



Modeling optimal long-term investment strategies of hybrid wind-thermal companies in restructured power market

Mohammad Tolou ASKARI¹, Mohd. Zainal Abdin Ab. KADIR^{2,3},
Mehrdad TAHMASEBI⁴, Ehsan BOLANDIFAR⁵



Abstract In this paper, a novel framework for the estimation of optimal investment strategies for combined wind-thermal companies is proposed. The medium-term restructured power market was simulated by considering the stochastic and rational uncertainties, the wind uncertainty was evaluated based on a data mining technique, and the electricity demand and fuel price were simulated using the Monte Carlo method. The Cournot game concept was used to determine the Nash equilibrium for each state and stage of the stochastic dynamic programming (DP).

Furthermore, the long-term stochastic uncertainties were modeled based on the Markov chain process. The long-term optimal investment strategies were then solved for combined wind-thermal investors based on the semi-definite programming (SDP) technique. Finally, the proposed framework was implemented in the hypothetical restructured power market using the IEEE reliability test system (RTS). The conducted case study confirmed that this framework provides robust decisions and precise information about the restructured power market for combined wind-thermal investors.

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✉ Mohammad Tolou ASKARI
m.asgary28@gmail.com

Mohd. Zainal Abdin Ab. KADIR
mzk@upm.edu.my

Mehrdad TAHMASEBI
tahmasebi86@gmail.com

Ehsan BOLANDIFAR
ehsan@baf.cuhk.edu.hk

- ¹ Department of Electrical Engineering, Semnan Branch, Islamic Azad University, Semnan, Iran
- ² Centre for Electromagnetic and Lightning Protection Research (CELP), Faculty of Engineering, Universiti Putra Malaysia, Serdang, Malaysia
- ³ Institute of Power Engineering (IPE), Universiti Tenaga Nasional, Kajang, Malaysia
- ⁴ Department of Electrical Power Engineering, Eyvan-e-Gharb Branch, Islamic Azad University, Eyvan, Iran
- ⁵ Department of Decision Sciences and Managerial Economics, Chinese University of Hong Kong, Hong Kong, China

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1 Introduction

The concept of “sustainable development” was proposed to international diplomats at the United Nations Framework Convention on Climate Change. It was established that the contribution of the energy sector to the greenhouse effect should play a major role in the policy for sustainable environmental development. Thus, several countries ratified an agreement to address this crisis by reducing greenhouse gas emissions. They offered to expand the existing renewable energy infrastructures to solve this problem. Moreover, countries in the European Union (EU) prepared a supportive policy to develop renewable technologies, and are committed to generate 20% of their total electrical power from renewable energies by 2020 [1]. Among the sustainable and renewable energies, the maturity rate of wind sources is the highest. This expansion occurred due to the economic, social, and



environmental advantages of wind [2]. Besides wind deployment, the structure of the electricity power market underwent a shift from the vertical integrated utility or centralized structure to the decentralized power market. Private companies and investors are the main participants in the restructured power markets, and the governments function as supervisors [3]. In traditional systems, the generation expansion planning (GEP) is modeled in the centralized environments, and there is a standard and reliable pattern for the GEP [4]. Moreover, the restructured power market of the GEP model is dependent on the decisions of private investors. These decisions have an influence on the undetermined parameters in the restructured power market. Hence, the companies encounter several risks in their investments. Furthermore, the aims of the participants in the restructured power markets are different from the objectives described in the centralized power markets. In the traditional power market, the aims of the GEP are to determine the ideal technology, capacity, time, and the location of the construction of power plants by considering the acceptable reliability, to effectively respond to the demand, and by considering the social welfare [5–7]. On the other hand, the aim of the investor in the restructured power market is to maximize profits [8–10]. Therefore, the investors should provide long-term optimal investment strategies to maximize their profits by considering the uncertainties and regulatory policies in the restructured power market.

Although thermal companies should consider uncertainties such as the demand and fuel price in their long-term planning, wind companies are subject to a greater number of uncertainties. This is due to the volatile and intermittent nature of the wind. Moreover, the capital costs of wind sources are higher than that of thermal power plants. Thus, it is difficult for wind investors to participate in a competitive power market. Consequently, the investors in the restructured power market prefer to invest in stable and reliable power plants. This could reduce the investments in renewable energy; thus preventing governments from realizing renewable energy sources [11].

The long-term revenue of wind-power companies in the restructured power market are therefore subject to more uncertainties than thermal companies. These uncertainties include the forecasted load, fuel price, and output power of the wind farm, which are referred to as stochastic uncertainties. Furthermore, in medium-term planning, wind-power companies are subject to fluctuations in the market clearing price (MCP). The MCP is affected by uncertain parameters, which include the demand, fuel price, wind fluctuations, and the strategic behavior of other investors. In addition to the previously mentioned uncertainties, several factors influence the MCP, such as the regulatory interventions and realities in the restructured power market.

These factors increase the investment risks for wind investors. Thus, the private wind investors require decision-making tools to determine their investment strategies in the long-term planning, by considering the medium-term effects of uncertainties, regulatory policies, and realities on the MCP in the restructured power market.

Until the end of the 1990s, a significant number of published researches were conducted on the GEP process in regulated electricity markets. During the last two decades, the GEP problem was solved in several studies by considering the stochastic or rational uncertainties individually; and in fewer studies, both types of uncertainties were evaluated to solve the GEP problem [6, 12–16]. Moreover, a major drawback of these approaches is that the wind sources and regulatory interventions with respect to wind sources were not considered. Until now, there has been little discussion on the economic issues of the GEP with respect to the hybrid wind-thermal investors, when considering the abovementioned risks and realities in the restructured power market.

