Bidding Strategies that Minimize Risk with Options and Futures Contracts

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Abstract: This research builds on earlier research in developing bidding strategies through the inclusion of options and futures contracts. In the competitive environment, electric traders' profits depend on the implementation of a successful bidding strategy. Bidding strategies are studied in an environment in which distribution companies (DISTCOs) and generation companies (GENCOs), buy and sell power via double auctions in regional commodity exchanges. The market framework being used was proposed by Kumar and Sheblé [11] and allows participants to trade in the spot, future, planning and swap markets, and also gives rise to the use of option contracts. Bid-strategy research previously published by the authors focused on increasing electric generators' profit as they participated in a spot/cash market. Here we incorporate techniques such as game theory and decision analysis to minimize the risk to the electric utility or energy trader. The goal is to ensure reliable power system operation while also ensuring that contracts are fulfilled and traders adopting the strategies remain profitable. The developed strategies are tested in our electric market trading simulator which can be used off-line to predict whether bid strategies will be profitable and successful.

Keywords: Competitive auction markets, optimization, genetic algorithms, bidding strategies, deregulation, energy broker, power systems, options and futures contracts, risk management.

1. INTRODUCTION

The US electric marketplace is in the midst of major changes designed to promote competition. No longer vertically integrated with guaranteed customers and suppliers, electric generators and distributors will have to compete to sell and buy electricity. The stable utilities of the past will find themselves in a highly competitive environment. Although some states (e.g., California) are poised to operate in a restructured environment, a standardized final market structure for the US has not yet been fully agreed upon. The authors believe that regional commodity exchanges selling electricity contracts will play a key role.

In previous papers [11,17,19,20] the authors have described a framework in which distribution companies (DISTCOs), generation companies (GENCOs), energy services companies (ESCOs) and transmission companies (TRANSCOs) interact via contracts. The contract prices are determined through a double auction. Buyers and sellers of electricity make bids and offers that are matched subject to approval of the independent contract administrator (ICA) who ensures that the system is operating safely within limits.

Operating within the framework described in this paper, traders will find it helpful to create and implement bidding strategies to make their bids and offers. Bidding strategies may be designed to limit the traders risk, to maximize profit, or some combination of both. The authors have done research in developing bidding strategies to maximize profit for the spot market using genetic algorithms and genetic programming [17,19,20]. Although our previous research focused on double auction bidding strategies for the spot market, the techniques may be used in the futures, options and forwards markets. In this paper, we extend our previous work by creating energy trader portfolios which combine the spot market contracts with options and futures contracts to manage the trader's risk and profitability.

This paper is organized as follows. Part 2 is a brief review of recent work in the deregulated electric marketplace and building bidding strategies for that marketplace. Part 3 outlines the competitive environment that we have proposed and assume to be the standard of the future. It also gives a brief introduction into commodity markets and associated trader jargon. Part 4 goes through various techniques that we consider in reducing risk and producing less risky strategies. Finally, Part 5 presents a plan to extend our research in bidding strategies using the techniques described in Part 4. Finally, Part 6 provides a brief summary of the paper.

2. RECENT RESEARCH

The electric marketplace used in this paper has been refined and described in various papers. Fahd and Sheblé [5] demonstrated an auction mechanism. Sheblé [22] described the different types of commodity markets and their operation and outlined how each could be applied in the evolved electric energy marketplace. Sheblé and McCalley [23] outline how spot, forward, future, planning and swap markets can handle real-time control of the system (e.g., automatic generation control) and risk management. Work by Kumar and Sheblé [10] brought the above ideas together and demonstrated a power system auction game designed to be a training tool. That game used the double auction mechanism in combination with classical optimization techniques.

Although much work has been done in the field of bidding strategies, little has been for the electrical industry. In [15], Rajan develops a sub-optimal bidding technique whose use could provide a lower bound for profit in a single-shot bidding. Much of the theoretical auction work described in economics literature has been developed using the single-shot bidding approach to auctions. The authors foresee multi-shot bidding (with opportunities to adjust bids and offers in order to reach price discovery) as a more probable and competitive alternative. Much less work has been done on bidding strategies for this type of auction.

