# Crediting Renewables in Electricity Capacity Markets: The Effects of Alternative Definitions upon Market Efficiency

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**ABSTRACT.** As the penetration of intermittent renewable energy in electricity markets grows, there is increasing need for capacity markets to account for the contribution of renewables to system adequacy. An important issue is the definition of capacity credits for resources whose availability may be limited. Inconsistencies in capacity counting methods used by system operators motivate this investigation into the market efficiency of renewable capacity credits. Inaccurate credits can distort investment between renewables and nonrenewables, and also among different types and locations of renewables. Using Texas (ERCOT) data, we use a market equilibrium model to quantify the resulting loss of efficiency as being as much as 0.37% of total generation costs. The inefficiency almost doubles for more ambitious renewable portfolio standards. A least-cost capacity market design should reward marginal capacity contributions by different resources considering how renewable penetration affects the timing of load peaks, net of renewable contributions.

**Keywords:** Electricity Markets, Capacity Mechanisms, Renewable Generation, Wind, Solar

## 1. INTRODUCTION

Electric system adequacy is defined as the ability of generation, storage, demand-side and other resources to meet the demand for electricity, as measured by indices such as loss of load probability or expected unserved energy. New investment in generation is necessary to maintain adequacy standards in competitive electricity markets. However, there are concerns that reliance on spot market energy prices or bilateral energy contracts alone will fail to attract needed new investment or prevent premature plant retirements due in part to declining energy prices resulting from subsidized renewable generation, especially wind and solar, according to Cramton (2012). Additionally, caps on energy

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bids and prices have been implemented in energy markets to control market power. These caps contribute to a "missing money" problem in that inadequate gross margins are earned to cover the cost of new generation investment (Neuhoff and De Vries 2004, Hobbs et al. 2007). Concerns over the amount of investment has led to implementation of capacity mechanisms in most organized markets in the U.S., and such mechanisms have recently been considered for implementation in Europe. These mechanisms make payments to installed capacity based upon various factors, including location, availability during peaks, and the total capacity relative to the need, based on reliability criteria.

When first implemented, the focus of capacity mechanisms was thermal generation capacity, whose contribution to meeting a target reserve margin was set equal to their (seasonally adjusted) installed capacity, often derated by a forced outage rate (as in PJM and NYISO). Usually assuming statistical independence of generator outages and load, the desired reserve margin would be calculated by convolving generator outages and loads, considering unit nameplate capacities, forced outage rates, and load distributions (Billinton and Allan 1984). However, these simple probabilistic methods do not capture the increased uncertainty introduced by intermittent renewable generators whose outputs, like load, depend on weather patterns and cannot be modelled as independent.

Although intermittent generators have low availability, with capacity factors that are typically 15-25% (solar) to 25-35% (wind), additions of such capacity can still contribute to system adequacy by enabling the system to accommodate more load while maintaining the same reliability. Therefore, it is necessary to expand capacity mechanisms to account for contributions from all resources to overall system adequacy. But this can be difficult, because many nontraditional resources have limitations that are not directly translatable into equivalent forced outage rates in adequacy calculations. These include wind or solar variability that is correlated with load, limitations on total energy production from storage, limited hours of use or number of starts, or advance notification requirements for demand response. Indeed, as system load net of renewables becomes more variable, even assessing the contribution of traditional fossil and nuclear sources becomes more complex, as other operational characteristics such as ramp rates may constrain the ability of the system to meet load. Quantifying capacity credits has therefore become more difficult. We focus on the market effects of credits for wind and solar; however, similar questions about the impact of alternative credit definitions upon market efficiency can be addressed for other technologies using our general methodology.

As we explain below, inconsistent methods are used by system operators for calculating the capacity contributions of variable renewables. The problem is that too much capacity credit for a particular resource is an implicit subsidy that may lead to overinvestment. Conversely, too little credit could divert investment away from a resource. Inaccurate credits can impact investment choices between renewable and thermal generation and can also affect profitability among different renewable types or locations. The purpose of this paper is to assess the impact on equilibrium generation mixes and possible cost increases (loss of efficiency) resulting from inaccurate credits for renewables.

Ideally, markets should provide the price signals that support investment that would result in the cost-minimizing portfolio of resources that meet reliability and environmental standards. The Ontario Independent Electricity System Operator (IESO) states that the qualified capacity should "equalize the reliability value of 1 MW of capacity" (IESO 2014a). The methodology and case study portions of this paper focus on the interaction of capacity, energy, and renewable credit markets, although the approach can be generalized to consider other markets, such as operating reserve and emissions. We assess how energy price caps and renewable portfolio standards (RPS) interact with inaccurate capacity credits to affect generation mixes and efficiency losses, including distortions among competing wind and solar developments. Additionally, we present a means to calculate renewable capacity contributions in a resource adequacy system based on the generator's marginal contribution during critical reliability hours, which we define as hours with nonzero expected unserved energy (EUE). A target for the system reserve margin can then be set for the capacity market, and generators paid according to their derated reserve margin contribution.

