Expert Systems with Applications 39 (2012) 4635–4646

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Behavioral simulation and optimization of generation companies in electricity markets by fuzzy cognitive map

S.F. Ghaderi, A. Azadeh *, B. Pourvalikhan Nokhandan, E. Fathi

Department of Industrial Engineering and Center of Excellence for Intelligent Based Experimental Mechanics, University College of Engineering, University of Tehran, P.O. Box 11155-4563, Tehran, Iran

ARTICLE INFO

Keywords:
Fuzzy cognitive map
Market behavior
Market simulation
Generation company
Electricity market
Optimization

ABSTRACT

Simulation can be used in a wide range of applications in an electricity market. There are many reasons that market players and regulators are very interested in anticipating the behavior of the market. Behavior of a generation company (GENCO) in electricity market is an important factor that affects the market behavior. Several factors affect the behavior of a GENCO directly and indirectly. In this study, a new approach based on fuzzy cognitive map (FCM) is introduced to model and simulate GENCO's behavior in the electricity market with respect to profit maximization. FCM helps the decision makers to understand the complex dynamics between a certain strategic goal and the related factors. This paper examines how effective factors affect on a GENCO's profit. To identify key factors relevant to the goal, a FCM is built and then analyzed. To analyze this problem, two cases as simple FCM and weighted FCM are considered. Simple FCM shows how the determined factors affect on goal. A hidden pattern is obtained by this case. Weighted FCM helps sensitivity analysis of the model. In addition, the weighted FCM is used usefully to clearly measure the composite effects resulting from changes of multiple factors. This application is shown by two different case studies. This is the first study that models and simulates the behavior of GENCO in electricity market with respect to profit maximization.

1. Introduction

Simulation can be used in a wide range of applications in an electricity market. For example, players in the electricity market can use simulation to decide whether or not an investment can be expected to be profitable, and authorities and regulators can by means of simulation find out which consequences a certain market design can be expected to have on electricity prices, environmental impact, etc. As known, in the electricity markets, market structure, market rules, demand levels, market concentration and energy sources to produce electricity have a strong influence on market performances. Modifications on these aspects may considerably affect market outcomes (Bomparda et al., 2008). There are many reasons that market players and regulators are very interested in anticipate the behavior of the market. System monitoring, test the rules before their implementation and detect market deficiencies are some goals of regulators; while the players wish to maximize their own profit (Bomparda et al., 2008).

Behavior of GENCOs in electricity market is an important factor affect on market behavior. Many factors affect of GENCOs behavior directly and indirectly. GENCO's behavior is a factor that affects market outcomes. Important market outcomes are price and quantity produced by market. In the competitive electricity markets, generation dispatching is based on bid, and each GENCOs are needed to compete with rivals via bidding to the market. Competition creates the opportunities for GENCOs to get more profit (Maa, Wena, Nia, & Liub, 2005).

In this paper, behavior of a GENCO is studied viewpoint of profit maximization. Advanced approaches for modeling are needed for simulating the behavior of participants in electricity markets over time and model how market participants may act and react to changes in the underlying economic, financial, regulatory environments and important output factors. This is particularly useful for developing whole market rules that will allow these markets to function properly.

To simulate the GENCO behavior, it is needed to determine how the GENCO will behave in each probable situation. In any electricity market, conditions are varying more or less randomly. Therefore, there are an infinite number of possible scenarios. All random events in the electricity market are represented by different scenarios. Also, parameter numbers describe the conditions of a particular scenario. All the scenario parameters are collected into the random vector. Furthermore, it is possible that there is some uncertainty in the input data of the simulation.

* Corresponding author. Tel.: +98 21 88021067; fax: +98 21 82084194.
E-mail addresses: aazadeh@ut.ac.ir, ali@azadeh.com (A. Azadeh).

0957-4174/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2011.08.097

Therefore, sensitivity analysis by varying the assumption of the behavior of the factors may be performed (Amelin, 2004). Sensitivity analysis needs proper simulation tools.

The complex interactions and interdependencies among participants in today's deregulated and decentralized electricity markets were studied in game theory (Picker, 1997). However, most power market participants use very complex strategies to be conveniently modeled by standard game theory techniques. In particular, the ability of market participants to repeatedly investigate markets and rapidly adjust their strategies adds extra complexity. Computational social science offers appealing extensions to traditional game theory.

The classical method to simulate electricity markets is probabilistic production cost simulation (PPC). This method was first presented in Baleriaux, Jamoulle, and deGuertechin (1967) and Booth (1972), respectively and has later been further developed by several authors; nowadays, PPC is included in most text books on power system planning (e.g. Stoll, Garver, & Stoll, 1994; Söder & Amelin, 2003; Wang & McDonald, 1994; Wood & Wollenberg, 1996).

In electricity markets, producers interact one with another taking into account that their results are influenced by competitors' decisions. Game theory is well suited for analyzing these kinds of situations (Ercetin & Tassiulas, 2003; Owen, 1995; The Essence of Game Theory, 2003). It has been successfully applied in many fields: information technology (Michael & Bell, 2000), transportation industry (Yang, 2003), stock market (Garćıa-Corťes, Yagüe, & Moreno, 2000), sociology (Galloway, 2004; Singh, 1999) and electricity markets (de la Torre, Contreras, & Conejo, 2004; Epstein & Axtell, 1996; Ferrero, Shahidehpour, & Ramesh, 1997; Martini et al., 2001).

One of simulation tools is agent-based modeling and simulation (ABMS). Computational social science involves the use of ABMS to study complex social systems (Epstein & Axtell, 1996). ABMS consists of a set of agents and a framework for simulating their decisions and interactions. ABMS is related to a variety of other simulation techniques, including discrete event simulation and distributed artificial intelligence or multi-agent systems (Law & Kelton, 2000; Pritsker, 1999). ABMS tools are designed to simulate the interactions of large numbers of individuals so as to study the macro-scale consequences of these interactions (Tesfatsion, 2002). Each entity in the system under investigation is represented by an agent in the model. Thus, an agent is a software representation of a decision-making unit. Agents are self directed objects with specific traits and typically exhibit bounded rationality, that is, they make decisions by using limited internal decision rules that depend only on imperfect local information. In practice, each agent has only partial knowledge of other agents and each agent makes its own decisions based on the partial knowledge about other agents in the system. Several electricity market ABMS tools have been constructed, including those created by Bower and Bunn (2000), Petrov and Sheblé (2000), Lai, Motshegwa, Subasinghe, Rajkumar, and Blach (2000), Skoulidas, Vournas, and Papavassilopoulos (2002), Veselka et al. (2002), North et al. (2002). These models have demonstrated the potential of agent simulations to act as electronic laboratories, or "e-laboratories", suitable for repeated experimentation under controlled conditions.

Krause et al. (2004) studied the bidding behavior of generating companies in an electricity market based on locational marginal prices (LMPs). Results from an agent-based model with reinforcement learning are compared with those for a computed Nash equilibrium on a five-node test power system. Ernst, Minoia, and Ilic (2004) also used agent-based model to analyze generators' bidding strategies in an LMP market. In this approach, it is assumed that the generators choose their strategy by maximizing their expected profits, based on available information about current and future market conditions. In a simulation of a two-node system, the influence of line transfer capacity and number and size of generators and GENCOs is analyzed.

Yin, Dong, and Saha (2007) applied generalized autoregressive conditional heteroskedastic methodology to accurately predict electricity prices and estimate the risks involved in electricity prices. They proposed a novel approach of designing the optimal bidding strategies based on generator's degree of risk taking. Fuzzy logic models recently have also received special attention for prediction purposes in energy context (Azadeh, Arab, & Behfard, 2010; Azadeh, Saberi, Gitiforouz, & Saberi, 2009).

Borrie, Isnandar, and Ozveren (2006) developed a simulation platform using Fuzzy Cognitive Agents based upon the encapsulation of FCM generated on the MATLAB Simulink platform within commercially available Intelligent Agent software. Bomparda et al. (2008) presented a medium run electricity market simulator based on game theory that incorporates two different games, one for the unit commitment of thermal units and one for strategic bidding and hourly market clearing. Borrie and Ozveren (2004) proposed that FCM can act as powerful inference engine within an autonomous adaptive agent based architecture to model complex system of electricity market. They examined the generic structure of the FCMs, their construction, and the learning algorithms to allow them to adapt to the dynamic market based environment. They also discussed about the concept of temporal delay within the FCMs to describe the inertia that exists in real time systems.

