Impacts of Spatial Resolution in a High-Fidelity Capacity Expansion Model: An ERCOT Case Study

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Impacts of Spatial Resolution in a High-Fidelity Capacity Expansion Model: An ERCOT Case Study

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***Abstract*—Capacity expansion models are important tools in examining the evolution of the electric power sector. Embedded in these tools are many modeling choices with consequential impacts on computational burden and associated analysis. In this study, we adjust the spatial resolution of the Regional Energy Deployment System (ReEDS) to understand the implications of higher-fidelity modeling on energy system projections and model solve times. The native ReEDS regions capture the contiguous United States in 134 balancing areas whereas the regions in the higher-resolution version are defined by over 3,000 U.S. counties. Using both resolutions, we conduct a case study of the Texas Interconnection (The Electric Reliability Council of Texas [ERCOT]) to explore differences in model projections and to inform appropriate applications of high spatial resolution in a large-scale, applied capacity expansion model.**

Keywords—Spatial resolution, capacity expansion, ReEDS, ERCOT, U.S. county

I. Introduction

Long-term strategic energy planning has been an established field for many decades. In recent years, the burgeoning needs to address climate targets and ensure reliability have led to global efforts to improve energy system optimization models, particularly in the electricity sector. The paradigm of relying on higher shares of renewable resources has challenged established methods based on large-scale centralized electricity generation, particularly with respect to spatial and temporal detail [1]. Several studies have reviewed the trade-offs associated with manipulating resolution levers across multidecade capacity expansion models [2], [3]. Models typically solve for the least-cost portfolio of generation, storage, and transmission; however, the regions represented in these models span a range of spatial resolutions and geographic areas—at times leading to conflicting trends that result from changes in spatial resolution [4], [5].. Despite the difficulty in identifying consistent trends associated with spatial resolution across models, some congruency exists: namely that spatial resolution has a meaningful impact on location of variable renewable deployment, transmission system congestion, and computational burden.

Enhancing the spatial resolution of long-term electricity system models creates several challenges. The electricity system is large and complex, necessitating limitations in its geographic scope to remain computationally tractable. Furthermore, input data with sufficient spatial detail are often unavailable. Notwithstanding, executing a capacity expansion model at multiple resolutions and comparing the results can provide valuable insight into the unintended consequences of model simplifications incurred from using a coarser spatial resolution. Uncovering these effects can help analysts and decision makers better interpret model results and better understand trade-offs when selecting the spatial resolution for a given study.

The focus of this case study is to evaluate the implications of spatial resolution on the National Renewable Energy Laboratory's Regional Energy Deployment System (ReEDS) long-term grid planning model. Prior research using ReEDS aggregated the 134 native regions to create a less spatially resolved model and examined the impact of using very large regions [6]. In contrast, this work showcases a spatially flexible and higher-resolution version of ReEDS in which the underlying model data exists at the U.S. county resolution. Although ReEDS is typically used to perform national scale studies, emerging interest in regional impacts has increased the need for greater spatial granularity. Unique user-defined focus areas, such as utility service areas, can now be constructed and examined. Furthermore, the model parameters for which spatial resolution has the greatest implications can be isolated by comparing the results of the native ReEDS spatial resolution to the results at county resolution.

II. Model Description

ReEDS is a linear least cost deterministic model that optimizes generation, storage, and transmission capacity investment for the contiguous United States given assumptions concerning electricity demand, technology costs, policies, and other key electricity sector characteristics. This section provides a brief introduction to the model along with details outlining the model differences that arise between the native ReEDS spatial resolution and the U.S. county resolution.