The plan of the paper is as follows. Section 2 of this paper reviews approaches for defining wind and solar capacity contributions in existing capacity markets. We show how the resulting capacity values significantly disagree, based on resource and demand data from the Texas (ERCOT) market. We then propose to quantify wind and solar contributions during critical reliability hours, corresponding to the marginal contribution of a generator to reducing the expected unserved energy when adding another unit of capacity. In section 3, we present a method to calculate equilibria for combined energy-capacity-renewable credit markets, thus allowing us to quantify the distortions from incorrect renewable credits. The distortions under several alternative definitions of capacity credits for intermittent resources are then analyzed using the market equilibrium model in the case study (section 4). Finally, section 5 offers some concluding observations.

## 2. CAPACITY DEFINITIONS: COMPARISON OF CURRENT PRACTICES

Table 1 reviews the wind capacity counting rules in several markets to illustrate their range, and below we contrast their numerical results for a case study.

**Table 1: Wind Capacity Credit Methods Used in US Markets, and Results of Application to ERCOT Wind Capacity Value as Percent of Installed Capacity[2,3,4]**

| Market | Capacity Value | Method |
|---|---|---|
| CAISO | 21% (Jun), 16% (Jul), 11% (Aug) | Average prior 3 years, exceedance level reached 70% of month |
| ERCOT | 12% | Average prior 10 years, average during top 20 load hours |
| IESO | 15% | Prior 10 year median, capacity factor of top 5 continguous demand hours |
| ISO-NE | 18% | Average prior 5 years, median value over 610 summer peak hours |
| MISO | 33% coast, 14% west | Average prior 10 years, ELCC study of all hours |
| NYISO | 33% | Prior year, capacity factor during 368 peak summer hours |
| PJM | 26% | Average prior 3 years, capacity factor during 368 peak summer hours |

Most markets compute capacity during peak periods, with the exception of CAISO that has

[2] CAISO: California ISO, CPUC: California Public Utilities Commission, ERCOT: Electric Reliability Council of Texas, IESO: Independent Electricity System Operator (Ontario), ISO-NE: ISO New England, MISO: Midcontinent ISO, NYISO: New York ISO, PJM: PJM Interconnection

[3] ELCC – Effective Load Carrying Capability (Keane et al. 2011)

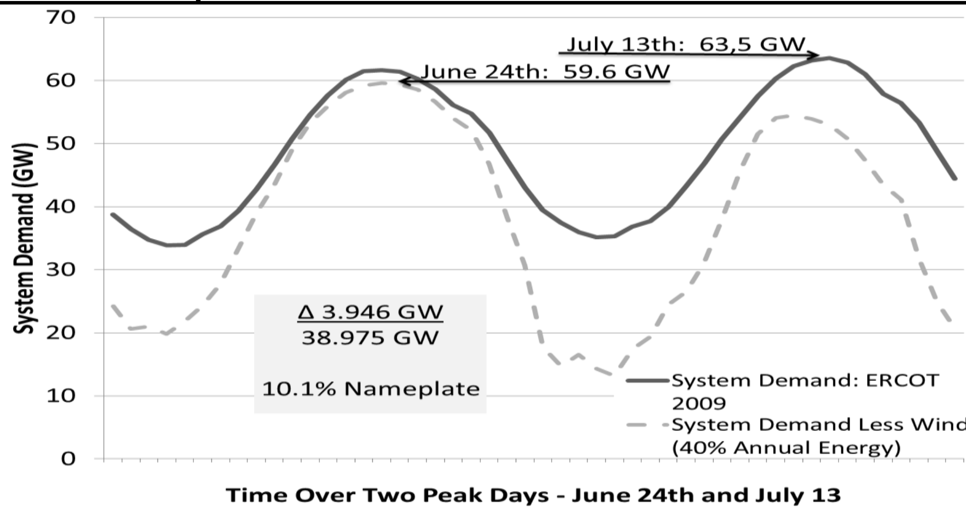
[4] Sources: (CPUC 2014), (ERCOT 2015a), (IESO 2014b), (ISO-NE 2016), (MISO 2015a), (ECCO 2013), (NYISO 2015), (PJM 2014).

monthly ratings and MISO who uses an annual reliability metric. All are based on historical resource performance using data from a sample of one to ten years. Use of limited historical samples can result in errors because of interannual variability, and because the contribution of existing renewable resources may exceed the marginal contribution of new resources. This is due to the often observed phenomenon that the marginal contribution of wind and solar (the capacity value of the next MW of installed capacity) decreases as the installed amount increases as shown by Keane et al. (2011) and Perez et al. (2006).

