Crediting Variable Renewable Energy and Energy Storage in Capacity Markets: Effects of Unit Commitment and Storage Operation

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Abstract— **As more variable renewable energy (VRE) and energy storage (ES) facilities are installed, accurate quantification of their contributions to system adequacy becomes crucial. We propose a definition of capacity credit (CC) for valuing adequacy contributions of these resources based on their marginal capability to reduce expected unserved energy. We show that such marginal credits can incentivize system-optimal investments in markets with installed capacity requirements and energy price caps. We simulated such markets using a LP-based capacity expansion planning model with convexified unit commitment (UC) constraints and ES. The impacts of UC and ES on capacity credits are investigated. Furthermore, we analyze technology and system cost distortions resulting from implementing inaccurate CCs in the capacity market. The results show that ignoring UC constraints can overestimate the CCs for VRE and ES. Building ES increases the CCs of VRE resources with higher capacity factors and a negative correlation with load. Assigning the wrong credit to VRE can significantly distort resource mixes and system cost. Implementing the proposed CCs can, in theory, eliminate those distortions and achieve the same overall optimum as a theoretical market without energy price caps.**

Index Terms— **resource adequacy, capacity markets, power system economics, wind power, solar power, battery storage**

NOTATION

A. Sets and Indices

B	Set of buses, index b
G	Set of all types of generation, index g
G^F, G^W, G^P	Fossil fueled, wind, and solar subsets of G
G_b	Set of generation located in bus b , subsets of G
H	Set of hours {1, …, T}, index h
L	Set of transmission lines, index l
S	Set of storage, index s
S_b	Set of storage located in bus b , subsets of S

B. Decision Variables

$c_{s,h}$	Charge of energy from grid to storage s at h [MWh]
$d_{s,h}$	Discharge of energy from storage s at h [MWh]
$gr_{g,h}$	Spinning reserve from g at h [MW]
n_g	Fraction of maximum capacity that is built g, unitless
$nrps_h$	Non-compliance with RPS policy at h [MW]
$p_{g,h}$	Electricity generation, g [MWh]
$pmin_{g,h}$	Minimum-run capacity online [MW], $g \in G^F$
s_h	State of charge of storage at end of h [MWh]
$scap_s$	Installed energy storage capacity [MWh]
$sd_{g,h}$	Shut-down action at the beginning of h, fraction
sr_h	Spinning reserve provided by storage [MW]
$su_{g,h}$	Start-up action for g at start of h, fraction
$ue_{b,h}$	Unserved energy at bus b in h [MWh]
$z_{g,h}$	Fraction of capacity g that is on-line in h, unitless

C. Parameters

$\alpha_{g,h}$	Capacity availability in h, unitless, $g \in G^W \bigcup G^P$
ϵ	Efficiency of charge-discharge cycle, unitless
$CMAX_g$	Maximum installed capacity of g [MW]
$DM_{b,h}$	Energy demand on bus b at h [MW]
DT_g	Minimum ramp down time of generator g [h]
DR_g	Maximum down-ramp rate, as fraction of capacity, g
FOR_g	Forced outage rate, g, unitless
$FPMIN_g$	Ratio of minimum-run capacity to installed capacity, g, unitless
IC_g/IS_s	Investment cost of generation/storage [$/MW/yr]
P_{rps}	Penalty for not meeting RPS requirement, [$/MWh]
PD	System peak demand [MW]
$PTDF_{b,l}$	Power transmission distribution factor, equal to flow through line l caused by a unit injection at bus b, unitless
R_g	Fraction of on-line capacity eligible for spinning reserve, generator g, unitless
RM	Reserve margin as fraction of peak, unitless
RPS	Renewable portfolio standard as fraction of annual energy demand, unitless
SC/SD	The maximum rates of charging/discharging, unitless
STC_g	Start-up cost, [$/MW]
T_l	Transmission thermal limits, [MW]
UR_g	Maximum up-ramp rate, as fraction of on-line capacity, unitless
UT_g	Minimum ramp up time of generator g [h]
VCG_g	Variable cost of generator g [$/MWh]
VCS_s	Variable cost of energy storage s [$/MWh]
$VOLL$	Value of loss of load [$/MWh]

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I. INTRODUCTION

According to some projections, renewable electricity generation including hydropower will double (from 19% in 2019 to 38% of the total electricity generation mix) by 2050 [1]. Battery-based energy storage (ES) is also expected to greatly increase. As shares of capacity and energy output of variable renewable electricity (VRE) and ES facilities increase, it becomes increasingly important to correctly identify the contribution they make to system reliability. Indeed, inaccuracies in assessing capacity credits for renewable resources may have contributed to the California blackouts of August 2020 [30], in part because increased VRE penetration means that the timing of gross load peaks diverges from when net load served by thermal generation (gross load minus VRE) is at its maximum.

Traditional resource adequacy assessments based on comparing the sum of installed or derated generator capacities to a desired reserve margin are generally satisfactory for predominantly thermal systems and can reasonably approximate whether a system will satisfy more sophisticated probabilistic criteria, such as a loss-of-load-expectation standard (LOLE) of 1 day in 10 years. However, such assessments are inadequate for systems with significant amounts of VRE or energy- or operating hours-limited resources such as ES, emissions-limited generators, and demand response (DR) [2]. Traditional metrics of resource contributions to system adequacy, such as nominal capacity derated by expected forced outage rates, cannot be simply applied to VRE or ES [3]. Therefore, the more general concept of capacity credit (CC) has been proposed and applied by system planners, based on Garver's [4] notion of Effective Load Carrying Capability (ELCC). Planners generally use CC to reflect the relative contribution of installed capacity of different types to meeting system adequacy requirements in resource planning. Properly defining how CCs could accurately gauge the capacity value of variable resources and ES then becomes key.

The fundamental idea behind calculating CC for a resource by ELCC-based methods is to compare the impact of adding that resource upon a system reliability index (e.g., LOLE or expected unserved energy EUE [3, 14, 15]) to the impact of a hypothetical perfectly flexible and reliable resource with no limitations on energy, operating hours, or starts. The amount of that hypothetical capacity that results in the same improvement in the index as the resource in question is the equivalent capacity. For instance, a 100 MW wind farm might reduce system EUE by the same amount as a hypothetical 20 MW combustion turbine that can be started and ramped instantaneously; the CC for that wind farm is therefore 20 MW. CCs are often expressed as a ratio (in that case, 20%).

