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Generation companies decision-making modeling by linear control theory

G. Gutiérrez-Alcaraz [a,*], Gerald B. Sheblé [b]

[a] Programa de Graduados e Investigación en Ingeniería Eléctrica. Departamento de Ingeniería Eléctrica y Electrónica, Instituto Tecnológico de Morelia. Av. Tecnológico 1500, Col. Lomas de Santiaguito 58120. Morelia, Mich., México
[b] INESC Porto, Faculdade de Engenharia, Universidade do Porto, Campus da FEUP, Rua Dr. Roberto Frias, 4200–465 Porto, Portugal

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ABSTRACT

This paper proposes four decision-making procedures to be employed by electric generating companies as part of their bidding strategies when competing in an ologopolistic market: naïve, forward, adaptive, and moving average expectations. Decision-making is formulated in a dynamic framework by using linear control theory. The results reveal that interactions among all GENCOs affect market dynamics. Several numerical examples are reported, and conclusions are presented.

1. Introduction

Generation companies (GENCOs) are the competitive players in today's liberalized electricity markets. The competition and interactions among them are the major sources of market dynamics. Analyzing their interactions and decision-making processes becomes particularly important when electricity markets are ologopolistic and there are few market players. To survive and succeed under such circumstances, GENCOs analyze the market behavior and expected output of their competitors by comparing actual market outcomes with forecasted outcomes based on simulations or static analyses. GENCOs must adaptively adjust market strategies as each new piece of information is gathered and understood to maximize profits, and will utilize several methods to accomplish this learning process, i.e. forward expectation, moving average expectation, and adaptive expectation [1,2].

Expectation plays a very important role in electric market dynamic analysis to understand dynamic interactions between players. The strategies one player anticipates other players may use will determine its decision and action in one of the next periods. Different expectations by market participants lead to different actions and market transitions.

Several models that attempt to formally model expectations in an effort to better understand decision-making in a world of uncertainty have been reported in the literature. Various limited information estimation methods applied to models within the framework of standard econometric estimators are reported in [2]. Game theory, evolutionary game theory, stochastic simulation, and agent-based modeling have been used to model the behavior of players and the impacts of their decision on market dynamics [3–5]. Maiorano et al. [6] and Yu et al. [7] studied dynamics of non-collusive oligopolistic electric markets. In [8] the authors present a theory and method for estimating the conjectural variations (CV) of GENCOs. CV is a game-theoretical concept in which players have a conjecture about the behavior of their opponents [16]. Based on these estimates of CV in an actual electricity market, an empirical methodology is also proposed to analyze the dynamic oligopoly behaviors underlying market power. Recently, there has been considerable interest in oligopoly models with "consistent" CV. A CV is considered consistent if it is equivalent to the optimal response of the other firms at the equilibrium defined by that conjecture. A new unified framework of electricity market analysis based on coevolutionary computation for both the one-shot and the repeated games of oligopolistic electricity markets is presented in [4]. Discrete event system simulation (DESS) has also been applied to model competition to study the effect of some control policies [7]. DESS is very useful when one is including a decision support system (DSS) as part of the trader's support via front, middle, or back office support software. DSS are often considered a database of rules to be applied to the observed conditions to authorize certain trader actions. DESS facilitates the study of transitions and changes in variables over time. Additional properties, controllability, and observability are also useful for monitoring market performance and for DSS rule analysis. Yang and Sheblé [1] introduced the expectations of GENCOs and electricity consumers and studied market dynamics in a discrete-time setting. Later, the authors modeled the electricity

* Corresponding author. Tel.: +52 4433171870; fax: +52 4433171870.
E-mail address: ggutier@itmorelia.edu.mx (G. Gutiérrez-Alcaraz).

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market as a DESS and studied various GENCOs' decisions as specific events unfolded [1]. Stothert has proposed and analyzed a model of an electricity generation bidding system formulated as a control problem [9]. The reasons for approaching generation bidding as a control problem center on the general principle that feedback reduces errors in strategy selection under uncertainty. In [10,11], the repeated bidding process in (hourly-based) real-time electricity markets as a dynamic feedback system is modeled. Recently, several other dynamic models have been developed to study the behavior of players in electricity markets, because their decisions are the most important variable. A dynamic replicator model of the power suppliers' bids in an oligopolistic electricity market, derived for fixed and variable demand cases, is reported in [17]. The replicator model is presented in a state-space structure. A dynamic model based on invasive weed colonization optimization is reported in [18]. It derives on concepts from game theory and supply function. The method is integrated with a power system simulator to consider all of the constraints of a realistic power system.

Simple learning rules have been implemented in dynamic models for strategic bidding in spot electricity markets [21]. This paper introduces more extensive models to simulate GENCOs' dynamic decision-making process with learning in an oligopolistic market. The paper is organized as follows: the electricity market model is described in Section 2. Section 3 develops different models of decision-making in a dynamic framework with learning effect. Numerical examples are reported in Section 4. Conclusions are presented in Section 5.

