MODELING THE STRATEGIC BIDDING IN COMPETITIVE ELECTRICITY MARKETS BASED ON FUZZY-LOGIC

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ABSTRACT

Competition has been introduced in the last decade into the electricity markets and is presently underway in many countries. This paper proposes a model able to capture the decision making approach of the producers in submitting strategic biddings to the market and simulate the market outcomes resulting from those interactions. The model is based on fuzzy logic takes into account the network constraints that may pose considerable limitations to the electricity markets.

I. Introduction

The electricity industry throughout the world, which has long been dominated by the vertically integrated utilities, is undergoing enormous changes. Because of the complexity of power markets, it is difficult to simulate the market participant's behaviors using traditional modeling methods. Therefore there is a potential to have a competitive rather than monopolistic market. In order to have competitive electricity market, the market operators and/or independent system operators (ISOs) need to study, analyze and monitor the strategic behaviors of market participants in the open access markets. Because of the complexity of power markets, it is difficult to simulate the market participants behaviors using traditional modeling methods.

Bower and Bunn in [1, 2] have presented studies on the behaviors of the market participants. However, in their research the competition among suppliers have not been considered.

Milgrom and Weber have modeled the behaviors of the power producers based on time series [3]. This method needs a lot of information about the power system topology and market variables which some of them are not easily accessible.

This paper introduces an approach to model the strategic biddings of the market participants in Double-Sided Electricity Auctions (DSEA) which is based on fuzzy logic.

II. Double-Sided Electricity Auction (DSEA)

In Double-Sided Electricity Auctions (DSEA), both suppliers and consumers participate and offer (bid) to sell (buy) electric power. After collecting the offers and bids from suppliers and consumers respectively, the market operator (ISO) clears the market by running an OPF solver to determine the optimal generator and load schedules and also the market clearing prices (MCP) at different nodes of the system considering the network constraints.

The generators supply functions are increasing functions with respect to their output powers. They can be formulated as continuous or discrete functions. In this paper continuous supply functions have been considered as follows:

$$C(\mathrm{P}_i) = \alpha_i \, \mathrm{P}_i^{\,2} + \beta_i \, \mathrm{P}_i + \gamma_i \tag{1}$$

In this equation, P_i is the *i*-th generator active power output, $C(P_i)$ is the *i*-th generator supply function, and $\alpha_i \succ 0$, $\beta_i \succ 0$, and $\gamma_i \succ 0$ are the supply function coefficients.

The load benefit functions are decreasing with respect to their demands. They can also be formulated as continuous or discrete functions. Continuous benefit functions for the loads have been considered in this paper as follows:

$$B(L_j) = -a_j \, L_j^{\,2} + b_j \, L_j + c_j \tag{2}$$

In this equation, L_j is the *j*-th load demand, $B(L_j)$ is the *j*-th load benefit function; and $a_j \succ 0$, $b_j \succ 0$, and $c_j \succ 0$ are the benefit function coefficients.

Electricity market and prices will be controlled by using double sided electricity market. If electric energy costs increase; consumer will decrease their load by using load management methods. Therefore the market and its prices will be controlled.

In this market behaviour of each participant is based on benefit; the more is the better. Therefore in condition consumers need more electricity power; generators increase their supply function and vice versa. Generators increase their costs by increasing α_i and β_i in equation (1). In other side, consumers decrease their proposed bid by increasing a_j and decreasing b_j in equation (2). It can be seen that overall cost and load will be controlled.

III. Modeling of Bidding Strategies

3.1. Bidding Strategy of Generators

The decision making process of the supplier agent is designed via fuzzy-logic with four fuzzy input sets and one fuzzy output set.

The inputs of a supplier agent are as follows:

a: Generator offer compared to the maximum accepted offer in its area (MCP) at hour *k-1*,
b: System demand rate of change,
c: Generator revenue at hour *k-1*,
d: Generator offer changes between the last two hours (i.e., hour *k-1* and *k-2*).

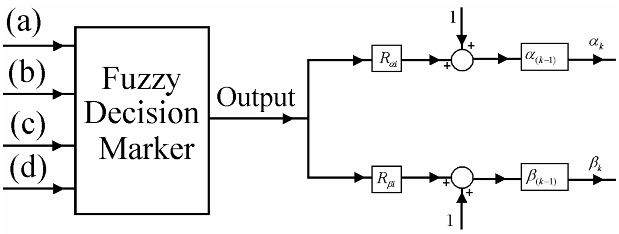

Fig. (1): Fuzzy decision making for supplier

In Fig. (1), $R_{\alpha i}$ and $R_{\beta i}$ represent the *i*-th generator risk attitude; and $\alpha_{(k-1)}$ *, and* $\beta_{(k-1)}$ are the supply function coefficients at hour (*k-1*) which is presented in equation (1).