Another way that markets differ concerns whether to differentiate wind or solar capacity contributions based on the individual facility accounting for the local quality, load correlations, and transmission constraints, or to apply a generic contribution value for each technology class. If all facilities are assigned the same capacity rating, distorted incentives can occur, resulting in suboptimal mixes of renewables. MISO (2015a) applies both positive and negative adjustments to acknowledge individual facility contributions.

We explore the practical implications of these differences by applying them to a common data set. Each of the methods described in Table 1 was applied to the available 2005-2014 ERCOT wind and load data (ERCOT 2015b and 2015c). By 2014 ERCOT installed wind was 19% of the system peak demand supplying 11.7% annual energy. The resulting credits for this capacity projected for planning year 2015 are shown based on each region's criterion. The table shows a large variation in capacity values when applied to the same set of data, ranging from 1451 MW to 4165 MW, or 11.3%-33.3% of the wind's installed capacity. If a market capacity payment was set at $80,000/MW/year (an approximate annualized investment cost of a new CT peaking plant), the difference among the capacity definitions amounts to about $217 million to the wind producers.

**Figure 1: Net Load Example – ERCOT 2009**




This example also allows us to illustrate how the issue of peak-shifting makes assessment of renewable capacity contributions difficult. Figure 1 shows an example of how the peak shift is calculated for an extreme case in which enough wind (38,975 MW) is constructed so that it provides 40% of annual energy. The right load curve shows the peak load day (July 13) for ERCOT in 2009. During this peak hour, wind would contribute 7171 MW, or 18.4% of its installed capacity. Meanwhile, June 14th is shown as the left load curve; although loads were lower on this day, wind contributed only 3.6% of its installed capacity during that day's peak hour. As a result, at 40% wind penetration, the annual net load peak occurs on that day, rather than July 13. The average impact of wind on the net system peak is 10.1% (3,946 MW), which lies between the single day contributions. Meanwhile the 3.6% value is likely to be closer to wind's marginal value.

In sum, existing capacity counting methods disagree strongly, and so at least some of them are likely to yield an inefficient portfolio of resources if used in a capacity mechanism. We will show that the most accurate capacity credit for a resource is its marginal contribution. Next, we present and apply a market model for comparing the efficiency of alternative renewable capacity definitions.

## 3. METHODS

### 3.1 Model

Below, we present a model of market equilibria for combined energy-capacity-renewable credit markets. With it, we test alternative capacity market designs by comparing equilibrium generation mixes and costs for the designs against an ideal least-cost system. For clarity of results and practicality of computation, we make the following simplifying assumptions: price-taking behavior by generators, perfectly inelastic demand, continuous capacity investment variables with no scale economies, no unit commitment constraints (ramping or start-up), and no transmission congestion or losses. Also, investment decisions are considered in a static (one-shot) framework. Of course, models with more elaborate assumptions could alter our conclusions and would be useful extensions of this research. The model represents investment and operation decisions by technology-specific profit maximizing producers, who seek to maximize their profit by selling: (1) energy in a spot market that may be subject to a price cap; (2) capacity in a capacity market, in which each generator is assigned a credit equal to a predetermined technology-specific percentage of its installed capacity; and (for renewable power producers) (3) renewable energy credits in a Renewable Portfolio Standard-type market. If available capacity is less than demand in a given hour, then the energy price rises to the price cap, or to the aggregate consumer value of lost load (VOLL), whichever is less. The first-order conditions for the profit maximization problems, together with market clearing for the markets for spot energy, capacity, and renewable credits, together define a market equilibrium problem.

Rather than solve the equilibrium conditions directly using, e.g., complementarity methods (Gabriel et al. 2010), we solve an equivalent single optimization problem structured as follows. The objective of the model is to minimize a surrogate social cost, including the cost of unserved energy (evaluated using the price cap, if less than VOLL) and investment and operations costs. Constraints include market clearing conditions and individual generator constraints. Although space limitations prevent providing a derivation here, it is readily proven that the first-order (KKT) conditions of this problem are equivalent to the market equilibrium problem just discussed.

The optimization model is implemented as a linear program using the CPLEX solver. One energy market per hour is simulated, with ten years of 8760 hours each. Our implementation has continuous generator sizing for coal-fired steam units, natural gas-fired combined cycle (CC) and combustion turbine (CT) units, and wind and solar plants at different locations with distinct operating profiles. The model formulation is as follows. Variables include:

- installed capacity ($x_g$) [MW] of each generation technology type ($g \in G$) including fossil generators ($g \in F$) and multiple wind ($g \in W$) and solar ($g \in S$) locations;
- hourly dispatch ($h \in$ H, 1,…, 87,600) of energy ($e_{g,h}$) [MWh] for each $g$;
- hourly curtailments ($ce_{g,h}$) [MWh] of excess wind or solar energy ($g \in W \cup S$) for all $h$; and
- unserved energy ($ue_h$) [MWh] for all $h$.