There are many variants of this basic method for calculating CCs. For instance, other definitions include: equivalent firm capacity, equivalent firm power, and equivalent conventional capacity, among others [8, 17]. One version of the above calculation (implemented in [4]) instead considers what increase in system load can be accommodated by the resource while maintaining the same level of the reliability index. On the other hand, in practice, many electricity markets in North America estimate CC of VREs based on simple rules of thumb (summarized in [18]), such as using average output during summer periods or a small subset of high load hours. Finally, CCs can also be calculated either on a marginal basis (such as the CC for a hypothetical 1 MW VRE addition) or on an average basis for collections of resources (e.g., the total wind capacity on the system). A well-known characteristic of VREs is that due to high correlations of availability among different facilities and their correlations with load, their marginal CCs of VREs decline quickly as VRE investment increases, and are much smaller than average CC under high VRE penetrations [20].

CC-based resource adequacy calculations can be used to evaluate whether a given plan or plant mix is likely to meet a system reliability criterion [16]. Many studies have investigated how VREs and ES impact system adequacy, some of which have used the CC definitions mentioned above [2, 10, 19-21].

CCs are also used in formal capacity markets to determine how much individual resources contribute to meeting a resource adequacy requirement defined by government regulators, and how much those resources should be paid [7]. There are various rationales for the creation of such capacity requirements, and the markets created to operationalize those requirements. One rationale is the presence of energy offer and price caps in many markets whose original purpose was to limit market power. Such caps can result in the so-called "missing money" problem in which operating profits from spot energy and ancillary services markets are too small to cover resource capital costs and fail to signal the need for investment, even if the system reliability target is not met [5, 6]. Another rationale is the absence of long-run contracting markets, which make it difficult for resource developers to raise capital [7]. Capacity payments from capacity markets are able to act as additional incentives for electricity generator investments, in which the CCs are used to quantify the proportions of nameplate capacity of different types eligible to receive such payments [11].

It has been debated whether "missing money" and adequacy problems might become more pressing as the penetration of zero marginal cost VRE grows. The concern is that a higher amount of VRE would drive overall market prices to zero for much of the time, reducing the ability of back-up generation and storage to recover their capital costs from the spot market [7-10]. Production-based tax credits for VRE could even exacerbate such problems by depressing marginal prices to become negative for significant number of hours [8, 11, 12]. For these reasons, most power markets in the US likely to retain their capacity markets, and are adjusting their calculation of CCs to reflect the contributions of VREs and ES [13]. In addition, increasing energy price caps and implementation of scarcity pricing mechanisms have been proposed to increase operating profits received by resources at times when additional capacity would enhance system reliability [32].

However, despite the attention that has been paid to capacity credit calculations in resource adequacy markets, there is significant debate over the specifics of how to calculate CCs for different types of resources, and even over whether average or marginal values should be used to determine remuneration in capacity markets [33]. To our knowledge there are no studies that 1) provide a theoretical foundation for defining accurate CCs for resources that would support optimal investment in a price-capped market and 2) apply that framework to a system with ES and VREs. In this paper, the framework of [18], which calculates optimal CCs for thermal resources and VREs subject

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only to hourly dispatch constraints, is extended to analyze systems with unit commitment (UC) costs and constraints and large amounts of ES.

The question of how CCs should be calculated is not merely of theoretical interest, as different CC definitions can have a large influence on system reliability assessments [8] and on how much resources are paid, thus impacting the profitability of new plants investment. Market simulations show that different definitions can incentivize very different mixes of VREs and other resources, and distort in the optimal locations of resources of a particular type (e.g., among different wind sites) [18]. The result can be increases in the cost of achieving a given reliability standard. Here, we assess those distortions for a system with ES and UC limitations, and we propose a new CC calculation procedure based on EUE that provides correct marginal investment incentives for VREs, ES, and other resources.

The literature is unclear about whether the limits on resource flexibility imposed by UC (start-up, ramp, minimum up and down times, and Pmin constraints and costs) significantly decrease CCs for resources subject to those constraints, or for VREs that require such resources for back-up. Palmintier *et al.* [22] use a capacity expansion model that includes UC constraints to argue that ignoring flexibility can overstate the ability of a system to meet demand, carbon, and renewable portfolio goals simultaneously. Here, we directly address this question by calculating CCs for a variety of resources while considering UC limitations and costs.

We implement a capacity expansion model with a tight relaxed UC (TRUC) formulation based on [24], which features relaxations of binary variables and imposition of additional feasible cuts. Start-up costs, ramp limitations, Pmin constraints and costs, minimum on- and off-times, and commitment variables are retained in TRUC. In [24], TRUC's performance is compared to the classic load duration curve-based dispatch formulation, which omits UC constraints and costs. The comparison addressed the accuracy of results relative to a full binary-constrained UC with all UC constraints, considering systems in size from 11 to 110 generating units and average loads of 3.5 to 35 GW. It was found that simple dispatch models lacking UC features underestimated production costs from full binary-constrained UC models by 12.5% on average, while TRUC approximation only underestimated them by 0.8% [24, pg. 38]. In addition, TRUC's addition of tight cuts significantly enhances accuracy relative to simple relaxations of binary variables in UC. Finally, [24] shows TRUC yielded prices and generator profits that were much closer than dispatch model results to the full binary UC model, although price results still were somewhat inaccurate relative to the full model, likely because of how prices are calculated from mixed integer programs. Similar convexification and cut-based UC models have been applied in other research [e.g., 35-38] and commercial large-scale generation expansion software [e.g., 46-48] in order to reduce or eliminate the use of binary variables and to improve computation efficiency, with only small sacrifices in the accuracy of cost and price estimates.

The remainder of this paper is organized as follows. Section II describes the model framework, our CC definition, data sources, and the design of our numerical experiments. The experiments address the following questions for a case study whose load and VRE characteristics are based on data from the Texas (ERCOT) electricity market:

- *Question 1:* What CCs within a capacity market would provide incentives to build the same generation mix as a hypothetical ideal energy-only market without price caps?
- *Question 2:* What is the impact of modeling ES operations and UC constraints on CCs of VRE and other technologies?
- *Question 3*: How much could inaccurate CCs distort the resource mix and costs under different renewable policies?

Section III presents and discusses the results of the case study, including sensitivity analyses concerning the presence of existing coal capacity and transmission network constraints. Section IV provides conclusions.

II. MODEL FORMULATION AND ASSUMPTIONS

A. Formulation: Basic Energy-Only (EO) Market Model

Below we present a resource expansion model that extends [18] by including battery energy storage, unit commitment and transmission constraints. The model determines the optimal (least-cost) installation and operation of generation and storage fleets to meet system demand and to provide ancillary services, while meeting renewable portfolio standard (RPS) and resource adequacy requirements. The basic "energy-only" (EO) model assumes a value of lost load (VOLL) for unserved energy (EUE), and this drives the optimal reliability of the system. Then, by incrementally varying the optimal capacities and noting their relative effects on EUE, capacity credits can be estimated, as described in Section II.B, below. The values of CC can then be applied in a capacity market version of this model (model EC, Section II.C), which we do using the case study data described in Section II.D. Section II.E then summarizes the experimental design, in which solutions to the two models are compared in order to answer the three questions defined at the end of Section I.