Trigo, Marques, and Coelho (2009) presented an electricity market multi-agent simulator of an artificial electric power market populated with learning agents. The simulator facilitated the integration of two modeling constructs: (i) the specification of the environmental physical market properties, and (ii) the modeling of the decision-making (deliberative) and reactive agents. Their multi agent based simulation approach to the electricity market, aimed at simulating the interactions of agents and to study the macro-scale effects of those interactions.

Akbari, Kabiri, and Amjady (2009) presented a method for calculating the optimal bidding strategies among GENCOs in electricity markets with assumption of imperfect competition and complete information and with consideration of uncertainty in load forecast. They employed the parameterized supply function equilibrium for modeling the imperfect competition among GENCOs in which they used proportionate parameterization of the sole and the intercept. They utilized fuzzy approach for modeling the uncertainty of load forecast and they compared the result with probabilistic approach. Wang, Audun, Guenter, and Koritrov (2009) applied agent based modeling and simulation to electricity market complex adaptive system to model the market participants in electricity markets as various types of agent with different strategies, risk preferences, and objectives. They expanded simulation capability of the model across several time horizons from day-ahead bidding and scheduling to long-term expansion planning.

Liu and Wu (2006) proposed a sequential optimization approach to electric energy allocation between spot and contract markets, taking into consideration the risks of electricity price, congestion charge, and fuel price based on the mean-variance portfolio theory. They analyzed and simulated the impact of the fuel market on electric energy allocation with historical data in respect of the electricity market and other fuel markets in the US. Chen, Tsay, and Gow (2009) presented a methodology for bidding strategies of electricity participants in a congestion environment. They modeled the problem as a two steps optimization problem. At first steps they maximized expected profit with a bidding strategy and at the second step they performed a curtailment strategy to maximize the participant's profit when the system occurs the transmission congestion.

Yin, Zhao, Saha, and Dong (2007) proposed a novel approach of designing the optimal bidding strategies based on incomplete market information that predict the expected bidding productions of each rival generator in the market based on publicly available bidding data. They used support vector machine to estimate the nonlinear relationship between generators' bidding productions and the market clearing price from historical bidding and price data. Finally they transformed the optimal bidding problem into a stochastic optimization problem and solved it with differential evolution and Monte Carlo simulation based on the predicted rivals' behavior and market clearing price. Botterud, Thimmapuram, and Yamakado (2005) used an agent-based simulation model to analyze market power in electricity markets focused on the effect of congestion management on the ability of GENCOs to raise prices beyond competitive levels. They compared a market design based on locational marginal pricing with a market design that uses system marginal pricing and congestion management. They also illustrated that agent-based modeling can contribute important insights into the complex interactions between the participants in transmission-constrained electricity markets.

Wang (2009) presented a novel conjectural variation-based bidding strategy combined with a Q-learning algorithm. They modeled GENCOs as adaptive agents in the electricity markets. They used Q-learning to model the bidding behavior of GENCOs that can learn and adjust their strategies over time. They applied SA-Q-learning algorithm with Metropolis criterion to balance exploitation and exploration in the reinforcement learning process. Saleh, Tsuji, and Oyama (2009) proposed a method to build optimal bidding strategies in a day-ahead electricity market with incomplete information considering both risk management and unit commitment. The proposed methodology employs the Monte Carlo simulation for modeling a risk management and a strategic behavior of rival. A probability density function, value at risk and Monte Carlo simulation used to build optimal bidding strategies for a GENCO.

Da-Wei and Xue-Shan (2009) presented a risk evaluation method considering fuzzy uncertainty of GENCOs' competitive bidding behaviors, the creditability of the real profit less than the fuzzy expected profit is taken as risk index and On this basis, the chance-constrained programming model of the GENCOs' optimal bidding strategy presented. They used a hybrid intelligent algorithm of fuzzy simulation and neural network combined with GA to solve the problem. Since in the chance-constrained programming model the object function and the chance-constrained formulas are uncertain functions, they used fuzzy simulation technique to obtain the function value and neural network to approach the uncertain function.

Hong and Hong (2005) proposed a bidding strategy using the fuzzy Markov decision process and fuzzy-c-means. They used fuzzy Markov decision process to transform the crisp transition probabilities into fuzzy transition probabilities. They used a 30-bus system to illustrate the applicability of the proposed method. Bajpai and Singh (2008) developed an optimal bidding strategy for a GENCO in the network constrained electricity markets and to analyze the impact of network constraints and opponents bidding behavior on it. A bi-level programming technique is formulated in which upper level problem represents an individual GENCO payoff maximization and the lower level represents the independent system operator's market clearing problem for minimizing customers' payments. The objective function of bi-level programming problem used for bidding strategy by economic withholding is highly nonlinear. Fuzzy adaptive particle swarm optimization applied to obtain the global solution of the proposed bi-level programming problem for single hourly and multi-hourly market clearings.

Badri, Jadid, Moghaddam, and Rashidinejad (2009) investigated the problem of developing optimal bidding strategies of GENCOs considering participants' market power as well as transmission constraints. The problem was modeled as a bi-level optimization that at the first level each GENCO maximizes its payoff through strategic bidding, while at the second level, an independent system operator dispatches power, solving an optimal power flow problem. The objective of proposed optimization model is generating optimal bidding strategies for GENCOs, while satisfying transmission constraints. Jain and Srivastava (2009) used equal incremental cost criteria for developing the optimal bidding strategy. They formulated the rival's bidding behavior using a stochastic optimization model. They used genetic algorithm to decide the optimal bidding strategy including congestion management to maximize the profit of the suppliers, considering single sided as well as double sided bidding. Both pure as well as probabilistic strategies have been simulated in their paper. Value at risk calculated as a measure of financial risk.

Gao and Sheble (2010) first identified a proper supply function equilibrium model, which can be applied to a multiple-period situation then developed the equilibrium condition using discrete time optimal control considering fuel resource constraints and finally they discusses the issues of multiple equilibria caused by transmission network and shows that a transmission constrained equilibrium may exist. Vahidinasab and Jadid (2009) described a method for developing optimal bidding strategy based on a bi-level optimization, considering suppliers' emission of pollutants. They employed supply function equilibrium model to represent the strategic behavior of each supplier. In their paper, locational marginal pricing mechanism assumed for settling the market and calculating the supplier profit. It modeled as a bi-level optimization problem in which the upper-level subproblem maximizes individual supplier payoff and the lower-level subproblem solves the independent system operator's market clearing problem.

Sadeh, Rajabi Mashhadi, and Latifi (2009) focusing on Iran's electricity market structure modeled the bidding problem from the viewpoint of a GENCO in a pay-as-bid auction. Their goal was to present a tool for determining the optimal bidding strategy of a price-taker producer in an electricity pay-as-bid auction taking into account the relevant risks. Due to uncertainties in power market, the market-clearing price of each hour is assumed to be known as a probability density function. The optimal solution of bidding problem obtained analytically based on the classical optimization theory. Also, the analytical solution for a multi-step bid protocol generalized and the properties of the generalized solution discussed. They developed a model to consider concept of risk using two different methods. The two proposed methods were then compared and the results interpreted using numerical examples.

Soleymani, Ranjbar, and Shirani (2007) considered the combined energy and reserve markets, and determined the Nash equilibrium points then presented the bidding strategies for each GENCO at these points. The bids for the energy and 10 min spinning reserve markets are separated in the second stage, and again, demonstrated the bidding strategies for each GENCO for the two separated markets. Comparison of the results showed that the separated bidding strategies, while being simplified with the algebraic optimization model and reducing the time consumed, give the same results as the combined ones. They employed the Western system coordinating council (WSCC) nine bus test system to illustrate and verify the results of the proposed method.

