Building Fuzzy Bidding Strategies for the Competitive Generator

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Abstract: In this paper, the authors build on previous research that they have done in the area of building bidding strategies for electric utilities in the competitive environment. The previous research is briefly reviewed. The deregulated market-place is defined and modeled. Fuzzy logic is included to make bidding strategies adaptive. Four methods for building bidding strategies which use fuzzy logic and/or genetic algorithms are discussed and outlined. Economical inputs are fuzzified for use in determining a generator's bid. Methods of tuning and searching for the optimal rule are discussed. We discuss how an agent using the bidding strategies can compare them based on profitability.

Keywords: Bidding Strategies, Auctions, Trading, Fuzzy Economics, Expert-System Bidding, Genetic Algorithms.

1.0 Introduction

Due to recent deregulation intended to bring about competition, the US electrical industry is in the midst of some major operational changes. Although the details of the deregulated marketplace for each region of the country are not yet fully defined, they are being more clearly defined as time passes. Many legislators, researchers, and electric customers and suppliers are convinced that electricity will be traded in a manner similar to other commodities at exchanges around the country.

Configuration of the transmission system and the fact that electricity flow is subject to the laws of physics, have some speculating that we will see the formation of regional commodity exchanges that would be oligopolistic in nature (having a limited numbers of sellers). Others postulate that the number of sellers will be sufficient to have near perfect competition. Regardless of the actual level of the resulting competition, companies wishing to survive in the deregulated marketplace must change the way they do business and will need to develop bidding strategies for trading electricity via an exchange.

Economists have developed theoretical results of how markets are supposed to behave under varying numbers of sellers or buyers with varying degrees of competition. Often the economical results pertain only when aggregating across an entire industry and require assumptions that may not be realistic. These results, while considered sound in a macroscopic sense, may be less than helpful to a particular company not fitting the industry profile that is trying to develop a strategy that will allow it to remain competitive.

Generation companies (GENCOs), energy service companies and distribution companies (DISTCOs) that participate in an energy commodity exchange must learn to place effective bids in order to win energy contracts. Microeconomic theory states that in the long term, a hypothetical firm selling in a competitive market should price their product at it's marginal cost of production. The theory is based on several assumptions (e.g., all market players will behave rationally, all market players have perfect information) which may tend to be true industry-wide, but might not be true for a particular region or a particular firm.

Section 2 of this paper describes the deregulated market-place to be considered during this research. Section 3, describes the authors' previous research on evolving bidding strategies for generation companies using genetic algorithms. We build on the idea and begin to discuss some of the advantages of strategies that are adaptive. Section 4 provides the reader with the basics of fuzzy logic, and looks at how the economic inputs of DISTCOs and GENCOs might be fuzzified in order to build better bidding strategies. Section 5 outlines the models we are using, and the research we are currently pursuing to build better bidding strategies. Finally, section 6 summarizes and lists areas which we plan to investigate in the future.

2.0 The Market-Place

The basic framework for the research described in this paper is adopted from Sheblé [14, 15, & 20], which is an extension to that being proposed in California. Sheblé [21] described the different types of commodity markets and their operation. He outlined how each could be applied in the evolved electric energy marketplace. Under this framework (Shown in fig. 1, which was presented in [24].) companies presently having generation, transmission, and distribution facilities would be divided into separate profit and loss centers. Power would be generated by generation companies GENCOs and transported via transmission companies (TRANSCOs). Energy service companies (ESCOs) would purchase the power from the generator for the customer. It has been proposed that NERC would set the reliability and security standards. It is predicted that we'll see energy services companies (ESCOs) replacing the current distribution utilities as the main customer representative. An Independent Contract Administrator (ICA) will review the power transactions to ensure that system security and integrity is maintained. Distribution companies would own and maintain the distribution facilities. Companies providing ancillary services (ANSILCOs) and energy mercantile associations (EMAs) will emerge in this new framework.

