Impact of model resolution on scenario outcomes for electricity sector system expansion

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Abstract

Power sector capacity expansion models (CEMs) explore least-cost infrastructure trends under alternate techno-economic and policy scenarios. To maintain computational tractability when considering investment decisions over multiple decades, CEMs typically rely on a compact representation of annual hourly grid operations. Even as CEMs are being used to explore the role of variable renewable energy (RE) sources in the transition to a low-carbon grid, the required temporal resolution and operational detail in a CEM to adequately capture the fundamental economics of RE sources remains an open question. Here, we investigate the impact of embedding additional operational and temporal detail in a CEM framework on the resulting projections for generation capacity additions and their utilization. Our approach is based on systematically comparing the outputs from a “chronological” CEM (C-CEM), which models annual grid operations using up to 12 representative days (288 hours), with outputs from a commonly used “time slice” CEM (TS-CEM), using seasonally-averaged time blocks. The CEMs mainly differ in their representation of operational flexibility of thermal generators as well as the temporal resolution of load and RE generation. Studying the Texas grid over a range of hypothetical RE penetration scenarios, we find that, more often than not, the TS-CEM estimates higher solar capacity and lesser wind and natural gas capacity relative to the C-CEM, with 35% higher solar capacity projected by the TS-CEM in one scenario. We also test capacity projections of both CEMs through an hourly grid operations model to explore operational metrics, such as the ability to meet demand subject to intra and inter-annual variations in load and RE generation. This experiment reveals that C-CEM projections consistently lead to lower unmet demand compared to the TS-CEM capacity projections. These findings imply the need for sufficient temporal resolution and chronology or validated parameterizations that yield similar behavior to be included in power sector CEMs and multi-sector energy-economic models using a time slice representation.

Keywords: power system modeling, multi-scale modeling, renewables integration, generation expansion planning, temporal resolution

1. Introduction

Power sector capacity expansion models (CEMs) are extensively used by grid operators and planners to evaluate the impact of techno-economic and policy drivers on the least-cost portfolio of generation, transmission and storage needed to reliably meet electricity demand over decadal time scales. CEMs are increasingly being used to assess the system impacts of integrating increasing shares of variable renewable energy (RE) sources like wind and solar as part of the transition to a low-carbon electric grid [1, 2, 3]. Such assessments have to contend with adequately representing various attributes of RE sources in CEMs, such as their non-dispatchable nature, in order to provide a holistic view on the cost impacts of RE integration while also remaining computationally tractable. Prior operational analyses have documented the key impacts of increased RE penetration, including increased cycling and startups of fossil-fuel generators along with their reduced utilization and declining wholesale electricity prices [4, 1, 5, 6]. The degree to which these operational impacts are considered in a CEM is likely to influence the capacity mix projections and their ability to satisfy one or more operational criteria, such as low-carbon intensity and reliability. Here, we perform a systematic comparison of two alternative CEM frameworks to quantify how the choice of temporal representation and operational detail in a CEM impacts the resulting capacity mix projections as well as operational metrics such as unmet demand, curtailment, and RE penetration.

Many power system CEMs (e.g. Regional energy deployment system (ReEDS) [7], Integrated Planning Model (IPM) [8], US REGEN - EPRI [9]) approximate annual grid operations by using representative “time slices” to capture the average trends in load, wind and solar power output throughout the day and across seasons. Several widely-used multi-sector energy-economic models (e.g. NEMS [10]) and integrated assessment models (e.g. GCAM [11]) also use this temporal representation to model power sector operation. Multiple analyses have indicated that such approximations may not be sufficient to represent the significant variability in RE generation observed at hourly or sub-hourly time-scales [12, 13, 14]. To account for the variability of RE sources, it may be necessary to distinguish thermal generators on attributes not previously considered in CEMs, such as their ramping capability, minimum on and off times and minimum operating levels [15, 16]. For example, in regions where the peak demand coincides with the peak solar power generation, electricity demand met by thermal generators is expected to decline during the middle of the day and increase towards the evening hours [17]. In such cases, the hourly ramping capability of thermal generators could pose operational constraints that are not captured in traditional CEMs with a time slice representation [18]. Instead, these “time slice” CEMs approximate the ramping limits of thermal generators by: 1) including so-called minimum turndown constraints, which set the minimum operating level for thermal generators as a function of their peak seasonal output [7]; 2) periodically decreasing the contribution of RE to planning reserves, with increasing RE penetration [10, 7]; and 3) imposing static limits on the fraction of load met by RE for each region/year [10]. As highlighted later, some of these and other approximations used to model grid operations under high RE scenarios could result in the CEM prescribing a sub-optimal capacity mix that is unable to meet the electricity load in certain times of the year.

Alternate models have been proposed in the literature to address some of these limitations; we briefly review some salient features here. In an extension of typical CEMs, the US-REGEN model considers an increased number (up to 103) of strategically selected time slices with hourly duration [9, 18]. The NEWS model [19] includes hourly grid operations, new generation and high voltage DC transmission capacity decisions in a single future year for the continental U.S., without considering unit commitment, ramping constraints or existing generator fleet operations/retirements. Other recently proposed CEMs model grid operations with hourly temporal resolution for a few representative weeks up to an entire year, while simultaneously considering startups and flexibility constraints of thermal generators as well as new capacity decisions [20, 21, 22, 23, 3]. To address increasing computational complexity, the formulation in [20] groups generators into clusters of different types (rather than modeling individual plants). Other efforts built on this clustering approach optimize for the capacity mix in some future year, while modeling features such as storage [21], alternative market mechanisms for reserve provisions [22], and system inertia requirements for frequency control [3]. These models, however, do not consider generation fleet turnover, i.e. the fact that certain generators reach their lifetime and must be retired or extended. The Resource Planning Model (RPM) [23] considers commitment states of existing thermal generators at each plant level, transmission flow limits, storage technologies and grid operations for 96 hours per season, while solving for a 30-year planning period at 5-year increments. These recently proposed CEM frameworks highlight the tradeoffs in different modeling assumptions that are typically required to make CEMs computationally tractable.

Despite these advances, to our knowledge, few studies have performed inter-model comparisons to critically examine the effect of temporal representation and grid operation constraints on the resulting capacity projections from these models. To that end, this paper offers four main contributions:

1. We develop a high-fidelity CEM with chronological time-representation of grid operations (referred to as C-CEM) that considers representative days, sampled from multiple years of historical load and RE generation data. This framework integrates a number of best practices from a range of CEMs recently proposed in the literature, which include using a clustering approach for choosing representative days [12] and modeling of generator types as bins with integral number of elements to improve run times [20].
2. We systematically compare the outputs of the C-CEM using 12 representative days against those of a traditional CEM, which uses a seasonal average or time-slice representation (referred as TS-CEM) to mimic the salient features in models like IPM [8], ReEDS [7], and the Electricity Market Module in NEMS [10]. This inter-model comparison across multiple hypothetical scenarios of RE penetration is an improvement to other recent multi-model comparisons, such as Cole et al. [24] who compare traditional models using time slice temporal resolution or the analysis by Bistline et al. [13] considering the effect of temporal resolution via inter-model comparison across only three scenarios.
3. We go beyond previous CEM studies in the literature to test the robustness of the grid operations approximations made by both CEMs by evaluating their projected capacity mix through a production cost simulation (PCS) model, which simulates annual grid operations at an hourly resolution. The proposed methodology illustrates the importance of evaluating operational outcomes associated with a CEM projected capacity mix when considering the prevailing variability in load and profiles, both within a year and across multiple years. For example, the capacity mix projected by the TS-CEM for a hypothetical 50% RE penetration scenario for the Texas grid in 2045 is estimated to result in 0.2%-0.5% of annual demand remaining unmet, when considering seven realizations of annual load and RE generation profiles. Most CEM studies tend to overlook the evaluation of operational impacts of the capacity mix projections. Among CEM studies focused on RE integration [1, 6], it is common to assess the operational performance of a capacity mix based on a single year of load and RE generation at hourly or sub-hourly resolution.
4. Within the developed C-CEM, we investigate the impact of the number of representative days selected to represent a year of grid operations on resulting capacity and generation projections. This contribution differs from that of Nahmmacher et al. [12], where representative days were

selected as a preprocessing step for a tradition time-slice model. Here, representative days are retained and used as-is in our C-CEM.

Our analysis is based on a power system that approximately represents the U.S. Electric Reliability Council of Texas (ERCOT) grid in 2015. Since we focus on highlighting and understanding the reasons for the relative differences in the outputs of alternate CEM frameworks, the results presented here should not be interpreted as a detailed analysis of the ERCOT system along the lines of other efforts in the literature (e.g. [25]). Indeed, transmission constraints both within and to and from ERCOT to other regions are not included (see Methods). Grid stability at every instant of time is not verified. Energy storage is not considered. Revenue sufficiency constraints are not imposed for any generators. Therefore, all scenarios evaluated here are meant to exclusively highlight differences in CEM outputs and should not be interpreted as ERCOT grid projections.

The rest of the paper is organized as follows. Section 2 provides a brief description of the two CEMs and the PCS model, with comprehensive algebraic mathematical modeling details in the supporting information (SI). This is followed by a discussion of the main data inputs and assumptions in section 3, including the methodology for generating representative time slices and days for the TS-CEM and C-CEM respectively. Section 4 presents the results of the inter-model comparison, along with the discussion of the impact of increasing the number of representative days in the C-CEM. Section 5 summarizes the key conclusions and policy implications.

2. Methods

Figure 1 summarizes the methodology used to investigate the impact of temporal resolution and operational detail in a CEM. Several works (e.g. [1] and [6]) have focused on evaluating scenario outcomes of high renewables penetration using a single CEM (thus, these would follow the left or the right side of Figure 1 in which a single CEM is evaluated). More recently, a few analyses [24, 13] have attempted to compare the capacity projections across CEMs for a few scenarios, but have stopped short of comparing operational metrics associated with the projected capacity in a detailed simulation of annual grid operations. The analysis presented here relies on a common input data set comprising generator performance attributes and costs, load and renewables generation across multiple historical years and other parameters (see Section 3 and SI). Based on this data set, we define the input parameters for each CEM, in particular load and RE generation for the specific temporal resolution in each model. Subsequently, we evaluate the TS-CEM and C-CEM for a range of hypothetical RE scenarios to estimate the generation capacity in future years. We go beyond prior CEM assessments by exploring the operational outcomes of the projected capacity mix of each CEM for multiple realizations of annual load and RE generation profiles, using the PCS model. For each RE penetration scenario, the PCS model simulates the annual hourly dispatch to meet demand and reports various metrics of interest, such as unmet demand, share of RE generation, curtailment and so on. Together, the differences in operational metrics and generation capacity outputs across the two CEMs form the basis for our conclusions on the impact of temporal resolution in a CEM framework.

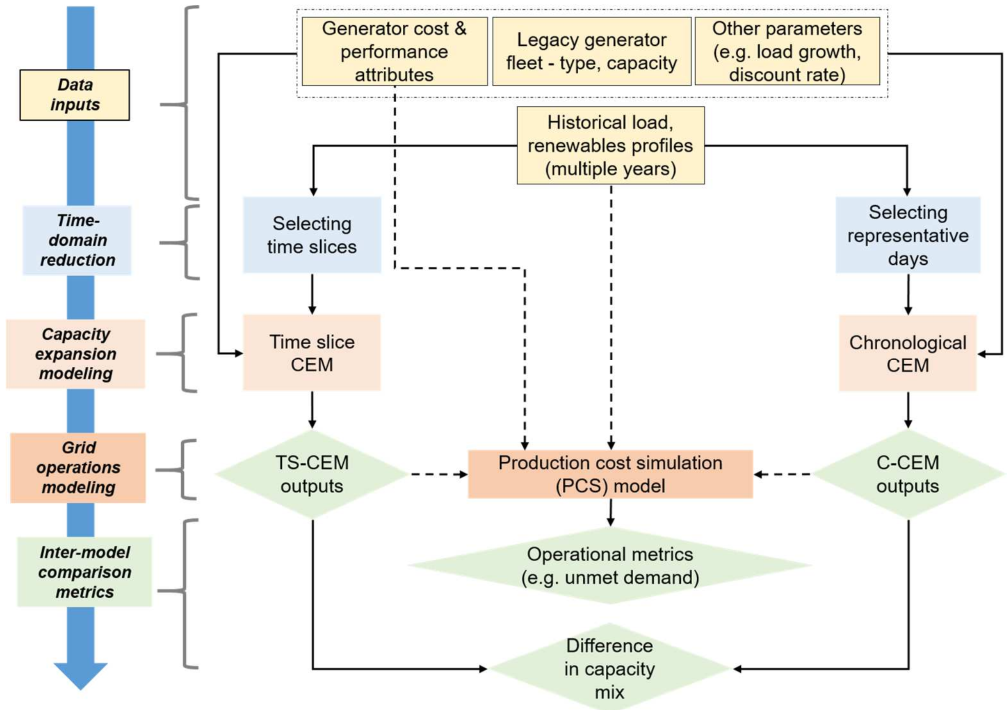

Figure 1. Methodology to systematically compare alternate temporal resolution in power system capacity expansion models across different scenarios. Diamonds refer to model outputs and dotted lines correspond to inputs to the production cost simulation (PCS) model. CEM = Capacity expansion model; TS = Time slice; C = Chronological.

