Renewable Energy 156 (2020) 634–644

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Learning is not enough: Diminishing marginal revenues and increasing abatement costs of wind and solar

Saptarshi Das*, Eric Hittinger, Eric Williams

Rochester Institute of Technology, USA

ARTICLE INFO

Article history:
Received 1 May 2019
Received in revised form
23 October 2019
Accepted 14 March 2020
Available online 27 March 2020

Keywords:
Renewable energy
Energy modeling
Marginal abatement cost curve (MACC)
Energy subsidy

ABSTRACT

The economics of wind and solar generation face two opposing drivers. Technological progress leads to lower costs and both wind and solar have shown dramatic price reductions in recent decades. At the same time, adding wind and solar lowers market electricity prices and thus revenue during periods when they produce energy. In this work, we analyze these two opposing effects of renewable integration: learning and diminishing marginal revenue, investigated using a model that assumes the status quo with regards to generation technology mix and demand. Our modeling results suggest that reduction in revenue from market forces may offset or even outpace technological progress. If deployed on current grids without changes to demand response, storage or other integrating technologies, the cost of mitigating CO_2 with wind will increase and will be no cheaper in the future than it is today for solar. This study highlights the need to deploy grid technologies such as storage and new transmission in order to integrate wind and solar in an economically sustainable manner.

1. Background

Wind and solar power are likely to play critical roles in mitigating climate change and other sustainability impacts of electricity systems. Understanding the cost of abating carbon via renewable energy versus alternatives, e.g. energy efficiency, is important in developing energy policies and allocating societal resources. While assessing the present cost of mitigating carbon with wind and solar is relatively straightforward, projecting into the future is more complicated. Technological progress has led to substantial cost reductions in wind and solar power: wind power dropped from over $4,000/kW in 1980 [1] to $1,500/kW in 2016 [2] and utility scale solar from over $22,000/kW [3] to $2,500/kW in 2016 [4]. Future cost reductions are expected as well. However, wind and solar power influence the economics of the grids in which they are deployed. Supply and demand implies that electricity prices tend to fall during the times that wind and solar are generating, which results in lower revenue to those generators. These two factors, technological progress and diminishing marginal revenue, pull carbon abatement cost in opposite directions. This work includes both factors and offers the first estimate of their combined effect.

Technological progress in renewable energy is well-studied using historical cost trajectories to find trends and inform forecasts. Experience curves and their variants are the most common approach used to describe technological progress. Developed first to describe cost reductions in aircraft manufacturing [5], the experience curve is an empirically observed power law decay of some characteristic of industrial processes and cumulative experience implementing that process [6,7]. In the energy domain, the single factor experience curve takes the form: $C(P) = C_0\ (P/P_0)^{-\alpha}$ where P is a measure of cumulative adoption of a technology (e.g., the total watt capacity of solar cells produced), C is the price per energy unit (e.g., $/Wp or $/kWh), C_0 and P_0 are initial cost and production values, and α is a (positive) empirical constant, known as the learning coefficient. α is related to the fractional reduction in costs for every doubling of production, known as the Learning Rate, given by the equation $LR = 1\text{-}2^{-\alpha}$. Despite its simplicity, the above equation fits empirical data quite well and prior research has shown that R-squared exceeds 90% for a majority of 62 technologies [8].

Starting from the 1990's, experience curves have been applied to describe cost reductions in renewable energy technologies, including wind and solar power [9,10]. The single factor experience curve has been generalized to into multi-factor models that distinguish different types of progress such as learning-by-doing, learning-by-research, and materials [11,12]. Rubin et al. (2015) reviewed 11 generation technologies and found substantial

* Corresponding author. 190 Lomb Memorial Drive, Rochester, NY, 14623, USA.
E-mail address: sd8781@rit.edu (S. Das).

https://doi.org/10.1016/j.renene.2020.03.082
0960-1481/

variability in learning rates depending on the method and data range. Learning rates for wind were found to vary between 3.1% and 13.1% while solar varied between 14% and 32% depending on the study [13]. Williams et al. (2017) found the sources of variability in the wind learning rate to be driven by starting and end year of datasets and the geographical scope of the analysis. Developing a model focused on cost of energy production, they found a narrower range for global wind learning rate: 7–11%. Overall, wind and solar costs have decreased significantly over the past few decades and the trend in those reductions has been reasonably regular. It is prudent to assume a future in which this pattern continues, with faster cost reductions expected for solar.

The second major factor affecting the economics of wind and solar is diminishing marginal revenue due to adoption of renewables, which is a topic of more recent and limited investigation. One approach to characterize this diminishing revenue effect is through use of electricity system models (e.g. with dispatch and capacity expansion) to study how locational marginal prices and other payments to renewables change as a function of adoption. Wiser and Mills (2012) use a long run long dispatch model that incorporates hourly generation and load profiles in order to account for factors that affect both renewable as well as conventional generators. These include variability in generation and ancillary service requirements for renewable technologies and part-load inefficiencies, minimum generation limits, ramp-rate limits, and start-up costs for conventional thermal. The model was used to run a case study that approximately matches the expected characteristics of California in 2030. They found that marginal economic value of wind and solar decline considerably with increase in penetration. Wind was seen to drop from $70/MWh to $40/MWh of value as penetration increased from 0% to 40% of the annual load. Solar showed an even more dramatic reduction dropping from $90/MWh to $30/MWh between a penetration of 0% and 30% of the annual load. While such models provide a highly resolved view of electricity systems that accounts for many system interactions, their complexity makes validation and broad application challenging.

Alternatively, econometric methods have also been used to establish relationships between electricity price and demand, and estimate the impact of renewable energy on prices. This approach develops a relationship between price and demand in a region based on time-resolved data for Locational Marginal Price (LMP) and historical load in a particular grid region. Models have been developed for Texas [14] and California [15] in the U.S. as well as entire nations: Italy [16], Ireland [17], Australia [18] and Germany [19,20]. They document statistically significant merit order effects of wind and solar energy. These studies find that increase in natural gas price, retirement of nuclear plants and economic growth tend to increase energy prices. On the other hand, demand side management and development of renewable energy reduce prices. In California for example, each additional GW of solar power output reduces the LMP by $3.4/MWh in the SP15 region, while the same amount of wind reduces the LMP by as much as $11.4/MWh. The two approaches are complementary: econometric approaches (as we use in this work) are better at reproducing and broadly applying current and near-future trends while capacity expansion models are required to understand long-term trends. Both approaches have been used to determine that revenue decline due to adopting wind and solar can be substantial.

Prior work has studied both technological progress and diminishing marginal revenue for wind and solar, but has not investigated how these two factors combine to influence the economic effectiveness of carbon mitigation. The economics of wind and solar can be considered a race between the declining costs due to technological progress and their declining value due to revenue erosion. Therefore, modeling both of these effects simultaneously can help us understand which of these effects is likely to proceed at a faster rate. We approach this question by developing modified Marginal Abatement Cost Curves (MACC) for wind and solar power in the continental U.S. The usual MACC curve approach develops an average expenditure (e.g. $/tonne CO_2) and mitigation potential (total tonnes CO_2) for aggregated technologies [21]. For wind and solar, this approach has yielded carbon mitigation costs that vary widely, depending on location/geographic aggregation and year of study, which affects the presumed technology cost. In prior research, abatement costs for wind was seen to vary from -€7(-$8)/tonne CO_2 in Italy [22] to €44 ($51)/tonne in Germany [23]. For solar, different estimates have varied from $18/tonne CO_2 in the U.S. [21] to €1,870 ($2,170)/tonne in Italy [22].

In this work we combine modeling elements (experience curve, regression of electricity demand and prices, and MACC) to yield the first characterization of how technological progress and declining revenue influence the cost of mitigating carbon with renewables. It is important to emphasize at the outset that our approach assumes wind and utility-scale solar are built out on the current grid (year 2016) with current fuel prices. In reality, the grid is evolving and technologies that help to integrate wind/solar (storage, demand response, etc) will influence outcomes. This said, accounting for all drivers of the future grid is not only challenging, but that future also depends on the plans that we develop today. Understanding the effect of building out renewables on the current grid provides valuable insights into current trends and future grid needs.

