Citation for published version:
Sharma, KC, Bhakar, R & Tiwari, HP 2014, 'Strategic bidding for wind power producers in electricity markets', *Energy Conversion and Management*, vol. 86, pp. 259-267. https://doi.org/10.1016/j.enconman.2014.05.002

DOI:
10.1016/j.enconman.2014.05.002

Publication date:
2014

Document Version
Peer reviewed version

Link to publication

Strategic Bidding for Wind Power Producers in Electricity Markets

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Abstract *In evolving electricity markets, wind power producers (WPPs) would increase their profit through strategic bidding. However, generated power by WPPs is highly random, which may result into heavy imbalance charges. In markets dominated by wind generators, they would optimize their offered bids, considering rival behavior. In oligopolistic day-ahead electricity markets, this strategic behavior can be represented as a Stochastic Cournot model. Wind uncertainty is represented by scenarios generated using Auto Regressive Moving Average (ARMA) model. With a consideration of wind power uncertainty and imbalance charges, strategic WPPs can maximize their expected payoff or profit through the proposed Nash equilibrium based bidding strategy. Nash equilibrium is obtained using payoff matrix approach. Proposed approach is evaluated on two realistic case studies considering different technical constraints. Obtained results shows that proposed bidding strategy mechanism offers quantum increase in profit for WPPs, when their behavior is modeled in a game theoretic framework. Flexibility of approach offers opportunities for its extension to associated challenges.*

Keywords Electricity Markets, Nash Equilibrium, Stochastic Cournot Model, Wind Power Uncertainty.

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Notations

The main notations used throughout the paper are listed below for quick reference. Other symbols are defined as required.

A. Sets or Indices	
Ω^{g}	Set of indices of conventional GENCOs
Ω^{d}	Set of indices of demands
Ω^{w}	Set of indices of WPPs
$\Omega^{n/r}$	Set of indices of buses
Ω^{n-r}	Set of indices of transmission lines
Ω^{ω}	Set of indices of scenarios
Ψ_{n}^{g}	Mapping of conventional GENCOs located at bus n
Ψ_{n}^{d}	Mapping of demand located at bus n
Ψ_{n}^{w}	Mapping of WPPs located at bus n
Υ_{l}^{d}	Set of indices of l^{th} blocks of d^{th} demand
B. Constants or Parameters	
B_{n-r}	Susceptance of line $n-r$ $\left[per\ unit\right]$
$f_{n-r}^{\max}$	Power transfer capacity of transmission line $n-r$ $\left[MW\right]$
$P_{d,l}^{\max}$	Upper limit of l^{th} block of d^{th} demand $\left[MW\right]$
$P_{g}^{\max}$	Installed capacity of g^{th} conventional GENCO $\left[MW\right]$
$P_{i}^{\max}$	Installed capacity of i^{th} WPP $\left[MW\right]$
$\lambda_{d,l}$	Marginal utility cost of l^{th} block of d^{th} demand $\left[\$/MW\right]$
λ_{g}	Marginal cost of g^{th} conventional GENCO $\left[\$/MW\right]$
$\text{prob}_{\omega,t}$	Weight (or occurrence probability) of scenario ω at time t
DF_{t}	Demand factor at time t $\left[per\ unit\right]$
C. Variables	
$f_{n-r,t}$	Power flow through transmission line $n-r$ at time t $\left[MW\right]$
$P_{d,l,t}$	Power scheduled to be consumed by l^{th} block of d^{th} demand at time t $\left[MW\right]$
$P_{g,t}$	Power scheduled to be produced by g^{th} conventional GENCO at time t $\left[MW\right]$
$\Delta_{i,\omega,t}$	Power bought from/sold to balancing market by i^{th} WPP at time t $\left[MW\right]$
$IC_{i,\omega,t}$	Imbalance charges of i^{th} WPP at time t $\left[\$\right]$
$Pof_{i,t}$	Power offered to day-ahead market by i^{th} WPP at time t $\left[MW\right]$

$P_{i,\omega,t}$	Power produced by i^{th} WPP in scenario ω at time t $\left[MW\right]$
$\delta_{n,t}$	Voltage angle at bus n at time t $\left[\text{rad.}\right]$
$\lambda_{n,t}$	Locational marginal price at bus n at time t $\left[\$/MWh\right]$
$\lambda_{n,t}^{+}$	Positive imbalance price at bus n at time t $\left[\$/MWh\right]$
$\lambda_{n,t}^{-}$	Negative imbalance price at bus n at time t $\left[\$/MWh\right]$
$\lambda_{n,t}^{UP}$	Upward balancing market price at bus n at time t $\left[\$/MWh\right]$
$\lambda_{n,t}^{DN}$	Downward balancing market price at bus n at time t $\left[\$/MWh\right]$

1. Introduction

Power sector is being restructured worldwide, with an aim to improve system efficiency and offer economic solutions. At the same time, uncertainties in fossil fuel prices and environmental concerns are enhancing the quantum of wind power generation [1]. Over the last few decades, governments over the world are trying to increase the contribution of green energy in electricity supply, by providing subsides and support schemes [2].

Evolving deregulated electricity markets are primarily designed for conventional or fossil fuel generators. These markets operate on a day-ahead timeline, where participants commit their generated power several hours before actual power delivery. Eventual power delivered by wind generators differs from their initial commitment due to intermittent nature of wind. Participants deviating from their committed schedule face penalties. Small capacities and random generation restrict the WPPs to act as strategic players. They participate in the market as ‘price takers’, and are not able to affect the market prices. Due to high capital cost and imbalance penalties, they cannot operate profitably in pool-based electricity markets. Therefore, they are forced to sell their power through bilateral contracts.

In pool-based electricity markets, conventional generators can increase their profit by optimal bid formulation using various bidding strategy models. Bidding strategy models are broadly classified into two categories, *i.e.* Game-theoretic and non-game theoretic models [3-19]. These models become stochastic when uncertainties like demand, unit availability, fuel price, and wind are incorporated in it [6-10]. Stochastic models developed for optimal bid formulation of WPPs help to minimize their imbalance cost. With a consideration of forecasting window length and market closure delay, Markov Probability based stochastic model can determine the optimal contracted energy level [11], [12]. Multistage stochastic programming approaches suggest various trading floors to derive the best offering strategy for a wind generator [13]. Uncertainties such as wind availability, day-ahead market price, adjustment market price and balancing market price, along with profit risk measures, have been considered. However, wind generators are still assumed to be price-takers. In addition, focus is on increasing the wind generator's profit by bid selection, with minimum imbalance cost. Opportunity cost based analytical approach can optimize bids of price-taker WPP in forward electricity market [14]. Strategic gaming by WPPs for bid selection in pool based electricity markets has generally been neglected.

With the present thrust and growth, in the near future, WPPs would increasingly supply power to an extent of 20% or more of market demand [15]. They would participate in pool based electricity markets strategically, without any regulatory support and benefits. They would tend to increase their profit by gaming in the market [16]. Strategic WPP can optimize their offering strategy either in day-ahead and balancing markets using stochastic mathematical program with equilibrium constraints approach [17], [18]. The duopoly competition between strategic power producers, consisting of wind generators as a part of their portfolio, has been modeled using equilibrium problem with equilibrium constraints approach [19].

This paper focuses on formulation of optimal offering strategy for multiple independent strategic WPPs, in a market dominated by intermittent wind generation. Strategic behavior of

WPPs in network constrained oligopolistic day-ahead electricity markets, considering wind uncertainty, is modeled using Stochastic Cournot model. In this model, WPPs aim to maximize profit by offering optimal bids, considering rival behavior and complete information. Imbalance charges consider strategic WPPs' profit calculation using location based dual imbalance price mechanism. Solution of the proposed model is Nash equilibrium, obtained by payoff matrix approach. Proposed game-theoretic bidding strategy approach is illustrated through two practical case studies with three independent strategic WPPs.

Rest of the paper is organized as follows. In Section 2, the market structure, uncertainty characterization, and stochastic Cournot model are described. Section 3 provides mathematical modeling of the problem and the simulation procedure. Section 4 includes numerical and graphical results of testing the proposed model through a comprehensive analysis on three WPPs located at different locations. In Section 5, relevant conclusions are drawn.