2.1. Summary of Chronological and Time Slice Capacity Expansion Models

The two least-cost power generation CEMs developed in this study, C-CEM and TS-CEM, are deterministic inter-temporal optimization models that take the vantage point of a centralized planner seeking to determine cost-optimal expansion decisions over a planning horizon of several decades. Regarding their similarities, both models minimize total cost (discounted to present value), which includes installation (CAPEX) costs for new capacity being built, costs to extend the lifetime of installed capacity, operating costs (fixed and variable), fuel costs, generator start-up costs (C-CEM only), and unserved load. The objective function also includes cost savings attributed to the December 2016 implementation of the investment and production tax credits for wind and solar photovoltaic (PV) generation in the U.S. context (see data inputs in Table S 4) [26, 27]. The models represent solar and wind capacity expansion decisions as “continuous” decisions meaning that a fractional wind generator can be built. Importantly, both models represent the existing fleet of coal, NG and nuclear as well as wind and solar PV generators in ERCOT by clustering the entire fleet into seven different generator types. As done in [28], both models also allow for aging capacity to be retired or extended, whereby the extension option incurs a one-time cost of extension and returns to operation with the same operational parameters. For each generation technology, both models include annual capacity installation limits [28] that implicitly account for supply chain constraints associated with emerging technology deployment. The models use as input the same forecasted load growth, the same suite of generation technologies to meet this growth, and the same associated cost assumptions to model grid evolution in 3-year time increments from 2015 to 2045 (see S.2).

It is precisely the dissimilarities described below that will help elucidate why different expansion decisions are made by the C-CEM and TS-CEM in certain scenarios. Figure 2 illustrates the differences in temporal representation of grid operations between the C-CEM and TS-CEM. Temporally, the C-CEM represents annual load as well as wind and solar generation using 12 representative days at an hourly time resolution, whereas the TS-CEM represents annual load as well as wind and solar generation, with 16 time slices representing different times of day and seasons. In other words, the TS-CEM averages load and RE capacity factor data (see Figure 3) in each of the four seasons (spring, summer, fall, winter) into time slices representing morning (7 am -2 pm), afternoon (2-6 pm), evening (6-11 pm), and night (11 pm -7 am). With the exception of minimum turndown constraints for coal and nuclear generators, discussed in section 2.3, the TS-CEM does not link two consecutive time slices with respect to operational constraints.

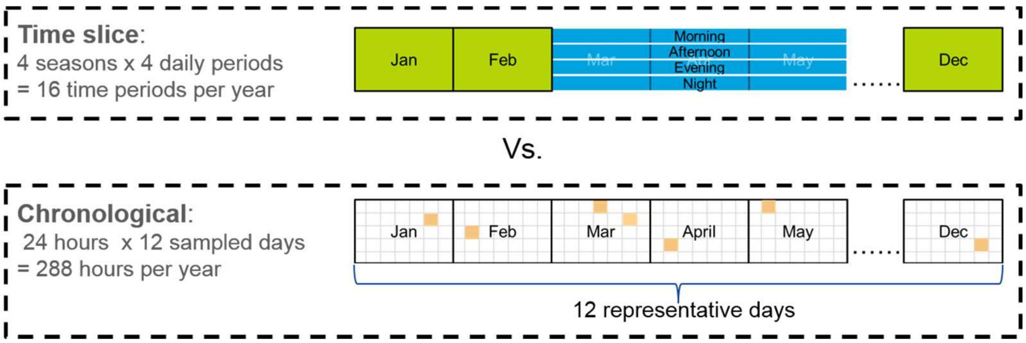

Figure 2. Differences in temporal resolution of the alternate capacity expansion models studied here: TS-CEM (top) and C-CEM (bottom).

In contrast, the C-CEM, as its name suggests, "sees" chronology, and therefore events that occur in a given hour are related to events that occur in the preceding and subsequent hours. The C-CEM is a deterministic mixed-integer linear program (MILP), while the TS-CEM is a deterministic linear program; both have perfect foresight. The complete mathematical formulation of the C-CEM and TS-CEM and data inputs are available in the supplementary information (SI).

Operationally, the C-CEM considers important details associated with thermal generators including: unit commitment decisions (i.e. on/off commitments of generators to meet load), hourly ramping constraints, spinning reserves, quick-start reserves, and start-up costs. In contrast, the TS-CEM omits these details, although spinning reserves are partially taken into account. Lastly, because the C-CEM includes unit commitment decisions, thermal generation expansion decisions are modeled as integer decisions, unlike the TS-CEM which allows for a fractional number of thermal generators to be built. Together, the different temporal resolution and operating constraints of the two models lead to different generator dispatch profiles to meet load in each time period, which ultimately impacts the capacity investment decisions.

2.2. Production cost simulation (PCS) model

As is typically done in long-term expansion studies (see, e.g. [14]), we use a PCS model, essentially a grid operations model, to independently assess annual operations (e.g. generation mix, unmet reserves, unmet load, and curtailment) given the installation decisions prescribed by the two CEMs. The PCS model simulates one year of grid operations at an hourly resolution. It takes as input a given installation of generators for a particular year (as determined by solving the CEMs) and solves a simultaneous unit commitment and economic dispatch problem over all 8760 hours in that year. Since the CEMs must approximate load and other features in order to be computationally tractable, the PCS model allows for extreme situations such as peak load, minimum RE output, which may not be considered by the CEMs, to be evaluated. Further, for each projected generation capacity mix, we evaluate annual grid operations via the PCS model for seven different realizations of load, wind and solar PV capacity factor profiles, based on historical load and RE generation data available from ERCOT. This approach allows for quantifying the robustness of capacity mix projected by the two CEMs to prevailing intra and inter-annual variability in load, wind and solar generation (see section 4.2 and 4.3).

The PCS model is a deterministic MILP with perfect foresight. It is quite similar to the C-CEM, except that it does not include any installation related decisions and it models a single year of operations with hourly granularity, as opposed to several representative days. As with the C-CEM, generators are clustered by generator type. Generators in a cluster have the same attributes. This allows on/off decisions for thermal generators to be modeled using integer decision variables as opposed to binary decision variables, which would be needed if each individual thermal generator were modeled. The PCS is solved using a rolling horizon heuristic with a one-day overlap in which unit commitment and economic dispatch decisions are made (optimally decided by the mixed-integer programming solver) for 21 consecutive days (504 hours), after which the first 20 days are implemented. The model then "rolls forward" to considering the next 21 days. Thus, days 1-21 are optimized, followed by days 21-41, and so forth. The one-day overlap allows the model to "correct" decisions made in the last 24 hours that may have been too myopic due to the lack of additional foresight. Each sub-problem (21-day horizon) is solved with a 30-second time limit and a relative optimality gap tolerance of 0.01%.

A key difference between the two CEMs and the PCS is the presence of unmet load and unmet reserves. Because the CEMs "see" only a coarse representation of load and renewables profiles, they prescribe installation decisions that avoid instances of unmet load based on the limited operational data present in the model. However, the PCS may encounter more extreme variability in net load and thus may need to shed some reserves, or worse, load. The PCS penalizes unmet load at $9000/MWh and approximates the penalty associated with unmet reserves using a step function, based on an approximation of the current operating reserve demand curve being used by ERCOT in clearing the market [29]. In particular, for the case when the total operating reserves of 7.5% of load are desired for every hour, the first 1.5% of unmet operating reserves has a cost of $100/MWh, the next 2% has a cost of $300/MWh, the next 2% has a cost of $3000/MWh, and the last 2% has a cost of $9000/MWh. As a consequence, if an extreme net load event occurs, the PCS first sheds reserves according to this step function before ultimately shedding load.

The PCS model does not consider a real-time market. In contrast, commercially-available grid operations models like PLEXOS or GE MAPS that are designed to closely mimic power system operations, solve for the cost-optimal dispatch for one day ahead and subsequently re-adjust the dispatch (without turning on or off generators) based on new information (e.g. improved weather, load forecast) available in real-time conditions (e.g. 4 hours prior to dispatch) [30]. Another limitation of the PCS model is that it does not represent the minimum on and off times of thermal generators, which could overestimate their ability to respond to changing load and renewables generation and consequently underestimate the extent of curtailment reported for each scenario. Despite these limitations, the PCS model provides a consistent basis for comparing the operational differences in the capacity mix projected by the two CEMs.

2.3. Key model constraints of CEMs and PCS

A summary of the key constraints in the CEMs and the PCS model that highlight their similarities and differences are presented in Table 1. The complete mathematical formulation of the two CEMs are presented the appendix. A "time period" refers to an hour of a representative day in the C-CEM, to a time slice, i.e. a season-time block pair (e.g. summer-afternoon) in the TS-CEM, and an hour of the 8760 hours simulated in the PCS model.

Table 1. Key constraints present in the capacity expansion and production cost simulation models.

Constraint type	Time Slice (TS-CEM)	Chronological (C-CEM)	Production Cost Simulation (PCS)
Load balance	X	X	X
Generator capacity balance	X	X	
Retirement or life extension decisions	X	X	
Annual installation limits	X	X	
Renewable Portfolio Standards	X	X	
Capacity planning reserve requirements	X	X	
System spinning and total operating reserve requirements	X	X	
Power output from generators upper and lower bounds		X	X
On/off commitment decisions		X	X
Generator ramping limits		X	X
Quick start and spinning reserves provided by thermal generation		X	X
Minimum turndown constraints to limit differences in seasonal max & min outputs	X		

The types of constraints governing investment and capacity decisions are:

- **Capacity balance constraints.** The capacity (MW) of each energy type in year *y* must equal the capacity in the previous year (*y*-1) plus the capacity that came on-line in year *y* minus the capacity that was retired in year *y*.
- **Annual installation limits.** There is an upper bound on the amount of capacity that can be built in each year for each technology type (see Table S 3).
- **Retirement/extension constraints.** Generators must not exceed their lifetime. They must be extended (with a cost penalty, see section S.2. and Table S 1) or retired before or once they have reached their lifetime. Retired capacity immediately exits the fleet, i.e. is not available for generation. Extended capacity is kept for the remainder of the planning horizon and preserves all of the defining characteristics (e.g. heat rate), except its age is reset to zero.
- **Minimum capacity reserve constraints.** Minimum capacity reserve requirements are included to ensure that there is sufficient capacity to meet forecasted peak load in every year plus some margin of error (see Table 3). Capacity values are used to determine the contribution of each generator type

to meet this constraint. Thermal generators are assumed to have a capacity value of one, while RE generator types have a capacity less than one (see section S.2, Table S 1 and Table S 2).

- **Renewable Energy (RE) constraints.** In the years when this constraint is implemented, total generation from renewables used to serve load must be at least a pre-defined percentage of the total system load in that year and beyond. This constraint is implemented to consider RE scenarios (40% to 70%) where applicable.

The types of constraints that govern optimal unit commitment and economic dispatch include:

- **Load constraints.** In each time period, the total power (dispatched from thermal generators and generated from RE) plus unserved load must equal total system load plus curtailment.
- **Ramping constraints.** These constraints, typically apply to thermal generators, and limit the increase/decrease in generation from one period to the next, i.e. rate of change in generation. They are particularly important when modeling generator operations at an hourly time scale when substantial load or RE output fluctuations in successive periods are present. These are explicitly considered in the C-CEM and PCS model.
- **Individual generator constraints.** When operating, each generator produces power between a minimum and maximum generation level. Because generator types are modeled, as opposed to individual generators, it is assumed that all units of a given type provide the same level of power and reserves capacity.
- **Quickstart reserves.** Thermal generators that are off during a given hour may contribute a fraction of their capacity to quickstart reserves. Total quickstart and spinning reserves must provide the necessary operating reserves (typically a % of load, say 7.5%) in every hour.
- **Minimum turndown constraints.** Due to its lack of high temporal resolution and chronology, the TS-CEM could choose to cycle, i.e. turn on and off, thermal plants at a higher frequency than permitted in practice. Minimum turndown constraints prevent this undesirable behavior by enforcing the following requirement: in each season, a thermal generator's power output in a time slice must be at least a pre-defined fraction of the maximum power output in that season. These are the only constraints in the TS-CEM that link operations in different time slices.

2.4. Modeling limitations

We focus our study on improving two aspects – operation detail and temporal resolution – of CEMs to evaluate scenarios of increasing RE penetration. However, there are other areas of improvement that have deliberately not been addressed here. We did not consider transmission in either CEM to restrict the analysis to the impact of the temporal resolution differences (as opposed to spatial resolution differences) between the models. Moreover, transmission constraints were omitted to ensure the models, particularly the C-CEM, can be solved to optimality while looking ahead for the 30 year planning horizon with available solution algorithms. Transmission constraints have been ignored by other studies [5] evaluating grid expansion in the ERCOT context, with the justification that there is ample transmission in the region as a result of the recently completed transmission upgrades connecting the Panhandle area to the rest of ERCOT. Additionally, the two CEMs and the PCS model do not consider uncertainty (beyond typical reserve constraints), outages (planned or forced), storage, demand response, distributed generation, nor heat rate deterioration due to partial operation of thermal generators. Although these deficiencies may seem many, they apply to numerous leading models used in practice, e.g. IPM, NEMS, and ReEDs.