A static planning model that minimizes annualized cost is assumed, in which the timing (year) of additions is not optimized; rather, the capacity mix is optimized for a given year, recognizing that the year's hourly loads and renewables cannot be predicted precisely due to year-to-year variability. A sample of 10 years of ERCOT load and resource data with different annual profiles, load factors, and capacity factors are used to estimate those costs. Other assumptions include the following. All generators are "greenfield", with the exception of one sensitivity analysis with existing coal plants. There is no uncertainty about capital cost, policy, or other factors. All generators and storage units are assumed to be price-takers (no market power). Demand is perfectly inelastic so that market equilibria can be simulated by minimizing cost. Prices are free to reflect system conditions based on locational marginal pricing principles, but in some cases are subject to a price cap. We assume battery storage rather than hydro pumped storage for new additions, given that there are presently few proposals for new pumped storage plants and that they are environmentally controversial. Our base simulations assume no transmission congestion (a single-node system) or losses, similar to many other studies of power system resource adequacy [41,42]. But we also simulate a twonode/one-line case as a sensitivity analysis to illustrate how transmission capacity limits can impact CC and other results.

Furthermore, as noted in Section I, thermal generation operations are subject to a convexified UC formulation [24], in which the (normally) binary {0,1} restrictions on commitment variables are relaxed. The start-up and shut-down movements occur at the beginning of the hour; the continuous UC approximation allows any fraction of capacity to be started-up or shut-down. Use of this continuous approximation facilitates calculation of marginal CCs.

The objective function and constraints are presented below.

1) Objective Function

The model minimizes total system cost, including capital investment, fuel, O&M, and UC costs (start-up and Pmin), along with penalties from unserved load and violations of the RPS. Shut-down costs are not explicitly shown because we assume that each start-up is paired with a subsequent shut-down, so that the cost of a single shut-down can be folded into the start-up cost without changing the solution.

$$MIN \sum_{g\in G^F,h\in H}\left(VCG_g * p_{g,h} + STC_g * CMAX_g * su_{g,h}\right) + \sum_{g\in G}\left(IC_g * CMAX_g * n_g\right) + \sum_{s\in S}\left(IS_s * scap_s\right) + \sum_{s\in S,h\in H} VSC_s * \left(d_{s,h} + c_{s,h}\right) + \sum_{h\in H,b\in B}\left(VOLL * ue_{b,h}\right) + \sum_{h\in H}\left(P_{rps} * nrps_h\right) \tag{1}$$

2) System Level Constraints

(a) System Demand and Supply Balance

Total generation plus unserved energy should equal load in each hour. Wind and solar output can be curtailed.

$$\sum_{g\in G} p_{g,h} + \sum_{s\in S}\left(d_{s,h} - c_{s,h}\right) + \sum_{b\in B} ue_{b,h} = \sum_{b\in B} DM_{b,h}, \forall h \in H \tag{2}$$

(b) Hourly Spinning Reserve Requirement

Spinning reserve is modeled as an example of ancillary services. ES can halt its charging to provide spin. In general, downward reserve variables could also be included. Since downward reserves only exist for regulation in most U.S. markets, and not for spinning reserve, and the price of down-regulation is usually much less than for up-regulation, we omit downward reserves in order to limit the model's size.

$$\sum_{g\in G^F} gr_{g,h} + \sum_{s\in S} sr_{s,h} + \sum_{s\in S} c_{s,h} \geq RM * \sum_{b\in B} DM_{b,h}, \forall h \in H \tag{3}$$

(c) Renewable Portfolio Standard (RPS)

This constraint requires that renewable generation plus the non-compliance should be no less than the RPS.

$$\sum_{g\in (G^W,G^P),h\in H} p_{g,h} \geq \sum_{h\in H}\left[nrps_h + \sum_{b\in B}\left(DM_{b,h} - ue_{b,h}\right)\right] * RPS, \tag{4}$$

3) Generation Unit Commitment and Dispatch

The UC constraints in our model are based on TRUC constraints in [24]. Under TRUC, $z_{g,h}, su_{g,h}, sd_{g,h}$ may be relaxed and kept physically meaningful. For example, the start-up variable means “what portion of the nameplate capacity starts up in hour *h*”.

(a) Minimum Run Limit

$$pmin_{g,h} = \left(1 - FOR_g\right) * FPMIN_g * CMAX_g * z_{g,h}, \quad \forall g \in G^F, h \in H \tag{5}$$

(b) State-transition Constraints

$$z_{g,h} - z_{g,h-1} = su_{g,h} - sd_{g,h}, \ \forall g \in G^F, h \in [2,T] \tag{6}$$

(c) Minimum Up/Down Time Constraints

$$\sum_{i=h-UT_g+1}^{h} su_{g,h} \leq z_{g,h}, \ \forall g \in G^F, \ h \in \left[UT_g + 1, T\right] \tag{7}$$

$$\sum_{i=h-DT_g+1}^{h} sd_{g,h} \leq n_g - z_{g,h}, \ \forall g \in G^F, \ h \in \left[DT_g + 1, T\right] \tag{8}$$

Eq. (7) constrains $z_{g,h}$, the proportion of capacity of generator g that is committed in hour h, to be at least equal to the proportion of capacity started up in the previous UT_g*-1* hours. Eq. (8) is the symmetric formulation for the minimum shut-down time.

(d) Lower and Upper Bounds of Thermal Generation

$$pmin_{g,h} \leq p_{g,h}, \ \forall g \in G^F, \ h \in H \tag{9}$$

$$p_{g,h} + gr_{g,h} \leq \left(1 - FOR_g\right) * CMAX_g * z_{g,h}, \ \forall g \in G^F, h \in H \tag{10}$$

(e) Generator Spinning Reserve Limit

$$gr_{g,h} \leq R_g * \left(1 - FOR_g\right) * CMAX_g * z_{g,h}, \forall g \in G^F, h \in H \tag{11}$$

(f) Ramp Up/Down Limits

$$\left(gr_{g,h} + p_{g,h} - pmin_{g,h}\right) - \left(p_{g,h-1} - pmin_{g,h-1}\right) \leq UR_g * \left(1 - FOR_g\right) * CMAX_g * z_{g,h}, \ \forall g \in G^F, h \in [2,T] \tag{12}$$

$$\left(p_{g,h} - pmin_{g,h}\right) - \left(gr_{g,h-1} + p_{g,h-1} - pmin_{g,h-1}\right) \geq -DR_g * \left(1 - FOR_g\right) * CMAX_g * z_{g,h}, \forall g \in G^F, h \in [2,T] \tag{13}$$

