Long-Term Stochastic Planning in Electricity Markets Under Carbon Cap Constraint: A Bayesian Game Approach

Amin Masoumzadeh
Electrical and Electronic Engineering,
The University of Melbourne.
amin.masoumzadeh@unimelb.edu.au

Ehsan Nekouei
Electrical and Electronic Engineering,
The University of Melbourne.
ehsan.nekouei@unimelb.edu.au

Tansu Alpcan
Electrical and Electronic Engineering,
The University of Melbourne.
tansu.alpcan@unimelb.edu.au

***Abstract*—Carbon price in an electricity market provides incentives for carbon emission abatement and renewable generation technologies. Policies constraining or penalizing carbon emissions can significantly impact the capacity planning decisions of both fossil-fueled and renewable generators. Uncertainties due to intermittency of various renewable generators can also affect the carbon emission policies. This paper proposes a Cournot-based long-term capacity expansion model taking into account carbon cap constraint for a partly concentrated electricity market dealing with stochastic renewables using a Bayesian game. The stochastic game is formulated as a centralized convex optimization problem and solved to obtain a Bayes-Nash Equilibrium (Bayes-NE) point. The stochastic nature of a generic electricity market is illustrated with a set of scenarios for wind availability, in which three generation firms (coal, gas, and wind) decide on their generation and long-term capacity investment strategies. Carbon price is derived as the dual variable of the carbon cap constraint. Embedding the carbon cap constraint in the game indicates more investment on renewable generators and less on fossil-fueled power plants. However, the higher level of intermittency from renewable generation leads to a higher carbon price to meet the cap constraint. This paves the way towards storage technologies and diversification of distributed generation as means to encounter intermittency in renewable generation.[1]**

I. Introduction

In deregulated power markets, electricity price is not set by regulators but by market forces. In order to make investment and operation decisions, generation companies have a strong interest in modeling anticipated prices using available engineering and economic information. They need appropriate decision making models considering not only technical operation constraints but also the interaction among market participants. A variety of physical and economic factors are included in market modeling, many of which are stochastic by nature. Moreover, policy makers can intervene and incentivize the market players to meet their desired goals, such as caps on carbon emission. This paper enhances a Cournot-based partly concentrated electricity market expansion model under carbon cap constraint by incorporating the stochasticity associated with renewable power generation availability using a Bayesian game.

[1]This work was supported in part by the ARC Discovery Project DP140100819.

Before electricity market deregulation, planning and operation scheduling were dependent on administrative and centralized procedures. Cost minimization models have been widely used in long-term capacity expansion models, e.g. planning in micro scale [1] and in macro scale [2]. During the last three decades, power industry in many countries and regions has transformed from being a centrally coordinated monopoly to a deregulated liberalized market. Although classical cost minimization and surplus maximization models do not incorporate strategic behaviors existing in the markets [3], [4], a heuristic cost minimization model is used for optimal investment planning in a competitive market assuming different forecasted market price scenarios [5]. Game-theoretic models including Cournot-Nash are capable of computing market equilibrium, price and generation, considering strategic behaviors. Cournot-based game models have been extensively used in energy systems analysis with formulations following the same logic, e.g. in electricity markets [6] and global oil markets [7].

Research on short and long-term capacity expansion in electricity markets using game-theoretic models has been conducted for a long time. Firms in the market compete by deciding on their generation quantities and expansion-planning decisions in a Cournot manner using an iterative solving algorithm [8] or a Mixed Linear Complementarity Problem [9]. Since solving the Cournot-based market games as a LCP could be cumbersome, the problem of computing the Nash Equilibrium (NE) is posed as a centralized optimization problem alternatively, e.g. on short term in [10] and on long-term in [11] and [12]. The centralized optimization formulation is developed for highly concentrated markets, in which all players are strategic.

Cournot-based models used in electricity market representation are mostly deterministic. By considering a set of scenarios, uncertainty on the conjectured price responses, i.e., the slope of the linear inverse demand function, has been introduced in an oligopoly Bayesian game where generation companies decide on their long-term generation and capacity investment [13]. Uncertainties on both sides of supply and demand are considered in an oligopoly model in [14]. The load uncertainty is due to errors in the load forecast, and the generator availability uncertainty is about generators that might have a forced outage.

In both optimization and game-theoretic formulations, maximum carbon production can be embedded in the model as a constraint, whose dual variable indicates the carbon price. In a cost minimization model, different values for maximum carbon production limit calculates different dual variables or carbon prices [2].

