4th WSEAS Int. Conf. on COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS and CYBERNETICS Miami, Florida, USA, November 17-19, 2005 (pp281-287)

An Open Multi-agent Platform for Price Strategy Optimization of Generators In Market Environment

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Abstract: - The generator's competition strategy has become a pressing research field since the opening of power market. In real market situation Generators have to deal with capacity allocation among different markets (i.e. day-ahead spot market, contract market and ancillary service market) and competition strategy optimization simultaneously. However these two interrelated problems have been studied separated with little practical reference. The allocation of capacity among three markets sets the foundation for strategy optimization while actual market performance is the evaluation criterion of capacity allocation. The key of decision-making is the risk of price uncertainty and its manipulation. Our work provides a new realistic platform of competition strategy optimization for Generation Companies. The process of strategy optimization is completed in a multi-agent system that is interactive with the user. Different kinds of software agents are designed to fulfill the optimization function. Scenario tree generation algorithm is used to deal with the uncertainty of electricity price and genetic algorithm is used to solve the complex optimization problem of generation capacity allocation among different periods. Then competition strategies in spot as well as contract and ancillary market are defined. Finally evaluation process is designed for strategy improvement, which effectively combines the problem of generation capacity allocation with competition strategy optimization.

Key-Words: - Electricity market; Agent-based system; Scenario tree generation; Capacity allocation; Trading strategy; Power system.

1 Introduction

With the advancement of electricity market, the generator's allocation of generation capacity among contract market (CM), spot energy market (EM) and ancillary service market (SM), as well as the competition strategy optimization in these markets, has become a compelling problem. While contract can fix the price for a long period, contract itself means loss of profit opportunity in the future and contract price is closely linked with spot price. So it is necessary to consider the market risk in a consistent fashion when allocating generation capacity. When capacity allocation is formulated then it is to optimize strategy in different markets and adjust the allocation dynamically according to competition results. So it is necessary to combine these two problems together. The purpose of the paper is to provide such an intelligent decision support system (IDSS) based on multi-agent systems (MAS).

There has been lots of literature discussing the strategy of generator in Pool and bilateral auction market, mainly based on game theoretic method and genetic algorithm [1-3]. However little efforts have been devoted to contract market. In [4] a negotiation system for CM is proposed but does not deal with the generation allocation. In [5-7] ABS is proposed to research power market but only for purpose of market simulation. In [8] the long-term capacity allocation of generator is formulated in a two-level optimization problem, however the premise of the research that the contract price is known is unrealistic. In [9] an Intelligent DSS is proposed for generators but contract market is omitted and no concrete strategy is proposed.

The market structure in the paper is assumed to be spot market and contract market, which is common in almost every power market around the world, while spot market includes spot energy and ancillary service market. Though ancillary service includes spinning reserve, supplemental reserve and regulation etc, for simplicity and without losing generality they are considered together. In spot market the uniform pricing mechanism is assumed.

2 Formulation of Generator's Strategy Optimization Problem

Assume that a generator is considering a problem of generation capacity allocation for period of T, with the goal of expectation utility maximization by allocating capacity among different market from $t = 1,2....T$. Assuming that the generator has N units. The expected income of generator in the three markets are given by Eq. (1) respectively

$$E(V)=\sum_{t=1}^{T}\sum_{i=1}^{3}\sum_{n=1}^{N} x^{t}{}_{i} Q_i^n(t) \quad (1)$$

Where $x^{t}{}_{i}, Q_i(t)$, $i = 1,2,3$ represent the price and trading volume in contract, energy and ancillary markets.

The cost function of the generator is,

$$C=\sum_{t=1}^{T}\sum_{h=1}^{24}\sum_{n=1}^{N} C_r^n\left(Q^n(t,h)\right)+s^n(t,h)C_{st}^n(t,h) \quad (2)$$

Where $Q^n(t,h), C_{st}^n(t,h), s^n(t,h)$ respectively represent the operation cost, startup cost and state of the unit, and

$$s^n(t,h)=\begin{cases}1 & on\\ 0, & off\end{cases}$$

The unit must meet with the constraints of maximum and minimum output, minimum up and down time, ramping up and down rate, etc. Then the strategy of capacity allocation is to maximize the expected profit

$$\underset{Q_i, i=1,2,3}{Maximize} \quad E(V)-C \quad (3)$$

Because the price is in uncertainty, it is a sequential decision problem under uncertain environment. Whatever the decision is made then generator has to compete in every market and adjust the allocation dynamically according to the competition performance.