(g) Renewable Availability Limits

$$p_{g,h} \leq CMAX_g * \alpha_{g,h} * n_g, \forall g \in (G^W, G^P), h \in H \tag{14}$$

(h) Operating Limits

$$z_{g,h} \leq n_g, \forall g \in G^F, h \in H \tag{15}$$

4) Storage Operation

The battery storage operation constraints. (16)-(19) include charging and discharging limits, the energy storage limit, and the energy transition constraint. We allow simultaneous charging and discharging for ES operation [39,40], as limited by constraint (16). This assumes that separate battery modules could be operated in different modes at the same time, which can occur if prices are negative although such operation does not occur in our simulations. We note that there is no consensus in the literature as to whether charging and discharging at the same time is physically sensible [24]; other assumptions are possible [49]. (20) requires that the energy stored at the start of an hour can serve at least one hour of discharge and one half-hour of spinning reserve.

$$\frac{c_{s,h}}{SC} + \frac{d_{s,h}}{SD} \leq scap_s, \forall h \in H \tag{16}$$

$$d_{s,h} + sr_{s,h} \leq SD * scap_s, \forall h \in H \tag{17}$$

$$s_{s,h} \leq scap_s, \forall h \in H \tag{18}$$

$$s_{s,h} = s_{s,h-1} + \epsilon * c_{s,h} - \frac{1}{\epsilon} * d_{s,h}, \forall h \in [2,T] \tag{19}$$

$$s_{s,h} \geq \frac{1}{\epsilon} * \left(d_{s,h} + 0.5 * sr_{s,h}\right), \forall h \in H \tag{20}$$

5) Transmission Line Constraints

Eq. (21) is a standard linearized DC load flow formulation. It calculates the power flow in each transmission component $l \in L$ as the sum of products of shift factors (or power transmission distribution factors, *PTDF*) and power injections, and places an upper bound T_l on that flow. The index functions $b(g)$ and $b(s)$ define the bus where each generator g or storage facility s is located.

$$\sum_{g\in G} PTDF_{b(g),l} * p_{g,h} - \sum_{s\in S} PTDF_{b(s),l} * \left(c_{s,h} - d_{s,h}\right) - \sum_{b\in B} PTDF_{b,l} * \ (DM_{b,h} - ue_{b,h}) \le T_l, \forall h \in H, l \in L \qquad (21)$$

B. Capacity Credit Definition

To estimate CCs, we add or subtract a 1 MW permutation to the optimal installed capacity of each type of generation and ES, one type at a time, and note the resulting impact on the system's EUE. We use EUE rather than frequency or duration indices (such as LOLE), as EUE is a more stable measure of system reliability**,** especially when ES is involved since by shifting the timing of ES discharge, different LOLE values can result without changing EUE. In particular, we compare the EUE reduction from a 1 MW increment of capacity of interest to the EUE reduction from a 1 MW increment of a hypothetical perfectly flexible and reliable generator, and then define CC as the ratio of the two quantities:

$$CC_g = \frac{EUE_0 - EUE_g}{EUE_0 - EUE_{pc}} \quad , \qquad (22)$$

where:

- EUE_0 is the total unserved energy of the optimal generation mix ($\sum_h^H ue_h$), which is the solution of (1)-(21);
- EUE_g is the total unserved energy of the re-dispatched system if 1 MW of resource type g is added to (or subtracted from) the optimal investment mix and system; and
- EUE_{pc} is the total unserved energy of the re-dispatched system resulting from adding (or subtracting) 1 MW of perfectly flexible and reliable generating capacity to optimal investment mix.

A similar expression is used to calculate ES credit CC_s.

C. Formulation: Price-Capped Energy & Capacity Markets

The model of Section II.A, which we call Model EO (Energy-Only), represents the situation in which energy price is allowed to rise to VOLL (which in our case study is assumed to be $10,000/MWh), which drives the optimal level of EUE. In this section, that model is modified to include an energy price cap and capacity market, which we call Model EC (Energy-Capacity Market). Energy price can only rise to an assumed price cap (here $1200/MWh), and a capacity market is added to ensure that system reliability is maintained (i.e., the optimal EUE found by Model EO is still achieved). To create Model EC, we add the following system adequacy constraint to Model EO and reduce VOLL in (1) to the assumed price cap.

$$\sum_{g\in G} CMAX_g * n_g * CC_g + \sum_{s\in S} scap_s * CC_s \ \ge PD * (1 + RM) \qquad (23)$$

The left-hand side (LHS) of (23) is total unforced capacity (derated using capacity credit *CC*)**,** and the right-hand side (RHS) is the target total system capacity including planning reserves (in terms of "unforced capacity"), which is set high enough such that the EUE from Model EO is achieved.

In [18], it is shown that it is possible to choose values of *CC* and *RM* such that the optimal solution of Model EC is also optimal for Model EC for a system of thermal and VER resources without UC constraints and costs (In particular, we choose a value of RM such that the weighted (by marginal CC) sum of capacity just equals (1+RM) times the peak load, so that Eq.(22) will be just binding at that optimal solution.). This is also the case for our more complex model with UC and ES, as demonstrated below.

D. Case Study Data

1) Load and VRE Time Series

It has been argued that capacity credit analyses for VRE sources require more than five years of data at an hourly resolution to obtain reliable results [25]. We use ten years of normalized hourly demand, wind, and solar data from ERCOT [26, 27]. We set 5000 MW as the maximum (peak) load for each year in our case study, and the hourly ERCOT load data is rescaled accordingly.

We chose four wind sites (three onshore sites: Wind1; Wind2; Wind3; and one offshore site, Wind4) and three solar sites (Solar1, Solar2**,** and Solar3) based on the differences in their geography and generation characteristics. Wind1 was found to have moderate annual energy production while exhibiting a relatively high variation during the study period. However, very little of this energy was produced during peak-load periods. Wind2 has lower annual energy but higher production levels during peak hours. Wind3 has the highest annual energy production and the lowest variability. Its average production during peak periods lies between Wind1 and Wind2. The offshore wind site profiles in Wind4 are obtained from a hypothetical profile developed for ERCOT. Most wind sites (except for Wind2) are negatively correlated with peak load, while all three solar sites positively correlate with peak load. Among solar sites, Solar3 has the highest annual production and the best peak load correlation, dominating the others.

2) Resource Assumptions

All resource characteristics and cost data are summarized in Table 1. Costs are derived from EIA or PJM [28]. Start-up costs, the fraction of minimum-run capacity as a fraction of total capacity ($pmin_{g,h}$), the up-ramp rate, the minimum up time, the minimum down time, spinning reserve capability, and forced outage rates are all based on Western Electricity Coordinating Council data [28, 29]. Batteries can store 4 hr of energy with a discharge/charge efficiency of 0.96. In our experiment, we reduced the storage investment cost to 40% of the WECC assumed value as storage costs are rapidly decreasing, and storage is not cost-effective at its originally assumed investment cost.