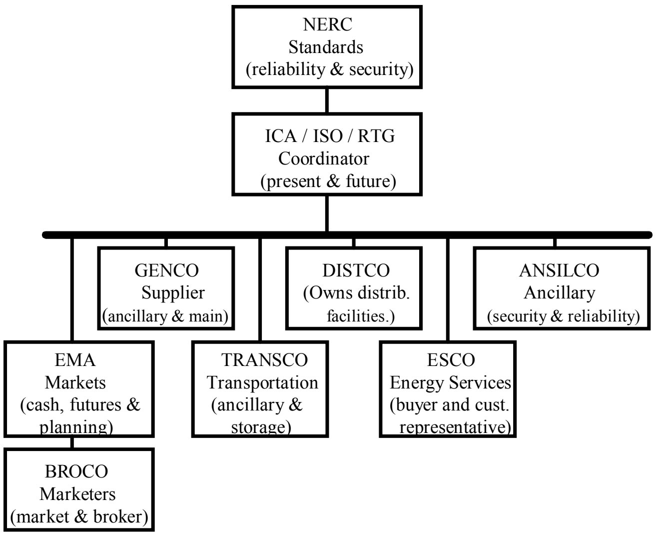

Fig. 1. Brokerage system model.

In the double auction used for this research, the bids and offers are sorted into descending and ascending order respectively, similar to the Florida Coordination Group approach as described by Wood and Wollenberg [27]. If the buy bid is higher than the sell offer that to be matched, then this is a potential valid match. The ICA must determine whether the transaction would endanger system security and whether transmission capacity exists. Specifically, the contract approval will be subject to meeting requirements for maintaining sufficient spinning reserve, ready reserve, reactive support, and area network control (contract-based AGC). If the ICA does approve, the valid offers and bids are matched and the difference in the bids ($/MW) is split to determine the final price, termed the *equilibrium price*. This is similar to the power pool split-savings approach that many regions have been using for years.

If there is an insufficient number of valid matches, then *price discovery* has not occurred. The auctioneer reports the results of the auction to the market participants. If all bids and offers are collected and insufficient valid bids and offers are found to exist, then the auction has gone through one cycle. The auctioneer then reports that price discovery did not occur, and will ask for bids and offers again. The auctioneer requests the buyers and sellers to adjust their bids and offers. To aid in eventually finding a feasible solution, during subsequent cycles within a round, buyers may not decrease their bid, and sellers may not increase their offer. The cycles continue until price discovery occurs, or until the auctioneer decides to bind whatever valid matches exist and continue to the next round or hour of bidding.

After price discovery, those buyers and sellers whose bids were bound will potentially have a contract. This contract is subject to the approval of the ICA, who verifies that none of the security criteria have been violated. Following the completion of one round of bidding, the auctioneer asks if another round of bidding is requested. If the market participants have more power to sell or buy, they request another round. Allowing multiple rounds of bidding each hour (vs. one-shot bidding) allows the participants the opportunity to use the latest pricing information in forming their present bid. This process is continued until no more requests are received or until the auctioneer decides that enough rounds have taken place. See Fig. 2 for a block diagram of the auction process.

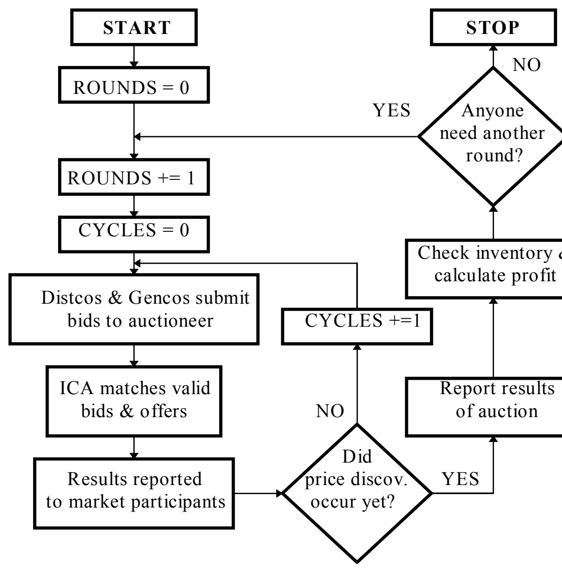

Figure 2. Block diagram of the auction process.

3.0 Evolving Bidding Strategies with Genetic Algorithms

A genetic algorithm (GA) is an algorithm which allows evolution of the contents of a data structure. GAs were developed by John Holland and are loosely based on the biological notion of evolution. The data structure being evolved contains a solution to the problem being studied. A population of syntactically valid solutions are initialized randomly during the first step of the algorithm. Each of the solutions is assigned a fitness based on its suitability for solving the particular problem being studied. If these solutions are initialized randomly, the chances of them being highly *fit* during the first *generation*, is not very high. At each generation, the GA will randomly chose members of the population to be "parents" favoring the highly-fit members. The parents will then produce offspring via the *crossover* and *mutation* processes. Crossover is the means by which two parents produces two offspring and involves combining parts of each parent to produce each child. Mutation can be thought of as copying errors introduced into the children due to background noise. The newly produced offspring replace the members of the population that have a low fitness. As the generations progress, there is a tendency for the contents of the data structures to adapt such that they become more suited to solving the problem. See [12] for a more complete description of genetic algorithms.