Ma, Wen, Nia, and Liu (2005) developed an approach for building optimal bidding strategies with risks taken into account for GENCO participating in a pool-based single-buyer electricity market. They assumed that each GENCO bids a linear supply function and that the system is dispatched to minimize the total purchasing cost of the single-buyer. In their model each GENCO chooses the coefficients in the linear supply function for making tradeoff between two conflicting objectives: profit maximization and risk minimization. They established a stochastic optimization model for the purpose and presented a novel method for solving this problem. Jia et al. (2009) presented a maintenance scheduling of generating units game in competitive electricity markets to analyze strategic behaviors of GENCOs. A simplified offer price methodology and a stochastic programming one are adopted to determine player's optimal bidding strategies for the day-ahead market, whose trends of game result are similar. The maximal payoff of each GENCO is obtained by tabu search algorithm. The solutions of non-equilibrium, unique equilibrium, and multiple equilibria are coordinated.

In this study, a new approach based on FCM is introduced to model and simulate GENCO behavior in the electricity market viewpoint of profit maximization where FCM helps the decision makers to understand the complex dynamics between a certain strategic goal and the related factors. Moreover, it is studied how determined factors by an expert affect on GENCO profit. An expert defines important factors that affect on strategic behavior performed by a GENCO. To identify key factors relevant to the goal, a FCM should be built and then analyzed. We consider two cases for analysis and illustration. In the case 1, expert determines simple values as $\{-1, 0, 1\}$ for connections. By this approach, decision maker can study how determined factors affect on goal. A hidden pattern is obtained by this case. In case 2, expert determines weighted values for connections. By this case, decision maker can analyze model sensitivity by changing factor values. In addition, the FCM matrix can be used usefully for clearly measuring the composite effects resulting from changes of multiple factors. To the best of our knowledge this is the first paper that studies how determined factors by an expert affect on GENCO profit using FCM. Also, it analyzes model sensitivity by changing weighted factor values to help understand the complex dynamics between a certain strategic goal and the related factors.

This article is organized as follow: Section 2 gives an introduction to FCM. Section 3 presents FCM procedure used for this study consisting of concepts and definitions and algorithm. Modeling of defined problem is given by Section 4. Simulation and sensitivity analysis are presented in Section 5. Concluding remarks are drawn in Section 6.

2. An overview of FCM

FCMs are fuzzy structures that strongly resemble neural networks. These structures have powerful and far-reaching consequences as a mathematical tool for modeling complex systems (Vsantha Kandasamy & Smarandache, 2003). The FCMs were first introduced by Kosko (1986). It was a fuzzy extension of the cognitive maps. The cognitive maps were introduced in 1976 by Axelord (1976).

In fact, a FCM incorporates the accumulated experience and knowledge about the system operation by using of human experts that know the system operation and system behavior in different situations. Furthermore, FCMs use learning techniques which have been implemented in Neural Network Theory, in order to train FCM and choose appropriate weights for its interconnections (Styliose & Groumpos, 1999).

It must be mentioned that experts play very critical role in the designing and development of FCMs. Experts who have knowledge and experience of the system operation and behavior determine concepts, interconnections and assigning casual fuzzy weights to the interconnections. Decision makers and policy proponents involve serious difficulties for approaching complicated dynamic systems. Modeling a dynamic system can be hard in a computational sense. In addition, formulation of a mathematical model may be difficult, costly, and even impossible. FCMs have been successfully used in decision making and simulation of complex situation. Additionally, they allow for the simulation and analysis of data. There are over a hundred research papers which deal with FCMs. This tool has been used to study real-world situations. Vasantha Kandasamy and RamKishore (1999) have adopted the FCM in case of symptom-disease model in children.

In general, FCM have been found useful in many applications: administrative sciences, game theory, information analysis, popular political developments, electrical circuits analysis, cooperative man–machines, distributed group-decision support and adaptation and learning, etc. (Craiger, Goodman, Wiss, & Butler, 1996; Dickerson & Kosko, 1994). Use of FCMs in the study of the maximum utility of a bus route in Madras city (in South India) happens to be a difficult one for the concept deals with the many aspects of modern metropolitan public transportation (Vasantha Kandasamy & Indra, 2000).

Ozesmi (1999) has used FCM to study the ecosystems of the Kizilirmar delta wetlands in Turkey using the expert opinions of the local people, non-governmental organizations (NGOs), government officials, stakeholder groups and vacation house owners. The data under study happens to be an unsupervised one and further his study was based on 31 FCM models, which were converted to adjacency matrices. Lee, Lee, Kwon, Han, and Yu (1998) used the mechanism of integrating FCM knowledge with a strategic planning simulation where a FCM helps the decision makers understand the complex dynamics between a certain strategic goal and the related environmental factors.

3. Method: the FCM procedure

FCMs are fuzzy structures that strongly resemble neural networks. The FCM can handle the unsupervised data. The FCMs work on the opinion of experts. The main advantage of this method is its simplicity. By FCMs, the world can be modeled as a collection of classes and causal relations between classes (Vsantha Kandasamy & Smarandache, 2003). Experts can represent factual and evaluative concepts in an interactive framework and also quickly draw FCM pictures or respond to questionnaires.

FCMs are fuzzy signed directed graphs with feedback. There are many causal feedback loops in FCMs. Feedback prevent the graph-search techniques used in artificial-intelligence expert systems. By existence feedback, experts can freely draw causal graphs of their problems and permit causal adaptation laws, conclude causal links from simple data. FCMs can be observed as a dynamical system and equilibrium behavior can be interpreted as a forward-evolved inference. Synchronous FCMs behave as temporal associative memories (TAM) (Vsantha Kandasamy & Smarandache, 2003).

As mentioned above, An FCM is a directed graph. This graph is composed nodes and edges. There are concepts like policies; events etc. as nodes and causalities as edges (Vsantha Kandasamy & Smarandache, 2003). The graph represents causal relationship between concepts. The nodes of the FCM can be selected from fuzzy sets. An example of directed graph is shown in Fig. 1.

The directed edge e_{ij} from causal concept C_i to concept C_j measures how much C_i causes C_j. The edge can be signed as follows: if increase (or decrease) in concept C_i direct to increase (or decrease) in concept C_j then causality between two concepts is positive. If there is no relation between two concepts then there exists no causality. If increase (or decrease) in concept C_i direct to decrease (or increase) in concept C_j then causality between two concepts is

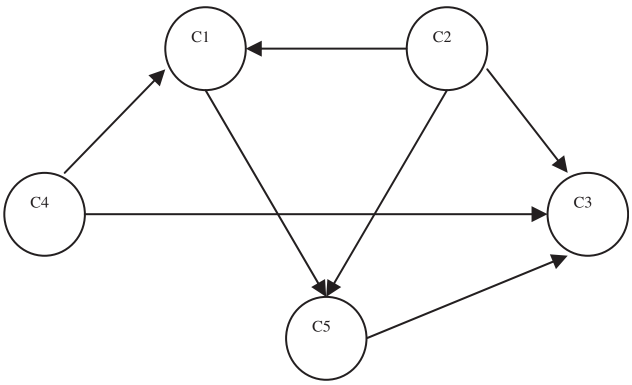

Fig. 1. Example of a directed graph.

negative. FCMs with edge weights or causalities from the set {−1, 0, 1} are called simple FCMs. In simple FCMs, edges can be signed as follows:

Positive causality is signed by $e_{ij} = +1$.
Negative causality is signed by $e_{ij} = -1$.
Non casualty is shown by $e_{ij} = 0$.

By simple FCMs, a quick first approximation is given to an expert stand or printed causal knowledge (Vsantha Kandasamy & Smarandache, 2003). The adjacency matrix or connection matrix of the FCM is defined by $E = [e_{ij}]_{N*N}$, where N is concepts numbers. An expert can use the adjacency matrix to list the cause and effect relationships between the nodes. In a FCM, instantaneous state ($A = [a_{ij}]_{1\times N}$) indicates the on-off position of the node at an instant.

If a_i = off; then $a_i = 0$.
If a_i = on; then $a_i = 1$.
For $i = 1, 2, \ldots, n$.