2. Problem Description

2.1 Market Structure

WPPs participate in network constrained pool based day-ahead electricity market, cleared several hours before actual power delivery. Real-time balance between supply and demand is maintained by the balancing market, few minutes before power delivery. Independent System Operator (ISO) manages operation of both day-ahead and balancing market. WPPs are considered as strategic power producers in only day-ahead electricity market, while in balancing market they participate non-strategically. WPPs get imbalance charges for their real-time generation deviations. This consideration realistically reflects electricity markets as electricity is traded largely on day-ahead timeline. Due to low liquidity of adjustment or intra-day market, participation of strategic WPPs in this market is neglected.

Imbalance charges resulting from balancing market are charged to generators causing that system imbalance. In this work, location based dual imbalance price mechanism is considered for imbalance charging, as widely used in European markets such as UK's New Electricity Trading Arrangements (NETA), Nord Pool, and Iberian Peninsula [2, 11-14].

In a location based dual imbalance price mechanism, generators are charged for their positive and negative deviation, reflecting system imbalance and their locations. This location based dual imbalance price mechanism can be treated as a traditional dual imbalance price mechanism for uncongested systems. For positive system imbalance, other Generation companies (GENCOs) would like to purchase excess energy at a downward price $\lambda_{n,t}^{DN}$, lower than LMP $\lambda_{n,t}$ of their location. In this case, generators producing excess power than scheduled get a downward payment for their overproduction. On the other hand, generators producing lower than their scheduled production are penalized as per the LMP. Positive imbalance price (PIP) and negative imbalance prices (NIP) at a particular location during system surplus are mathematically expressed as

$$\lambda_{n,t}^{+} = min\left(\lambda_{n,t}, \lambda_{n,t}^{DN}\right) \tag{1}$$

$$\lambda_{n,t}^{-} = \lambda_{n,t} \tag{2}$$

With negative system imbalance, generators are willing to provide the energy needed to cover negative imbalance at LMP. In this case, generators producing excess power than scheduled, get payment for this overproduction as per LMP at the bus where they are located. On the other hand, generators responsible for negative imbalance are penalized with upward price $\lambda_{n,t}^{UP}$. PIP and NIP during system deficit are mathematically expressed as

$$\lambda_{n,t}^{+} = \lambda_{n,t} \tag{3}$$

$$\lambda_{n,t}^{-} = max\left(\lambda_{n,t}, \lambda_{n,t}^{UP}\right) \tag{4}$$

2.2 Uncertainty Characterization

Stochastic wind speed is considered as a continuous random variable, represented by scenarios. Scenarios are possible outcomes of the random input, with corresponding occurrence probability [20], [21]. To generate wind speed scenarios, statistical time series based ARMA model is used. A typical ARMA (p , q) model is expressed as

$$Z_t = \sum_{j=1}^{p} \phi_j Z_{t-1} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-1} \tag{5}$$

With p autoregressive parameters $\phi_1, \phi_2, ..., \phi_p$, and q moving average parameters $\theta_1, \theta_2, ..., \theta_q$. The term ε_t is a normal distributed random number with zero mean and σ standard deviation, referred as a white noise or error.

Generated wind speed scenario Z_t can be converted into power scenario, using power curve of wind turbines installed at the wind farm. For accurate representation of any stochastic process, a large number of scenarios are required. Due to computational complexity and time limitations, generated scenarios need to be reduced [22], [23]. These reduced scenarios reflect expected power generated by the WPPs. In this work, only wind power uncertainty is considered, and other uncertainties like demand, fuel price and unit outage are not considered [7], [8].

2.3 Stochastic Cournot Model

Cournot game theory is a general approach to represent strategic behavior of GENCOs in oligopolistic electricity markets. GENCOs make decisions independently and simultaneously, without cooperating with each other. With an aim to maximize profit, each GENCO chooses quantity bids to be offered, considering rival behavior. Nash equilibrium is a solution of Cournot model; this is a standoff condition where no GENCO can unilaterally increase its profit by changing its production level. Supply Function Equilibrium (SFE) is another popular game theoretical approach to represent strategic behavior of GENCOs in oligopolistic electricity markets. However, Cournot model is still popular because of its attractive features, such as easy calculation of equilibrium, computational tractability, flexibility to model physical or bilateral contracts, and easy incorporation of various technical limits and uncertainties [27]. In addition, SFE may fail to find any pure strategy equilibrium or may provide multiple equilibrium, when practical constraints are considered [28].

In a deterministic Cournot model, input variables are scalar and independent, while in a Stochastic Cournot model, input variables are stochastic in nature or dependent on other stochastic variables [6-8]. In this paper, Stochastic Cournot model with complete information is used to formulate bidding strategy of WPPs in oligopolistic electricity market. Each WPP has complete information about their rivals' type, payoff function and installed capacity. Due to zero marginal cost and generation uncertainty, Stochastic Cournot model is most suitable approach for optimal decision-making of strategic WPPs in oligopolistic electricity markets.

3. Mathematical Formulation

This section provides mathematical formulation of WPP' profit maximization problem, ISO' market clearing problem and Stochastic Nash equilibrium problem. In addition, proposed simulation procedure is briefly described.

3.1 Wind Power Producer Problem

Consider $i \in \Omega^{w}$ WPPs participating strategically in a network constrained oligopolistic electricity market. Each WPP aims to maximize its profit by offering a certain quantity bid. The profit maximization problem of i^{th} WPP in a day-ahead electricity market is formulated as follows:

$$\underset{Pof_{i,t}}{Max} \quad U\left(Pof_{i,t}, Pof_{-i,t}\right) = \sum_{\omega \in \Omega^{\omega}} prob_{\omega,t}\left[\lambda_{n(\mathrm{i}),t} Pof_{i,t} + IC_{i,t,\omega}\right], \quad \forall i, \forall \omega, \forall t \tag{6}$$

Subject to

$$0 \le Pof_{i,t} \le P_i^{\max}, \quad \forall i, \forall t \tag{7}$$

$$\Delta_{i,\omega,t} = P_{i,\omega,t} - Pof_{i,t}, \quad \forall i, \forall \omega, \forall t \tag{8}$$

$$IC_{i,\omega,t} = \begin{cases} \lambda^{+}_{n(\mathrm{i}),\omega,t}\Delta_{i,\omega,t}, & \Delta_{i,\omega,t} > 0 \\ \lambda^{-}_{n(\mathrm{i}),\omega,t}\Delta_{i,\omega,t}, & \Delta_{i,\omega,t} < 0, \quad \forall i, \forall \omega, \forall t \\ 0, & \Delta_{i,\omega,t} = 0 \end{cases} \tag{9}$$

Objective function (6) shows the profit of i^{th} WPP, under the assumption that wind power generation cost is zero; therefore, expected profit is equal to expected revenue. It is assumed that WPPs individually participate in the market without any control strategy. Each WPP selects offered power $Pof_{i,t}$, which maximizes its expected profit, considering imbalance charges. Due to the presence of multiple strategic power producers in oligopolistic electricity markets, profit of strategic WPP depends not only on their optimal decisions but also on rival's decisions (represented by negative sign). Constraint (7) limits the strategic WPPs' offered bids in day-ahead electricity market. The maximum value of offered power is equal to the installed capacity of WPPs, while the minimum power production is considered to be zero. WPP do not generate any power when wind speed is below cut-in or above cut-out speed of the installed turbines. Constraint (8) defines the total deviation for each WPP in each scenario and time. Equation (9) reflects per scenario imbalance charges at a particular time interval for each strategic WPP in electricity market.