Until the end of 1990s, a significant number of public studies were conducted on the GEP process in the regulation of electricity markets, and several key contributions are presented in [17–19]. In a significant review paper [10], mathematical programming-based and heuristic-based techniques used to solve GEP problems in regulated settings were discussed. In recent times, several researches have addressed GEP in restructured power markets using game theory (GT) [20]. As a field of applied mathematics, GT involves the investigation of mathematical models of conflict between rational private investors [21]. Moreover, it has been used to model the systematic behavior [22]. The expansion planning of wind power plants in the regulated power market was discussed in [23]. The authors suggested the Monte Carlo simulation for the calculation of the wind speed, to estimate the output power of wind power plants.

Reference [6] developed one of the initial GEP models in a restructured power market. The GEP was modeled as a Cournot game by assuming that the generators compete only in quantities, new entries do not occur in the middle of the game, and all the generators make investment decisions simultaneously. However, the GEP problem was solved despite the stochastic uncertainties. Reference [24] presented three different GEP models. Moreover, for the models in [6] and [24], the transmission constraints were not considered. Reference [14] considered the transmission constraints and extended the Hobbs linear complementarity problem (LCP) formulation [25] for power markets by incorporating GEP-related decision variables into the objective function. In [26], reliability criteria were assumed for the GEP model based on GT, to solve the generation investment problem, where the forecasted average market

prices were assumed as a known parameter. A model based on the Nash Cournot equilibrium was proposed in [27] to solve the GEP problem that considers the power production in the energy market where the uncertainties have not been considered. An agent-based model was proposed to solve the generation investment problem, where interactions among agents were represented by a conjectured variation approach in [28]. In [12], a novel hybrid dynamic programming (DP)/GT framework was proposed to evaluate the impact of regulatory interventions on the dynamic behavior of investments in the new generation capacity in electricity markets. In [29], [12] was expanded by considering wind uncertainty. A framework for simulating the medium-term restructured power market was proposed. Moreover, the scenario-based method was used to model a wind-power plant in the restructured power market. In [30], a Monte Carlo simulation was used to model the uncertainties. In addition, the risk of a power system overload was evaluated for various penetration levels of wind plants. This assessment was conducted based on the measurement of the wind speed and the correlation between the wind resources. In this study, the minimization of the overload risk for each penetration level of wind resources was the basis of the expansion planning. In [31], the impact of climate policy and machine learning on future investments in the Swedish power sector was analyzed, in addition to the influence of carbon pricing policies on future investments in the Swedish power sector. In [32], a method to determine the optimum location of wind resources based on geographic information systems (GIS) was proposed. In [33], a novel method based on the load duration curve (LDC) for the GEP of large-scale wind plants was proposed. In [34], investment strategies were developed for wind power generation under the assumption that the generation capacity and investment resources are flexible. The investment problem was formulated as a mixed-integer programming (MIP) problem with the constraints specified as intervals, and the net present value (NPV) of generation profits specified as the objective. The general algebraic modeling system (GAMS) was used to solve the optimization problems. In [35], an integrated power generation expansion (PGE) planning model toward a low-carbon economy was proposed. Moreover, wind power plants should be considered, to complete the model.

A simple mathematic model was proposed in [36] to evaluate the impact of fixed feed-in-tariffs (FITs). Accordingly, the stochastic uncertainties and realities of the power market were not considered in [36]. In another article, the system dynamics model was reviewed to assess the power market policy. It was revealed that policy assessment and GEP are the most critical factors [37]. Moreover, a dynamic system model was proposed in [38]. Although the proposed model presented more useful

information about the impact of incentive policies in the deregulated power market, the realities of the power market such as the CO₂ tax were not considered.

Based on the literature review, it was concluded that the wind investor met more risks for their expansions. The private wind investors therefore require decision-making tools to evaluate investment strategies in long-term planning by considering the uncertainties, regulatory policies, and realities in the restructured power market. However, only a limited overview of the GEP of the combined wind-thermal investor by considering the abovementioned risks in the restructured power market is available.

In this paper, a novel framework is proposed to calculate the long-term optimal investment strategies for the combined wind-thermal investor by considering the medium-term and long-term uncertainties. Moreover, a mathematical model is proposed to simulate the medium-term restructured power market by considering the medium-term stochastic and rational uncertainties. The wind uncertainty was modelled using a data-mining technique. The method was previously validated in [29]. The electricity demand and fuel prices were simulated based on the Monte Carlo method. The Cournot concept was applied to model the strategic behavior of other investors in the restructured power market. Furthermore, the fixed FIT and bilateral contract were considered in the proposed model. The growths of the electricity demand and fuel prices, as two important long-term stochastic uncertainties, were modelled for several years using a binomial Markov chain process. The long-term optimal investment strategies were then estimated for the combined wind-thermal investor based on the stochastic dynamic programming (SDP) method and real options theory.

2 Description of proposed framework

The primary aim of this study was the development of an algorithm to model the restructured power market by considering the wind sources. Moreover, a method is proposed to solve the GEP for wind investors based on the SDP. The proposed framework is illustrated in Fig. 1. It consists of three main blocks, which are discussed below.

According to the literature review, the intermittent nature of wind resources increases the investor risks. Therefore, the features of wind power plants are different from that of the traditional power plants. In particular, the output power of thermal power plants is considered almost equal to the nominal power; whereas in electrical power systems that are integrated with wind sources, a fraction of the installed capacity of the wind farm is considered as an output power of the wind power plant. This concept is