In recent publications [17,18,19,20], the authors describe some of their research in developing bidding strategies with evolving trading agents for the deregulated electrical utility industry. Apart from the electrical utility industry, interest has grown in recent years for using evolving, or adapting, agents to simulate trading behavior. Research with these adaptive agents has proved to be useful in simulating the behavior of markets outside of the electrical industry. LeBaron [12] used evolving agents to learn to play financial markets. Tesfatsion [27] described research in which trading agents decide who to trade with based on an expected payoff. Ashlock, in reference [2], used genetic programming combined with a finite state automata to play a classic academic game involving bidding behavior and strategies.

Andrews and Prager [1] used a game based on a double auction to verify that genetic search is useful. They show that GP-based agents actually can learn and they compare the performance of the GP-based strategies to those developed using simulated annealing. In addition, they rediscover that at the beginning of the genetic algorithm it is possible to use a less rigorous fitness test than needed in later generations. While their findings may be useful to the genetic algorithm community, their experiments don't realistically model the auction scenario and leave room for further improvements in strategy-building for the competitive electricity marketplace.

3. COMPETITIVE ELECTRIC MARKETPLACE

3.1 The corporate environment

Under the framework described by Sheblé [21], companies presently having both generation and distribution facilities would be divided into separate profit and loss centers. Power is generated by GENCOs, transported via TRANSCOs, and all power is sold to DISTCOs. NERC will set the reliability and security standards [25]. ESCOs providing ancillary services (ANCILCOs), and energy mercantile associations (EMAs) will emerge in the competitive electric industry. See Fig. 1 which was presented in [25].

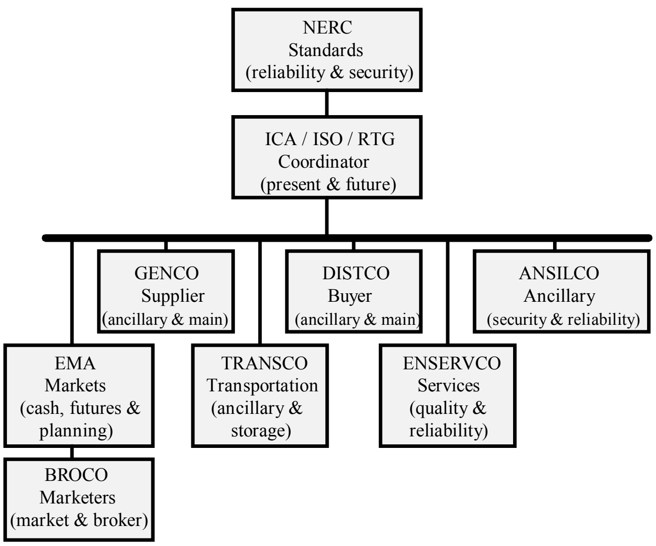

Fig. 1. Brokerage system model.

The framework described by Sheblé [21] allows for cash (consists of spot and forward markets), futures and planning markets. The spot market allows for trading power each hour (or other duration, e.g., 30 minutes) in the next 30 days. Forward contracts allow energy traders to buy or sell firm electricity contracts as specified in the contract from 1 to 19 months into the future. The futures market allows traders to purchase a non-firm electricity contract for a given month, 1 to 18 months into the future. Futures contracts provide a means for electricity traders to manage their risk. The planning market is a longer term market used to develop capital for building new plants and transmission lines. More detail about the commodity markets is given later in this paper.

As in [17], the authors assume the existence of regional commodity exchanges in which buyers and sellers participate in a double auction. This framework has been adopted from Sheblé [21], which is an extension to that being proposed for implementation in California. For the results presented in this paper, TRANSCOs are considered to be exogenous to the market, DISTCOs and GENCOs are allowed to interact in an environment as described in the previous section. Although our framework covers the futures and options markets, the research described in this paper is written up for only the spot market.

