LMP is actually increasing for all the buyers. It is obvious that obtaining additional power is not really a competitive advantage in a high inflow market. Fig. 2 shows the results for buyer 17 in the scenario where all buyer agents adopt a greedy strategy.

2) Demand-driven strategy

Fig. 3 shows the results when all buyers adopt a demand-driven bidding strategy. As the total available supply exceeds the demand, all buyer agents are successful in obtaining the required amount of power.

3) 10 “Demand-driven” vs. 10 “Greedy”

When all the 20 buyers adopt demand-driven algorithms, the buyers are demand sensitive. Through learning during successive generations, they slowly evolve the bidding strategies to reduce the LMP together, while obtaining the requisite amount of power. The LMP reduces for all the 20 buyers, illustrating that demand-driven co-EA is an effective cost-saving algorithm under a high flow situation.
In this case, 50% of the buyer agents adopt a greedy strategy while the other 50% use a demand-driver bidding strategy. The simulations show interesting behavior in the form of rivalry between two groups of learning buyers who have different objectives in mind. As expected, the greedy buyers tends to get more and more power while the demand-driven buyers eventually follow the demand pattern after some generations. Simulation results in Fig. 4 show an example in which buyer 17 uses a demand-driven strategy while buyer 18 uses a greedy strategy. Although the demand-driven buyers significantly contribute to pull down the LMP, the overall LMP is not reduced, since their effort has been nullified by the greedy buyers who bid too high.

In the second set of simulation studies, constraints are placed on the power available. As such, in some cases, the demand exceeds the supply.

4) 20 “Greedy” buyers

When the amount of total generation is reduced such that the total generation is much less than the total demand, simulations show that out of the 20 greedy buyers, there are only 4-6 small buyers which manage to get enough power to meet their demand. LMP goes up almost linearly due to the fact that the greedy algorithm allows bids with high price to survive since they tend to grab more power. Apparently “greedy” algorithm does not perform well here.

5) 20 “Demand-driven” Buyers

In the scenario when the demand exceeds the available supply, the demand-driven co-evolutionary algorithm does not perform very well. The LMP shoots up exponentially due to the correction component which manipulates the bid prices up when demand is not met. The simulation result shows if everyone is fighting, no one wins. Therefore, some form of cooperation would be needed in this case.

6) 10 “Demand-driven” vs. 10 “Greedy” buyers

When half of the buyer agents adopt a greedy strategy and the other half a demand-driven strategy, the greedy buyers are outbid by their counterparts. This is due to the more responsive learning used by the demand-driven buyers which react to the simulation by correcting their prices much faster than the greedy buyers which use random mutation to adjust bids. It can be observed that the LMP increases slightly because even though the greedy buyers are losing to the demand-driven buyers, they do not give up trying bids which give them higher power.
trying to outbid each other. Fig. 12 shows the LMP for buyer 17 in a scenario where supply exceeds demand, and all buyer

V. GAME-THEORETIC DEMAND-DRIVEN MODEL

In the previous section, it has been shown that the demand-driven co-evolutionary algorithm is an effective learning algorithm under both high inflow and low inflow scenarios. However, in situations when all buyers adopt the demand-driven algorithm in a low inflow market, the LMP increases substantially. A novel hybrid model has been implemented to solve this problem while retaining the main features of the demand-driven model. The hybrid model adopts a game-theoretic decision making component built on top of the existing demand-driven algorithm. Fig. 11 shows the flowchart of the hybrid model.

The decision-making session firstly allows each buyer to check whether it has been betrayed by others during trading on the previous day. Based on this information, the buyer increases its bid prices to close the gap with others if evidence of betrayal has been found. However, if it discovers that all other buyers cooperated on the previous day, the bids are not increased. Each buyer then goes through a decision making process to determine whether to cooperate with others in the next 24 hours using a probability function. If the buyer agent finally decides to cooperate, its bidding strategies for the previous day are sent to the PowerWorld simulator directly without going through the co-evolutionary process, whereas if the buyers decide not to cooperate, its demand bids are determined through the co-evolutionary process described earlier.

Extensive simulations using this hybrid model indicate that this model not only retains all the good characteristics of the demand-driven algorithm, but also successfully solves the problem of the exponentially increasing LMP described in the previous section where all 20 demand-driven buyers are
agents adopt a hybrid learning strategy to learn from their past experiences. Simulation results for a scenario where demand exceeds the supply, are shown in Fig. 13. As in the previous case, all buyer agents use experiential learning. It is noted that LMP for Buyer 17 stabilizes after 45 days.

It was observed that in this game-theoretic hybrid model, all buyer agents learn to cooperate with each other, resulting in stabilization of LMP in all simulation scenarios.

VI. CONCLUSION

The paper proposed a co-evolutionary multi-agent system emulating a real-world electrical power market. Individual buyers submit higher priced demand bids to protect themselves against the dynamics of the behavior of other buyers or other non-systematic risks. The results on a test system showed that buyers who cooperate obtain a set of robust demand bids, such that the required amount of power can be received at the lowest possible cost to the buyer. Learning from past experiences helps to protect them against continuing market trends as they know when and how much to revalue their demand bids by. Due to the tradeoff between the LMPs and the amount of power delivered, agents can adopt a wide array of strategies to suit their specific needs.

The simulation are conducted using PowerWorld simulator to effectively validate the system configuration and ensure that various constraints have been met.

Though the demand-driven co-evolutionary algorithm has been proved to be an effective learning algorithm that buyers can adopt, it was observed when all buyer agents are equally smart and try to outbid each other, no one actually benefits. The hybrid model further improves this model by incorporating a game-like decision making feature. With this hybrid algorithm, the buyers are more sensitive and tactful, since they are able to decide when or whether to seek for cooperation, especially if they sense that they are in a tough situation where the available power supply is less than the total demand. Simulation results show that the hybrid model do not only retain all the strengths of the pure demand-driven algorithm, it also helps the buyers to start cooperation.

REFERENCES