An FCM with feedback has cycles. Cyclic FCM possesses at least a directed cycle and acyclic FCM does not possess any directed cycle. Dynamical system is an FCM with feedback, in this system causal relations flow through a cycle in a revolutionary way. The equilibrium state for this dynamical system is called the hidden pattern (Vsantha Kandasamy & Smarandache, 2003). If the equilibrium state of a dynamical system is a unique state vector, then it is called a fixed point. The algorithm for performing FCM is given as follows based on (Vsantha Kandasamy & Smarandache, 2003):

Step 1: Read the input vector $A(t)$.
Step 2: Give the connection matrix, E.
Step 3: Calculate the output vector $O(t) = A(t) * E$.
Step 4: Apply threshold to output vector: $O(t) \cong A(t+1)$.
Step 5: If $(A(t+1) = A(t))$, stop
else go to step 1.
End

The state vectors A are repeatedly passed through the FCM connection matrix E. After each pass, concluded vector is threshold or non-linearly transformed. Independent of the FCMs size, it quickly stays in a temporal associative memory hidden pattern of the system for that state vector A. The hidden pattern inference summarizes the joint effects of all the interacting fuzzy knowledge. In the runtime operation, the next value of each concept is determined from the current concept and connecting edge values (Brubaker, 1996). We can infer from model by studying the final state of the iterations. When there are a set of repeated patterns; equilibrium in the system have been attained. Repeating patterns can be fixed points or limiting cycles or a chaotic attractor (Vsantha Kandasamy & Smarandache, 2003). In this study, MATLAB is used for coding the algorithm. Codes are represented by Appendix I.

In this paper, strategic behavior of GENCO in an electricity market is modeled and simulated based on an FCM. FCM helps the decision makers understand the complex dynamics between goals and the related environmental and cognitive factors. For the modeling, an expert defines important factors affecting strategic behavior performed by a GENCO. A GENCO behavior is analyzed form viewpoint of profit maximization. This is because, each GENCO that participates in an electricity market wishes to maximize its own profit. From this viewpoint, all factors can be classified into three categories: Uncontrollable, semi-controllable, and controllable. Factors such as market rules, market structure, etc. are uncontrollable. Proposed quantity for bid, proposed price for bid are controllable because might become favorable or unfavorable according to the efforts of the company. Semi-controllable environments possess two aspects of both uncontrollable and controllable environments. Examples are revenue, profit, etc. semi controllable factors are determined complicated interacting forces of various exogenous and/or endogenous factors described so far. For example, revenue depends on market clearing price and proposed price for bid in a day a head market. In addition, some factors are cognitive such as intelligence of a player. To identify key factors relevant

Table 1
The defined concepts for FCM.

Node No.	Concepts	Status
C1	Profit of GENCO	Increase–decrease
C2	Revenue of GENCO	Increase–decrease
C3	Total cost of GENCO	Increase–decrease
C4	Total proposed quantity	Increase–decrease
C5	Highest proposed price	Increase–decrease
C6	Market price cap	Increase–decrease
C7	Market demand	Increase–decrease
C8	Rival numbers	Increase–decrease
C9	Bidding productivity	Increase–decrease
C10	Forecasted price accuracy	Increase–decrease
C11	Forecasted load accuracy	Increase–decrease
C12	Demand and supply equilibrium	Stable–non-stabel
C13	Total market supply	Increase–decrease
C14	Selection of load forecasting method	Appropriate–inappropriate
C15	Selection of price forecasting method	Appropriate–inappropriate
C16	Selection of inputs for load forecasting	Appropriate–inappropriate
C17	Selection of inputs for price forecasting	Appropriate–inappropriate
C18	Risk of GENCO	Increase–decrease
C19	Risk cost for GENCO	Increase–decrease
C20	Selection of strategy for bidding	Appropriate–inappropriate
C21	Accessibility to market information	Increase–decrease
C22	Accessibility to rival's information	Increase–decrease
C23	Experience of a player	High level–low level
C24	Knowledge of a player	High level–low level
C25	Intelligence of a player	High level–low level
C26	Competition	Increase–decrease
C27	Changes in rival's bidding strategy	Increase–decrease
C28	Market clearing price volatility	Increase–decrease
C29	Market manipulation	Increase–decrease
C30	Market demand uncertainty	Increase–decrease
C31	Changes of climate	Increase–decrease
C32	Production cost for GENCO	Increase–decrease
C33	Defect of market design	High–low
C34	Weakness of market rules	High–low
C35	Congestion in transmission lines	Increase–decrease
C36	Changes in rival's profit	Increase–decrease
C37	Change of regulator behavior and politics	Increase–decrease
C38	Market clearing price	Increase–decrease

to the goal, a FCM should be built and then analyzed. In this study, the strategic goal to be pursued is profit. Defined factors are listed as concepts in Table 1. These concepts are considered as graph nodes.

4. Experiments and results: simulation and sensitivity analysis

In this study, we have modeled and simulated strategic behavior of a GENCO based on FCM in electricity market of Iran. We asked an expert to define important factors that have influence on strategic behavior of the GENCO from its profit maximization view. We chose the expert from the ministry of energy in Iran who has served as a senior expert on electricity market monitoring projects. Our expert defined 38 issues introduced as "defined concepts for FCM", as shown in Table 1. Also, we considered two simple statuses for each concept. For example, profit of GENCO "C1" could increase or decrease when other concepts have impacts on it. Therefore, status of GENCO could be stated as "increase-decrease" as seen in Table 1. Consider a situation consisting of all these concepts that are balanced for the GENCO. We figured out how any changes on each concept can change other related concepts to get balanced, and which changes can maximize the profit. Therefore, we needed to find the related concepts, which are defined as connection matrix. Two cases are considered for the analyses.

At the first case, our expert expected to determine a simple connection matrix. For providing a simple connection matrix, we composed a matrix from concepts as both rows and columns and completed the matrix. We asked expert to determine the relations between concepts. These relationships could be determined from the following procedure:

(1) Consider row 2 including concept C2 defined as "revenue". If increase (decrease) in amount or value of concept C2 have any increase (decrease) on each concept of columns then determine that component of matrix as +1. As shown from Table 2, row 2, that increase (decrease) in revenue (row 2) can increase (decrease) the profit (column 1). This is a direct effect.

(2) Consider row 3 including concept C3 defined as "total cost of GENCO". If increase (decrease) in amount or value of concept C3 have any decrease (increase) on each concept of columns then determine that component of matrix as -1. As shown from Table 2, row 3, increases (decrease) in total cost (row 3) can decrease (increase) the profit (column 1). This is a direct reverse effect.

(3) In this way, the expert can determine any direct or direct reverse effects. However, if a concept from a row of matrix did not have any direct or direct reverse effect on a concept from a column, then that component of matrix would be determined as 0, as shown in Table 2. The connection matrix is then used for the FCM analysis.

For the second case, the expert expected to determine a weighted connection matrix. We asked the expert to determine the relations between concepts with values from $[-1,+1]$. These relationships could be determined from following procedure:

(1) If relation between concept i from row and concept j from column is determined as +1 in the simple connection matrix (Table 2) then we asked the expert to determine the value of this relation from $(0,+1]$. For example, consider row 2, column 1 from Table 2. This component has been determined as +1 in Table 2. The expert claimed that increase or decrease in revenue (row 2) could affect directly 50% on profit (column 1). Therefore, this claim could be determined as +0.5 in Table 3, as the weight for this relation.

(2) If relation between concept i from row and concept j from column is determined as -1 in the simple connection matrix (Table 2) then we asked the expert to determine the value of this relation from $[-1,0)$. For example, consider row 3, column 1 from Table 2. This component has been determined as -1 in Table 2. The expert examined that increase or decrease in total cost (row3) could have reverse affect of about 30% on profit (column 1). Therefore, this examination could be determined as -0.3 in Table 3, as the weight for this relation. The weighted connection matrix is then used for further analysis.

As mentioned, two cases are to be analyzed. In case 1 the selected expert determines simple values as $\{-1,0,1\}$ for connections. By this approach, one can study how determined factors affect on goal. A hidden pattern is obtained by this case. In case 2, expert determines weighted values for connections. By this case, the model sensitivity can be analyzed by changes of factors value. The structure is elaborated in the following two subsections.