3. Case study and data inputs

3.1 Summary of data inputs

The power system we analyze as a case study approximately represents the ERCOT grid. We approximately model the existing ERCOT generator fleet by clustering individual generators into seven generator types as per the capacities as of May 2015 [31]: coal, nuclear, NGST, NGCC, Natural gas combustion turbine (NGCT), solar PV (single axis tracking) and wind. For simplicity, we do not include the relatively small amount of biomass and hydro capacity present within ERCOT. Electricity imports or exports to and from the region are ignored in this analysis, given their relatively small share of system demand for ERCOT [32]. Within each cluster, there are an integer number of generators whose operating parameters are assumed to be the same. Table 2 summarizes the total installed capacity for each cluster type and the number of plants within that cluster. Each of the seven generator clusters are associated with an age distribution, based on the age of the individual generators that belong to that cluster as of 2015. This information, coupled with the economic lifetime of each generator type, is used in the TS-CEM and C-CEM to make retirement or extension decisions on the portion of the capacity that is scheduled to retire in each year of the planning period.

Table 2. Summary of existing (2015) generator capacity used in the TS-CEM and C-CEM.

System parameters	Installed capacity (MW)	Number of plants
Total	96,996	
Nuclear	5,164	4
Coal	17,397	27
NGCC	39,527	55
NGCT	7,481[1]	48
NGST	6,219	10
Solar PV	663	17
Wind	20,545	153

[1]Includes private use network capacity (i.e. cogeneration plants) totaling 4433 MW [31]

For new capacity additions, both CEMs are allowed to choose from nine different generator clusters: coal with and without carbon capture and sequestration (CCS), NGCC with and without CCS, NGCT, nuclear, new solar PV (single axis tracking), new solar concentrated solar thermal power (CSP) generation and new wind. The projected capital, variable operating costs and fixed costs over time for each generator type are retrieved from the NREL 2016 technology baseline database [33]. Fuel costs of coal and NG over the planning period are taken from the EIA Annual Energy Outlook 2016 (see Figure S 3) [10]. A full description of the cost and technological assumptions for the existing and new generator clusters can be found in Table S 1 and Table S 2 of the SI, respectively.

A summary of key system parameters used in both CEMs is presented in Table 3. The spinning and operating reserve requirements, implemented for each representative time block (hour or season) modeled in both CEMs, are based on parameters reported in the ReEDs model [7]. The planning reserve margin of 13.75% corresponds to the value used by ERCOT as part of its annual resource adequacy assessments. The annual load growth rate is derived from the forecast developed by ERCOT [34]. The discount rate is set to be equal to the nominal value of weighted average cost of capital assumed in the NREL annual technology baseline [33]. In this study, we consider one unique discount rate for all technologies, as is commonly implemented for CEM studies. However, in practice, this need not be the case. It is also worth noting that the assumed capital costs of individual generator types, sourced from the NREL annual technology baseline (Figure S 1), considers the unique cost of construction period financing for each technology.

Table 3. Summary of key system parameters used in the TS-CEM and C-CEM.

System parameters	Value	Reference
Spinning reserve requirement (% of load)	3%	[7]
Total operating reserve requirement (% of load)	7.5%	[7]
Planning reserve margin (% of peak load)	13.75%	[29]
Annual load growth rate	1.4%	[34]
Discount rate	5.4%	[33]

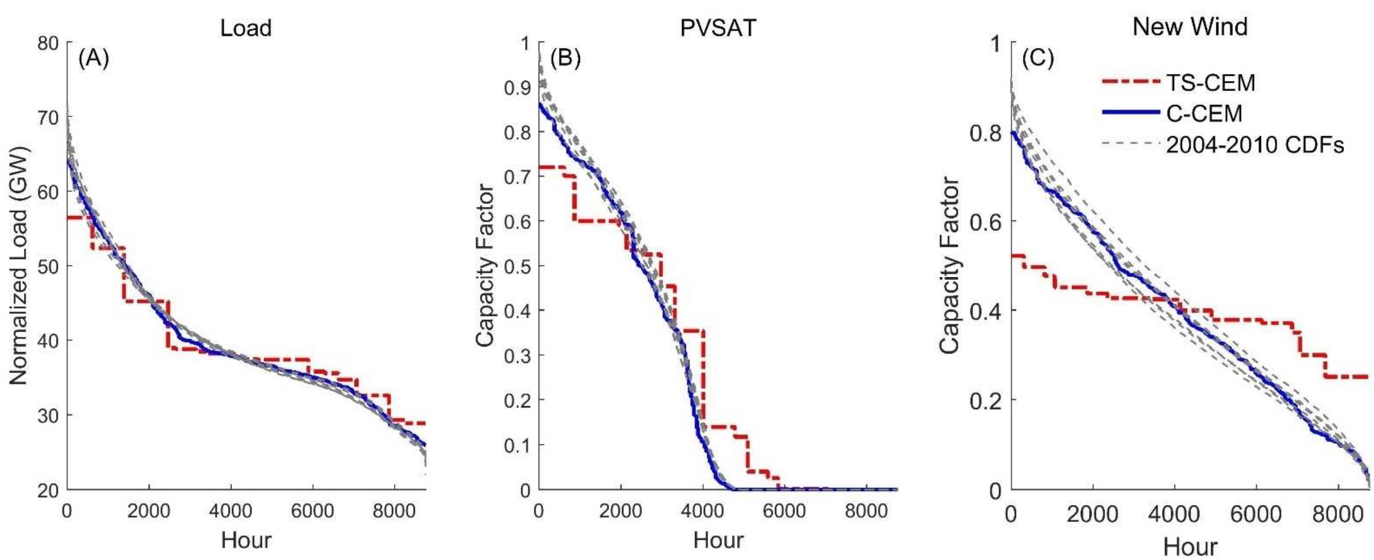

Figure 3. Load and renewable energy (RE) capacity factor duration curves comparison between historical data (2004-2010, shown in gray) and the corresponding duration curves assumed in the TS-CEM and C-CEM. A) Load duration curve comparison after the historical load data for all years is adjusted to have the same mean as observed in 2014. The mean absolute error (MAE) between the duration curves is smaller for the C-CEM (MAE = 694 MW) compared to the TS-CEM (MAE = 1941 MW). B) PV with single axis tracking (PVSAT) capacity factor duration curves result in an MAE of 0.015 and 0.056 for the C-CEM and TS-CEM, respectively. C) New Wind capacity factor duration curves result in an MAE of 0.022 and 0.125 for the C-CEM and TS-CEM, respectively, again indicating that the C-CEM better approximates the historical curves than the TS-CEM.

We develop the load and RE data for both CEMs based on the historical hourly profiles for ERCOT during the period 2004-2010 [35, 36] and the methodological approaches described in Section 3.1 and 3.2. Because the load profiles of both CEMs are sampled from historical data, the extremes in their load duration curves are less pronounced than what is present in the actual data as shown in Figure 3A, although the load representation in the C-CEM is a better approximation of the historical data than the TS-CEM. Similar trends are observed when comparing the sampled data sets and historical data for RE technology capacity factors (Figure 3B-C). In particular, Figure 3C illustrates how the time slice representation based on averaging time series over seasonal time blocks results in a poor characterization of the extreme observations in the historical wind capacity factor data (low and high). It is also worth noting that despite the differing temporal resolutions of both CEMs, the average annual capacity factors of all RE technologies modeled are very similar (Table S 5). For example, the annual average capacity factor for new wind generators modeled in TS-CEM and C-CEM are 39.2% and 38.9%, respectively. In both CEMs, we model RE generation based on a capacity factor time series that remains constant from one planning year to the next within the model time horizon, while we model the load as a time series with the same variability, but increasing annual average to reflect the assumed annual load growth of 1.4% per year (Table 3).

3.2. Selecting time slices for the TS-CEM

Since we are interested in comparing the outputs of two CEMs with differing temporal resolution of grid operations, the method of selecting the sampled load and RE capacity factor data is essential to the analysis. For the TS-CEM, we construct time slices by first clustering consecutive days into "seasons" (loosely corresponding to spring, summer, fall, and winter). Within each resulting season, four time slices were created using the hourly clusters as proposed in ReEDS [7]: morning (7 am - 2 pm), afternoon (2 - 6 pm), evening (6 - 11 pm), night (11 pm - 7 am). Note that ReEDS considers a 17th time slice to capture the 40 peak load days in a year.

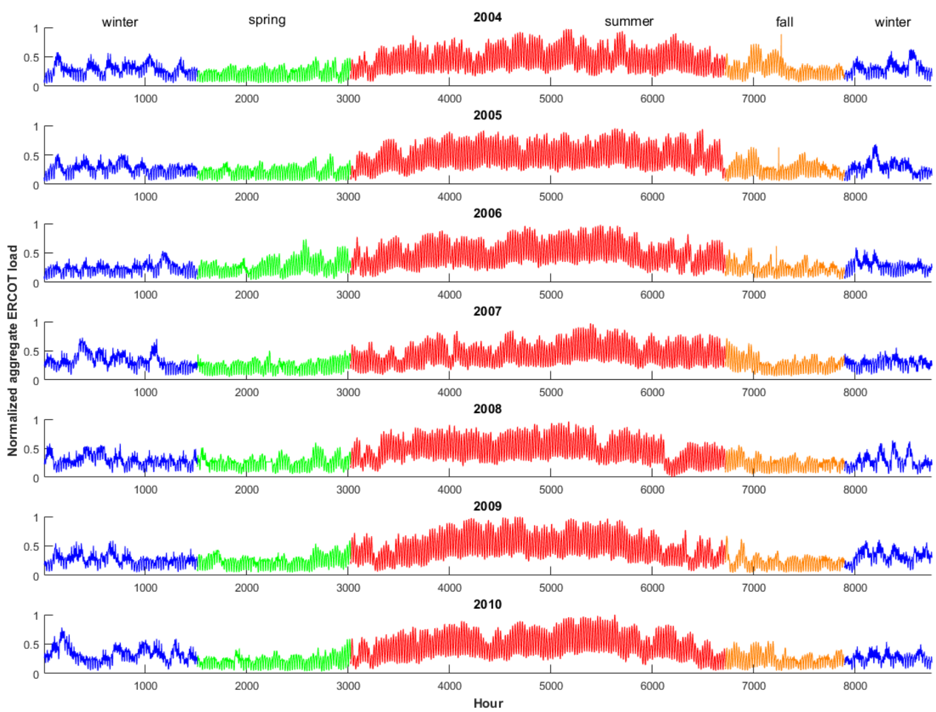

Figure 4: Seasons used in the TS-CEM, defined using a variance minimizing clustering method applied to seven years of historical load data (normalized between 0 and 1). The "start week" of each season is: spring = week 9, summer = week 18, fall = week 40, winter = week 47.

We determined seasons for the TS-CEM using aggregate ERCOT load data from 2004-2010 while excluding leap days. As shown in Figure 4, aggregate load for each year was normalized between 0 and 1. A variance-minimizing clustering method was used to determine the four seasons and works as follows: The year was partitioned into 4 clusters by specifying 4 values marking the "start week" of each season. The same "start week" was used for each of the seven historical years of data. Given clusters, the variance within each cluster was computed using each day (a 24-hour vector) as a sample point/observation. To determine the optimal clusters, i.e. the best "start weeks," we iterated over all possible "start weeks" for each season, such that no two seasons overlapped, and identified the cluster with the smallest variance. For example, the start week for summer was chosen from weeks 20-48. This approach is arguably more systematic than the procedure used in ReEDS where seasons are determined simply by grouping consecutive months [7]. Once time slices were determined, RE capacity factors in each time slice were computed as the average capacity factor over all hours in each time slice.

3.3. Selecting representative days for the Chronological CEM

For the C-CEM, we utilize a k-means clustering procedure to determine representative days for modeling annual grid operations. The goal of the clustering procedure is to select representative days that closely approximate (i) the cumulative distribution functions (also known simply as "duration curves") of historical load and RE time series, (ii) the temporal correlation of each time series, and (iii) the hourly correlation between load and RE time series. The first aim ensures that annual load and RE capacity factors are adequately represented. The second attempts to ensure that inter-hour variability is characteristic of the actual system, and thus adequately captures the need for increased ramping in certain hours of the day. The third attempts to ensure that load and RE profiles sufficiently characterize the correlation between these time series throughout the year.

The data set used for clustering was the hourly ERCOT data [35, 36] for the seven year period from 2004 to 2010, with leap days excluded. Let $\mathcal{D} = \{1, \dots, D = 2555\}$ denote the set of days for the seven year period from 2004 to 2010, let $\mathcal{H} = \{1, \dots, 24\}$ denote the set of hours in a day, and let $\mathcal{K} = \{'\text{load}', '\text{csp}', '\text{pvsat}', '\text{old wind}', '\text{new wind}'\}$ denote the set of load/technology types considered for clustering. Note that we assume the capacity factor profile for new and existing PV plants to be identical, partly because of data availability and the small amount of installed PV capacity in ERCOT as of 2015 (Table 2). In what follows, a "point" denotes a vector or time series of data associated with a given day. Specifically, let $\mathbf{x}_d = (x_{dhk})_{h\in\mathcal{H},k\in\mathcal{K}'}$ denote a vector of hourly data associated with a subset of types in $\mathcal{K}'$. For example, if $\mathcal{K}' = \{'\text{load}'\}$, then $\mathbf{x}_{44}$ denotes a vector of hourly load data, for all of ERCOT, corresponding to the 44th day in the data set.