Our modeling approach adds wind or solar to U.S. electricity grids in discrete blocks (2.5 GW at a time) and then tracks how technological progress and revenue decline affect successive installations. As geographic heterogeneity is expected for both revenue and carbon mitigation from wind and solar installations, we separately model 13 regions based on the Federal Energy Regulatory Commission (FERC) regions in the continental U.S. A single factor experience curve is used to describe technological progress and an econometric regression model is developed to estimate revenue decline. Net Present Value, carbon mitigated and marginal abatement cost are calculated for a proposed 2.5 GW addition in each region. We then assume successive build-out in the region with lowest carbon abatement cost. Solar or wind capacity is added until the "economic potential" is reached, a new measure we develop here. The total potential of wind or solar is typically assessed by geophysical analysis that assesses the physical limitations on solar/wind deployment [24–26]. "Economic potential", in contrast, is the amount of wind or solar that can be adopted in a region before the addition of a new plant makes no contribution to the total revenue of that technology's generation fleet.

2. Methodology

Fig. 1 shows an overview of data and flow of the model. Each electricity system in the U.S. has its own combination of renewable resources, energy prices and grid mixes. These factors, when combined, result in marginal abatement costs that differ by location. We limit our spatial analysis to disaggregation into 13 electricity market regions that are based on FERC regions (Table S2 in supporting information). We collect data on locational marginal price (LMP) from ISOs and demand from EIA [27] for each region and use regression to establish an empirical relationship between them. We then assume capacity expansion of wind and solar to take place 2,500 MW at a time, building out wind or solar separately. We assume that renewable energy is able to generate at zero marginal cost and is effectively modeled as negative demand. Therefore, as renewable energy is added, it drives down the LMP during the hour it produces and reduces the revenue the renewable energy

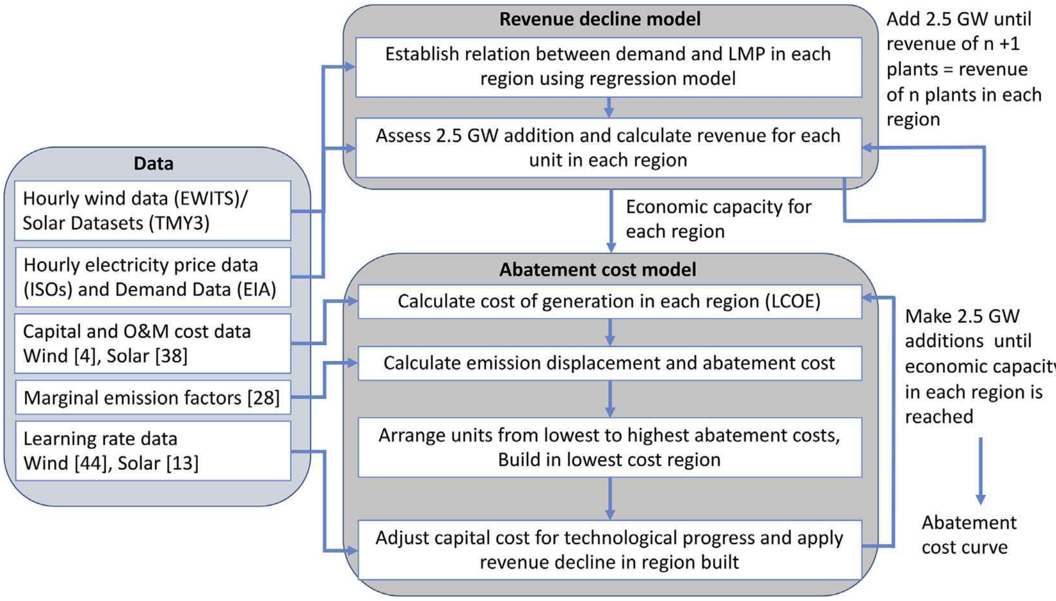

Fig. 1. Overview of model: data, process and output (EWITS = Eastern Wind Integration and Transmission Study, TMY3 = Typical Meteorological Year (TMY3) dataset, EIA = Energy Information Administration, O&M = Operations and Maintenance, ISO = Independent System Operator, LMP = Locational Marginal Price, LCOE = Levelized Cost of Energy).

receives. At the same time, as more renewables are built out, the cost of later wind/solar is reduced due to learning. This drives down the levelized cost of energy (LCOE). Because government support of renewables is already related to the pollution abatement costs, we do not include subsidies in our calculations. Rather, we calculate the required subsidy as a difference between cost of generation and expected market revenue. The difference between the revenue and LCOE is a profit if positive and a subsidy requirement if negative. Wind and solar also generate zero onsite emissions, therefore displaced emissions depends on the grid mix in which they operate. We find the emission savings, Δ *emission*, using region-specific data on hourly marginal emissions [28]. We then go on to calculate marginal abatement cost:

$$Abatement\ \ cost\left(\frac{\$}{tonne\ \mathrm{CO_2}}\right) = \left(LCOE\left(\frac{\$}{MWh}\right) - revenue\left(\frac{\$}{MWh}\right)\right) \times \Big/ \Delta\ emission(tonne\ \mathrm{CO_2}). \tag{1}$$

The abatement cost is positive, i.e. net cost to society, if cost (LCOE) > revenue.

Our methodology is primary based on econometric analyses which have been widely used for similar studies around the world including Texas [14] and California [15] in the U.S. as well as entire nations: Italy [16], Ireland [17], Australia [18] and Germany [19,20]. One of the main advantages of this methodology is the relatively small data requirement and therefore potentially lower exposure to model uncertainties. The type of modeling also does not require explicit assumptions on other related variables for e.g.: the price of fossil fuels because they are inherently a part of the independent variable here, that is the energy demand. Because we model renewable generation as negative demand and our objective is to establish a relation between LMP and energy demand and track the change in LMP with renewable generation, we found an econometric methodology to be the best suited given the methodological literature review, data requirements, and exposure to uncertainties.

The different components of our methodology have been explained in greater details in sections 2.1 to 2.5.

2.1. Relationship between price and demand

To calculate the revenue to wind and solar, we first establish a relationship between demand and locational marginal price (LMP). This can be done using dispatch models [29]. However, we, along with other authors [15,16], use regression of price and demand data to make an econometric model. We use hourly data for the year 2016—8,784 data points for LMP and demand in each of 13 regions. Analysis accounts for daily as well as seasonal change in loads, prices and renewable generation in each region. Electricity market wholesale prices are gathered from Independent System Operators (ISOs) [30–35] and the EIA Wholesale Electricity and Natural Gas Market dataset (EIA, 2015). LMP for regulated markets were assumed to be the prices at which they trade with deregulated markets (data selection is described in the SI, Table S5).

We use a linear regression [14,16,17,36] with zero intercept to establish the relation between price and LMP. As the grid operates differently throughout the year, we divide the year into 4 seasons (summer, winter, spring and fall), running separate regressions for each of the 13 regions. Fig. 2 shows example regressions for the California ISO.

The slopes for all four seasons are all statistically significant (p-value ranges from 8.5E-23 to 3.4E-07), but the r-squared values can be low. This is because there are other factors that influence price such as congestion. We are not concerned here with precisely predicting price, only the effect of changes in demand on price. A dispatch curve is often shown with a flat part and an exponential part, e.g. Ref. [37]. However, we observed that they appear relatively flat in the observed data, presumably due to heterogeneity in the cost of operation and efficiency for plants using the same fuel. This results in the coefficient for the exponential segment being orders of magnitude smaller in comparison to the coefficient for linear segment. We thus assume that the dispatch curve can be approximated as linear. Fig. 2 shows an example for CAISO and we find similar patterns for ISOs across the country.