E. Experimental Design

First, we conduct a numerical experiment to show how these two market designs (energy-only and capacity markets) could achieve the same optimal generation investments if our proposed marginal CCs are used in the capacity market (*Question 1,* defined at the end of Section I). We solve Model EO first and then calculate the marginal CC for each resource (as described in Section II.B). Then in Model EC, we plug these CCs into the left-side of constraint (23) and adjust *RM* in that constraint's right-side so that the constraint is just satisfied. It turns out that this results in the optimal solution of Model EO being both an optimal and feasible solution of Model EC, if, as described later in this paper, we account for nonuniqueness of the CCs.

Second, to examine the impacts of unit commitment constraints and storage on CC (*Question 2*), two experiments are implemented. One drops all UC constraints (5)-(13), costs, and the other deletes the storage capacity variable $scap$. Then we compare the resulting CCs in each case to the original values

Table I. Generators and Storage Data Assumptions

Technology	Investment Cost ($/MW/yr)	Variable Cost ($/MWh)	Heat Rate (Btu/kWh)	Fuel Cost ($/MMBtu)	Start-Up Cost ($/MW)	Pmin	Up-Ramp Rate	Minimum Up/Down Time (h)	Spinning Reserve	Forced Outage Rate
Advanced Combustion Turbine (ACT)	$85,591	$0.38	9,241	$3.26	$33.92	60%	100%	1	16.7%	2.90%
Advanced Combined Cycle (ACC)	$113,641	$1.09	6,296	$3.26	$90.07	60%	100%	6	16.7%	3.28%
Coal	$562,747	$4.03	9,250	$2.11	$111.31	40%	36%	168	6.0%	4.19%
Wind On-Shore (W1, W2, W3)	$214,780									
Wind Off-Shore (Wind4)	$460,730									
Solar PV (Solar1, Solar2, Solar3)	$232,230									
Energy Storage (ES)	$81,552	$28.92								

from the full models.

Third, we show how equilibrium generation mixes and costs can be distorted by implementing inaccurate CCs in the capacity market simulated in model EC (*Question 3*). We assume three sets of inaccurate CCs: low (VRE and ES equal to 0%), medium (wind 15%, solar 40%, and ES 60%), high (wind 25%, solar 100%, and ES 100%). These test cases represent CC values that might be yielded by various methods (e.g., ELCC and rules of thumb that are often implemented in practice). Because VRE penetration levels dramatically affect VRE CCs, we conduct experiments under different RPS levels: 0%, 20%, and 40% with or without renewable tax credit subsidies (30% investment tax credits for solar and $23/MWh production tax credits for wind). The baseline cases are represented in Model EO under various renewable policies. The corresponding distorted CC cases are modeled in Model EC using the low medium, and high CC levels. In each case, the reserve margin (right side of (23) in Model EC) is adjusted to yield the same EUE as the corresponding baseline Model EO cases. This allows us to gauge the inefficiency from distorted CCs in terms of just the cost metric (since for a given RPS, the EUE will by design be the same for all EO and EC solutions).

Each model has approximately 4.5M variables and 6.9M constraints, and takes about 2 hours to solve on a commodity desktop computer (Intel Core i7-5930K CPU @3.50 GHz, with 32 GB of memory). The software used is the AIMMS platform with CPLEX V20.1.

III. CASE STUDY AND RESULTS

We start by showing optimal capacity expansion results in an ideal energy-only market (Model EO), and then address the three questions. *Question 1* by demonstrating how we can achieve the same optimal resource mix after introducing an energy price cap as well as a capacity market that pays each type of capacity in proportion to their marginal CC (Model EC). Then we investigate *Question 2:* how UC constraints and ES operation would affect optimal resource mixes and the corresponding CCs. Lastly, we consider *Question 3* by comparing resource mixes and market efficiency from using marginal CCs versus inaccurate CCs. The last two subsections (III.D and E) present sensitivity analyses, in which we examine the effect of including existing coal capacity (which introduces UC inflexibilities) and transmission network constraints.

A. Question 1: Energy-Only & Equivalent Capacity Markets

In the baseline energy-only market run (Model EO, Section II.A), the model parameter assumptions include 40% RPS, renewable tax credits, 10,000 $/MW VOLL (no price cap), and no capacity market ((23) omitted). We solve this energy-only market to obtain the optimal resource mix. By design, that solution minimizes the economic cost of meeting demand, under the assumed VOLL and RPS noncompliance penalties. The solutions include a mix of wind, solar, ES, and natural gas plants; it turns out that coal investments are not justified. The marginal CCs for the resource mix are calculated according to the method described in Section II.B (equation (22)).

After an EO market solution is obtained, we then solve for the corresponding EC (capacity market) solution. This is done by imposing an energy price cap of $1200/MWh and add a capacity market (23) using the calculated marginal CCs and the corresponding value of the reserve margin that results in the same EUE as the Model EO solution (as in Section II.C). (For instance, in case EC1 below, the sum of capacity weighted by marginal CCs in the energy-only EO solution is 4832 MW. As a result, the reserve margin RM applied to the 5000 MW peak is -3.4%, which when applied in the EC model yields the same solution as the EO model.) A comparison of the solutions shows that the theoretical equivalence of those two models in the case of no ES and no UC constraints in [18] also applies in this more complex case. Table II shows the numerical results.

Table II. Equilibrium Results Comparison: Energy-only Market (Model EO) Versus Capacity Market (Models EC1/EC2)

Market Case	Price Cap	ACT (MW)	ACC (MW)	Wind2 (MW)	Wind3 (MW)	Solar3 (MW)	ES (MW)	VOLL ($)	System Cost (million$)
EO	No	2352	1952	209	2422	303	532	10000	12760.41
EC1	Yes	2348	1953	210	2427	294	540	1200	12760.35
EC2	Yes	2354	1951	209	2423	300	532	1200	12760.41

In Table II, we present 3 cases: Model EO is the energy-only market without a price cap, and Models EC1 and EC2 are capacity markets with energy price caps. In Model EC1, we use a marginal CC calculated by incrementing unit generation capacity (adding 1 MW of each type in turn), while in Model EC2 we impose two capacity constraints (23), based respectively on two sets of CCs calculated by incrementing and decrementing, respectively, resource capacity by 1 MW in Model EO.