3 Design of Optimization Platform Based on Open MAS

3.1 Methodology

3.1.1 Agent-based system

An agent is an encapsulated computer system that is situated in some environment, and is capable of flexible, autonomous action to meet its designing objectives [10]. The paradigm of ABS is that when establishing the system human being should not intervene with it. However current artificial intelligence is still in its infancy and is inept when the related knowledge is unable to be expressed. So in our platform the agent is designed to be open to the user.

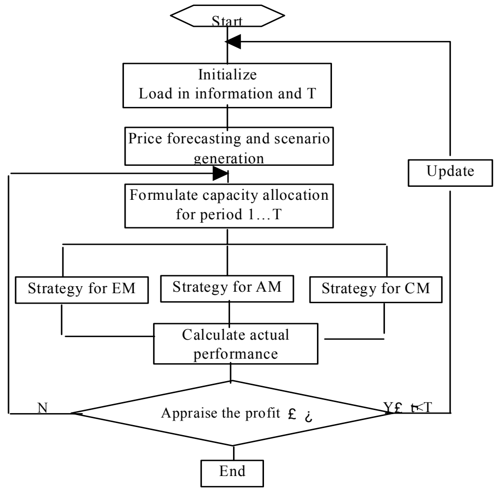
3.1.2 Intelligent engineering (IE)

In [11] the theoretic framework of intelligent engineering is proposed, which is to provide multiple kinds of knowledge representation and an intelligence space for coordinated problem solving. Among the problem solving process human being is supposed to participate actively.

In the open-agent based platform proposed in the paper, the agent is designed based on IE to resolve the matters with MAS and better meet with practical requirements.

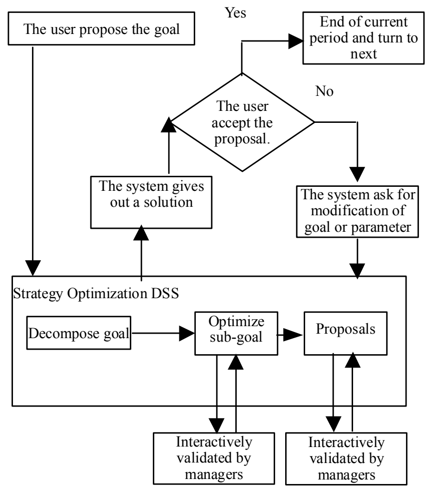
3.2 Agent-human interactive problem solving

Fig 1 Optimization process of the problem



The generator's strategy optimization process is shown in Figure 1, while agent-human interactive problem solving is shown in Figure 2.

Fig. 2: Optimization based on human agent cooperation



3.3 Multi-agent system designing

A MAS system for strategy optimization is proposed, with its kernel being to integrate the processes of capacity allocation and bidding (or negotiation) strategy optimization into an intelligent system.