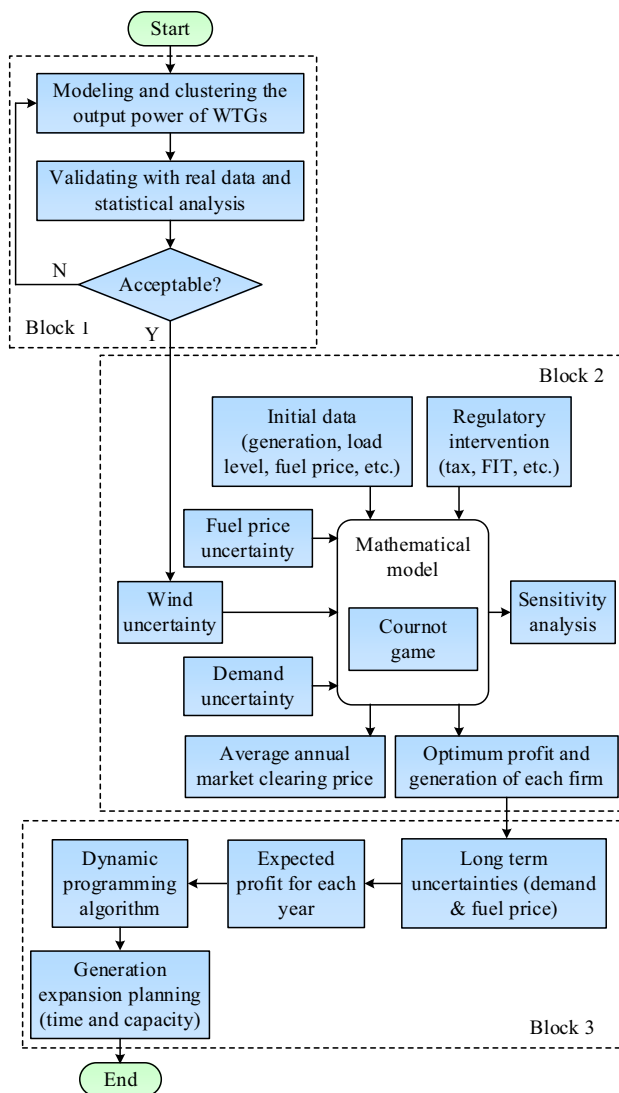


Fig. 1 Research methodology flowchart

referred to as the capacity factor [39–41]. The capacity factor is commonly used to evaluate intermittent power sources. In this study, the wind scenarios were generated based on a method proposed in [29] by the authors of this paper. Moreover, in this study, the wind scenarios and their corresponding probabilities were generated based on a data mining algorithm. The proposed method in [29] was implemented on a real system, to illustrate the efficiency of the approach, as presented in block 1.

In block 2, a model was developed to evaluate and analyze the medium-term restructured power market while considering combined wind-thermal companies. The short-

term uncertainties include the demand and fuel price, which have an effect on the MCP, simulated for a period of one year using the Monte Carlo method. Moreover, the wind generation scenarios and their probabilities were calculated using the output of block 1. These are the stochastic uncertainties that are considered in the proposed model for the simulation of the medium-term power market. Besides the stochastic uncertainties, as a critical parameter of the MCP, the strategic behavior of the investors is considered in the model based on the Cournot GT concept. Moreover, in this model, the regulatory interventions such as the CO₂ tax, fixed FIT, and bilateral contracts are considered as the exogenous parameters. The sensitivity analysis of the investment, average annual MCP, and maximum profit of each company are the outputs of the developed model.

In block 3, an algorithm was proposed based on the SDP algorithm, to solve the GEP problem of wind-power companies. In this method, the demand and fuel price, which are considered as long-term uncertainties, were modelled using a binomial Markov chain. The Markov chains prepare the long-term uncertainties for the application of the SDP, to determine the optimal investment strategy of the wind investor. The maximum expected profit of the wind investor is calculated for each state and stage of SDP. The expansion planning problem of the wind investor was solved using backward recursion DP.

2.1 Mathematical formulation for simulation of medium-term restructured power market

As mentioned in the previous section, a comprehensive model requires the determination of the MCP. In particular, the model should consider the realities and uncertainties in the restructured power market. The realities include the bilateral contracts and regulatory interventions such as the FIT incentive policy and carbon tax for thermal power plants. Moreover, the uncertainties in the restructured power market include the stochastic and rational uncertainties.

The objective of this model is to maximize the profit for each company, which is determined in the medium-term based on the difference between the revenue of the private companies from the energy sales in the spot price power market and the operating and CO₂ tax rate costs. The mathematical formulation of the proposed model is as follows:

$$\begin{aligned}
 \max \text{ Profit} = & \sum_e \sum_s \sum_l \sum_{sl} \left[\left(\sum_u N_{e,u} P_{e,u,sl} \right) - Q_{e,sl} \right] \cdot SP_{sl} \\
 & + \sum_{e'} \sum_s \sum_l \sum_{sl} \left[\left(\sum_{u'} N_{e',u'} P_{e',u',sl} \right) - Q'_{e',sl} \right] \cdot SP_{sl} \\
 & + \sum_e \sum_s \sum_l \sum_{sl} d_{sl} Q_{e,sl} \cdot BP_{sl} \\
 & + \sum_{e'} \sum_s \sum_l \sum_{sl} d_{sl} Q'_{e',sl} \cdot BP_{sl} \\
 & + \sum_{e'} \sum_s \sum_l \sum_{sl} d_{sl} \left(\sum_{uw} N_{e',uw} \cdot PW_{e',uw,sl,n} \right) (SP_{sl} + inc) \\
 & - \sum_e \sum_s \sum_l \sum_{sl} d_{sl} \left[\sum_u N_{e,u} \cdot FP_u \left(a_u + b_u P_{e,u,sl} + c_u (P_{e,u,sl})^2 \right) \right] \\
 & - \sum_e \sum_s \sum_l \sum_{sl} d_{sl} \left[\sum_u N_{e,u} \cdot Tax \cdot \left(a_u + b_u P_{e,u,sl} + c_u (P_{e,u,sl})^2 \right) \cdot EM_u \right] \\
 & - \sum_{e'} \sum_s \sum_l \sum_{sl} d_{sl} \left[\sum_{u'} N_{e',u'} \cdot FP_{u'} \cdot \left(a_{u'} + b_{u'} P_{e',u',sl} + c_{u'} (P_{e',u',sl})^2 \right) \right] \\
 & - \sum_{e'} \sum_s \sum_l \sum_{sl} d_{sl} \left[\sum_{u'} N_{e',u'} \cdot Tax \cdot \left(a_{u'} + b_{u'} P_{e',u',sl} + c_{u'} (P_{e',u',sl})^2 \right) \cdot EM_{u'} \right]
 \end{aligned} \tag{1}$$

$$g_{e,sl} = \sum_u N_{e,u} P_{e,u,sl} \tag{2}$$

$$g_{e',sl} = \sum_{uw} N_{e',uw} \cdot PW_{e',uw,sl} + \sum_{u'} N_{e',u'} P_{e',u',sl} \tag{3}$$

s.t.

