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The impact of market design and clean energy incentives on strategic generation investments and resource adequacy in low-carbon electricity markets

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ABSTRACT

Well-designed electricity markets play a crucial role in maintaining reliable electric power systems, which are critical in modern society. This study examines the impact of different electricity market designs and clean energy incentive schemes on supporting renewable energy integration and achieving clean energy goals. To this end, we utilize a game-theoretical generation expansion planning model where generation companies make investment and retirement decisions to maximize their expected profit. The model is structured as an equilibrium problem with equilibrium constraints (EPEC) and solved using a diagonalization approach combined with progressive hedging. We analyze three types of electricity market designs: an energy-only market, a capacity market, and a clean energy market, and consider a wide range of market parameters resulting in 14 total scenarios. Wind and solar capacity comprise the majority of new investments in all considered scenarios, but the resultant system planning reserve margin (PRM) can differ significantly depending on market parameters. We also find that profit-driven investments lead to lower PRMs than a traditional system cost minimization approach. These individual scenario results further demonstrate how different market designs and clean energy incentive schemes may influence investor decision-making and impact resource adequacy throughout the clean energy transition.

Introduction

Maintaining reliable electric power systems is critical in modern society, especially given the increasing electrification of other sectors such as transportation and industry. Meanwhile, the power industry is facing a rapid evolution driven by recent technical advancements, increasing penetrations of variable renewable energy (VRE), e.g., wind and solar, and energy storage (ES) resources, increasing interdependence with other energy systems, and increasing intensity and frequency of extreme weather events caused by a changing climate. These challenges increase the complexity of power system planning while also highlighting the critical importance of designing systems that can deliver reliable, clean, and affordable electricity to consumers.

Generation expansion planning (GEP) models have been widely developed and applied in power system planning studies to assess future generation portfolios in terms of their economic impacts, resultant resource adequacy and reliability, while also analyzing the implications of different policies and regulations. Least-cost optimization-based GEP models are commonly used to determine optimal investments and retirements in generation resources of different types, sizes, and locations, while also maintaining a target reliability standard and satisfying various techno-economic constraints [1]. Least-cost GEP models are often used by vertically integrated utilities that own both the generation resources and the transmission infrastructure in a given region and conduct their own expansion planning through integrated resource planning studies. However, in the U.S., seven independent system operators (ISOs) and regional transmission organizations (RTOs) operate bulk electric power systems that collectively serve more than two-thirds of the electricity demand in the country. In these regions, the power systems are operated through a set of wholesale markets that match competitive supply offers with demand on an hourly or sub-hourly basis,

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Nomenclature

Sets and Indices

$d \in D$ Set of representative days
$g \in G$ Set of generator technologies
$k \in K$ Set of transmission lines
$n \in N$ Set of transmission nodes
$t \in T$ Set of time periods
$\Psi_u \in G$ Set of generators owned by actor u
$\Psi_u^{ES} \in G$ Set of energy storage generators (including pumped storage hydropower) owned by actor u

Parameters

C_g^{OP} Variable operating and maintenance cost of generator g
C_g^{RU} Reserve up cost of generator g
C_g^{RD} Reserve down cost of generator g
$\overline{ce}_g^+$ Annual expected power generation generator g
D_h^{CE} Clean energy market demand curve price for segment h
D_h^{+CE} Clean energy market demand curve step size for segment h
D_i^C Capacity market demand curve price for segment i
D_i^{+C} Capacity market demand curve step size for segment i
D_{nt} Real power demand at node n, in period t
DS_{ntd} Load shedding limit at node n, in period t, in day d
F_k^+ Thermal rating of transmission line k
N_g^0 Existing number of units of generator g
P_{ntl}^{ens} Cost of load shedding at node n, in period t for segment l
P_o^{RSU} Penalty price for reserve up shortage for segment o
P_r^{RSD} Penalty price for reserve down shortage for segment o
P_g^+ Maximum output of generator (nameplate capacity)g
P_g^0 Existing number of units of generator g
RSU_{tdo} Step size of reserve up shortage in period t, in day d, for segment o
RSD_{tdr} Step size of reserve up shortage in period t, in day d, for segment r
RU_{td}^{req} Reserve up requirement in period t, in day d
RN_{td}^{req} Reserve down requirement in period t, in day d
R_g Reserve provision capability of generator g in percent
RT_g^+ Maximum number of units for retirement of generator g
S_g^+ Maximum state-of-charge level of energy storage generator g
X_g^+ Maximum number of units for investment of generator g
δ_{gt} Annual renewable generation forecast factor of generator g, in period t
η_g^C Charging efficiency of energy storage generator g
η_g^D Discharging efficiency of energy storage generator g
ω_g Capacity credit of generator g in capacity market

Variables:

c_g Capacity market clearing quantity of generator g
ce_g Clean energy market clearing quantity of generator g
d_i^C Capacity market clearing quantity of demand segment i
d_h^{CE} Clean energy market clearing quantity of demand segment h
f_{ktd} Power flow on transmission line k, in period t, in day d
ls_{ntdl} Load shedding at node n, in period t, in day d, for segment l
pc_{gtd} Charging power of energy storage generator g, in period t, in day d
p_{gtd} Power output of generator g, in period t, in day d
r_{gtd}^{up} Procured reserve up of generator g, in period t, in day d
r_{gtd}^{dn} Procured reserve down of generator g, in period t, in day d
rs_{tdo}^{up} Reserve up shortage in period t, in day d, for segment o
rs_{tdr}^{dn} Reserve down shortage in period t, in day d, for segment r
rt_g Capacity retirement decision of generator g (integer)
s_{gtd} State-of-charge level of energy storage generator g, in period t, in day d
x_g Capacity investment decision of generator g (integer)
λ^C Capacity market clearing price
λ^{CE} Clean energy market clearing price
λ_{ntd}^E Energy market clearing price at node n, in period t, in day d,
$\lambda_t^{R_{up}}$ Reserve up market clearing price in period t, in day d
$\lambda_t^{R_{dn}}$ Reserve down market clearing price in period t, in day d

generating corresponding locational marginal prices in each dispatch period. At the same time, the ISO/RTOs are responsible for maintaining reliability within their systems. Since ISOs and RTOs don't own generation and transmission assets, long-term resource adequacy is primarily achieved by incentivizing efficient investments from profit-seeking generating companies (GenCos) through market signals and policy incentives. GenCos are not responsible for system reliability, but rather strategically plan their own portfolios to maximize profit based on expected revenue from participating in wholesale markets.

Therefore, electricity market design plays a crucial role in incentivizing efficient market entry and exit and maintaining both long-term and short-term system reliability in these systems. There is a growing body of literature that examines how well-functioning electricity markets contribute to ensuring resource adequacy [2,3,4,5]. The existing studies have primarily used least-cost GEP or production cost models and highlights the importance of utilizing additional models and tools to examine the effectiveness of current wholesale market designs and investigate how potential future market designs and environmental policies could shape future generation portfolios in a market environment. Understanding the investment decision-making of profit-seeking GenCos under a competitive (but policy-constrained) market framework requires a market-based GEP model that can analyze interactions between market participants (i.e., GenCos), wholesale markets, and renewable energy policies. The modeling of strategic interactions between competing profit-seeking entities in the context of power system expansion planning has been investigated in the literature. The most common approach is using a game-theory concept, as comprehensively explained in [6]. In [7]-[8], bi-level models are introduced to simulate the strategic interactions of GenCos in generation and transmission expansion planning within a non-cooperative framework. The bi-level models are converted to a mathematical program with equilibrium constraints (MPEC) by replacing the lower-level optimization problems with a set of equilibrium constraints using the Karush-Kuhn-Tucker (KKT) conditions or a Primal-Dual reformulation approach. Then the collection of the MPECs of each GenCo represents the non-cooperative gaming framework and defines an equilibrium problem with equilibrium constraints (EPEC). In [9]-[10], the Strategic Capacity Investment Model (SCIM) is proposed. In this study, we expand on the SCIM model, which considers markets for capacity, energy, and ancillary services. Recently, the studies in [11]-[12] proposed stochastic bi-level models to analyze regulatory competition between regions. In addition to the bi-level modeling approach, agent-based modeling approaches have also been applied in [13,14], and [15] to analyze strategic interactions between investors in electricity markets.

This work draws inspiration from a review that identified market challenges and research opportunities in wholesale electricity market design, which was led by a team of five research institutions within the U.S. Department of Energy (DOE) Grid Modernization Laboratory Consortium [16].[1] To this end, we investigate the impact of the different wholesale market designs surveyed in [16] on near-term investment decisions made by profit-seeking GenCos and analyze the resulting system generation portfolios using SCIM, a market-based GEP model [10]. This work makes four primary contributions to the literature. First, we extend the market-based GEP model, SCIM, to include a forward clean energy market. Second, we consider potential investments in ES technologies and introduce a representation of energy storage with time-coupling constraints to dictate state-of-charge management. Third, we propose and implement a new and enhanced solution technique to solve an EPEC problem using a progressive hedging algorithm. Four, as a case study, we use the enhanced modeling framework to examine the effectiveness of various wholesale market designs and highlight the importance of well-designed wholesale markets in promoting efficient new investments and maintaining a proper level of resource adequacy in rapidly evolving power systems.

Methods

Modeling framework

This paper analyzes the impact of different market designs on future generation portfolios when considering the strategic investment and retirement decisions of profit-seeking GenCos. To this end, we apply SCIM, a model formulated as a Stackelberg Leader-follower game that simulates GEP while capturing the strategic interactions between profit-maximizing GenCos in their portfolio optimization decisions (Fig 1.). The portfolio optimization model of a single profit-seeking GenCo in SCIM determines its optimal investment and retirement decisions based on anticipated revenues from forward and spot markets in which market parties submit cost-based bids assuming effective short-run market power mitigation. This model is formulated as a hierarchical bi-level optimization problem to represent Stackelberg Leader-follower games. In the bi-level model structure for an individual GenCo, the strategic upper-level optimization problem for the investment and retirement decision-making is constrained by the lower-level optimization problems that represent clearing of forward and spot markets. The spot markets are assumed to be functionally competitive as a result of effective market power mitigation; since the 2000 California power crisis, market monitors report that US ISO-based markets have experienced spot market prices at or near competitive levels [18]. The modeled hierarchical structure assumes that a GenCo makes a capacity expansion and retirement decision while anticipating that these decisions will influence market outcomes, but the markets take the investment and retirement decisions as given parameters. Furthermore, we assume that each GenCo takes other GenCos' investment and retirement decisions as given exogenous parameters (à la Nash) in making their own portfolio optimization decision. The goal of SCIM is to find a Nash equilibrium (in investment strategies) among the multiple GenCo portfolio optimization models, subject to competitive spot markets (as in [7]). In this study, we use an Enhanced Diagonalization Method (EDM) to find a Nash Equilibrium, the details of which will be further discussed in the following section. While we examine the relative impact of various market design configurations on the investment decision-making of profit-seeking entities, we do not attempt to prove that any specific market designs can promote a socially optimal generation mix. Similarly, our model applications and case studies are exploratory and should not be interpreted as providing any subjective judgement regarding what will or should happen in the future.