3.3.1 Architecture of the system

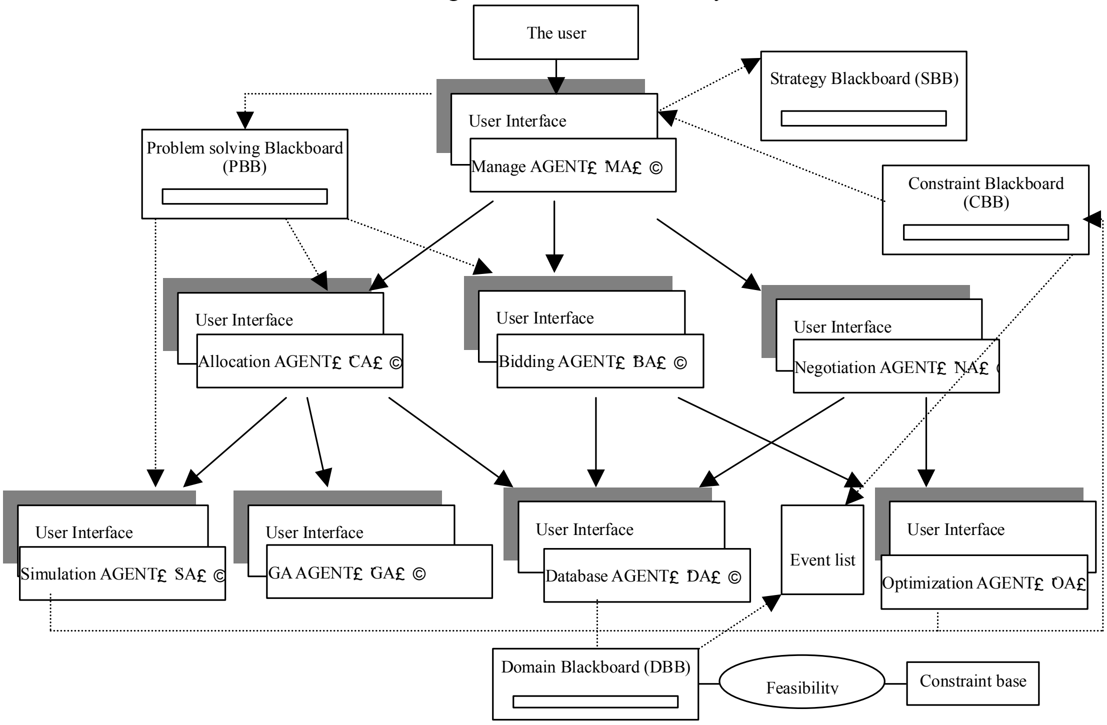
The system consists of three types of elements: the agents, the blackboards and the constraints base, as shown in Figure 3.

Three kinds of agents—manager agent (MA), strategy agents (SAs) and task agents (TAs)---- cooperate at three different hierarchical levels to resolve the problem.

Four types of blackboards are represented to allow communication between agents: the problem blackboard (PBB), the domain blackboard (DBB), the compatibility blackboard (CBB) and the strategic blackboard (SBB).

The constraint base contains the institutional, economic and technological constraints of the problem domain, for example, the price cap according to the market rules, the output limit of the unit, etc.

Fig.3: Architecture of the system



3.3.2 Architecture of the agent

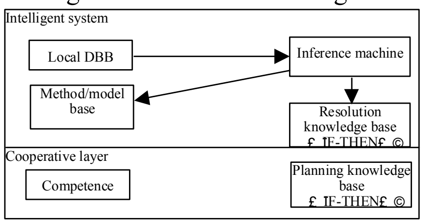
MA is responsible for human-computer interaction, to receive user-defined strategy goal and task, then to decompose the goal to the SAs.

SAs include capacity allocation agent (CA), bidding strategy agent (BA) and negotiation strategy agent (NA), which are responsible for the strategy optimization accordingly and to decompose the task to the subordinated task agents.

Task agents are responsible the elementary task management, for example, the database agent (DA) is to store, transfer and manage the data related to the problem domain, such as price data, load data and unit data; Simulation agent is to simulate the price scenario and Genetic agent is to manage the genetic algorithm for multi-period capacity allocation.

The architecture of the agent is designed based on [11-14], as is shown in Figure 4. The intelligent layer (IL) is responsible for the useful work of the agents while cooperative layer (CL) is responsible for the cooperation with other agents and for the control of the IL tasks. In the IL the knowledge base is user-defined rules for agent inference, for example the fuzzy rules of opponents' behavior for the BA. The interaction between human and the agent is to avoid the knowledge abstraction and representation puzzle; the inference machine is a small-scale expert system to reason based on knowledge base. The method/model base manages a set of methods, such as simulation and optimization methods for SA, load forecasting and optimization methods for BA. In the CL, the planning and coordination module (PKB) is a knowledge base representing the knowledge other agents and responsible for deciding when and how to cooperate with other agents. The competence module supports the knowledge the agent about itself.

Fig.4: Architecture of the agent



3.3.3 Operation of the system

The operation of the system is as the follows:

Phrase 1: user-computer interaction. The user provides the goal of optimization to the system.

Phrase 2: activation of MA and goal decomposition. The MA broadcasts the goal information to the SBB and problem information to the PBB after structuring the goal into problem, based on its PKB.

Phrase 3: activation of CA and sub-goal decomposition. For the similar fashion, the sub-goal is decomposed and posted on the CBB and DBB.