A. Model Formulation

ReEDS determines the minimum capital and operational costs for the U.S. electricity sector subject to system constraints. The total system costs captured in the objective function include the overnight capital costs of each generation, storage, and transmission technology scaled by a financial multiplier (which accounts for regional factors, construction financing costs, cost of capital, and tax incentives), the fixed operation and maintenance costs of each technology, any policy costs (e.g., alternative compliance payments), growth penalties, and the dispatch costs. This objective is subject to energy balance constraints within each modeled region, transmission constraints, planning reserve constraints, operating reserve constraints, technology-specific operational constraints, resource constraints, and emissions constraints [5]. For this case study, the temporal horizon extends until 2050, with model solve years occurring every 3 years starting in 2020. Two spatial resolutions are evaluated as part of this work, both encompassing the interconnection managed by The Electric Reliability Council of Texas (ERCOT). Fig. 1 presents maps of this region at the two resolutions considered, the native ReEDS model balancing area (BA), and U.S. county. The BA resolution contains 7 modeled regions; the county representation contains 192.

B. Model Inputs

The initial generation fleet in ReEDS is taken from the National Electricity Modeling System (NEMS) [7] and the Energy Information Administration's form 860M [8]. It consists of existing plants, expected builds, and announced retirements. The data set includes each plant's latitudes and longitudes, allowing each unit to be assigned to the appropriate BA or county. Technology costs and performance assumptions for these generation units are taken from the 2023 Annual Technology Baseline [9], with moderate cost assumptions used across the scenarios in this case study. Renewable energy generation is characterized by supply curves that estimate the amount of resource available and the associated cost of accessing it. For wind, concentrating solar power (CSP), and utility-scale solar PV (UPV), unique supply curves are created for the BA and county resolutions using the renewable energy potential model (reV) [10]. Each wind and solar supply curve site from reV is mapped to its corresponding BA or county and aggregated to produce a representative curve for each modeled region. Embedded in the supply curves are the land use costs, investments required to reinforce the bulk transmission network, and the interconnection costs to tie the renewable plant to the existing grid infrastructure. In the case of the county resolution supply curves, the network reinforcement costs are not included because the more granular transmission network at county resolution can capture transmission upgrade needs. All remaining supply curve technologies (hydropower, biomass, pumped storage hydro, geothermal) have supply curve data at the native BA resolution; data are disaggregated to county resolution using the methods discussed later in this section.

The underlying transmission networks for the BA and county resolutions are unique, although both are synthetic networks derived from the nodal transmission data set assembled as part of the North American Renewable Integration Study (NARIS) [11]. The transfer capacity between interfaces— BA-BA or county-county— is approximated by solving a linear power flow optimization that maximizes the total flow between interfaces subject to transmission line limits, the locational injection and withdrawal limits, and the relationships between power

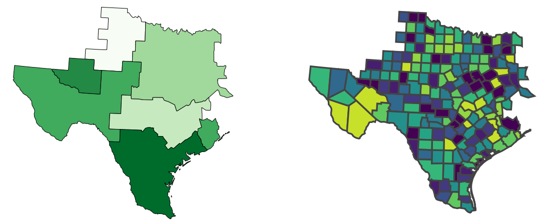

Fig 1. Maps Illustrating ERCOT at BA (left) and County (right) Resolutions

transfer and line flows [12]. This optimization is run independently for the BA and county resolutions, with the transmission nodes and capacity from the NARIS data mapped to the corresponding model region. The resulting networks are fundamentally different because of their different geographic resolutions.

C. Disaggregation Methods

All remaining inputs to ReEDS exist at their default resolution, typically the 134 BA resolution. To solve the model at the county resolution, these data sets must be downscaled using one of the following methods. Uniform disaggregation assigns the BA value to all counties within that BA. The regional technology financial multipliers are an example of data treated with this approach. Population-based disaggregation uses population-based weighting to spread the BA value across all counties within a BA. The hourly load data are one example data set downscaled in this way. Geographic size disaggregation is similar to the population method, but the fraction assigned to each county is determined based on geographic area of each county relative to the entire BA. Examples of data subject to geographic disaggregation include geothermal supply curves and inputs associated with water availability. Some hydropower data sets have their own unique disaggregation method. This procedure assigns multipliers to each county based on the amount of existing hydropower capacity in the county, as reported in the NEMS database, relative to the total hydropower capacity in the BA.