The **contributions** of this paper include the following. Firstly, we theoretically develop a stochastic game-theoretic Cournot-based model which calculates a Bayes-NE point in partly concentrated electricity markets, having both strategic and perfectly competitive (fringe) generation players. In addition to generation portfolio, the firms decide on expanding their capacities during the study period dealing with the uncertainties due to intermittency of certain renewables, e.g., stochasticity of wind and solar. Players decide on new capacity investment by considering a set of scenarios for wind and solar availability during the study period. Secondly, we calculate the carbon price required to meet the targeted carbon emission cap, i.e., greenhouse gas control or green network policies, in the market as the dual variable of the cap constraint. The stochastic nature of our model enables us to find the renewable intermittency effect on the carbon price. Lastly, joint of capacity retirement and remaining value of new technologies is included in our model. It means that power plants become retired once time passes their plant life and the remaining value of each new invested technology at the end of the study period is subtracted from its investment cost. For instance, a generator having $\mathbf{T}'$ years plant life pays just $\frac{1}{\mathbf{T}'}$ of the investment cost in our model if it decides to install a new capacity exactly at the end time. However, the annualized investment cost ($/MW/yr) is an alternative way instead of considering the remaining values of new invested technologies, e.g. in [13]; although it is not hard to construct an unusual example where this is not true.

The rest of the paper presents the wholesale electricity market model with strategic and perfectly competitive generation players in Section II, illustrative results in Section III, and ends with a discussion and conclusion in Section IV.

II. Game-Theoretic Formulation of Long-term Wholesale Electricity Market

In a Cournot-Nash wholesale electricity market model, the generation players (firms) make their decisions strategically in order to maximize their utility functions, and the equilibrium price is equal to the inverse demand function. However, participants in a partly concentrated liberalized electricity market are either strategic or perfectly competitive. The strategic players, in order to maximize their utility (profit), affect the price by changing their generation decision, i.e. they hold market power. However, the perfectly competitive players either are not large enough to affect the price (fringe participants) or are regulated to not benefit from their market power.

At the same time, intermittency in wind and solar availability is stochastic, which brings a great deal of uncertainty to the market. Decisions on new capacities have to be made considering a set of scenarios for wind and solar availabilities during the study period taking also into account a carbon emission cap constraint. Accordingly, we define the following extended Cournot-based Bayesian game model to find the long-term equilibrium point of the market based on the input data.

A. Game Definition and Bayes-Nash Equilibrium

In the well-known Cournot electricity market model, several strategic generation companies make their generation decision non-cooperatively given that the price follows the inverse demand function. However, we study a partly concentrated market in which there is perfectly competitive generation companies besides the oligopoly generators.

In a Bayesian game, players maximize their expected utility over alternative possibilities with a known probability distribution [15]. Availability of the stochastic renewables is captured in our model in a set of scenarios with given probabilities, consistent with the Bayesian game definition.

Definition 1: A perfectly competitive (PC) player does not have the market power to raise the wholesale price, where a strategic player may deliberately withholds its available capacity to increase the price.

Let $k \in \mathcal{K} = \{1, ..., \mathrm{K}\}$ be in the set of generation firms (generators) participating in the electricity market, $y \in \mathcal{Y} = \{1, ..., \mathrm{Y}\}$ be in the set of times with length of $\Delta \mathrm{Y}_y$ (yr), $s \in \mathcal{S} = \{1, ..., \mathrm{S}\}$ be in the set of load zones (like seasons in a year) with length of $\Delta \mathrm{S}_s$ ($\frac{\text{day}}{\text{yr}}$), $t \in \mathcal{T} = \{1, ..., \mathrm{T}\}$ be in the set of sub-load zones (like off-peak, shoulder and peak times in a day) with length of $\Delta \mathrm{T}_t$ ($\frac{\text{hr}}{\text{day}}$), and $w \in \mathcal{W}$ be in the set of scenarios on wind availability in our Bayesian game. Total duration of sub-load zone t that repeats on load zone s from period y is $\Delta \mathrm{l}_{y,s,t} = \Delta \mathrm{Y}_y \Delta \mathrm{S}_s \Delta \mathrm{T}_t$ hours.

In our game $\mathcal{G}$, firm k decides on its generation $q_{w,k,y,s,t}$, $\forall w, y, s, t$, and new capacities $Q^{\text{new}}_{k,y}$, $\forall y$ in order to maximize its utility U_k. We assume that the generator k has constant marginal cost of production ($/MWh), $\mathrm{c}_k \geq 0$, constant capacity maintenance cost ($\frac{\$/\text{MW}}{\text{yr}}$), $\mathrm{m}_k \geq 0$, and constant investment cost ($/MW), $\mathrm{inv}_k \geq 0$. All parameters and variables used in the formulations are listed respectively in Tables I and II.

