Genetic Algorithm Evolution of Utility Bidding Strategies for the Competitive Marketplace

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Abstract: This paper describes an environment in which distribution companies (discos) and generation companies (gencos), buy and sell power via double auctions implemented in a regional commodity exchange. The electric utilities' profits depend on the implementation of a successful bidding strategy. In this research, a genetic algorithm evolves bidding strategies as gencos and discos trade power. A framework in which bidding strategies may be tested and modified is presented. This simulated electric commodity exchange can be used off-line to predict whether bid strategies will be profitable and successful. It can also be used to experimentally verify how bidding behavior affects the competitive electric marketplace.

Keywords: Competitive auction markets, optimization, genetic algorithms, bidding strategies, deregulation, energy broker, power systems, operations.

I. INTRODUCTION

Presently, regulations governing the electric utility industry in the United States (US) are being changed to promote competition. Since 1992 when the Energy Policy Act (EPAct) was signed into law, the Federal Energy Regulatory Commission (FERC) has given indications that it intends to make the electric system in the United States more competitive. By increasing competition through deregulation of the transmission network, FERC hopes to increase system efficiencies and improve benefits to electric consumers.

For decades, electric consumers in the US had only one source for their electricity—the local vertically integrated utility. Under the EPAct, entities that did not own transmission-lines were granted the right to use the transmission system. This was termed *open access*. US electric utilities began to see limited competition in power production. The United Kingdom (UK), Norway and Chile have recently re-regulated to allow a more competitive electric marketplace. The FERC, in its recent Notices of Proposed Regulation (NOPRs), has announced its intent to expand competition in the US electric marketplace. Attitudes toward re-regulation vary between states. Many states are adopting a wait and see attitude, some are performing investigations, and others are almost ready to restructure their electric marketplace. California has recently announced plans to adopt a structure similar to that used in the UK.

The research presented in this paper assumes an electric marketplace similar to commodities exchanges like the Chicago Mercantile, Chicago Board of Trade, and New York Mercantile Exchange (NYMEX) where commodities (other than electricity) have been traded for many years. NYMEX has recently added electricity futures to their offerings.

In this research, trading agents use a genetic algorithm (GA) coupled with various price forecasting techniques to select appropriate bidding strategies for the current market conditions. The bidding strategies adapt, or evolve, as other traders change their trading behavior. The results have been written up for the electricity marketplace, but may be used directly for other types of trading.

Part II of this paper briefly mentions recently published work in this area. It discusses research with evolving economic agents, developing successful bidding strategies, deregulation, and the auction environments. Part III describes the methods investigated, including genetic algorithms and various price forecasting techniques. Part IV presents the results of a typical simulation done during this research. Finally, part V presents the conclusions made as a result of the research and lists several directions in which this research may be extended.

II. REVIEW OF RECENT WORK

Some work has been done in developing bidding strategies for other electric systems. Finlay [4] analyzed bidding strategies for the restructured Power Pool of England and Wales system, and showed mathematically that there exists an optimal bidding strategy for its bidders. Finlay's work differs in that his objective was not to maximize the profit of the individual generation companies, and the system itself is different from those proposed in the USA.

Post [14] described and compared the various types of basic auctions including the multiple auction, which allows more that one bidder to be awarded a bid, and the double auction where several buyers and sellers submit bids and offers for one unit of a good. If and when a buyer accepts a seller's offer, or a seller accepts a buyer's bid, a binding contract is made. Post pointed out that "few theoretical results of double auctions exist since modeling strategic behavior on both sides of the market is difficult."

Work by Fahd and Sheblé [3] demonstrated an auction mechanism. Sheblé [17] described the different types of commodity markets and their operation and outlined how each could be applied in the evolved electric energy marketplace. Under the framework described by Sheblé [16], companies presently having both generation and distribution facilities would, at a minimum, be divided into separate profit and loss centers. Power is generated by generation companies (gencos), transported via transmission companies (transcos), and all power is sold to distribution companies (discos). In a recent short course [20], it was proposed that NERC would set the reliability and security standards, and predicted that we'll see energy

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services companies (ENSERVCOs), companies providing ancillary services (ANSILCOs), and energy mercantile associations (EMAs) emerging in this new framework. See Fig. 1 which was presented in [20].