D. Scenario Description

This case study examines four scenarios: business as usual (BAU) and decarbonization (Decarb) at native ReEDS balancing area and county-level resolutions. The BAU conditions reflect current policies as of September 2023, moderate projections for all technology costs, default load growth, and reference case fuel costs. These assumptions are consistent with the 2023 Standard Scenarios [13]. The decarbonization scenario assumptions align with the BAU scenario, except that carbon emissions from the electricity sector are reduced to net-zero by 2035, with a required ramp-down from current emissions to zero between 2023 and 2035. The study area in all cases is the isolated ERCOT interconnection. In the remainder of this paper, the four scenarios considered will be referred to as follows. BA BAU and BA Decarb denote the cases solved at the native ReEDS BA resolution for the BAU and Decarb scenarios, respectively. Similarly, county BAU and county Decarb refer to the cases solved at the county resolution for the BAU and Decarb scenarios, respectively.

III. Scenario Analysis and Results

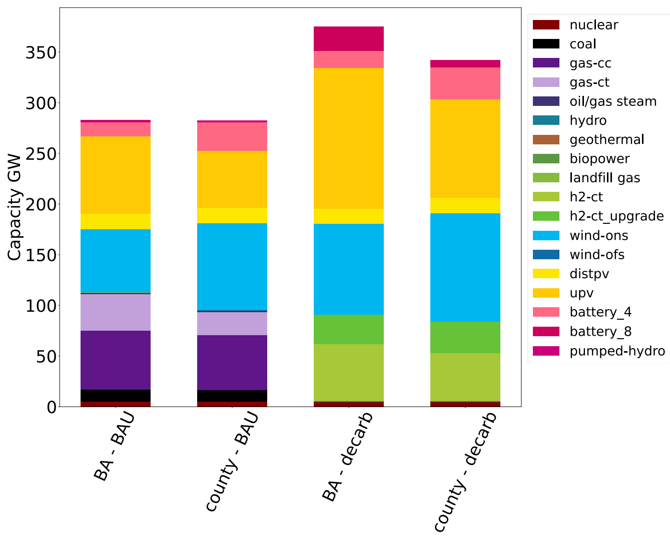

Fig. 2. 2050 Installed Capacity by Technology: All ERCOT Scenarios. gas-ct: gas-combustion turbine; gas-cc: gas-combined cycle; h2-ct: hydrogen-fueled combustion turbine

Fig 2 shows the total capacity in 2050 across all four scenarios. In the BAU scenarios, the installed land-based wind capacity is 37% greater in the county level relative to the BA resolution. This increase is accompanied by a 26% decrease in UPV and a combined 34% decrease in natural gas combined cycle (gas-CC) and natural gas combustion turbine (gas-CT) capacity. For the Decarb scenarios, land-based wind capacity increases by 20% at the county resolution relative to the BA case, meanwhile the UPV capacity is 30% less than what is observed in the BA results. Under the enforced decarbonization, the combined gas-CC and gas-CT capacity is replaced by hydrogen CT capacity. The relative 2050 installed capacity of these H2 technologies in the county-level solution is 19% less than the BA case.

Fig. 3 shows the locational buildout of wind and solar for the BAU scenarios at BA and county resolution, respectively, for 2050. Regarding wind, the county-level solution shifts much of the installed capacity from northern to southern ERCOT. Part of the impetus for this change is the underlying