Definition 2: A non-cooperative Bayesian game among $\mathcal{K} = \{1, ..., K\}$ players having the decision variables $q = [q_1, ..., q_K]$ and $Q^{new} = [Q^{new}_1, ..., Q^{new}_K]$ that aim to maximize their expected profit U over scenarios $w \in \mathcal{W}$ with probabilities $\mathrm{Pr_w}$ is defined as $\mathcal{G} = \{\mathcal{K}, (q, Q^{new}) \succeq 0, U\}$.

In a Cournot-based model such as [10], the commonly-used linear price p follows the inverse demand function with intercept of α and slope of β,:

$$p_{y,s,t} = \alpha_{y,s,t} - \beta_{y,s,t} D_{w,y,s,t} \quad \forall y, s, t \tag{1}$$

where $D_{y,s,t}$ is the total electricity demand at time (y, s, t).

Players in the market are categorized into two groups:

TABLE I

THE PARAMETERS USED IN THE PAPER.

Parameters	Description
w, k	Indices used for scenario and generators
y, s, t	Indices used for time such as year, season and hour
r	Discount rate
Pr_w	Probability of scenario w
$\Delta \mathrm{l}_{y,s,t}$	length of time segment (y, s, t)
$\Delta \mathrm{Y}_y$	length of time segment y
$\Delta \mathrm{S}_s$	length of time segment s
$\Delta \mathrm{T}_t$	length of time segment t
$\alpha_{y,s,t}$	Intercept of inverse demand function
$\beta_{y,s,t}$	Slope of inverse demand function
γ_k	$\in \{0,1\}$ to differentiate strategic and competitive players
c_k	Operation cost ($\frac{\$}{\mathrm{MWh}}$) of generator k
inv_k	Investment cost ($\frac{\$}{\mathrm{MW}}$) of generator (k)
m_k	Maintenance cost ($\frac{\$/\mathrm{MW}}{\mathrm{yr}}$) of generator (k)
b_0	base time
PL_k	Plant life of generator k
$Q^{\mathrm{old}}_{k,y''}$	Historical capacity (MW) of generator k installed at y''
RampUp_k	Ramp-up limit of generator k
RampDn_k	Ramp-down limit of generator k
$\mathrm{Avail}_{w,k,y,s,t}$	Availability limit of generator k at time (y, s, t)
$\mathrm{G}^{\max}_{k,y}$	Inter-temporal generation limit of generator k during y
ζ_k	Emission coefficient of generator k ($\frac{\mathrm{tonne\ CO_2}}{\mathrm{MWh}}$)
Cap_y	No policy emission of the system at time y ($\frac{\mathrm{tonne\ CO_2}}{\Delta \mathrm{Y}_y}$)
ϕ	Percentage of total CO_2 limit
σ	Percentage of wind availability domain change

TABLE II

THE VARIABLES USED IN THE PAPER.

Variables	Description
$D_{w,y,s,t}$	Electricity demand (MW) at time (y, s, t) and scenario w
$q_{w,k,y,s,t}$	Generation (MW) of generator k at time (y, s, t) and scenario w
$Q^{\mathrm{new}}_{k,y}$	New capacity (MW) of generator k installed at y
$Q^{\mathrm{total}}_{k,y}$	Total capacity (MW) of generator k at y

- perfectly competitive ($\gamma_k = 1$): which could be a set of fringe participants or a regulated competitive firm
- strategic ($\gamma_k = 0$) or Cournot players

Player k calculates its Best Responses, $q^*_k = \{q^*_{w,k,y,s,t}\}_{w,y,s,t}, Q^{\mathrm{new}*}_k = \{Q^{\mathrm{new}*}_{k,y}\}_y$, by solving the following utility maximization problem:

$$\max_{\substack{q_k, Q^{\mathrm{new}}_k \\ Q^{\mathrm{total}}_k, D \succeq 0}} U_k = \sum_y \frac{1}{(1+r)^y} \Bigg(\sum_{w,s,t} \mathrm{Pr}_w \Delta \mathrm{l}_{y,s,t} \Big((\alpha_{y,s,t} - \beta_{y,s,t} D_{w,y,s,t}) q_{w,k,y,s,t} + \gamma_k \frac{\beta_{y,s,t}}{2} q^2_{w,k,y,s,t} - \mathrm{c}_k q_{w,k,y,s,t} \Big) - \mathrm{m}_k \Delta \mathrm{Y}_y Q^{\mathrm{total}}_{k,y} - \mathrm{inv}_k Q^{\mathrm{new}}_{k,y} \Bigg) + \frac{1}{(1+r)^{\mathrm{Y}}} \max(0, \frac{\mathrm{PL}_k + y - \mathrm{Y} - 1}{\mathrm{PL}_k}) \mathrm{inv}_k Q^{\mathrm{new}}_{k,y} \tag{2}$$

s.t.