The optimal values of these variables are found by minimizing objective (1) below, subject to market and generating constraints. The investment costs, variable costs, price cap, and wind subsidies (forgone during wind curtailment[5]) are represented by $FC_g$, $VC_g$, $PC$, and $WS$, respectively.

$$MIN \sum_{g \in G} FC_g * x_g + \sum_{h \in H, g \in F} VC_g * e_{h,g} + \sum_{h \in H} ue_h * PC - \sum_{h \in H, g \in W} WS * ce_{h,g} \quad (1)$$

$$s.t. \quad \sum_{g \in G} e_{h,g} + ue_h = DM_h \qquad \forall h \in H \quad (2)$$

$$\sum_{g \in F} x_g * (1 - FOR_g) + \sum_{g \in W} x_g * WCC_g + \sum_{g \in S} x_g * SCC_g \geq PD * (1 + RM) \quad (3)$$

$$\sum_{h \in H,\, g \in (W,S)} (e_{h,g} - ce_{h,g}) \geq \sum_h DM_h * RPS \quad (4)$$

$$\sum_{g \in F} e_{g,h} \geq DM_h * MG \qquad \forall h \in H \quad (5)$$

$$e_{h,g} \leq x_g * (1 - FOR_g) \qquad \forall g \in F; h \in H \quad (6)$$

[5] Our application assumes zero wind and solar subsidies, but alternative assumptions are possible.

$$e_{h,g} \leq x_g * AVAIL_{h,g} \qquad \forall g \in W,S;\ h \in H \quad (7)$$

$$x_{Coal} \leq PD * 0.45 \qquad (8)$$

$$\Sigma_{h \in H}\, e_{g,h} \leq x_g * AF_g \qquad \forall\, g \in F \qquad (9)$$

as well as nonnegativity for all variables. Although the general model statement includes all the above constraints, some are omitted depending on the policies being simulated. The first three constraints are market clearing conditions: (2) establishes hourly energy balances between supply and demand; (3) is the capacity market which maintains a minimum reserve margin (*RM*) [fraction] to meet adequacy requirements, where *RM* is a function of the annual peak demand (*PD*) [MW] and $x$ is derated to account for forced outage rates (*FOR* [fraction]) among fossil generators and wind and solar capacity credits (*WCC* and *SCC*, respectively [fraction]); and (4) ensures sufficient renewable energy less any curtailments to meet a renewable portfolio standard (*RPS* [fraction of annual energy]). Constraint (5) is another system condition that requires a minimum amount of fossil generation (*MG*) [fraction] for system inertia and other reliability purposes.

Constraints (6)-(9) instead restrict decisions for individual generators. These include hourly limits (6) on fossil output considering forced outage rates; (7), which defines generation plus curtailment of wind/solar as equal to each $g$'s hourly availability ($AVAIL_g$ [fraction]), which depends on wind or sun conditions; a limit (8) on coal capacity based on existing facilities that can be life-extended (set here to be 45% of peak demand reflecting existing installations); and an upper bound (9) on annual fossil generation based on an annual availability factor (*AF*) [fraction] to account for maintenance.

By choosing model parameters appropriately, we can use this simple model to simulate impacts of alternative policies on investment and operations. In sum, alternative capacity policies are represented by the capacity market's constraint (3), including parameters $FOR_g$, $WCC_g$, and $SCC_g$, and the reserve margin *RM*; alternative energy price caps are modeled by changing *PC* in the objective (1); and renewable portfolio standards are determined by parameter *RPS* (4).

### 3.2 Experimental Design

The model is used to compare market designs through a series of simulations that vary the above parameters. We focus on capacity markets, which become necessary for system reliability if there is an energy price cap. In particular, we emphasize the issue of what credit to award renewables, and the consequences of suboptimal credits. Capacity assigned to wind and solar is based on a representative subset of the existing methods described in section 2. We consider three specific sets of capacity values: 0% for both wind and solar; 15% wind (which is similar to PJM's value) with 75% for solar; and 25% wind with 100% solar. We also examine fossil generation capacity with and without an adjustment for forced outage rates. We consider the interaction of these policies with renewable portfolio standards by considering two levels of standards.