Electricity market designs

In this section, we briefly describe the market mechanisms that are considered in our analysis, particularly focusing on capacity remuneration mechanisms (CRMs). There are different types of CRMs, including a centralized capacity market, strategic reserves, and a capacity obligation [19]. In the U.S., all seven wholesale markets compensate resources for providing energy and ancillary services, while only ERCOT in Texas does not have a formal CRM, choosing instead to rely on an "energy-only" framework with scarcity pricing in its real-time spot market. The remaining six wholesale markets compensate resources for providing capacity through centralized capacity markets or capacity obligation programs, as summarized in [20]. Therefore, we consider both an energy-only market framework and a capacity market in this study. In addition, we introduce a forward clean energy market, a concept that was recently proposed in [21]. The modeled market designs are briefly described below:

Energy and ancillary services market

We model a daily energy and ancillary services market using a transmission-constrained economic dispatch formulation, which determines hourly plant-level dispatch setpoints and ancillary service procurements while minimizing the total system-wide operating costs. We formulate the energy and ancillary services market, for each representative day d, as:

$$\begin{aligned}\underset{\Phi_d^{EAS}}{\text{Min}}\sum_{gt}\left(C_g^{OP}p_{gtd}+C_g^{RU}r_{gtd}^{up}+C_g^{RD}r_{gtd}^{dn}\right)+\sum_{nt}P_{nt}^{ens}ls_{ntd}+\sum_{to}P_o^{RSU}rs_{tdo}^{up}\\+\sum_{tr}P_r^{RSD}rs_{tdr}^{dn}\end{aligned}\tag{1.1}$$

Subject to:

$$\sum_{k(n,)}f_{ktd}-\sum_{k(,n)}f_{ktd}+\sum_{\forall\Omega_G^n}p_{gtd}-\sum_{\forall\Omega_{ES}^n}pc_{gtd}+ls_{ntd}=D_{ntd}:\lambda_t^E\quad\forall n,t,d\tag{1.2}$$

$$-f_{ktd}\geq-F_k^+\forall k,t,d\tag{1.3}$$

$$f_{ktd}\geq-F_k^+\forall k,t,d\tag{1.4}$$

$$-p_{gtd}-r_{gtd}^{up}\geq-\delta_{gtd}(P_g^+(x_g-rt_g)+P_g^0)\forall g,t,d\tag{1.5}$$

$$p_{gtd}-r_{gtd}^{dn}\geq0\forall g\notin\Psi^{ES},t,d\tag{1.6}$$

$$-r_{gtd}^{up}\geq-R_g(P_g^+(x_g-rt_g)+P_g^0)\forall g,t,d\tag{1.7}$$

$$-r_{gtd}^{dn}\geq-R_g(P_g^+(x_g-rt_g)+P_g^0)\forall g,t,d\tag{1.8}$$

$$\sum_{g(z)}r_{gtd}^{up}+\sum_o rs_{tdo}^{up}=RU_{td}^{req}:\lambda_t^{R_{up}}\forall t,d\tag{1.9}$$

$$\sum_{g(Z)}r_{gtd}^{dn}+\sum_r rs_{tdr}^{dn}=RN_{td}^{req}:\lambda_t^{R_{dn}}\forall t,d\tag{1.10}$$

$$-rs_{tdo}^{up}\geq-RSU_{tdo}\forall t,o,d\tag{1.11}$$

$$-rs_{tdr}^{dn}\geq-RSD_{tdr}\forall t,r,d\tag{1.12}$$

$$-ls_{ntd}\geq-DS_{ntd}\forall n,t,d\tag{1.13}$$

$$s_{gtd}-s_{g,t-1,d}-\eta_g^C pc_{gtd}+\frac{1}{\eta_g^D}p_{gtd}=0\forall g\in\Psi^{ES},t,d\tag{1.14}$$

[1] Other work within this project focuses on improving resource adequacy modeling methods [16] and reviewing energy and reserve scarcity pricing mechanisms in the United States [17].

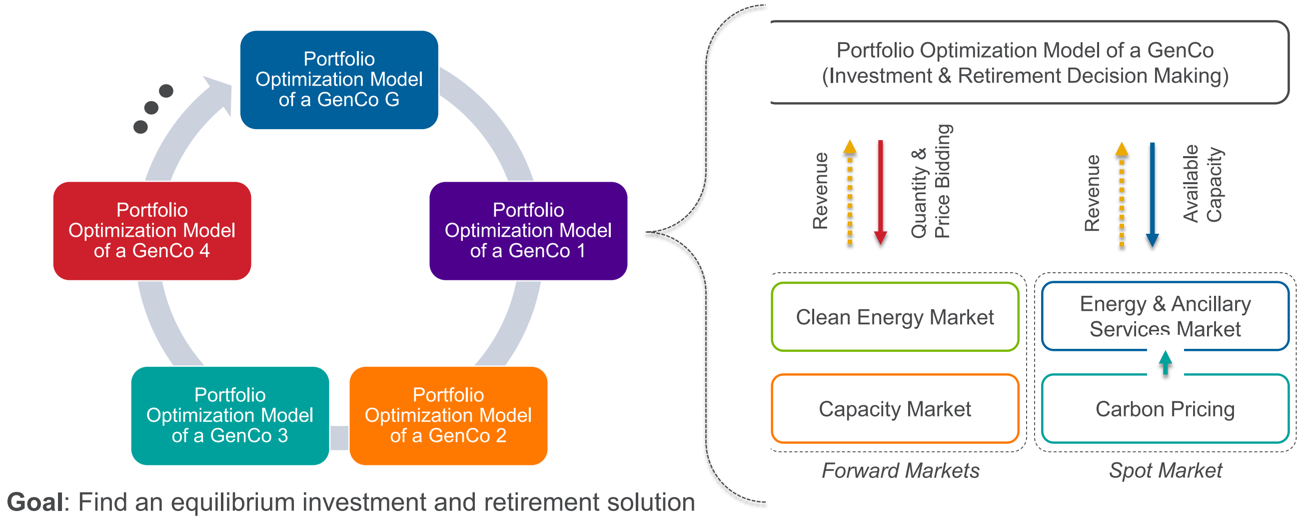

Fig. 1. Overview of the multi-leader multi-follower Stackelberg game modeled in the Strategic Capacity Investment Model.

$$-s_{gtd} - \eta_g^C r_{gtd}^{dn} \geq -S_g^+ \left(x_g - rt_g + N_g^0\right) \forall g \in \Psi^{ES}, t, d \tag{1.15}$$

$$s_{gtd} - \frac{1}{\eta_g^D} r_{gtd}^{up} \geq 0 \forall g \in \Psi^{ES}, t, d \tag{1.16}$$

$$s_{gTd} = 0 \forall g \in \Psi^{ES}, d \tag{1.17}$$

$$-pc_{gtd} - r_{gtd}^{dn} \geq -(P_g^+(x_g - rt_g) + P_g^0) \forall g \in \Psi^{ES}, t, d \tag{1.18}$$

where $\Phi_d^{EAS} = \left\{\left(p_{gtd}, pc_{gtd}, r_{gtd}^{up}, r_{gtd}^{dn}, ls_{ntd}, rs_{tdo}^{up}, rs_{tdr}^{dn}\right) \geq 0; (\lambda_t^E, \lambda_t^{R_{up}}, \lambda_t^{R_{dn}}) : free\right\}$. The objective function (1.1) minimizes the total operating costs and cost of load shedding and reserve shortages. The equality constraint (1.2) enforces the power balance between generation and consumption in each time segment. Transmission limitations are imposed by the power flow constraints (1.3)–(1.4). The set of inequality constraints in (1.5)–(1.8) enforce the power output and ramping limits of generators. We use unforced capacity (UCAP) as the maximum capacity of generators in the energy and ancillary service markets to reflect the mean effect of unforced outages of the resources. For simplicity, we consider two generic types of reserves: 1) reserve-up and 2) reserve-down. The reserve-up product reflects the operating reserve requirements for regulation-up, spinning, and non-spinning reserves. The reserve-down product models the capability for regulation-down service. In addition, the reserves markets include an operating reserve demand curve (ORDC) with a price cap, which reflects the value of operating reserves for the system, as shown in (1.9)–(1.12). Similarly, energy prices are set to an administrative value of lost load if involuntary demand curtailment occurs in (1.13). The operation of energy storage is bounded by the state-of-charge balance constraint (1.14) and generator power output as well as ramping constraints (1.15)–(1.18). We assume that the energy and ancillary services market is fully competitive. All generators offer their full capacity at their marginal costs to isolate the assessment of market design effectiveness in incentivizing new investments from the issue of spot market failure. However, the market clearing price could still be higher than marginal cost of the most expensive unit because the ORDC considers the possibility of reserve scarcity events and associated scarcity pricing. The role of energy and reserve scarcity pricing is essential in the energy-only market design because it provides peaking power plants (e.g., gas turbines), which seldom generate electricity, the possibility of recovering investment costs and thus helps incentivize investments in these units and maintain resource adequacy. Lastly, the energy and ancillary service markets consider carbon pricing in some scenarios. The carbon pricing mechanism mandates generating resources to pay a unit cost for their carbon emissions, which is reflected in their offers into both the energy market and ancillary services market.

Capacity market

A centralized capacity market is modeled as an annual auction with an administratively designed capacity demand curve. We formulate the annual capacity market as:

$$\underset{\Phi^{CM}}{Max} \sum_i D_i^C d_i^C - \sum_g \overline{B}_g^{FM} c_g \tag{2.1}$$

Subject to

$$\sum_i d_i^C - \sum_g c_g = 0 : \lambda^C \tag{2.2}$$

$$c_g = \omega_g (P_g^+(x_g - rt_g) + P_g^0) \forall g \tag{2.3}$$

$$d_i^C \leq D_i^{+C} \forall i \tag{2.4}$$

where $\Phi^{CM} = \left\{\left(d_i^C, c_g\right) \geq 0; (\lambda^C) : free\right\}$. The objective function (2.1) maximizes the difference between total of consumer surplus and producer surplus in the capacity market. The equality constraints in (2.2) ensure the clearing of the capacity market subject to the capacity market clearing conditions modeled in (2.3)–(2.4). The capacity demand curve in (2.2) reflects the desired planning reserve margin needed to meet resource adequacy requirements. Broadly, there are two types of capacity demand curves. First, as adopted by the Midcontinent Independent System Operator (MISO), the capacity demand curve can be vertical, i.e., a fixed capacity requirement regardless of cost. Other regions that have a centralized capacity market use a downward-sloping demand curve. A detailed comparison of the capacity market designs across multiple ISO/RTOs in the U.S. can be found in [20]. In our analysis, we only consider scenarios with various downward-sloping demand curves each assuming that all resources offer their total capacity, derated by predetermined capacity credits, at zero price, as shown in (2.3). That is, the capacity market is cleared based on the intersection of the capacity demand curve and the available firm capacity (i.e., the vertical supply curve) in the system. Note that we do not model so-called performance obligations, which are common in U.S. capacity markets [20], because we assume all the generators offer their full capacity in the energy and ancillary services market.