Phrase 4: activation of TA and task solving. The TAs solve the tasks by searching in its knowledge base and mobilize related model and method.

Phrase 5: integration. The TAs post the results on the CBB and DBB and the feasibility is tested. If they are compatible and confirmed by the managers, they are integrated to the SA level, and to the MA.

Phrase 6: user-computer interaction. The user accepts the optimization propose of the system. If it is rejected the user is asked to refine the goal and then the system is to optimize it again.

In section 4 and 5 the principle of capacity allocation and bidding strategy optimization will be introduced.

4 Algorithms for Capacity Allocation Optimization

4.1 Price simulation based on hybrid scenario tree generation

The key of capacity allocation is the price risk and its manipulation. Currently in literature the risk of price is measured in VAR [8,15,16]. The limitation of VAR is that the electricity price does not necessarily conform to normal distribution and the co-risk among markets is not considered. In the paper the density function of the price is assumed to be unknown and the SA models the randomness of the price by the hybrid scenario tree generation algorithm.

4.1.1 Simulation approach

The main steps of our algorithm can be outlined as follows:

Step 1 (Initialization): Create a root node, with N scenarios. Initialize all the scenarios (including the centroid) with the desired starting point. Form a job queue consisting of the root node.

Step 2 (Simulation): Remove a node from the job queue. Simulate one time period of growth (from 'today' to 'tomorrow') in each scenario.

Step 3 (Randomized seeds): Randomly choose a number of distinct scenarios around which to cluster the rest: one per desired branch in the scenario tree.

Step 4 (Clustering): Group each scenario with the seed point to which it is the closest. If the resulting clustering is unacceptable, return to step 3.

Step 5 (Centroid selection): For each cluster, find the scenario that is the closest to its center, and designate it as the centroid.

Step 6 (Queueing): Create a child scenario tree node for each cluster (with probability proportional to the number of scenarios in the cluster), and install its scenarios and centroid. If the child nodes are not leaves, append to the job queue. If the queue is non-empty, return to step 2. Otherwise, terminate the algorithm.

For the technical details of every step, see [17,18] for reference.

4.1.2 Optimization approach

In the optimization approach the decision maker specifies the price expectations by the statistical properties that are relevant for the problem. The event tree is constructed so that these statistical properties are preserved. This is done by letting stochastic prices and probabilities in the scenario tree be decision variables in a non-linear optimization problem where the objective is to minimize the square distance between the statistical properties specified by the decision maker and the statistical properties of the constructed tree.

Generally the problem is to minimize (4), where S denote the set of all specified statistical properties and SVi be the value of specified statistical property i, i $\in$S, x and p denote the price vector and the probability vector, respectively.

$$\min_{x,p} \quad \sum_{i\in S} w_i \left(f_i(x,p) - SV_i\right)^2 \qquad (4)$$

4.1.3 hybrid approach to price scenario tree generation

A hybrid approach [17] combines the main ideas of the simulation and optimization approaches. In this approach, prices are obtained as the centroids of clustering of simulations and substituted for decision variables in the optimization problem. The probabilities are then determined by solving the optimization problem, whose size has been greatly reduced. But it is worthwhile noticing that when SA cannot find feasible solution for the optimization problem new price scenario should be given until satisfied.

4.2 Multi-period capacity allocation

The multi-period capacity allocation problem is solved by substituting the price vector scenario calculated in the above section into the profit function, Eq(3), which is performed by GA. For constraints of space the detail of GA process is omitted here.

5 Strategy Optimizations in Different Markets

After CA posts the results of capacity allocation on the PBB and SBB, BA and NA are then to optimize the strategy for spot and contract market.

5.1 Bidding strategies optimization in day-ahead market

According to [6] three kinds of strategies: based on self's past bidding performance, based on opponent's behavior and based on price forecasting are defined for BA in the paper.

5.1.1 bidding strategy based on own past behavior

An effective strategy based on own past behavior is defined as

$$x_{t+1} = x_t \pm amount_{t+1} \qquad (5)$$

$$amount_{t+1} = x_t * \left(\beta + \frac{\Delta_t}{capacity\_available_t * \alpha} \right)$$

$$\Delta = capacity\_available - energy\_sold_t$$

The formula means that the generator adjusts its bidding price according to its last bidding and the adjusting amount based on available capacity and residual capacity. In the formula α and βare parameters to be learned, which will be discussed in section 6.