$$BP_{sl} = SP_{sl,t-1} (1 + GP) \tag{4}$$

$$g_{e,e',sl} \leq D_{sl} \tag{5}$$

$$P_{e,u,\min} \leq P_{e,u} \leq P_{e,u,\max} \tag{6}$$

$$P_{e',u',\min} \leq P_{e',u'} \leq P_{e',u',\max} \tag{7}$$

$$PW_{e',uw,n,\min} \leq PW_{e',uw,n} \leq PW_{e',uw,n,\max} \tag{8}$$

where e represents traditional generation company; s represents the season; e' represents the combined traditional and renewable generation company; l represents the load level; u represents the thermal unit of traditional company; u' represents the thermal unit of combined traditional and renewable generation company; uw represents the wind unit of combined traditional and renewable generation company; d_{sl} is the duration of time; $N_{e,u}$ and $N_{e',u'}$ are the numbers of thermal units in e and e' ; $P_{e,u,sl}$ and $P_{e',u',sl}$ are the power generation by thermal unit u and u' of company e and e' in sl ; $Q_{e,sl}$ and $Q_{e',sl}$ are the total generation contracted by company e and e' in sl ; SP_{sl} is the average electricity price of power market in sl ; inc is the fixed FIT incentive; $N_{e',uw}$ is the number of wind units in e' ; BP_{sl} is the contracted electricity price in sl ; FP_u is the fuel price of unit u ; a_u, b_u, c_u and $a_{u'}, b_{u'}, c_{u'}$ are the constant coefficients of heat rate function for unit u and u' ; Tax is the CO₂ tax rate; EM_u is the CO₂ produced by unit u ; GP is the

percentage of electricity price; D_{sl} is the average demand in sl ; $P_{e,u,\min}$ and $P_{e,u,\max}$ are the minimum and maximum generation of thermal unit u of company e ; $P_{e',u',\min}$ and $P_{e',u',\max}$ are the minimum and maximum generation of thermal unit u' of company e' ; $PW_{e',uw,n,\min}$ and $PW_{e',uw,n,\max}$ are the minimum and maximum generation of wind unit uw of company e' for scenario n ; $g_{e,e',sl}$ is the total power generation of companies e and e' .

The objective function proposed in (1) estimates the maximum benefits of private investors in the electricity power market, and it is composed of two main parts. The first part includes the revenue from the either energy sales in the spot power market, from traditional or wind sources, in addition to the revenue of the company in contractual markets. Moreover, the revenue from the incentive policy for wind units estimates in (1). The first and second components of (1) indicate the revenue of the thermal units of the traditional and combined traditional-renewable private companies in the spot market, respectively. The third and fourth components indicate the revenue in the contractual market. The fifth component of (1) represents the revenue of the wind units of the combined wind-thermal company in the spot market, by considering the incentive for wind generation units. The second part of (1) includes the operating and CO₂ tax rate costs for the thermal units of the traditional and combined wind-thermal companies. Thus, the sixth and seventh components represent the fuel cost and carbon taxes of the thermal units of the traditional investor, respectively. Furthermore, the eighth and ninth components represent the fuel cost and carbon taxes of the thermal units of the combined wind-thermal company, respectively. The wind unit costs are neglected in this study.

The generation amounts of the traditional and combined wind-thermal private companies are represented in (2) and (3), respectively. The price of the electricity in the contractual market is given by (4). The constraint in (5) is related to the demand constraint, given that the generation companies are not responsible for the total demand of the market. The boundary limitations of the decision variables in the thermal units of the traditional and combined wind-thermal companies are given by (6) and (7), respectively. The boundary limitation of the decision variable in the renewable units of the combined wind-thermal company is represented by (8).

The optimization problem, as discussed in the previous section, was solved based on the initial electricity price. The results of this model include the total electricity produced in the power market, the electricity generated by each company, the total market profit, and the profit of each company. In this case, participants in the competitive power market with lower operating costs than the other companies maximize their profits by increasing their



production. On the other hand, other participants with high operating costs prefer not to participate in the power market, or they do so with minimum production. The equilibrium price and equilibrium quantity are therefore provided. In the equilibrium condition, the quantity demanded is equal to the quantity supplied, which is the most critical parameter for decision-making in the competitive power market. Moreover, the players in the competitive power market have less information about the operating decisions of other investors, and they require a logical model and approach for decision-making. GT is defined as the study of mathematical models of conflict and cooperation between intelligent rational decision-makers [42]. Various games are considered in a competitive environment. Cournot, Bertrand, and van Stackelberg are the foremost GT models. In the Cournot model, each company chooses an output quantity to maximize profit. Companies are assumed to produce homogeneous goods that are non-storable. Thus, all quantities produced are immediately sold. The market price in the model is determined through an auction process that equates the industry supply with the aggregate demand. The model also assumes that all the companies in the industry can be identified at the start of the game, and the decision-making of all the companies occurs simultaneously [6, 43, 44]. Therefore, due to the similarities between the Cournot model and the competitive power markets, the concept of the Cournot game was applied in this study, to determine the MCP. This algorithm is explained by the following steps, and it is shown in Fig. 2.

Step 1: Each private company calculates its generation by solving the optimization problem discussed in Section 2.1.

