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MEETING ELECTRICITY DEMAND WITH DISTRIBUTED WIND AND SOLAR GENERATION: SYSTEM FLEXIBILITY DRIVES OPTIMAL SITING

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ABSTRACT

Hundreds of gigawatts of renewable technologies, such as wind and solar, need to be installed to reach a zero-carbon electricity system that meets current and future energy needs. Locations of new installations are typically chosen based on wind and solar availability to maximize facilities' capacity factors. Here, we show that this is not always true in least-cost models, and optimal siting depends also on the flexibility of the electricity system. To show this, we use a macro-scale energy model to evaluate capacities and dispatch in least-cost electricity systems with distributed wind and solar generation supported by battery storage. If battery storage were free and widely available, chosen locations for wind and solar installations would inevitably be in regions with the highest wind and solar capacity factors. However, as the battery storage cost increases and thus storage capacity decreases, chosen locations have lower capacity factors and the electricity system is more reliant on wind generation. In the case of a system without energy storage, only wind generation would in fact meet certain periods of electricity demand. This study suggests that current optimal wind and solar siting may no longer be the least-cost solution as the storage cost decreases.

Keywords: macro energy modeling; distributed wind and solar generation; optimal siting.

1. INTRODUCTION

Transitioning to net-zero emissions electricity systems relies primarily on the use of renewable or zero-carbon sources. In 2019, electricity generated from renewables was globally around one-quarter of the total generation, with hydropower being the largest contributor and wind and solar being the fastest growing [1]. Ambitious climate policies in the USA, the EU, India, and China, among others [2]–[4], along with the continuous fall in costs of solar and wind technologies [5] have driven a rise in renewable capacities and power generation. Meeting targets of net-zero emissions electricity systems, however, is still likely to require substantial increases in solar and wind generation capacity. Currently wind and solar make less than 10% of the worldwide electricity generation.

Large shares of variable renewable energy technologies, such as wind and solar, added to power systems can pose several system integration challenges. The primary challenge arises from the fact that wind and solar resources are highly variable in space and time and not always available when needed to meet electricity demand [6]–[8]. Although wind and solar resources have some degree of complementarity that helps mitigate and smooth their variability [9], [10], reliable power systems mostly based on variable energy sources require effective grid management, backup power systems, and energy storage capacity [11]–[13]. For example, energy storage enables temporal shifting of the variable energy generation: energy is stored in times when it would be otherwise curtailed and used in times when the variable energy generation is lower than current demand [14]. Energy is stored both for short-duration (e.g., in Li-on batteries), when quick, daily demand compensation is needed [15], and long-duration (e.g., in power-to-gas-to-power, pumped hydro, or compressed air storage), when inter-season and multi-year storage is needed [16], [17]. In addition to storage, adding low- or zero-carbon firm generators (e.g., nuclear) can also lower the overall cost of decarbonized systems [18], [19]. Despite these challenges faced by utilities and operators when systems depend on large amounts of variable renewables, a variety of operational and technical solutions exist to add and integrate wind and solar generation and will likely be implemented in future years [20]–[25].

Planning for new power generation facilities at the system level requires strategic decision making. This is particularly important for wind and solar installations because their economic viability depends largely on the availability of resources, which are highly variable in space and time. Optimal site selection of solar installations is mostly driven by solar irradiance and equivalent sun hours [26], [27] whereas preferred locations for wind power plants are the ones with higher mean wind power potential at the turbine hub height [28]–[31]. For wind power plants, system level planning is then followed by turbine micro-siting to determine the positions of the individual turbines [32]–[36]. Methods for optimal siting in a distributed network have been developed to consider also other criteria related to environmental, economic, social, and technical aspects [37]–[39]. Studies on integration of distributed generation into the electrical grid have focused for example on line loss reduction or increased system voltage profile [40], [41]. However, these electrical integration studies have addressed small-scale, local distribution networks [42], [43]. At large-scale, evaluation of distributed wind and solar power developments has been conducted to meet certain generation thresholds without considering integration with the electric grid and demand profiles [44].

Here, we evaluate optimal siting of distributed wind and solar generation supported by energy storage to meet aggregated hourly electricity demand at the system level, with application to the U.S. We use hourly averaged wind and solar resource data from the year 2019, obtained from a reanalysis weather dataset [45], and hourly electricity demand data from the year 2019, obtained from balancing authorities across the contiguous U.S. [46], as inputs to a macro-scale energy model [47]. The spatial distribution of wind and solar generation is evaluated by subdividing the contiguous U.S. into 2,586 regions, corresponding to the grid cells of the reanalysis dataset. For each cell, we calculate hourly wind and solar capacity factor time series. The macro-scale energy model allows us to evaluate least-cost solutions with installed capacities and dispatch schedules of each grid cell to meet the aggregated hourly demand time series. In evaluating capacities and dispatch schedules, we consider a varying cost for energy storage. This evaluation is important if we consider that the energy storage could become much cheaper (relative to variable renewable energy generation) in the future as long duration energy storage becomes widely available [48].