The total social cost for each design's solution is calculated by summing capital and operating costs and the consumer's value of lost load (*VOLL***EUE*) [$] (rather than the price cap *PC***EUE*), which can then be compared with the cost of the benchmark least-cost solution. The latter solution is obtained by solving the model using setting $PC = VOLL$, and omitting the capacity market (3). One benchmark is defined for each *RPS* case considered (0% and 40%). Additionally, the benchmark includes no renewable subsidies.

The benchmark level of expected unserved energy ($EUE^*$) under each RPS target is assumed to represent the optimal level of system adequacy. Therefore we search over a range of *RM* for each capacity market design and identify the value that achieves this level of *EUE* so that we can compare capacity market designs in terms of their economic efficiency in meeting this adequacy target. As a result the difference in social cost is then only due to investment and operating costs. (Thus, for simplicity, we disregard any differences in emissions among the scenarios; a more general analysis would also consider emissions costs.) The difference in social cost quantifies the loss of efficiency, while changes in investment mix represent technology distortions.

Additionally, we propose a method for calculating capacity credits based on the marginal contribution of each renewable producer to reducing *EUE* [MWh]. It can be proven that with an appropriate value of *RM,* use of this marginal contribution will result in the same solution as the efficient benchmark; we illustrate this result below in our application. To calculate the marginal contribution, we take the benchmark capacity mix, and then redispatch the system, adding 1 MW of capacity type of interest. Then the reduction in *EUE* is noted. This is repeated for each capacity type *g,* and the following capacity credit $pc_g$ is calculated for each:

$$pc_g = (EUE^* - EUE)/EUEH \tag{10}$$

where *EUEH* = the number of hours in which there is a positive amount of unserved energy. The value of *RM* that would yield $EUE^*$ if the $pc_g$ are used to credit each generation type *g* can then be obtained by replacing (1-$FOR_g$), $WCC_g$ and $SCC_g$ in (3) with the corresponding $pc_g$ for each producer, inserting the benchmark values of $x_g$, and finally solving for *RM*:

$$RM = [\Sigma_{g \in G}\, x_g * pc_g]/PD - 1 \tag{11}$$

## 4. CASE STUDY

A case study is used to evaluate efficiency losses and investment distortions that can arise from alternative capacity market designs. We address the following specific questions. First, what market changes result from market design features such as a price cap, capacity market, or renewable portfolio standard? Second, what are best practices in setting capacity credits in a capacity market? In particular, how do different renewable capacity counting methods affect the optimal generation mix and how should capacity for fossil generation be derated by their forced outage rates to maximize efficiency? Lastly, does an aggressive RPS change the answer to the above questions?

### 4.1 Case Study Data

We consider a ten year (87,600 hour) case study. The model uses actual time coincident load, and wind and solar profiles for the ERCOT system based on ERCOT reported system-wide demand from 2005-2014 (ERCOT 2015c), normalized based on the annual peak and fitted to a common system peak. The ten annual load factors range from 55% to 58.3%.

The wind profiles are based on four specific ERCOT wind producers. To examine windfarm design tradeoffs between energy production and peak load contribution, three on-shore and one off-shore representative windfarms are modeled based on differing characteristics. The windfarms represent a range of tradeoffs between high capacity factors (annual energy contribution) and contribution to meeting the system's demand peak. Each windfarm's data is normalized based on windfarm installed capacity, preserving annual capacity factor. The ranges of capacity factors are: 31.7%-39.8% (Wind1), 30.9%-37.9% (Wind2), 39.4%-44.3% (Wind3), and 33.3%-40.9% (offshore).

The solar profiles are based on ERCOT (2015b) data for specific locations and technologies. Three solar photovoltaic (PV) sites are modeled, two corresponding to residential solar in highly populated regions of Texas: Dallas-Fort Worth (DFW) and Houston (HOU) and one representing a large-scale single axis tracking system in a prime solar area, Midland (MID). The ranges of solar capacity factors are: 19.9%-22.5% (DFW), 18.6%-20.4% (HOU), and 26.2%-29.6% (MID).

Generation assumptions (Table 2) are based on U.S. Energy Information Administration (EIA 2015a, 2015b) data for investment costs and heat rates. Coal construction costs represent the going-forward costs of maintaining existing facilities instead of new construction. Availability and forced outage rates are based on North American Electric Reliability Corporation data (NERC 2015).

