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.

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

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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 the 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., 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 $k \in K = \{1, \ldots, K\}$ be in the set of generation firms (generators) participating in the electricity market, $y \in Y = \{1, \ldots, Y\}$ be in the set of times with length of $\Delta Y_y$ (yr), $s \in S = \{1, \ldots, S\}$ be in the set of load zones (like seasons in a year) with length of $\Delta S_s$ (yr), $t \in T = \{1, \ldots, T\}$ be in the set of sub-load zones (like off-peak, shoulder and peak times in a day) with length of $\Delta T_t$ (hr), and $w \in W$ 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 $\Delta l_{y,s,t} = \Delta Y_y \Delta S_s \Delta T_t$ hours.

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

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

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

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

(1)

where $D_{w,y,s,t}$ is the total electricity demand at time $(y, s, t)$. Players in the market are categorized into two groups:
\[ Q_{k,y}^{\text{total}} = \sum_{w} y'=\max(1, -PL_y + 1) \sum_{y'}\left( y'' - b_{y''} - PL_y + 1 \right) \]

\[ q_{w,k,y,s,t} \leq Q_{k,y}^{\text{total}} \forall w, y, s, t \]  

\[ Q_{k,y}^{\text{new}} = \sum_{y} y' q_{w,k,y}^{\text{new}} \forall y \]

\[ q_{w,k,y,s,t} \leq Q_{k,y}^{\text{total}} \forall w, y, s, t \]  

\[ q_{w,k,y,s,t} - q_{w,k,y,s,t-1} \leq \text{RampUp}_k Q_{k,y}^{\text{total}} \forall w, y, s, t \]

\[ q_{w,k,y,s,t-1} - q_{w,k,y,s,t} \leq \text{RampDn}_k Q_{k,y}^{\text{total}} \forall w, y, s, t \]

\[ q_{w,k,y,s,t} \leq \text{Avail}_w k, y, s, t Q_{k,y}^{\text{total}} \forall w, y, s, t \]

\[ \sum_{w,k,y,s,t} q_{w,k,y,s,t} \leq Q_{k,y}^{\text{max}} \forall w, y, s, t \]

where \( q_{w,k,y,s,t} \) and \( Q_{k,y}^{\text{new}} \) are independent variables and \( Q_{k,y}^{\text{total}}, D \) are intermediate variables \((Q_{k,y}^{\text{total}} = (Q_{k,y}^{\text{total}}) y)\).

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, \( c_k q_{w,k,y,s,t}, \) with probabilities of \( Pr_w \) over scenarios \( w \in W \), the maintenance cost, \( m_k Q_{k,y}^{\text{new}}, \) and the investment cost of new capacity, \( \text{inv}_k Q_{k,y}^{\text{new}}, \) excluding its remaining value at the end time, \( \max(0, \text{inv}_k Q_{k,y}^{\text{new}}, \text{inv}_k Q_{k,y}^{\text{new}}). \) The revenues and costs over periods \( Y \) are discounted with respect to a specific base year \( b_0 \) assuming discount rate \( r(\% / \Delta Y_y) \). However, for a perfectly competitive player, the objective function has additional term \( \frac{\gamma_k}{2} q_{w,k,y,s,t}^2 \), 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 \( Q_{k,y}^{\text{new}}, \) and historical ones \( Q_{k,y}^{\text{old}} \), which are not retired at time \( y \) as total capacity \( Q_{k,y}^{\text{total}}. \) 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 CO2 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.

\[ \sum_{w,k,y,s,t} Pr_w \Delta y_{s,t} \text{Cap}_y \leq \text{Cap}_y (1 - \phi) : \theta_y \forall y \]

where \( \text{Cap}_y \) is the upper limit of CO2 (tonne) production in electricity industry during time \( y \), and \( \text{Cap}_y \) is the CO2 emission coefficient of generator \( k \left( \frac{\text{CO2 \ (tonne)}}{\text{MW}} \right) \). The dual variable of constraint (10), \( \theta_y \), illustrates the target carbon price \( (\frac{\text{\$}}{\text{tonne}}) \) at time policy makers require 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 \( \theta_{y} \) 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.

\[
\max_{q, Q_{\text{new}}^{\text{on}}, D > 0} \sum_{y, s, t} \frac{1}{(1 + r)^y} \left( \sum_{w, k, y} P_{rw} \Delta y_{w, k, y, s, t} \left( \alpha_{y, s, t} - \frac{\beta_{y, s, t} D_{w, y, s, t}}{2} D_{w, y, s, t} - \frac{\beta_{y, s, t}}{2} \sum_{k} (1 - \gamma_{k}) q_{w, k, y, s, t}^2 - \sum_{k} c_{k} q_{w, k, y, s, t} \right) \right) - m_{k} \Delta Y_{y} Q_{\text{total}}^{\text{on}}(y) - \sum_{k} \delta_{y, s, t} Q_{k, y}^{\text{new}} + \frac{1}{(1 + r)^y} \sum_{k} \max(0, PL_{k} + y - Y - 1) inv_{k} Q_{k, y}^{\text{new}} \right)
\]

\[
\text{s.t.} \quad (3) - (10) \quad \forall k
\]

where \( q, Q_{\text{new}}^{\text{on}} \) are independent variables and \( Q_{\text{total}}, D \) are intermediate variables.

The objective function (11) sums the total surpluses of demand 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 (\( \Delta T_{y}=5 \) years), consisting of peak (\( \Delta T_{\text{peak}}=4 \) hours a day), shoulder (\( \Delta T_{\text{shoulder}}=10 \) hours a day) and off-peak (\( \Delta T_{\text{off-peak}}=10 \) hours a day) load zones for a whole year (\( \Delta D=365 \) days a year). The parameters for the inverse demand function (1) are listed in Table III, which indicate the highest values for \( \alpha \) and the lowest values for \( \beta \) at peak load zones. Assuming electricity demand increases over years, the parameter \( \alpha \) 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 \( \gamma \) is zero for coal and gas-fueled generators, which shows how they play strategically, and is one for the wind firm, which means that it plays perfectly competitively.

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>THE PARAMETERS FOR THE INVERSE DEMAND FUNCTION.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_{y, t} )</td>
<td>peak 240 252 264 277 291</td>
</tr>
<tr>
<td></td>
<td>shoulder 200 210 220 231 243</td>
</tr>
<tr>
<td></td>
<td>off-peak 160 168 176 185 194</td>
</tr>
<tr>
<td>( \beta_{y, t} )</td>
<td>peak .08 .08 .08 .08 .08</td>
</tr>
<tr>
<td></td>
<td>shoulder .1 .1 .1 .1 .1</td>
</tr>
</tbody>
</table>

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 \( \sigma \% \) above and under its base values as indicated in Figure 1.

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

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\( \text{CO}_2 \)/MWh for coal and .55 tonne\( \text{CO}_2 \)/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.

<table>
<thead>
<tr>
<th>$y$ (5-years)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Cap}_y$ (million tonne)</td>
<td>31.8</td>
<td>33.0</td>
<td>34.3</td>
<td>35.6</td>
<td>37.0</td>
</tr>
</tbody>
</table>

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.

**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 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.

**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.

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


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.
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