2. MATERIALS AND METHODS

In this study, we use a macro-scale energy model, illustrated in Fig. 1. It includes a set of electricity generation facilities and a firm electricity load in the form of an hourly demand time series. For each generation facility, the model requires cost assumptions and hourly capacity factor time series. The model uses a linear optimizer (Gurobi Optimizer) to find the installed capacities and hourly dispatches, for all electricity generation facilities included in the system, that minimize total system cost. This system representation assumes lossless transmission from generation to load over the contiguous U.S. In such a system, location matters only for wind and solar power, while batteries and demand can be considered in aggregate because their contribution to the system cost is not affected by their spatial variability. Curtailment is allowed for variable renewable energy generation when supply exceeds demand, resulting in a loss of energy. The model includes an unmet demand component represented with a penalty cost (10 \$/kWh). We use the term flexibility here to refer to the degree to which the power system can adjust generation by means of storage (e.g., batteries) in reaction to variability of demand or non-dispatchable technologies (e.g., wind and solar).

We use this model to understand where variable renewable energy facilities supported by energy storage would be built to meet electricity demand most cost-effectively. The spatial distribution of wind and solar generation is evaluated thanks to the subdivision of the contiguous U.S. into the grid cells of the MERRA-2 reanalysis dataset. The dataset has a spatial resolution of 0.5° latitude x 0.625° longitude. Over the contiguous U.S., there are 2,586 grid cells with horizontal dimensions ranging from about 50 km x 50 km to 60 km x 60 km. For each cell, we calculate hourly capacity factor time series of wind and solar. For each cell, we also set maximum generation limits to prevent unrealistic, concentrated installations of wind or solar generation that could otherwise be selected by the optimizer. Specifically, we use two fixed values of mean power density that are consistent with observations, namely, 1 and 5 W/m^2 for wind and solar generation, respectively [49], [50]. The maximum installed capacity for each cell is calculated by multiplying the maximum power density by the cell area. Further, the macro energy system assumes lossless transmission from generation to load.

Each technology (wind, w, solar, s, or battery, b) is characterized by a fixed hourly cost resulting from the capital expenditure, $c_{capital}$, and operation and maintenance costs, $c_{O\&M}$:

$$c_{fixed}^{w,s,b} = \frac{\gamma c_{capital}^{w,s,b} + c_{O\&M}^{w,s,b}}{8{,}760}, \tag{1}$$

where γ is the capital recovery factor, defined as:

$$\gamma = \frac{i(1+i)^n}{(1+i)^n - 1}, \tag{2}$$

where i is the discount rate and n is the asset lifetime in years. In the model, we introduce constraints on the installed capacity for both wind and solar, C:

$$0 \le C^{w,s} \le C_{max}^{w,s}, \tag{3}$$

as well as constraints on the dispatch time series at each time step, D_t:

$$0 \le D_t^{w,s} \le C^{w,s}. \tag{4}$$

Batteries are characterized by constraints on the energy flowing into them, D_t^{to-b}:

$$0 \le D_t^{to-b} \le \frac{C^b}{\tau^b}, \tag{5}$$

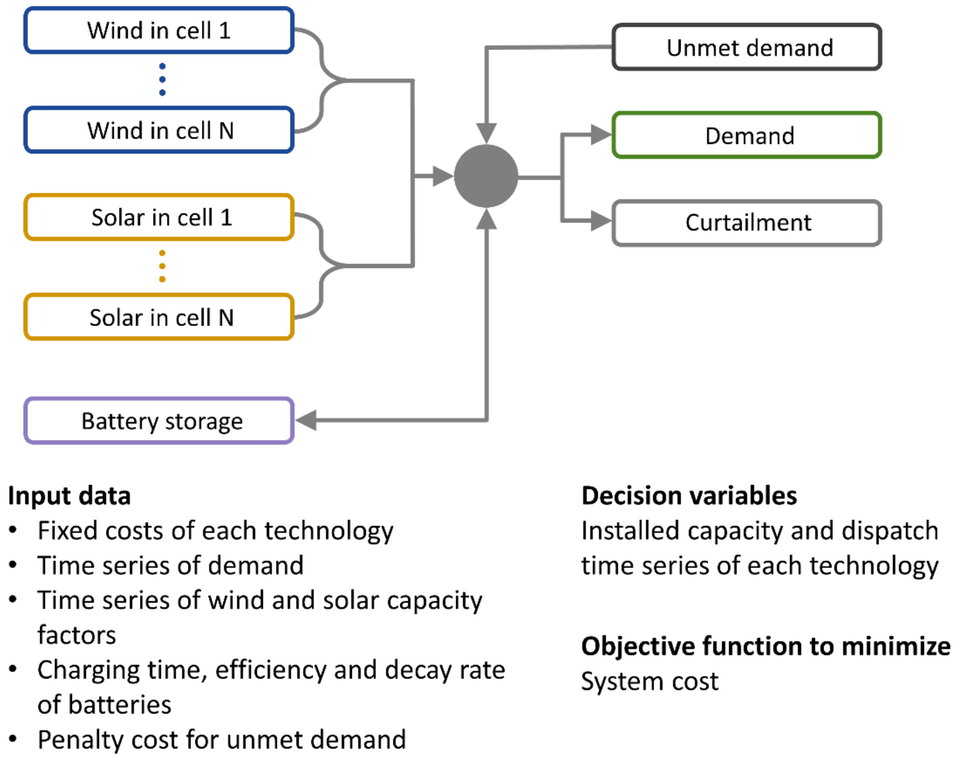

FIGURE 1: ILLUSTRATION OF THE MACRO ENERGY MODEL USED TO UNDERSTAND THE OPTIMAL SITING OF WIND AND SOLAR GENERATION SUPPOERTED BY BATTERY STORAGE.

and energy flowing from them, D_t^{from-b}:

$$0 \leq D_t^{from-b} \leq \frac{C^b}{\tau^b}, \quad (6)$$

where τ^b is the storage charging duration. The total energy available in the batteries, S_t, is also constrained by the total capacity:

$$0 \leq S_t \leq C^b, \quad (7)$$

and the energy flowing from the batteries is affected by the battery decay rate (fraction of energy loss per hour), δ^b:

$$0 \leq D_t^{from-b_t} \leq S_{t-1}(1-\delta^b). \quad (8)$$

The battery storage energy balance is modeled with the following equations:

$$S_1 = (1-\delta^b)S_T\Delta t + \eta^s D_T^{to-b}\Delta t - D_T^{from-b}\Delta t, \quad (9)$$

$$S_{t+1} = (1-\delta^b)S_t\Delta t + \eta^s D_t^{to-b}\Delta t - D_t^{from-b}\Delta t, \quad (10)$$

where η^s is the battery electrolysis efficiency.

The whole system energy balance is defined as follows:

$$\sum\nolimits_{w,s} D_t^{w,s}\Delta t + D_t^{from-b}\Delta t = M_t + D_t^{to-b}\Delta t + C_u + U_d, \quad (11)$$

where M_t is the demand at time t, C_u the curtailment, and U_d the unmet demand.
Lastly, the objective function to minimize is the system cost:

$$\sum\nolimits_{w,s,b} c_{fixed}^{w,s,b} C^{w,s,b} \quad (12)$$

3. RESULTS AND DISCUSSION

In this section, we present results of the optimization cases that we performed. Specifically, we evaluate optimal siting of distributed wind and solar generation supported by battery storage to meet aggregated hourly electricity demand at the system level for different battery storage costs. This evaluation is relevant if we consider that battery storage could become much cheaper in the coming decades. We consider cases with no battery storage, battery storage at today's cost (366 $/kWh [51]), and four other variations in cost, namely 1.5, 0.5, 0.25, and 0.10 times today's cost.