The membership functions of input *a* are shown in Fig. (2). It can be seen that this input has three Tow-Sided-Gaussian membership functions. The membership functions have been named as EQUAL, LOW, and VLOW. The first membership function, EQUAL, shows that generator offer is equal to the maximum cost in area. And this generator determines MCP. The LOW membership function shows that generator offer is approximately lower than maximum cost, and VLOW shows that generator offer is very lower than maximum.

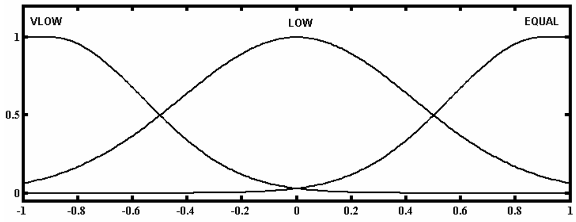

Fig. (2): Membership functions for the input *a*

The input *b* of Fig. (1) has tow Gaussian membership functions which is shown in Fig. (3).in this figure HIGH and LOW mean positive and negative derivative for load changes at hour (*k-1*), respectively.

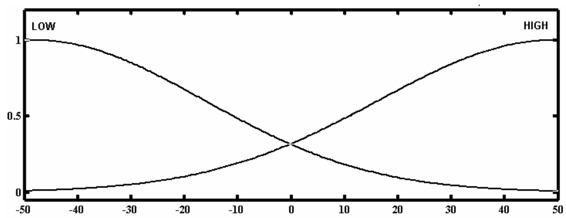

Fig. (3): Membership functions for input *b*

The third input signal, i.e. signal *c*, is generator revenue at hour *k-1*. Fi. (4) shows the membership functions for this fuzzy set. In this figure HIGH means that generator revenue at hour *k-1* is higher than generator revenue at hour *k-2*. FIX means that the generator revenue at hour *k-1* is equal to the generator revenue at hour *k-2* and LOW has the opposite meaning of HIGH.

In this paper the *i*-th generator revenue at hour *k* is defined as follows:

$$\pi(i,k) = \lambda_{ik} \cdot P_{ik} - C(P_{ik}) \tag{3}$$

Where P_{ik} is *i*-th generator active power at hour *k*, $C(P_{ik})$ is *i*-th generator actual cost and λ_{ik} is the *i*-th generator energy cost (at hour *k*).

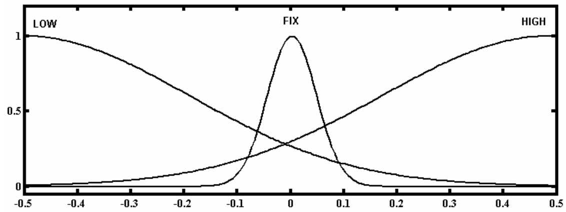

Fig. (4): Membership functions for input *c*

Fig. (5) shows the membership functions for the forth input signal *d*. It can be seen that membership functions have been presented by HIGH and LOW functions.

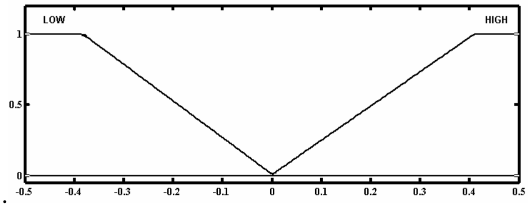

Fig. (5): Membership functions for input *d*

Membership functions for the output fuzzy set are chosen as shown in Fig. (6). Membership functions VLOW, LOW, FIX, HIGH, and VHIGH mean that the offered cost at hour *k* must be decreased too much, decreased, fixed, increased and increased too much, respectively.

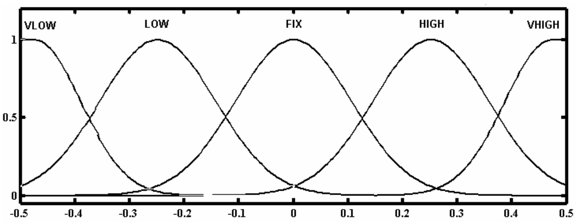

Fig. (6): Membership functions for output of supplier agent

Decision rule base table is shown in table (1). Dashed lines show impossible conditions.