Clean energy market

Lastly, we model a clean energy market (CEM) that procures clean energy attribute credits. We follow the conceptual framework of the forward CEM that was introduced by the Brattle Group in [21] and [22]. We formulate the annual clean energy market as:

$$\underset{\Phi^{CEM}}{Max} \sum_h D_h^{CE} d_h^{CE} - \sum_g \zeta_g \overline{b}_g^{FM} ce_g \tag{3.1}$$

Subject to

$$\sum_h d_h^{CE} - \sum_g ce_g = 0 : \lambda^{CE} \tag{3.2}$$

$$d_h^{CE} \le D_h^{+CE} \forall h \tag{3.3}$$

$$ce_g \le \overline{ce}_g^{+} \forall g \tag{3.4}$$

where $\Phi^{CEM} = \left\{ \left(-d_h^{CE}, ce_g \right) \ge 0; (\lambda^{CE}) : free \right\}$. Similar to the capacity market, the objective function (3.1) maximizes the difference between total of consumer surplus and producer surplus in the clean energy market. The equality constraints in (3.2) ensure the clearing of the clean market. In our analysis, we model the CEM using a downward-sloping demand curve that reflects the social cost of carbon emissions and a clean energy procurement target in (3.3). We assume that PV, wind, nuclear, and hydro resources are all eligible to participate in the CEM, and the supply curve is constructed based on the expected annual generation of each eligible unit in (3.4). Note that we do not model many other design components proposed in [21] and [22], including possible multi-year auctions and trade of clean energy attribute credits in spot markets. Model formulation

Strategic Capacity Investment Model Formulation

This section presents the portfolio optimization formulation of each profit-seeking GenCo in SCIM. The foundation of the presented model can be found in [9]-[10]. We formulate a bi-level optimization problem as:

$$\underset{\Xi^U, \Phi^{EAS}, \Phi^{CM}, \Phi^{CEM}}{Max} \omega \{ f^{EAS}(x_g, rt_g, \Phi^{EAS}) + f^{CM}(x_g, rt_g, \Phi^{CM}) + f^{CEM}(x_g, rt_g, \Phi^{CEM}) - C(x_g, rt_g) \} \tag{4.1}$$

Subject to:

$$x_g \le X_g^{+} \forall g \in \Psi_u \tag{4.2}$$

$$rt_g \le RT_g^{+} \forall g \in \Psi_u \tag{4.3}$$

Energy and Ancillary Services Market: Eq. (1.1)–(1.18) (4.4)

Capacity Market: Eq. (2.1)–(2.4) (4.5)

Clean Energy Market: Eq. (3.1)–(3.4) (4.6)

The objective function (4.1) maximizes the sum of the GenCo's annual profits obtained through participation in the markets for energy and ancillary services (f^{EAS}), capacity (f^{CM}), and clean energy (f^{CEM}), minus the annualized investment and retirement costs (C). The set of inequalities in (4.1)–(4.2) captures the constraints on the expansion and retirement decisions, x_g, rt_g. The sequential hierarchy between the investment and retirement decisions in the upper- and lower-level markets is enforced by ensuring that the upper-level decision variables enter the lower-level problems as input parameters. The lower-level problems (4.4)–(4.6) represent the wholesale markets for capacity, clean energy, and energy and ancillary services, respectively. The lower-level problems are linear and, therefore, can be replaced with their equivalent primal-dual formulations as follows:

$$\underset{\Xi^U, \Phi^{EAS}, \Phi^{CM}, \Phi^{CEM}}{Max} \omega \{ f^{EAS}(x_g, rt_g, \Phi^{EAS}) + f^{CM}(x_g, rt_g, \Phi^{CM}) + f^{CEM}(x_g, rt_g, \Phi^{CEM}) - C(x_g, rt_g) \} \tag{5.1}$$

Subject to:

Upper-Level: (4.2)–(4.3) (5.2)

Primal-Constraints in (4.4), (4.5), (4.6) (5.3)

Dual and Strong Duality Constraints:

$$SD^{EAS}\left(\Phi^{EAS}, x_g, rt_g, \overline{x_{-g}}, \overline{rt_{-g}}\right) \ge 0 \tag{5.4}$$

$$SD^{CM}\left(\Phi^{CM}, x_g, rt_g, \overline{x_{-g}}, \overline{rt_{-g}}\right) \ge 0 \tag{5.5}$$

$$SD^{CEM}\left(\Phi^{CEM}, x_g, rt_g, \overline{x_{-g}}, \overline{rt_{-g}}\right) \ge 0 \tag{5.6}$$

The reformulation of the bi-level model includes the same objective function (5.1), upper-level constraints (5.2), and the primal constraints in (4.4)–(4.6). The collection of equations in (5.4)–(5.6) represents the dual formulations and the strong duality conditions of (4.4)–(4.6), respectively. Note that the reformulated model is still non-linear. As discussed in [10], we linearize the reformulated model using the KKT conditions, strong duality conditions, and auxiliary variables in order to formulate the final MPEC model as a mixed-integer linear program (MILP). Finally, we formulate an EPEC as the collection of the MPEC of each GenCo that is represented by (5.1)–(5.6), which each share the same lower-level problems.

Solution technique

In this study, we apply a Progressive Hedging (PH) algorithm to enhance the computational performance of SCIM in finding a solution to the EPEC problem. The PH algorithm is a computational technique that typically employed to solve complex optimization problems. It achieves this by breaking down a complex problem into smaller, more manageable sub-problems. These sub-problems are solved independently, and their hedging solutions are then iteratively refined and adjusted. This iterative process gradually brings the hedging solutions of the sub-problems closer together, ultimately leading to a converged solution for the overarching complex problem. In our case, PH is used to decompose the extensive formulation of the MPEC problem, which is MILP, into sub-problems with smaller number of days used in the energy and ancillary services lower-level problem (as in [23]). Second, we use PH to enhance the diagonalization technique, which is used to find a Nash equilibrium among multiple leaders of the modeled Stackelberg game in SCIM, as presented in [10]. The diagonalization technique solves each GenCo's MPEC model iteratively and terminates when 1) all the optimal solutions of each GenCo do not deviate from the last iteration and 2) a consensus is reached among market clearing variables (i.e., the investment and retirement decisions are made based on the same market clearing results). The use of PH to solve an EPEC problem was first introduced in [11], where the authors used the PH algorithm to solve an EPEC problem by treating each MPEC as a scenario of PH. The proposed approach in [11] finds an EPEC solution when the consensus is reached among market clearing variables of the lower-level problems. Therefore, this approach is guaranteed to satisfy the second condition; however, it is not guaranteed to satisfy the first condition and find a Nash equilibrium.

To overcome this limitation, we apply PH to enhance the diagonal-

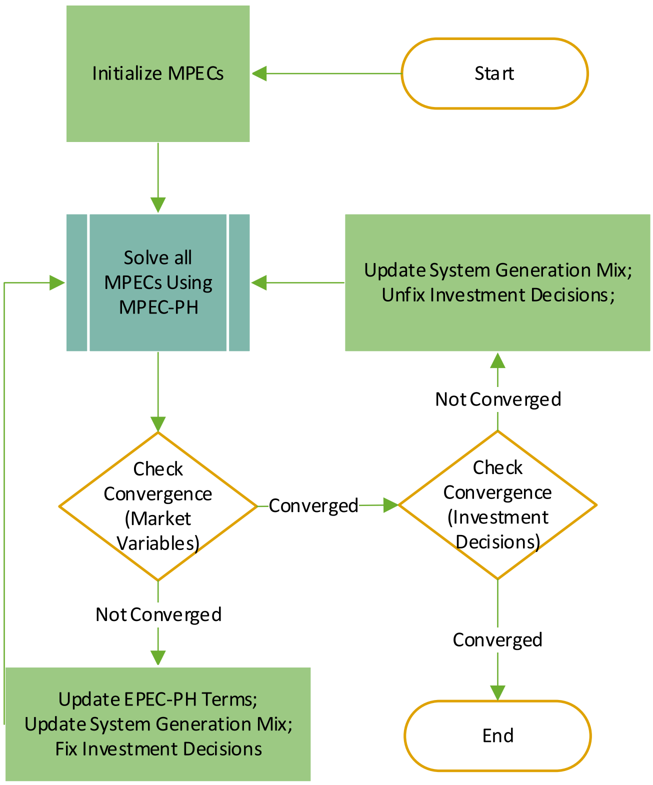

Fig. 2. Flowchart of the diagonalization approach to find a Nash equilibrium in investment strategies among multiple GenCos.

ization technique in this study using a two-step process, as shown in Fig. 2. We define two layers of PH in the EDM. First, the MPEC-PH is applied to decompose an MPEC using the investment and retirement decisions as hedging variables. Second, the EPEC-PH is used to find consensus among market clearing variables using the lower-level market clearing variables (i.e., Φ^{CM}, Φ^{CEM}, Φ^{EAS}, λ^{CM}, λ^{CEM}, λ^{E}, and λ^{R}) as hedging variables. In EDM, we first solve each MPEC independently using the MPEC-PH algorithm. Then the process finds the consensus of hedging variables of EPEC-PH while fixing the investment and retirement decisions of MPECs. When the consensus is reached, the EDM checks the first condition of termination (i.e., the convergence of investment and retirement decisions of MPECs). If the investment and retirement decisions have not converged, we update the system generation mix and repeat the process to find new MPEC solutions. The process terminates when both conditions are met. The proposed EDM advances the solution technique proposed in [11] by guaranteeing the first condition while still utilizing the benefits of using PH to ensure the second condition.

The proposed method offers the advantage of ensuring a unique market clearing status among profit-seeking entities, thereby preventing the possibility of cycling behavior that is frequently observed in conventional diagonalization methods. However, it's important to note that the presented method cannot guarantee the finding of an equilibrium solution or provide proof of the uniqueness or existence of such solutions. As another advantage of the proposed approach, the use of PH enables the use of parallel computing because each MPEC can be solved independently. To our knowledge, this is the first use of a combined PH-diagonalization method to solve EPECs; our computational experience, in which equilibria were found rapidly indicates that this is a promising approach to solving this difficult, non-convex equilibrium problem.