We assume that buyers and sellers interact through the ICA, who matches the bids subject to all operational constraints. This central coordinator is responsible for ensuring that the energy transactions resulting from the matched bids do not overload or render the electrical transmission system insecure. GENCOs and DISTCOs coordinate only via the prices transmitted to a central auctioneer. The ICA may submit information to an independent system operator (ISO) for implementation. The key element is that the ICA is responsible for maintaining the security and reliability of the system. The ICA monitors and responds to the power system limits and transmission capacities. GENCOs and DISTCOs are required to cooperate with the ICA in maintaining system reliability. Supplying crucial generator parameters to the ICA during the bidding process is part of this cooperation.

3.2 The markets

As the electric energy marketplace deregulates, many experts expect the cash market to be joined by markets specializing in futures contracts, options contracts, and planning contracts. A swaps market will enable these contracts to be traded to maximize trader utility. Fig. 2 shows how these markets connect and how they allow contracts to move over time.

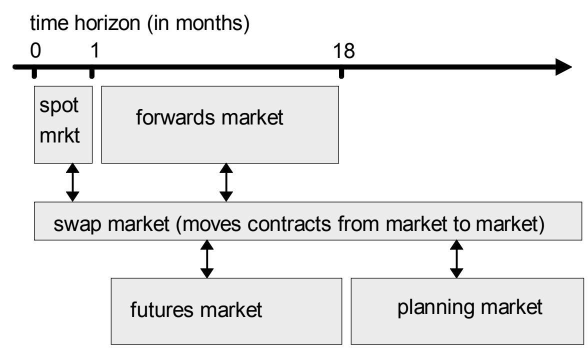

Fig. 2. Interconnection between the markets.

We will now describe the markets/contracts previously mentioned. The *spot market* is what we are most familiar with in the electrical industry. A seller and a buyer agree (either bilaterally or through an exchange) upon a price for a certain number of MWs to be delivered sometime in the near future (e.g., 10 MWs from 1:00 p.m. to 4:00 p.m. tomorrow). The buyer needs the electricity, and the seller wants to sell. They arrange for the electrons to flow through the electrical transmission system and they are happy. A *forwards contract* is a binding agreement in which the seller agrees to deliver an amount of a particular product with a specified quality at a specified time to the buyer. The forward contract is further into the future than is the spot market. In both the forwards and spot contracts, the buyer and seller want to exchange the physical good (e.g., the electrons). A *futures contract* is primarily a financial instrument which allows traders to lock-in a price for a commodity in some future month. This helps the traders to manage their risk by limiting potential loses or gains. Futures contracts exist for commodities in which there is sufficient interest, and in which the goods are generic enough that it is not possible to tell one unit of the good from another (e.g., 1 MW of electricity of a certain quality, voltage level, etc.). A futures *options contract* is a form of insurance that gives the option purchaser the right, but not the obligation, to buy (sell) a futures contract at a given price. For each options contract, there is someone "writing" the contract who in return for a premium, is obligated to sell (buy) at the strike price. See Fig. 3. Both the options and the futures contract are financial instruments designed to minimize risk. Although provisions for delivery exist, they are not convenient (e.g., the delivery point is not located where you want it to be located). The trader ultimately cancels his position in the futures market either with a gain or loss. The physicals are then purchased on the spot market to meet demand with the profit or loss having been locked in via the futures contract. A *swap* is a customized agreement in which one firm agrees to trade its coupon payment for that of the other firm involved in the swap. Finally, we have the *planning market* which exists to finance long term projects like transmission lines and power plants.