4.1. Case I: simple FCM

There are 38 nodes to be used and an expert opinion is obtained. As mentioned, the connection matrix for simple FCM is shown in Table 2. Also, the directed graph for the expert opinion can be obtained by using the corresponding relational matrix, as shown in Fig. 2.

Consider the first node C29 = 1. This node can be observed as market manipulation by players in Table 1. It will be shown how market manipulation by players can affect on profit of GENCO. Node C29 is hold or clamped on the temporal associative memories recall process. Threshold signal functions synchronously update each concept after each pass, through the connection matrix E. The process is started by the population by the following vector:

$$C1 = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0)$$

The process is continued and performed as follows:

$$B_1 = C_1 * E \rightarrow C2 \tag{1}$$

$$C2 = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,1,1,0,0,0,0,0,1,1,1,1)$$

where symbol '→' means the resultant vector has reached threshold and updated.

$$B2 = C2 * E \rightarrow C3 \tag{2}$$

$$C3 = (0,0,0,0,1,1,0,1,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,1,1,1,0,0,0,0,0,1,1,1,1)$$

$$B3 = C3 * E \rightarrow C4 \tag{3}$$

$$C4 = (0,1,1,0,1,1,0,1,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,1,1,1,0,0,0,0,0,1,1,1,1)$$

$$B4 = C4 * E \rightarrow C5 = C4 \tag{4}$$

It was observed that C4 = C5. Therefore, a fixed point is obtained. Thus, at the end of process, we can infer increase the market manipulations by players vary the revenue of GENCO, total costs of GENCO, highest proposed price, Risk of GENCO. Therefore,

Table 2
Simple FCM connection matrix.

Cause	Effects																																				
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31	C32	C33	C34	C35	C36	C37	C38
C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
C2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C3	−1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	0
C5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	0	0	0	0	0
C13	0	0	0	1	0	0	0	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
C14	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C16	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C17	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C19	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C21	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	1	−1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C22	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	−1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C23	0	0	0	0	0	0	0	0	1	1	1	0	0	1	1	1	1	−1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C24	0	0	0	0	0	0	0	0	1	1	1	0	0	1	1	1	1	−1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C25	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C26	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	−1	0	0	1	1	0	0	0	0	0	0	−1	0	0	0	0	0	0	0	0	−1
C27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	−1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0
C28	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	0	0	1	0	−1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1
C29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	−1	1	1	0	0	0	0	0	0	1	1	1	1
C30	0	0	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	1	0	−1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
C31	0	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
C32	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C35	0	0	0	0	0	0	0	0	0	0	0	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
C36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C37	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C38	0	0	0	0	1	0	−1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3
Weighted FCM connection matrix.

Cause	Effects																																				
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31	C32	C33	C34	C35	C36	C37	C38
C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	0	0	0	0
C2	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C3	−0.3	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0.45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.6	0	0	0	0	0	0
C5	0	0.35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0	0	0.2	0	0	0	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0.2	0	0	0.4	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.2	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.1	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.5	0	0	0	0	0	0	0	0	0	0
C13	0	0	0	0.3	0	0	0	−0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0	0	0
C14	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	0	0.6	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C16	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C17	0	0	0	0	0	0	0	0	0	0.6	0	0	0	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C19	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C21	0	0	0	0	0	0	0	0	0.2	0.5	0.5	0	0	0	0	0.6	0.6	−0.4	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C22	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	−0.5	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C23	0	0	0	0	0	0	0	0	0.4	0.5	0.4	0	0	0.6	0.6	0.5	0.5	−0.5	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C24	0	0	0	0	0	0	0	0	0.3	0.5	0.4	0	0	0.6	0.6	0.5	0.5	−0.5	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C25	0	0	0	0	0	0	0	0	0.2	0.2	0.2	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C26	0	0	0	0	0	0	0	0.3	0	0	0	0.8	0	0	0	0	0	−0.2	0	0	0.7	0.3	0	0	0	0	0	0	−0.6	0	0	0	0	0	0	0	0	−0.5
C27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	−0.5	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0	0.5	0	0
C28	0	0	0	0	0	0	0	0	0	−0.5	0	0	0	0	0	0	0	0.5	0	−0.4	0	0	0	0	0	0	0	0	0.6	0	0	0	0	0	0	0.3	0	0.4
C29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.6	0	0	0	0	0	0	0	−0.6	0.6	0.6	0	0	0	0	0	0	0.5	0.4	0.5	0.5
C30	0	0	0	0	0	0	0	0	0	0	0	−0.4	0	0	0	0	0	0.3	0	−0.3	0	0	0	0	0	0	0	0.5	0.4	0	0	0	0	0	0	0	0	0
C31	0	0	0	0	0	0	0	0	0	0	−0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0	0	0
C32	0	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0	0	0	0
C34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0	0	0	0
C35	0	0	0	0	0	0	0	0	0	0	0	−0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0.3	0	0	0	0	0	0	0	0	0
C36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C37	0	0	0	0	0	0.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0	0	0	0	0	0	0	0	0
C38	0	0	0	0	0.4	0	−0.4	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

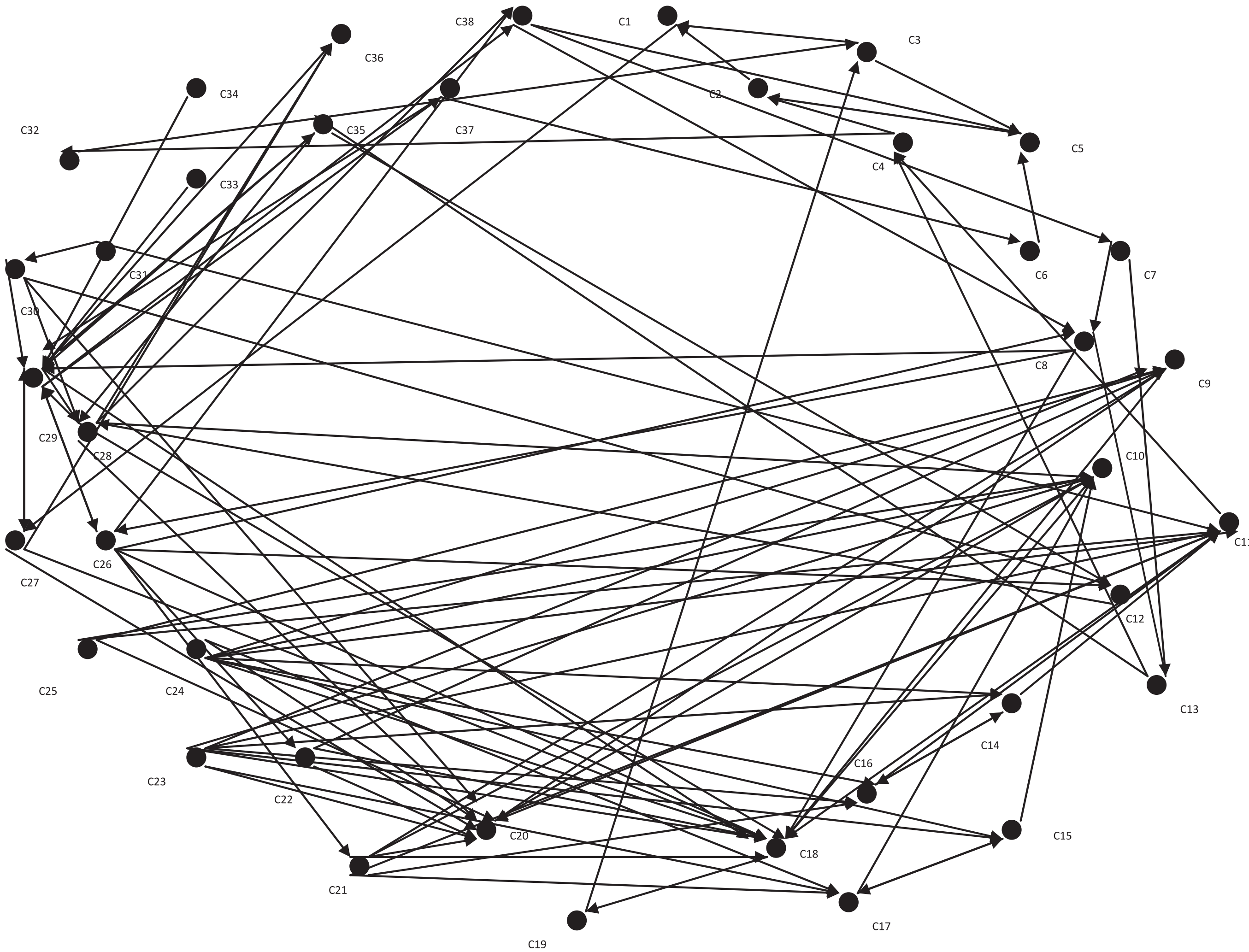

Fig. 2. The directed graph for the expert opinion.

by using FCM, other concepts can be held as on state. This proposed process can be used for analyzing complex systems like as defined system in this study. Thus, the FCMs give us the hidden pattern. It should be noted that other methods do not provide these results with the unsupervised data.