$$D_{w,y,s,t} = \sum_k q_{w,k,y,s,t} \qquad \forall w, y, s, t \tag{3}$$

$$q_{w,k,y,s,t} \le Q^{\mathrm{total}}_{k,y} \qquad \forall w, y, s, t \tag{4}$$

$$Q^{\mathrm{total}}_{k,y} = \sum_{y'=\max(1, y-\mathrm{PL}_k+1)}^{y} Q^{\mathrm{new}}_{k,y'} + \sum_{y''=\mathrm{b}_0-\mathrm{PL}_k+y+1}^{\mathrm{b}_0} Q^{\mathrm{old}}_{k,y''} \qquad \forall y \tag{5}$$

$$q_{w,k,y,s,t} - q_{w,k,y,s,t-1} \le \mathrm{RampUp}_k Q^{\mathrm{total}}_{k,y} \qquad \forall w, y, s, t \tag{6}$$

$$q_{w,k,y,s,t-1} - q_{w,k,y,s,t} \le \mathrm{RampDn}_k Q^{\mathrm{total}}_{k,y} \qquad \forall w, y, s, t \tag{7}$$

$$q_{w,k,y,s,t} \le \mathrm{Avail}_{w,k,y,s,t} Q^{\mathrm{total}}_{k,y} \qquad \forall w, y, s, t \tag{8}$$

$$\sum_{s,t} q_{w,k,y,s,t} \le \mathrm{G}^{\max}_{k,y} \qquad \forall w, y \tag{9}$$

where q_k, Q^{new}_k are independent variables and Q^{total}_k, D are intermediate variables ($Q^{\mathrm{total}}_k = \{Q^{\mathrm{total}}_{k,y}\}_y$).

For strategic player k, the objective function (2) sums the expectation of revenue, $q_{w,k,y,s,t}(\alpha_{y,s,t} - \beta_{y,s,t} D_{w,y,s,t})$, minus the operation cost, $\mathrm{c}_k q_{w,k,y,s,t}$, with probabilities of Pr_w over scenarios $w \in \mathcal{W}$, the maintenance cost, $\mathrm{m}_k Q^{\mathrm{total}}_{k,y}$, and the investment cost of new capacity, $\mathrm{inv}_k Q^{\mathrm{new}}_{k,y}$, excluding its remaining value at the end time, $\max(0, \frac{\mathrm{PL}_k + y - \mathrm{Y} - 1}{\mathrm{PL}_k}) \mathrm{inv}_k Q^{\mathrm{new}}_{k,y}$. The revenues and costs over periods $\mathcal{Y}$ are discounted with respect to a specific base year b_0 assuming discount rate $\mathrm{r}(\%/\Delta \mathrm{Y}_y)$. However, for a perfectly competitive player, the objective function has additional term $\frac{\beta_{y,s,t}}{2} q^2_{w,k,y,s,t}$, which means the market surplus loss if the player k was playing strategically.

The supply/demand balance equation (3) equalizes the net consumption with the total generation. Capacity constraint (4) binds generation to its total capacity. Equality (5) (This is the modified version of capacity constraint in [16]) sums the new capacities $Q^{\mathrm{new}}_{k,y'}$ and historical ones $Q^{\mathrm{old}}_{k,y''}$ which are not retired at time y as total capacity $Q^{\mathrm{total}}_{k,y}$. Constraints (6) and (7) respect the ramping up and down limits of the generator. Period-by-period power availability limit applicable to all generators especially intermittent wind turbines is shown in (8). Lastly, constraint (9) considers the inter-temporal generation limits due to planned/forced outages or fuel scarcity.

B. Carbon Price Calculation as a Dual Variable

Due to local and global concerns on greenhouse gases, there are upper bound restrictions on carbon emission each industry is producing. When fossil-fueled generators burn coal, natural gas or petroleum to produce electricity, they emit CO_2 gas as a side product. Considering the policy of pollution generation control in the market, we can calculate the desired carbon price required to achieve the environmental policy goals.

$$\sum_{w,k,s,t} \mathrm{Pr}_w \Delta \mathrm{l}_{y,s,t} \zeta_k q_{w,k,y,s,t} \le \mathrm{Cap}_y (1-\phi) \ : \ \theta_y \quad \forall y \tag{10}$$

where Cap_y is the upper limit of CO_2 (tonne) production in electricity industry during time y, and ζ_k is the CO_2 emission coefficient of generator k ($\frac{\mathrm{tonne}}{\mathrm{MWh}}$). The dual variable of constraint (10), θ_y, illustrates the target carbon price ($\frac{\$}{\mathrm{tonne}}$) at time y policy makers require to announce to achieve their environmental goals on carbon pollution control. Note that the dual variable of carbon cap constraint must be consistent in all individual profit maximization problems of all players in NE point. Considering the first order optimality conditions of all individual problems (Karush-Kuhn-Tucker conditions), it can be shown that the variable θ_y is the pollution tax that carbon producer pays at time y.