Step 2: After the optimization problem has been solved for each company, the demand function of the power market is used to update the electricity price. To simplify the model performance, a linear demand function is used as follows [12, 45]:

$$D_{sl}(SP_{sl}) = -A_{sl} \cdot SP_{sl} + B_{sl} \quad (9)$$

Due to the importance of the balance between the demand and supply in the power market, the total generation of all the companies is substituted by the demand (D_{sl}) at each season and load level. Constants A and B are calculated for each season and load level, according to (10) and (11), respectively [12]:

$$A_{sl} = \frac{B_{sl}}{pc \cdot \pi_{base,sl}} \quad (10)$$

$$B_{sl} = dc \cdot D_{base,sl} \quad (11)$$

where dc is the demand coefficient introducing demand intercept; pc is the price coefficient introducing price

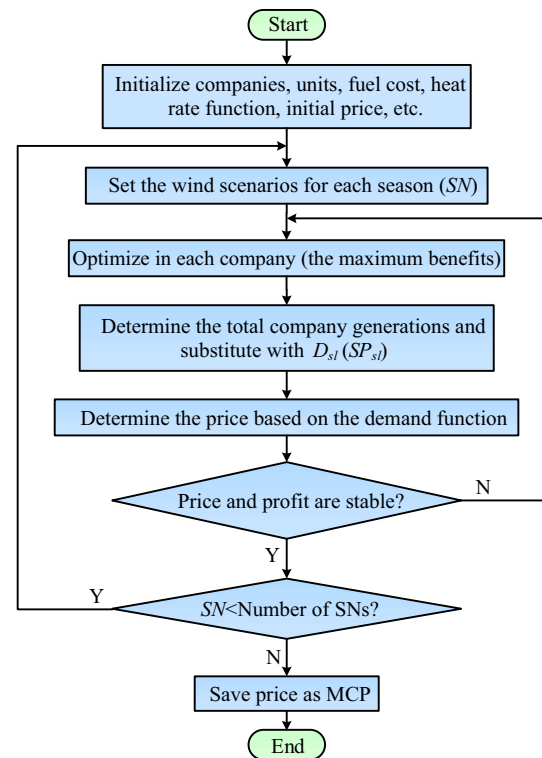


Fig. 2 Proposed model to estimate MCP

intercept; $\pi_{base,sl}$ is the competitive electricity price in sl . The forecast demand $D_{base,sl}$ at each season and load level can be determined based on the predicted average load at each season and load level, and the reference electricity price is calculated from the traditional unit commitment [46].

Step 3: The calculated price is then compared with the initial price. If the initial price is equal to the calculated price, the program stores the consequences. Otherwise, the first and second steps are repeated until this condition is fulfilled. Under these circumstances, the Nash equilibrium of the Cournot game is obtained, and none of the companies receive profits from changing their generation amounts. For the determination of the MCP for each of the wind scenario, these three steps are represented by the internal loop of Fig. 2

Step 4: Steps 1–3 are repeated for all the wind scenarios in a season. The external loop of Fig. 2 displays this process.

Step 5: The demand and fuel price uncertainties are considered using a Monte Carlo simulation. The Monte Carlo simulation produces distributions of possible outcome values. Using probability distributions, the variables can assume different probabilities. Probability distributions are significantly more realistic descriptions of the uncertainty in variables of a risk analysis. The probability distribution function of the demand and fuel price was

estimated based on historical data. In this study, the normal distribution function was selected to generate random data for these uncertainties. The algorithm is depicted in Fig. 3.

Step 6: The outputs of the proposed algorithm, which are indicated in Fig. 2 and Fig. 3, include the average MCP for each scenario in a season, in addition to the investor profit for each scenario in a season. In this study, each year was divided into four seasons. Specific wind scenarios were then generated for each season based on the proposed framework in [29]. Thereafter, the approach discussed in this section was implemented for all the seasons, to calculate the average MCP and investor profit for each scenario in each season.

Step 7: The expected profit and MCP for each season and load level is determined using (12) and (13).

$$E(Profit) = \sum_{SN=1}^n B_n \cdot Prob_n \tag{12}$$

$$E(MCP) = \sum_{SN=1}^n MCP_n \cdot Prob_n \tag{13}$$

where B_n is the benefit for each season; $Prob_n$ is the probability for each season; MCP is the market clearing price for each season.

2.2 Long-term optimal investment strategies for wind investor

In the field of economics, an investment is defined as the act of incurring an immediate cost in the expectation of future rewards. The financial estimations of the expansion project consist of three main aspects. First, the project type includes the capacity size and choice of technology for new

power plants. Second, the timing for the investment; and third, the location of the investment. The first two aspects were investigated in this study.

In this section, a novel technique is proposed to solve the long-term optimal investment decision based on the SDP and real options theory. The NPV is typically used to evaluate a new investment project. The static form of the NPV rule states that a project should be undertaken given that the sum of discounted cash flows from the project (i.e., the NPV) is positive, whereas projects with a negative NPV should be rejected. However, this method has drawbacks, i.e., the uncertainties in an investment project are not considered. Moreover, the NPV method only compares two alternatives: ① making an investment today; ② making no investment [47, 48]. In several cases, the private investors can choose to defer the investment. The most common options for investment projects are presented in [49], i.e., the option to defer an investment, the option to alter the operating scale, the option to abandon a project, the option to switch inputs or outputs from a process, and different types of growth options.

Dynamic programming is an optimization method that is suitable for solving decision-making problems in accordance with the real options theory. Moreover, DP is a general optimization technique with applications within a range of different fields, including power system planning. In addition, DP is based on Bellman principle of optimality, as follows [47]: “an optimal path has the property that whatever the initial conditions and control variables over some initial period, decision variables chosen over the remaining period must be optimal for the remaining problem, with the state resulting from the early decisions taken to be the initial condition”. Hence, a DP optimization problem is typically solved stepwise, starting from either the beginning or the end of the considered period.

Therefore, to solve the decision-making problem using the DP optimization method, the components of the problem should be initially determined. The components include the stages and states of the DP. In the long-term expansion planning, the sequential years build the stages. Moreover, the demand, fuel price and the new capacity of wind generation construct the states of the DP. The long-term uncertainties of the demand and fuel price were modelled based on the binomial discrete Markov tree that was proposed in [19].