**Table 2: Generation Data Assumptions**

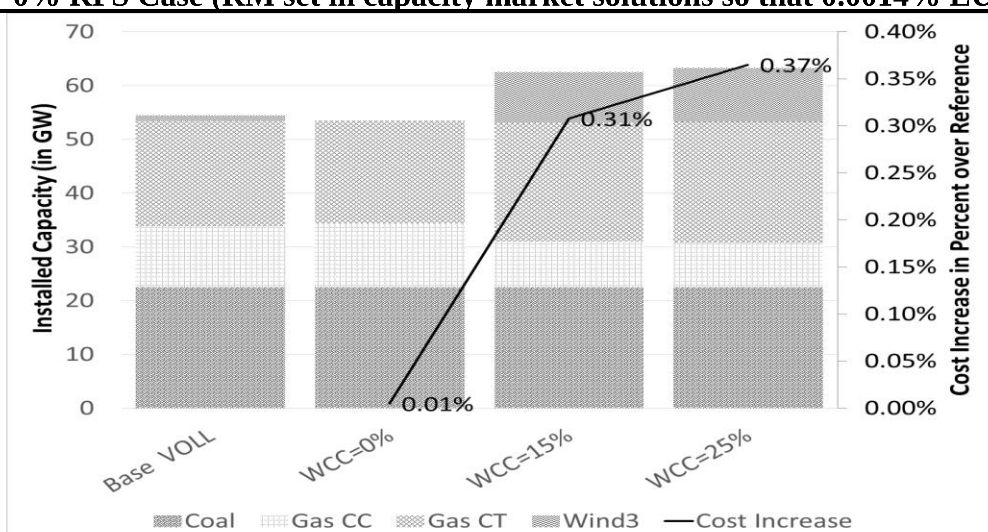
| Technology | Investment Cost $/MW/yr | Variable Cost & Fuel $/MWh | Heat Rate Btu/kWh | Availability Factor | Forced Outage Rate |
|---|---|---|---|---|---|
| Advanced Natural Gas Combustion Turbine | $ 80,154 | $ 79.60 | 11378 | 90.0% | 11.0% |
| Advanced Natural Gas Combined Cycle | $ 136,419 | $ 53.60 | 7658 | 86.0% | 5.4% |
| Conventional Coal - Depreciated | $ 120,253 | $ 29.40 | 10080 | 85.0% | 7.0% |
| Wind On-Shore (Wind1, Wind2, Wind3) | $ 222,329 | | | | |
| Wind Off-Shore | $ 636,134 | | | | |
| Solar PV (all sites) | $ 265,428 | | | | |

A value of $10,000/MWh is modeled as VOLL. MG is set to 20% of hourly demand to provide a conservative amount of flexible generation to respond to changes in system conditions. The MG value is held constant for policy analysis but should be further explored in subsequent research along with a broader range of resources capable of supplying system response.

### 4.2 Optimal Generation Mix Under 0% and 40% RPS

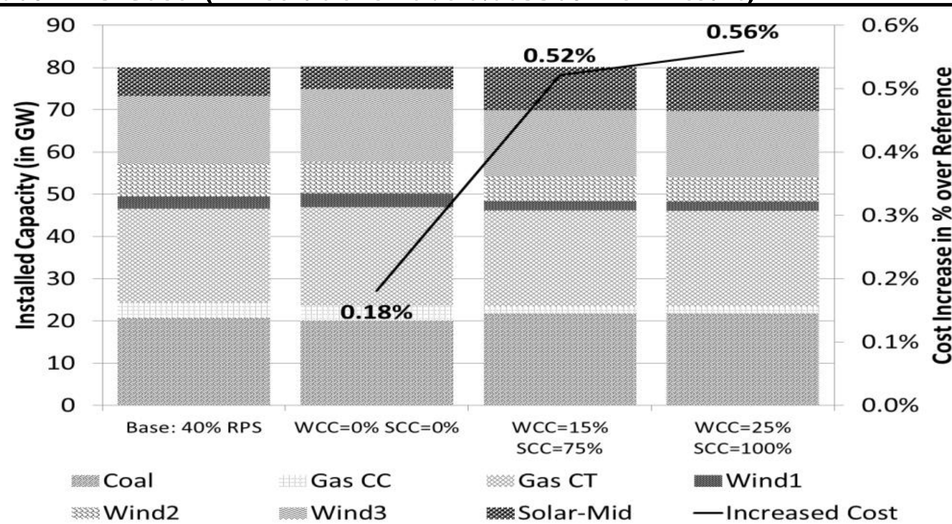
The assumed optimal portfolio for the 0% RPS case is determined using the full ten years of ERCOT data assuming no subsidies and no capacity market (3) but including the design VOLL of \$10,000/MWh. Social welfare is maximized with consumers having unmet demand when costs of supply exceed *VOLL*; due to the linearity assumptions, all renewable producers break even, with energy prices covering their capital costs. Fossil producers, however, might not break even because of constraints (5) and (8). The resultant portfolio of generation investment, shown in the leftmost column of Figure 2, includes the maximum allowed coal, a mix of natural gas technologies, and a single type of wind plant (Wind3, the type with the maximum capacity factor). Total generation costs for the system are \$153.66 billion/yr. The *EUE* is 0.0014% of total energy (approximately 390 MW, on average, in each hour in which unserved energy occurs), where the average number of hours per year in which unserved energy occurs is 9 hours/yr (= *EUEH*/10).