In [5], the authors use a GA to evolve a structure containing bid multipliers. Others have used GAs for computational economics [18, 25]. The bidding strategies that come from the evolved structures (shown in Fig. 3) are fairly simple. The expected price of the electricity (obtained via some prediction scheme) is multiplied by the bid multipliers and the result is used as the bid for that particular round of bidding. In addition to the bid multipliers, the number of MWs to offer for sale at each round of bidding and the choice of price prediction techniques are also evolved. The results presented in [5] are promising. As the GA progresses, they bidding strategies become better and yield more profit, indicating that "intelligent agents" are learning. However, the strategies are somewhat limited because they do not make use of inputs that are available during a particular round of bidding. Evolving bidding strategies as in [5] is like learning the steps of a dance or memorizing a list of things to do mechanically in order to make a successful bid for a particular set of circumstances. Using the approach in [5], means that the evolved rules will not be very adaptive, i.e., they don't react to the environment. Each set of rules is evolved to be used only for a specific set of circumstances. If the circumstances vary from that, the set of rules may yield disappointing results. We could attempt to create scenarios in which we are interested, but we would find that the number of credible scenarios is so large that we could not possibly hope to cover them all. So the question becomes: How can we develop adaptive bidding strategies that will take advantage of currently available information?

4.0 Fuzzy Bidding

The field of "fuzzy logic" was made popular by Lotfi Zadeh during the 1960s. Fuzzy logic provides a methodical means of dealing with uncertainty and ambiguity. It allows its users to code problem solutions with a natural language syntax with which people are comfortable. In fact many of us regularly use fuzzy terms to describe things or events. For instance, if we were asked to describe a person, we might use terms like "pretty tall", with a "big nose" and "somewhat overweight". These terms can mean be defined differently by different people. There is a certain amount of ambiguity or uncertainty associated with any description involving natural language terms such as these. Most of the things we deal with daily in this universe are ambiguous and uncertain. "The only subsets of the universe that are not in principle fuzzy are the constructs of classical mathematics." [28]

Agent *N*	Rounds of Bidding ----------------------->				
MWs each round	12	4	20	...	14
Mult. each round	01011	01101	10101	...	00101
Prediction Technique	moving average				

Figure 3. Data structure used in previous research.

Fuzzy logic allows us to represent the ambiguous or uncertain with membership functions. The membership functions map the natural language descriptions onto a numerical value. Membership to a particular description or class is then a matter of degree. For instance, if we define a person's height as described in fig. 4, then we can see that a person that is 6 feet in height is tall with a membership value of one. This membership value is also known as a truth value. From the same figure, we can see that a person who is 5 feet 9 inches is tall to a lesser degree and but at the same time he is also short to a certain degree.

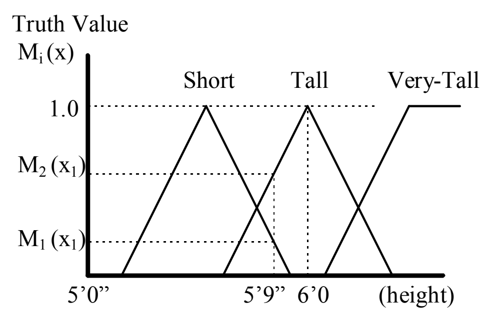

Figure 4. Fuzzy membership functions.

Using similar reasoning, we might say that electrical demand is high in a region if it goes above 100MW, and normal if it is between 50MW and 75MW. What if the demand is 90MW? Using traditional logic we would classify it neither high nor normal. However using fuzzy logic, we might find that this demand is actually both high and normal, each to a certain degree (based on its membership function). Similarly we could have fuzzy membership functions for other inputs like fuel costs, risk aversion, level of competition, etc.