5.1.2 fuzzy bidding based on opponent's behavior

Even precisely understanding the opponent's bidding behavior is impossible, fuzzy set can be used to describe it based on past information [19]. The bidding of opponent n in the next period can be expressed by fuzzy set $\widetilde{P}_i^n = \{x_i^n\}$ with its domain $\left[\widetilde{P}_{i\min}^{rt}, \widetilde{P}_{i\max}^{rt}\right]$. When the domain is discretized in M pieces, the fuzzy set can be formalizes as

$$\widetilde{P}_i^n = \frac{u_{\widetilde{p}_i^o}\left(x_i^n(1)\right)}{x_i^n(1)} + \frac{u_{\widetilde{p}_i^{1o}}\left(x_i^n(2)\right)}{x_i^n(2)} + \ldots + \frac{u_{\widetilde{p}_i^o}\left(x_i^n(M)\right)}{x_i^n(M)} \quad (6)$$

Write all the I piece of opponent n's bidding as a fuzzy vector $\widetilde{P}^{rt} = \left(\widetilde{P}_1^{rt}, \widetilde{P}_2^{rt}, \ldots \widetilde{P}_I^{rt}\right)$, then all the N opponents' bidding is a fuzzy matrix $\widetilde{P} = \left(\widetilde{P}_1, \widetilde{P}_2, \ldots \widetilde{P}_N\right)$. Its membership degree is solved by operation of fuzzy intersection

$$u_{\widetilde{P}}(X(m)) = u_{\widetilde{P}^1}\left(X^1(m)\right) \wedge u_{\widetilde{P}^2}\left(X^2(m)\right) \wedge \ldots \, u_{\widetilde{P}^N}\left(X^N(m)\right) \quad (7)$$

Then BA must decide its bidding based on its estimate over opponent's bidding. It is obvious that the generator's profit is decided by its own as well as opponent's bidding and is written in a discrete space as $R = (r(1), r(2) \ldots r(m))$. After defuzzification R is transformed to its precise form $\hat{r}$. Then the BA's goal function is to maxmize its profit by determining the optimum bidding. To see the detail of the solution, see [19] for reference.

5.1.3 bidding based on price forecasting

A simple forecasting based bidding strategy is defined as

$$x_{t+1} = x_t \pm amount_{t+1} \quad (8)$$

$$amount_{t+1} = \delta * x_t * \frac{demand^f_{t+1} - demand_t}{demand_t}$$

Where BA forecasts the demand of next period to adjust its bidding based on current period, and the δ is learning parameter, which will be illustrated in section 6.

5.1.4 combination of the above strategies

In real market agents can utilize one of the strategies listed above, or the combination of them, while the weight of the combination can be decided by their respective effectiveness in the past.

Similarly the strategies in ancillary service market can be defined.

5.2 Negotiation strategies in contract market

In contract market the strategies are to optimize the electricity contract parameter, such as the volume, price, etc [20]. Different tactics are utilized in the paper.

5.2.1. Time-dependent tactics

In this tactics model, the value of the contract parameter j during time t, is given by formula (9)[4,20].

$$X^t_{a\to b}[j] = \begin{cases} \min_j^a + \alpha_j^a(t)\left(\max_j^a - \min_j^a\right) & if \quad V_j^a \downarrow \\ \min_j^a + \left[1 - \alpha_j^a(t)\right]\left(\max_j^a - \min_j^a\right) & if \quad V_j^a \uparrow \end{cases} \quad (9)$$

$\max_j^a, \min_j^a$: Maximum and minimum value of parameter j accepted by agent a.

$V_j^a \uparrow, V_j^a \downarrow$: Increasing and decreasing, scoring function representing a score agent a assigns to x of j.

$a_j^a(t)$: Offer proposed by generator a to buying party b for a contract parameter and is expressed as

$$a_j^a(t) = \left(\frac{\min\left(t, t^\alpha_{\max}\right)}{t^\alpha_{\max}}\right)^{\frac{1}{\beta_j}} \quad (10)$$

Where $t^a_{\max}$ is the maximum negotiation time for agent a and β_j is the parameter of agent type.