Case study analysis

Planning design

We use the publicly available system data in [24] that loosely represents the ERCOT power system in Texas for our case study. The dataset was originally adapted from the 2012 Texas A&M University (TAMU) ERCOT dataset, with additional solar power plants and transmission buildout based on the ERCOT interconnection queue. We made several modifications to the test system for our analysis. We reduced the original nodal system into a single-node system. In addition, we aggregated the existing generators by technology and assumed that each technology is owned by a single incumbent GenCo. We also adjusted the capacity of each technology to reflect the current generation mix and load in ERCOT [25]. After adjustment, the system has a peak demand of 76,505 MW, an installed capacity of 120,260 MW, and an unforced capacity of 86,932 MW. Thus, the initial reserve margin of the system is 13.6%. We set the target planning year to 2027 in this study with target PRM of 12.25%. The peak load in 2027 is assumed to increase from the current level by 1.2 % annually to 81,206 MW. In addition, we consider anticipated age-based retirements by 2027 based on the information available in [25]. The considered investment options include natural gas combined cycle with carbon capture and storage technology (NGCC-CCS), natural gas combustion turbine (NGCT), utility-scale PV, land-based wind, and 4-hour battery storage. It is assumed that there are five new investors, and each investor will only invest in a single technology, with an unlimited budget. All the financial parameters are obtained from the 2020 NREL Annual Technology Baseline (ATB) moderate scenario [26]. Table 1 summarizes the model parameters for each technology in the test system after these adjustments.

In this study, we consider the potential unforced outages of generating units in the energy and ancillary service markets by derating the installed capacity of the resources by the unforced outage rates. This is a proxy to model supply scarcity without explicitly modeling individual contingency events. Therefore, the simulation results should be interpreted in terms of the relative differences between the future portfolios driven by modeled market designs under the modeling assumptions used in this study. Specifically, the modeling framework does not capture all of the possible scarcity events and associated high price periods that provide incentives for new capacity investments. These assumptions apply to all considered cases, but may be more impactful in energy-only market cases that rely heavily on brief high price periods to support new capacity.

We further apply a backward scenario reduction algorithm as presented in [27] to select a set of 25 representative days from a full year of data that are explicitly modeled on our analysis. These 25 representative days effectively capture the operational conditions in terms of net load distribution of the entire year, as shown in Fig. 3. The simulation is performed using CPLEX 12.8 using the Bebop cluster in the Laboratory Computing Resource Center at Argonne National Laboratory. The cluster has an Intel Xeon E5-2695v4 CPU with 128GB memory.

Market design scenarios

We define fourteen cases with different wholesale market design configurations and policies, as summarized in Table 2. For each market design case we analyze two scenarios, first we execute SCIM to determine the generation portfolio that results from the strategic investment decisions made by profit-seeking GenCos. We then analyze a corresponding scenario using a traditional least-cost generation expansion planning (LC-GEP) model to establish a corresponding system-optimal portfolio as a benchmark. The first two cases, EO-OR3 and EO-OR4, are based on the energy-only market framework with different price caps and ORDC schemes. We will use the abbreviations "EO" for energy-only market and "OR" for different ORDC schemes consistently throughout the paper. The corresponding least-cost scenarios utilize the same scarcity pricing mechanisms for operating reserves but do not

Table 1
Test system summary and model parameters for generating units

Technology	Existing Capacity (MW)	Age-based Retirement (MW)	Capacity New Units (MW)	CAPEX ($/kW)	Fixed O&M Cost ($/kW-year)	Variable O&M Cost ($/MWh)	Fuel Cost ($/MWh)	Forced Outage Rate (%)
Coal	14,703	840	300	2,632	71.0	8.0	22.05	3.9
NGCC	31,541	809	350	912	28.0	2.0	24.65	3.3
NGCT	19,870	3,822	250	781	21.0	5.0	34.27	3.1
Nuclear	5,268	0	600	6,966	146.0	3.0	7.31	3.0
Hydro	569	8	100	-	64.0	0	0	3.0
PV	11,341	0	300	754	15.0	0	0	0.0
Wind	35,214	109	300	956	39.0	0	0	0.0
Storage (4-hr battery)	1,751	40	300	895	22.0	0	0	3.3
NGCC-CCS	-	-	350	2,001	62.0	6.0	23.53	3.3

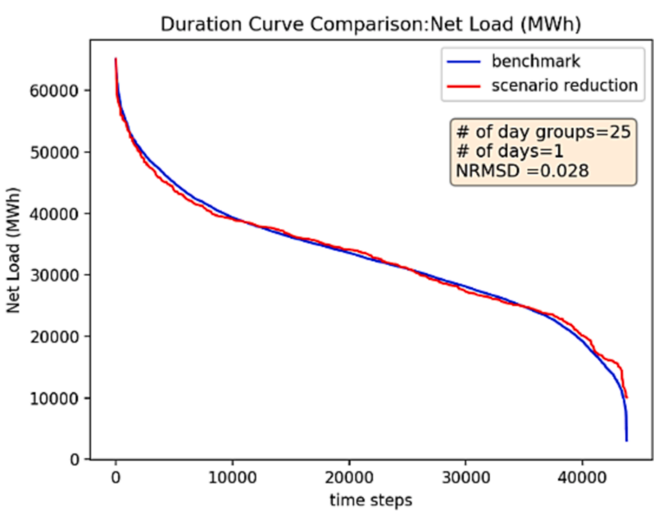

Fig. 3. Comparison of net load duration curves from the 25 selected representative days (in red) and the whole year data (in blue)

enforce a minimum planning reserve margin (PRM) constraint. The next six cases have a capacity market, which is abbreviated as "CM", with varying capacity market demand curves, methods for determining capacity credits for VRE resources, and scarcity pricing schemes in the energy and ancillary services market. In particular, the CM1-ELCC-OR1 case uses the effective load carrying capacities (ELCCs), obtained from [28] for the current system and summarized in Table 3, as capacity credits for wind and PV resources; these credits are still exogenously defined and not determined within the model framework. The latter is an important direction for future research, as capacity credits of individual resources are a function of the total system portfolio [29]. The

Table 3
Capacity credits for wind and PV

Technology	Peak Average Output	ELCC
Wind	0.25	0.14
PV	0.76	0.72

capacity credit for storage is assumed to be 100%. Fig. 4 and Fig. 5 describe the shapes of ORDC and capacity market demand curves used in the case study. The corresponding least-cost cases include a minimum PRM constraint for cases with a capacity market to ensure that the target PRM level indicated by each capacity demand curve in Fig. 5 is achieved. In addition, we consider six policy-oriented scenarios. The carbon price scenario, abbreviated as "CP", introduces a $40/ton carbon price for greenhouse gas emissions to generators based on their emission levels; we added the emission cost into the marginal variable cost of generators. In the tax credit scenario, abbreviated as "TC", we use an investment tax credit (ITC) of 10% for PV and a production tax credit of 1.5 cents/kWh for wind resources. These same credits are considered in both the SCIM and LC-GEP cases. Lastly, the clean energy market scenario, which is abbreviated as "CEM", has a procurement target of 50% of annual demand and $1.30/MWh as a reference price, which is determined based on the average renewable energy certificate price in Texas in 2021. The clean energy market demand curve is adopted from [22] and shown in Fig. 6. To capture this effect in the least-cost cases, we implement a minimum clean energy attribute constraint at the target procurement level indicated in Fig. 6. Note that SCIM is set up differently for each market design case, tailored to the modeled markets. For example, in the energy-only market cases, we exclude the constraints related to capacity markets and clean energy markets from the model.

Results

The objective of this study is to assess the impact of various

Table 2
Description of Market Design Cases

Case	Capacity Market		Energy & AS Market		Clean Energy Policy & Market
	Demand Curve	Capacity Credits for VREs	Price Cap ($/MWh)	ORDC option	
EO-OR3	NA	NA	5,000	ORDC #3	NA
EO-OR4	NA	NA	9,000	ORDC #4	NA
CM1-OR1	CM #1	Peak Av. Output	850	ORDC #1	NA
CM1-OR2	CM #1	Peak Av. Output	3,500	ORDC #2	NA
CM1-OR3	CM #1	Peak Av. Output	5,000	ORDC #3	NA
CM2-OR1	CM #2	Peak Av. Output	850	ORDC #1	NA
CM3-OR1	CM #3	Peak Av. Output	850	ORDC #1	NA
CM1-ELCC-OR1	CM #1	ELCC	850	ORDC #1	NA
EO-OR3-TC	NA	NA	5,000	ORDC #3	Tax Credit
CM1-OR1-TC	CM #1	Peak Av. Output	850	ORDC #1	Tax Credit
EO-OR3-CP	NA	NA	5,000	ORDC #3	Carbon Price
CM1-OR1-CP	CM #1	Peak Av. Output	850	ORDC #1	Carbon Price
EO-OR3-CEM	NA	NA	5,000	ORDC #3	Clean Energy Market
CM1-OR1-CEM	CM #1	Peak Av. Output	850	ORDC #1	Clean Energy Market

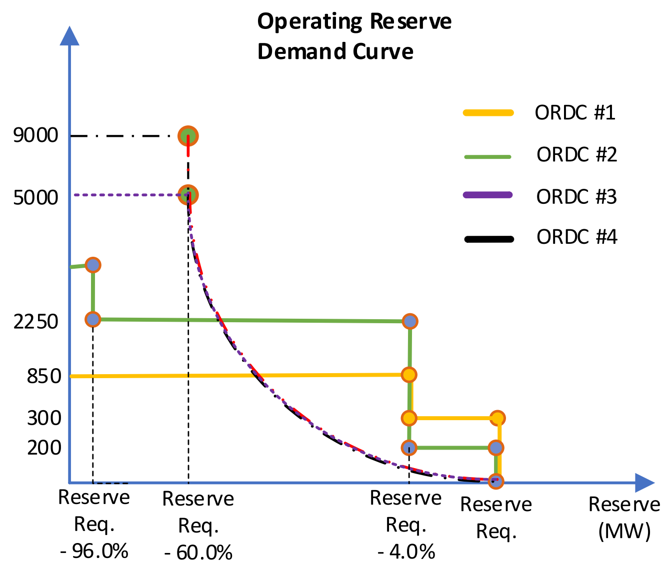

Fig. 4. Comparison of the ORDC options

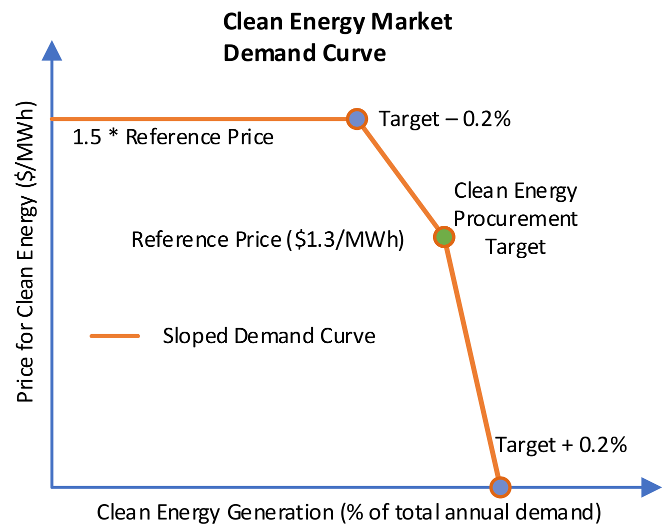

Fig. 6. Downward-sloping Demand Curve for the Clean Energy Market

configurations of wholesale market designs on the investment decision-making of profit-seeking GenCos. In order to show the importance of considering the impact of market designs when analyzing the investment decision-making of profit-seeking entities, we compare simulation results obtained from SCIM with ones obtained from the LC-GEP model for the fourteen cases presented in Table 2. Fig. 7 and Table 4 present a summary of the simulation results obtained from SCIM and LC-GEP. The following sub-sections provide further details on the simulation results along with a discussion of key findings and implications for efficient electricity market design.