The reason for using two sets of CCs is that when we consider UC and the ES in the model, we found that the relationship between the CCs and installed capacities was not smooth, in that EUE is a piecewise convex function of installed capacity. Marginal CCs change abruptly at the vertices of those functions. Because LPs choose extreme point solutions, such a discontinuity in CC values tends to occur at precisely the capacity levels found in Model EO. Therefore, a single constraint (23) based on one set of CCs may be insufficient to guarantee the solutions of Models EO and EC precisely coincide; model EC may yield a slightly less expensive solution with slightly more EUE (EC1 in Table II). This error can be corrected by imposing

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more than one version of (23) (Model EC2), in which the CC's in different versions represent the range of marginal capacity values within a subgradient of EUE with respect to resource capacity. The resulting Model EC1 resource mix and cost are close to those of the original Model EO, while the results of Models EO and EC2 are almost identical, consistent with the theoretical expectation in [18].

This result extends the theoretical result from [18] that even for a market with UC constraints and ES, an appropriately calibrated capacity market can, in theory, yield the same cost-minimizing solution as an energy-only market. Of course, many real-world complications would cause markets based on Models EO and EC to diverge. Among them are errors in estimating CC, whose impacts we consider in Section III.C, below.

B. Question 2: Impacts of UC & ES on Resource Mix & Capacity Credits

Rules of thumbs used by ISOs to calculate CCs often disregard operating inflexibilities, such as unit commitment or storage limitations [18]. We now consider how models that omit UC constraints and ES affects resource mixes and CC values.

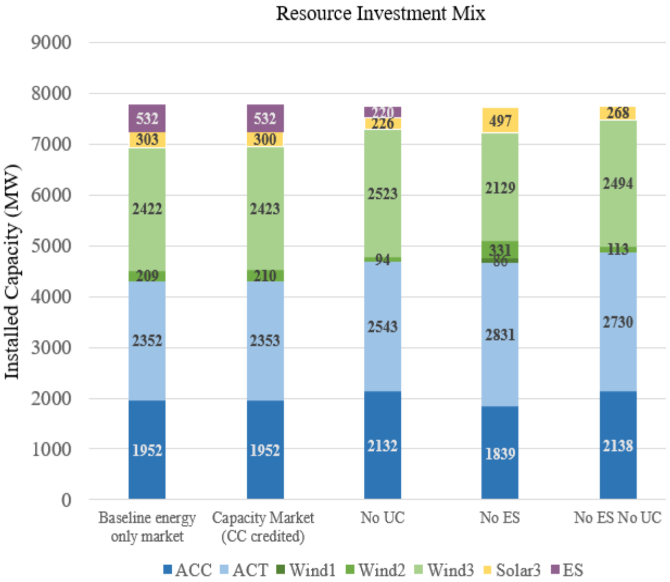

Fig. 1. Installed resource capacity (MW) in EO market and EC market with or without UC and/or ES

Fig. 1 represents the results obtained using Model EO under the assumptions that no price cap exists (prices can climb to the assumed VOLL of $10,000/MWh) and that both a 40% RPS and renewable tax credits are applied. In the baseline run with UC and ES, the optimal solutions show that more than half of the mix involves thermal generators (ACC, ACT); a VRE mix consisting only of Wind2, Wind3, and Solar3; and ES amounting to 8% of total capacity. However, after deleting UC constraints (5-13) along with start-up and Pmin costs (No UC, second bar in Fig. 1), more conventional generators are favored, at the expense of VRE and ES capacity. This is in part because omitting UC constraints allows thermal capacity to more effectively back up Wind3, which has the highest capacity factor (CF) as well as the highest negative correlation with the load.

Meanwhile, comparing the baseline column and the "No Storage" column (fourth bar), combustion turbine capacity is increased to replace ES and provide needed back-up during peaks. In addition, VREs are more diversified with Wind1 added into the system for the first time and greater investment in Wind2, which is positively correlated with load; thus, ES allows a system to take advantage of higher capacity factor VREs which can weaken incentives to diversify sources.

Finally, when the model omits both UC and ES, we also obtain increased thermal capacity and slight decreases in the total renewable capacity and its diversity.

Following our capacity credit definition (Section II.B), the CCs for each resource in the above cases are calculated (Fig. 2). The resulting CCs for VRE and ES vary across the cases. First, omitting UC constraints (5-13) and start-up variables inflates the CCs of VRE and ES (compare the No UC and baseline cases), indicating that more flexible thermal capacity increases the ability of the other sources to meet the system's reliability needs. Under the assumption that TRUC is a reasonable approximation of binary-based UC models, we conclude that including UC can bias CCs of non-thermal resources upwards. Further analysis indicates that the crucial UC constraints are ramp constraints, based on comparing EUE values from simulations in which generation capacity is fixed and then just one type of UC constraint is relaxed (ramp, Pmin, min on- and off-time constraints, or start-ups).

Second, omitting ES instead decreases the CCs of VRE capacity (Fig. 2, No ES case vs. Baseline case), so the effects of disregarding both UC and ES are partially offsetting (No ES & UC case vs. Baseline). However, additional solutions in which VRE capacity is held constant show that this decrease in CCs is due to the greater penetration of VREs that ES makes possible, and not directly due to ES itself. In particular, in our case study, adding ES to a system with fixed VRE capacity has a slight decreasing effect on wind CC, and none on solar CC. Similarly, additional analysis (not presented here) shows that the decrease in ES CCs in Fig. 2 is due to the decline of CC with ES penetration, and not to the omission of UC considerations.

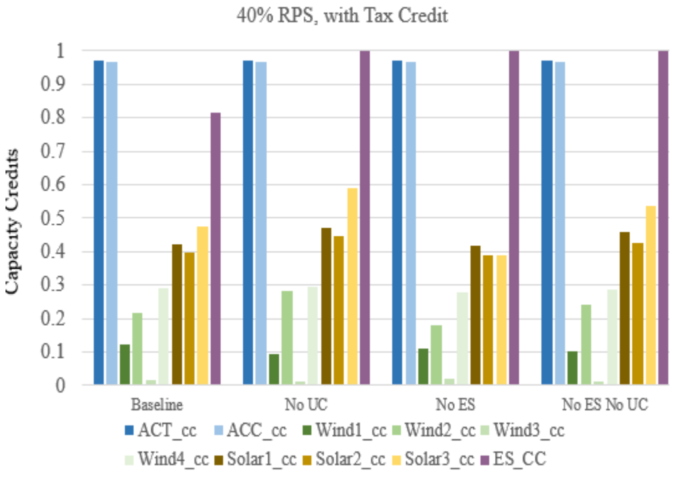

Fig. 2. Impact of inclusion of UC and ES on capacity credits

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Generally, the order of magnitude of the UC and ES impacts is a change of between one-tenth and two-fifths of the original CC value. The largest impacts occur for VREs with relatively more penetration (Wind2, Solar3). This is confirmed by market simulations of lower RPS levels (0%, 20%), where these impacts diminish. This suggests that representing system flexibility becomes more important for assessing the reliability impacts of VREs as the penetration of individual technologies and sites increases.