3.2 ISO Market Clearing Problem

After receiving generation bids from GENCOs and demand bids from consumers, ISO can solve market-clearing problem optimally to schedule market operation. The mathematical formulation of day-ahead market-clearing problem with an objective of social welfare maximization, subject to different technical constraints is detailed below:

$$Max \sum_{d\in\Omega^{d}}\sum_{l\in\Upsilon_{l}^{d}}\lambda_{d,l}P_{d,l,t}-\sum_{g\in\Omega^{g}}\lambda_{g}P_{g,t} \tag{10}$$

subject to

$$\sum_{g\in\Psi_{n}^{g}}P_{g,t}+\sum_{i\in\Psi_{n}^{w}}Pof_{i,t}-\sum_{d\in\Psi_{n}^{d}}\sum_{l\in\Upsilon_{l}^{d}}P_{d,l,t}=\sum_{r\in\Omega^{n/r}}f_{n-r}:\lambda_{n,t},\forall n,\forall t \tag{11}$$

$$f_{n-r,t}=B_{n-r}\left(\delta_{n,t}-\delta_{r,t}\right),\quad \forall n-r,\forall t,n\neq r \tag{12}$$

$$-f_{n-r}^{\max}\leq f_{n-r,t}\leq f_{n-r}^{\max},\quad \forall n-r,\forall t,n\neq r \tag{13}$$

$$0\leq P_{g,t}\leq P_{g,t}^{\max},\ \forall g,\forall t \tag{14}$$

$$0\leq P_{d,l,t}\leq DF_{t}P_{d,l,t}^{\max},\quad \forall d,\forall l,\forall t \tag{15}$$

$$-\pi\leq\delta_{n,t}\leq\pi,\ \forall n,\forall t \tag{16}$$

$$\delta_{1,t}=0,\forall t \tag{17}$$

Objective function (10) represents social welfare, defined as the difference between consumer's and conventional generators surpluses. Since strategic WPPs offer their generation at zero prices, their bids are always accepted. Equality constraint (11) ensures that sum of scheduled power from wind or conventional generators, or both, at any particular bus must be equal to the demand and injected power at the bus. The lagrangian multiplier of this equality constraint represents LMP at a particular bus. Constraint (12) states that power flow in a particular transmission line is equal to the product of corresponding susceptance and difference between voltage angle at sending and receiving bus of line. For the sake of simplicity, DC power flow without transmission losses is considered, thus reactive power and voltage security are neglected. Inequality constraint (13) enforces MW flow limit on transmission lines. Constraints (14) and (15) impose upper and lower bound on scheduled output of conventional generators and demand. Hourly demand is obtained by multiplication of demand factor and peak demand. Constraint (16) represents limits of voltage angle at the buses. Constraint (17) shows that voltage angle at the reference Bus 1 should be equal to zero.

Balancing market's upward and downward prices at a particular location can be modeled as a function of day-ahead LMP [14]. System imbalance depends on sum of WPPs' excess/deficit generation at real time.

3.3 Stochastic Equilibrium Problem

This decision-making problem of all strategic WPPs is formulated as a stochastic equilibrium problem, to maximize their payoff by optimizing their offered quantities considering rivals behavior. In mathematical terms, stochastic Nash equilibrium is a vector, which solves a collection of profit maximization problems of the form

$$U\left(Pof_i^*, Pof_{-i}^*, \omega_i\right) \geq U\left(Pof_i, Pof_{-i}^*, \omega_i\right), \quad \forall i \in \Omega^w \qquad (18)$$

Nash equilibrium condition (18) shows that payoff of any strategic WPP at optimal strategy is always greater than or equal to payoff of its other available strategies, while rival decisions are dependent on their optimal strategies. In stochastic Cournot model, Nash equilibrium is obtained from resultant payoff matrix comprising of aggregate payoff of each strategic WPP. Aggregate payoff can be calculated as summation of product of payoff and scenario occurrence probability.

Cournot Nash equilibrium provides optimal offered bids, considering behavior of rival generators. Conventional generators and consumers are assumed to be non-strategic and they are only considered for market clearing problem.

3.4 Simulation Procedure

This section describes the procedure used for obtaining solution of proposed Stochastic Cournot model.

Step 1: Time Counter Initialization: Initialize time counter to obtain optimal hourly offers of WPPs. Time counter starts with $t = 1$.

Step 2: Scenario Generation and Reduction: Initialize the strategic WPPs' expected outcome by generation of scenarios. For scenario generation and reduction, the algorithms proposed in [23] are used.

Step 3: Stochastic Cournot model: Each WPP has a discrete set of possible offering outputs. They select only one offer among possible offers, which maximizes their expected payoff calculated using (6)-(9). To obtain Nash equilibrium, resultant payoff matrix is constructed with probabilistic information about each scenario. For each combination in payoff matrix, LMP is calculated by solving market clearing problem (10)-(17). For resultant payoff matrix, Nash equilibrium is obtained by payoff matrix approach [24]. This equilibrium gives optimal power output that can be offered by the WPPs.

Step 4: Update Time Counter: For each considered hour, offer for each WPP is obtained. In the next step, update time counter by $t+1$ and go step 2.

Step 5: End

4. Case Studies

The present studies consider a network constrained pool-based market, where three WPPs interact strategically. The results obtained on three-bus system and IEEE 24-bus RTS systems illustrate effectiveness of the proposed model for WPPs' bidding strategy formulation.

4.1 Data

The present study considers three WPPs situated at three different locations, Barnstable, Savoy and Kingston, of Massachusetts State, USA. Each WPP has a number of wind turbines according to installed capacity, with commercial 2.5 MW, VENSYS100 turbine installed at 100 m hub height. Air density and temperature conditions are assumed same for each installed wind turbine. The used turbine model and its power curve are detailed in manufacturer database [25]. For all these WPPs, actual wind speed data of August 2005 is taken, publically available at Wind Energy Center, University of Massachusetts, USA [26].

Wind uncertainty of each WPP is characterized by scenarios. The estimated parameters' time series based ARMA model used for scenario generation is shown in Table 1. For accurate modeling of wind power uncertainty, 1000 scenarios are generated and then reduced to 10 scenarios for each WPP. From these reduced scenarios, in every hour, each WPP can formulate its resultant payoff matrix.

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4.2 Three-bus system

A three-bus system, each with a conventional generating unit and a single load connected with three transmission lines is considered. All transmission line has identical reactance 0.13 per unit and 1000 MW power transmission capacity. A conventional 350 MW coal, 250 MW oil and 150 MW gas generating unit is connected at bus 1 to 3 respectively. Thus, total capacity of conventional generating unit is 750 MW. The coal, gas and oil unit can offer their generation at their marginal cost 40, 50 and 60 \$/MWh respectively. A single demand with peak value of 684

MW is connected to bus 3. Hourly demand profile can be obtained using multiplication of peak demand to hourly demand factor profile as shown in Fig. 1. The demand is assumed to be elastic, with 70% bids at 70 \$/MWh and 30% bids at 80 \$/MWh. Three strategic WPPs, each with an installed capacity of 100 MW, are considered in this study. These WPPs namely WPP1, WPP2 and WPP3 are connected on buses 1 to 3 respectively. According to considered installed capacity, each WPP have 40 wind turbines. Wind power's share is 28.57% of total installed capacity.

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In order to compare proposed approach, two cases are considered in this work.

Case I: Base Case: In this cse, each WPP offers their forecasted generation in day-ahead electricity market. For forecasted generation, ISO market-clearing problem (10)-(17) is solved to calculate LMP, then WPPs' expected profit and imbalance charges are obtained using (2)-(9). Rival behavior is not considered in this case for WPPs' offer selection.

Case II: Strategic Firms: In Case II, WPPs behave strategically and offer output power, which gives maximum payoff considering rivals behavior, as obtained by proposed simulation procedure. In this case, market operation and imbalance price mechanism are similar to Case I.

Both test cases are simulated on Windows based laptop has a 1.67 GHz, Intel Core 2 duo processor and 2.50 GB RAM. Simulation for scenario generation and reduction is performed on MATLAB platform and rest of simulations are performed on GAMS [29] software using CPLEX 12.0 solver.

For the base case, the hourly offered bids of each WPP are shown in Fig. 2. At the first hour, power offered by WPP1, WPP2 and WPP3 is 47.1143 MW, 51.0163 MW and 48.8089 MW, respectively.

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--------------------------PASTE FIGURE 3 HERE------------------------------

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Hourly imbalance charges for each WPP are shown in Fig. 3. At first hour, all WPPs face negative imbalance charges because power offered by WPPs falls short of generated power. WPP2 and 3 offer zero generation bids at 22 Hours and at 12, 18, 24 Hours, respectively. At these hours, imbalance cost is zero and WPPs earn revenue for any surplus generation.