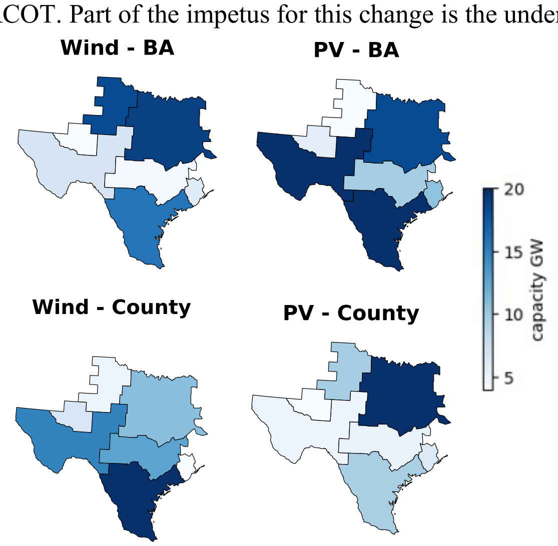

Fig. 3. ERCOT land-based wind and UPV buildout per BA in 2050 for the BAU BA (top) and County (bottom) scenarios

resource supply curves. Regardless of the spatial resolution, each model region—either county or BA—is assigned one unique supply curve per resource class. In the case of land-based wind, ReEDS groups individual sites into 1 of 10 resource classes based on capacity factor [5]. Therefore, at the BA resolution there are 70 unique profiles for wind across ERCOT, while at the county resolution there are 1,920. The additional detail in the county resolution allows the model to identify higher-value resources in areas for which the potential is diluted at lower resolution. Furthermore, the granularity of the transmission representation can alter the accessibility of high potential resources. In the county-level resolution, the network reinforcement costs are excluded from the resource supply curve costs because the transmission investment decisions between counties are explicitly represented in the model. The impact of the supply curves is exemplified in the southernmost model region. The installed wind capacity in this model balancing area in 2050 amounts to 31 gigawatts (GW) in the BAU county-level solution and 15 GW in the BAU BA solution. A closer look at the county-level results reveals that most of this capacity lies along the coast, a region that is less attractive in the BA resolution because of the network reinforcement costs required to transfer the capacity to the nearest network node located at the BA's load center in the north. In addition, this region has an average curtailment rate of 0.17 in the higher-resolution county scenario and a curtailment rate of 0.003 in the BA results. This indicates that at higher fidelity, the utilization of wind capacity is lower; however, the granularity of the underlying network still enables the high potential resources to be accessed as part of the least cost solution. Fig. 4 shows the curtailment rate across ERCOT for all four scenarios. In the BAU scenarios, lower spatial resolution leads to lower curtailment rates because of the enforced linkage between the amount of installed capacity and amount of required transmission reinforcement. In the Decarb scenarios, lower spatial resolution leads to higher curtailment in earlier years, in part because the required installed capacity, storage investments, and transmission investments are higher; however, the county and BA curtailment converge by 2050.

Regarding UPV, the county-level solution in both the BAU and Decarb scenarios has less installed capacity in 2050 relative to the BA solution. Fig. 3 shows that the displacement

