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Co-evolutionary approach for strategic bidding in competitive electricity markets

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ABSTRACT

Determining optimal bidding strategies in a competitive electricity market to maximize the profit of each bidder is a challenging economic game problem. In this paper, it is formulated as a bi-level optimization problem in which, in the lower level, the community's social welfare is maximized by solving a power flow problem while, in the upper level, the profits of individual bidders are maximized. In this bidders' game, instead of using a set of discrete strategies as is usual, we consider continuous functions as strategies. To solve the upper-level problem, two co-evolutionary approaches are proposed and, for the lower level, an interior point algorithm is applied. Three *IEEE* benchmark problems in four different scenarios are solved and their results compared with those obtained from two conventional approaches and the literature which indicate that the proposed approaches have some merit regarding quality and efficiency.

1. Introduction

Over the last decade, the electricity markets in many countries have become more decentralized and deregulated in order to increase their economic efficiency and reduce costs. As a consequence, they are no longer monopolistic but being opened up to competition among both suppliers and consumers [1–3]. In this situation, suppliers, i.e., generator companies (GENCOs) and consumers (e.g., large industries, distributor companies, residential loads, etc.) simultaneously submit their bids to an independent system operator (ISO) that determines the market clearing price (MCP) and power dispatch (PD) of each winning bidder by solving an optimal power flow (OPF) problem, with the aim of finding an optimal operating point of a power system by maximizing its community social welfare (CSW) subject to its network and physical constraints. The CSW is defined as the difference between the profits obtained by trading electricity to consumers and the expenses of purchasing it from GENCOs. Once a winning bidder is informed about the MCP and its allocated quantity of PD, its profit is calculated based on its actual cost and revenue. Note that the MCPs of all bidders are the same when transmission congestions (TCs) are ignored but, if they are considered, the MCPs vary significantly from location (or node) to location which is called the locational market price (LMP) [4].

As the profit of a bidder depends on both its own submitted bid and those of its rivals, each bidder plays a game by optimizing its own bidding behavior with respect to those of its competitors as well as power system constraints. An excessively high bid by a player may not be selected by the ISO while a lower one may not cover its own costs. Therefore, it is a challenging optimization problem to select an appropriate bidding strategy for maximizing the profits of all bidders [5].

During the last decade, numerous studies have been conducted to determine the optimal bidding strategy based on different market models, of which optimization and game theory-based equilibrium models are the most popular [2,6]. In optimization, the problem is solved for a particular player by ignoring other players' bidding behaviors [1]. In this process, a GENCO or consumer first forecasts the MCP and rivals' bidding strategies, and then solves a profit maximization problem using an appropriate algorithm, such as dynamic, fuzzy linear or stochastic dynamic programming [7]. However, estimating the MCP and rivals' bidding strategies is very difficult and, even after doing it, the actual profits may significantly vary from predictions as it is assumed that the LMP is independent of the players' submitted bids [8].

On the contrary, in a game theory-based equilibrium model, a player optimizes its bidding strategy by investigating the interactions of its rivals' bidding behaviors. In it, a GENCO or consumer is represented as a player, economic benefits constitute payoffs and players' options are treated as strategies while it is assumed that all players are rational and have some common knowledge of the

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Nomenclature

i, j, n, p, g	Indices of GENCO, consumer, player, individual of a sub-population, and current generation number, respectively;
K	;Total number of transmission grid nodes ;
I	;Total number of generators ;
J	;Total number of loads (customers) ;
N	;Total number of bidders in market ;
I_k	Number of generators at node
J_k	Number of loads at node
P_i	Real power injection by generator
P_i^{min}, P_i^{max}	Minimum and maximum real power limits of
q_j	Real power demand for load
δ_1	Voltageangle at reference bus with fixed value of 0;
δ_k	Voltageangle (in radians) at node
F_{km}	Real power flow through branch connection from nodes
BR	Set of all distinct branches of
$PNetInject_k$	Net injected real power at each node
x_{km}	Reactance for branches
B_{km}	Susceptance
F_{km}^U,	Lower and upper limits of real power flow for branches
a_i, b_i, c_i	Cost coefficients of
$b_i^{'}, c_i^{'}$	Quiescent coefficients of marginal cost coefficient at i^{th} generator;
d_j, e_j	Coefficients of j^{th} consumers' utility function;
$d_j^{'}, e_j^{'}$	Quiescent coefficients of j^{th}demand curve;
k_{g_i}	Bidding coefficient of i^{th} generator;
k_{d_j}	Bidding coefficient of j^{th} consumer;
$k_{g_i}^{min}, k_{g_i}^{max}$	Lower and upper limits of i^{th} generator;
$k_{d_j}^{min}, k_{d_j}^{max}$	Lower and upper limits of
λ_k	Locational marginal price (LMP) at
$\lambda_{P_i}, \lambda_{dj}$	LMPs of i^{th}generator and j^{th}consumer, respectively

actual cost function of each bidder from historical data. Each player ultimately chooses one strategy from a set of known ones which, as each has a payoff assigned to it by the profit function, means that the optimal solution can be reached via the Nash equilibrium (NE). A NE is based on the strategies of all players in which one player cannot increase its payoff by changing its own strategy while the others' strategies remain the same, with the solution known as a saddle point of the equilibrium model. This approach is very popular among researchers and practitioners for solving energy market problems [6,9,10].