Having established the relation between LMP and demand, we

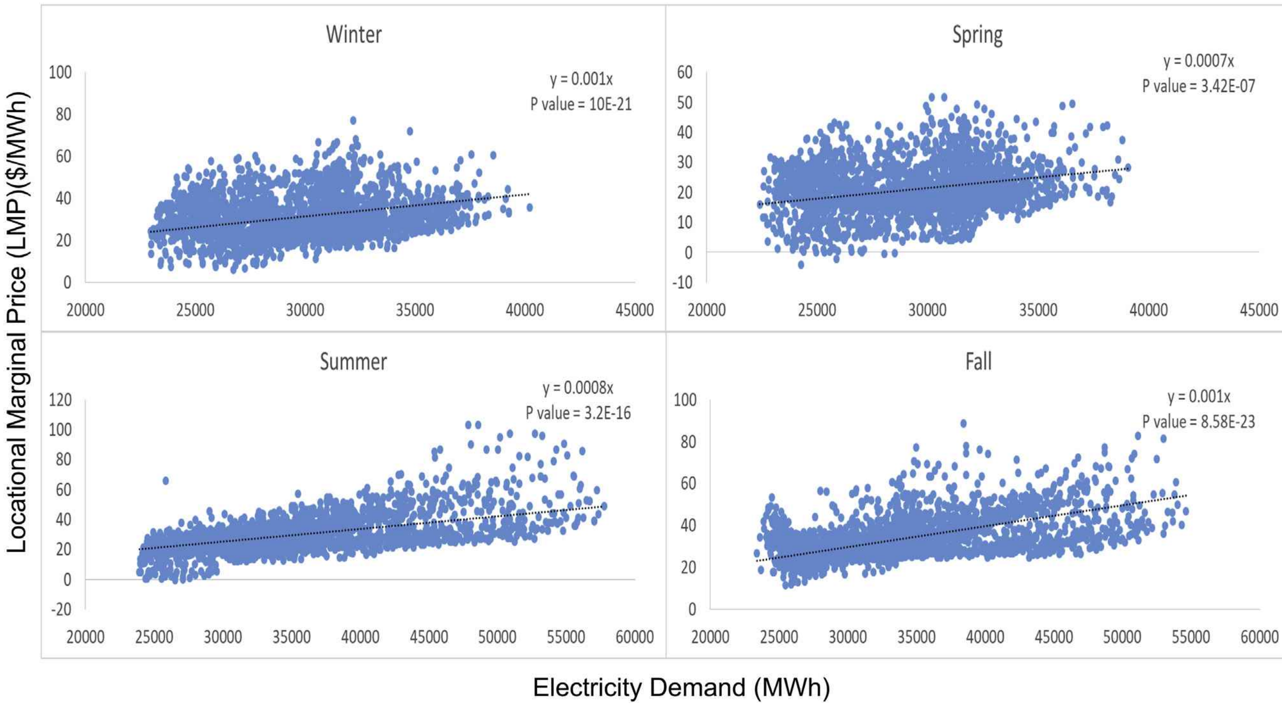

Fig. 2. Regression to establish relation between Locational Marginal Price (LMP) and demand in California ISO (CAISO). Although, theoretically, a dispatch curve is expected to have a linear part and an exponential part [37], in reality there is much heterogeneity in the cost of operation even for plants using the same fuel, such that the coefficient for the exponential segment is orders of magnitude smaller in comparison to the coefficient for linear segment. The curve is therefore approximated to a linear function.

model renewable generation as negative demand, calculating LMP in a given hour with the equation:

$$\begin{aligned} LMP\ \ new = LMP\ \ original - Seasonal\ \ slope \\ of\ \ LMP\ \ vs\ \ Demand * Hourly\ \ capacity \\ factor * Installed\ \ capacity\ \ of\ \ wind\ \ or\ \ solar \end{aligned} \tag{2}$$

This method retains the observed hourly fluctuations in prices in the actual data, but adjusts the prices down in a linear way as wind or solar is added. Hourly capacity factor is a plant's energy output over an hour (MWh) divided by the installed capacity of the resource (MW). For wind, the hourly capacity factors are taken from the Eastern Wind Integration and Transmission Study (EWITS) and Western Wind datasets (NREL, 2015). We average hourly capacity factors of between 50 and 200 individual locations depending on the size of the region to arrive at the hourly capacity factor of each resource for each region. There is large geographic variability, e.g. annual capacity factors of wind is seen to range from 30% in Georgia to 49% in Texas. For solar photovoltaics, we use the Typical Meteorological Year (TMY3) dataset, which provides one year of hourly simulated solar insolation for 1,020 locations in the U.S. (NREL, 2015). We use the same method of taking the average of several individual locations as we did in the case of wind. The annual capacity factor of solar is observed to range between 17% in NEISO to 22% in CAISO.

The annual revenue to wind and solar for the year can be calculated as a summation of hourly revenues, using the formula:

$$Annual\ \ Revenue = \sum_{k=1}^{8784} \text{Installed capacity} * \text{Hourly capacity factor renewable}_{(\text{hour k})} * \text{LMP}\ new_{(\text{hour k})} \tag{3}$$

2.2. Revenue decline and economic capacity

There are different perspectives on estimating the amount of renewable energy that may be integrated into the grid (Brown et al., 2016). Technical potential refers to the total generation that may be feasible given geo-spatial constraints and current state of technology. Lopez et al. (2012) provides GIS based technical potential of several technologies for all of the U.S. Economic potential is typically defined as the subset of the technical potential that is available where the cost required to generate the energy (which determines the minimum revenue requirements for development of the resource) is below the revenues available in terms of displaced energy and displaced capacity.

With every subsequent addition of renewable energy, demand reduces, lowering the LMP. In effect, the addition of renewable energy reduces the clearing price, such that every subsequent unit of renewable energy earns less money. This concept of diminishing marginal revenue or revenue decline is well known and has been explored in several studies for the U.S. and other countries [15,17,29]. The extrapolation of revenue decline implies that there will come a point when it will no longer make economic sense to invest in a renewable source.

For this analysis we obtain the economic potential by continuing to build plants until no additional revenue is gained by building a plant, i.e. the annual revenue of N+1 plants = annual revenue of N plants. This assumes that capacity expansion would continue even when average revenue has dropped below LCOE or average cost (AR < AC).

This method is different from that used by Brown et al. (2016). Brown et al. assume economic capacity is reached when average cost = average revenue (AC = AR) and considers government subsidy as part of the revenue income. In contrast, we do not consider subsidies as part of the revenue stream and instead consider economic capacity to be reached when the additional renewable installation adds zero net economic value. As a result, our numbers for economic potential are higher when compared to Brown et al. (2016).

2.3. Wind and solar costs

To calculate the costs of solar and wind, we assume a present investment cost of $1,400/kW for solar for utility scale fixed-tilt PV [38] and $1,000/kW for wind [4], with operation and maintenance cost of $23.40/kW per year for solar and $22.90/kW per year for wind [4]. In addition, we assume a life span of 20 years for both technologies [4] and a real discount rate of 1.75% [39]. All calculations are in real US $2016. We use the Federal Reserve discount rate, the amount that the U.S. Central Bank charges its member banks to borrow from its discount window. This discount rate is low, and we also run the model with discount rate of 5%, shown in the Supplementary Information (Section 3). Note that a higher discount rate penalizes the economics of capital-intensive renewables, leading to higher abatement costs, meaning that our baseline discount rate is optimistic for the economics of wind and solar. To model capital cost reduction, we use a learning rate of 16% for solar (Rubin et al., 2015) and 9.9% for wind (Williams et al., 2017). Learning is assumed to be national in scope, i.e. cost reduction after adopting in any one region applies to future adoption in all regions. As discussed in Williams et al. (2017), this is equivalent to assuming a global learning rate and a U.S. deployment rate that is proportional to the global deployment rate.

In addition to abatement cost (Eq. (1)), we calculate the equivalent per-MWh subsidy that would be required for each 2.5 GW block of wind or solar generation:

$$Subsidy\left(\frac{\$}{MWh}\right) = LCOE\left(\frac{\$}{MWh}\right) - Revenue\left(\frac{\$}{MWh}\right) \tag{4}$$

2.4. CO_2 emissions reductions

We calculate the displacement of emissions with each capacity addition using hourly marginal emissions factors for each region for the year 2016 [28]. This dataset provides marginal emission factors for 24 h in a day for 3 seasons (summer, winter and transition) for all U.S. eGRID regions. We considered fall and spring as transition. The eGRID regions do not line up exactly with the market regions. We mapped the eGRID regions to our market regions based on the state that most closely represents each region and part of both classifications. The mapping of eGRID regions to our regions is summarized in Table S3 in the supporting information.

The general form for annual greenhouse gas (GHG) mitigation of a technology intervention is:

$$\Delta GHG\ emissions = \sum_{k=1}^{k=8784} \left[hourly\ marginal\ emission\ factor_{(hour\ k)} * renewable\ generation_{(hour\ k)}\right] \tag{5}$$

2.5. Iterative adoption model

We assume that wind and solar are adopted 2,500 MW at a time. With each adoption we determine the change in demand induced and resulting revenue decline. Adoption continues until the point when an additional 2,500 MW has no net economic value in a region. We call this the economic potential. We then calculate the emission displaced using marginal emission factors and calculate cost of emission mitigation. We arrange the mitigation costs for every 2,500 MW installed around the U.S. from lowest to highest abatement cost to create the MAC curve. Emissions of non-CO_2 greenhouse gases have not been included (see Fig. 1).