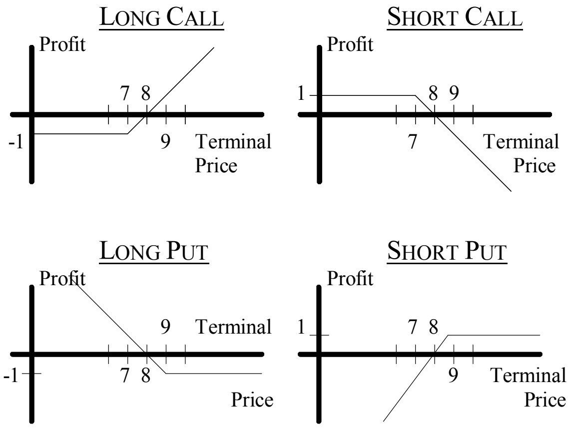

Fig. 3. Methods of using options.

Fig. 3. uses some terminology with which many in the electrical industry may be unfamiliar. "Long" denotes ownership; "to go long" means to purchase the item in question. In the figure, "long" indicates that the trader has purchased the option and now has the right to buy (call) or the right to sell (put) the future. A trader who writes the option is "short"; to go short is to sell the item in question. Let's assume that the item in question is a MWh of electricity In the long call diagram, the long trader has paid a premium (e.g., $1) to the option writer for the call option. This call option gives the trader the right to buy a MWh for the strike price (e.g., $7). At any price greater than the strike price, the option exercised, and the trader is said to be "in-the-money" regardless of whether he gains or loses. If the price goes above the strike price plus the premium (e.g., $8), the trader has made a profit. The long trader has reduced risk by limiting his losses to the premium. On the other side of the figure, we see what happens from the option writer's point-of-view. He receives the premium for assuming the risk and is obligated to sell the MWh at the strike price even though the market price is higher. The bottom half of the figure shows how the "put" works. The long trader pays a premium to lock in a maximum price (exercise price) that he will have to pay for the MWh. The short trader takes that premium in return for promising to sell the MWh for that same exercise price.

3.3 Double auctions

The double auction is the pricing mechanism for the markets assumed in our framework. In each of the markets, bids and offers are sorted into descending and ascending order respectively, similar to the Florida Coordination Group approach as described by Wood and Wollenberg [29]. If the buyer's bid is higher than the seller's offer to be matched, then this is a potentially valid match. For the spot and forward markets (which are to be firm), the ICA must determine whether the transaction would compromise system security and whether sufficient transmission capacity exists. Futures contracts are not Subject to ICA approval, the potentially valid offers and bids are used to determine the final price, termed the *equilibrium price*. The average of the bid and offer of each pair of valid matches (weighted by the number of MWs) is used to determine one overall equilibrium price. This is similar to the power pool split savings approach used in many regions except that each of the valid contracts will have the same price. An example is given in Table 1 where each bid and offer is for the same size and number of contracts.

Table 1. Example of auction bid matching.

Buy bids ($/MW)	Sell offers ($/MW)	Contract?	Average of bid and offer	Equilibrium price ($/MW)
12.50	8.50	Yes	10.50	10.63
12.00	9.00	Yes	10.50	10.63
11.80	10.00	Yes	10.90	10.63
10.00	10.50	No	NA	NA
9.50	11.00	No	NA	NA

In the example shown in the table, there are three bids that are higher than the corresponding offers. If there is not a sufficient number of valid matches, then *price discovery* has not occurred; the auctioneer then reports that price discovery did not occur, and will ask for bids and offers again. The buyers and sellers adjust their bids and offers and another cycle of the auction is played. The cycles continue until price discovery occurs, or until the auctioneer decides to match whatever valid matches exist and continue to the next round or hour of bidding.

After price discovery, 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 time period allows the participants the opportunity to use the latest pricing information in forming their present bid. (One could have a single round with a single bid at each time period, and consider multiple time periods with very little change to the model. This would be similar to theoretical auction research which requires some unrealistic assumptions.) This process is continued until no more requests are received or until the auctioneer decides that enough rounds have taken place.