Several approaches for selecting representative days for long-term power systems expansion models have been considered. de Sisternes and Webster [37] introduce an approach for optimally selecting sample weeks to approximate net load for long-term generation planning problems. Poncelet et al. [38] present a mixed-integer linear optimization approach to simultaneously address the three objectives listed at the outset. Nahmmacher et al. [12] propose an agglomerative clustering algorithm that begins with D clusters, each consisting of exactly one of the original D observations (days) in the data set. The two "closest" clusters are then merged reducing the number of clusters by 1. This procedure continues until a single cluster consisting of all D observations remains.

Since we ultimately selected a k-means approach over a hierarchical approach, it is worth making some qualitative remarks about the latter. Agglomerative clustering is known to perform well (often better than centroid-based methods like k-means) when the underlying data consists of multiple disjoint "islands." This superior performance occurs because there will eventually be an iteration in which two dissimilar "islanded" clusters are deemed "closer" to one another than all other cluster pairs, and merging these clusters will result in a significant increase in the intra-cluster variance for the new cluster. In the context of power systems planning where observations are historical load and capacity factor profiles, one is tempted to claim that the data naturally decomposes into easily separable "islands." In our experience, this was not the case. For example, while there are clearly days (observations) with a single peak load and other days with multiple peaks, there were many days that possess characteristics of both profiles (see Figure 5). As a consequence, there are few iterations in which the intra-cluster variance significantly "jumps." Worse, an agglomerative clustering algorithm often produced a single large cluster with many observations and large intra-cluster variance, along with many small clusters with only a handful of observations.

In contrast, centroid-based clustering is much more blunt in forming clusters, meaning it assumes that the underlying data come from spherical (Gaussian distributed) clusters. Below, we provide a step-by-step description of our approach along the lines of what was done in [12].

Step 1: Normalizing all time series and selecting a distance metric

Clustering algorithms attempt to group similar observations into the same cluster. Fundamental to any clustering method is the choice of distance metric used to quantify the degree of similarity between two observations. Indeed, the importance of choosing an appropriate distance metric is often under-emphasized and/or poorly understood. Because most off-the-shelf algorithms have a set of pre-defined distance metrics (e.g. L1, L2, and cosine), most practitioners decompose the distance metric selection problem into two problems: data normalization and selecting a pre-defined distance metric. We have chosen this approach as well. Together, the choice of normalization and distance metric have a significant impact on the ultimate clusters.

We normalize all load data between 0 and 2 for each year. RE capacity factors were already normalized between 0 and 1, due to their inherent nature. The normalization is shown in each subplot in Figure 5 where load, the first 24 components of the 120-sized vector, is normalized between 0 and 2, and the RE capacity factors are normalized between 0 and 1 in the remaining 96 (=24 x 4) components. We test this normalization scheme with two distance metrics – L1 and L2 norms – and use the L2 norm method to develop clusters for the C-CEM. As part of a sensitivity analysis, we present the outputs of the C-CEM using the L1 norm based clustering approach in section S.3.

Step 2: Applying the clustering algorithm and deriving a candidate set of clusters

Clusters were determined using the "kmeans" function in MATLAB with 100 replications. Because our interest is to select a small number of representative days to include in the model, we called "kmeans" R times, for values $r = 1, \dots, R = 12$, producing results with 1 to R clusters.

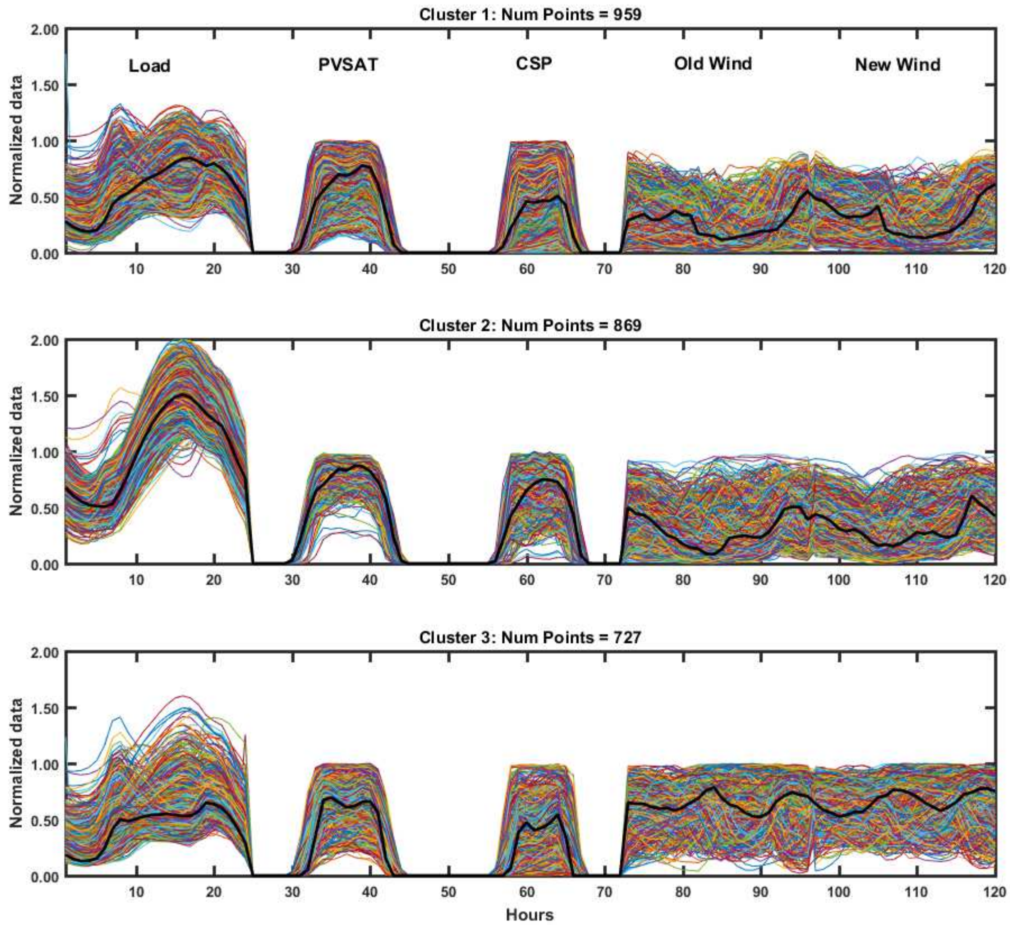

Figure 5: Clusters produced by k-means algorithm when k=3 clusters using aggregate ERCOT data, 100 replications, and the L2 distance metric. Five times series – Load, PVSAT, CSP, Old Wind, and New Wind – are "stitched together" so that each historical day is stored as a single 120-dimensional vector. Load is normalized between 0 and 2, whereas all RE capacity factors are normalized between 0 and 1. Each subplot depicts the points/days in the cluster (shown in color) and then most representative day (shown as a single black line). The title of each subplot indicates the number of points/days assigned to that cluster.

Step 3: Choosing one representative day per cluster

For each cluster, we select the historical day closest (using the a priori selected distance metric) to the centroid of that cluster as the most representative day. This is different from using the centroid of the cluster, which may not capture the true variability seen within a day. Thus, the most representative days are indeed historical days. Figure 5 shows the most representative day selected for each cluster when three clusters are used.

Step 4: Weighting each representative day according to its cluster size

Each representative day is assigned a weight proportional to the number of historical days in the corresponding cluster. Specifically, given a total of $D = 2555$ days in the data set and D_c days in cluster c, the weight assigned to each representative day is $w_c = D_c/D$. For example, cluster 1 in Figure 5 possesses 959 days and receives a weight of 959/2555.

Step 5: Scaling single time series in order to reach the correct annual average

Finally, the weighted load profile was normalized to equal 2015 aggregate ERCOT load of 347.5 TWh so that a fair comparison between runs with different numbers of clusters could be made. Let $\mathbf{x}_c^*$ denote the historical days selected as the most representative days. Then, the data is scaled such that:

$$\sum_c w_c \sum_h x^*_{c,h,Load} = 347.5\, TWh$$

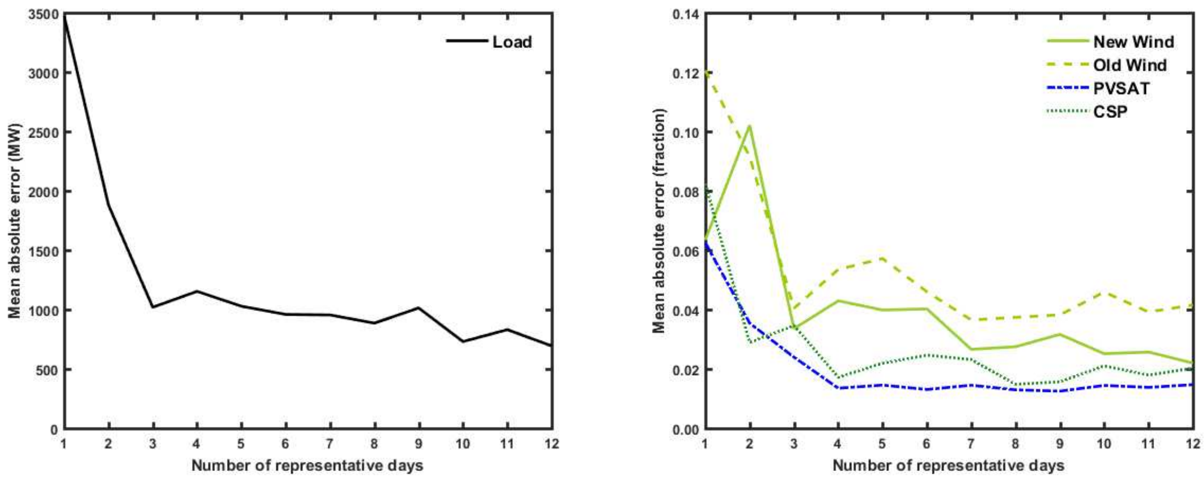

Figure 6: Mean absolute error in the load duration curve (left panel) and the cumulative distribution curves of renewable capacity factors (right panel), relative to the corresponding historical ERCOT curves, for a varying number of representative clusters

Figure 6 presents the approximation accuracy improvement in the load duration curve and cumulative distribution curves due to the above clustering procedure, for an increasing number of representative days. Specifically, it shows the mean absolute error (expressed in MW) in the load duration curve and the mean absolute error (expressed as a fraction) in the cumulative distribution curves of the RE resources relative to seven years (2004-2010) of hourly ERCOT data. As expected, the error tends to decrease as more representative days (more clusters) are included. There are at least two reasons why the curves are not monotonically decreasing. First, the day chosen as "most representative" is not the centroid of the cluster, but the one closest in Euclidean distance to the centroid. Second, to determine the clusters, hourly profiles for load and all RE technologies are considered simultaneously, not individually. Thus, while the error in the aggregate profile (the 120-sized vector including all technologies simultaneously) declines nearly monotonically as the number of clusters increases, the individual technologies do not exhibit this trend. On the other hand, Figure 6 shows that the error in two technologies tend to offset each other. For example, given two clusters, the sudden decrease in error for CSP is met with a simultaneous rise in error for New Wind. With three clusters, the opposite occurs: error in New Wind decreases, whereas CSP error increases. Note that the mean absolute error in the cumulative distribution curves used for the TS-CEM are 1941 MW for load, 0.125 for New Wind, 0.132 for Old Wind, 0.056 for PVSAT, and 0.071 for CSP. These values are close to the errors found for a 1-representative day cluster, but otherwise uniformly larger than any other choice of number of clusters.