3. Results: Renewable integration and electricity prices

3.1. Revenue decline

Wind and solar can generate with near zero marginal cost. Because they are the lowest-cost generation sources, increased deployment of wind and solar drive down the clearing price in the LMP market during the periods when they generate. As a result, more wind or solar generation drives down the revenue earned by all nearby generators of the same type (as well as other generators, though that is outside of the current scope). This drop in revenue is proportional to the power output of wind/solar and inversely proportion to the total demand of the region. Fig. 3 illustrates revenue decline for the case of wind and solar in 13 energy market regions. As expected, larger ISO regions (such as Midcontinent Independent System Operator (MISO)) can absorb more renewable energy in comparison to smaller regions. Also, areas with higher capacity factor (CF) see a faster drop with capacity addition in comparison to those with lower CF because they generate more energy from a given deployment of wind/solar.

Comparing our results with prior models, Mills and Wiser (2012) study solar impacts on prices in the California ISO using an energy system model with dispatch and capacity expansion. They find that average revenue for solar starts at $89/MWh at 0% of generation and drops to $25/MWh when the solar share of generation reaches 30% (72% drop). In comparison, our model predicts a smaller drop from $34/MWh to $20/MWh (38% drop) for the same adoption. It is difficult to explain the difference in results because energy system models with dispatch and capacity expansion are complex and qualitatively different from our econometric approach. However, their higher initial revenue could occur because their model uses IEA's projection of natural gas price of $7.8 per MMBtu in 2030 (IEA, 2011), which is much higher than actual natural gas prices in 2016: $2.49/MMBtu [40]). As a result, the Mills and Wiser study predicts much higher clearing prices even with today's renewable portfolio and a more dramatic decline with additional solar, presumably because it may be replacing more expensive gas generation during peak hours.

Woo et al. (2016) use econometric models to examine the impact of wind and solar on wholesale electricity prices for regions within California (NP15 and SP15), considering the impact of 1 GW of additional wind or solar power production in either region. They

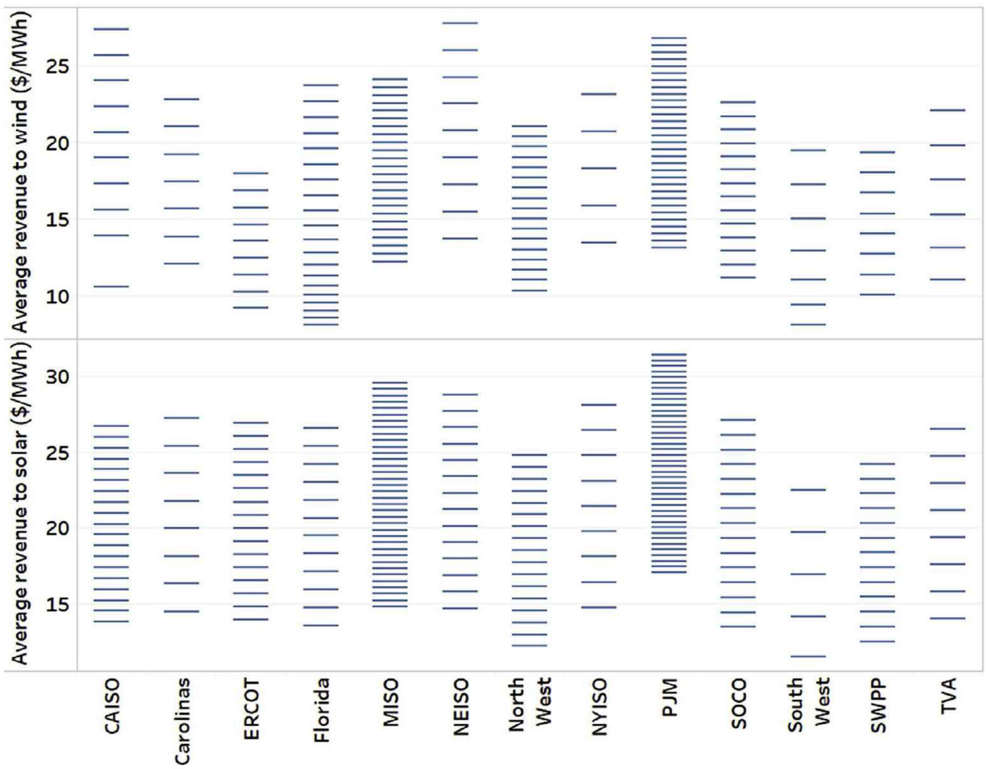

Fig. 3. Diminishing average revenue for wind (top) and solar (bottom) for thirteen U.S. regions. Each line represents an installation of 2,500 MW. The revenue from the first installment is the line on top. The gap between the lines represent the drop in revenue with subsequent installations and may be interpreted as the rate of reduction of average revenue to wind or solar with a capacity expansion of 2,500 MW. For example, revenue to wind is nearly the same in CAISO and PJM for the first unit. However, revenue decline occurs much more quickly in CAISO than in PJM because PJM is a larger system, allowing PJM to accommodate more total wind capacity than CAISO. (CAISO = California ISO, ERCOT = Electric Reliability Council of Texas, MISO = Midcontinent Independent System Operator, NEISO = New England ISO, PJM = Pennsylvania, Jersey, Maryland, SOCO = Southern Company Services, SWPP = Southwest Power Pool, TVA = Tennessee Valley Authority).

find that the wholesale price reduction from 1 GW of solar in an hour can vary between \$1/MWh to \$3.7/MWh depending on area of installation and supply. The effect of 1 GW of wind on LMP is higher, varying between \$1.5/MWh and \$11.5/MWh. In comparison, we find that adding 1 GW of solar power output in CAISO reduces LMP by \$0.4/MWh while the same amount of wind reduces LMP by \$0.8/MWh. The results here are not directly comparable since the demand in the sub-regions are naturally lower than the whole of CAISO and an additional GW has greater impact on revenue reduction if conceptually limited to a smaller region. The demand in the NP15 and SP15 regions are each about 45% of the total CAISO demand, suggesting that the price effect in CAISO should be approximately 45% of the effect limited to either region. Our estimated price reductions are in that order of magnitude: 11%–40% of the Woo et al. result for solar and 7%–53% for wind. The higher revenue erosion from Woo et al. may be attributed to regional transmission congestion that is not accounted for in our model. For more details comparing our revenue erosion estimates with other studies see the Supporting Information (Section 1).

3.2. *Maximum income-earning adoption of wind and solar (Economic potential)*

As revenue decline continues, it is expected that a system will reach a capacity of utility-scale wind and solar for which an addition does not increase total revenue to the generation fleet of that technology in a region. We term this capacity level the “economic potential” because it represents the point where additional deployment of the technology will actually result in lower total revenue. Plotted in Fig. 4, we find that the economic potential varies across the 13 electricity market regions.

The economic potential of a region varies with size of the ISO and the nature of load and dispatch curves. Converting the capacity results into shares of total generation, the economic capacity of solar ranges from 16% in the Carolinas to 32% of generation in CAISO. The economic potential for wind ranges from 24% of generation in the Carolinas to 42% in South West. MISO and PJM, the two largest ISO areas, have the highest economic potential in capacity terms for wind and solar. The total economic capacity in the U.S. was found to be 580 GW of solar and 500 GW of wind. In terms of generation, the number would to be around 1,100 TWh/year for solar and 1,500 TWh/year for wind.

Brown et al. (2016) also estimate the economic potential of wind and solar in the U.S. using a condition of long-term equilibrium where average revenue $\geq$ average cost. Their results are a national economic potential of 441–617 TWh of solar and 715–1,036 TWh of wind energy, the range depending on the scenario. Our estimates are slightly higher than that of Brown et al. (2016) and the difference may be due to different equilibrium conditions, i.e. our short-term equilibrium condition where revenue to the marginal plant is zero versus their long-term condition.