**Figure 2: Investment Mix for Social Optimum and Three Capacity Market Equilibria: 0% RPS Case (RM set in capacity market solutions so that 0.0014% EUE results)**



We also can calculate the social optimum, given an aggressive renewable portfolio standard of 40%. Costs increase by 16% compared to the 0% RPS case, and the resulting capacity mix is the first column in Figure 3. With the exception of the costly off-shore wind, all types of wind farms are developed plus utility-scale solar, illustrating the complementary nature of renewable development at different sites. Total renewable capacity is now 33,523 MW (versus 1,086 MW in the 0% case), while CT capacity has also increased (from 19,520 to 22,390 MW). These plant types displace CC and, to a lesser extent, coal capacity. The optimal *EUE** is higher than in the 0% RPS case (0.0053% vs 0.0014%), showing that it is more expensive, on the margin, to maintain a given reliability level (as measured by *EUE*) in a renewables-dominated system.

**Figure 3: Investment Mix for Social Optimum and Three Capacity Market Equilibria: 40% RPS Case (All solutions have 0.0053% EUE result)**




### 4.3 Energy Price Cap and the Need for Capacity Mechanism

When an energy price cap is set less than the VOLL in our model, a market failure occurs because energy prices during times of scarcity no longer reflect the actual value of consumption, and social costs increase in the resulting equilibrium. In our case study, a cap of $1200/MWh, similar to caps in some U.S. markets, is imposed on energy prices instead of the VOLL of $10,000/MWh. Consequently, in the absence of a capacity mechanism, the equilibrium investment decreases, and the mix shifts away from renewables. The resulting high level of unserved energy is over three times the benchmark case. Total social cost increases by 5.1% over the benchmark, due to the higher unserved energy.

To attempt to correct the market failure from constraining peak prices to be less than the consumer's value of energy (*VOLL)*, some U.S. markets implement a capacity market. We implement that market here by adding the reserve margin constraint (3) to the model, and paying each type of capacity the shadow price of the constraint times the per unit capacity credit. It can be shown that the efficient solution results if we (1) give credit to each producer in proportion to its marginal ability to lower EUE (or, more generally, whatever reliability metric is adopted), and (2) the reserve margin (or more generally, the demand curve, as in NYISO and PJM, Hobbs et al. 2007) should be set so that the aggregate reliability is the same as the social cost. This procedure is illustrated in section 4.5, below.

### 4.4 Comparison of Capacity Market Solutions without an RPS

In this subsection, we consider the extent to which incorrect capacity credits in (3) can increase costs and distort investments if there is no RPS; in the next subsection, we add a 40% RPS to the model.

First we consider the capacity credit given to fossil capacity. As is already done in PJM and NYISO, we conclude that a capacity mechanism should discount capacity. Our results show that when *FOR* is omitted from (3), the resulting market equilibrium is 0.005% more costly (~$1.6 million/yr), with a shift in investment towards low cost CTs at the expense of more reliable CC units. However, we note that if we explicitly simulated stochastic outages of generators in (6) (random outages in some *h* but not others), the optimal capacity credit might deviate from (1-*FOR*), especially for large generators whose outages would be more difficult to manage.

Next, we consider alternative sets of credits for renewables in (3), assuming *FOR* is applied to fossil facilities. Our results show that each of the three sets of credits defined in section 3.2 is inefficient due to either under- or overvaluing wind. When wind is overvalued in the analysis – the 15% and 25% cases for wind--constraint (3) mischaracterizes the adequacy of the system's resources, so that the required reserve margin *RM* must be adjusted up to achieve the socially optimal reliability (*EUE* = 0.0014%). Figure 2 shows that the overvalued wind results in an overbuilding of wind (by a factor close to 9 times) and CTs, as shown by comparing the right hand bars with the left bar. More CTs represent the cheapest way to firm up system adequacy in response to the higher *RM* that is required with greater wind capacity. Overall capital and operating costs are 0.31-0.37% higher (about $47-$56 million/yr), which is the social cost of the incorrect renewable credits.

On the other hand, when wind is undervalued, it fails to develop at all. To make up for the loss of 1086 MW of wind capacity, 456 MW more CC capacity is built, raising portfolio investment and operating costs.