An equilibrium model is classified as a: *(i)* Bertrand game; *(ii)* Cournot game; *(iii)* Stackelberg model; and *(iv)* supply function equilibrium (SFE). In the Bertrand game, the market price is considered a bidding parameter in which it is assumed that all players have a constant unit cost, with capacity constraints ignored when competing on the price offered to consumers. In both the Cournot and Stackelberg models, the amount of power to be produced by each player is considered a strategic variable, with the difference between these approaches being that the former allows the strategic variables of all players to be simultaneously improved while, in the latter, the leader improves its strategic variable first and then the followers sequentially change theirs. As a consequence, because all players in the Stackelberg model do not choose their quantities simultaneously, the largest one acts as the leader and can manipulate the market. In the SFE model, a linear function is used for each bidder's strategic variable, where the coefficients of the supply function are simultaneously improved to reach the maximum profit [11].

Apart from the above classifications, the players in an equilibrium model can be either cooperative or non-cooperative. In the former, the participants coordinate their strategies in order to maximize the profits of all players while, in the latter, a player maximizes its own profit regardless of those of its rivals, with no commitment to coordinating their strategies [12]. Of the above methods, the non-cooperative SFE game model is more appealing due to its realistic characterisations of the strategic variables which reflect real-life bidding rules in the electricity market [1,13]. It is widely used both in literature and practice [11]; for example, English and Welsh wholesale electricity spot markets [6].

Solving a non-cooperative SFE model has gained a great deal of attention over the last decade, with bi-level programming techniques widely used. In it, each independent player maximizes its profit in the upper level while the ISO's CSW is maximized in the lower level by solving a nonlinear OPF optimization problem [14–16]. Each decision entity independently optimizes its own objective but is affected by the actions of other entities in a hierarchy. However, this bi-level problem is a challenging optimization problem because it contains a nested optimization task within the constraints of another optimization problem [14]. It becomes more complex in the presence of difficult mathematical properties of the problem, such as multi-modality, non-convexity, non-differentially and others. This problem is inherently harder to solve than traditional mathematical programs, as pointed out in [17]. Therefore, compared with classical techniques, various evolutionary algorithms (EAs), such as genetic algorithms (GAs) [18–24], differential evolution (DE) [25–28], evolutionary programming (EP) [29] and a bat-inspired algorithm [1,30] are now generating interest in the research community for solving this problem. In these algorithms, a conventional iterative (IT) approach is used to determine the optimal bidding strategies of all participating players, with the bidding strategy of each updated sequentially by one in an iteration to maximize its profit while those of its rivals remain unchanged. This process continues until the bidding strategy of a player improves, with the algorithm terminated as soon as the NE is reached [1]. However, as it solves the bidding problem of each bidder one after the other, it may take too long when there are many bidders which is one of the issues addressed in this paper. Moreover, as most of the abovementioned methods, a game based bidding strategies were used that the bids were represented as discrete quantities such as bidding high, bidding medium or bidding low, the payoff matrices were easily determined by computing all possible combinations of strategies. However, in reality, a player in the energy market submits its bid within a given range [31] that results to the size of payoff matrix becomes infinite and impossible to evaluate all the combinations [32].

In this paper, a non-cooperative bi-level SFE model of an electricity market is considered, in which the bidding strategies represented as the supply functions of the bidders instead of a set of known discrete strategies as is usually applied. We develop two co-evolutionary (CE) approaches for solving the upper-level problem, the first is based on a real-coded GA and the other on a self-adaptive DE. In both variants, each bidder's strategies are evolved in a sub-population with exchanging information among these subpopulations to find the overall best solutions. The lower-level problem is formulated as an OPF problem and solved using an interior point (IP) algorithm with the aim of maximizing the CSW considering power system constraints. In addition, the non-convex OPF problem is formulated as a strictly convex quadratic programming (SCQP) using the linear formulation of the power flow constraints with the quadratic cost function. In the SFE model, both GENCOs and consumers act as independent players that maximize their own profits considering the interactions of their rivals.