C. Question 3:Resource Mix & Cost Impact of Inaccurate CCs

Here we consider the investment and cost effects of adopting incorrect CCs. Three sets of arbitrary CCs for VREs and ES in Model EC are considered: low (all 0%), medium (wind 15%, solar 40%, and ES 60%), and high (wind 25%, solar 100%, and ES 100%). Renewable tax credits are assumed. Thermal resources are derated by (1-FOR). These CC values are representative of the range used in practice [18]. Note that even though actual marginal contributions of different wind or different solar resources can differ greatly (Fig. 2, above), these simplified cases assume the same CCs for all wind or all solar, consistent with many US markets. The experiments were conducted at two levels of RPS (20%, and 40%) and with or without tax credits (ITC and PTC). As before, we first solve for the baseline case using the energy-only market (Model EO) under each RPS to find the overall cost-minimizing portfolio of resources, subject to the VRE target. Then, we solve Model EC with an energy price cap and capacity market using the correct marginal CCs (not shown, since that case yields the same solution as Model EC) as well as the three inaccurate sets of CCs. Right sides of the capacity constraint (23) are adjusted to achieve the same EUE as the baseline Model EO, so that the solutions can be compared based on just cost. Below, we describe how much the generation mix changes and costs increase in each solution relative to Model EO.

Fig. 3 depicts the investment mix and system cost deviations under the arbitrary VRE and ES CCs. At the higher penetration level (40% RPS, Fig. 3a), the capacity market equilibria cases reveal varying degrees of distortion in the solutions. When applying low CCs (all 0%), the mix of VRE changes (maintaining the same total MWh, meeting the RPS) while additional conventional generating capacity is constructed and system costs increase by 1.97% compared to the Model EO baseline. Meanwhile, under medium CCs (wind 15%, solar 40%, and ES 60%), system costs are impacted less compared to the low CC case (0.48% rather 1.97% increase). In the high CC case (wind 25%, solar 100%, and ES 100%), however, overinvestment in Solar3 and ES occurs at the expense of combustion turbines and wind, resulting in 2.85% higher costs than the baseline case.

But a somewhat different resource mix results in the moderate (20%) RPS case (Fig. 3b). More combustion turbine capacity is installed when VRE and ES CCs are low, but this also occurs when those CCs are high. This is because even though high CCs for VREs and ES disadvantage combustion turbines, the disadvantage for combined cycle plant is even greater, so on net, more peakers are installed while combined cycle capacity is reduced, unlike Fig. 3(a).

Fig. 3. Resource mixes and increases in system cost relative to Baseline Model EO resulting from EC model with low, medium, and high arbitrary CCs under different levels of RPS (a. 40 % and b. 20%) (Note: marginal CCs under Model EO under 40% RPS: Wind2, 22%; Wind3, 1.5%; Solar3, 48%; ES 82%; under 20% RPS: Wind2, 32%; Wind3, 1.6%; Solar3, 67%; and ES 100%)

Examining the impact on VREs shows that given a specified RPS, by definition total VRE energy doesn't change, but the mix of types does. Under either RPS (Fig. 3(a)), the two lower levels of CCs favor Wind3 at the expense of solar, as solar is either entirely or largely eliminated from the mix; the highest CCs on the other hand increase the amount of solar several-fold. All three arbitrary sets of CCs reduce the diversity of wind resources, favoring Wind3. Thus, complex interactions of renewable policies and technological characteristics can result in unexpected impacts from distorting CCs away from their true marginal values.

D. Sensitivity Analysis 1: Existing Coal-Fired Facilities.

Here, we consider how the above conclusions change if the system has existing coal plants, and how more accurate modeling of forced outages of those plants could affect the generation mix.

Although coal plants are no longer being built in the U.S., existing facilities and decisions about retirement and life extension are still important in planning. Here, we consider two sensitivity cases: existing coal power capacity amounting to 1000 MW and 2500 MW. Their impacts on the mix generation investment are illustrated in Fig. 4. Coal plants function similarly to the combined cycle plants of the previous solutions, serving mainly as baseload generators; consequently, the existing coal capacity mainly displaces combined cycle facilities. In terms of the impacts upon the answers to the questions addressed above, the largest difference concerns the effect of omitting UC constraints. As Fig. 4 shows, omitting UC constraints biases the generation mix by increasing Wind3 and especially combustion turbines, at the expense of ES and other VREs.

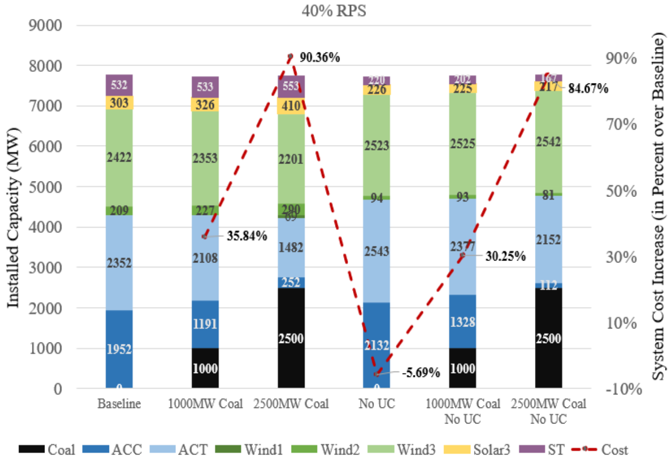

Fig. 4. Existing coal plant sensitivities: Resource mixes and cost deviations under different amounts of existing coal capacity with or without UC constraints

In all the above analyses, we have made two simplifying assumptions about uncertainties other than from load and renewable generator variability. The first is to disregard short-term forecast uncertainty, which can affect UC decisions and the reliability contribution of renewables; modeling this uncertainty is very challenging in capacity expansion and is deserving of further research [43].

The second simplifying assumption is to derate thermal capacity for forced outages, rather than simulate random forced outages using, for instance, Monte Carlo simulation (as in some production costing models e.g., PLEXOS [37]). We have tested the effect of the latter assumption on the results for the case of 2500 MW of existing coal, assuming, as in ERCOT, that this capacity is divided among 20 units, each with identical forced outage rates (0.0419). For simplicity, independent outages are also assumed, consistent with classic reliability methods [45] but which do not account for correlated outages due to weather [44]. Assuming a mean outage duration of 7 days, these assumptions can be translated into transition probabilities for each unit in each hour, from which a Monte Carlo sequence of total available coal capacity for 87.600 hours was generated. Using that random sequence rather than the average derated coal capacity of 0.9581*2500 MW in each hour made a negligible difference in the model solution, changing the each type of gas additions by no more than 17 MW and altering VRE and ES additions by 6% (measured by the ratio of the sum of absolute capacity changes to total capacity of those types). Since the focus of our paper is on renewable capacity credits, this indicates that the derating approximation for thermal plants is acceptable, assuming independent outages and a reasonably large number of thermal units. Future research should address the impact of weather correlated thermal outages interacting with renewable availability.