The above assumed capacity values are quite different from the actual marginal capacity value $pc_g$ in the social optimum which we calculated using the procedure described in section 3.2. The derived capacity credit for the only renewable producer in the capacity mix is 7.61%, which is less than a fourth of its annual capacity factor, and well below any of the markets reviewed including ERCOTs 12% value. When this $pc_g$ value, along with (1-*FOR*) for fossil units are used in the capacity market clearing equation (3) together with *RM* = -1.756% and *PC* =$1200/MWh, then, as we anticipated, the socially optimal values of generation mix, *EUE,* and costs result. This confirms our assertion that the marginal contribution to system reliability should be used rather than the procedures in Table 2, which may be only rough approximations of that contribution.

### 4.5 Comparison of Capacity Market Solutions with 40% RPS

We now repeat the analyses of the last subsection considering an aggressive *RPS* = 40% level. Figure 3 shows that the social cost distortions have approximately doubled to as much as $100 million/year, or 0.56% of the cost of the social optimum under a 40% RPS. Because a mix of renewable resources are now used, it is now important to differentiate the capacity credit among the different sources, accounting for trade-offs between energy production and peak shift contribution. Comparing the last two bars of Figure 3 to the social optimum (first column), we see that applying the same high credit to all wind sources biases the market equilibria in favor of Wind3 (the highest capacity factor resource) and against Wind1 and Wind2, as well as solar (which have more contributions to the system peak, but lower energy output). Meanwhile, the fossil mix shifts slightly from CC to coal. On the other hand, if the same low (0%) credit is given to all renewables, then the mix changes in the opposite direction (compare bars 1 and 2 of Figure 3).

**Table 3: Optimum Renewable Producer Capacity Credits with 40% RPS**

| | Capacity Credit, $pc_g$ | Annual Capacity Factor | Installed Capacity (MW), $x$ | % Annual Energy Supplied | Reserve Margin, *RM* |
|---|---|---|---|---|---|
| Wind1 | 8.56% | 36.66% | 2916 | 2.39% | -7.50% |
| Wind2 | 12.49% | 34.53% | 7589 | 7.91% | |
| Wind3 | 3.97% | 42.32% | 16239 | 23.03% | |
| Solar MID | 28.15% | 27.63% | 6779 | 6.66% | |
| Aggregate Wind | 6.89% | 39.50% | 26744 | 33.34% | -7.50% |

However, these distortions disappear if the capacity market constraint (3) uses $pc_g$, the marginal contribution to reducing EUE as the basis for calculating capacity credits. The values of the wind $pc_g$ shown in the first three rows of Table 3 differ appreciably from each other unlike the identical values assumed in the three capacity market equilibria we simulated above. The highest capacity factor wind source (Wind3) turns out to have a marginal contribution far below the other wind sources (and indeed well below Wind3's $pc_g$ of 7.61% in the 0% RPS social optimum), largely because of its higher penetration but also because its output coincides less with demand peaks. As expected, when these $pc_g$ values are used in (3), along with 1-*FOR* for fossil facilities, *RM* = -7.5%, and a price cap of \$1200/MWh, the socially optimal costs result, as in the 0% RPS case.

But if instead we calculate the capacity-weighted average $pc_g$ for all wind (6.89%, Table 3), and apply it rather than a differentiated $pc_g$, a suboptimal investment mix results. Wind3 investment increases, and Wind2 decreases, because the latter's capacity contribution is under recognized. Generation costs increase 0.018% (\$3.2 million/yr) relative to the social optimum.

## 5. CONCLUSIONS

We analyze potential market distortions that can result from using inaccurate capacity credits for renewables in electricity markets that have energy price caps and capacity markets. The methodologies in use in U.S. markets to calculate the capacity contributions of wind and solar energy result in greatly different estimates of those contributions, and are suboptimal relative to using the marginal contribution of each resource to improving system reliability. In our case, we demonstrate that making capacity payments based upon the relative marginal ability of each resource to decrease expected unserved energy (in MWh/year) can yield the social least-cost mix of generation investment. These values can differ greatly even among resources in a single class, such as wind at different locations, and significantly decrease as the penetration of a particular resource type increases.

We analyze potential market distortions with a market equilibrium model that considers investors' decisions concerning construction and operation of several types of generation resources who participate in energy, capacity, and/or renewable energy credit markets. The model confirms the well-known result that imposing an energy price cap that is less than consumers' value of lost load results in a market failure that can be at least partially corrected by implementing a capacity market. However, granting capacity credits that differ appreciably from their actual marginal contribution to system reliability can yield significant distortions, which in our case study amounted up to 0.37% of generation costs, which equals more than a hundred million dollars per year in a market the size of

Texas. These distortions are amplified by an aggressive renewable portfolio standard.

Our equilibrium model made a number of assumptions that future work should address. This would include consideration of the important impacts of transmission, elastic demand, and unit commitment constraints on system flexibility and reliability. The relative size of the above cost distortions relative to other distortions in capacity markets, such as using too small a sample of years to estimate renewable output distributions, should also be analyzed.

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