Table (1): Fuzzy rule base used for generator bidding strategy

	Second input	High			Low		
Forth input	First input / Third input	Equal	Low	Vlow	Equal	Low	Vlow
High	High	Vhigh	Vhigh	High	High	Vhig h	High
	Fix	-------	-------	-------	Fix	Fix	Fix
	Low	-------	-------	-------	Low	Vlow	Vlow
Low	High	Low	Vlow	Vlow	-------	-------	-------
	Fix	Fix	Fix	Fix	-------	-------	-------
	Low	Vhigh	High	High	Vlow	Vlow	High

3.2. Bidding Strategy of Consumers

Decision making process of our consumer agent is also designed via fuzzy-logic with two fuzzy input sets shown in Fig. (7).

The inputs of a consumer agent are as follows:
a: System demand rate of change and
b: The Marginal Cost Power (MCP) at hour *k-1* compared to the MCP at hour *k-2*.

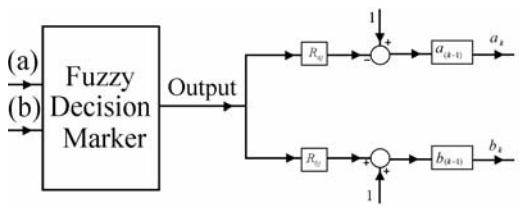

Fig. (7): Fuzzy decision making for consumer

The membership functions for the both input fuzzy sets have been chosen as shown in Fig. (8). In the first input, HIGH means that the system demand rate is higher than the base case and LOW means that the system demand rate is lower than the base case. For the input *b*, HIGH means that the bus MCP at hour *k-1* increases compared to the MCP at hour *k-2* and LOW means that the MCP at hour *k-1* decreases compared to the MCP at hour *k-2*.

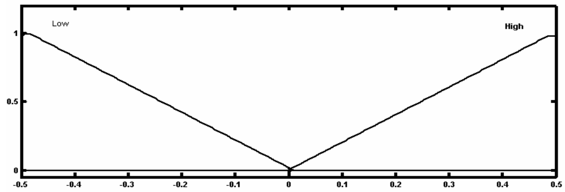

Fig. (8): Membership functions of first input for consumer

Output fuzzy set membership functions are shown in Fig. (9). In this figure HIGH means that the bus MCP at hour *k* increases compared to the MCP at hour *k-1* and LOW means that MCP at hour *k* decreases compared to the MCP at hour *k-1*.

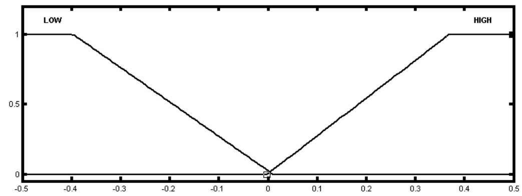

Fig. (9): Membership functions for output of consumer agent

The fuzzy rule base used for consumer bidding strategy is given in table (2),

Table (2): Fuzzy rule base used for consumer bidding strategy

First input / Second input	Low	High
Low	High	Low
High	Low	Low

IV. Simulation Results

In this section, a numerical example is presented to show the capability of the proposed modeling method. A three area power system shown in Fig. (10) has been studied.