4. Results

4.1. Comparing CEMs with differing temporal resolution

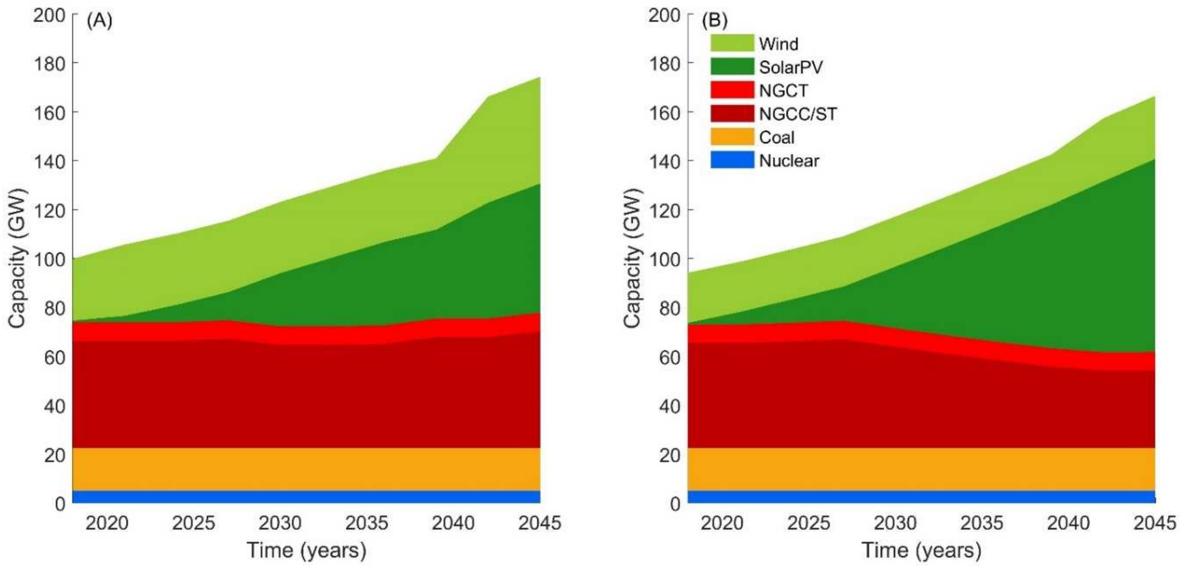

Figure 7. Comparison of capacity projections by (A) the chronological CEM (C-CEM) and (B) the time slice CEM (TS-CEM) in the 50% RE case.

Figure 7 presents projections of capacity (2015-2045) for a hypothetical 50% RE scenario, estimated by the C-CEM and TS-CEM using a consistent set of input assumptions described in the prior section and SI. In this scenario, a target of 50% RE penetration is set for model years 2040 and beyond. The main drivers for capacity additions in both models are the assumed growth in electricity demand of 1.4% per year over the planning horizon [34] and the imposed RE penetration target in 2040 and beyond. Both CEMs project approximately 175 GW of grid capacity in 2045, where solar PV dominates new installations. However, the magnitude of solar PV installed varies in both models, with the C-CEM demonstrating a preference for a portfolio of options including wind and natural gas combined cycle (NGCC) capacity. Figure S 4 demonstrates a similar preference for solar PV in the TS-CEM annual generation mix over the planning period. Both models also project that some existing natural gas (NG) capacity will be retired – mainly older natural gas steam turbines (NGST) in both models and some additional natural gas combined cycle (NGCC) plants in the TS-CEM. The TS-CEM's time slice representation of load and capacity factors for RE generation overlooks the hour-to-hour variability in load and capacity factors within these time blocks and the limited ability of thermal generators to adjust their output accordingly. In contrast, the C-CEM better approximates the observed hourly variability in load and RE and includes explicit limits on the flexibility of thermal generator fleet, through hourly ramping limits and startup costs. The C-CEM therefore projects the need for adding flexible thermal capacity, mostly as new NGCC plants, and projects lower solar PV penetration than the outputs of the TS-CEM. In addition, the variability in wind capacity factors may not be well characterized by a time slice representation (see comparison of time slice sampling results and historical data in Figure 3) [13, 18]. This may partly explain why the TS-CEM results undervalue wind capacity additions compared to the C-CEM, even though the average annual capacity factors of new wind plants are similar in both CEMs (Table S 5).

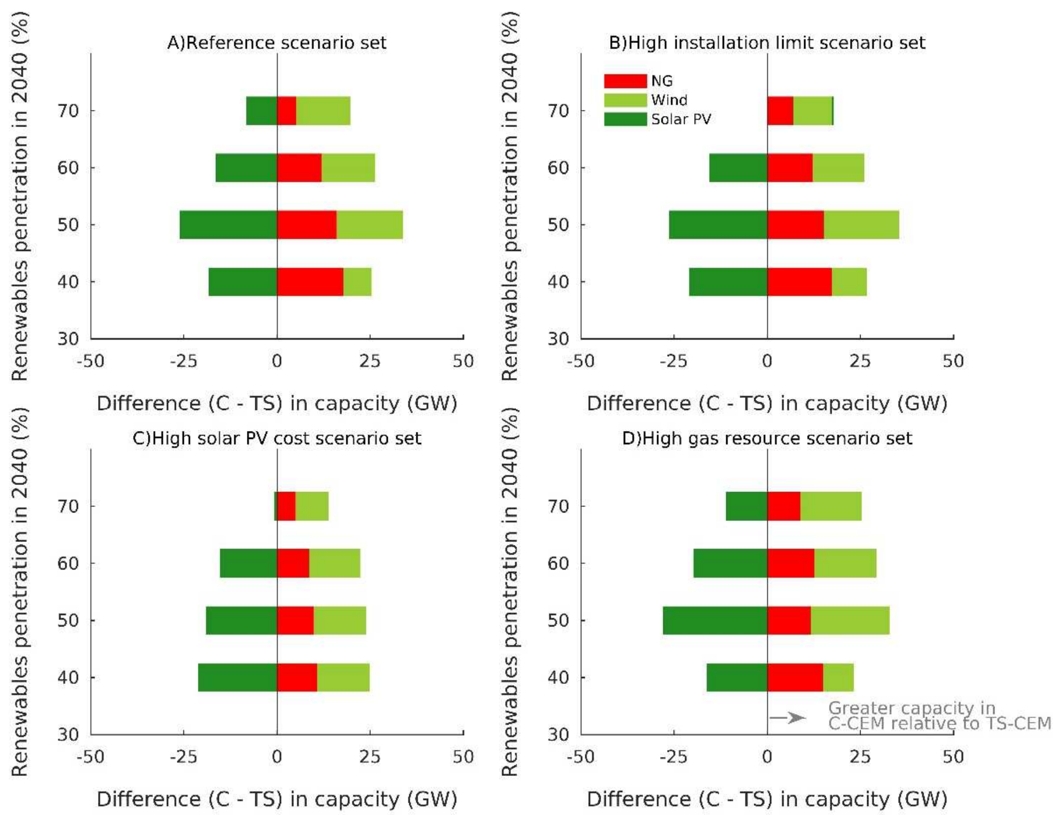

Figure 8. Difference in 2045 capacity projections for solar PV, wind and natural gas (NG) in the chronological CEM (C-CEM) compared to the time slice CEM (TS-CEM) for a range of renewable energy (RE) scenarios up to 70%, and across 4 alternate scenario sets. Here "NG" includes all types of natural gas plants including NGCC, NGCT and NGST.

In addition to the 50% RE scenario, we analyze a range of hypothetical scenarios to evaluate how the outputs of both CEMs change with increasing RE penetration. We test the two CEMs by constraining them to meet a specific percentage (40% - 70%) of dispatched generation by 2040 (and beyond), resulting in a total of 4 RE scenarios[1]. We compare the capacity mix at the end of the planning period across the 4 RE scenarios between both models. The results, presented in Figure 8A (reference scenario set), suggest that the TS-CEM shows a strong preference for solar PV installations over wind and NG compared to the C-CEM for a majority of scenarios. For instance, in the 40% RE scenario, the C-CEM projects only ~50 GW of solar PV by 2045, while the TS-CEM projects ~70 GW (35% higher). As the RE penetration target is increased, however, the difference in PV capacity estimated by the TS-CEM and the C-CEM tends to decrease. This trend is partly an outcome of the two models diverging in their estimates of curtailed RE generation with increasing RE penetration[2] (see Figure 9 and Figure S 5). For example, for the 70% RE scenario, the C-CEM projects ~11% of RE generation is curtailed in 2045 as compared to 6%

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[1] These RE targets were chosen to exercise and ultimately contrast the two expansion models and do not reflect the authors' opinion or endorsement that such targets are economically viable or attainable.

[2] The C-CEM's increased granularity of representing hourly grid operations, including ramping limits and on/off status of individual thermal generators, partly explains why it estimates increasing curtailment with increasing RE penetration. In contrast, the curtailment observed for the TS-CEM tends to plateau with increasing RE penetration, likely because it does not capture the hour-to-hour variability in load and RE output and overlooks on/off commitment of all thermal generators (see Table 1).

estimated by the TS-CEM. All else equal, higher curtailment implies that greater wind and solar PV capacity is required to dispatch the same amount of RE generation. Under higher RE penetration scenarios (e.g. 70% RE), this effect counterbalances the preferential additions of PV over wind in the TS-CEM due to its lower temporal resolution, resulting in a diminished PV capacity difference between the model outputs. In higher RE scenarios (60% and 70%), some coal (2-5 GW) and nuclear (<3 GW) retirements are also seen in the TS-CEM, which are not observed in the C-CEM (not shown in Figure 8). The TS-CEM's minimum turndown constraints on coal and nuclear plants (Table 1) result in the inability of these plants to cycle to the same extent as in the C-CEM, which explains why the TS-CEM chooses to retire some coal and nuclear capacity under higher RE scenarios.

To evaluate how robust the aforementioned differences in the projected capacity mix of the TS-CEM and C-CEM are to various technology and cost assumptions, we compare CEM outputs for three additional scenario sets: B) doubling the annual installation limits on wind and solar PV compared to the reference scenario set (see reference data in Table S 3); C) higher solar PV cost compared to projections used in the reference scenario set (presented in Figure S 2); and D) a higher gas resource scenario (i.e. lower gas price), also from the EIA Annual Energy Outlook 2016 *[10]* (presented in Figure S 3). Results across all scenario sets confirm the same trends observed in the reference scenario set: the TS-CEM shows a strong preference for solar PV installations over wind and NG, compared to the C-CEM across a majority of the evaluated scenarios, with reduced differences seen at higher RE scenarios. Notably, in the high solar PV cost scenario, both models are directly dis-incentivized to build solar PV and therefore the differences between the model outputs are relatively smaller (Figure 8C).

4.2. Using detailed production cost simulations to assess CEM results

Annual hourly grid operations are approximated in both CEMs, although in different ways. To test how robust these approximations are, we solve the PCS model to simulate grid operations for a single year (2045) with hourly resolution, using the capacity projected by both CEMs. To account for inter-annual variability in load and RE generation, we solve the PCS model for seven different realizations of time series for load and RE capacity factors, for each RE scenario. The data for the load and RE capacity factor profiles were derived from historical data (2004-2010) available from ERCOT [35, 36]. We then compare the outputs of the CEMs and the PCS model for each RE scenario using a range of metrics, including annual curtailment (Figure 9A), unmet demand (Figure 9B), annual RE penetration (Figure S 6), and annual thermal generation mix (Figure S 7).

In Figure 9A, the individual bars refer to the 4 RE scenarios presented earlier and the height of each bar represents the range of outputs from the PCS model when considering seven different realizations of load and RE generation time series. The inability of either CEM to accurately capture extreme situations such as maximum or minimum net load (i.e. load minus RE generation), maximum RE generation or rapid changes in RE output partly explains why both CEMs underestimate curtailment. For the C-CEM capacity mix, curtailment projected by the PCS generally tends to increase as the prescribed RE penetration level increases. This is not surprising since both the C-CEM and the PCS have similar thermal generator operating constraints that directly contribute to instances of curtailment.

Both CEMs estimate that demand is met for all the representative time steps included in the models. In contrast, when the capacity mix estimated by these models is input to the PCS model, demand remains unmet in some hours. This is expected, since both CEMs approximate grid operations and do not capture the full extent of variability of grid conditions. As seen in Figure 9B, increasing the model resolution (C-CEM) as compared to seasonal-average modeling (TS-CEM) certainly reduces instances of unmet demand. It is also worth noting that, although the unmet demand for the C-CEM capacity mix increases with increasing RE targets, the maximum value is still relatively small at 0.023% of load for the 70% RE scenario, which is comparable to the loss of load threshold values considered in estimating reserve margin requirements [39]. Finally, the C-CEM outputs also better approximate the annual generation mix by technology type, when compared to the TS-CEM outputs, as shown in Figure S 6 and Figure S 7.

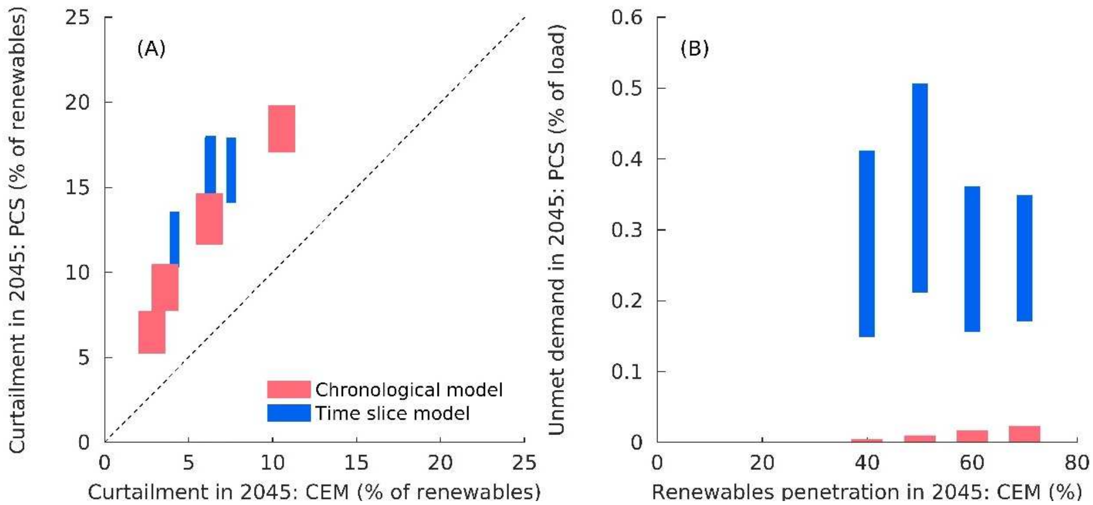

Figure 9. (A) Comparison of 2045 curtailment in the CEMs to curtailment in the Production Cost Simulation (PCS) model for the same capacity mix. (B) Comparison of unmet demand in 2045 in the PCS model for the same capacity mix as projected by the CEMs. The CEM outputs correspond to the reference scenario set (Figure 2A). The height of each bar corresponds to the range of values obtained from the PCS model by simulating seven different realizations of time series for load and capacity factors for renewable energy (RE) generation (further details on load and RE data available in section 3).