Importance of considering strategic decision-making in capacity expansion planning

We first illustrate the importance of considering the strategic decision-making of profit-seeking entities in capacity expansion planning, with a discussion of the energy-only market cases (i.e., the EO-OR3 and EO-OR4 cases). A comparison of system generation portfolios and PRMs between SCIM and LC-GEP in Fig. 7 shows that in the energy-only market cases the generation portfolios driven by strategic decision-making have significantly lower PRMs than those produced by system least-cost modeling. The difference in the new investment decisions between the two models is shown in Fig. 8. The SCIM portfolios have less PV and NGCT and more storage and wind than the LC-GEP portfolios for corresponding scenarios. The SCIM results show higher system-wide costs than the corresponding LC-GEP results, as shown in Fig. 9, in particular for EO-OR3 and EO-OR4. The SCIM system experiences a substantial increase in involuntary load shedding costs due to the decreased investments in PV and NGCT, compared to the LC-GEP results in these cases. The summary of annual revenue streams for new investments in Table 5 shows that the increased scarcity events increase energy prices and make storage and wind more profitable in the energy-only market cases compared to the other SCIM cases. In addition, Table 5 shows that the PV resources that are selected by the LC-GEP model are not ultimately profitable, and therefore would not be developed by a strategic, profit-seeking GenCo. This explains the relative decrease in PV investments that is observed in the SCIM results.

The capacity market cases show PRM levels close to the target PRM of 12.25% in both the SCIM and LC-GEP results. However, despite the similar systemwide PRM levels, the generation portfolios identified by the two models are quite different, as shown in Fig. 7 and Fig. 8. Similar

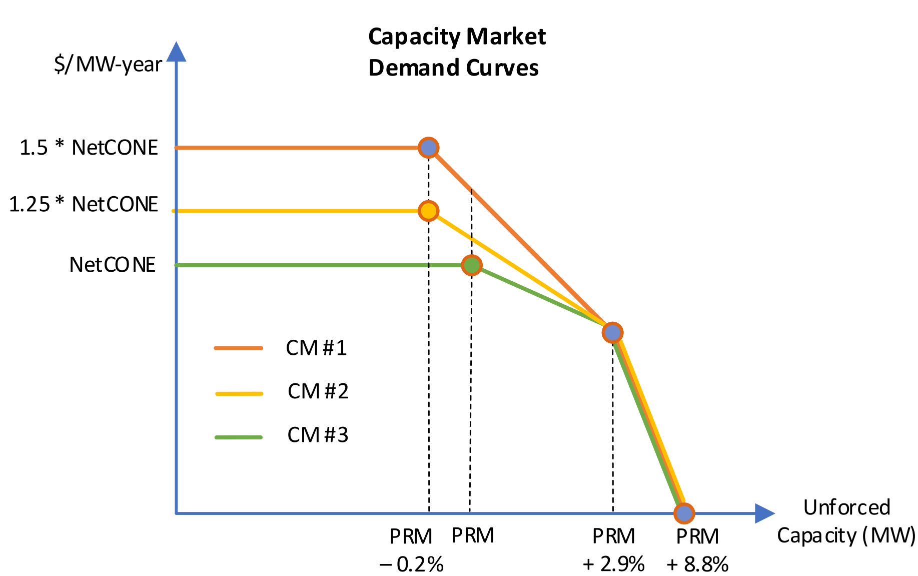

Fig. 5. Comparison of the Downward-sloping Capacity Demand Curves. Net CONE is the net Cost of New Entry, estimated from a natural gas combined cycle unit

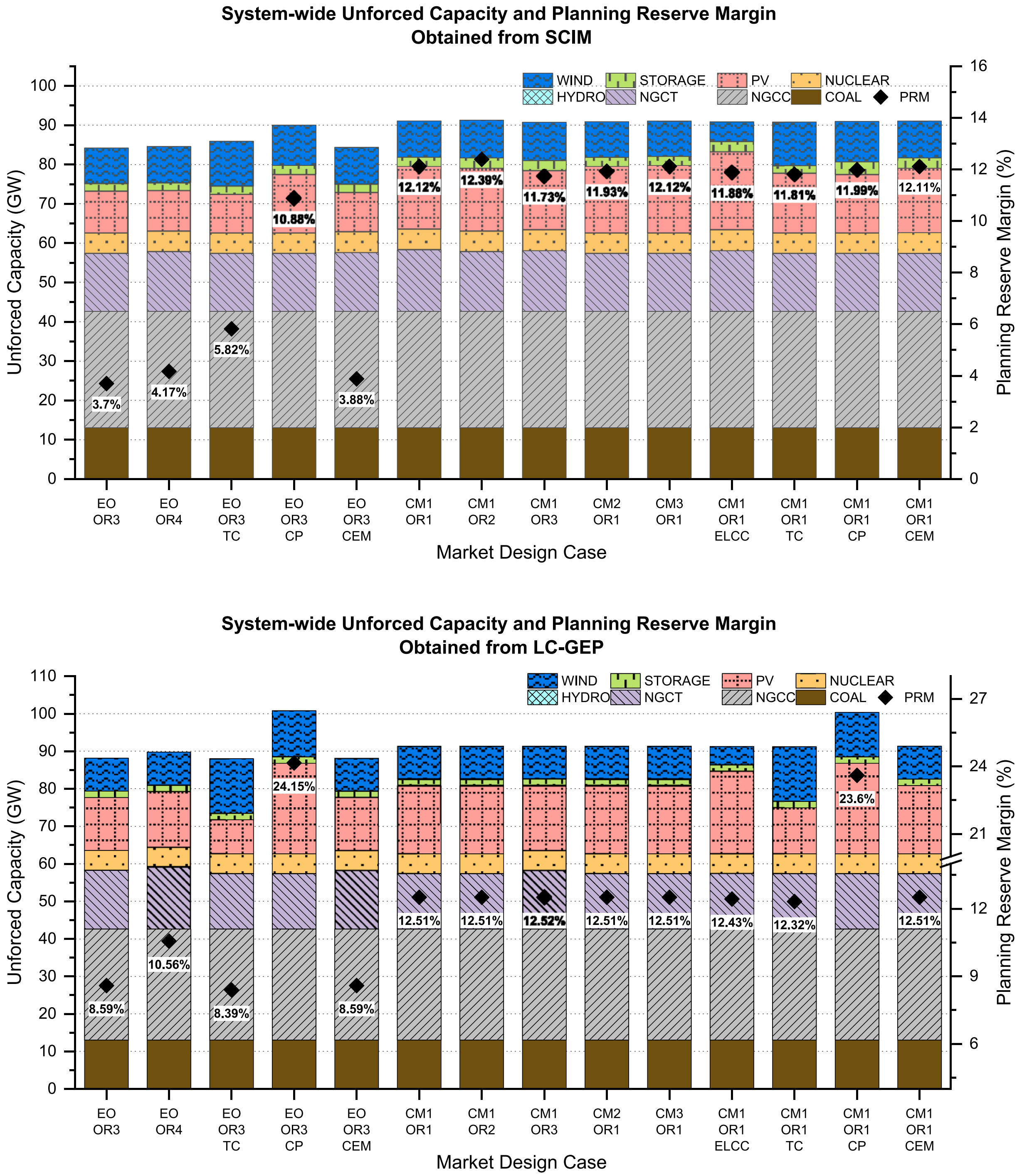

Fig. 7. System-wide unforced capacity and planning reserve margins obtained from SCIM (above) and LC-GEP (below) under different market design cases.

to what is observed with the energy-only cases, there is consistently less PV capacity in the SCIM generation portfolios than the corresponding LC-GEP portfolios, and more storage and wind. The SCIM portfolios also have more NGCT capacity than the LC-GEP portfolios in some of the capacity market cases, which contrasts the situation in the energy-only cases. The system experiences less involuntary load shedding in the SCIM results in the capacity market cases because of the additional investments; however, the total system-wide costs from SCIM are still higher than the LC-GEP results.

In general, we see that the energy-only case results obtained from SCIM clearly have lower PRMs than the least-cost results or the cases with CRMs. There are three possible reasons to explain this result. The first explanation is that the target PRM may be set too high for the modeled energy-only market designs to achieve. The results of the energy-only cases obtained from the LC-GEP model appear to support this explanation, as they also reveal PRMs that are lower than the assumed target level. The second explanation is that SCIM does not capture the full potential of scarcity events, which is critical in the energy-only market design. Lastly, the modeled GenCos, which are profit-seeking in nature, may be influencing market outcomes by exercising market power. These entities may be collectively limiting the systemwide capacity to create artificial supply shortages and thereby increase profits during scarcity events.

These results also demonstrate that price signals that manifest during

Table 4
Summary of the simulation results obtained from SCIM and LC-GEP.

Case	Model	New Capacity (Unforced Capacity, MW)					Market Prices			PRM (%)	Total Cost ($B)
		NGCC-CCS	NGCT	PV	Storage	Wind	Average Energy ($/MWh)	Capacity ($/MW-day)	Clean Energy ($/MWh)		
EO-OR3	SCIM	0	0	1,824	300	300	78.1	–	–	3.70	12.09
	LC-GEP	0	917	5,472	0	0	58.3	–	–	8.59	11.19
EO-OR4	SCIM	0	459	1,596	300	450	86.8	–	–	4.17	12.13
	LC-GEP	0	1,834	6,156	0	0	60.4	–	–	10.56	11.23
CM1-OR1	SCIM	0	1,146	6,612	300	375	31.3	209.1	–	12.12	11.45
	LC-GEP	0	0	9,576	0	0	37.5	193.6	–	12.51	11.10
CM1-OR2	SCIM	0	917	6,840	600	750	38.1	202.5	–	12.39	11.43
	LC-GEP	0	0	9,576	0	0	61.0	193.6	–	12.51	11.19
CM1-OR3	SCIM	0	0	9,120	300	525	28.4	209.1	–	11.73	11.41
	LC-GEP	0	917	8,664	0	0	54.8	193.2	–	12.52	11.19
CM2-OR1	SCIM	0	0	8,208	600	225	33.5	174.2	–	11.93	11.44
	LC-GEP	0	0	9,576	0	0	61.0	163.9	–	12.51	11.19
CM3-OR1	SCIM	0	0	9,120	600	225	34.4	139.4	–	12.12	11.47
	LC-GEP	0	0	9,576	0	0	61.0	136.3	–	12.51	11.19
CM1-ELCC-OR1	SCIM	0	1,146	11,232	900	84	29.0	209.1	–	11.88	11.47
	LC-GEP	0	0	13,824	0	0	56.8	196.3	–	12.43	11.26
EO-OR3-TC	SCIM	0	0	1,140	300	2,700	44.4	–	–	5.82	11.63
	LC-GEP	0	0	456	0	5,775	24.8	–	–	8.39	11.68
CM1-OR1-TC	SCIM	0	0	6,384	300	2,325	28.2	209.1	–	11.81	11.45
	LC-GEP	0	0	3,648	0	5,775	21.1	200.0	–	12.32	11.75
EO-OR3-CP	SCIM	0	0	6,156	600	1,500	50.0	–	–	10.88	11.49
	LC-GEP	0	0	15,504	0	3,525	49.2	–	–	24.15	11.73
CM1-OR1-CP	SCIM	337	0	5,472	1,800	1,575	45.8	209.1	–	11.99	11.55
	LC-GEP	0	0	15,504	0	3,075	39.5	0.0	–	23.60	11.65
EO-OR3-CEM	SCIM	0	229	1,596	300	375	67.7	–	2.3	3.88	11.97
	LC-GEP	0	917	5,472	0	0	58.3	–	1.2	8.59	11.19
CM1-OR1-CEM	SCIM	0	0	7,752	900	600	30.8	209.1	2.0	12.11	11.43
	LC-GEP	0	0	9,576	0	0	36.7	193.6	1.1	12.51	11.18