4.2. CASE II: weighted FCM

In this case, an expert gives weighted connection matrix. This matrix is represented in Table 3. In addition, the FCM matrix can be used usefully for clearly measuring the composite effects resulting from changes of multiple factors. For example, consider two situations:

Situation 1: Suppose that three factors changed. Then stimulus input vector may be obtained as follows:

Stimulus Input
Forecasted price accurate = −0.1.
Changes of climate = 0.2.
Market clearing price = −0.3.

This information can be organized into stimulus input vector1.

$$Stimulus\ vector\ 1 = (0,0,0,0,0,0,0,0,0,-0.1,0,0,\\ 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,\\ 0,0,0,0.2,0,0,0,0,0,0,-0.3)$$

Therefore multiplying this stimulus input vector with FCM matrix, a consequence vector can be obtained as follows:

$$Stimulus\ vector\ i * weighted\ matrix = stimulus\ vector(i+1) \qquad (5)$$

Therefore, stimulus vector 2 can be obtained using (5) as follows:

$$Stimulus\ vector\ 2 = (0,0,0,0,-0.12,0,0.12,-0.15,0,0,\\ -0.08,0,0,0,0,0,0,0,0.02,0,\\ -0.02,0,0,0,0,0,0,0,0,0,0.08,\\ 0,0,0,0,0,0,0,0)$$

It can be observed from the above that considered changes can vary some concepts as follows:

Highest proposed price by GENCO = −0.12.
Market demand = 0.12.
Forecasted load accuracy = −0.08.
Risk for GENCO = 0.02.
Selection of appropriate strategy for bidding = −0.02.
Market demand uncertainty = 0.08.

Obtained results from the last transition are shown by Table 4.

The consequence vector may be interpreted such that changes in those three factors including forecasted price accuracy by GENCO, changes of climate, and market clearing price affect the profit

Table 4
Results from sensitivity analysis.

Node no.	Concepts	Status
C1	Profit	−0.021
C2	Revenue	−0.007
C3	Total cost	0.002
C4	Total Proposed quantity	0.022
C8	Rival numbers	−0.016
C9	Bidding	−0.020
C10	Forecasted price	−0.020
C12	Demand and supply	−0.024
C18	Risk	0.020
C19	Risk cost	−0.010
C20	Selection of strategy for bidding	−0.016
C21	Accessibility to market information	−0.021
C22	Accessibility to rival's information	−0.009
C26	Competition	0.022
C27	Changes of Rival's bidding strategy	−0.017
C28	Market clearing price volatility	−0.001
C29	Market manipulation	0.052
C32	Production cost	0.010
C35	Congestion	−0.007
C36	Changes of rival's profit	0.001
C37	Change of regulator behavior and politics	−0.014
C38	Market clearing price	0.017

of GENCO negatively by −0.02, the market manipulation positively by 0.05, and so on. Therefore, we conclude that changes of three factors may affect the profit of a GENCO most unfavorably.

Situation 2: If four factors change including forecasted price accuracy (+0.3), experience of GENCO (+0.4), changes of climate (+0.1), and market clearing price (+0.4), stimulus input vector 1can be organized as follows.

$$\begin{aligned} \textit{Stimulus vector } 1 = (&0, 0, 0, 0, 0, 0, 0, 0, 0, 0.3, 0, 0, 0, 0, 0, 0, 0,\\ &0, 0, 0, 0, 0, 0.4, 0, 0, 0, 0, 0, 0, 0, 0.1, 0,\\ &0, 0, 0, 0, 0, 0.4) \end{aligned}$$

Then a consequence vector may be obtained as follows.

$$\begin{aligned} \textit{Consequence vector} = (&0.03, 0.01, -0.02, 0.02, 0, 0, 0, 0.02,\\ &0.03, 0.08, 0.08, 0.03, 0, 0.03, 0.03,\\ &0.02, 0.02, -0.08, -0.04, 0.09, 0.03,\\ &0.01, 0, 0, 0, -0.06, 0.06, 0.07, -0.02,\\ &0, 0, -0.01, 0, 0, 0.04, 0.04, 0.05, 0.04) \end{aligned}$$

Consequence vector show composite effect of stimulus input vectors on the goal is +0.03 which means that changes of those factors may affect the profit of GENCO positively by 0.03.

By this way, one can analysis different scenarios viewpoint of profit maximization of a GENCO and determine key factors. After determining key factors, more factors can be considered. Finally, the GENCO can determine its strategy for profit maximization. Also, FCM approach can be used for each goal.

5. Conclusion

Simulation can be used in a wide range of applications in an electricity market. There are many reasons that market players and regulators are very interested in anticipate the behavior of the market. Behavior of a GENCO in electricity market is an important factor affect on market behavior. Many factors affect the GENCO's behavior directly and indirectly.

In this study, a new approach based on FCM was introduced to model and simulate GENCO behavior in the electricity market viewpoint of profit maximization. It was studied how determined factors by an expert affect on GENCO profit. Important factors that affect on strategic behavior of a GENCO were defined. To identify key factors relevant to the goal, a FCM was built and then analyzed. To analyze defined system, two cases as simple FCM and weighted FCM were considered. Simple FCM showed how determined factors affect on goal. For example, we analyzed how market manipulation by players can affect on profit of GENCO. Therefore, by the proposed approach, we inferred how the market manipulations by players vary the revenue of GENCO, total costs of GENCO, highest proposed price and risk of GENCO. Therefore, a hidden pattern was obtained using simple FCM. The proposed process can be used for analyzing complex systems such as the defined system of this study. Thus, the FCM provides the hidden pattern. Other method can't provide these results with the unsupervised data.

Also, weighted FCM was used for sensitivity analysis of the model. In this case, the weighted FCM was used usefully for clearly measuring the composite effects resulting from changes of multiple factors. This application was shown by two different situations. In the first situation, the change of three factors was assumed. Therefore, we concluded that changes of three factors including forecasted price accuracy by GENCO (−0.1), changes of climate (+0.2), and market clearing price (−0.3) affect the profit of GENCO negatively by −0.02. In situation 2, it was assumed that four factors changed. Changes include forecasted price accuracy (+0.3), experience of GENCO (+0.4), changes of climate (+0.1), and market clearing price (+0.4). Consequence vector showed composite effect of stimulus input vectors on the goal was +0.03 which means that changes of those factors affected the profit of GENCO positively by 0.03. By this approach, one can analyze different scenarios viewpoint of profit maximization of a GENCO and determine key

Table 5
The features of the FCM approach versus other methods.

Method	Feature					
	Application of FCM for GENCO modeling	Behavioral simulation	Sensitivity analysis using weighted FCM	Identifying key factors related to profit maximization	Data uncertainty and environmental ambiguity	Optimization
The proposed FCM approach of this study	√	√	√	√	√	√
Ernst et al. (2004)		√				√
Yin et al. (2007)	√	√				
Borrie et al. (2006)	√	√				
Akbari et al. (2009)						√
Liu and Wu (2006)						√
Chen et al. (2009)						√
Yin et al. (2007)		√				√
Da-Wei and Xue-Shan (2009)		√				√
Hong and Hong (2005)		√		√		
Bajpai and Singh (2008)						√
Jain and Srivastava (2009)		√				√

factors. At the end, GENCO can determine the strategy to maximize its own profit based on analysis.