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Day-ahead market LMP determined by solving ISO market clearing problem and imbalance price obtained from location based imbalance mechanism are shown in Fig. 4. Balancing market's downward and upward prices are assumed to be 0.70 and 1.20 times of day-ahead LMP respectively. This assumption is based on historical balancing and spot market prices of Nord-pool and UK electricity market [12]. From these figures, it is observed that PIP is less than LMP and NIP is equal to LMP during surplus generation, and *vice versa*. Since all transmission lines are uncongested in this case, LMP is uniform at all buses. Expected profit obtained by each WPP is shown in Fig. 5. For the first hour, profit of WPPs 1, 2 and 3 are \$1000.25, \$1767.89 and \$1009.25, respectively.

In Case II, WPPs behave strategically and consider rival behavior for their offer selection. They offer power as per Nash equilibrium solution of the proposed Stochastic Cournot model. Hourly profile of the power offered by different WPPs is shown in Fig. 6. At the first hour, power offered by WPP1, WPP2 and WPP3 is 28.64 MW, 12.24 MW and 10.08 MW, respectively.

--------------------------PASTE FIGURE 6 HERE------------------------------

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Imbalance charges for the WPPs arise due to deviation between offered and generated power, as shown in Fig. 7. For the first hour, power generated by WPP 2 and 3 is more than that originally offered, and hence it earns revenue corresponding to this positive imbalance. However, power generated by WPP1 is less than their offered power, and hence has to pay negative imbalance prices.

Fig. 8 shows hourly imbalance charges for each WPP. From this figure, it is evident that at the first hour, NIP is higher than both LMP and PIP due to negative system imbalance. Hourly profile of the expected profit for different strategic WPPs is shown in Fig. 9. At the first hour, profit earned by WPP1, WPP2 and WPP3 are \$1146.76, \$1813.12 and \$1166.44, respectively.

Considering the results obtained from the two cases for the first hour, it is evident that the proposed Stochastic Cournot model increases profit earned by different WPPs and reduces imbalance charges significantly. A comparative evaluation of profit earned by different WPPs at the first hour, as evident from Figs. 5 and 9, shows that the profit of WPPs 1, 2 and 3 increases by \$146.51, \$45.46 and \$157.18 respectively. This is because WPPs decrease their offered bid in Case II, as shown Figs. 2 and 6. WPPs behave strategically, and change their offered bids, when they have the opportunity to earn. As WPPs reduce their offered power outputs, their corresponding imbalance charges also change.

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Profit earned by different WPPs over a period of 24 hours is shown in Table 2. The overall profit earned by different WPPs increases significantly, when the offered bids are selected by Stochastic Cournot model. To evaluate the impact of transmission congestion, both test cases are simulated again by limiting transmission line (1-2) capacity to 30 MW. From Table 2 it is visualized that daily profit of WPP2 increases while that of WPP1 decreases by 23.96 % and 22.39 %, respectively. Because of congestion, LMP at Bus 2 is mostly higher than LMP at bus 1. Profit of WPP3 is minimally changed as LMP at Bus 3 is not affected significantly by congestion. A comparative reflection of the daily benefit earned by each WPP clearly shows that increase in profit earned by different WPPs would be substantial over a longer period of time.

4.3 IEEE 24-Bus RTS System

To validate the proposed approach on a large system, the two test cases are simulated for single area IEEE 24-Bus RTS system consisting of 24 buses, 32 generating units, 17 demand and 38 transmission lines. Network configuration, data of generating units, line capacities and demand is considered from [30]. For the sake of simplicity, it is assumed that all generating units located at the same bus can be represented as a single GENCO, with installed capacity equal to sum of individual generating units' capacity. Marginal cost of GENCO is equal to average marginal cost of corresponding generating units. Peak system demand is 2650.50 MW. Information about conventional GENCOs installed capacities and load distribution across the system is provided in Table 3. Similar to the three-bus system, hourly demand is considered from the demand factor profile shown in Fig. 1.

Installed capacity of WPP1, WPP2 and WPP3 is considered equal to 600 MW, 400 MW and 400 MW, respectively. WPP1, WPP2 and WPP3 are connected at buses 7, 13 and 18 respectively. According to considered installed capacities, WPP1 has 240 wind turbines, while

WPP2 and WPP3 have 160 wind turbines each. Wind power's share in total installed system capacity is 29.62%. Uncertainty characterization and other parameters in this study are similar to that of three-bus system.

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In this study, base case reflects a similar pattern as that from three-bus system. However, in this case, the offered bids, imbalances charges, imbalance prices and expected profits have been modified according to new installed capacities of WPPs and new network configuration.

For Case II, hourly bids offered by strategic WPPs using the proposed stochastic Cournot model are shown in Fig. 10. At the first hour, power offered by WPP1, WPP2 and WPP3 are 159.36 MW, 126.40 MW and 116.48 MW, respectively. Hourly imbalance charges of strategic WPPs are given in Fig. 11. At the first hour, WPP1 and WPP2 can earn additional revenue for their surplus generation while WPP3 gets penalty for its deficit generation. Hourly LMP and imbalance prices at Bus 7 are shown in Fig. 12. These prices would differ from those at other buses during network congestion. Hourly profit earned by strategic WPPs is shown in Fig. 13. From these figures, it is evident that proposed approach is helpful to maximize profit of strategic WPPs in larger systems.

An understanding of daily profits earned by strategic WPPs in Case II shows that WPP1 earns a profit of \$88949.01 *i.e.* 11.80 % higher than its profit \$79554.78 in Case I. Similarly, WPP 2 and WPP3 daily profits are \$95591.80 and \$82540.82 respectively in Case II. WPP2 and WPP3 get 15.81% and 15.43% higher profit in Case II, as compared to their corresponding profit \$82540.82 and \$61197.44 in Case I. From the obtained daily profit of different WPPs, it is observed that increment in WPP1's daily profit is slightly less among WPPs. This is due to the network topology of 24-bus system. In the 24-bus system, Bus 7 is connected to the system through Bus 8 only. Due to limited transmission capacity, this transmission line may be congested for some scenario of WPP1 generation during off peak demand. Due to congestion, LMP at Bus 7 is usually less than rest of system LMP, therefore WPP 1 earns less profit as compared to other strategic WPPs.

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---------------------------PASTE FIGURE 13 HERE------------------------------

5. Conclusions

In a pool-based day-ahead electricity market, strategic behavior of WPPs is modeled by a Stochastic Cournot model. Wind uncertainty and imbalance costs are considered for evaluating the expected profit. Wind uncertainty is represented as scenarios generated by ARMA model, which are reduced by Simultaneous Backward Reduction method, so as to reduce computational burden. Nash equilibrium is obtained with payoff matrix approach. Proposed bidding strategy approach is implemented on three and 24-bus system with three WPPs. Historical data of these WPPs is considered from three different locations at Massachusetts, USA. A comparative study of two cases on each system shows that consideration of rival behavior in selecting the bid offer results in a significant increase in the WPPs' profit. This work considers a near-future scenario, when system demand would predominantly be supplied by wind generators. The proposed model can be improved by considering behavior of conventional generators and uncertainties of demand and price.

Acknowledgements

The first author acknowledges financial support by University Grants Commission Grant No. 39-894/2010 (SR).