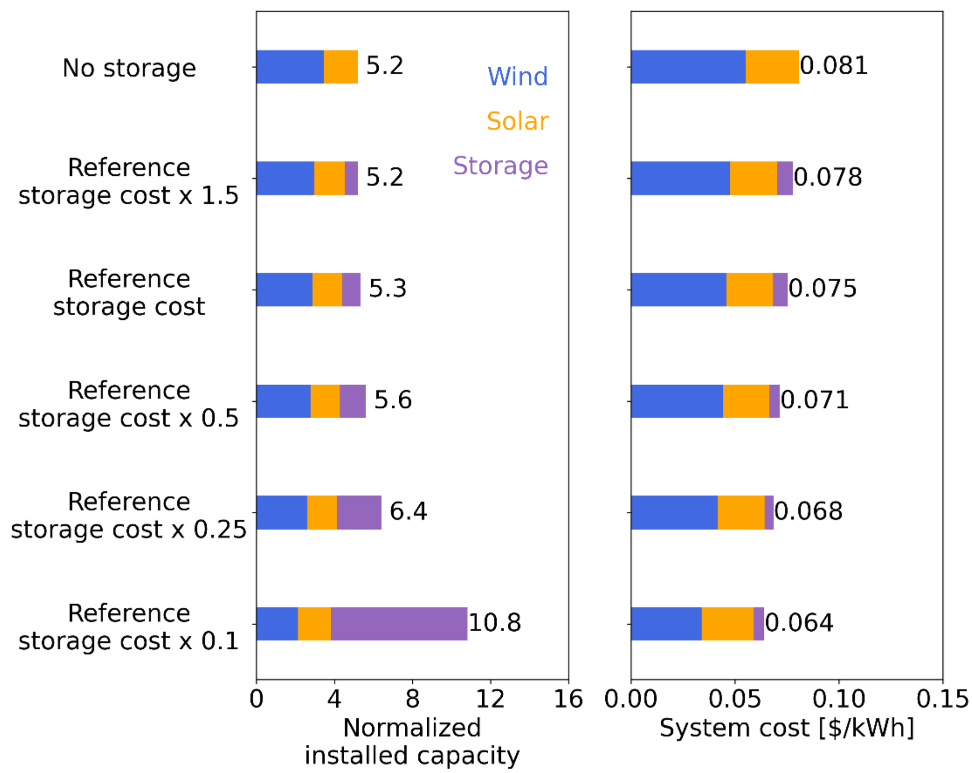

FIGURE 2: NORMALIZED INSTALLED CAPACITY AND SYSTEM COST FOR DIFFERENT ASSUMPTIONS IN BATTERY STORAGE COST.

In Fig. 2, we show a high-level analysis of the system architectures and costs resulting from the various cases we simulated. The installed capacity is normalized with the mean electricity demand, approximately equal to 450,000 MW. For example, the no storage case has a normalized installed capacity of 5.2, which indicates that the installed capacity is 520% of the mean demand. Note that for storage we show power-related capacity. In the case without storage, the system is characterized by the highest cost at 8.1 c$/kWh and a normalized installed capacity of 5.2, where wind has the largest share. At today's battery storage cost, the system does not benefit much from the additional availability in energy storage. In fact, the system cost decreases to 7.5 c$/kWh, which is 7.5% less expensive than a system with wind and solar only. As the energy storage cost decreases, the storage capacity in the least-cost solutions increases. System costs decrease to 6.4 c$/kWh when battery storage costs are reduced by 90% from current estimates. This system cost represents a 21% decrease with respect to a no storage case. The high level of flexibility provided by battery storage leads to a better management of the energy generated by variable renewable resources, which are not always available when needed to meet electricity demand. The high system flexibility results in less electricity being unused and curtailed (quantified as the excess power generated with respect to the demand that is not used to charge batteries).

In Fig. 3, we show the optimal locations of wind and solar installations to meet the aggregate electricity demand for various assumptions in battery storage cost. The color maps indicate the mean capacity factor of wind or solar for each cell in which we have subdivided the contiguous U.S. We notice that when cheap battery storage is available, preferred locations for both wind and solar are in regions with the highest mean capacity factors. Even though power generation fluctuations in these locations may not coincide with fluctuations in demand, cheap and widely available batteries can store the energy for times when it is most needed. As battery storage becomes more expensive and less diffuse, the energy system has less flexibility for temporal shifting of the variable renewable energy generation. This results in chosen locations that are characterized by lower mean capacity factors but that likely generate energy when it is needed. The optimal locations are more spread over the continental U.S. to leverage the spatial and temporal complementarity of the wind and solar generation. When no storage is available, the system becomes more reliant on wind generation because solar cannot meet nighttime demands.