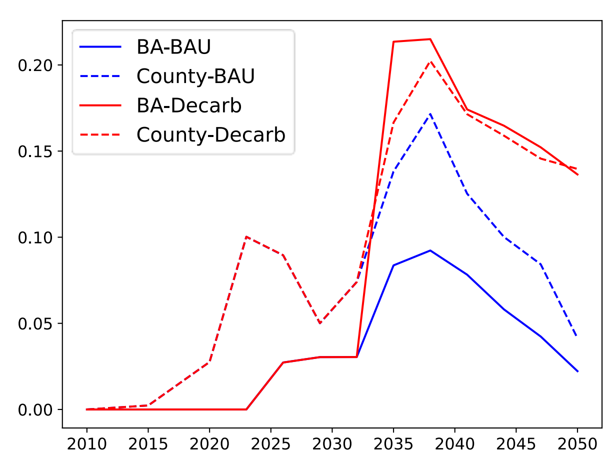

Fig. 4. ERCOT Curtailment Rates Across All Scenarios

of UPV is prominent in the regions associated with increased wind. From a systemwide perspective, the shift to more land-based wind is offset by a reduction in the amount of UPV. Nevertheless, the details in the underlying supply curves can still be associated with the resulting buildout in the county-level and BA-level solutions. For instance, in the southwestern region the BA-level UPV supply curve cost is an order of magnitude less than the land-based wind supply curve cost in that region. As a result, the BA-level solution includes 21 GW of UPV capacity in this southern BA compared to the 4.2 GW installed at the county resolution. Similarly, in the northeastern region, the UPV supply curves at the BA resolution are comparable to the land-based wind supply curves; however, at the county resolution UPV is significantly more attractive, leading to a 130% increase of installed UPV capacity in 2050 in the county-level solution for the region. In broader terms, a shift in UPV capacity near load centers occurs at the county resolution in part because the intermittency of wind is less suitable to meet concentrated localized demand.

To isolate the impact of the higher-resolution renewable supply curves, the transmission cost and congestion in the underlying BA and county-level data must be eliminated. This is achieved by removing the network reinforcement costs from the BA-level resource supply curves and increasing the initial AC transmission capacity of both networks, effectively rendering them as copper plates. With this topology, the BAU and Decarb scenarios are solved again at the BA and county resolutions. In general, the results show that the regions which were most advantageous at each resolution for wind and UPV remain palatable; in fact, the preference for the resources in these areas is exacerbated. In the initial BA BAU scenario, 59% of the installed wind capacity in 2050 is in the northern BAs. In the copper plate BA BAU scenario, 79% of installed wind capacity in 2050 is in these northern regions. In the county resolution BAU scenarios, the installed wind capacity for the original network in the southern BAs amounts to 54% of the total installed wind; in the copper plate scenario, the proportion increases to 75%. Holistically, the total installed UPV and wind capacity in 2050 for the copper plate BAU scenarios converge to similar values at both spatial resolutions. However, the misalignment of where the model prefers to build each technology—despite disregarding transmission constraints—highlights the spatial resolution of the underlying supply curves as the primary driver in the locational shift. This observation is less obvious but still pervasive in the Decarb scenarios. As the carbon cap is enforced, the model must reach beyond the areas where the highest potential resources exist, diluting the dominance of the most attractive regions in the BAU scenarios. Nevertheless, the role of transmission cannot be excluded and is integral to the accessibility and allocation of resources.

Capacity credit is another important factor in the evaluation of technology buildout. This value represents the fraction of a resource's installed capacity that can reliably contribute to resource adequacy requirements. In ReEDS, resource adequacy is ensured in every model year by enforcing planning reserve margins with levels taken from the reserve margin recommended by the North American Electric Reliability Corporation [4]. Fig. 5 shows the firm capacity contributions required to ensure sufficient resources during system stress periods.[1] In both the BAU and Decarb county-level scenarios, the installed wind capacity in the south contributes to a larger share of the total firm capacity, which is congruent with [15], in which the authors concluded that these southern regions have the highest capacity credit values in ERCOT. The remaining firm capacity is covered by dispatchable sources, with gas and coal in the BAU scenario being replaced by hydrogen-fueled turbines under decarbonization constraints. Interestingly, the BA Decarb scenario exhibits a larger share of 8-hour storage. In [14], the authors demonstrate that increasing deployment of solar in ERCOT can result in a winter peaking system with a wider net load peak, favoring longer-duration storage. Fig. 2 shows that the BA Decarb scenario installs the largest share of solar capacity across all scenarios and the corresponding solar generation is 41% of total generation in 2050. This suggests that the higher deployment of 8-hour storage in the BA Decarb scenario is in part a result of longer-duration storage receiving a higher capacity credit than its 4-hour counterpart, which is no longer sufficient to meet peak load.