2. Electricity market model

In this paper we consider a spot market operated on an hourly basis. The market model is based on the Cournot oligopoly. Consider a n-GENCOs spot electricity market with an inverse market demand curve $P^E(k) = a - bQ(k)$, where $P^E(k)$ is the price at period k, $Q(k) = \sum_{i=1}^{n} q_i(k)$ is the total generation in the market at period k, $q_i(k)$ is the quantity generated by GENCO i at period k, a and b are positive market demand coefficients, publicly known for every GENCO, and k is the time period index. GENCOs make decisions according to their internal estimates of the aggregated electricity buyer, competitor behavior, and delayed market information. GENCO i must determine its generation output $q_i(k)$ to maximize its profit at period k, mathematically represented by:

$$\begin{aligned} &\max_{q_i} \pi_i(k) = (a - bQ(k))q_i(k) - C_i(q_i(k)) \\ &S.\,to\; Q(k) = \sum_{i=1}^{n} q_i(k) \\ &q_i^{\min} \le q_i \le q_i^{\max} \end{aligned} \quad (1)$$

where $q_i^{\min}$ and $q_i^{\max}$ are the lower and upper generation limits.

Its generation cost is given by $C_i(q_i(k)) = d_i + e_i q_i(k) + f_i q_i^2(k)\, \forall i = 1, \ldots, n$ where d_i, e_i and f_i are the coefficients of GENCO i's production cost function.

Treating inequality constraints (the lower and upper generation limits) as if they did not exist, the corresponding optimization problem for GENCO i is represented by:

$$\max_{q_i} \pi_i(k) = \left(a - b \sum_{\substack{j=1 \\ i \in j}}^{n} q_j(k) \right) q_i(k) - (d_i + e_i q_i(k) + f_i q_i^2(k)) \quad (2)$$

To achieve the maximum profit, its first-order condition for optimality should be satisfied; this is:

$$\frac{\partial \pi_i(k)}{\partial q_i(k)} = a - 2bq_i(k) - b \sum_{\substack{j=1 \\ i \neq j}}^{n} q_j(k) - e_i - 2f_i q_i(k) = 0 \quad (3)$$

Grouping terms in (3), we have:

$$2(b + f_i)q_i(k) + b \sum_{\substack{j=1 \\ i \neq j}}^{n} q_j(k) = a - e_i \quad (4)$$

Similarly, GENCO j's profit maximization decision is represented as:

$$\max_{q_j} \pi_j(k) = \left(a - b \sum_{\substack{i=1 \\ j \in i}}^{n} q_i(k) \right) q_j(k) - (d_j + e_j q_j(k) + f_j q_j^2(k)) \quad (5)$$

The first-order condition to maximize profits at period k is:

$$\frac{\partial \pi_j(k)}{\partial q_j(k)} = a - 2bq_j(k) - b \sum_{\substack{i=1 \\ j \neq i}}^{n} q_i(k) - e_j - 2f_j q_j(k) = 0 \quad (6)$$

Grouping terms in (6), we have:

$$b \sum_{\substack{i=1 \\ j \neq i}}^{n} q_i(k) + 2(b + f_j)q_j(k) = a - e_j \quad (7)$$

For the n-GENCOs, in matrix form we have:

$$\begin{aligned} &\begin{bmatrix} 2(b+f_1) & b & \ldots & b \\ b & 2(b+f_2) & \ldots & b \\ \vdots & \vdots & \ddots & \vdots \\ b & b & \ldots & 2(b+f_n) \end{bmatrix} \begin{bmatrix} q_1(k) \\ q_2(k) \\ \vdots \\ q_n(k) \end{bmatrix} = \begin{bmatrix} a-e_1 \\ a-e_2 \\ \vdots \\ a-e_n \end{bmatrix} \\ &P^E(k) = \begin{bmatrix} -b & -b & \ldots & -b \end{bmatrix} \begin{bmatrix} q_1(k) \\ q_2(k) \\ \vdots \\ q_n(k) \end{bmatrix} + a \end{aligned} \quad (8)$$

Given that electricity markets operate repeatedly on an hourly basis, GENCOs might learn from available historical market data to forecast or estimate their competitors' strategic behavior. Similarly, market analysts can learn from such market simulation to determine unintended outcomes, misstated market rules, etc. In the next section four kinds of expectations are introduced to the basic Cournot model to build Cournot–like models with learning to improve strategic bidding performance.

A representation of the electricity market used in this paper is shown in Fig. 1.

In the "Market Clearing Mechanism" block in Fig. 1, the market operator conducts a market clearing mechanism. Once market equilibrium and price-quantity are discovered, this information is made public. A GENCO observes this new market information and chooses from a finite set of actions. GENCO i does not know its competitors' decisions at the time of decision-making. Therefore, it needs to estimate the decisions of its rivals, which is the "estimator" block in Fig. 1. The key target of estimating rivals' decisions is to obtain accurate adjusting factor values. It should be noted that