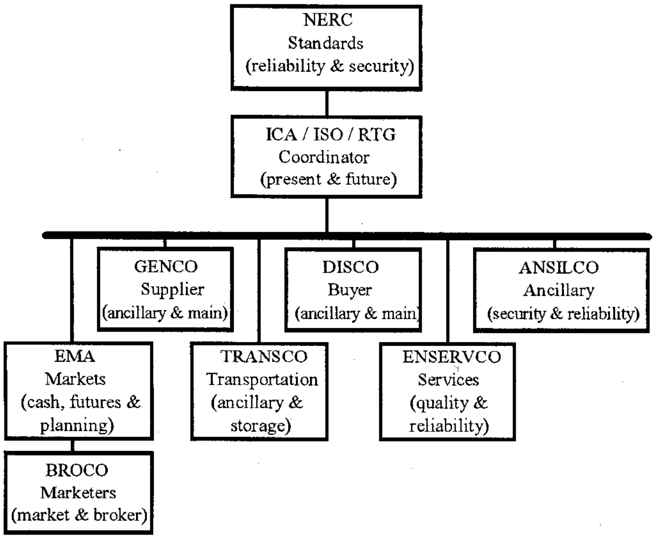

Fig. 1. Brokerage system model.

The framework described by Sheblé [16] allows for a cash market, a futures market and a planning market. The cash market is for trading power for each 30 minute period in the next 30 days. The futures market allows electricity trading from 1 to 18 months into the future. Futures contracts are non-firm for a specific month. This futures market provides a means for electricity traders to manage their risk. The other market is a planning market that can be used to develop capital to build new plants and would allow trading more than 18 months into the future. Sheblé and McCalley [18] outline how cash, 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 [9] 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. The buyers and sellers in their research interact through a central coordinator, an Independent Contract Administrator (ICA), who matches the bids subject to all operational constraints. The 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 discos coordinate only via the prices transmitted to a central auctioneer. The ICA may submit information to the independent system operator (ISO) or to individual system operators 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 discos 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.

Developing bidding strategies with evolving trading agents for the deregulated electrical utility industry is a new field of research. Apart from the electrical utility industry, interest has grown in recent years for using evolving, or adaptive, agents to simulate trading behavior. Research with adaptive agents has proved to be a useful means of exploring trading markets outside of the electrical industry.

LeBaron [11] uses evolving agents to learn to play financial markets. Tesfatsion [22] describes research in which trading agents decide who to trade with based on an expected payoff. Ashlock, in reference [1], uses genetic programming combined with a finite state automata to play a classic academic game involving bidding behavior and strategies.

III. IMPLEMENTING THE BIDDING STRATEGY DEVELOPER

This section outlines the methods that were used to simulate the marketplace, the basics of genetic algorithms and how agents were modeled and evolved.

A. *The Marketplace*

This research assumes the existence of regional commodity exchanges in which buyers and sellers participate in a double auction. This framework is adopted from Sheblé [16], which is an extension to that being proposed in California. For the results presented in this paper, transcos are considered to be exogenous to the market, discos and gencos are allowed to interact as described in the above environment. Although Sheble's framework makes use of the futures markets, only the cash market was modeled for the results presented here.

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 [24]. 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. If the ICA approves, 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. An example is given in Table 1.

TABLE 1
EXAMPLE OF AUCTION BID MATCHING

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

In this example, there are three bids that are higher than the offers. If there are not a sufficient number of valid matches, then *price discovery* has not occurred. The auctioneer reports the results of the auction to the market participants. When all bids and offers are collected and insufficient valid bids and offers are found to exist, 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 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. See Fig. 2 for a block diagram of the auction process.

B. Basics of Genetic Algorithms

Derived from the biological model of evolution, genetic algorithms (GAs) operate on the Darwinian principle of natural selection [6]. A population of data structures appropriate for the optimization problem are "randomly" initialized. Each of these candidate solutions is termed an individual or a creature. Each creature is assigned a fitness, which is simply a heuristic measure of its quality. Then during the evolutionary process, those creatures that have a higher fitness are favored and allowed to procreate.