C. Solving the Game as a Centralized Optimization Problem

The Bayes-NE point of the game including both strategic and perfectly competitive players at generation level with objective function and constraints of all players explained in Section (II-A) can be computed by solving the following centralized optimization problem.

$$\max_{\substack{q,Q^{\text{new}} \\ Q^{\text{total}},D \geq 0}} \sum_y \frac{1}{(1+\mathrm{r})^y} \Bigg(\sum_{w,s,t} \mathrm{Pr}_w \Delta \mathrm{l}_{y,s,t} \Big((\alpha_{y,s,t} - \frac{\beta_{y,s,t}}{2} D_{w,y,s,t}) D_{w,y,s,t} - \frac{\beta_{y,s,t}}{2} \sum_k (1-\gamma_k) q_{w,k,y,s,t}{}^2 - \sum_k \mathrm{c}_k q_{w,k,y,s,t} \Big) - \mathrm{m}_k \Delta \mathrm{Y}_y Q^{\text{total}}_{k,y} - \sum_k \mathrm{inv}_k Q^{\text{new}}_{k,y} \Bigg) + \frac{1}{(1+r)^{\mathrm{Y}}} \sum_k \max(0, \frac{\mathrm{PL}_k + y - \mathrm{Y} - 1}{\mathrm{PL}_k}) \mathrm{inv}_k Q^{\text{new}}_{k,y} \tag{11}$$

s.t.

$(3) - (10) \quad \forall k$

where q, Q^{new} are independent variables and Q^{total}, D are intermediate variables.

The objective function (11) sums the total surpluses of demand and supply in the market minus the market surplus loss regarding the suppliers' strategic behaviors. The centralized optimization problem is subjected to the constraints of all individual players' profit maximization problems.

In this paper, the centralized quadratic optimization problem is solved to find the NE point of the game. However, it is possible to write the KKT conditions of individual profit maximization problems and solve it as a Linear Complementarity Problem in distributed fashion.

III. Numerical Analysis

For illustrative purposes, we numerically investigate a single-node hypothetical system comprising three generation firms- coal, gas, and wind- planning for capacity installation during next 25 years, including 5 time steps ($\Delta \mathrm{Y}_y$=5 years), consisting of peak ($\Delta \mathrm{T}_{\text{peak}}$=4 hours a day), shoulder ($\Delta \mathrm{T}_{\text{shoulder}}$=10 hours a day) and off-peak ($\Delta \mathrm{T}_{\text{off-peak}}$=10 hours a day) load zones for a whole year (ΔS=365 days a year). The parameters for the inverse demand function (1) are listed in Table III, which indicate the highest values for α and the lowest values for β at peak load zones. Assuming electricity demand increases over years, the parameter α is raised with rate of 5% every 5 years.

Considering investment, maintenance, operation and fuel costs in addition to life time of technologies and their ramping up and down specifications, listed in Table IV [17], the generation firms decide on participating in the market. The parameter γ is zero for coal and gas-fueled generators, which shows they play strategically, and is one for the wind firm, which means that it plays perfectly competitively.

TABLE III
THE PARAMETERS FOR THE INVERSE DEMAND FUNCTION.

	t \ y (5-years)	1	2	3	4	5
$\alpha_{y,t}$	peak	240	252	264	277	291
	shoulder	200	210	220	231	243
	off-peak	160	168	176	185	194
$\beta_{y,t}$	peak	.08	.08	.08	.08	.08
	shoulder	.1	.1	.1	.1	.1
	off-peak	.12	.12	.12	.12	.12

TABLE IV
COSTS AND TECHNOLOGY SPECIFICATIONS OF GENERATION FIRMS.

firms	Investment (\$/KW)	Maintenance $(\frac{\$/\text{KW}}{\text{yr}})$	Operation & Fuel (\$/KWh)	Plant Life (5years)	RampUp & Dn
coal	2500	25	0.015	8	0
gas	1000	10	0.055	6	0.9
wind	3000	30	0	4	1

The base values for wind power availability is assumed 40% at off-peak times, 30% at shoulder times, and 10% at peak times. In wind availability scenarios, wind power availability is assumed to vary σ% above and under its base values as shown in Figure 1.