4.3. Impact of the number of representative days within the C-CEM

Within the C-CEM, the number of sample days selected to represent the entire year's load and RE generation may also impact results, including capacity and generation projections. We assessed this aspect by solving the C-CEM using a range of sample days (1 day up to 12 days). Such a question has been considered in the context of a linear CEM by Nahmmacher et al. [12], who concluded that a CEM with fewer representative days selected to represent annual grid operations may result in higher projections of RE capacity. In our experiments using the C-CEM, which is a MILP model, we use a k-means clustering approach with the L2-norm used as the distance metric, to select these days from the historical data, with the total annual load adjusted to be identical across all 12 scenarios. Figure 4 compares the resulting capacity projections for NG, solar PV and wind, for each of the scenarios with a different number of sample days, under a 50% RE penetration target (comparison of generation shown in Figure S 8). Although the total RE capacity remains nearly the same across all scenarios, the projected PV capacity and wind capacity have increasing and decreasing trends, respectively, with increasing number of representative days selected. For instance, the solar capacity in the 1-day scenario is approximately 20% higher than the capacity for the scenario with 12 representative days. The NG capacity also follows an increasing trend with increasing representative days, with up to 10% differences between the two bookend cases in Figure 10. The non-monotonic trends in the installed capacity of individual technologies in Figure 4 are partly an outcome of the approach for selecting representative days. Specifically, as discussed in section 3.3, historical data are clustered according to the joint distribution of load and RE capacity factors, which does not guarantee that the error in representing individual distributions (capacity factor or load) will exhibit a monotonically decreasing trend. The capacity trends observed in Figure 10 were also found to be robust to changing the distance metric used in the selection of representative days from the L2-norm to the L1-norm (see Figure S 9 and Figure S 10). Overall, the results are consistent with the trends reported when comparing the CEMs: with lower temporal resolution (number of sample days selected, in this case), solar PV capacity is overestimated while wind and NG capacity are underestimated relative to the higher resolution CEMs.

For long-term energy planning models like NEMS or ReEDS with multi-sector scope or large spatial coverage or both, computational issues may make it impractical to include 12 representative days in the power system expansion model. In such cases, representing annual grid operations using fewer representative days could still provide some improvement over a traditional time slice approach, with regard to addressing the variability of load and RE generation and other grid operating constraints. This point is illustrated in Figure 10, where for instance, the solar, wind and NG capacity projected using 6 representative days is within 5% of the total installed capacities projected by the CEM using 12 representative days.

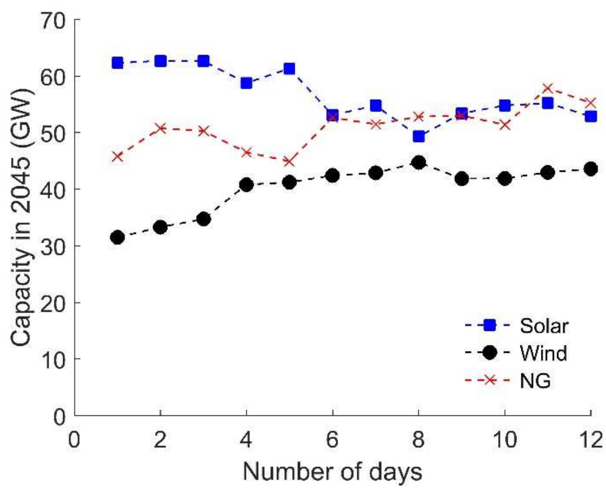

Figure 10. Capacity projections for solar, wind and natural gas (NG) in 2045, using the chronological CEM (C-CEM) under a 50% renewable energy (RE) scenario, varying as a function of the number of sample days selected to represent load and renewables data for annual grid operations. (The L2-norm is used in the k-means clustering approach for choosing the representative days)

5. Conclusions

In this work, we perform a systematic comparison of two alternate CEM frameworks to demonstrate how the choice of representing grid operations within a power system CEM framework can impact future projections of grid evolution. For the same set of technology and cost assumptions, we find that a CEM with time slice representation of grid operations (e.g. the TS-CEM developed here) is in general likely to overestimate solar PV capacity (by 35% in one case) and underestimate wind and the supporting NG capacity requirements, compared to a CEM with higher temporal resolution and generator ramping and startup constraints (C-CEM). This finding is explained primarily by the limited representation of the temporal variability in RE generation, notably wind, and its correlation with load when using the time slice approach as compared to the chronological approach. For solar PV, using values of capacity factors based on 4-hr seasonal averages (as in the TS-CEM) overvalues the coincidence between peak solar PV generation and peak system load (also a 4-hr seasonal average) and consequently underestimates the declining value of solar PV generation with increasing penetration, as compared to the chronological approach using 12 representative days (as in the C-CEM) at an hourly resolution. The differences in the capacity mix to achieve the same RE targets have reliability implications, as reflected by the lower unmet demand projected for the C-CEM capacity mix when tested in a detailed hourly simulation of annual grid operations.

While it is common for policy-focused CEM studies to test the capacity mix estimated by a CEM through a PCS framework [1, 6], our study highlights the importance of evaluating the operational performance of the capacity mix projections for multiple years of load and renewables generation profiles. Such an analysis benchmarks the ability of the capacity mix to achieve the desired reliability and/or environmental attributes. For instance, the results presented here suggest that the unmet demand resulting from the capacity mix estimated by the C-CEM (using 12 representative days) is less sensitive to the annual variations in load and RE generation profiles compared to the outputs projected by the TS-CEM (Figure 9B).

Even within a C-CEM framework, selecting fewer than 4 sample days may lead to considerable overestimation of solar PV capacity. This finding has implications for the choice of temporal resolution in not just power sector planning models, but also more broadly for multi-sector, multi-country energy economic and integrated assessment models. For example, it was recently suggested that the current time slice implementation in the electricity grid planning implementation of the 2016 NEMS energy-economic model for the US may be overestimating solar PV capacity projections [40]. Similarly, Bistline et al. [13] performed an intra-model comparison of alternative temporal representations in the US-REGEN model and concluded that using a seasonal-average approach (akin to TS-CEM) is likely to overstate renewables capacity and understate investment in dispatchable generation, compared to the representative hours approach (akin to C-CEM). Our study contributes to the growing body of evidence on the need for using a temporal representation based on a few representative days or other parameterizations that yield similar behavior in multi-sector, energy-economic models and other energy system models supporting policy analysis and decision-making.

There are several future research directions worth investigating. While this study focused on the effect of changing temporal resolution in a CEM while keeping the spatial resolution constant, it would be interesting to consider the relative importance of spatial and temporal resolution by repeating the analysis in the context of a CEM co-optimizing generation and transmission expansion. Given the growth in energy storage technologies, it would be instructive to understand the impact of energy storage on RE penetration projections in future electricity grids, as well as the necessary temporal resolution required to adequately account for their attributes in a CEM. Note that we have developed a CEM similar to the C-CEM that considers energy storage [41]. Since parameter uncertainty (e.g., in construction lead times and capex costs) in CEMs is always a prominent issue, it could be valuable to implement stochastic versions of our models and perform a similar analysis. Finally, it would be interesting to consider within a CEM framework, the trade-offs between deploying storage, solar PV systems at the centralized and distributed scale, given the different types of grid services available from deployment at each scale.

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Supplementary information

S.1. Capacity expansion models (CEM) mathematical formulation

The precise mathematical optimization models for the TS-CEM and C-CEM are presented in the appendix.

S.2 Data assumptions

Table S 1 and Table S 2 summarize technology and cost assumptions used to model operations of existing and new generators, respectively, in the two CEMs and the PCS model. Unless otherwise stated, all cost parameters reported below are reported in 2015 dollars. Some key points to note regarding the data in Table S 1 and Table S 2:

- Both CEMs do not explicitly consider the construction time for power plants. Instead the construction time is implicitly considered by accounting for the cost of capital financing during the construction period in the capital cost assumptions of each technology, following the methodology presented in the 2016 NREL technology baseline [33]. In this manner, both CEMs implicitly distinguish between the relative construction times of different technologies. The capital multiplier associated with new generator clusters is meant to account for differences in depreciation schedules applicable to each technology in the U.S. context, with higher values being indicative of a slower depreciating schedule and vice versa.
- In the absence of better data sources, we assume the startup costs for nuclear power plants to be the same as the values reported for coal power plants.
- The capacity contribution of wind plants to the planning reserve margin is based on the average value of their capacity contribution to peak demand in summer and winter months between 2009-2014 [42]. Currently, ERCOT estimates the capacity value of solar PV plants to be 0.8-1, due to the small amount of total installed capacity [42]. We use a lower value of 0.6 to reflect the declining contribution of solar PV to peak demand with increasing installed PV capacity.
- The life extension costs for existing generators is based on a review of FERC form 1 data regarding the reported annual capital expenditures made by older units and is reported in the IPM documentation as a proportion of the capital costs of the corresponding new generators [28]. For example, the life extension cost of an existing NGCC plant in a given year is assumed to be 9.3% of the capital cost of a new NGCC plant in that year. We assume that the life extension costs for natural gas boiler plants (NGST) to be the same as the extension costs for existing coal plants, due to the similar equipment in use (e.g. boilers, steam turbines). In all cases, the life extension costs are assumed to double the lifespan of the generator [28].

Table S 1. Technology and cost assumptions for existing generator fleet. HHV = Higher heating value

	Source	Coal	NGCT	NGCC	NGST	Nuclear	Solar PV	Wind
Nameplate capacity (MW)	Estimated based on generator categories in [43]	644	156	719	622	1291	39	134
Heat rate - HHV (Btu/kWh)		10484	11395	8409	13216	10479	-	-
Ramp rate – up & down (% of nameplate capacity/hr)	[44, 45, 46]	25%	100%	100%	25%	17%	-	-
Min. output (% of nameplate capacity)	[43]	48%	25%	32%	28%	90%	-	-
Max. spin reserves (% of nameplate capacity)	[23]	10%	50%	10%	10%	0%	-	-
Max. quick start reserves (% of nameplate capacity)	Assumption	0%	100%	100%	0%	0%	-	-
Lifetime (years)	[47]	60	30	30	60	60	30	20
Start-up costs ($/MW)	[23]	140.94	37.15	86.31	140.94	140.94		
Start-up fuel usage (MMBtu/MW)	[23]	14.5	1.53	0.24	14.5	14.5		
Fixed O&M cost ($/kW)	[43, 45]	26.87	5.27	13.96	16.59	76.91	42.48	30.82
Variable O&M cost ($/MWh)	[43]	5.27	4.21	3.16	6.85	4.21	-	-
Life extension cost as a proportion of new unit capital cost (%)	[28]	7.0	4.2	9.3	7.0	9.0	4.2	4.2
Capacity contribution to reserve margin	[42, 48]	1	1	1	1	1	0.6	0.15
Minimum turndown fraction (only TS-CEM)	[7]	0.4	0	0	0	1	-	-

Table S 2. Technology and cost assumptions for new generator clusters. HHV = Higher heating value

	Source	Nuclear	Wind	Solar PV	Solar CSP	Coal IGCC	Coal IGCC CCS	NGCC	NGCC CCS	NGCT
Capacity (MW)	[49]	2234	100	20	100	600	520	400	340	210
Heat rate – HHV (Btu/kWh)	[49, 50]	10479				7450	8307	6260	7493	8550
Ramp rate – up & down (% of nameplate capacity/hr)	[44, 45, 46]	17%				25%	25%	100%	100%	100%
Min. output (% of nameplate capacity)	[51, 50, 52]	50%	-	-	-	30%	30%	40%	40%	30%
Max. spin reserves (% of nameplate capacity)	[23]	-	-	-	-	10%	10%	10%	10%	50%
Max. quick start reserves (% of nameplate capacity)	Assumption	-	-	-	-	0%	0%	100%	100%	100%
Lifetime (years)	[47]	60	20	30	30	60	60	30	30	30
Capital cost multiplier	[33]	1.28	1.13	1.13	1.13	1.33	1.33	1.28	1.28	1.28
Start-up costs ($/MW)	[23]	140.94	-	-	-	140.9	140.9	86.31	86.31	37.15
Start-up fuel usage (MMBtu/MW)	[23]	-	-	-	-	14.5	14.5	0.24	0.24	1.5
Fixed O&M cost ($/kW)[1]	[33]	94.68	46-50	8-16	51-68	52.1	73.9	14.48	32.27	7.3
Variable O&M cost ($/MWh)	[33]	2.17	-	-	3	7.3	8.6	3.50	6.8	13.1
Capacity contribution to reserve margin	[42, 48]	1	0.15	0.6	0.6	1	1	1	1	1
Minimum turndown fraction (only TS-CEM)	[7]	1	-	-	-	0.5	0.5	0	0	0

[1]Fixed O&M cost data for some new generators changes with time, as reported in the NREL technology baseline [33].