3.3. *Carbon abatement costs for wind and solar*

The cost of carbon abatement for a technology is the ratio of net economic cost and carbon displaced. The economics of wind and solar result from the outcome of opposing drivers: revenue decline and technological progress. As mentioned in the introduction, we

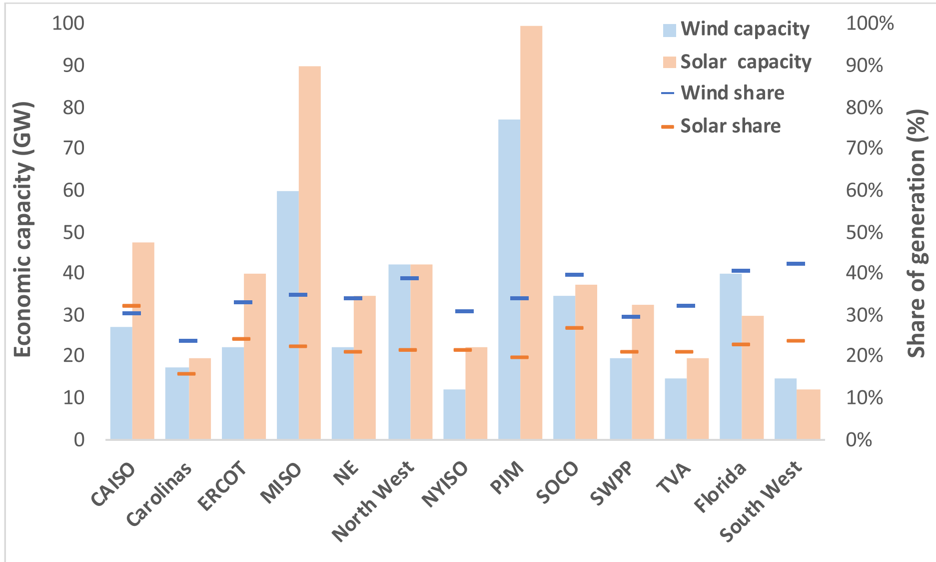

Fig. 4. Economic capacity of wind and solar in ISOs across the U.S. Vertical bars (left y-axis) represent economic capacity in GW, horizontal lines (right y-axis) represent the share of total energy generation of wind or solar in each region. Economic potential is the subset of technical potential at which point the annual average revenue of the marginal additional unit equals the lost revenue it induces in other generators of the same technology. (CAISO = California ISO, ERCOT = Electric Reliability Council of Texas, MISO = Midcontinent Independent System Operator, NEISO = New England ISO, PJM = Pennsylvania, Jersey, Maryland, SOCO = Southern Company Services, SWPP = Southwest Power Pool, TVA = Tennessee Valley Authority).

incorporated technological progress using a single factor experience curve. The learning rates, or fractional cost reduction per doubling of cumulative production, have been well-studied for wind and solar power [13,41–44]. From this literature we use a learning rate of 16% for utility solar and 9.9% for wind.

Wind and solar generate with zero onsite emissions and reduce system-level emissions by displacing emissions from generators that do emit carbon pollution. We estimate the carbon mitigated by wind and solar using hourly generation data in combination with hourly marginal emission factors (MEFs) to assess emission displaced, divided by region and hour of the year. The marginal abatement cost is calculated from these estimates of emissions benefits as well as the revenue estimates discussed above. We do not expect marginal emissions factors for carbon dioxide to change significantly over time with the adoption of more renewables. This is because renewables usually displace fossil plants at the margin, i.e. the mix of coal and natural gas plants generating at a given time, which changes slowly. Retrospective analysis indicates very slow changes in the MEFs of CO_2. For example, in the U.S. the average MEF for CO_2 fell only 7% between 2006 and 2012. In contrast, criteria pollutants showed more dramatic reductions over the same period: 20% for NOx and 30% for SO_2 [45]. Also, note that lower MEFs would increase abatement costs and would result in higher MACs than we calculate in this work. Figs. 5 and 6 show marginal

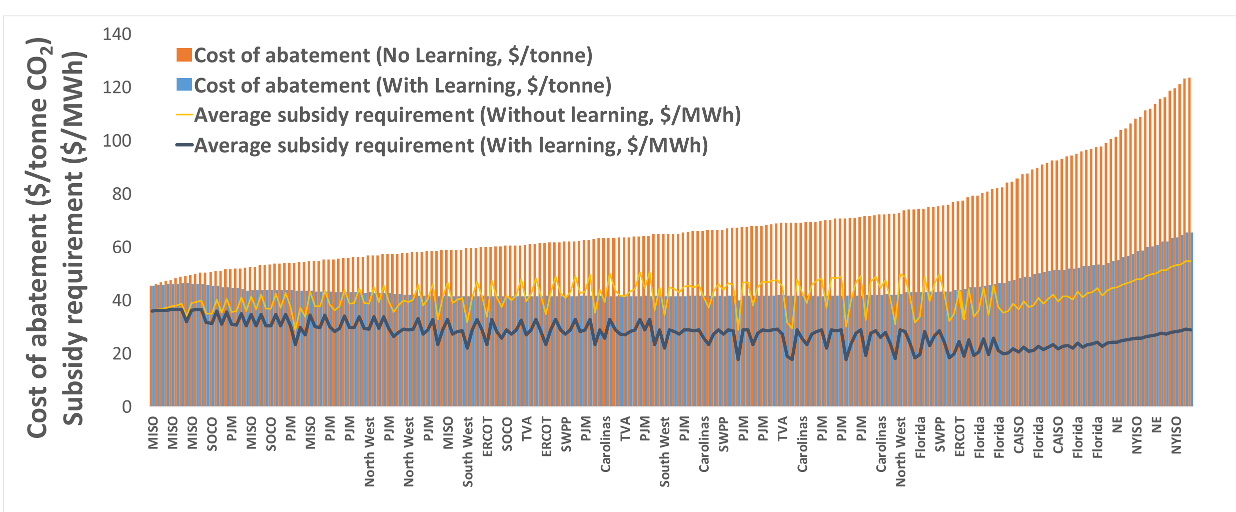

Fig. 5. Marginal Carbon Abatement Costs for Solar (colored bars) and Subsidy required (colored lines). Results both with learning (blue bars and lines) and without learning (orange bars and lines) are shown. When accounting for both learning and revenue degradation, the effective cost of CO_2 abatement from solar stays relatively flat over 530 GW of deployment. Each vertical bar represents installation of 2,500 MW of solar in one of 13 ISO regions, ordered from lowest to highest abatement cost. (CAISO = California ISO, ERCOT = Electric Reliability Council of Texas, MISO = Midcontinent Independent System Operator, NEISO = New England ISO, PJM = Pennsylvania, Jersey, Maryland, SOCO = Southern Company Services, SWPP = Southwest Power Pool, TVA = Tennessee Valley Authority).

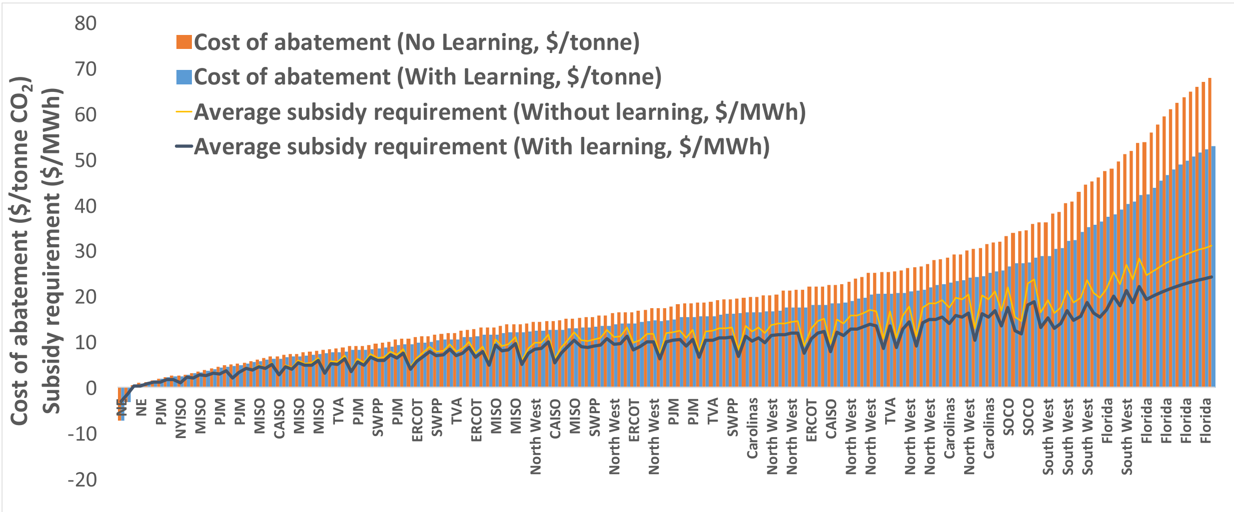

Fig. 6. Marginal Carbon Abatement Costs for Wind (colored bars) and Subsidy required (colored lines). Results both with learning (blue bars and lines) and without learning (orange bars and lines) are shown. When accounting for both learning and revenue degradation, the effective cost of CO_2 abatement from wind increases over the 417 GW of economic capacity. Each vertical bar represents installation of 2,500 MW of wind in one of 13 ISO regions, ordered from lowest to highest abatement cost. (CAISO = California ISO, ERCOT = Electric Reliability Council of Texas, MISO = Midcontinent Independent System Operator, NEISO = New England ISO, PJM = Pennsylvania, Jersey, Maryland, SOCO = Southern Company Services, SWPP = Southwest Power Pool, TVA = Tennessee Valley Authority).

abatement cost estimates for wind and solar, starting from the buildout in the region with lowest abatement cost (MISO for solar and New England for wind) and running out to the total economic potential in each region.