As mentioned in previous sections, the objective of the investor in generation expansion in the restructured power market is the maximization of profit. Therefore, the investment optimization problem for an investor is defined by (14)–(17). The backward recursion DP was used to solve this problem.

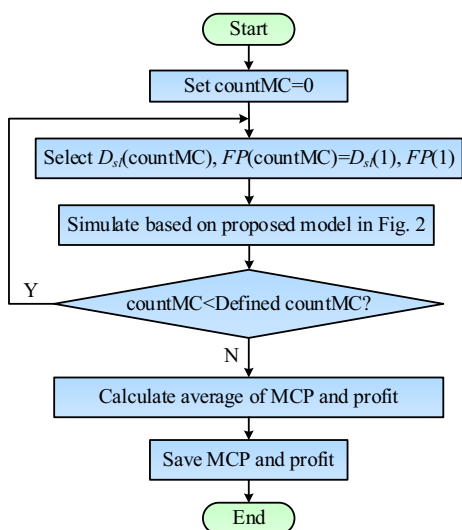


Fig. 3 Monte-Carlo method for demand and fuel price uncertainties



$$Prof_{total} = \max E \left[\sum_{t=0}^T [(1+r)^{-t} P_t (X_{e,t}, X_{e',t}, D_t, FP_t, MCP_t, U_{e',t})] \right] \tag{14}$$

s.t.

$$X_{e',t+1} = X_{e',t} + U_{e',t-lt+1} \tag{15}$$

$$D_{t+1} = D_t + \Delta D_t \tag{16}$$

$$FP_{t+1} = FP_t + \Delta FP_t \tag{17}$$

where E is the expected profit of each stage and each state of the planning period; r is the discount rate; X_e is the electricity generation of company e (thermal-power company); $X_{e'}$ is the electricity generation of company e' (hybrid wind-thermal company); $U_{e'}$ is the new candidate capacity of company e' for the wind unit; D_t is the demand for year t ; FP_t is the fuel price for year t ; lt is the construction delay of new wind units.

The total expected profit of a planning period establishes in (14) that the expected profit for each year contains three main components. These components are indicated in (18). The first and second terms represent the revenue of the hybrid wind-thermal company from the energy sales market and FIT incentive policy, respectively. The capital investment cost is represented by the third term. The capital cost of wind sources for each stage of the DP was calculated according to (19).

$$P_t (X_{e,t}, X_{e',t}, D_t, FP_t, MCP_t, U_{e',t}) = E(P_{e',energy,t}) + E(FIT_{e',t}) - C_{cap}(U_{t,e'}) \tag{18}$$

$$C_{cap,t}(U_{e',t}) = (1+r)^{(-lt/2)} C_{e',t} U_{e',t} \frac{\sum_{m=1}^{T-t} (1+r)^{-m}}{\sum_{n=1}^{nt} (1+r)^{-n}} \tag{19}$$

where $C_{e',t}$ is the investment cost of the wind technology in year t ; nt is the total lifespan of the wind technology; C_{cap} is the capital cost.

3 Case study

The proposed framework was tested using the IEEE reliability test system (RTS) [50]. The total installed capacity and peak demand of the studied system were 2595 MW and 2072 MW, respectively. The duration of the study was one year. Each year was divided into four windy seasons, and three load levels were considered, which include the off-peak, medium, and peak levels. The historical wind-speed data were obtained from a wind farm near the town of Swift Current in the southern part of the Saskatchewan province in Canada, as presented in [51]. Moreover, the wind scenarios for each season are presented

Table 1 Scenarios for each season

Season	Parameters	Scenario for electricity generation in wind farm					
1	Output (MW)	0	3.31	10.02	16.63	24.66	34.90
	Probability (%)	14	23	24	19	14	6
2	Output (MW)	0	1.41	5.92	12.42	26.05	–
	Probability (%)	24	22	17	26	11	–
3	Output (MW)	0	5.13	11.71	19.61	27.17	38.20
	Probability (%)	20	29	30	11	8	2
4	Output (MW)	0	2.73	11.48	28.31	–	–
	Probability (%)	20	23	35	22	–	–

in Table 1 and Table 2. The forecasted demands and durations for each season and load level were collated from [12], and they are presented in Table 3. Specifications with respect to the units of companies in the system considered are presented in Table 4. The system contains five price-maker companies. The fuel prices and data associated with the generating units of the companies were obtained from [28, 52], and they are presented in Table 5. Other input parameters such as the CO₂ tax rate and the bilateral contract price were obtained from [12]. The CO₂ emissions

Table 2 Weibull parameters and statistical results for scenarios

Season	Weibull parameters of scenarios		Weibull parameters of simulated data		Statistical results	
	Shape	Scale	Shape	Scale	P-value	Anderson-Darling statistic test
1	2.18	7.25	2.15	6.52	> 0.25	0.15
2	2.29	6.36	2.17	5.12	> 0.25	0.17
3	2.28	7.67	2.58	7.00	> 0.25	0.14
4	2.43	8.44	2.85	8.03	> 0.25	0.20

Table 3 Forecasted demands and duration in each season and load levels for the first stage

Season	Load level and duration (MW)&(hours)		
	Off-peak (duration)	Medium (duration)	Peak (duration)
1	950 (876.0)	1800 (985.5)	2300 (328.5)
2	1200 (876.0)	1650 (985.5)	2370 (328.5)
3	1300 (766.5)	1900 (876.0)	2500 (547.5)
4	1000 (876.0)	1550 (985.5)	2250 (328.5)

Table 4 Type and number of units for each company

Company	Type of units			
	Oil/steam	Coal/steam	Wind	Nuclear
1	2	2	–	–
2	3	3	–	1
3	4	4	–	–
4	1	2	–	–
5	1	2	6	–

for the different types of generating units are presented in Table 6.