4. RISK MANAGEMENT

With neither an obligation to serve nor guaranteed rates of return the energy trader's objective becomes the maximization of profit for his shareholders. In a competitive environment there may be times when DISTCOs or ESCOs may be unable to purchase enough energy for their customers, or times when GENCOs may have excess generation. This uncertainty, combined with fluctuating prices and demand, makes profit difficult to predict in any particular scenario. We might then consider a distribution of bids and offers and develop strategies that maximize the trader's expected profit. If a trader uses the strategy long enough, he should get the expected profit associated with that strategy. In the short run, he might see gains or losses very different from the expected profit. This unpredictability means we consider the strategy risky. The term *risk* can be loosely defined as a measure of the lack of predictability of an outcome associated with a particular decision. Different strategies producing the same expected profits might well have different risks associated with each. See Fig. 4. Since most traders cannot endure low or even negative profits for long periods, he would probably be willing to sacrifice some long term expected profit in return for reduced risk. Economists use "utility functions" to describe and order preferences. Among other things, a trader's utility should vary directly with actual profit (should be similar to expected profit) and indirectly with risk.

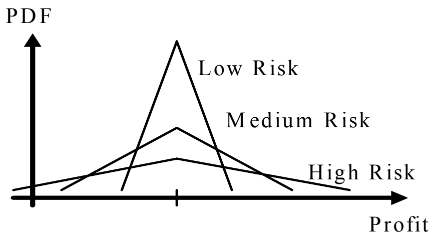

Fig. 4. Different risks with the same expected profit.

4.1 Using futures contracts to reduce risk

Futures contracts allow producers to hedge so that they can limit their losses. Other things being equal, a GENCO's profit varies with the price of electricity. Trying to predict the price months in advance so that profit can be known in advance is tricky. Suppose it is April, and because of some big decisions (unrelated to insider trading) the board-members want to know what the GENCO's profit will be in July. Simply by considering our fuel contracts and using demand forecasts we can draw a profit curve based on the price as in Fig. 5. In the figure, this corresponds to the line segment labeled "with no hedge". Not knowing the price means that we have the potential for large losses. The board-members don't want to see just a line on a graph— they want a simple number. This is where the futures hedging comes into play. For the example in Fig. 5, the GENCO can short (i.e. sell non-firm electricity they don't have yet) July electricity with futures contracts. When July arrives, if the spot price is low, they make money on their futures contract and lose on the electricity sold on the spot market. The gain on the futures market offsets the loss in the spot market. If the spot price in July is high, then the electricity sold on the spot market yields a profit while the futures contract will produce an offsetting loss. The result is that the net profit is much more predictable due to the hedge, and now we can give the board-members that number they were looking for.

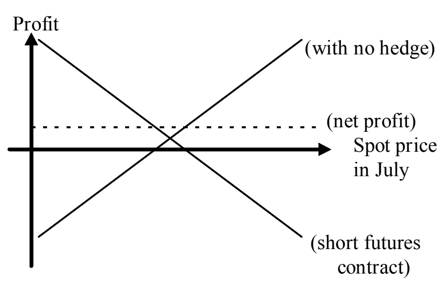

Fig. 5. Hedging with futures contracts.

4.2 Using futures option contracts to reduce risk

As discussed previously, a futures option contract gives its holder the right to buy (or sell) at the strike price without any obligations (other than paying the premium). Let's again consider a GENCO wanting to maximize its profit, and at the same time minimize its risk. One alternative is that the GENCO pays a premium for an options contract that would give it the right to sell (short) electricity at the strike price. (If the price was higher than the strike price, the GENCO would let the option expire). Fig. 6 shows how the option contract can be used to hedge profit. Notice that when the price is low, the GENCO can exercise the option and have a futures contract as in the previous example to offset our losses in the spot market. When the price is high, the GENCO has no obligation to sell at the strike price, the net profit is the profit from the electricity produced by the GENCO and sold on the spot market less the premium paid for the options contract. The GENCO has limited the amount of money that it can lose, but can still reap the benefits of a high price in July. Another alternative using swaps would be a short call.