To show the effect of technological progress in solar, we plot abatement cost with zero progress (orange bars) and with 16% learning rate (blue bars). With no learning, the cost of CO_2 abatement for solar (Fig. 5) starts at $46 per tonne of CO_2 for the first 2.5 GW in MISO and increases to $124 per tonne for the last 2.5 GW in NEISO. However, if learning is included, the abatement cost is nearly constant over the entire economic potential, dropping to a low of $41 for several installations before going back up to $66 per tonne.

Solar power has historically been subsidized to bring its cost of generation in line with other sources. Presuming that society wants to continue this support, it is important to understand how it might evolve considering the co-evolution of revenue decline and technological progress. We explore this by calculating the annual price subsidy per MWh needed to make the Net Present Value of a solar installation positive. Results for subsidy requirements for solar are shown in Fig. 5 with the blue line including learning and the yellow line neglecting it. Without learning, the subsidy ranges between $25 and $55 per MWh (40% and 60% of the cost of generation). Learning should be included to reflect expected trends, and subsidy levels in that case do fall (to a low point of 18 $/MWh), but subsidies continue to be needed for the entire economic potential. After the addition of 530 GW of solar, despite the much lower capital cost of the technology (47% lower than the starting point of $1,400/kW), the carbon abatement cost of solar is actually higher ($66/tonne) than where it started ($46/tonne).

Fig. 6 shows results for abatement cost and subsidy requirements for wind power. The abatement curve starts negative, indicating that initially there are savings from mitigating CO_2 using wind in NEISO and PJM. However, the revenue decline effect is stronger for wind than solar (see Fig. 3), with revenue declines exceeding cost reductions from the 9.9% learning rate. This results in mitigation costs soon switching from negative to positive and increasing over the entire roll-out of 417 GW, even though our model suggests that the capital cost of the final wind deployment is 22% lower than the first one. Despite an increasing trend in abatement costs, the abatement cost of wind remains lower than solar for almost the entirety of its economic potential. This suggests that wind may be a more cost effective method of CO_2 mitigation compared to utility solar across the U.S., now and in the future.

The subsidy requirement for wind start at $-3/MWh (profitable) and climbs to $25/MWh, ranging between −10% and 40% of the cost of generation. Even though the investment cost of wind and solar are expected to go down in the future due to technological progress, the loss of revenue occurs at a pace that approximately keeps up with cost declines for solar and exceeds it in the case of wind over very large deployments (equivalent to six times the current wind deployment [46] and ten times the solar deployment [47] as of 2018).

4. Caveats

The results discussed above are an outcome of specific modeling assumptions and their interpretation should be placed in an appropriate context. We are aware that these results, in particular a need for increasing subsidies for wind, will be controversial and thus set aside this section to explain modeling assumptions and caveats. First and foremost, we reiterate that our model builds out wind and solar on the current grid, essentially assuming that the rest of the generation fleet does not change in response to the wind/solar deployment that continues to occur across the U.S. In reality, the grid could evolve in a number of ways that affect revenue decline, including capacity retirements/additions other than wind/solar, or deployment of technologies that improve renewables integration, such as storage, demand response and new transmission. It also does not account for the possible impacts of changes in fossil fuel prices on the revenue to wind and solar though it does implicitly account for seasonal variability in prices.

To first discuss retirements/additions: adopting wind or solar has the potential to lead to retirements for other types of plants, e.g. coal, nuclear, and natural gas. These retirements reduce supply, potentially pushing prices up, and countering revenue decline. However, renewables are not firm capacity and therefore cannot be used to meet grid capacity requirements. The most likely scenario for grids to maintain firm capacity in the near term is replacement of coal plants with natural gas that would operate with lower capacity factor, filling in for gaps in wind/solar output. The effect of replacing coal with gas on revenue decline depends on the relative price of coal versus natural gas electricity during periods when wind/solar are generating. Because wind/solar have very low marginal costs, they can be considered market price takers with an energy value equal to the marginal generator's production cost. Thus, wind/solar revenues depend on the extent to which the grid relies on more expensive price-setting generators, e.g. coal and natural gas. If natural gas replaces coal with lower or similar marginal cost, the revenue decline of wind and solar is similar or accelerated compared to our model. If the marginal cost of natural gas is higher than coal, then revenue decline is countered to the degree that the grid calls on more expensive natural gas. While the future of fuel prices is difficult to know with certainty, recent history generally shows comparable marginal costs between natural gas and coal. In this case, the replacement of coal with natural gas would not appreciably affect the operating cost of the marginal generator, suggesting that revenue decline for wind and solar would not shift significantly with the additional gas capacity that is mainly used to fill in when renewables are not available.

By enabling temporal fungibility between supply and demand, storage and demand response capacity would mitigate revenue decline. Implicit in our model are additions to transmission and distribution infrastructure required to integrate new wind and solar power into each of the 13 regions. However, addition of long-distance transmission connecting across markets would create a more nationally aggregated dispatch curve, influencing prices and revenue decline. The potential of these grid changes is discussed further in the discussion section below.

Finally, changes in fossil fuel prices, particularly natural gas, would impact the wholesale clearing price and therefore the revenue earned by renewable resources. Because natural gas plants are the primary price-maker during peak load, changes in natural gas prices would impact peak prices. Our study uses hourly data from 2016 and therefore implicitly assumes that the cost of fossil fuels is that of 2016, including seasonal variability. In 2016, natural gas prices ranged between \$2.33 in March to \$4.15 in December. In 2019, gas prices were similar, ranging between \$2.62 in June and \$4.16 in January. Therefore, the findings of the model are relevant for some years other than 2016, though we recognize that change in gas prices would impact both economic potential and abatement costs. Specifically, increased gas prices would raise peak prices and therefore revenue earned by wind and solar. This would in turn slow revenue decline and accommodate more renewable energy into the grid. This would also reduce the subsidy required and thereby abatement cost of carbon. A reduction in natural gas prices would have the opposite impact. Current U.S. natural gas prices are historically low, though with current supplies and export constraints it is plausible that the status quo may continue for a decade or more, absent policy changes that increase the cost of natural gas generation [48].

As with any modeling exercise, outcomes depend on numerical values of input data. The pace of technological progress is an important assumption. While our learning rates are based on reasonable empirical extrapolations of historical trends, we tested sensitivity by considering values of $\pm$50% of the base case. We find that the trends in abatement cost and subsidy requirement are similar even with such a broad range of learning rates. Details of our sensitivity analysis can be found in the supplementary information (Section 2).

5. Discussion

In this paper we examine two opposing effects of renewable integration, revenue reduction and learning, for 13 electricity market regions across the U.S. Results indicate that learning alone is not enough to ensure reduction in the cost of abatement using wind or solar technologies. The revenue earned by these technologies degrades too quickly in most regions to retain or improve their economic viability. Our results reveal that while technological progress reduces costs, revenue reductions through the merit order effect may cancel or outpace it. This finding contradicts existing research that concludes that learning tends to reduce abatement cost of carbon [49,50] because these studies did not consider both revenue decline and learning. There are caveats and uncertainties in our modeling, discussed above, yet we argue that we identify a plausible future in which the economic prospects of wind and solar are no better than today. There are significant policy implications: absent other efforts to address revenue decline, subsidies for wind and solar adoption may need to continue and even increase. This possible future should be taken seriously.

A variety of technical and operational strategies (storage, demand response) have been identified to help with renewable integration and mitigate the revenue degradation challenge that we characterize. Most of these strategies are currently being pursued and all of them would be further encouraged by market forces as greater amounts of wind and solar are added to existing electricity systems. This is encouraging, but the contribution of our research is to show that these electricity system changes are actually necessary if wind and solar are to continue their historical trajectory of decreasing carbon mitigation costs.