The proposed FCM approach is also compared with some of the current studies and methods in electricity markets. Its features are compared with previous methods to show its advantages over previous ones (Table 5). The proposed FCM approach is capable of simulating and modeling the behavior of GENCO to maximize its profit. Also, it has the ability of evaluating the influential and effective factors with respect to the objective of FCM model, i.e. profit. Moreover, using the proposed approach leads to identification of the key factors related to the objective of the FCM model.

Future research topics are as follows: (1) how can we obtain a unified knowledge about factors when several experts have different opinions and (2) what if we use more refined FCM in which edge values are defined more rigorously such as fuzzy partial relationship.

An alternative to the existing logics is neutrosophic logic. In this approach, a mathematical model of uncertainty, vagueness, ambiguity, imprecision, undefined, unknown, incompleteness, inconsistency, redundancy, contradiction are represented. By this logic, we can estimate that each proposition has the percentage of truth, the percentage of indeterminacy, and the percentage of falsity (Vsantha Kandasamy & Smarandache, 2003). In this approach, a subset of truth (or indeterminacy, or falsity), is used instead of using a number, because in many cases, the percentages of truth and of falsity can not be exactly determined but approximated; for example a proposition is between 30% and 40% true. Neutrosophic logic is a further generalization of the theory of fuzzy logic (Vsantha Kandasamy & Smarandache, 2003). Sensitivity analysis by this new structure — the NCM can be greater than the FCM; therefore NCM is capable of giving results. Also, by NCM, an expert has a larger liberty of intuition, because he can express not just the positive, negative and absence of impacts but also the indeterminacy of impacts. For future study, we are going to develop our study by using of NCM-approach.

Acknowledgements

The authors would like to acknowledge the financial support of University of Tehran for this research under Grant number 25652/1/01.The authors are grateful for the valuable comments and suggestion from the respected reviewers. Their valuable comments and suggestions have enhanced the strength and significance of our paper.

Appendix I

```
% read the input vector, suppose there are N concepts and
  element j is 1 and others are zeros
% Give the connection matrix. It is a matrix with dimension N
  by N
While input_vector ~= conclude_vector
Conclude_vector=input_vector*FCM_matrix;
For i=1:N
If conclude_vector(i)>0
Threshod_vector(i)=1;
End %endif
If conclude_vector(i)<0
Threshold_vector(i)=-1;
End%endif
end %endfor
threshold_vector(j)=1;
input_vector=threshold_vector;
end%end while
```

References

Akbari, s., Kabiri, M., & Amjady, N. (2009). Optimal bidding strategy of power generating companies with consideration of load forecast uncertainty. *Journal of Applied Science, 9*(12), 2218–2227.

Amelin, M. (2004). *On Monte Carlo simulation and analysis of electricity markets*. Stockholm: Royal Institute of Technology. Department of Electrical Engineering.

Azadeh, A., Arab, R., & Behfard, S. (2010). An adaptive intelligent algorithm for forecasting long term gasoline demand estimation: The cases of USA, Canada, Japan, Kuwait and Iran. *Expert Systems with Applications, 37*(12), 7427–7437.

Azadeh, A., Saberi, M., Gitiforouz, A., & Saberi, Z. (2009). A hybrid simulation adaptive-network-based fuzzy inference system for improvement of electricity consumption estimation. *Expert Systems with Applications, 36*, 11108–11117.

Badri, A., Jadid, S., Moghaddam, M. P., & Rashidinejad, M. (2009). Impact of generators' behaviors on Nash equilibrium considering transmission constraints. *European Transactions on Electrical Power, 19*(6), 765–777.

Bajpai, P., & Singh, S. N. (2008). Strategic bidding in network constrained electricity markets using FAPSO. *International Journal of Energy Sector Management, 2*(2), 274–296.

Baleriaux, H., Jamoulle, E., & de Guertechin, F. L. (1967). Simulation de l'exploitation d'un parc de machines thermiques de production d'électricité couplé à des stations de pompage. *Extrait de la revue E (édition S.R.B.E.), 5*(7).

Bomparda, E., Carpaneto, E., Ciwei, G., Napoli, R., Benini, M., Gallanti, M., et al. (2008). A game theory simulator for assessing the performances of competitive electricity markets. *Electric Power Systems Research, 78*(2), 217–227.

Bomparda, E., Carpaneto, E., Ciwei, G., Napoli, R., Benini, M., Gallanti, M., et al. (2008). A game theory simulator for assessing the performances of competitive electricity markets. *Electric Power Systems Research, 78*, 217–227.

Booth, R. R. (1972). Power system simulation model based on probability analysis. *IEEE Transactions on Power Apparatus & Systems, PAS-91*(1), 62–69.

Borrie, D., & Ozveren, C. S. (2004). The electric power market in the United Kingdom: Simulation with adaptive intelligent agents and the use of fuzzy cognitive maps as an inference engine. In *39th International universities power engineering conference, UPEC* (Vol. 3, pp. 1150–1154).

Borrie, D., Isnandar, S., Ozveren, C. S. (2006). The use of fuzzy cognitive agents to simulate trading patterns within the Liberalised UK electricity market. In *Proceedings of the 41st international universities power engineering conference, UPEC '06* (Vol. 3, pp. 1077–1081).

Botterud, A., Thimmapuram, P., & Yamakado, M. (2005). Simulating GENCO bidding strategies in electricity markets with an agent-based model. In *Proceedings of the 7th annual IAEE European energy conference (IAEE-05)*.

Bower, J., & Bunn, D. W. (2000). A model-based comparison of pool and bilateral market mechanisms for electricity trading. *Energy Journal, 21*(3).

Brubaker, D. (1996). *More on fuzzy cognitive maps*. EDN ACCESS, 25 April.

Chen, S. L., Tsay, M. T., & Gow, H. J. (2009). Bidding strategies for electricity suppliers in a congestion environment. *International Journal of Electrical and Power Engineering, 3*(1), z 43–49.

Craiger, J., Goodman, D., Wiss, R., & Butler, B. (1996). Modeling organizational behavior with fuzzy cognitive maps. *International Journal of Computational Intelligence and Organizations, 1*, 120–123.

Da-Wei, H., & Xue-Shan, H. (2009). Study on generation companies' bidding strategy based on hybrid intelligent method. In *Proceedings of ninth international conference on hybrid intelligent systems* (Vol. 3, pp. 409–412).

de la Torre, S., Contreras, J., & Conejo, A. J. (2004). Finding multiperiod Nash equilibria in pool-based electricity markets. *IEEE Transactions on Power Systems, 19*, 643–651.

Dickerson, J., & Kosko, B. (1994). Virtual worlds as fuzzy cognitive map. *Presence, 3*(2), 173–189.

Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies: Social science from the bottom up*. MA: Brookings Institution Press.

Ercetin, O., & Tassiulas, L. (2003). Market-based resource allocation for content delivery in the Internet. *IEEE Transactions on Computers, 52*(12), 1573–1585.

Ernst, D., Minoia, A., & Ilic, M. (2004). In *Proceedings of bulk power system dynamics and control – IV managing complexity in power systems: From micro-grids to mega-interconnections, Cortina D'Ampezzo, Italy*.

Ferrero, R. W., Shahidehpour, S. M., & Ramesh, V. C. (1997). Transaction analysis in deregulated power systems using game theory. *IEEE Transactions on Power Systems, 12*(3), 1340–1347.

Galloway, J. F. (2004). Game theory and the law and policy of outer space. *Space Policy, 20*(2), 87–90.

Gao, F., & Sheble, G. B. (2010). Electricity market equilibrium model with resource constraint and transmission congestion. *Electric Power Systems Research, 80*(1), 9–18.

Garćıa-Corťes, L. A., Yağue, G., & Moreno, C. (2000). Optimum family size in progeny testing and the theory of games. *Livestock Production Science, 64*(2-3), 193–202.

Hong, Y. Y., & Hong, B. H. (2005). A bidding strategy based on the fuzzy Markov decision process and fuzzy-C-means for a competitive electronic power market. *Journal of the Chinese Institute of Engineers, 28*(1), 67–75.