During each generation of the evolutionary process, creatures are randomly selected for reproduction with some bias toward higher fitness. After parents are selected for reproduction, they produce children via the processes of *crossover* and *mutation*. The creatures formed during

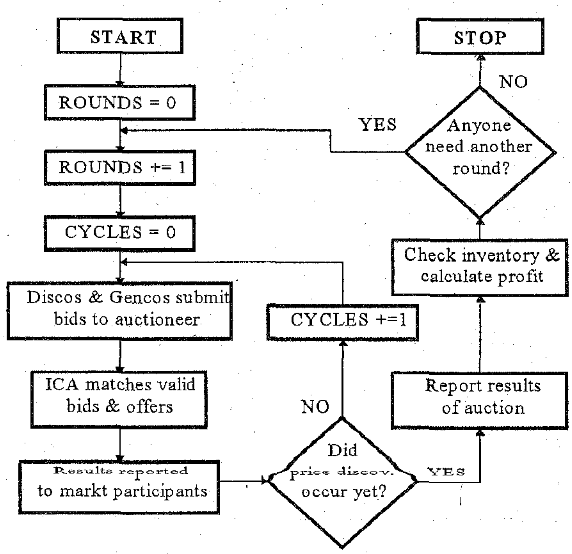

Fig. 2. The auction process.

reproduction explore different areas of the solution space than did the parents. These new creatures replace lesser fit creatures of the existing population. The basic algorithm can be written as follows:

1. Randomly initialize a population and set the generation counter to zero.
2. Until done or out of time, do the following:
   - Calculate the fitness of each member of the population.
   - Select parents using some fitness bias.
   - Create offspring from the selected parents via crossover.
   - Mutate these new offspring.
   - Replace the lesser fit members of the population with the newly created offspring.
   - Increment the generation counter and go to the beginning of step 2.

The parents are required to be in pairs for reproduction, and the result is two children. Children are created by copying the contents of parent 1 into child 1 and of parent 2 into child 2 until a randomly selected crossover location is reached. At this point, bits are copied from parent 1 into child 2, and from parent 2 into child 1. See Fig. 3.

Following the crossover process, the children are mutated. Mutation introduces new genetic material into the gene at some low rate. If the gene to be mutated in the child is represented by a binary string, mutation involves flipping the bit (0 goes to 1, 1 goes to 0) at each location in the string with some probability. If the gene is represented by an integer, mutation might involve adding an integer that will result in a different valid integer occupying that gene location (loci).

C. Using Genetic Algorithms for Agent Evolution

In the research described in this paper, parameters used to develop gencos' bids are evolved using a GA. Each member of the GA population corresponds to a genco participating in an auction. There are three distinct evolving parts, or genes, for each of the gencos. First, the number of 1 MW contracts to offer at each round of bidding is evolving. This gene is filled with integer values. Valid integers are between 0 and a maximum value that corresponds to that genco's maximum capability divided by the number of rounds of bidding. Secondly, bid multipliers for each round of bidding are evolved. These bid multipliers are used in combination with the gencos' costs and their expected equilibrium price to develop a bid. This gene is represented by binary strings that are mapped to a value between the genco's cost and forecasted equilibrium price during the bidding process. Thirdly, each genco has a gene that selects which prediction technique to use to forecast the equilibrium price. This is an integer valued gene with valid integers being from 0 to 4, since there are 5 classical prediction techniques from which each genco may choose. Additional forecasting methods can be incorporated easily. See Fig. 4 for a representation of the trading agent's data structures.

Roulette selection was chosen to select parents each generation of the genetic algorithm. Roulette selection is a parent selection method that chooses more highly fit creatures

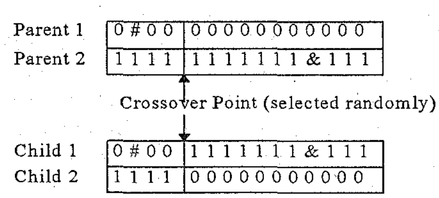

Fig. 3. Example of single point crossover.

Agent *0*	Rounds of Bidding ----------------------->				
MWs each round	12	4	20	...	14
Mult. each round	01011	01101	10101	...	00101
Prediction Technique		0			

Agent *1*	Rounds of Bidding ----------------------->				
MWs each round	15	7	1	...	6
Mult. each round	10011	01100	10100	...	10111
Prediction Technique		2			

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Agent *N*	Rounds of Bidding ----------------------->				
MWs each round	15	3	19	...	20
Mult. each round	00011	11101	11001	...	00111
Prediction Technique		3			

Fig. 4. Data structure of evolving agents.

with a greater probability than the lesser fit creatures. This fitness bias is more pronounced (especially when population sizes are small) than other parent selection methods like tournament selection or rank selection. However, the authors intend to do sensitivity testing on all of these methods in the future.