Energy storage is a well-discussed option for integrating wind and solar. It has the potential to mitigate revenue decline by charging during low cost hours (with high renewable generation) and raising the demand, then discharging when prices are higher. For example, Shafiee et al. consider a 140 MW storage plant added to the Alberta electricity system (12 GW of generation, so storage is 1.2% of generation) and evaluate its effect on electricity prices [51]. This storage deployment has a noticeable effect on prices, but decreases peak price far more than it increases off-peak prices (~\$35/MWh decrease when discharging, ~\$2.50/MWh increase when charging). However, it is the increase in off-peak price that affects the rate of wind/solar revenue erosion. Much research on storage has focused on the operationally and economically appropriate amount to accommodate a given level of renewable energy. For example, in an analysis for the state of Texas, de Sisternes et al. examine various deeply decarbonized electricity systems with and without storage [52]. In a scenario where average emissions are limited to 100 kg/MWh with no new nuclear plants, the addition of some storage (along with wind and solar) is needed to meet peak demand, and going from 10 to 20 GW of storage reduces the operational costs of generation by 5–10%. While this and similar studies do not directly address revenue decline, they reflect a growing body of work that aims to clarify how storage can enhance wind and solar deployment.

Demand response is another mechanism to help incorporate large amounts of renewables into the grid. For storage, the objective is to "buy low, sell high". For demand response, it is "use low, save high". Traditionally, demand response programs are used to reduce peak demand. Such programs incorporate a "trigger point", which for example in the case of PJM was at an LMP of \$75/MWh, beyond which payments for load reduction included a subsidy payment to the consumers [53]. These help utilities save money by not having to pay hundreds of dollars per MWh to generators at the peak hour. Typically these programs shift demand from later in the afternoon, when the demand is highest, to other hours like late evening. Addressing revenue decline with demand response would be

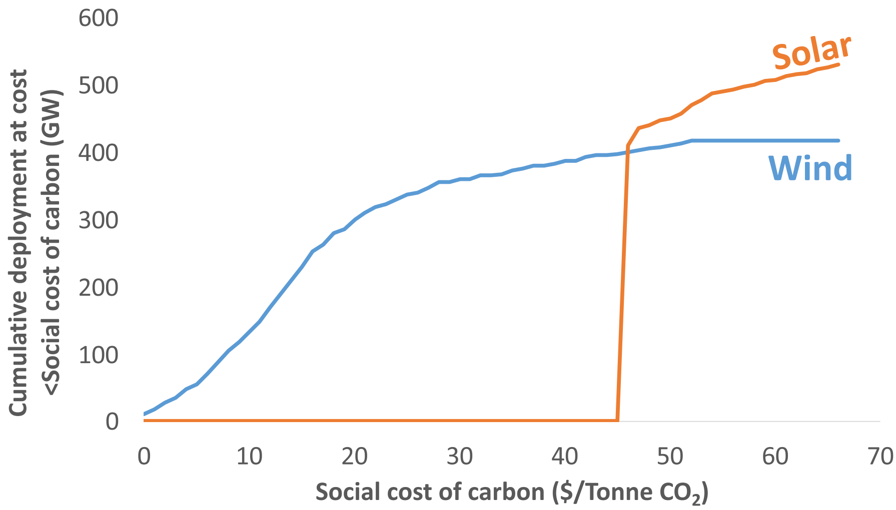

Fig. 7. Cumulative capacities of wind and solar with mitigation cost less than a given value of social cost of carbon. The y-axis represents the cumulative deployment with cost <social cost of carbon) fo and the x-axis represents the social cost of carbon. Our results suggest different carbon mitigation cost trajectories for wind and solar. From $0–20/tonne allowed mitigation cost, the amount of wind power increases rapidly, decreasing in slope for higher costs. Solar power does not emerge as an option at all until $46/tonne is reached, but at that threshold point there is dramatic increase to a nominal capacity above wind.

similar in principle to peak reduction but with a different focus: shifting demand from times when electricity is expensive (renewables are not available) to times when it is cheap (renewables are available). More sophisticated consumer rate structures can achieve this and several states, led by California, are planning time-of-use or related rate designs as a way of improving grid flexibility and helping to integrate additional wind and solar [54].

Expansion of transmission capacity is another change that could address revenue decline. It is important to distinguish between transmission needed for balancing within an area and transmission intended to expand the geographic scope of markets. Regarding the former, Brown et al. (2016) suggest that the calculated economic potential (which is similar to our findings) can be supported by the present transmission system. Denholm et al. (2013) suggest 33% of California's energy demand could be supplied by renewables without substantial changes to the transmission system. Even if not needed to counteract revenue decline, there are economic advantages to expanding transmission. Reducing congestion charges within an area is one benefit of transmission, as is enabling plants to trade with markets further away and balance renewables over larger regions. For example, if prices are low during peak wind generation in ERCOT, the ERCOT region may be able to supply low-cost electricity to SWPP or other markets farther away where the clearing prices are higher, providing benefits to both systems.

While our results indicate challenges for wind and solar to become economically self-sufficient, this does not imply that the technologies are not justifiable and in the public interest. Even if revenue decline proceeds as our "status quo" model suggests, hundreds of gigawatts of deployment have abatement costs well below most estimates of social cost of carbon. A comprehensive estimate of climate change impacts, the social cost of carbon accounts for damages to agricultural productivity, human health, property from increased flood risk and changes in energy system costs. The current central estimate of this number is around $40 per tonne, though it is recognized that this does not include all impacts of climate change [55]. Other estimates put this number at $68 in 2015 and expected to reach $115 in 2050 [56]. In addition to carbon benefits, solar and wind power also reduce emissions of criteria pollutants. Sexton et al. (2018) estimated that every kW of solar results in $117 in annual avoided damages. This can be attributed to reduction of SO_x ($82), CO_2 ($23.5), $PM_{2.5}$ ($7.4) and NO_x ($3.6) and varies widely by location [57]. If we add these up, the social benefits are greater than the required subsidy per MWh and abatement cost per tonne of CO_2 through the hundreds of GWs of wind and solar deployment that we model.

One approach to assess mitigation potential is to find the cumlative adoption with mitigation cost below the social cost of carbon. This reflects the deployment justifiable from a benefit-cost perspective. Results are showm in (Fig. 7) with social cost of carbon as a variable. For social cost of carbon from $0–20/tonne, the amount of wind power increases rapidly, decreasing in slope for higher costs. Solar power does not emerge as an option at all until a threshold $46/tonne is reached, but at that point there is dramatic increase in solar deployment to a nominal capacity above wind.

The benefits of lower prices for wind and solar are often assessed assuming they do not influence the energy markets in which they are adopted. The contribution of this work is to show that accounting for the negative effect of wind and solar adoption on their own revenue may cancel out or even exceed the economic benefits of lower capital costs through technological progress. This said, the degree of revenue decline found here is by no means written in stone. The grid is evolving in directions that tend to mitigate revenue decline and purposeful action to address it could go further, improving the ability of intermittent renewables to deliver carbon benefits at low cost. The key is to recognize the relevance of revenue decline, work to better understand it, and make appropriate decisions to realize a sustainable and economic grid.

Declaration of competing interest

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

Acknowledgements

This research has been supported by the U.S. National Science Foundation, Environmental Sustainability Program (grant CBET #1605319).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2020.03.082.