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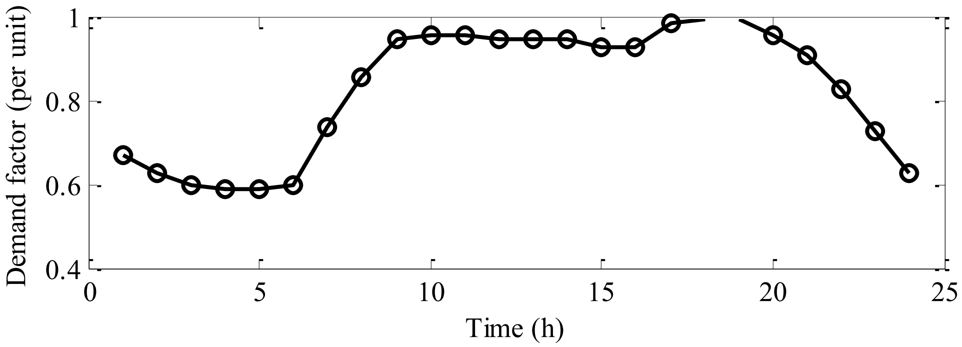

Fig. 1. Hourly demand factor

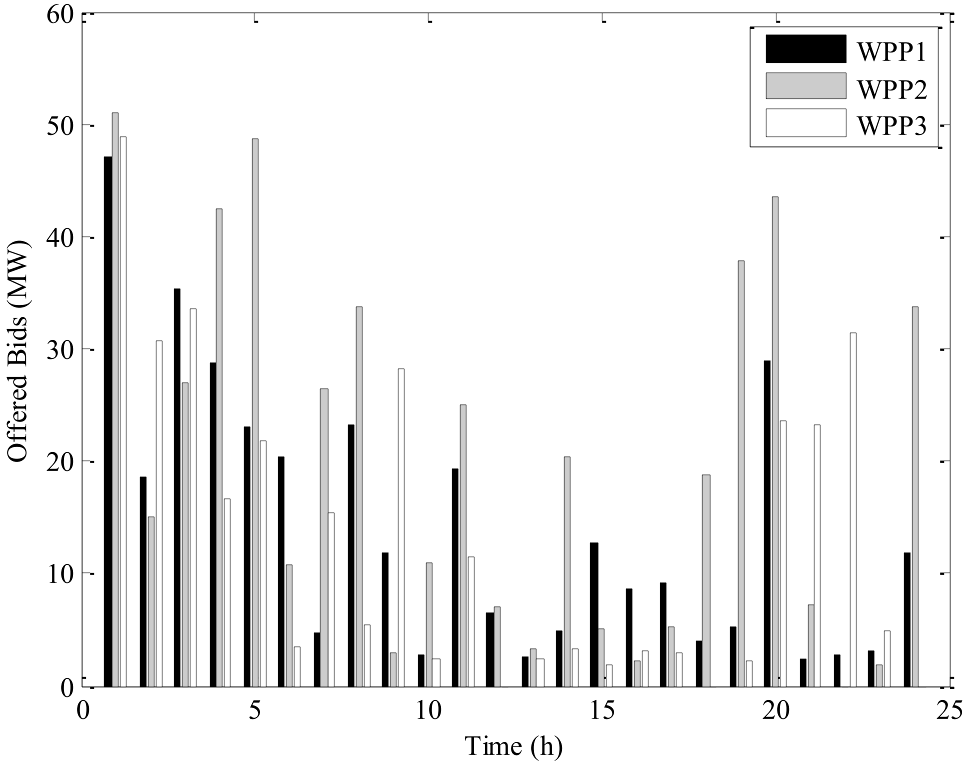

Fig. 2. Bid offered by WPPs for Case I (Three-bus system).

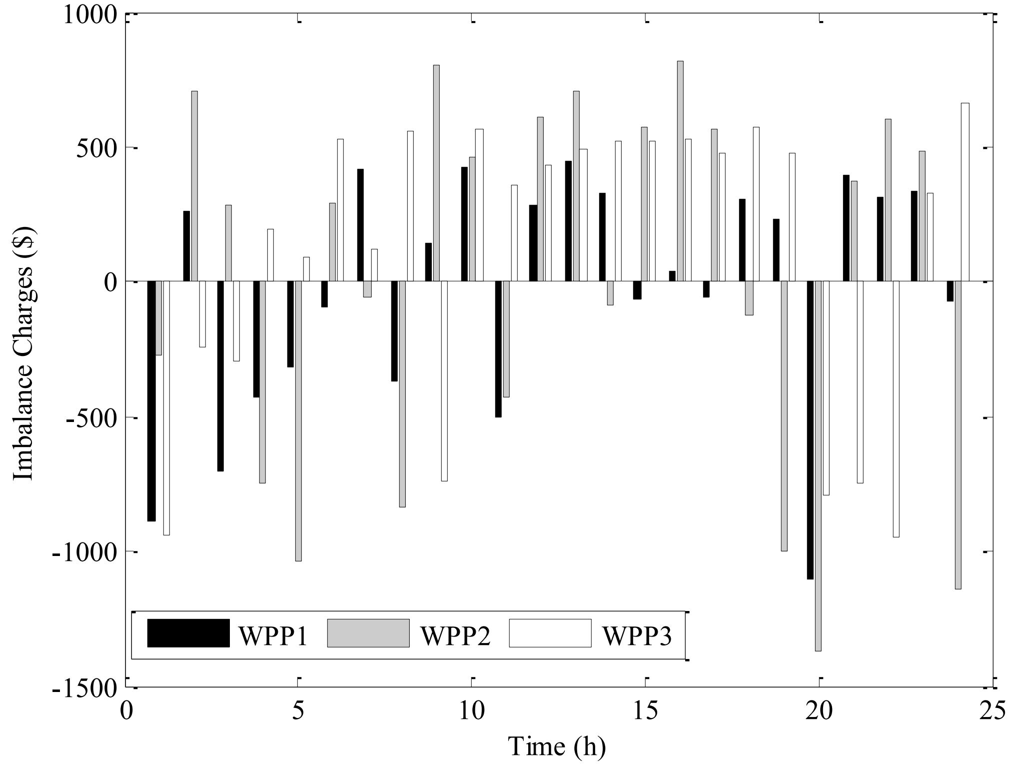

Fig. 3. Imbalance charges for each WPPs in Case I (Three-bus system).

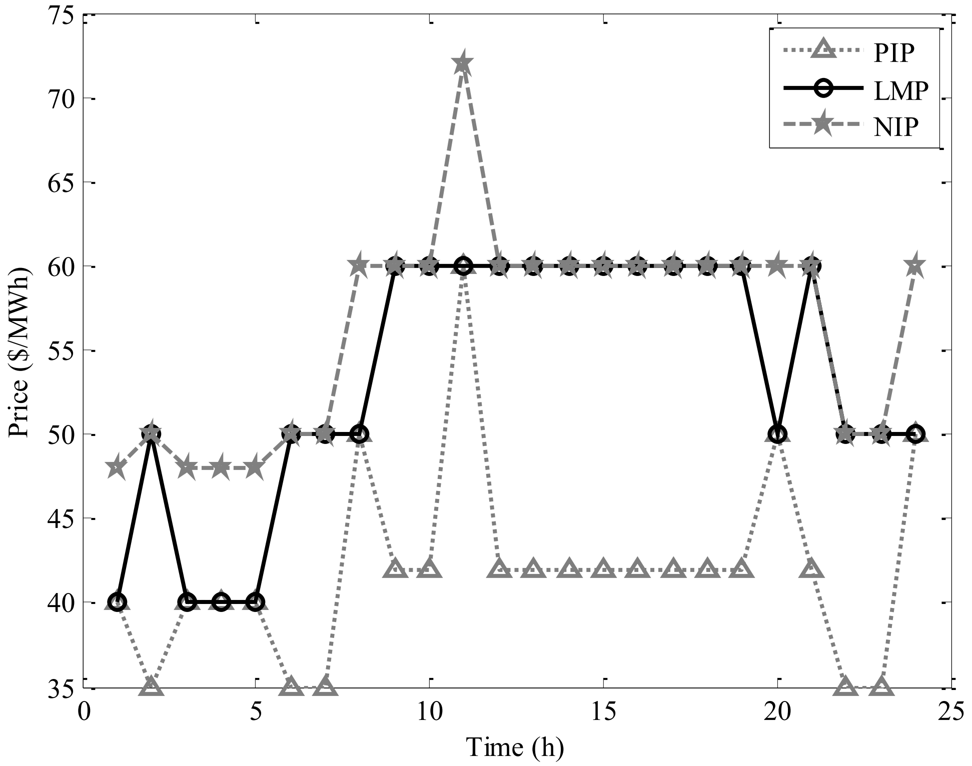

Fig. 4. LMP and imbalance prices at Bus 1 for Case I (3-bus system).