Based on sensitivity tests, three point crossover was selected to create the children. Crossover is used on both the no. of contracts desired and the bid multiplier. The bid multipliers for each genco are concatenated together into one string prior to crossover, and three crossover locations are selected randomly from a uniform distribution over the gene's entire length.

The standard bit-flip mutation operator is used on the binary strings representing the bid multipliers. The number of contracts gene has the possibility of being mutated by two different mutation operators. The first mutation operator (mutation_A) adds an integer to the existing integer. If the result is not a valid integer, the value is wrapped around, i.e. if the result is greater than the maximum, then the maximum is subtracted from it. Further investigation might reveal better results if the gene is set to its maximum rather than wrapping it around. The second mutation operator (mutation_B) shuffles the values among the different loci. This way if a good number is found in one locus, it can spread to other locations more quickly. Mutation on the prediction technique selection gene involves randomly selecting one of the valid predication techniques.

The fitness of each creature is exactly equal to its profit after participating in an auction. A generation level for each genco can be determined by the number of contracts that the genco was able to obtain during the auction process. Profit becomes the total cost to generate at that level, minus the total revenue. Total revenue is equal to the sum of the contract price multiplied by the number of contracts over all rounds of bidding.

At each generation, one half of the population is replaced with the children. Although the parents were not taken strictly from the top half of the population, it is always the creatures on the bottom of the population that are replaced each generation.

D. Developing the Bid

This subsection explains how to develop a bid from the previously shown data structures. The number of 1 MW contracts is taken directly from the "MWs each round" gene. The bid multipliers can be used in the following two different methods. In the first of these, it can be mapped into a range where all 1s would be the expected equilibrium price (EEP), and all 0s would be the cost of the generator. With the second method it can be multiplied by the EEP such that the bid will be within some tolerance of that EEP (e.g., 0.75-1.25 x expected eq. price). For the results shown in this paper the first method was used.

There are two methods included for determining the EEP. The first method uses no prediction techniques, and simply assumes that the current round's price will be the same as the previous round's equilibrium price. This is a fair assumption given a stable market where the prices do not fluctuate very much. The other method uses a prediction techniques to forecast the price. (A gene on in the genco's data structure determines which method to use.) The gencos are able to make use of any prediction method, examples might be:

- moving average (MVA)
- weighted moving average (WMVA)
- exponentially weighted moving avg. (EWMVA)
- linear regression (LR)

The MVA, WMVA, EWMVA and LR are standard and can be found in any statistics text book. The number of inputs and inputs to be considered can be adjusted until the best predictions are observed (minimum mean squared error). It was originally intended that each genco would have a unique set of parameters for its own prediction technique, but this was found to be too computationally expensive. Therefore, each genco that uses the same prediction technique gets the same forecasted equilibrium price.

See Fig. 5 for a block diagram of how the genetic algorithm, the price prediction and the auction processes fit together to evolve the gencos that are trading electricity.

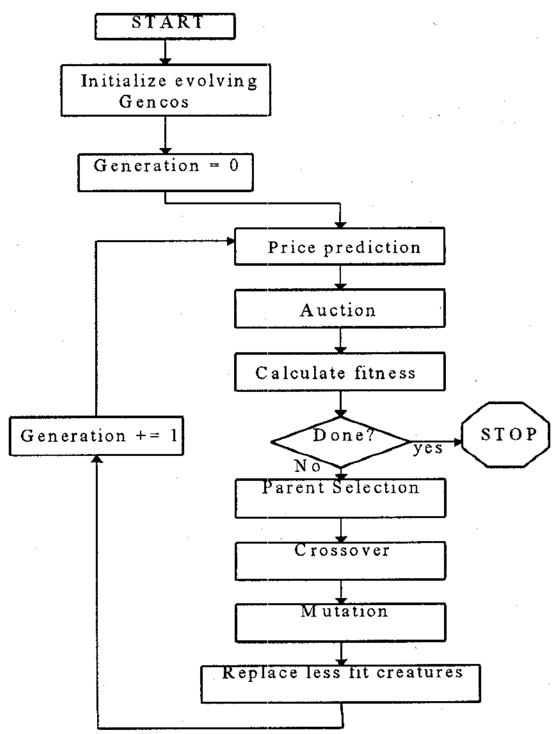


Fig. 5. The GA agent evolution process.