4. CONCLUSION

In this preliminary study, we have analyzed the drivers of optimal siting of wind and solar installations to meet electricity demand. The use of an idealized macro-energy system model has allowed us to conduct a high-level analysis of electricity systems

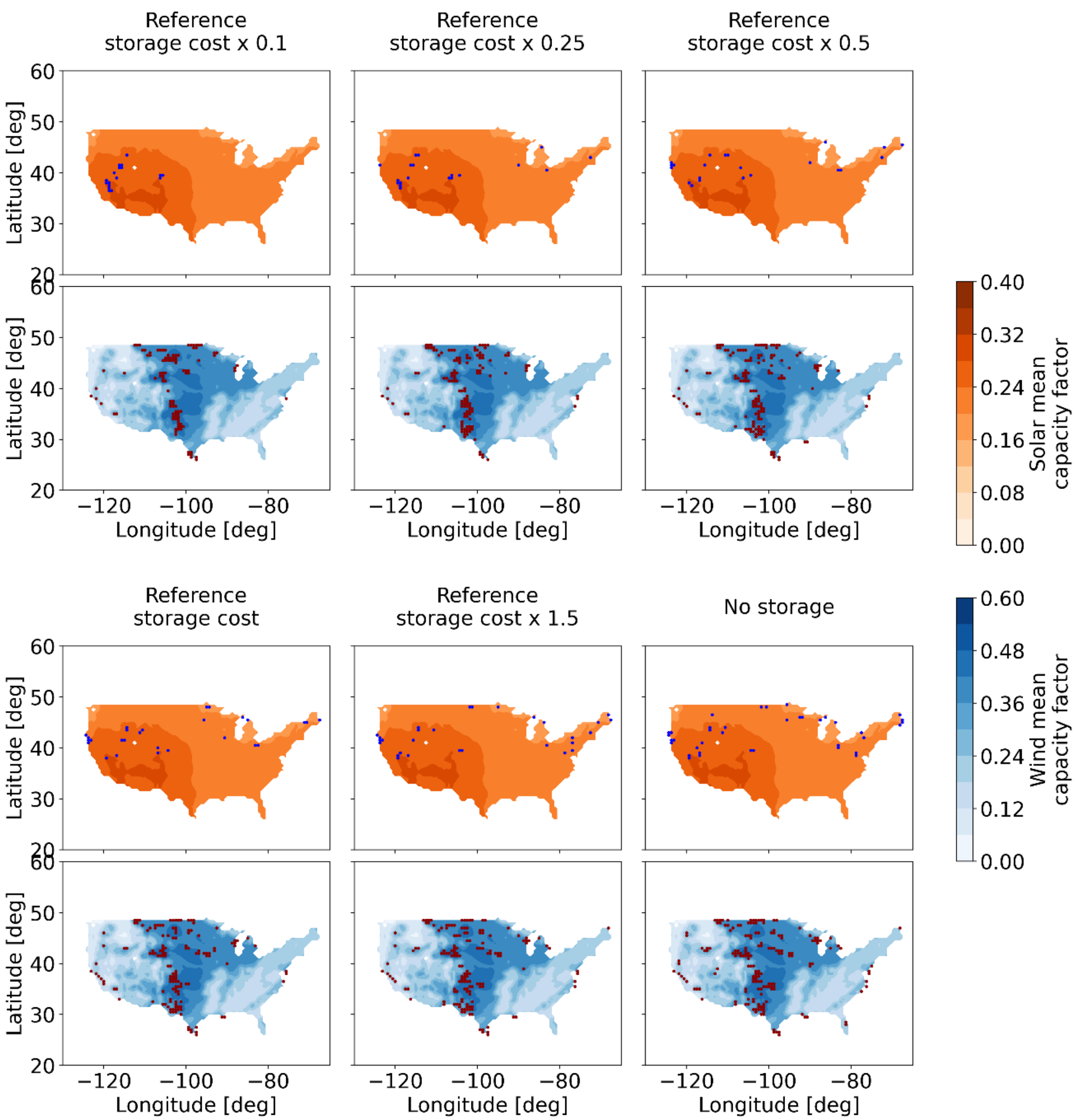

FIGURE 3: OPTIMAL LOCATIONS OF WIND AND SOLAR INSTALLATIONS TO MEET ELECTRICITY DEMAND FOR DIFFERENT ASSUMPTIONS IN BATTERY STORAGE COST.

and assess system-level impacts of various degrees of system flexibility represented by a varying battery storage cost. If energy storage were free and widely available, chosen locations for wind and solar installations would inevitably be in regions with the highest levels of resource availability. However, as the energy storage cost increases, and thus storage capacity decreases, chosen locations have lower capacity factors and the electricity system is more reliant on wind generation. This study also suggests that current optimal wind and solar siting may no longer be the least-cost solution as the storage cost decreases.

Further studies should consider sensitivity analyses of additional parameters to better understand all the drivers of optimal siting decisions. Such sensitivity analyses could be conducted for system assumptions and constraints but also for the demand and weather data. For example, climate change projections for wind and solar could be incorporated to study the influence of climate change on siting decisions.

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