short-term operations can impact long-term investment decisions. They also show how the investment decisions made by profit-seeking entities can differ from the idealized least-cost simulation outcomes under the same market design assumptions. Specifically, these results suggest that LC-GEP models may identify new resources that are needed to support resource adequacy from a system perspective, but are not necessarily profitable investments under certain market designs. This highlights the importance of implementing market designs that are incentive compatible with the social objectives of the independent system operator and support competitive market entry and exit to minimize the potential for exertion of market power. Finally, these results highlight the necessity of using both least-cost and market-based modeling approaches when assessing the long-term investment impacts of different market design options.

Overall, we observed that the least-cost and profit-maximization models resulted in different system-wide generation mixes. While it's commonly understood that both models should yield the same outcomes in a perfect competition scenario, it's also important to consider various factors that can lead to different results. Apart from the potential impact of market power, factors like price caps, non-continuous decision variables, and a fixed number of new entrants can also contribute to outcomes that don't align with the ideal of perfect competition, even within least-cost models. Therefore, this outcome should not be interpreted as a limitation of a certain market design. Rather, it emphasizes the importance of utilizing carefully constructed simulation models and case studies. In the following subsections, we will further discuss the impact of market designs on the strategic investment decision-making of profit-seeking entities.

Impact of market design on strategic investment decisions

In this section we discuss the impact of different market designs on the strategic decision-making of profit-seeking GenCos. Therefore, all the results that are presented below were generated with SCIM.

Capacity demand curves and price caps for energy and ancillary services

All of the energy-only market case results from SCIM show lower planning reserve margins than the 12.25% target value regardless of the associated scarcity pricing scheme, as shown in Fig. 7. As a result of the low PRMs, the system experiences scarcity events in the two energy-only cases. The increase in energy prices associated with these energy scarcity events leads to relatively higher profits for the resources that are developed. On the other hand, the capacity market cases result in higher planning reserve margins, typically above or just below the target planning reserve margin level. The results further indicate that the downward-sloping design of the capacity demand curves helps maintain the planning reserve margins around the target value in all the modeled capacity market cases in SCIM. The impact of the downward-sloping

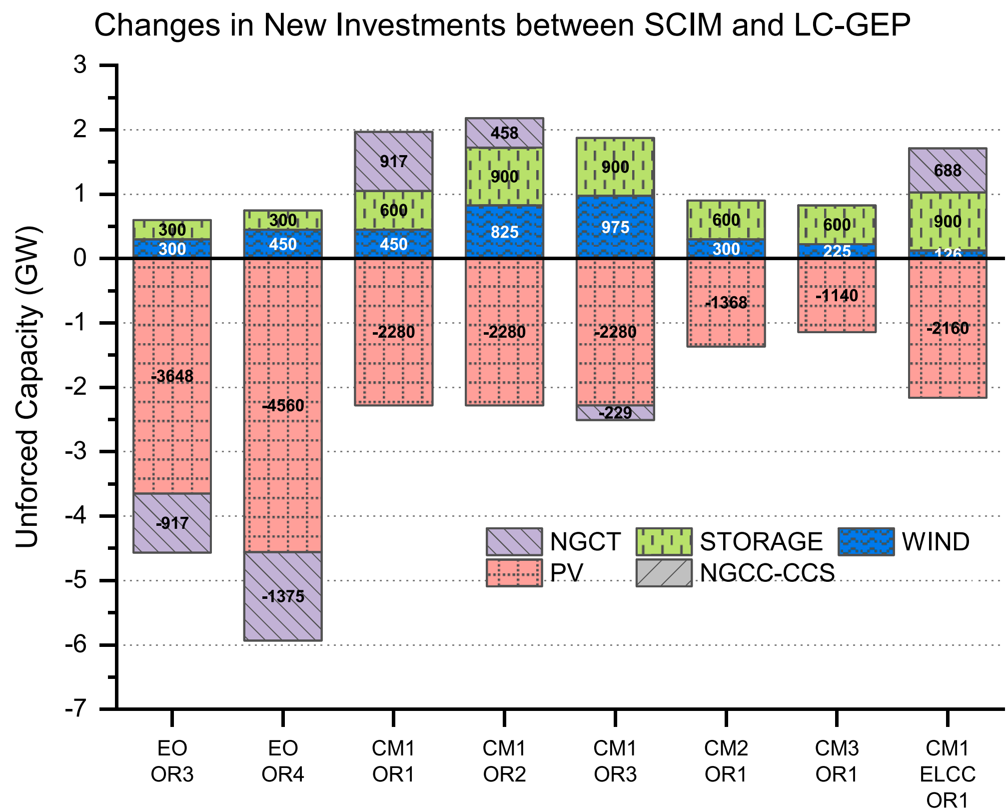

Fig. 8. Difference in new investments in SCIM compared to LC-GEP under difference market design cases. The text label indicates the net change in unforced capacity obtained from SCIM results relative to the LC-GEP results.

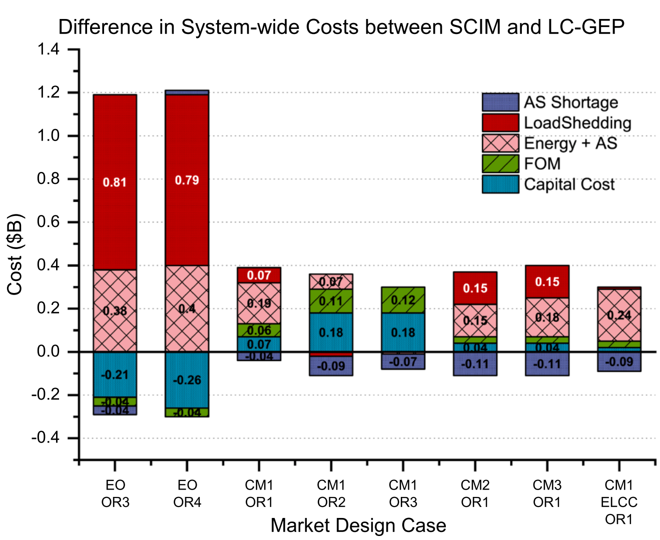

Fig. 9. Difference in system-wide costs in SCIM compared to LC-GEP under different market design cases. The text label indicates the net change in system costs obtained from the SCIM results relative to the LC-GEP results.

design of the capacity demand curves is apparent in the CM2-OR1 and CM3-OR1 cases. The downward-sloping capacity demand curve design promotes higher competition in the first segment of the capacity demand curve, which has the highest capacity prices, and gradually discourages investment with lower prices, as shown in Fig. 5.

We observe that the CM1 case, which features a capacity demand curve with an initial segment set at 150% of net CONE, is the only scenario resulting in new NGCT capacity. As this capacity demand segment is lowered to 125% and 100% of net CONE in the CM2 and CM3 cases, respectively, these NGCT investments are replaced by approximately two to three times as much solar capacity. The results with lower first segment capacity prices in the CM2-OR1 and CM3-OR1 cases show the significance of capacity revenues for wind and NGCT investments. The CM2-OR1 case results in 600 MW and 1,250 MW less wind and NGCT capacity in terms of installed capacity, respectively, compared to the CM1-OR1 case. These resources are replaced by 2,100 MW of additional PV capacity, which relies less on capacity revenues, as shown in Table 4. Similarly, the CM3-OR1 case results in 600 MW less wind capacity and 1,250 MW less NGCT capacity compared to CM1-OR1. These resources are replaced by 3,300 MW of additional PV capacity. Hence, the shape of the demand curve for capacity clearly impacts technology choice.

In addition, we see the impact of higher price caps on the investment decisions. The higher scarcity pricing in the energy-only market case (i.e., the EO-OR4 case) adds incentives for additional investments, resulting in higher planning reserve margins compared to the EO-OR3 case. Similarly, the higher scarcity pricing in the CM1-OR2 case promotes additional investments in wind, PV, and storage resources compared to the CM1-OR1 case. Furthermore, the increased price caps for energy and ancillary services in the CM1-OR3 case increase PV investments. The high penetration level of PV in the CM1-OR3 case results in reduced investments in NGCT, wind, and storage compared to the CM1-OR2 case.