5.2.2 Behavior-dependent tactics

In these tactics agents base their actions on the behavior of their negotiation opponent. The value of the contract parameter j for a Relative Tit-for-Tat action is given by [21]:

$$X^{t_{n+1}}_{a\to b}[j] = \min\left(\mu, \max_j^a\right) \quad (11)$$

Where $\mu = \max\left(\xi, \min_j^a\right)$ and

$$\xi = \frac{X^{t_{n-2\delta_j}}_{a\to b}[j]}{X^{t_{n-2\delta_j+2}}_{a\to b}[j]} X^{t_{n-1}}_{a\to b}[j]$$

The functions min and max in (11) take the minimum and maximum values of the given arguments, respectively.

5.2.3. Strategy

If the offer is unsatisfactory, the agent generates a counter offer. Different combinations of tactics can be used to generate a counter offer. A weighted counter offer $X^{t+1}_{a\to b}[j]$ would then be a linear combination of the tactics given in a matrix $\Gamma^t_{a\to b}$ [22], that defines a state of an agent MS containing information about the agent knowledge, resource, attitude, goals, obligations and intentions. The agent's counter strategy is then

$$X^{t_{n+1}}_{a\to b}[j] = \left(\Gamma^{t_n+1}_{a\to b} T^a \left[MS_a^{t_n+1}\right]\right)[i, j] \quad (12)$$

in which $\left(T^a\left[MS_a^{t_n+1}\right]\right)[i,j]=\left(\tau_i\left(\left[MS_a^{t_n+1}\right]\right)\right)[j]$

and $\Gamma_{a\to b}^{t_n+1}$ is a newly updated matrix, which is a function of agent state and previous matrix $\Gamma_{a\to b}^{t_n+1}=f\left(\Gamma_{a\to b}^{t_n},MS_a^{t_n}\right)$.

6 Strategy Evaluations and Learning

6.1 Strategy evaluation

Upon the end of every period, the strategies are evaluated according to the realization of the generator's expectant profit:

- The effectiveness of capacity allocation algorithm. The effectiveness is evaluated based on the difference between planned sales (or volume) and the actual one, simulated price and the actual one. If deemed necessary by user, new price scenarios should be formed based on updated price data and new strategies for next periods formulized.
- The effectiveness of competition strategies in different markets can be evaluated in a similar fashion and the modification of parameter will be discussed below.

6.2 Parameter modification

The determination of parameter is important for the success of the strategies. Here in the paper the idea is that the initial value of the parameter is given by experienced experts while in the optimization process agent can learn about the appropriateness of parameter based on reinforced learning.

For simplicity, the state of market that the generator agent face is an enumerable set of elementary outcomes $S=\{S1,S2,......Si,......\}$.

After making market situation analysis agent get an imprecise impression of the state of the market $\Theta^t=\{\upsilon_1^t,\upsilon_2^t,......\upsilon_j^t\}$,Where $\upsilon_j^t\subseteq S,\quad \Theta^t\subseteq 2^s$.

For each parameter of the strategy suppose it is defined in a discrete space and denumerable. Agent adjust the value of parameter according to Eq. below [23]:

$$F_k^{t+1}=F_k^t\frac{f\left(\pi^t(a_k)\right)}{\sum_k f^k\left(\pi^t(a_k)\right)} \tag{13}$$

$$P^t(a_k)=\frac{F^t{}_k}{\sum_i F_i^t}$$

Where

This selection mechanism induces a stochastic process on the strengths assigned to competing value of each parameter. If the action of selecting k^{th} value under certain state in the past gives out better payoff then its strength in next period is enhanced, else the strength is decreased.

7 Conclusions

In the paper the integrated process and algorithm of competition strategy optimization for generators in power market is proposed. For purpose of practical requirements, the interaction between capacity allocation and competition strategies among different markets is explicitly considered and is incorporated into an open agent-based system, which is endowed with learning capability to dynamically improve and is designed to interact with its user. For the complexity of the problem intersted this is a preliminary study and only a framework is outlined. There are lots of defections in the current research. For example, the bidding strategy is too simple, the strategy evaluation and learning process is straightforward but without deeper consideration, ect. These should be our goal in the future work.

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