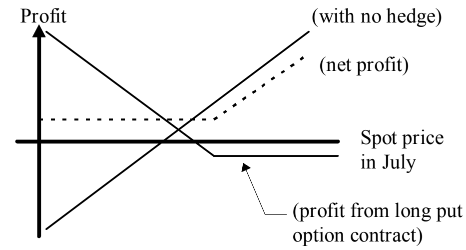

Fig. 6. Hedging with futures options contracts.

4.3 Fuzziness and uncertainty

Above we said that "other things being equal, a GENCO's profit varies with the price of electricity". In reality, those other things (e.g., demand forecasts, production costs, etc.) have uncertainty associated with them. One natural way to deal with risky (uncertain) situations is to use "fuzzy logic", 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.

Fuzzy logic allows us to represent ambiguous or uncertain quantities 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. Using fuzzy logic, we might say that electrical demand is high in a region if it is 1200 MW or so, and normal if it is more or less 700 MW. What if the demand is 1000 MW? 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. Fig. 7 shows how these classifications (membership functions) in graphical form.

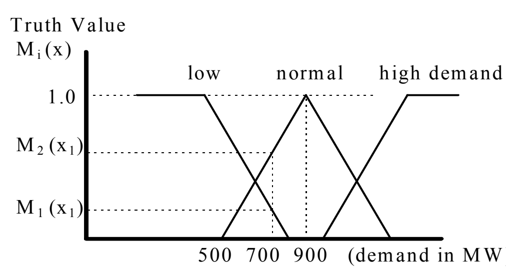

Fig. 7. Fuzzy membership functions.

Once defined, these inputs can then be used in a set of fuzzy rules. Multiple input conditions can be considered by combining rules with the "and' and "or" functions. For instance, some simple rules might be as follows:

- IF demand is HIGH, THEN bid should be HIGH
- IF (demand is LOW) AND (risk aversion is HIGH) THEN (bid should be LOW)
- IF (position is RISKY), THEN hedge with option contracts

where "high" and "low" bid would be defined using another membership function.

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.

8. 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. The output

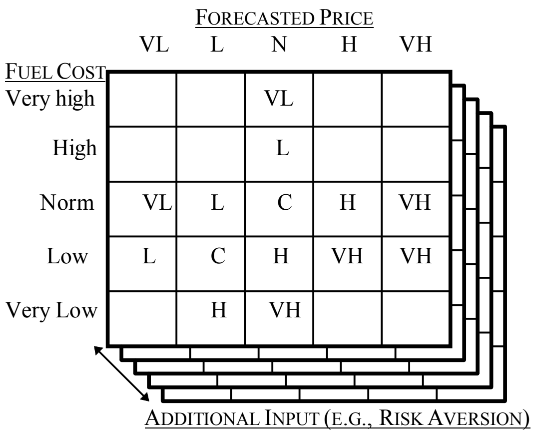

Fig. 8. Three input fuzzy rule set to determine bid

(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, fuzzy the "bid high" is converted to a single number using the defuzzification process which can be found in Kosko [9].

4.4 Fuzzifying decision analysis

The traditional method of decision analysis involves drawing a decision tree. Trees consist of branches and nodes. Decision nodes are drawn with a square and mean that there is a decision to be made. Each option choice will lead to a different possible set of circumstances/outcomes. Circular nodes are chance nodes where analysis has indicated that many possible futures exist each with a certain anticipated probability and each with a different affect on the final outcome. Each branch must be assigned a specific probability value.