4 Sensitivity analysis

In this section, the verification of the proposed mathematical model to simulate the medium-term restructured power market is presented. In general, sensitivity analysis is a technique used to determine the influence of different values of an independent variable on a given dependent

Table 5 Fuel price and the capacity of generating units

Parameters	Oil/steam	Coal/steam	Wind	Nuclear
Fuel price (\$/MBTU)	5.27	1.68	–	1.65
P_{max} (MW)	12–197	76–350	50	400
P_{min} (MW)	2.4–68.95	15.2–140	0	100

Table 6 CO₂ emission

Units	CO ₂ emission (lb/MMBTU)
Oil/steam	170
Wind	0
Coal/steam	210
Nuclear	0

Table 7 Sensitivity analysis of increasing fuel price in restructured power market

Growth of fuel price (%)	Profit (M\$)						Average annual clearing price (\$/MWh)			
	Company 1	Company 2	Company 3	Company 4	Company 5	Total	Low	Medium	Peak	Average
2	25.56	78.99	51.11	62.95	29.66	248.3	21.98	42.81	90.23	51.68
4	24.55	75.29	49.10	62.06	27.59	238.6	22.01	42.84	90.28	51.71
6	24.18	73.96	48.36	61.33	25.35	233.2	22.05	42.82	90.4	51.76

variable, with specified constraints. This technique is used within specific boundaries that depend on one or more input variables, such as the effect of fuel-price changes in on the total profit of the electricity market. In addition, this technique can be used to test the robustness of the model or system in the presence of uncertainties. To complete this discussion, the expected effect of the increase in the fuel price was investigated, as presented in this section. Based on economic principles, the costs of the electric generating units are increased by an increase in the fuel price. Consequently, the total profit of the power market decreases, and the equilibrium price of the power market increases. Furthermore, due to the nonlinear features of the proposed model; by considering the increase in the fuel price, the outputs of the proposed model indicate a nonlinear behavior. If the previously mentioned results are obtained by solving the proposed model, the validity and the robustness of the model can be confirmed. Thus, the proposed mathematical model was solved under an additive set of fuel prices. The analysis results are presented in Table 7. Furthermore, the incremental effect of the increase in the fuel price on the MCP and the subtractive effect of the increase in the fuel price on the total profit of the power market are presented in Figs. 4 and 5, respectively. In summary, the results confirmed the robustness of the proposed mathematical model for the simulation of the medium-term restructured power market.

To complete the discussion, the proposed framework was solved without any incentives for the wind power plants. The contributions of each company in the power market were then compared with the scenarios wherein the fixed FIT was considered. The results are presented in Fig. 6. In the figure, it can be seen that the generation share of company 5 as a hybrid wind-thermal company increased by considering the fixed FIT as an effective incentive policy for the wind power plants. This evaluation was used to analyze the effect of the incentive policy on the proposed framework, to simulate the restructured power market.



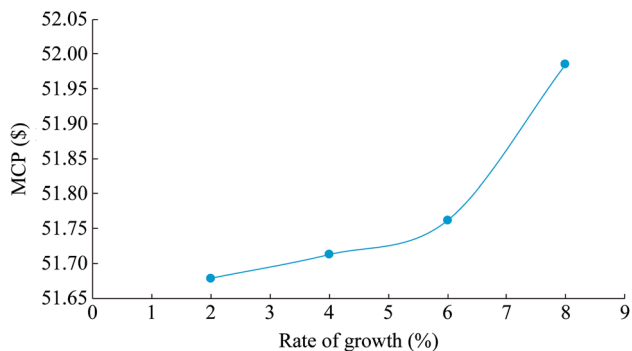


Fig. 4 Incremental effect of fuel price augmentation on MCP

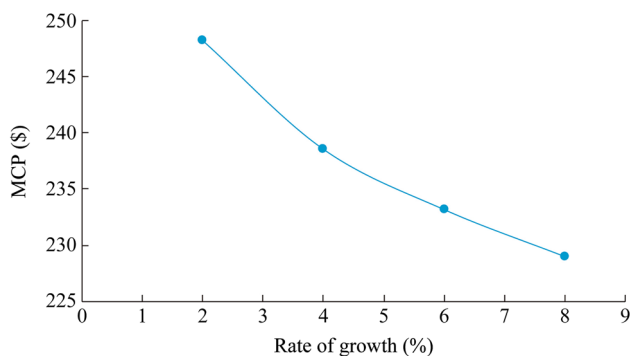


Fig. 5 Subtractive effect of fuel price augmentation on total profit of power market

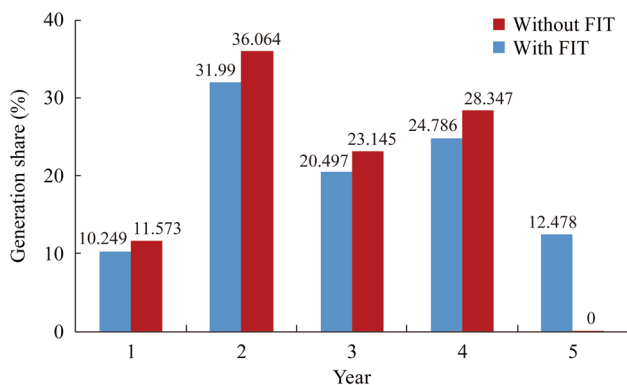


Fig. 6 Effect of incentive policy in restructured power market

5 Simulation results for long-term optimal investment for a wind-power company

Given the dynamic and multistage nature of the GEP problem, the DP technique was used to solve the optimization problem. Moreover, by considering the long-term stochastic uncertainties, the DP algorithm was converted to SDP. Each stage of the SDP was over a period of one year, and the increase in the demand and fuel price was considered in each state of the SDP. The medium-term proposed model was solved for each stage and state of the SDP. In this study, the demand and fuel price were considered as two long-term uncertainties. The expected upper and lower bounds of the increase in demand related to the binomial Markov chain were 7% and 4%, respectively. Moreover, the annual increase in the fuel price was considered as 2%. The planning period was assumed to be five years, due to the five-year outlook of regulators. Company 5 was considered as an investor in wind resources, and the maximum capacity for the candidate wind plant was assumed to be 300 MW. Given that the effect of regulator interventions is considered in the proposed model, it is given as investment sensitivity to solve the GEP problem. The SDP algorithm was solved for three scenarios. These scenarios include the cases wherein FIT is not considered, the fixed FIT is equal to 92 \$/MWh, and the fixed FIT is