Jain, A. K., & Srivastava, S. C. (2009). Strategic bidding and risk assessment using genetic algorithm in electricity markets. *International Journal of Emerging Electric Power Systems, 10*(5) (Article No. 1).

Jia, D., Cheng, H., Zhang, W., Hu, Z., Yan, J., & Chen, M. (2009). A new game theory-based solution methodology for generation maintenance strategy. *European Transactions on Electrical Power, 19*(9), 225–239.

Axelord, R. (Ed.). (1976). *Structure of decision: The cognitive maps of political elites*. New Jersey: Princeton Univ. Press.

Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man–Machine Studies, 24*, 65–75.
Krause, T., Andersson, G., Ernst, D., Beck, E. V., Cherkaui, C. R., & Germond, A. (2004). Nash equilibria and reinforcement learning for active decision maker modelling in power markets. In *Proceedings of the sixth European IAEE conference, Zurich, Switzerland*.
Lai, L.L., Motshegwa, T., Subasinghe, H., Rajkumar, N., Blach, R., 2000. Feasibility study with agents on energy trading. In *Proceedings of the 5th international conference on advances in power system control, operation, and management, Hong Kong*.
Law, A. M., & Kelton, W. D. (2000). *Simulation modeling and analysis* (3rd ed.). New York: McGraw-Hill.
Lee, K. C., Lee, W. J., Kwon, O. B., Han, J. H., & Yu, P. I. (1998). A strategic planning simulation based on fuzzy cognitive map knowledge and differential game. *Simulation, 71*(5), 316–327.
Liu, M., & Wu, F. F. (2006). Managing price risk in a multimarket environment. *IEEE Transactions on Power Systems, 21*(4), 1512–1519.
Ma, X., Wen, F., Nia, Y., & Liu, J. (2005). Towards the development of risk-constrained optimal bidding strategies for generation companies in electricity markets. *Electric Power Systems Research, 73*(3), 305–312.
Maa, X., Wena, F., Nia, Y., & Liub, J. (2005). A game theory simulator for assessing the performances of competitive electricity markets. *Electric Power Systems Research, 73*(3), 305–312.
Martini, A., Pelacchi, P., Pellegrini, L., Cazzol, M. V., Garzillo, A., & Innorta, M. (2001). A simulation tool for short term electricity markets. In *Proceedings of the 22nd IEEE power engineering society international conference on power industry computer applications, PICA 2001, 20–24 May* (pp. 112–117).
Michael, G. H., & Bell (2000). A game theory approach to measuring the performance reliability of transport networks. *Transportation Research, Part B: Methodology, 34*(6), 533–545.
North, M. J., Conzelmann, G., Koritarov, V. S., Macal, C. M., Thimmapuram, P., & Veselka, T. D. (2002). E-Laboratories: Agent-based modeling of electricity markets. In *Proceedings of the 2002 American power conference, April 15–17, Chicago*.
Owen, G. (1995). *Game theory* (3rd ed.). Academic Press.
Ozesmi, U. (1999). Ecosystems in the mind: fuzzy cognitive maps of the Kizilirmak delta wetlands in Turkey. Ph.D. dissertation. *Conservation strategies for sustainable resource use in the Kizilirmak Delta, Turkey* (pp. 144–185). <http://www.env.erciyes.edu.tr/Kizilirmak/UODissertation/uozesmi5.pdf>.
Petrov, V., & Sheblé, G. B. (2000). *Power auctions bid generation with adaptive agents using genetic programming. Proceedings of the 2000 North American power symposium*. Waterloo-Ontario, Canada: Institute of Electrical and Electronic Engineers.
Picker, R. C. (1997). *Simple games in a complex world: A generative approach to the adoption of norms*. Chicago, USA: University of Chicago Law Review, University of Chicago.
Pritsker, A. A. B. (1999). *Introduction to simulation and visual SLAM*. New York: Wiley.
Sadeh, J., Rajabi Mashhadi, H., & Latifi, M. A. (2009). A risk-based approach for bidding strategy in an electricity pay-as-bid auction. *European Transactions on Electrical Power, 19*(9), 39–55.
Saleh, A., Tsuji, T., & Oyama, T. (2009). Optimal bidding strategies for generation companies in a day-ahead electricity market with risk management taken into account. *American Journal of Engineering and Applied Sciences, 2*(1), 8–16.
Singh, H. (1999). Introduction to game theory and its application in electric power markets. *Computer Applications in Power, IEEE, 12*(4), pp. 18–20,22.
Skoulidas, C., Vournas, C., & Papavassilopoulos, G. (2002). Adaptive game modeling of deregulated power markets. *IEEE Power Engineering Review*, 42–45.
Söder, L., & Amelin, M. (2003). *Efficient operation and planning of power systems, fifth edition, course compendium, A-ETS/EES-0308b*. KTH, Stockholm: Department of Electrical Engineering.
Soleymani, S., Ranjbar, A. M., & Shirani, A. R. (2007). New approach for strategic bidding of GENCOs in energy and spinning reserve markets. *Energy Conversion and Management, 48*(7), 2044–2052.
Stoll, H. G., Garver, L. J., & Stoll, B. E. (1994). *Least-cost electric utility planning*. New York: John Wiley & Sons.
Styliose, C. D., & Groumpos, P. P. (1999). Mathematical formulation of fuzzy cognitive maps. In *Proceedings of the 7th Mediterranean conference on control and automation (MED99) Haifa, Israel*.
Tesfatsion, L. (2002). Agent-based computational economics: Growing economies from the bottom up. *Artificial Life, 8*(1), 55–82.
The Essence of Game Theory (2003). Potentials. *IEEE, 22*(2), 3.
Trigo, P., Marques, P., & Coelho, H. (2009). *TEMMAS: The electricity market multi-agent simulator* (Vol. 5517). Berlin/Heidelberg: Springer, pp. 569–576.
Vahidinasab, V., & Jadid, S. (2009). Multiobjective environmental/techno-economic approach for strategic bidding in energy markets. *Applied Energy, 86*(4), 496–504.
Vasantha Kandasamy, W. B., & Indra, V. (2000). Applications of fuzzy cognitive maps to determine the maximum utility of a route. *Journal of Fuzzy Mathematics, 8*, 65–77.
Vasantha Kandasamy, W. B., & RamKishore, M. (1999). Symptom-disease model in children using FCM. *Ultra Science, 11*, 318–324.
Veselka, T. D., Boyd, G., Conzelmann, G., Koritarov, V. S., Macal, C. M., North, M. J., et al. (2002). Simulating the behavior of electricity markets with an agent-based methodology: The electricity market complex adaptive systems (EMCAS) model. In *Proceedings of the 22nd annual USAEE/IAEE conference, Vancouver, Canada*.
Vsantha Kandasamy, W. B., & Smarandache, F. (2003). *Fuzzy cognitive maps and neutrosophic cognitive maps*. Phoenix, USA.: Xiquan.
Wang, J. (2009). Conjectural variation-based bidding strategies with Q-learning in electricity markets. In *Proceedings of the 42nd Hawaii international conference on system sciences*.
Wang, J., Audun, B., Guenter, C., & Koritrov, V. S. (2009). Multi-agent system for short and long-term power market simulations. *International Journal of Innovations in Energy Systems and Power, 4*(1), 36–43.
Wang, X. F., & McDonald, J. R. (1994). *Modern power system planning*. London: McGraw-Hill Book Company.
Wood, A. J., & Wollenberg, B. F. (1996). *Power generation operation and control* (second ed.). John Wiley & Sons.
Yang, Z. (2003). A pseudo 'folk' theorem in the strategic provision of stock externalies. *International Game Theory Review, 5*(4), 347–360.
Yin, X., Dong, Z., & Saha, T. K. (2007). Optimal GENCO's bidding strategies under price uncertainty with bilateral contracts. In *Proceedings of the 8th Asia-Pacific complex systems conference, Surfers Paradise Marriott Resort Queensland Australia*.
Yin, X., Zhao, J., Saha, T. K., & Dong, Z. Y. (2007). Developing GENCO's strategic bidding in an electricity market with incomplete information. In *Power engineering society general meeting* (pp. 1–7). IEEE.