Once defined, these inputs can then be used in a set of fuzzy rules. For instance, a simple rule might be as follows:

IF demand is HIGH, then bid should be HIGH

where a "high" bid would be defined using another membership function. Multiple input conditions can be considered by combining rules with the "and" and "or" functions. For example a rule might be as follows:

IF (demand is LOW) AND (risk aversion is HIGH) THEN (bid should be LOW)

Although it may not be necessary, we could have an output for all combinations of inputs. A three input fuzzy rule system where each input is broken into five classifications might be represented as in fig. 5. The small squares each contain the output of a rule on how to bid relative to cost. Since some conditions might be very unlikely to occur each of these squares need not have an output. In addition, a particular input maybe classified in more than one square at a given instant. In the figure, the letters V, L, H, C, and N stand for very, low, high, cost, and normal respectively. The output of the rule states how to bid with respect to generation cost. We could have more or fewer inputs, and we could use different classifications. Figure 6 shows the fuzzy system

FORECASTED PRICE

FUEL COST	VL	L	N	H	VH
Very high			VL		
High			L		
Norm	VL	L	C	H	VH
Low	L	C	H	VH	VH
Very Low		H	VH		

ADDITIONAL INPUT (E.G., RISK AVERSION)

Figure 5. Three input fuzzy rule set.

architecture. The inputs are fed into the rule base. The output (i.e., the bid values in the example) of each rule can be classified by a fuzzy membership function in the same manner as the inputs. The output of each rule may be assigned a certain weight depending on how important we determine that rule or corresponding inputs to be. We can then sum the weighted output of the rules and determine an overall fuzzy output. However, when the time comes to place the bid we can't just say, "bid high". We need a way to convert the fuzzy output to a single number. This is called the defuzzification process.

According to Kosko [28] defuzzification formally means to round off a fuzzy set from some point in a unit hypercube to the nearest bit-vector vertex. Practically defuzzification has been done by using the mode of the distribution of outputs as the crisp output, or by the more popular method of calculating the centroid or center of mass of the outputs and using that as the crisp output. The fuzzy centroid, $\overline{B}$, can be calculated as follows:

$$\overline{B} = \frac{\sum_{j=1}^{p} y_j m_B(y_j)}{\sum_{j=1}^{p} m_B(y_j)}, \qquad \text{where } B = \sum_{k=1}^{m} w_k B_k'$$

and where B is the output distribution that contains all information, and $m_B(y_j)$ is the membership value of y_j in the output fuzzy set B. See fig. 6.

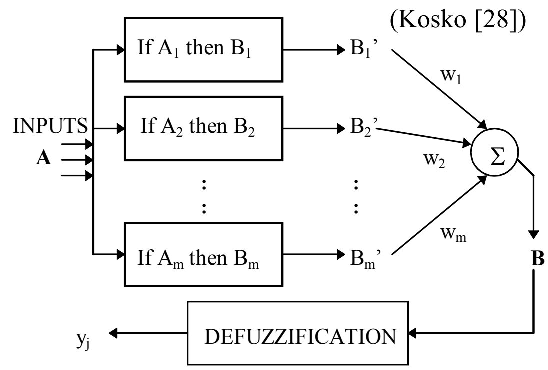

Figure 6. Fuzzy system architecture.

5.0 Comparing Bidding Strategies

This section provides a comparison of approaches that we are taking in developing bidding strategies. First, we will be generating fuzzy bidding rules manually using expert knowledge. Secondly, we shall search for good rule-sets from a limited search space. With a small number of inputs and a limited number of weighting, we can do an exhaustive search of all rules and determine the best possible rule. (The best rule is the one whose use results in the largest amount of profit for its user.) Thirdly, we note that if we increase the number of fuzzy inputs, increase the number of membership functions describing the inputs, and allow more flexibility with the weighting, that perhaps it becomes desirable to use a genetic algorithm to search for the "optimal" rule, rather than do an exhaustive search. Finally, we will attempt the use of a technique developed in [7] to extract, from a historical database containing the bidding details of an auction, the rules that were used by others in developing their bids.

The research described here builds on the techniques used by the authors and described in[5]. To measure the performance of the bidding rules created in each of the methods described below, a group of GENCOs will compete to serve the electrical demands of the ESCOs. Electricity buyers will be aggregated into a single large ESCO. See figure 7. TRANSCOs and transmission constraints will not be considered directly here, but can be accounted for after-the-fact if desired.