Table S 3 summarizes the annual installation limits assumed for wind, solar PV and solar CSP generators. These values were obtained from scaling down the annual installation limits assumed in the Integrated Planning Model [8] for the entire U.S., based on the relative of share of annual power generation in ERCOT. Additionally, the installation limits for the period beyond 2018 shown in Table S 3 are scaled up in the CEMs by a factor 3 to account for the fact that both the CEMs step forward in three year time increments. Under some scenarios investigated here, such as 50-70% RE scenarios, the assumed installation limits for each model year are found to be binding in a few years and limit the rate of deployment of wind or solar PV technologies. The installation limits assumed for the remaining new generator clusters were always much larger than the installed capacity for all the scenarios considered here and therefore are not shown in Table S 3.

Table S 3. Annual installation limits for RE technologies. Data source: [8].

	2015-2018	2018-2021	2021-2024	2024-2027	2027-2030	2030-2033	2033-2036	2036-2039	2039-2042	2042-2045
Wind	1570	3139.9	3139.9	3139.9	7849.8	7849.8	7849.8	7849.8	7849.8	7849.8
Solar PV	744.1	1488.2	1488.2	1488.2	3720.6	3720.6	3720.6	3720.6	3720.6	3720.6
Solar CSP	900	900	900	900	900	900	900	900	900	900

Figure S 1 shows the assumed capital cost projections over time for the new generator technologies considered in both CEMs. The data was derived from 2016 NREL technology baseline [33]. As a sensitivity analysis, we considered an alternative trajectory for capital costs of solar PV over time that does not go below $1300/kW, as shown in Figure S 2.

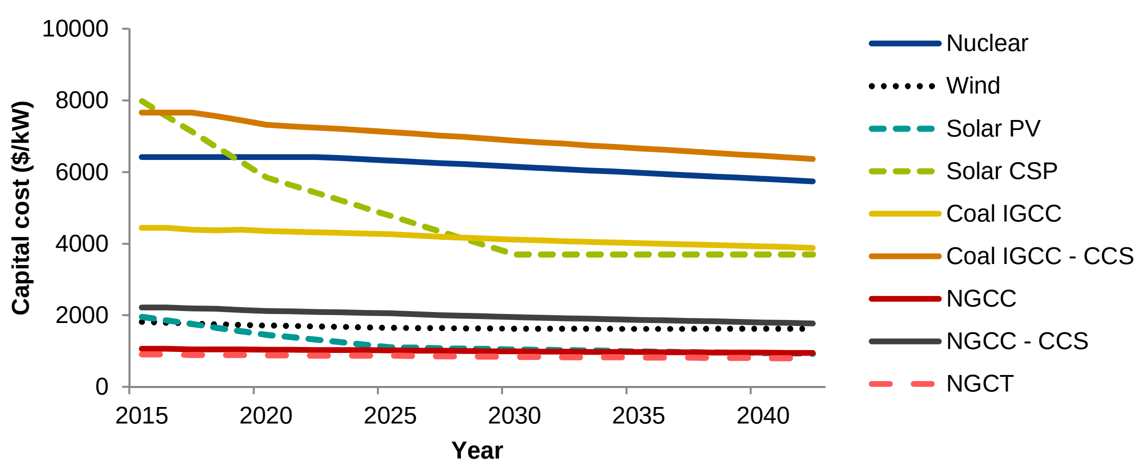

Figure S 1: CAPEX over time for all new generator types (source: [33]).

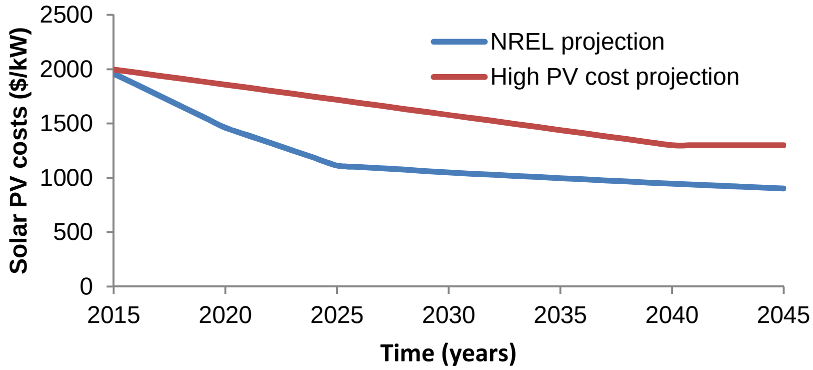

Figure S 2. High solar PV cost projections (input to high solar PV cost scenario set shown in Figure 8C) relative the NREL projections [33] used in the reference scenario set.

Figure S 3 plots the fuel price projections over time considered in both CEMs and the PCS model. The data was derived from EIA Annual Energy Outlook 2016 [10]. Unless otherwise stated, all results presented consider the "reference" set of fuel price projections.

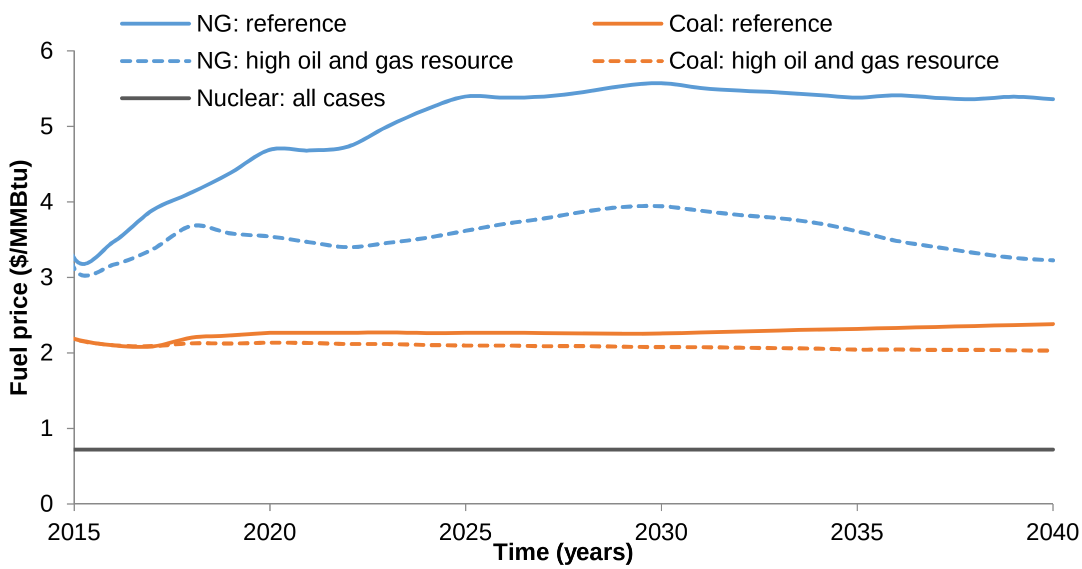

Figure S 3. Fuel price projections for "reference" scenarios and "high oil and gas resource" scenarios. Data source: EIA Annual Energy Outlook 2016 [10]. All values reported on a Higher Heating Value (HHV) basis.

Table S 4 summarizes the implementation of the investment tax credits for wind and solar PV technologies in the two CEMs that approximates the current policy [26]. In each case, the investment tax credit effectively reduces the capital cost by the specified percentage. The production tax credit (PTC) is also incorporated in both CEMs according to current policy [27]. Specifically, the PTC is available for wind generators, both existing and new, constructed before 2019. For each plant, the PTC is available for the first 10 years of their operation. Additionally, the PTC of plants built in the 2018-2021 period is 60% of the current PTC value, i.e. $23/MWh. It should be noted that we did not consider the PTC for the PCS model runs for different RE scenarios.

Table S 4. Investment tax credits for new installations of wind and solar PV technologies as % percentage of capital cost implemented in the two CEMS. Data source: [26]

	2015-2018	2018-2021	2021-2024	2024-2027	2027-2030	2030-2033	2033-2036	2036-2039	2039-2042	2042-2045
Wind	30%	18%	0%	0%	0%	0%	0%	0%	0%	0%
Solar PV	30%	30%	22%	10%	10%	10%	10%	10%	10%	10%

Table S 5. Average annual capacity factors for wind and solar PV technologies for the different temporal representations used in the chronological (C-CEM) and time-slice (TS-CEM) models. Solar PV capacity factors correspond to single-axis tracking PV technology.

	C-CEM	**TS-CEM**
Wind (existing)	34.6%	36.5%
Wind (new)	38.9%	39.2%
Solar PV (existing and new)	26.3%	27.4%

S.3 Comparison of generation and curtailment between TS-CEM vs C-CEM

We compare the annual generation projections by both CEMs under a hypothetical 50% renewable energy (RE) scenario in Figure S 4.

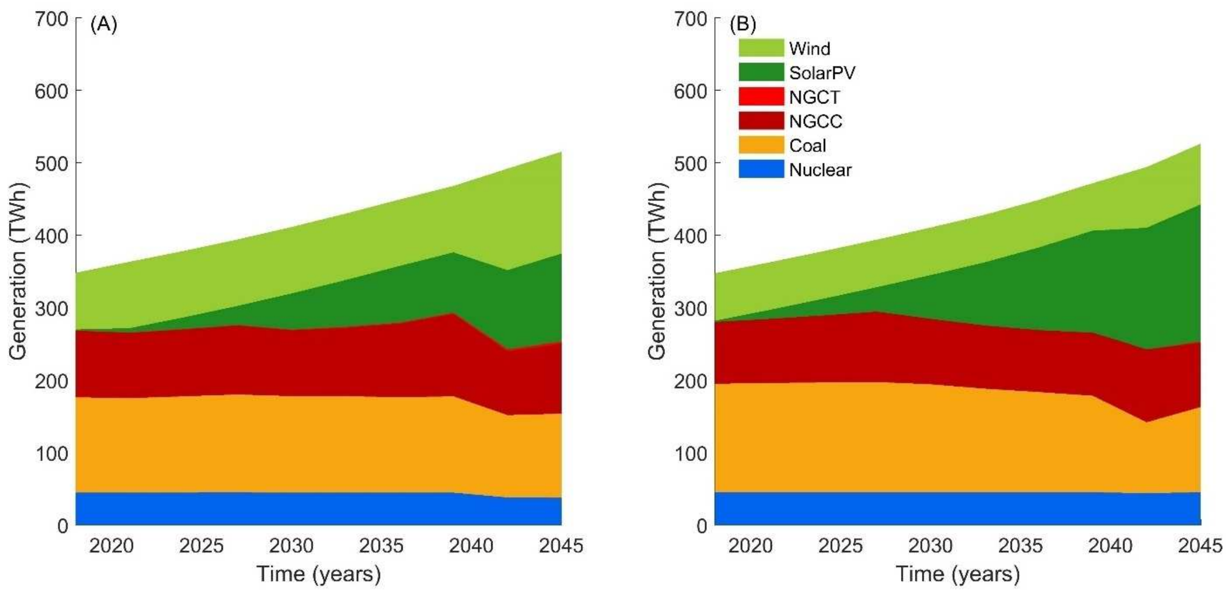

Figure S 4. Comparison of ERCOT generation projections by (A) the chronological model and (B) the time slice model in the 50% RE case.

We also compare the annual curtailment between both CEMs for the 4 RE scenarios in the reference scenario set. Curtailment typically occurs when generation from all sources is higher than the load at a given time, and slow-responding thermal generators cannot be ramped down quickly enough. RE generation is often curtailed in these instances, and therefore we report annual curtailment as a fraction of RE generation. As seen in Figure S 5, the curtailment in 2045 across the 40-60% RE scenarios in the reference scenario set for the TS-CEM model is similar to the curtailment projected by the C-CEM; for the 70% RE scenario, the C-CEM projects much higher curtailment than the TS-CEM (11% vs 6%). The TS-CEM models generation from thermal plants as a continuous variable between zero and the installed nameplate capacity. Therefore, subject to other model constraints, the TS-CEM assumes greater flexibility from the thermal generator fleet than would be available when considering their minimum generation levels (as in the C-CEM). This modeling assumption and the limited representation of temporal variability of load and RE output partly explain why the TS-CEM estimates lower curtailment compared to the C-CEM at higher RE scenarios like 70%.