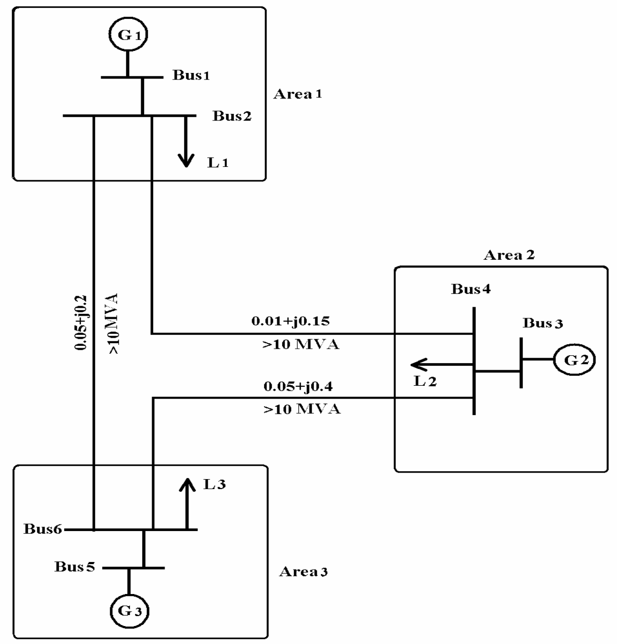

Fig. (10): A 3-zone deregulated power system

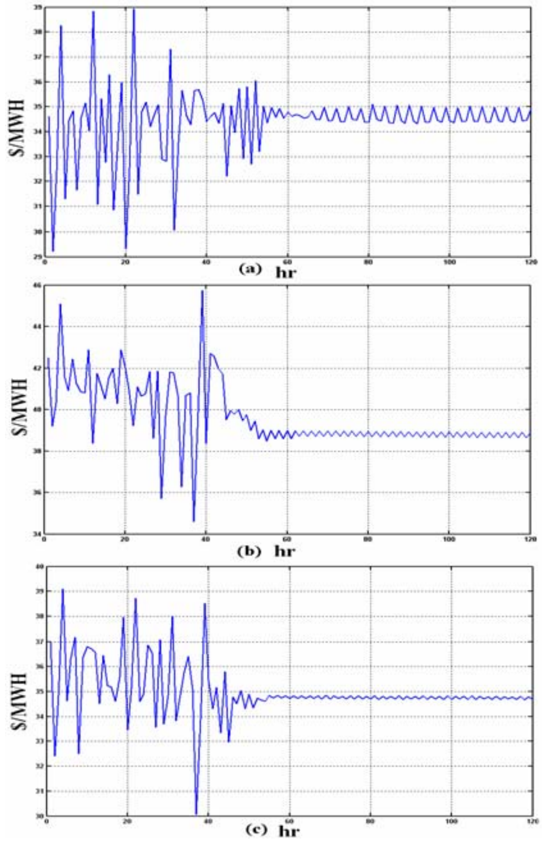

Fig. (12): Average cost variation of a) area1 b) area2 c) area3

Figures (11) to (13) show the generator power, average cost variation, and $\alpha, and \ \beta$ variation for the all three areas, respectively.