The CM1-ELCC-OR1- case assumes that wind and solar resources have capacity credits that are derived from their ELCC values as calculated in [28] instead of their average generation during peak periods (Table 3). In the CM1-ELCC-OR1 case, the ELCC-based capacity credits for both wind and solar are lower than their respective credits derived from average peak generation, which is used in the CM1-OR1 case. However, the relative decrease in terms of new investment in both cases

Table 5
Summary of annual revenue streams for new investments in LC-GEP and SCIM under different market design cases ($/kW) [2]

Case	Technology	LC-GEP				SCIM			
		Capital & FOM Cost	Capacity Revenue	Energy & AS Profit	Total Profit	Capital & FOM Cost	Capacity Market Revenue	Energy & AS Profit	Total Profit
EO-OR3	NGCC-CCS	–	–	–	–	–	–	–	–
	NGCT	72.7	–	90.5	17.8	–	–	–	–
	PV	95.8	–	72.4	(23.4)	72.1	–	130.3	58.1
	Storage	–	–	–	–	116.7	–	220.0	103.3
	Wind	–	–	–	–	111.4	–	133.0	21.6
EO-OR4	NGCC-CCS	–	–	–	–	–	–	–	–
	NGCT	72.7	–	88.0	15.4	72.6	–	137.6	65.0
	PV	93.1	–	72.8	(20.3)	72.1	–	148.8	76.7
	Storage	–	–	–	–	116.7	–	246.3	130.0
	Wind	–	–	–	–	111.4	–	132.7	21.3
CM1-OR1	NGCC-CCS	–	–	–	–	–	–	–	–
	NGCT	–	–	–	–	72.7	70.0	18.5	15.8
	PV	85.6	53.7	62.4	30.5	69.7	56.0	68.7	55.0
	Storage	–	–	–	–	116.7	76.3	126.7	86.3
	Wind	–	–	–	–	111.5	19.1	110.7	18.3
CM1-OR2	NGCC-CCS	–	–	–	–	–	–	–	–
	NGCT	–	–	–	–	72.7	70.0	26.6	23.9
	PV	85.6	53.7	65.2	33.3	72.1	58.0	70.9	56.7
	Storage	–	–	–	–	116.5	76.3	119.2	78.8
	Wind	–	–	–	–	111.4	19.1	104.7	12.4
CM1-OR3	NGCC-CCS	–	–	–	–	–	–	–	–
	NGCT	72.7	64.8	82.0	74.1	–	–	–	–
	PV	87.1	53.7	66.4	33.1	63.1	41.2	60.4	38.5
	Storage	–		–	–	116.7	62.0	153.3	98.7
	Wind	–		–	–	111.4	16.1	111.1	15.8
CM2-OR1	NGCC-CCS	–		–	–	–	–	–	–
	NGCT	–		–	–	–	–	–	–
	PV	85.6	45.5	65.2	25.1	58.1	38.9	55.6	36.5
	Storage	–		–	–	116.5	63.7	109.3	56.3
	Wind	–		–	–	111.4	15.9	115.8	20.2
CM3-OR1	NGCC-CCS	–		–	–	–	–	–	–
	NGCT	–		–	–	–	–	–	–
	PV	85.6	37.8	65.2	17.4	48.1	24.2	45.5	21.6
	Storage	–		–	–	116.5	46.2	107.8	37.3
	Wind	–		–	–	111.4	11.6	115.1	15.2
CM1-ELCC-OR1	NGCC-CCS	–		–	–	–	–	–	–
	NGCT	–		–	–	72.7	70.0	8.9	6.2
	PV	81.0	50.9	57.9	27.8	44.4	33.8	39.3	28.8
	Storage	–		–	–	116.6	76.3	90.0	49.8
	Wind	–		–	–	111.5	10.7	116.0	15.3

[2] The capacity revenue for the LC-GEP cases is estimated using the capacity price at the intersection of the capacity market demand curve and the target PRM level.

is much larger for wind (44%) than it is for solar (5%). Therefore, using the ELCC values increases PV and decreases wind investments. Storage investments also increase in this case even though their capacity credit is unchanged because these storage resources are able to take advantage of arbitrage opportunities and help balance the volatility of additional PV generation.

Incentive mechanisms for clean energy investments

We also consider three different incentive schemes to support investments in clean low-carbon energy resources, including a 1) tax credit for renewables, 2) carbon price, and 3) forward clean energy market. First, we examine the impacts of a 10% investment tax credit for PV and a $15/MWh production tax credit for wind in the tax credit scenario. Overall, the results show that considering tax credits has a greater impact on wind investments than PV, as shown in Fig. 10. In the energy-only market case, new wind investments increase from 300 MW to 2,700 MW, while new PV investments actually decrease slightly from 1,824 WM to 1,140 MW. In the capacity market case, new wind investments increase from 375 MW to 2,325 MW, while solar investments decrease from 6,612 MW to 6,384 MW and NGCT investments decrease from 1,146 MW to zero. The larger relative increase in wind capacity suggests that the $15/MWh PTC is relatively more attractive than the 10% ITC, while the elimination of new NGCT investments in the capacity market case suggests that such clean energy tax credits can contribute to reducing carbon-emitting generation capacity, as intended. The additional wind investments in the energy-only case increase the PRM from 3.7% to 5.8%, still well below the target value of 12.25%. In the capacity market case, the PRM decreases from 12.12% to 11.81% despite the additional new wind investments, due to the fact that wind has a lower capacity credit than NGCT.

In the carbon price scenario, a $40/ton carbon price is added to the marginal cost of carbon-emitting generators based on their emission levels, which makes them more expensive to dispatch in the energy and ancillary services markets. The net effect of this shift in marginal cost on both new capacity and total generation is shown in Fig. 11. Unsurprisingly, the results show that considering a carbon price increases investments in low- or zero-emissions resources (i.e., PV, wind, battery, and NGCC-CCS). In the energy-only case this results in a substantial increase in PV and wind capacity, while no existing carbon-emitting capacity is retired. The net impact is that the PRM increases from 3.7% to 10.9% as new clean energy resources come online to displace generation from carbon-emitting resources, but they also remain online to provide reserves and support system reliability. Similar to the tax credit scenario, the consideration of carbon price in the capacity market case eliminates investment in NGCT, which is replaced by increased investments in wind and storage resources, as well as a small amount of NGCC-CCS capacity. In addition, consideration of a carbon price in the capacity market case increases new energy storage investments from 300 MW to 1,800 MW. This result indicates that the combination of the higher marginal cost of thermal resources and frequent low prices

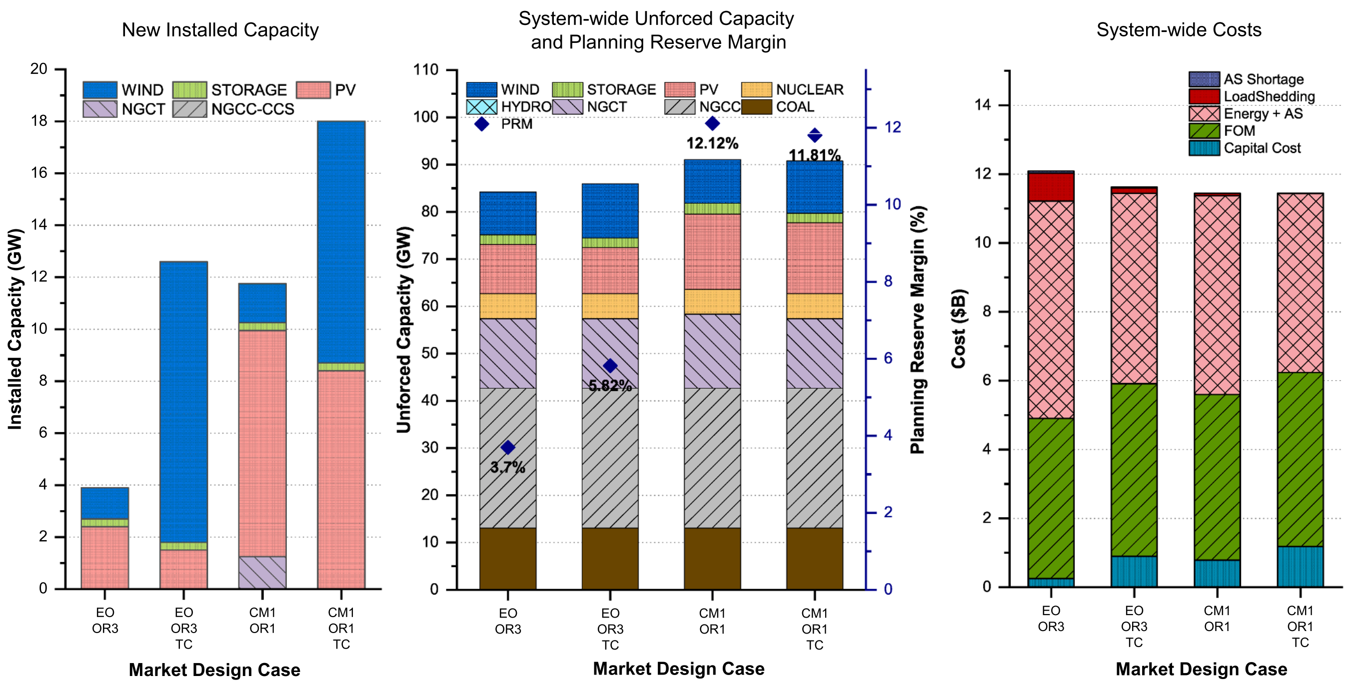

Fig. 10. Comparison of the new installed capacity (left), system-wide unforced capacity and planning reserve margin (middle), and system-wide costs under the tax credit scenario.

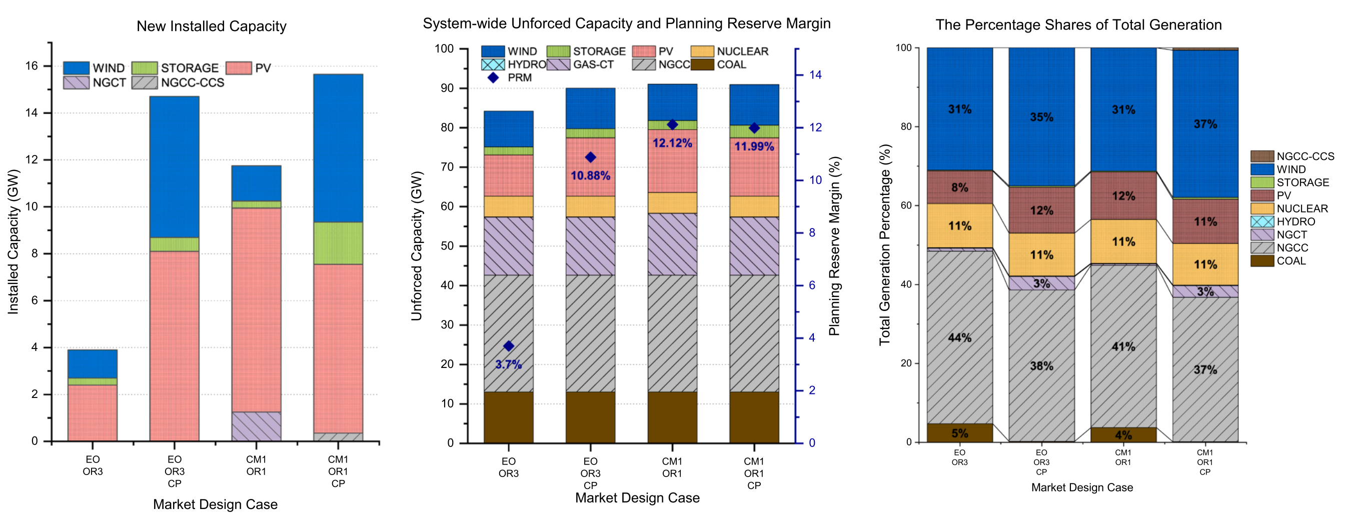

Fig. 11. Comparison of the new installed capacity (left), system-wide unforced capacity and planning reserve margin (middle), and percentage shares of total generation (right) under the carbon price scenario.

caused by high VRE investments makes energy storage resources dispatch more frequently and provides higher energy arbitrage revenues.