IV. RESULTS

The algorithm was initialized with a population size of 24, i.e., 24 gencos. Each generation 12 new creatures replaced the 12 worst fit of the population. Roulette selection was used to select the parents. A mutation rate of twenty percent was used at each loci of the new creatures for the standard mutation operation. Mutation_B was used 50% of the time, and the Mutation_A was used the other 50%. Three point crossover was used during reproduction. Fitness was taken as the raw profit each genco received.

For simplicity one disco was bidding against all of the gencos. The disco bid a constant amount each round. No transmission constraints nor system stability violations were considered. The minimum generation of each genco is 200 MWs; the maximum is 480 MWs. Trading occurs for 24 rounds each generation. A maximum of 20 cycles is allowed for price discovery, at which time the round number is incremented. Each of the gencos has the same generation cost curve, represented by (MW is the generation level):

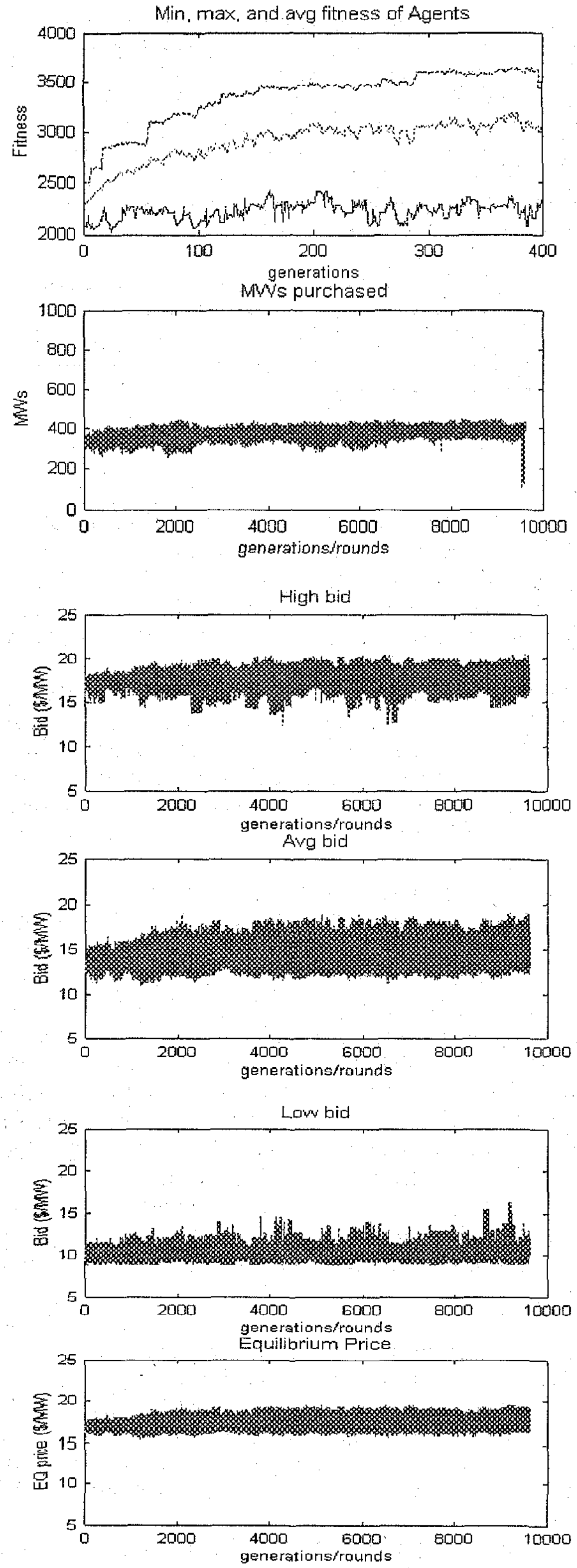
$$[200 + (8.0)(MW) + (0.00251)(MW)^2] \text{ [Fuel cost]} \qquad (1)$$

For the case shown in the following figures, the expected equilibrium price was taken to be the previous round's equilibrium price. The bid multiplier was used to bid between the genco's cost and the expected equilibrium price.

The case shown is a sellers market, where the electricity demand is twice the supply. The disco wants 960 MW each round, but the maximum total supply is 480 MW/round. The disco bids $20 each round. The gencos are allowed to evolve for 400 generations.