Consider the tree in Fig. 9. The objective is to maximize expected profit subject to our risk tolerance. The choice is to bid high, or to bid low. In the traditional case, our analysts would have to give us crisp numbers to describe the possibilities. For instance, demand will be 1000 MW with a probability of 0.25, and it will be 500 MW with a probability of 0.75. The costs will be $10/MW with a 0.25 probability and $5.0/MW with a 0.75 probability. We can then calculate an expected profit with each of the decision node branches. In the traditional case, we would have actual bids (e.g., high = $15.0/MW and low = $10.0/MW). We would then make the bid that maximized our expected profit. With the traditional decision tree, we must work with a limited number of possible scenarios assigned crisp probabilities. The crisp probabilities are taken as certain even though our planners might have liked to use fuzzy terms like "high" or "low" defined by a membership function. We are basically ignoring the part about "subject to our risk tolerance" when making the initial decision. Risk can then be accounted for after the fact using the traditional means (futures and options), but the measures taken to reduce risk could change which decision produces the highest expected profit.

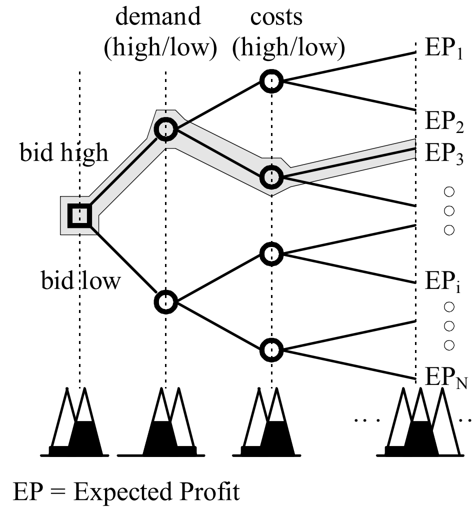

Fig. 9. Evaluating the alternatives with decision analysis.

Fuzzy logic provides a means of incorporating the uncertainty into the decision tree. We propose using fuzzy terms to describe the conditions that the chance nodes may take on and use membership functions to describe how much emphasis to place on the various outcomes. In Fig. 9, we may be fairly certain that the demand is high, but we think there is a small chance that it could be low (where high and low are described by membership functions). Rather than choosing any one particular path through the tree, the fuzzy method is influenced by all possibilities. Likewise the expected value is expressed in a membership function which basically has a built in description of the risk associated with that scenario. In addition to the inputs, the output is described by a fuzzy membership function.

5. BIDDING STRATEGIES THAT MINIMIZE RISK

In [17,19,20] the authors describe efforts to evolve bidding strategies using both genetic algorithms and GP-Automata (a hybrid of genetic programming and finite state automata). We are presently extending that research to incorporate risk by changing from a fitness/objective function solely dependent on profit, to one that rewards less risky strategies. In addition to changing the fitness function to reduce risk, we intend to allow the economic agents access to options and futures contracts. The shape of an options position can be defined by four numbers. One needs only specify the type of option (long call, long put, short call, or short put), the strike price, the contract amount, and the premium. The agents which learn to use the options properly will have an advantage in reducing the risk of their strategies.

The authors are working on building fuzzy bidding strategies using the techniques described previously. The fuzzy membership functions for demand and costs can be defined through the use forecasting methods. Functions describing others bidding behavior will be defined from historical data. In addition to the trading data available from NYMEX, simulations will provide data with which to test the strategies. Adaptive agents representing bidding strategies for various corporate models will participate in our auction simulator to provide this historical data.

To judge fitness, the agents will participate in our auction simulator which until now has been used only in one market at any given time.

We plan to extend our auction simulator to allow agents to participate in multiple markets. Fitness will not consist only of short term profit in the spot market, but will depend on the trader's performance over the long term.

6. SUMMARY

In the competitive deregulated electric energy marketplace bidding strategies will be important to profitability. In addition to maximizing profit, traders should consider the risk involved with a particular strategy.

We have presented an introduction to using options and futures contracts to reduce the risk associated with an energy trader's position in the market. In addition to futures and options, we have proposed other methods of reducing risk including the use of fuzzy logic, enhancement of our genetic algorithm and GP-Automata bidding strategy evolvers so that fitness function incorporates risk.

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8. BIOGRAPHIES

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