5.1 Generating the fuzzy rule-sets manually

If we consider only a limited number of fuzzy economical inputs, (e.g., expected price, risk aversion, and generating costs) then it is possible to generate rules manually with expert knowledge from power traders. We can transform the rules-of-thumb used by experienced power traders into a fuzzy rule base. We may also use theoretical economics to influence the rule-sets that we construct. If we have 3 fuzzy inputs, each divided into 5 classifications, then we could have need for as many as 125 rules in each rule-set (one for each little square in fig. 5). Each of the rules can be

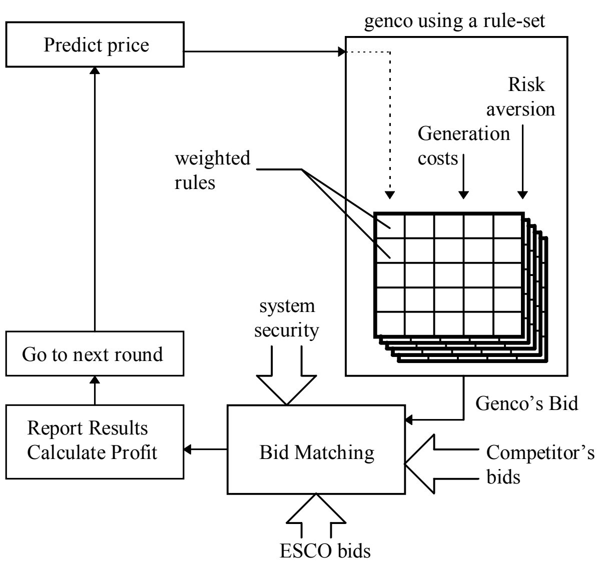

Figure 7. Using the rule-set.

weighted according to its importance, if any weighting is allowed we have infinitely many possibilities.

5.2 The search for the "optimal" fuzzy rule-set

To reduce the amount of time spent tuning the rule-sets, we can predefine a structure and allow a computer program to search through the possibilities to find the optimal rule-set. If we predefine each of the three inputs by five fixed ranges, and only allow discrete rule weightings (e.g., 0.0, 0.1, 0.2, ..., 1.0), then there are a finite number of permutations to investigate. A possible indication of optimality would be obtained by having an agent use each of the possible rule-sets while engaging in a fixed set of trial-auctions competing with a set of agents that had evolved to play the market described in [5]. To ensure that the rules aren't market specific, the set of agents against which the rule will be competing can be taken from different populations and from various stages of evolution. This increases the certainty the tested rule will be profitable against a diverse set of agents and circumstances.

5.3 Using a GA to evolve fuzzy rules for bidding

If we relax the requirement that each rule have a discrete weighting, we can see that the size of the search space becomes quite large. If we also increase the number of inputs to consider, the search space grows even larger. The exhaustive search no longer remains feasible. In addition, if we do not wisely chose the set of agents against which are rules will be tested, then we would be left with rules that are not extremely robust. Therefore, the authors plan to use a GA to evolve rule-sets in a similar fashion as in [5], but with slightly modified data structures.

Each of the GENCOs will have it's own evolving data structure consisting of a fuzzy set of rules, and weights associated with each of those rules. The weights will allow some rules to have more importance than others. In previous work, the authors allowed each of the individual GENCOs to have their choice of price forecasting techniques. This created a lot of overhead, and for simplicity, current research will have each GENCO receiving globally forecasted data. In addition, the contract size (i.e. number of MWs to offer) at each round of bidding would be fixed rather than evolvable to reduce the search space.

5.4 Using a GA to extract expert-system bidding rules from a historical database

The authors have investigated the use of GAs and other so-called artificial intelligence techniques to search through large databases in order to learn the expert system rules that can be used to reproduce the historical results. Presently this technique is being used to develop standardized treatment methods for hospital patients receiving medical care. Based on extensive records, the software is able to determine what the doctor did based on patient conditions. Similarly, a database of trading data could be fed into the software (which would require tuning and some restructurization) to figure out what bidding rules were being used by the traders. Determining the rules that other electricity traders and brokers are using could be of great benefit to those who wish to gain a competitive edge when participating in the deregulated market.

6.0 Summary and Future Research

Building good bidding strategies for electricity traders as they move into the deregulated marketplace will continue to be important for those companies wishing to remain profitable. The authors have performed research in this area, and this paper describes directions in which they are currently investigating in order to build more robust adaptive bidding strategies. The deregulated market-place that we assume will become standard throughout the USA has been defined and is incorporated into our auction simulator. The bidding rule-sets or strategies obtained from each method described in this paper will be tested in auction simulations. They will be compared via profitability to each other and to the method of using the bid multipliers rules developed in previous work by the authors and ranked.

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