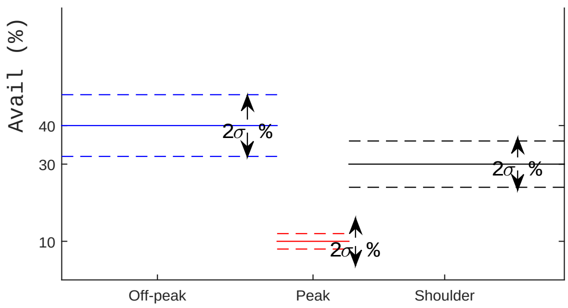

Fig. 1. Normalized wind capacity availability (Avail) during off-peak, shoulder, and peak load zones, distributed on [(1-σ)E(Avail), (1+σ)E(Avail)] with the given expected value E(Avail) .

Employing the commercial solver CONOPT in GAMS software [18], the centralized quadratic optimization problem is solved with the mentioned input data to calculate the Bayes-NE point of the game.

A. Carbon Cap Effect on Capacity Planning

Total carbon production of the system without any pollution control policy is calculated in our model based on the emission factors of 0.93 tonne_{CO_2}/MWh for coal and .55 tonne_{CO_2}/MWh for gas as listed in Table V.

The simulation is repeated for two different values of carbon cap percentage $\phi \in \{20, 40\%\}$ and compared with no carbon

TABLE V
TOTAL CO_2 PRODUCED EVERY FIVE YEARS IN THE SYSTEM WITH NO POLLUTION CONTROL POLICY.

y (5-years)	1	2	3	4	5
Cap_y (million_tonne)	31.8	33.0	34.3	35.6	37.0

cap scenario in Figure 2. Total carbon production in the system becomes restricted to a part of no policy pollution values using constraint (10) in the game model. Restricting the carbon production in the system leads to more investment on renewables and less on fossil-fueled power plants, especially coal stations. The observed price increase is the reason motivating renewables to invest in capacity expansion taking into account the carbon cap constraint in the game.

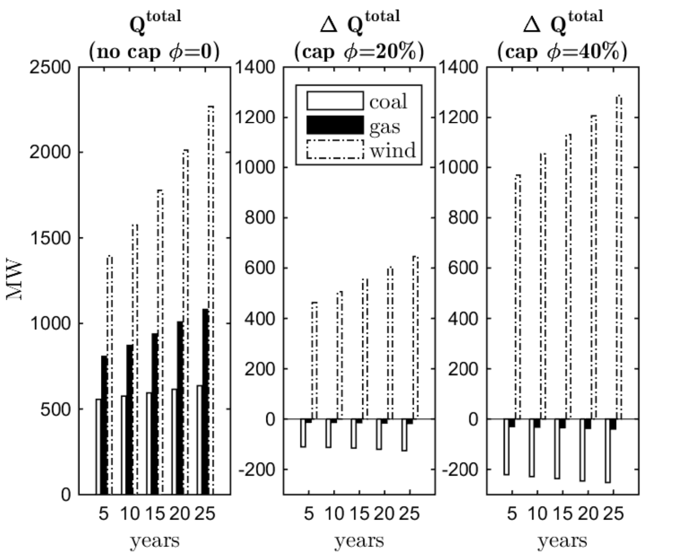

Fig. 2. Capacity investment Q^{total} and its change ΔQ^{total} due to carbon cap constraint with coefficient $\phi \in \{20, 40\%\}$.

B. Wind Stochasticity Effect on Carbon Price

The dual variable of the carbon cap constraint in our model calculates the carbon price. Policy makers can announce it to power plants as a tax to make them meet the pollution policies. Stochasticity arising from intermittent generators impacts the values of carbon price. Figure 3 represents the calculated carbon price at every five-year period respectively for $\phi \in \{20\%, 60\%, 100\%\}$ carbon emission reduction policies in two scenarios of deterministic ($\sigma = 0$) and stochastic ($\sigma = 60\%$) wind power availability. It is observed from the simulation results that the stricter the pollution reduction policy, the higher the carbon price, and the higher the intermittency, the higher the required carbon price to meet the carbon cap constraint.

C. Wind Player's Strategy Effect on Capacity Planning

We compare the capacity planning of all generators when wind firm participating in the market is strategic or perfectly competitive. The player representing all wind turbines in our