Lastly, we consider a forward clean energy market that provides revenues to the clean energy resources, including PV, wind, hydro and nuclear, based on their estimated annual energy production levels. In this study, we use a clean energy procurement target of 50% of the total annual demand and a clean energy price of $1.30/MWh, which was the average price of a renewable energy credit in ERCOT in 2021. The results in Fig. 12 show that the additional revenues from the forward clean energy market do not significantly affect PV and wind investments in the energy-only market. Unlike the carbon price scenario, the forward clean energy market does not directly impact the marginal cost of resources. Therefore, the only difference between the EO-OR3 and EO-OR3-CEM cases is the additional revenue potential for the clean energy resources in the latter case. The result indicates that the additional revenue at the price of $1.30/MWh is not sufficient to promote sufficient additional investments in the energy-only market case. However, the forward clean energy market clearly promotes more wind, PV, and storage investments in the CM1-OR1-CEM case, while eliminating investments in new NGCT capacity. The net result is an essentially unchanged PRM. Note that this study does not examine the potential double compensation issue, which occurs when a single resource is compensated for both its capacity and clean energy attributes. Instead, we assume that clean energy resources can be compensated for both capacity and clean energy attributes at the same time.

Conclusions

A market review conducted by a team of five research institutions

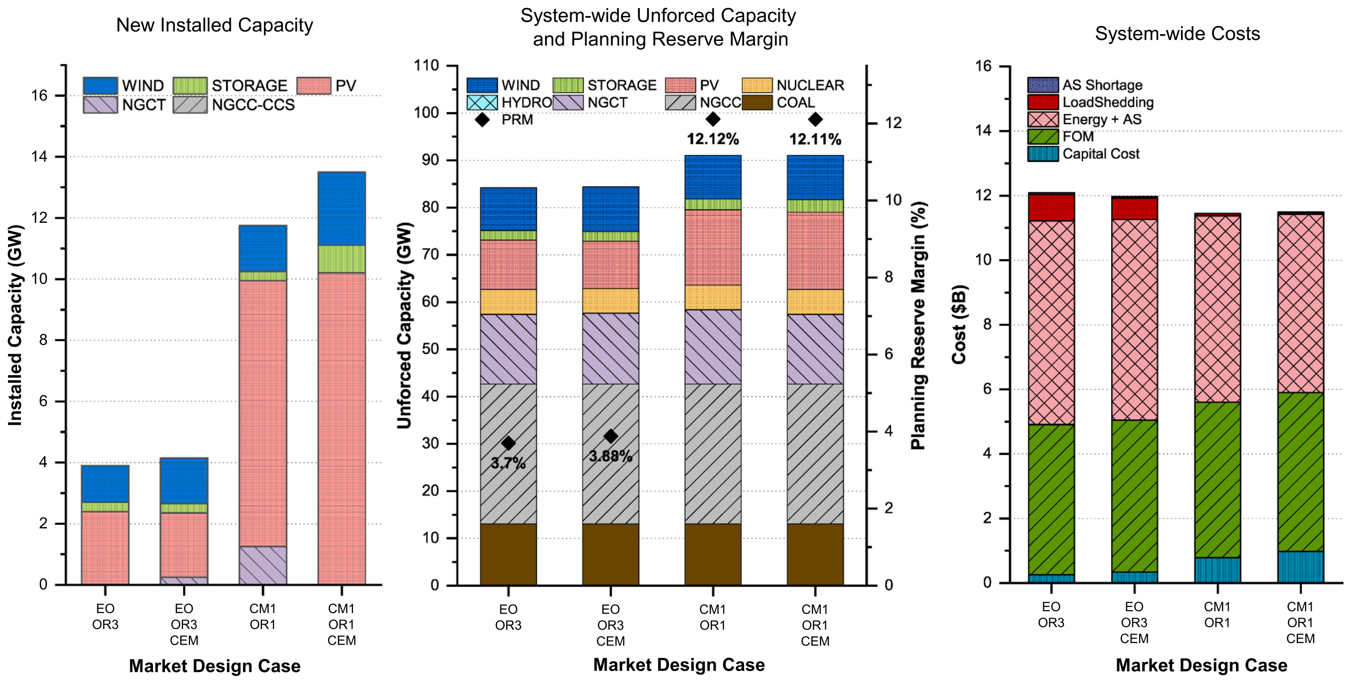

Fig. 12. Comparison of the new installed capacity (left), system-wide unforced capacity and planning reserve margin (middle), and system-wide costs under the clean energy market scenario.

within the DOE Grid Modernization Laboratory Consortium [16] emphasizes the crucial role of well-designed electricity markets in ensuring system reliability. This study builds upon those findings and analyzes how current and potential future wholesale market designs and clean energy incentive schemes could drive renewable energy integration and help maintain system reliability throughout the clean energy transition. This study utilizes a market-based GEP model, SCIM, which models the strategic interactions among all profit-seeking participants. We also compare game-theoretical results against those obtained from a traditional least-cost capacity expansion model to highlight the importance of considering strategic interactions in capacity expansion analysis for competitive electricity markets.

This study explores the effects of three different types of market designs, which include (1) an energy-only market, (2) a capacity market, and (3) a clean energy market. To thoroughly analyze the impact of these market designs, we conducted a comprehensive analysis of fourteen market design scenarios that incorporated various market design parameters and additional clean energy policies. We observe that the energy-only case results obtained from both SCIM and LC-GEP consistently have lower system-wide PRMs than the target level across a range of market design parameters. This result suggests two things. First, the modeled target PRM level may be set too high, making it difficult for the modeled energy-only market framework to achieve under the modeled system and techno-economic conditions. Another consideration is the potential importance of accounting for supply-side scarcity conditions through the explicit modeling of contingency events, as opposed to estimating impacts solely based on unforced capacity. The modeling methodology employed in this study does not directly incorporate generator contingency scenarios that could lead to scarcity events. This might inadvertently undermine the effectiveness of scarcity pricing within these markets. While explicitly modeling contingencies would indeed result in a significant increase in the computational complexity of the optimization model, doing so would enhance the model's ability to depict scarcity events more accurately, as opposed to relying solely on basic derated capacity figures in the spot markets. This is particularly important in systems with relatively high penetrations of wind, PV and storage resources.

In addition, the PRM levels obtained from SCIM were lower than those obtained from LC-GEP in all 14 considered market cases. The difference between the results of SCIM and LC-GEP could mean that profit-seeking market participants have the ability to exert some level of market power, i.e., by investing in less capacity than the system optimum dictates; this effect is not captured in traditional least-cost GEP models. The capacity market cases all resulted in PRM levels that were close to the target level with both SCIM and LC-GEP. This finding indicates that the presence of capacity markets may be able to attract new market entries and reduce the potential for exertion of market power. However, even in cases where the PRM levels were similar, the generation portfolios obtained from each model were often different. In 11 of the 14 considered market cases, SCIM identified generation portfolios with more solar capacity than the corresponding LC-GEP portfolio, and 10 of the SCIM portfolios had less wind capacity. This is because the SCIM model places a greater emphasis on the role of market revenues on investment decisions, while the LC-GEP model focuses on finding a least-cost solution to achieve the desired system-wide PRM.

Next, we analyzed the impact of varying market design parameters, such as scarcity pricing and the shape of the capacity market demand curve, on the generation portfolios. The results showed that higher scarcity pricing in the energy-only market cases provided incentives for additional investments as expected. Moreover, the results also indicated that the design of the capacity demand curves play an important role in achieving the desired PRM level. This highlights the importance of carefully considering these parameters in the design and implementation of a capacity market. Specifically, the cases that considered a capacity demand curve with an initial segment at 150% of net CONE were the only SCIM capacity market cases to result in new NGCT capacity. None of the LC-GEP capacity market cases invested in new NGCT capacity. As this capacity demand segment was lowered to 125% and 100% of net CONE these NGCT investments were replaced by approximately two to three times as much solar capacity.

We then examined the impacts of three different incentive schemes to support investments in clean low-carbon energy resources, including a tax credit for renewables, carbon price, and forward clean energy market. The way each incentive scheme promotes the intended technologies differs, as described in 4.2.2, and, as expected, the outcomes were not uniform. In an energy-only market framework, the carbon price scenario shows the most significant contribution in supporting clean low-carbon energy resources. Specifically, the increased marginal cost of carbon-emitting thermal resources in the carbon price scenario raises electricity prices in periods where those resources are on the margin. This, in turn, attracts new strategic investments in wind, PV, and storage resources. The PRM was observed to increase from 3.70% to 10.88% due entirely to additional solar, wind, and storage investments supported by the higher energy prices induced by the carbon price. However, in the forward clean energy market scenario, which provides an additional source of income for clean energy resources based on their projected annual energy production levels, we observed minimal impact on new strategic investments in low- or zero-emission resources. This implies that the $1.30/MWh additional revenue yielded by the clean energy market may be insufficient to attract new investments in the energy-only market setting. In the capacity market cases, all three incentive schemes clearly promote wind and PV investments while reducing investments in new NGCT capacity. While we did not conduct a sensitivity analysis to assess the impact of varying clean energy incentive levels (e.g., clean energy reference prices), this paper demonstrates how different incentive mechanisms for clean low-carbon energy investments could yield different results and shape future generation portfolios. However, reaching a conclusive assessment necessitate a comprehensive in-depth analysis, which we will further explore in the future study.

Our application of SCIM and LC-GEP across a range of different market designs and policy parameters demonstrates the importance of considering the behavior of profit-seeking GenCos in GEP. We find that there are particularly substantial differences in outcomes between the two modeling approaches in the context of an energy-only market framework or when a carbon price is implemented. We wish to be clear that we are not asserting that such exertion of market power is present in current markets or even that it will necessarily arise in future market interactions. However, our findings do suggest that traditional least-cost optimization models may fail to capture such market power dynamics if and when they do occur.

This study has several limitations because of the simplifications and assumptions made in the simulation models that we will seek to address in future work. First, the number of profit-seeking GenCos modeled in SCIM was limited to reduce computational complexity, which may result in excessive exercise of market power in the SCIM results, particularly in the energy-only market cases. Second, the system-wide PRM is a simplified reliability metric and a more comprehensive reliability assessment would be required to quantify system reliability levels across scenarios with more precision, especially in systems with high VRE penetration levels. Despite these limitations, the study provides insights into how different market designs can affect market signals and investment decisions and highlights the importance of using both market-based and traditional least-cost models in evaluating market design impacts and policy implementations.

Future work will focus on several key areas to extend the findings presented in this analysis. First, we will aim to address computational limitations by implementing advanced algorithms to improve computational performance and enable us to analyze larger systems. Second, we will combine our GEP modeling with more detailed reliability assessment models to calculate operational metrics beyond the system PRM to better reflect the reliability implications of different portfolios. Third, we plan to endogenize the capacity credit calculations for individual resources, to reflect that they are a function of the overall system portfolio. Fourth, we will analyze how transmission congestions affect the investment decision-making of profit-maximizing GenCos. Fifth, we will conduct a detailed analysis to precisely quantify the economic and environmental implications of diverse clean energy incentive levels and mechanisms. Finally, we will also evaluate system outcomes with different numbers of GenCos, including new entrants, and levels of resource ownership centralization while holding market design parameters constant. This will enable us to better assess the potential for market power to impact system generation portfolios.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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