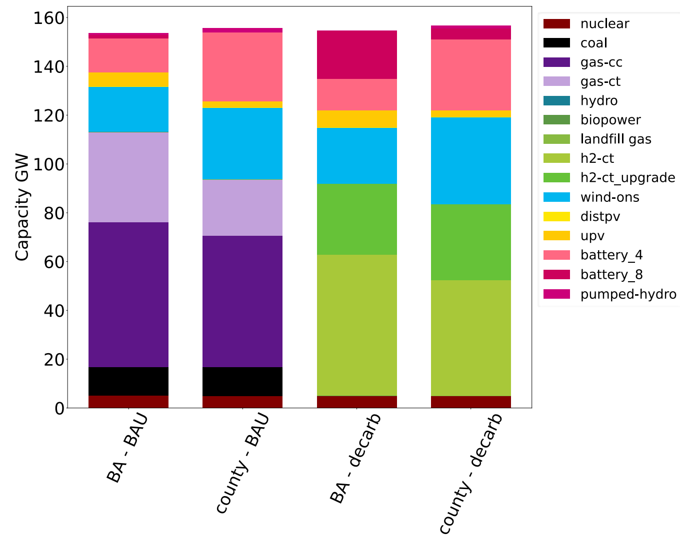

Fig. 5. 2050 Firm Capacity by Technology: All ERCOT Scenarios

Lastly, Table 1 summarizes the net present value of total system costs and the runtime of each scenario. The county resolution cases have lower costs than their lower-resolution counterparts for both the BAU and Decarb scenarios. This can be attributed to high-potential and lower-cost resources being more accessible. The runtime largely depends on the machine specifications and model functionality enabled; however, preliminary testing has shown that increasing the number of regions by an order of magnitude leads to at least an order of magnitude increase in runtime.

[1] Stress periods refer to highest-risk hours ideally identified as the hours with the highest loss of load probability (LOLP). In practice, an 8760-based approach is used to determine the highest seasonal demand hours of the load duration curve, which serve as a proxy for hours with highest LOLP [5].

TABLE I. NET PRESENT VALUE OF TOTAL SYSTEM COST AND RUNTIME

	Scenarios			
	BA BAU	***County BAU***	***BA Decarb***	***County Decarb***
NPV Total System Cost (billions of $)	232.9	229.3	305.8	288.4
Runtime (hours)	0.2	2.94	0.19	2.05

IV. CONCLUSION

Spatial resolution is a consequential lever in long-term energy system modeling. Higher-resolution models provide an opportunity to investigate custom, user-defined focus areas and can enhance the granularity of model results, especially regarding the transmission system, resource quality, and temporal profile. However, the input data needed to create high-fidelity models are often unavailable at the desired resolution and must therefore be created using disaggregation techniques. The methods chosen could bias the results; that is, higher resolution should not automatically be conflated with higher accuracy. In this ERCOT case study, the native ReEDS resolution is compared to a higher-resolution county version to begin to identify key implications of spatial fidelity on model outcomes. These findings are unique to the ReEDS ERCOT representation, though work is underway to more broadly define trends associated with different spatial resolutions for the contiguous United States.

The results of the ERCOT study revealed that the relative competitiveness of wind and UPV is largely dependent on the underlying resource supply curves and transmission networks. The confluence of results for installed capacity, annual generation, and resource adequacy requirements shifts the model towards land-based wind capacity at higher spatial resolution. Enhanced granularity of the resource supply curves enables the model to better identify areas with more valuable resources, both in terms of cost as well as capacity credit contribution. The higher-detail representation of available resources, coupled with the higher capacity factor of wind compared to UPV, ultimately results in less overall installed capacity across ERCOT and a geographic shift in the allocation of resources. The ERCOT results indicate that higher spatial resolution leads to more opportunistic allocation of resources and an augmented valuation of resource adequacy contribution. The county solution offers more granular reporting at a substantial computational expense, therefore the value added must be evaluated on a case-by-case basis. Generally, for resources with heterogenous capacity factors across the scope of the analysis, the spatial resolution has a more meaningful impact on the results. Additionally, studies with a particular emphasis on transmission infrastructure may benefit from higher-fidelity representation as bottlenecks and curtailment are better captured.

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