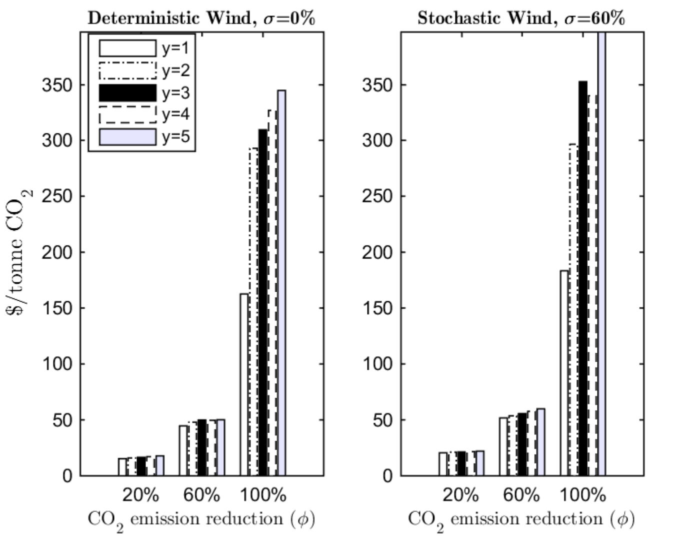

Fig. 3. Carbon pricing for different CO_2 emission reduction scenarios ($\phi \in \{20\%,60\%,100\%\}$).

model is a profit maximizer (fringe) player for the strategic (perfectly competitive) case. When the strategic case is compared to the perfectly competitive one, it is observed that proportionally the coal firm adds more capacity, the gas firm slightly decreases its new capacity decisions, and the wind player strategically reduces its new capacity investment plan, as is shown in Figure 4.

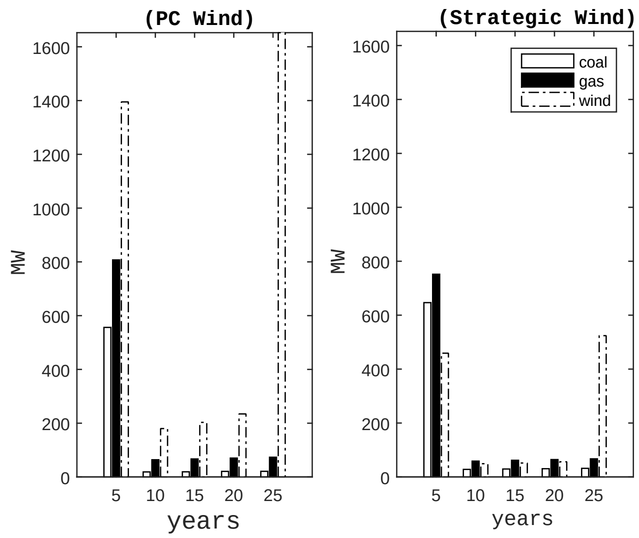

Fig. 4. New capacity installation Q^{new} considering wind strategy (perfectly competitive and strategic).

D. Remaining Value Effect on Capacity Planning

Note that zero historical capacity, no incumbent plant, for the system is assumed in our simulation. We compare the effect of considering remaining value of technologies on their investment decisions. Figure 5 indicates that ignoring the remaining values biases the new capacity installation decisions. In fact, it leads to installation decisions in earlier periods. The reason is that without considering the remaining values a firm cannot return its investment cost during the study period if it decides to add installations at the end.

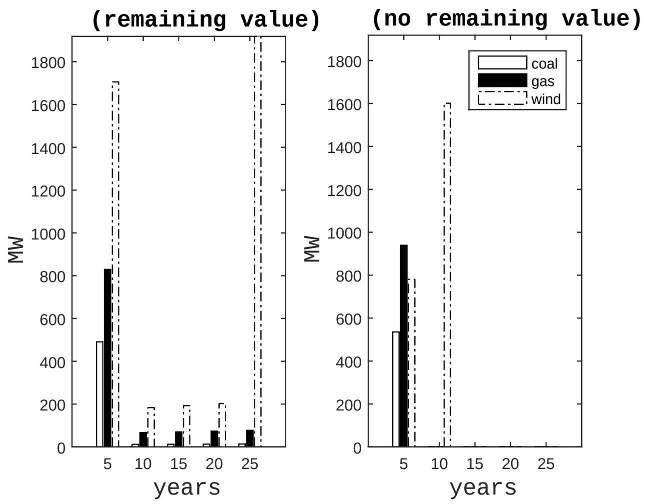

Fig. 5. New capacity installation considering remaining value.

Considering the remaining values, the coal firm and the gas firm install their new capacities almost in the first period, but the wind firm renews its capacity in the fifth period as its technology retires after four periods. Further technological maturity of renewable technologies, i.e., achieving longer plant life, would lessen their annualized investment cost and increase their competitiveness in the market.