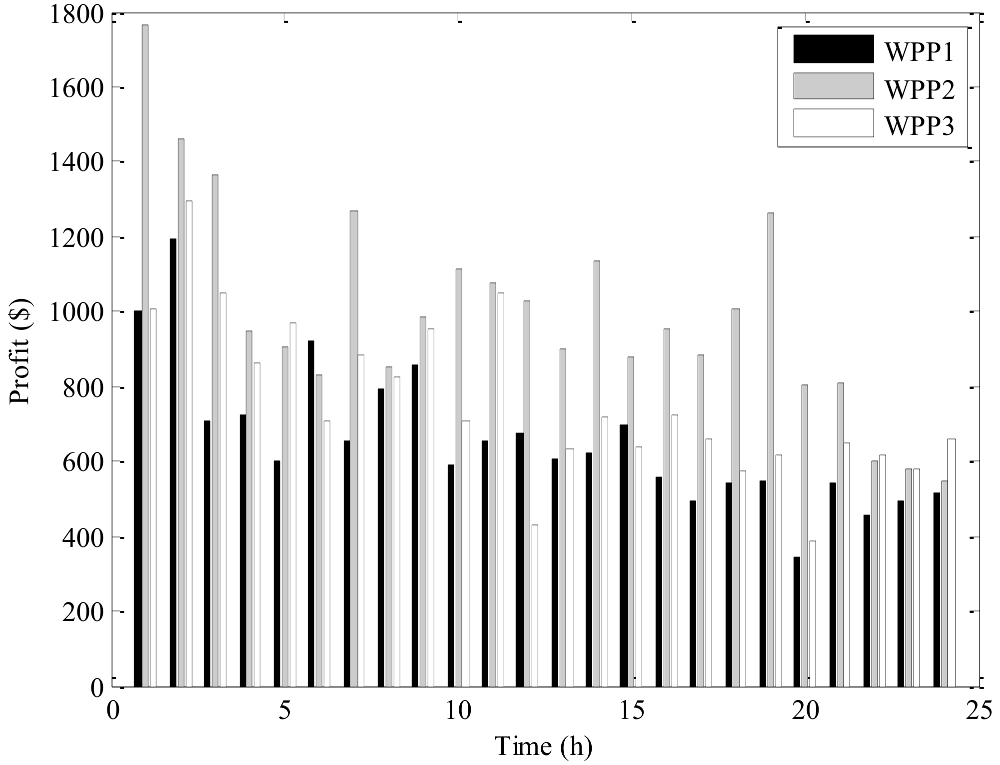

Fig. 5. Expected profit of WPPs for Case I (Three-bus system).

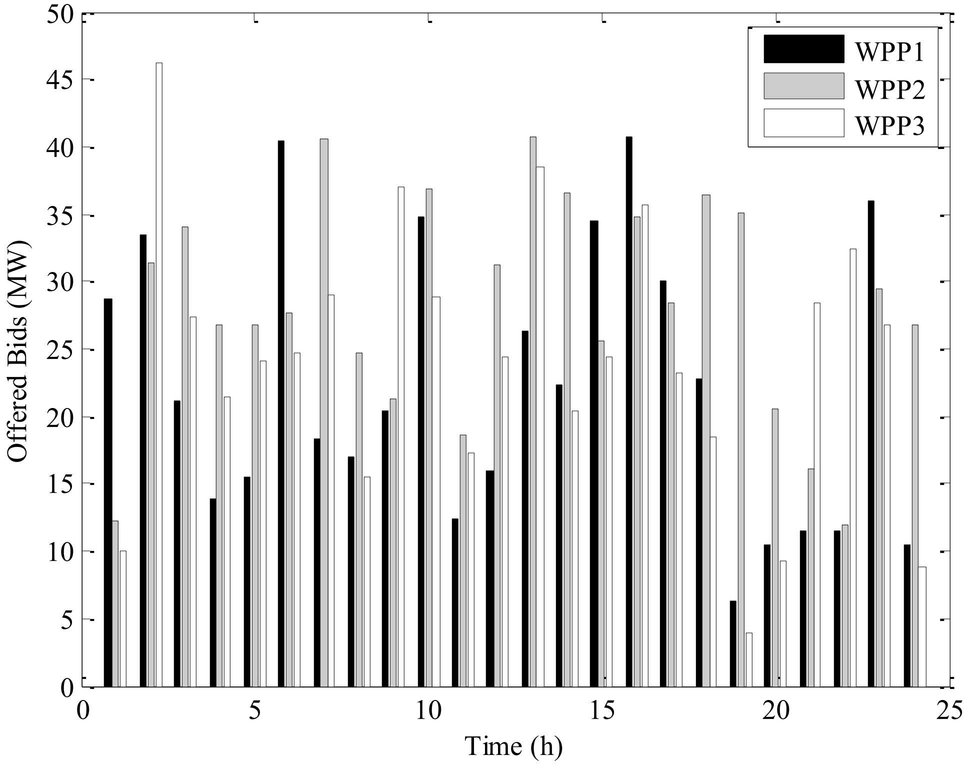

Fig. 6. Bids offered by strategic WPPs for Case II (Three-bus system).

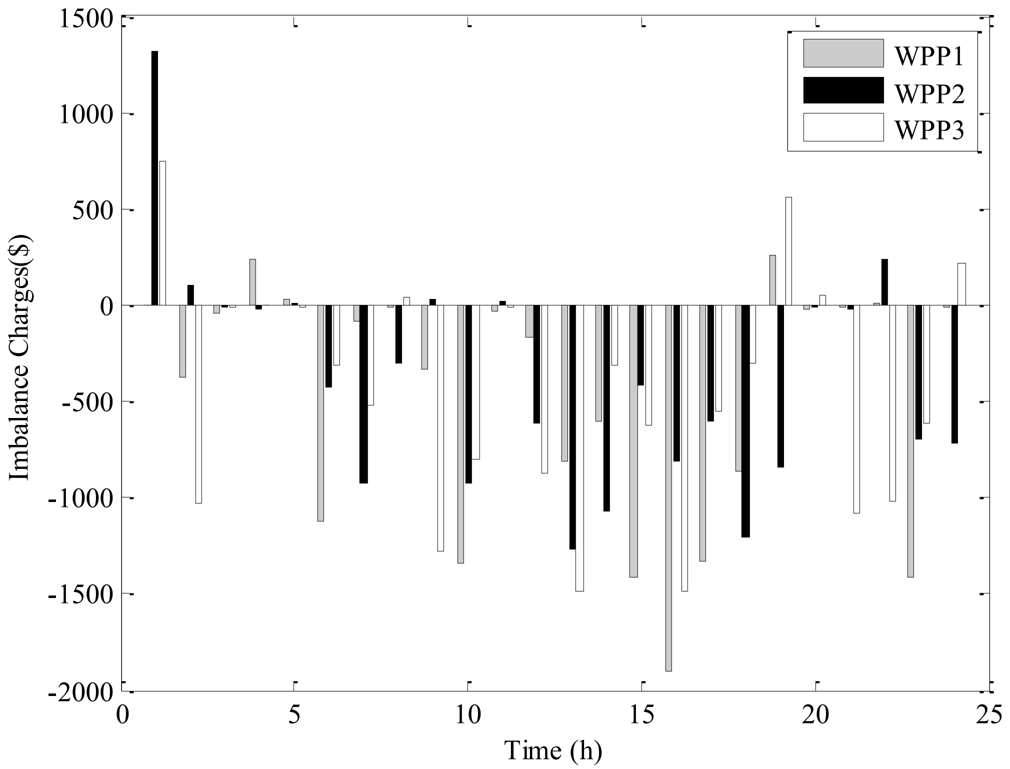

Fig. 7. Imbalance charges for each strategic WPPs in Case II (Three-bus system)