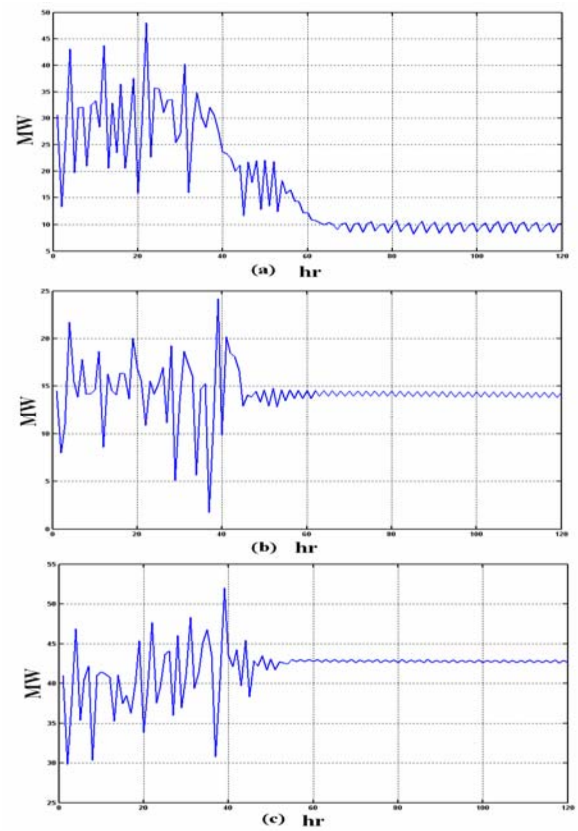

Fig. (11): Generators power of a) area1 b) area2 c) Area3

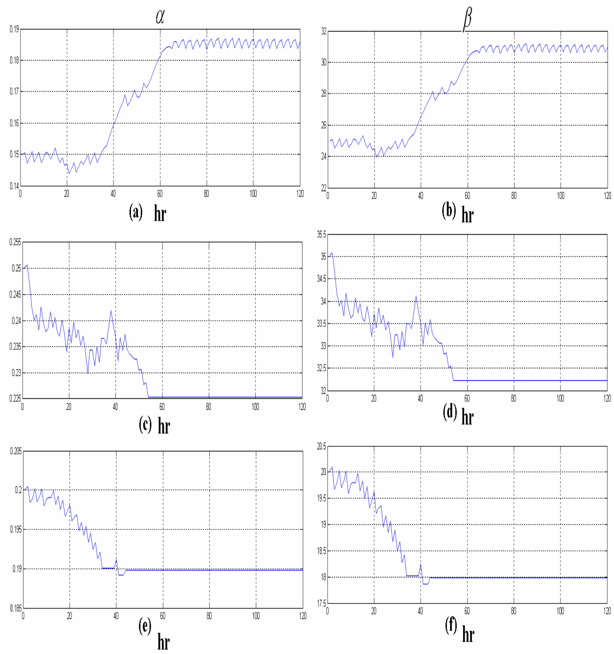

Fig. (13): α_i coefficient of a) area1 c) area2 e) area3 and β_i coefficient of b) area1 d) area2 f) area3, respectively

Figures (14) and (15) show the consumer load and a, and b coefficients variation in all areas, respectively.

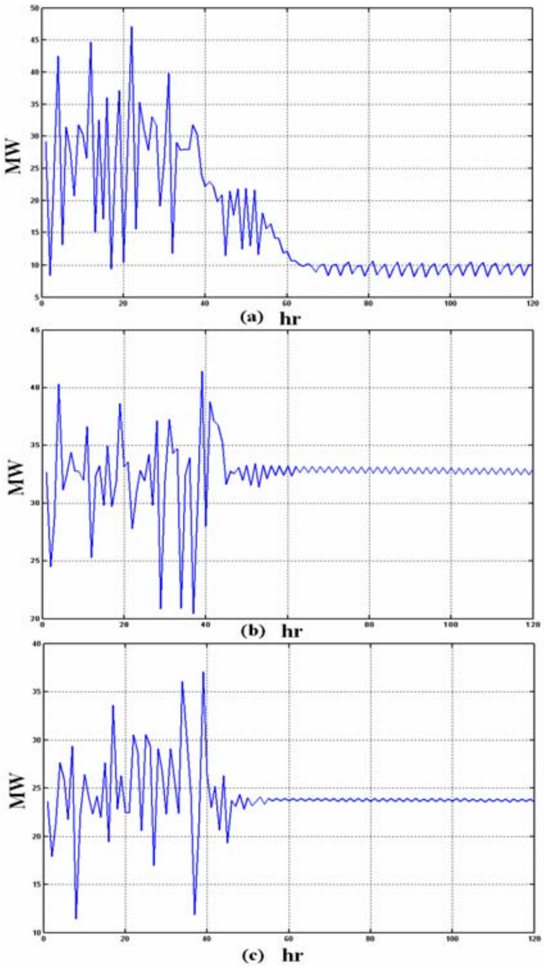

Fig. (14): Consumers load variation of a) area1 b) area2 c) area3

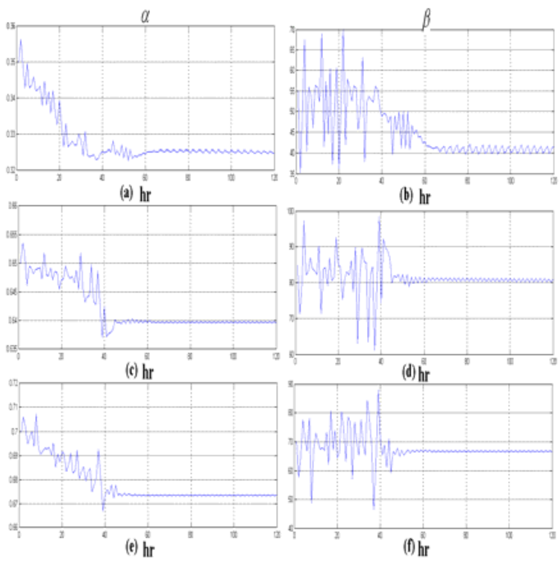

Fig. (15): a_j coefficient of a) area1 c) area2 e) area3 and b_j coefficient of b) area1 d) area2 f) area3 respectively

The simulation results indicate that this power system has a stable market condition and in the steady state condition all generators and consumers accept the market condition. Risk attitudes (*R*) of market participants have a significant effect on market conditions. If the (R) is a big value the market could be unstable. In this example R=0.1 is critical value. R can change the market variation period (or steady state condition achievement time) too.

V. Conclusion

This paper introduces an approach to model the market participants strategic biddings in Double-Sided Electricity Auctions (DSEA) which is based on fuzzy-logic Simulation results show that how an agent can dynamically adjusts its bidding behavior to response effectively to changes in the supply and demand in the marketplace.

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