IV. Conclusion

New capacity expansion is dependent on the market price expectation, and renewables availability can affect the wholesale price significantly. Moreover, policy makers can intervene in the market via setting tax on carbon production to meet their goals. The modeling analysis presented in this paper sheds light on the effects of carbon cap constraint on long-term capacity investment decisions of generation firms facing stochastic renewable power availability. Based on our model and simulation results, the empirical findings about the carbon cap effects on capacity expansion of the three assumed generation firms are:

- Carbon cap constraint in the game model results in proportionally more new renewable and less fossil-fueled, especially coal-fueled, capacity expansion decisions.
- Dual variable of the carbon cap constraint in our model represents the carbon price or carbon tax. Policy makers can announce it in the market as carbon production tax, which encourages to invest on more renewable capacities.
- Higher stochasticity from renewables makes them financially less attractive. Higher tax on carbon production can make renewables able to compete with fossil-fueled generators even if renewable powers intermittency increases. The difference in the carbon price can be used towards storage technologies and diversification of distributed generation as means to encounter intermittency in renewable generation.
- We intend to survey the long term investment on storage technologies and transmission lines in addition to generation technologies in a stochastic game model in our future work. In the future, storage technologies, similar to renewables, are expected to achieve longer plant life and experience high capacity expansion due to reduction in their annualized investment costs.

References

[1] A. Masoumzadeh, H. Rasekhi, and A. Fathi, “A comprehensive energy supply model in an office building based on the reference energy system,” *International Journal of Sustainable Energy*, vol. 35, no. 1, pp. 88–102, 2016.

[2] M. Jeppesen, M. Brear, D. Chattopadhyay, C. Manzie, R. Dargaville, and T. Alpcan, “Least cost, utility scale abatement from australia’s NEM (national electricity market). part 1: Problem formulation and modelling,” *Energy*, vol. 101, pp. 606 – 620, 2016.

[3] A. G. Kagiannas, D. T. Askounis, and J. Psarras, “Power generation planning: a survey from monopoly to competition,” *International Journal of Electrical Power & Energy Systems*, pp. 413–421, 2004.

[4] R. Loulou, U. Remne, A. Kanudia, A. Lehtila, and G. Goldstein, “Documentation for the times model part i,” Energy Technology Systems Analysis Programme, Tech. Rep., 2005.

[5] W. El-Khattam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama, “Optimal investment planning for distributed generation in a competitive electricity market,” *IEEE Transactions on Power Systems*, vol. 19, no. 3, pp. 1674–1684, Aug 2004.

[6] W. Jing-Yuan and Y. Smeers, “Spatial oligopolistic electricity models with cournot generators and regulated transmission prices,” *Operations Research*, vol. 47, no. 1, pp. 102–112, 1999.

[7] A. Masoumzadeh, D. Möst, and S. C. Ookouomi Noutchie, “Partial equilibrium modelling of world crude oil demand, supply and price,” *Energy Systems*, pp. 1–10, 2016.

[8] A. S. Chuang, F. Wu, and P. Varaiya, “A game-theoretic model for generation expansion planning: problem formulation and numerical comparisons,” *IEEE Transactions on Power Systems*, vol. 16, no. 4, pp. 885–891, Nov 2001.

[9] M. Ventosa, R. Denis, and C. Redondo, “Expansion planning in electricity markets. two different approaches,” in *Proceedings of the 14th Power Systems Computation Conference (PSCC), Seville*, 2002.

[10] D. Chattopadhyay and T. Alpcan, “A game-theoretic analysis of wind generation variability on electricity markets,” *Power Systems, IEEE Transactions on*, vol. 29, no. 5, pp. 2069–2077, Sept 2014.

[11] D. Chattopadhyay, “Modeling greenhouse gas reduction from the australian electricity sector,” *Power Systems, IEEE Transactions on*, vol. 25, no. 2, pp. 729–740, May 2010.

[12] D. Chattopadhyay and T. Alpcan, “Capacity and energy-only markets under high renewable penetration,” *Power Systems, IEEE Transactions on*, vol. PP, no. 99, pp. 1–11, 2015.

[13] S. Wogrin, E. Centeno, and J. Barquin, “Generation capacity expansion in liberalized electricity markets: A stochastic mpec approach,” *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2526–2532, Nov 2011.

[14] L. Wang, M. Mazumdar, M. D. Bailey, and J. Valenzuela, “Oligopoly models for market price of electricity under demand uncertainty and unit reliability,” *European Journal of Operational Research*, vol. 181, no. 3, pp. 1309 – 1321, 2007.

[15] J. C. Harsanyi, “Games with incomplete information played by ”bayesian” players, i-iii. part ii. bayesian equilibrium points,” *Management Science*, vol. 14, no. 5, pp. 320–334, 1968. [Online]. Available: http://www.jstor.org/stable/2628673

[16] Y. Saboohi, “Energy supply model: Esm 84,” Sharif Energy Research Institute (SERI), Tech. Rep., 2005.

[17] EIA, “Updated capital cost estimates for utility scale electricity generation plants,” U.S. Department of Energy, Tech. Rep., April 2013.

[18] A. S. Drud, “CONOPT a large-scale GRG code,” *ORSA Journal on Computing 6*, p. 207216, 1992.