The graphical results in Figs. 6-8 show that the auction is working as expected. The average, maximum and minimum genco fitness is plotted for 400 generations. The number of MWs actually purchased by the disco is plotted. The average, minimum and maximum bids of the gencos are plotted at each of the rounds for each generation, as well as the resulting equilibrium price. The number of MWs sold by the best genco each generation is plotted. The best gencos bid multipliers are plotted at the first generation and the last generation.

The fitness of the best genco/agent each generation is increasing. The best genco is taking advantage of the high demand by increasing the number of MWs it is offering for sale. However, many of the lesser fit gencos are not finding that it is beneficial to sell as much as possible. Consequently the disco is purchasing less than half of the electricity it would like. The equilibrium price tends to stay in the $17-$18/MW range. It is smooth over the generations, but fairly mobile over the rounds during each generation. This is because the equilibrium price is the difference between sell offer and the buy bid, and the buy bid is constant. The offer prices of the lesser fit gencos prevent the equilibrium price from reaching $20/MW. The average bid is about $15/MW for this case. The bid multipliers of the best genco evolved so that the bids were closer to the expected equilibrium price as opposed to the genco's cost.



Figs. 6. (a-f). Fitness and trading results.

V. CONCLUSIONS AND FUTURE RESEARCH

The auction simulation is working as desired. The evolution of the gencos is also functioning as expected. The framework used and developed for this research should be a helpful tool for those who will be participating in the competitive electric marketplace of the future. It would also be helpful for those wishing to develop bidding strategies for other types of markets. Several other cases were run that have not been included in this paper. Multiple runs verified that the bid

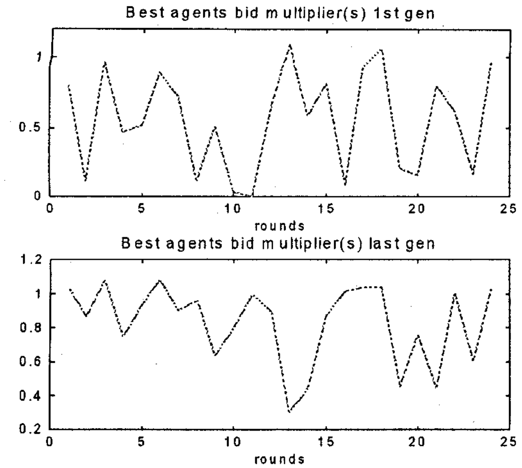


Fig. 7. Bid multipliers of best agents at first & last generation.

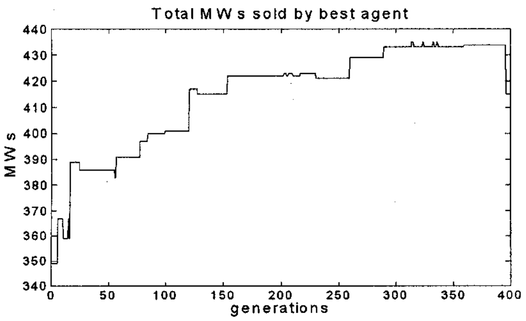


Fig. 8. MWs sold by best agent.

multipliers were functioning. The bid multiplier gene evolved to increase fitness while the other genes were held constant. The prediction techniques must be properly tuned to get good forecasts. If the market is not volatile, using the previous equilibrium price works well. Market specific information including knowledge about the volatility can help to fine-tune the parameters for better performance. The GA is able to make use of a more complex data structure. Separate multipliers for each round of bidding evolve to result in a better solution than that derived from a single multiplier for all rounds.

The better agents of a particular generation have a strategy which obtains a higher profit. Since all agents are adapting their strategies at each generation, a particular strategy may prove to work well during one generation, but not so well during a later generation. It is difficult (but of great interest) to determine what makes a particular strategy a good one. Identifying the common features of the best agents at each generation and building an expert system rule base is the subject of continued research. Sensitivity analysis and testing will provide valuable information on the robustness of the best strategies.

Future research includes a more detailed model that considers startup and shutdown costs, ramp constraints, minimum up and down times for the generators. Separate cost curves for each generating unit will be included. Future research will also include power marketers that both buy and sell power. Future research will verify that the results are valid when using "intelligent" buyers, in addition to the "intelligent" sellers, i.e. including multiple discos with their own bidding strategies that react to the genco's bids.

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