References

[1] Eric Lantz, Ryan Wiser, Maureen Hand, IEA Wind Task 26: The Past and Future Cost of Wind Energy, National Renewable Energy Laboratory, Golden, 2012.
[2] Tyler Stehly, Donna Heimiller, George Scott, 2016 Cost of Wind Energy Review, National Renewable Energy Laboratory, Golden, 2017.
[3] U.S. DOE, 2008 Solar Technology Market Report, U.S Department of Energy, 2010.
[4] LAZARD, Lazard's Levelized Cost of Energy Analysis - Version 11.0, LAZARD, 2017.
[5] T. Wright, Factors affecting the cost of airplanes, J. Aeronaut. Sci. 3 (2) (1936) 122–128.
[6] L. Yelle, The learning curve: historical review and comprehensive survey, Decis. Sci. J. 10 (2) (1979) 302–328.
[7] C. Teplitz, J. Carlson, The Learning Curve Deskbook: A Reference Guide to Theory, Calculations, and Applications, Praeger, New York, 1991.
[8] B. Nagy, J.J. Farmer, Q. Bui, J. Trancik, Statistical basis for predicting technological progress, PloS One 8 (2) (2013).
[9] IRENA, Renewable Power Generation Costs in 2014, International Renewable Energy Agency, 2015.
[10] A. McDonald, Learning rates for energy technologies, Energy Pol. 29 (4) (2001) 255–261.
[11] G.F. Nemet, Beyond the learning curve: factors influencing cost reductions in photovoltaic, Energy Pol. 34 (2006) 3218–3232.
[12] U. Pillai, Drivers of cost reduction in solar photovoltaics, Energy Econ. 50 (2015) 286–293.
[13] E.S. Rubin, I.M. Azevedo, P. Jaramillo, S. Yeh, A review of learning rates for electricity supply technologies, Energy Pol. 86 (2015) 198–218.
[14] C. Woo, I. Horowitz, J. Moore, A. Pacheco, The impact of wind generation on the electricity spot-market price level and varience: the Texas ecperience, Energy Pol. 39 (2011) 3939–3944.
[15] C. Woo, J. Moore, B. Schneiderman, T. Hoc, A. Olson, L. Alagappan, K. Chawla, Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets, Energy Pol. 92 (2016) 299–312.
[16] S. Clò, A. Cataldi, P. Zoppoli, The merit-order effect in the Italian power market: the impact of solar and wind generation onm national wholesale electricity prices, Energy Pol. 77 (2015) 79–88.
[17] M. O'Flahertya, N. Riordanb, N. O'Neilla, C. Aherna, A quantitative analysis of the impact of wind energy penetration on electricity prices in Ireland, Energy Procedia 58 (2014) 103–110.
[18] S. Forrest, I. MacGill, Assessing the impact of wind generation on wholesale prices and generator dispatch in Australian NAtional Electricity Market, Energy Pol. 59 (2013) 120–132.
[19] F. Parachiv, D. Erni, R. Peitsch, The impact of renewable energies on EEX day-ahead electricity prices, Energy Pol. 73 (2014) 196–210.
[20] J.C. Ketterer, The impact of wind power generation on the electricity price in Germany, Energy Econ. 44 (2014) 270–280.
[21] McKinsey, Pathways to a Low-Carbon Economy: Version 2 of the Global Greenhouse Abatement Cost Curve, McKinsey and Company, 2009.
[22] J. Abrell, K. Mirjam, R. Sebastian, The economic cost of carbon abatement with renewable energy policies, in: CER-ETH – Center of Economic Research at ETH Zurich Working Paper No. 17/273, 16 6 2017.
[23] C. Marcantonini, A.D. Ellerman, The Cost of Abating CO2 Emissions by Renewable Energy Incentives in Germany, MIT Center for Energy and Environmental Policy Research, Cambridge, US, 2013.
[24] J. Cochran, P. Denholm, B. Speer, M. Miller, Grid Integration and the Carrying Capacity of the U.S. Grid to Incorporate Variable Renewable Energy, NREL, Golden, 2015.
[25] X. Lu, M.B. McElroy, J. Kiviluoma, Global potential for wind-generated electricity, Proc. Natl. Acad. Sci. Unit. States Am. 106 (27) (2009) 10933–10938.
[26] A. Possner, K. Caldeira, Geophysical potential for wind energy over the open oceans, Proc. Natl. Acad. Sci. U.S.A. 114 (43) (2017) 11338–11343.
[27] U.S Energy Information Administration, U.S. Electric system operating data [Online]. Available, https://www.eia.gov/realtime_grid/#/status?end=20171129T20, 2018. (Accessed 16 December 2018).
[28] I.L. Azevedo, P.L. Donti, N.C. Horner, G. Schivley, K. Siler-Evans, P.T. Vaishnav, Electricity Marginal Factor Estimates. Center For Climate and Energy Decision Making, Carnegie Mellon University, Pittsburgh, 2019. http://cedmcenter.org.
[29] R. Wiser, A. Mills, Changes in the Economic Value of Variable Generation at High Penetration Levels: A Pilot Case Study of California, Ernst Orlando Lawrence Berkeley National Laboratory, Berkeley, 2012.
[30] Electric Reliability Council of Texas, Market prices [Online]. Available, http://www.ercot.com/mktinfo/prices, 2018. (Accessed 20 May 2018).
[31] California Independent System Operator, Market price maps [Online]. Available, http://www.caiso.com/PriceMap/Pages/default.aspx, 2018. (Accessed 20 May 2018).
[32] Midcontinent independent system operator, Real time displays [Online]. Available, https://www.misoenergy.org/markets-and-operations/real-time-displays/, 2018. (Accessed 20 May 2018).
[33] New York Independent System Operator, Pricing data [Online]. Available, http://www.nyiso.com/public/markets_operations/market_data/pricing_data/index.jsp, 2018. (Accessed 20 May 2018).
[34] New England ISO, Pricing reports [Online]. Available, https://www.iso-ne.com/isoexpress/web/reports/pricing/-/tree/ancillary-five-minute-rcp, 2017. (Accessed 29 January 2018).
[35] PJM, Settlements verified hourly LMPs [Online]. Available, https://dataminer2.pjm.com/feed/rt_da_monthly_lmps/definition, 2017. (Accessed 20 January 2018).
[36] S. Forrest, I. MacGill, Assessing the impact of wind generation on wholesal eprices and generator dispatch in the Australian National Electricity Market, Energy Pol. 59 (2013) 120–132.
[37] Energy Information Administration, Electric generator dispatch depends on system demand and the relative cost of operation [Online]. Available, https://www.eia.gov/todayinenergy/detail.php?id=7590, 2012. (Accessed 20 May 2018).
[38] Ran Fu, David Feldman, Robert Margolis, Margolis Woodhouse, Kristen Ardani, U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017, National Renewable Energy Laboratory, Bolder, 2017.
[39] The Federal Reserve, The discount rate [Online]. Available, https://www.federalreserve.gov/monetarypolicy/discountrate.htm, 4 12 2017. (Accessed 10 December 2017).
[40] Energy Information Administration, Today in energy [Online]. Available, https://www.eia.gov/todayinenergy/detail.php?id=29552, 17 1 2017. (Accessed 28 December 2018).
[41] C. Benson, C. Magee, On improvement rates for renewable energy technologies: solar PV, wind turbines, capacitors, and batteries, Renew. Energy 68 (2014) 745–751.
[42] B. van der Zwaan, A. Rabl, Prospects for PV, a learnign curve analysis, Sol. Energy 74 (1) (2003) 19–31.
[43] E. Williams, S. Matteson, S. Sekar, B. Rittman, Sun-to-Wheels exergy efficiencies for bio-fuels and photovoltaics, Environ. Sci. Technol. 49 (11) (2015) 6394–6401.
[44] E. Williams, E. H, R. Carvalho, R. Williams, Wind power costs will continue to decrease due to technological progress, Energy Pol. 10 (2017) 427–435.
[45] K. Siler-Evans, I. Azevedo, G. Morgan, Marginal emissions factors for the US electricity system, Environ. Sci. Technol. 46 (9) (2012) 4742–4748.
[46] American Wind Energy Association, Wind Energy in the United States, 2018 [Online]. Available, https://www.awea.org/wind-101/basics-of-wind-energy/wind-facts-at-a-glance. (Accessed 10 November 2018).
[47] Solar Energy Industries Association, U.S. Solar Market Insight, 2018 [Online]. Available, https://www.seia.org/us-solar-market-insight. (Accessed 10 November 2018).
[48] McKinsey, Global Gas and LNG Outlook to 2035, McKinsey, 2018.
[49] A. Manne, R. Richels, The impact of learning-by-doing on the timing and costs of CO2 abatement, Energy Econ. 26 (4) (2004) 603–619.
[50] M. Grubb, Technologies, energy systems and the timing of CO2 emissions abatement, Energy Pol. 25 (2) (1997) 159–172.
[51] S. Shafiee, P. Zamani-Dehkordi, Z.A.M. Knight, Economic assessment of a price-maker energy storage facility in the Alberta electricity market, Energy 111 (2016) 537–547.
[52] F.J. de Sisternes, J.D. Jenkins, A. Botterud, The value of energy storage in decarbonizing the electricity sector, Appl. Energy 175 (2016) 368–376.
[53] R. Walawalkar, S. Blumsack, J. Apt, S. Fernands, An economic welfare analysis of demand response in the PJM electricity market, Energy Pol. 36 (10) (2008) 3692–3702.
[54] H.K. Trabish, As California Leads Way with TOU Rates, Some Call for Simpler Solutions, Utility Dive, 20 09 2018 [Online]. Available, https://www.utilitydive.com/news/as-california-leads-way-with-tou-rates-some-call-for-simpler-solutions/532436/. (Accessed 26 December 2018).
[55] EDF, The True Cost of Carbon Pollution, Environmental Defense Fund, New York, 2017 [Online]. Available, https://www.edf.org/true-cost-carbon-pollution. (Accessed 21 August 2018).
[56] EPA, EPA Factsheet: Social Cost of Carbon, Environment Protection Agency, 2016.
[57] S. Sexton, J. Kirkpatrick, B. Harris, N. Muller, Siting Solar PV Capacity to Maximize Environmental Benefits, 2018. Philadelphia.