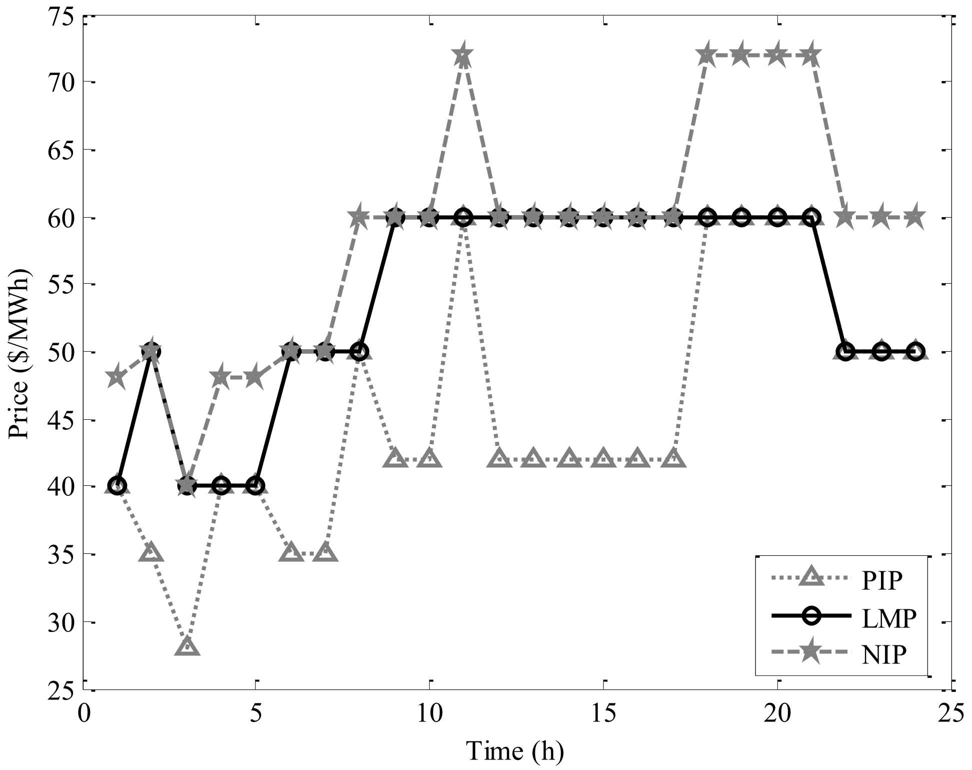

Fig. 8. MCP and imbalance prices at Bus 1 for Case II (3-bus system).

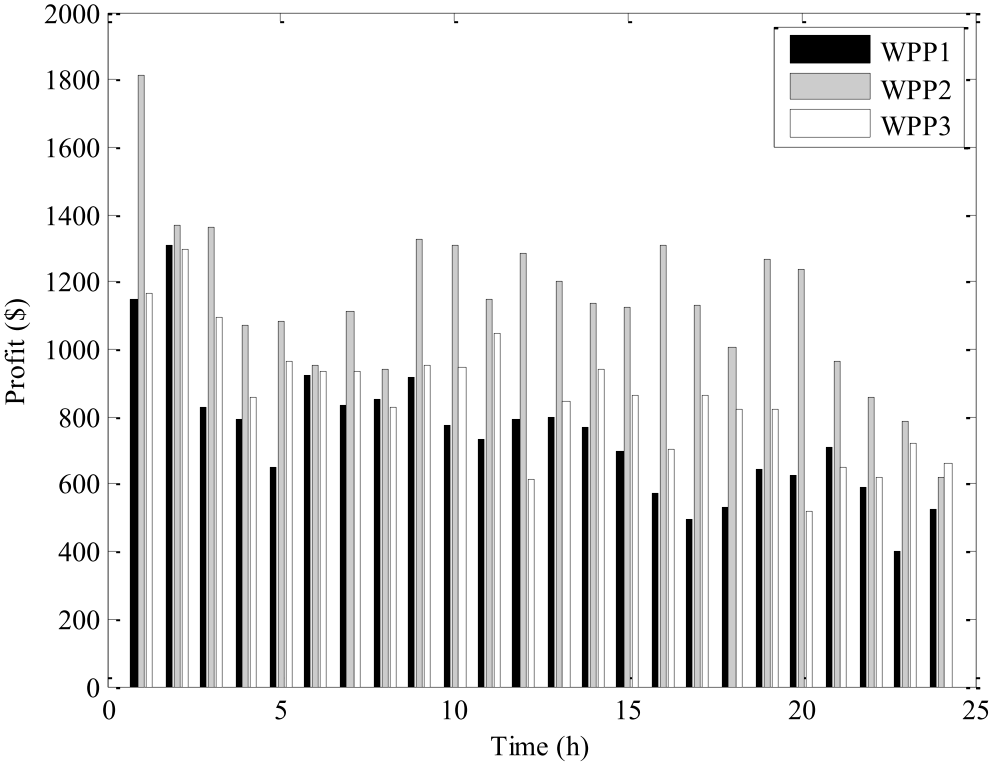

Fig. 9. Expected profit profile of strategic WPPs for Case II (Three-bus system).

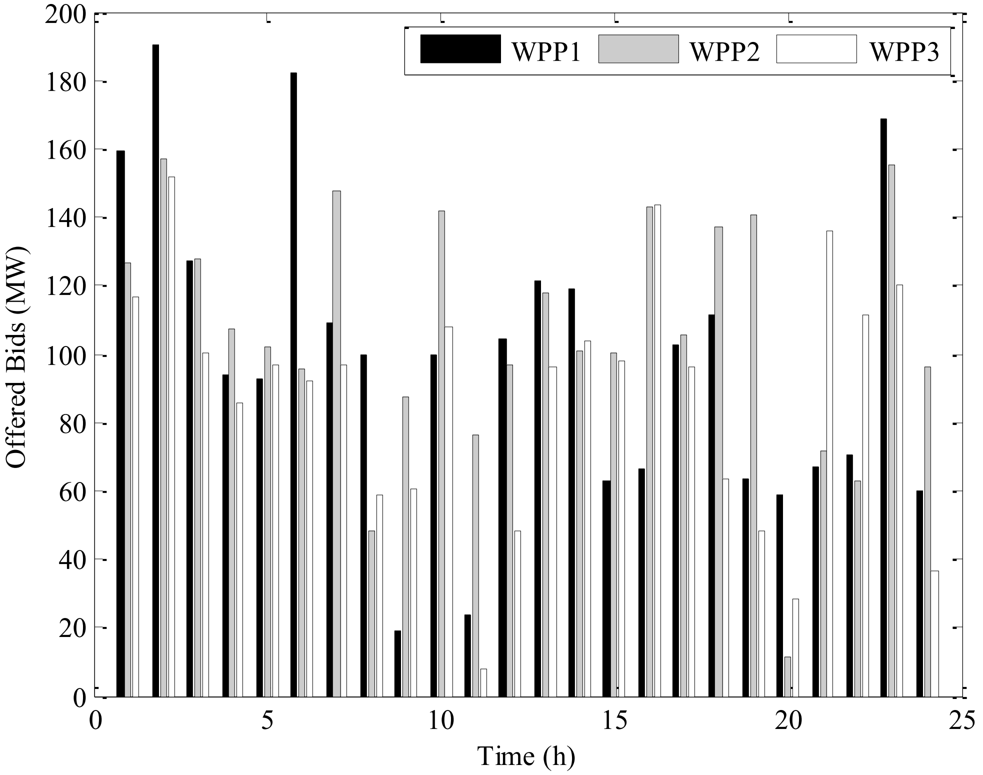

Fig. 10. Offered bids by strategic WPPs for Case II (24-bus system).