E. Sensitivity Analysis 2: Transmission Network Impacts.

In this subsection, we investigate how transmission and congestion can affect our conclusions about capacity credits, and the theoretical equivalence of energy-only and capacity markets.

Here, we solve a two-zone, radially connected market in which there is a renewable zone (wind and solar plus storage) and a demand-only zone where all thermal generation is sited. All generator cost, renewable resource distributions, and load distribution assumptions are the same as our single zone examples (e.g., the highest demand is still 5000 MW). We did several runs with the line limits set at infinity (copper plate), 2000 MW, 1500 MW and 1000 MW, respectively. In addition, we tested our method for calculating marginal capacity credits and including them in a capacity market constraint, and confirmed that the same solution results as our original energy-only market without a price cap. Selected capacity expansion results are shown in Fig. 5, including a case in which solar is instead located in the demand-zone along with storage resources.

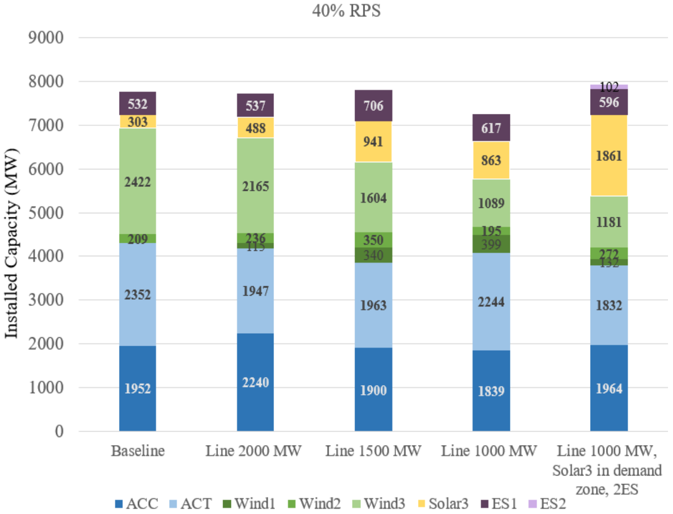

Fig. 5. Resource mixes under different levels of line capacity limits. (Note: ES1 is storage sited in the renewable zone, while ES2 is in the demand zone. ACC and ACT are in the demand zone, and all wind is in the renewable zone, as is solar except in the fifth solution, which sites solar in the demand zone. Marginal CCs in Line 2000 MW case: Wind1, 12%; Wind2, 21%; Wind3, 2%; Solar3, 33%; ES1, 78%; Line 1500 case: Wind1 8%, Wind2, 22%; Wind3, 4%; Solar3, 20%; and ES1, 70%; Line 1000 MW case: Wind1, 4%, Wind2, 14%; Wind3, 2%; Solar3, 11%; and ES1, 50%; Line 1000 MW &Solar3 in demand zone & 2 ES case: Wind1, 13%, Wind2, 27%; Wind3, 5%; Solar3, 12%; and ES1/ES2, 75%.)

Comparing the first four columns in Fig. 5, stricter line capacities yield a more diverse installed renewable mix by increasing solar in the demand zone due to congestion between the renewable and demand zones, and having a more diverse set of wind investments in order to use the scarce transmission capacity more efficiently. Therefore, transmission congestion can change the installed optimal generation mix. As a result, the corresponding CCs of renewables and storage would likely change compared to the no transmission case. However, the transmission network did not alter any of our general conclusions concerning, first, the impacts of UC or ES on capacity credits and, second, our claim that using marginal CCs to credit resources in capacity markets can incentivize the same optimal resources investment as in an ideal energy-only market. In particular, defining a capacity market constraint based on marginal CC's yielded the efficient the solution, even though resources were located in different zones.

In the last case in Fig. 5, we move the Solar3 resource to the demand zone and allow storage installation in either zone. As expected, more Solar3 is built if it is in the demand zone (compared to the fourth column), since its production would not be curtailed by congestion. Also, we can see that it is advantageous to site most of the storage in the renewable zone, because it enables more efficient use of scarce transmission capacity. If renewable curtailment due to congestion and unserved energy occur during the same hour, the marginal capacity credit of renewables could be reduced. However, renewable and demand curtailment did not coincide in our solutions, since energy went unserved only during low renewable energy periods. It is also possible that, for the same reason, resources that can be sited in either zone (here, energy storage) could have differing capacity credits in the two zones, but this did not occur in our case.

IV. CONCLUSIONS

We propose a method for calculating marginal capacity credits and including them in capacity markets based on the resource's capability to reduce EUE within a resource investment planning model. The method uses a LP-based chronological production costing approach that extends Ref. [18] to include systems with battery energy storage and (convexified) unit commitment constraints and costs, as well as simplified network limits. Use of these marginal CCs to determine financial settlements in capacity markets is shown to be potentially consistent with the results of the theoretical ideal of energy-only markets, as in ERCOT or as originally proposed by Schweppe and his colleagues [33].

We find that the presence of ES and UC considerations can significantly affect assessments of CCs for VREs, sometimes altering them by as much as 40%. Therefore, ES and UC should not be disregarded or simplistically treated in resource adequacy studies. The results also confirm the well-known observation that the marginal capacity contributions of VRE decline when more capacity is installed, and also show that this is true for ES [34]. However, numerical experiments that exclude the influence of capacity mix changes confirm that building ES can directly increase the marginal CCs of VRE in the current system (see also [21]). Our runs for a two-zone system show that transmission network can change the resources mix and corresponding marginal CC. However, transmission constraints did not affect our conclusions regarding the impacts of UC or ES on capacity credits, or the ability of a capacity market based on marginal CCs to incentivize efficient levels of investment.

Our analyses show that details of implementation of capacity markets matter, so in practice, the results of energy-only and capacity markets are likely to diverge. In particular, we show that incorrect CCs for variable renewable resources and storage—either too high or too low—can distort investment and raise costs. Correct values should reflect diminishing returns (declining marginal CCs as penetration increases) as well as differences within categories of resources (e.g., different wind locations) as well as between resource types. Other real-world complications, such as state environmental policies, effects of risk on investment, transmission limits, discrimination between existing and new facilities in setting CCs, absence of long-run energy contract markets, and ineffective energy scarcity pricing mechanisms can also cause capacity markets and energy-only markets to diverge. Thus, debates over the need and roles for capacity markets will continue [5,7].

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