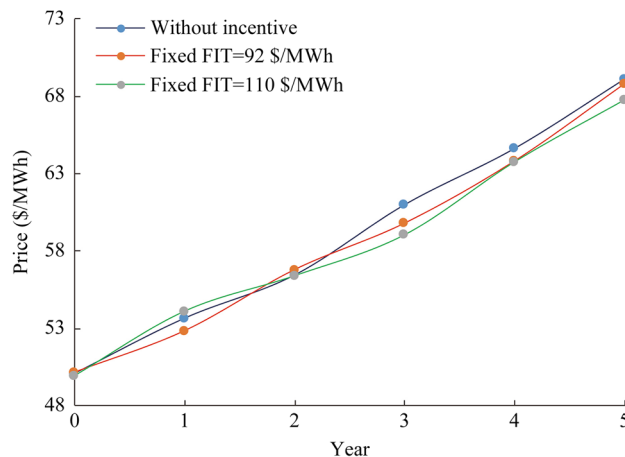


Fig. 7 Variations of EAMC

Table 8 AEAMC and EAMC

Scenario	EAMC (\$/MWh)						AEAMC (\$/MWh)
	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	
Without FIT	50.11	53.67	56.46	61.00	64.64	69.12	59.17
FIT = 92 \$	50.21	52.89	56.83	59.83	63.85	68.83	58.74
FIT = 110 \$	49.93	54.11	56.41	59.07	63.80	67.83	58.53

Table 9 Expansion strategies and expected profit of investment

Scenario	Capacity of investment (MW)						Expected profit of investment (M\$)
	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	
Without FIT	–	–	–	–	–	–	–
FIT = 92 \$	–	–	–	50	50	50	4.81
FIT = 110 \$	–	–	–	–	50	250	11.5

equal to 110 \$/MWh. The expected annual market prices (EAMC) and the average of the expected annual market prices (AEAMC) are presented in Table 8. The variations of these prices are compared in Fig 7. As can be seen from the figure, the market equilibrium price decreases by increasing the incentive policy for wind resources. The expansion strategies for the investor and the expected profit due to the wind investment during the planning period are presented in Table 9 for the different scenarios.

6 Conclusion

In summary, the investment in wind resources is a high-risk investment in the restructured power market. A comprehensive and sophisticated framework is therefore required to evaluate and analyze the impact of wind resources in the restructured power market. In this paper, a novel comprehensive framework was proposed to simulate the medium-term restructured power market, and to determine the long-term optimal investment strategies for the wind investor. Thus, the stochastic and rational uncertainties were considered to simulate the medium-term restructured power market. A novel method was proposed for the evaluation of the output power of wind farms based on the data mining method. Sensitivity analysis was then conducted to verify the proposed framework, for the simulation of the medium-term restructured power market. The effects of regulatory intervention, CO₂ tax, and the bilateral contract were also investigated using the mathematical model. The long-term optimal investment strategies were then estimated based on the SDP and real options theory. The results confirm that the generation share of a hybrid wind-thermal company is increased when the fixed FIT is considered as an effective incentive policy for wind power plants. Furthermore, the market equilibrium price decreases in accordance with an increase in the incentive policy for wind resources. Finally, a new option was proposed for real options theory. With this approach, the investor could invest in his properties in consecutive years during the planning period. Although a comprehensive model was

developed in this study, which may be useful to investors, future work should consider more uncertainties using this model. These uncertainties include the policies of regulators, the CO₂ tax rate, hydro-power plants, etc. The simulation of a restructured power market can be used for long-term planning, and it can also be applied to other issues in the restructured power market such as efficient carbon taxation, which will be evaluated in future work.

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Mohammad Tolou ASKARI received his Bachelor degree in Power Electrical Engineering from University of Applied Science and Technology of Mashhad in 2005, and the Master degree in Power Electrical Engineering in 2008. He received Ph.D. degree in Power Electrical Engineering from University Putra Malaysia in 2004. Currently, he is a senior lecturer in the Department of Electrical and Electronics Engineering, Faculty of Engineering, Islamic Azad University (Semnan Branch). His research interests include electrical transformers, smart grids, micro grids, GEP & TEP, and distribution systems.

Mohd. Zainal Abidin Ab. KADIR received the B. Eng degree in Electrical and Electronic Engineering from Universiti Putra Malaysia in 2000 and Ph.D. degree in High Voltage Engineering from The

Universiti of Manchester in UK in 2006. Currently, he is a professor in the Department of Electrical and Electronics Engineering, Faculty of Engineering, University Putra Malaysia. His research interests include high voltage engineering, insulation coordination, lightning protection, EMC/EMI, kerauna-medicine and power system transients.

Mehrdad TAHMASEBI received his B.Sc. degree in Electrical Power Engineering from Islamic Azad University (south Tehran Branch), Tehran, Iran in 2002 and, the M.Sc. degree in Power Engineering & Electrical Energy Management from Amir Kabir University of Technology (Tehran Polytechnic), Iran, in 2010. Presently, he is preparing for his Ph.D. degree in Universiti Tenaga Nasional, Malaysia. His research interests include renewable energy, energy policy and power market.

Ehsan BOLANDIFAR received his M.Sc. degree from Sharif University of Technology, Tehran, and the Ph.D. degree in Business Administration from Washington University, USA. He is an assistant professor of operation management at the Chinese University of Hong Kong, China. His research mainly focuses on supply chain procurement and healthcare operations. In particular, he is interested in how supply chain procurement interacts with finance and marketing. His research has been featured in journals like Manufacturing and Service Operations Management, Production and Operations Management and Academic Emergency Medicine.