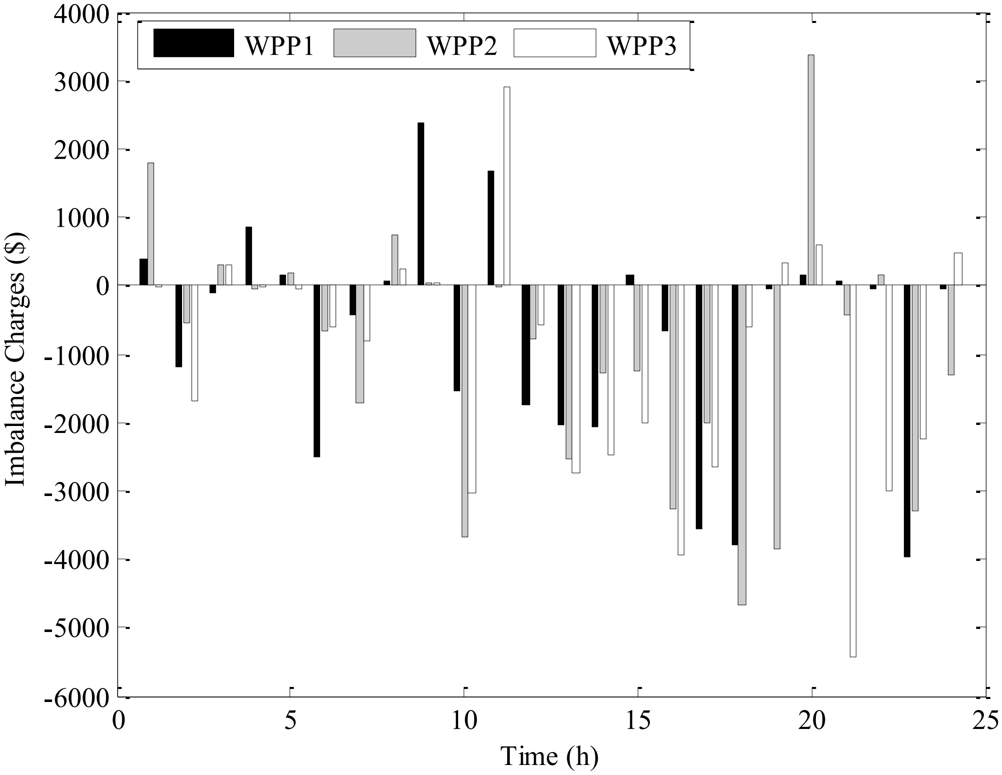

Fig. 11. Hourly imbalance charges for Case II (24-bus system).

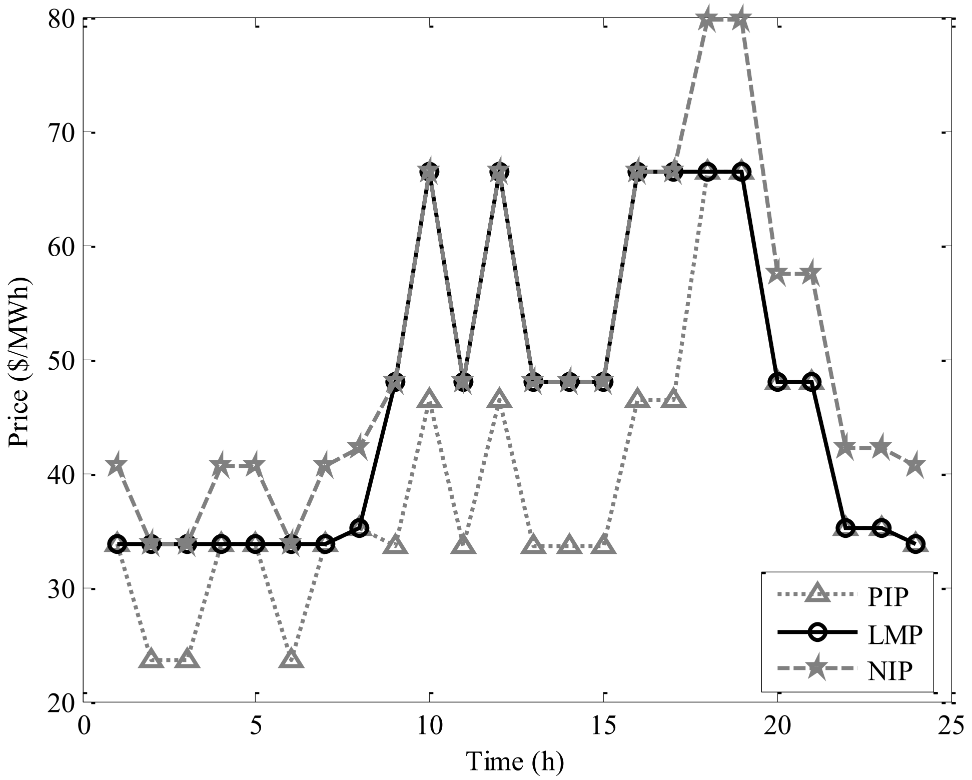

Fig. 12. LMP and imbalace prices at Bus 7 for Case II (24-Bus system).

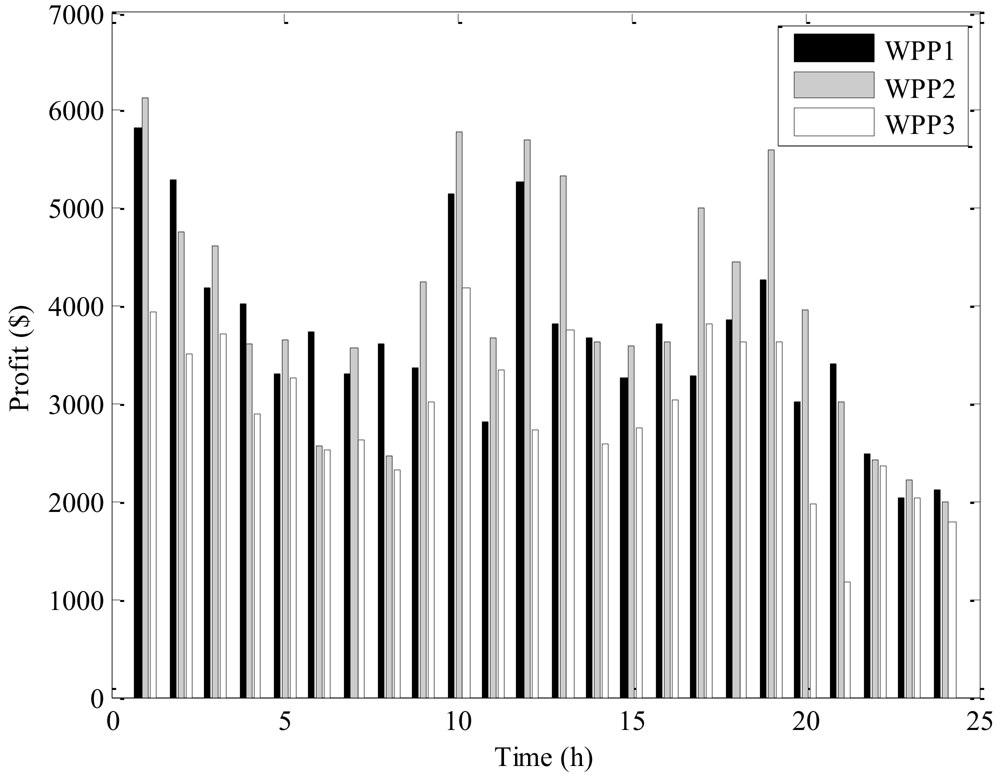

Fig. 13. Hourly profit earned by strategic WPPs for Case II (24-bus system)

Table 1
WPPs’ Time Series Model Parameters

Parameters	WPP1	WPP2	WPP3
Order	ARMA (1,0)	ARMA (1,1)	ARMA (2,0)
ϕ_1	0.8693	0.8933	0.6313
ϕ_2	-	-	0.9711
θ_1	-	0.0654	-
Variance	0.5141	0.6048	0.6213

Table 2
3-Bus System: Comparative analysis of wind firms daily expected profit ($)

	Uncongested network			Congested Network		
WPPs	1	2	3	1	2	3
Case I	15790.28	23957.42	18195.53	12254.02 (-22.39)	29697.57 (+23.96)	18201.08 (+0.03)
Case II	17916.04	27404.76	20668.33	14058.95 (-21.52)	33653.85 (+22.80)	20866.21 (+0.95)
Increment (%)	13.46	14.38	13.59	14.73	13.32	14.64

TABLE 3
24-BUS SYSTEM: DATA OF CONVENTIONAL GENCOs AND DEMANDS

Bus No.	GENCO installed capacity (MW)	GENCO marginal cost ($/MWh)	% share of total demand
1	152	47.91	3.8
2	152	47.91	3.4
3			6.3
4			2.6
5			2.5
6			4.8
7	300	68.16	4.4
8			6.0
9			6.1
10			6.8
13	591	66.39	9.3
14			6.8
15	215	62.49	11.1
16	155	33.78	3.5
18	400	16.98	11.7
19			6.4
20			4.5
21	400	16.98	
22	300	0	
23	660	34.42	