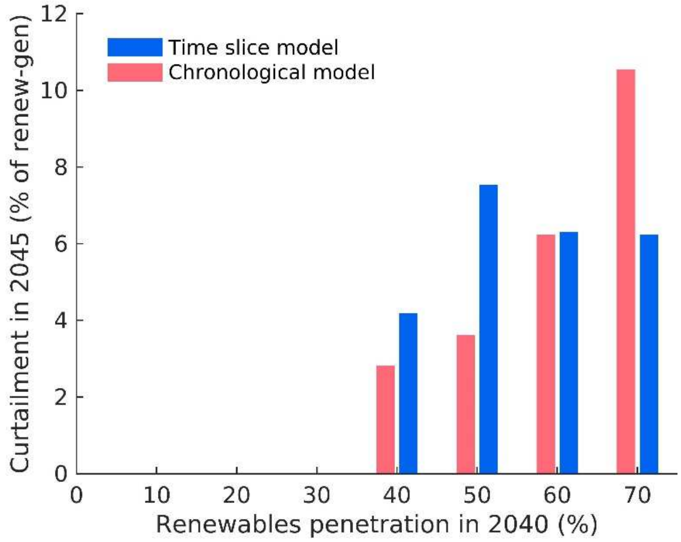

Figure S 5. Curtailment in 2045 estimated by both capacity expansion models across a range of renewables penetration scenarios in the reference set.

S.4 Comparison of outputs between TS-CEM vs. C-CEM using the PCS model

Both CEMs meet RE penetration targets across all the scenarios considered. The PCS model was used to test whether the capacity mix estimated by the CEMs did in fact allow for these targets to be met when considering a full-year simulation of grid operations at hourly resolution for different possible realizations of load and RE outputs. This comparison is presented in the parity plot in Figure S 6. The individual bars refer to the 4 RE scenarios, while the height of the bar represents the range in RE penetration predicted by the PCS for 7 realizations of load and RE capacity factor profiles for each scenario. This figure suggests that that both CEMs are able to meet RE penetration targets reasonably well in these hypothetical model scenarios, given the proximity of the bars to the parity line, although the C-CEM performance is marginally improved compared to the TS-CEM.

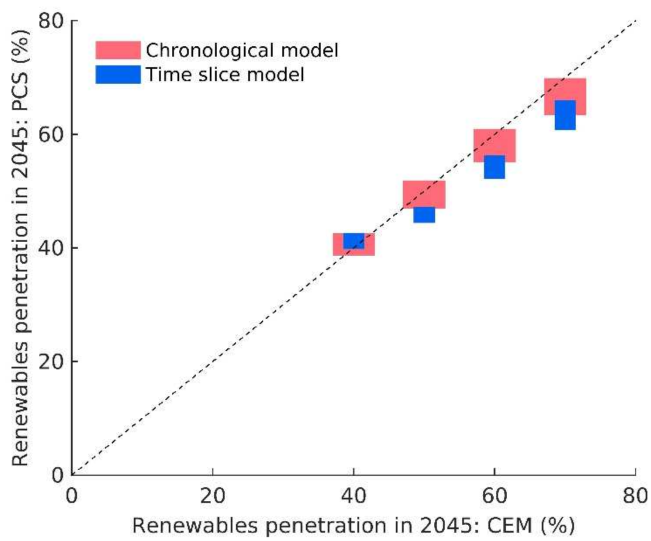

Figure S 6. Comparison of 2045 renewables (RE) penetration in capacity expansion models (TS-CEM and C-CEM) to those in the grid operations model (PCS) for the same capacity mix. The height of each bar corresponds to the range of values obtained from *simulating the PCS model for seven different realizations of profiles for load and capacity factors for RE generation (based on 2004-2010 historical data for ERCOT).*

In addition, we compare annual thermal generation projected by the CEMs to the PCS model for consistent capacity mix assumptions across the 4 hypothetical RE scenarios (see Figure S 7). In general, the C-CEM projects annual generation from all thermal sources better than the TS-CEM, as shown in Figure S 7D, specifically, where the C-CEM bars are closer to the parity line. Note that only 3 bars representing nuclear generation from the TS-CEM appear in Figure S 7C because the results of 2 RE scenarios are almost identical and the bars overlap each other.

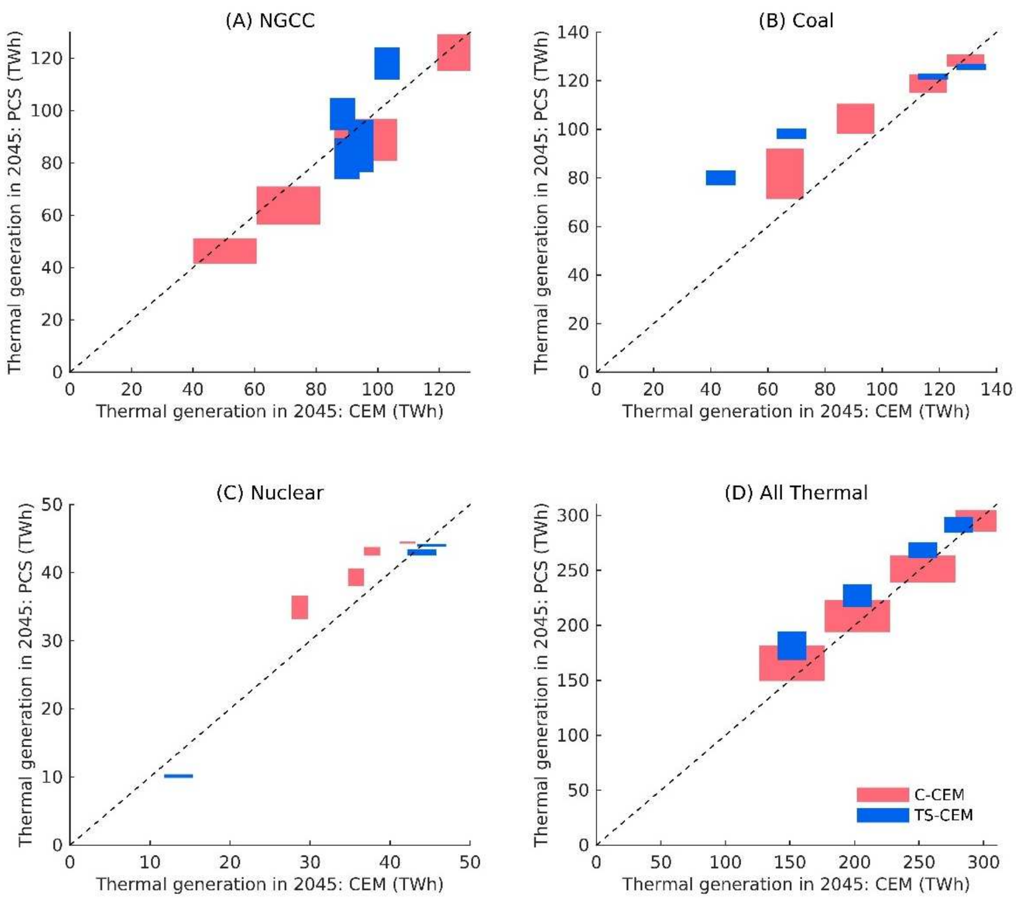

Figure S 7. Comparison of 2045 thermal generation in capacity expansion models (TS-CEM and C-CEM) to those in the grid operations model (PCS) for the same capacity mix. The height of each bar corresponds to the range of values obtained from simulating the PCS model for seven different realizations of profiles for load and capacity factors for renewables generation.

S.5 Additional C-CEM results highlighting impact of number of representative days

Figure S 8 compares the resulting generation projections for NG, solar PV and wind, for each scenario with a different number of sample days used in the C-CEM, under a hypothetical RE 50% target.

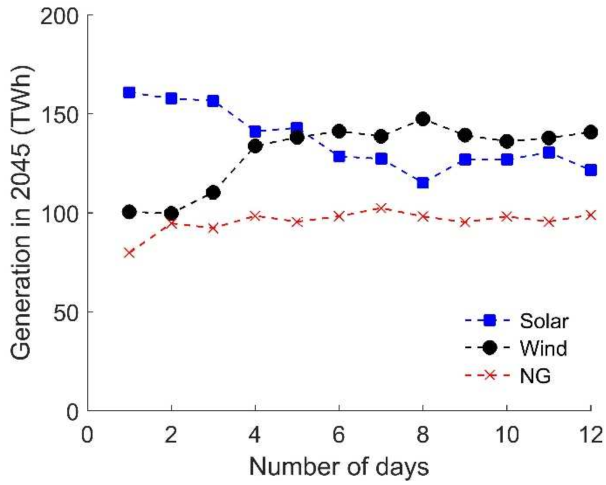

Figure S 8. Generation projections for solar, wind and natural gas in 2045, using the C-CEM under a 50% renewable energy (RE) scenario, varying as a function of the number of sample days selected to represent load and renewables data for annual grid operations. (The L2-norm is used in the k-means clustering approach).

Figure S 9 and Figure S 10 compare the resulting capacity and generation projections for NG, solar PV and wind, for scenarios with a different number of sample days used in the C-CEM, under a RE 50% target, while using the L1-norm as the distance metric in the k-means clustering procedure.

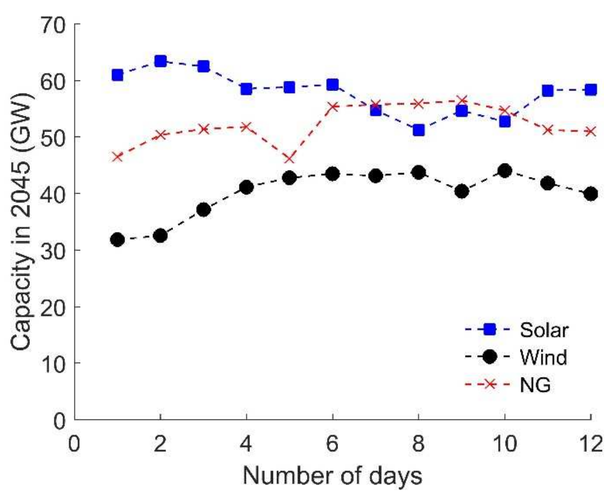

Figure S 9. Capacity projections for solar, wind and natural gas in 2045, using the C-CEM under a 50% renewable energy (RE) scenario, varying as a function of the number of sample days selected to represent load and renewables data for annual grid operations. (The L1-norm is used in the k-means clustering approach).

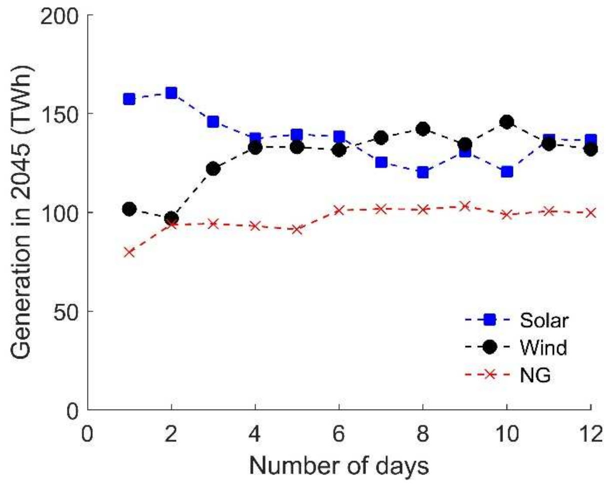

Figure S 10. Generation projections for solar, wind and natural gas in 2045, using the C-CEM under a 50% renewable energy (RE) scenario, varying as a function of the number of sample days selected to represent load and renewables data for one year's operations. (The L1-norm is used in the k-means clustering approach).

Appendix: Detailed Algebraic Modeling Descriptions

This appendix provides the detailed mathematical optimization formulations associated with the chronological capacity expansion model (C-CEM) and the time slice capacity expansion model (TS-CEM). Regarding their similarities, both are deterministic optimization models that take the vantage point of a centralized planner seeking to determine cost-optimal expansion decisions over a planning horizon of several decades. Both models build and utilize generation capacity to satisfy load in their respective time steps. Both models use as input the same forecasted load growth, the same suite of generation technologies to meet this growth, and the same associated cost assumptions to model grid evolution in 3-year time increments from 2015 to 2045. They represent solar and wind expansion decisions as continuous decisions meaning that a fractional wind generator can be built. Importantly, both models represent the existing fleet of thermal and renewable generators (wind and solar) by clustering the entire fleet into seven different generator types. C-CEM and TS-CEM also allow for aging capacity to be retired or retrofitted, whereby the latter options incurs a one-time cost of retrofit and returns to operation with the same operational parameters as before. For each generation technology, both models include annual capacity installation limits that implicitly account for supply chain constraints associated with technology deployment.

Despite these similarities, the two models significantly differ in their temporal resolution and operational detail. It is precisely the dissimilarities described below that will help elucidate why different expansion decisions are made in certain scenarios. Temporally, the C-CEM represents monthly load, as well as wind and solar generation, by a single day at an hourly time resolution, whereas the TS-CEM represents annual load, as well as wind and solar generation, with 16 time slices representing different times of day and seasons. In particular, while the chronological model sees an hourly load and renewables capacity factor time series corresponding to twelve representative days of the year. In other words, the TS-CEM averages load and renewables capacity factor data in each of the four seasons into time slices representing morning (7 am - 2 pm), afternoon (2-6 pm), evening (6-11 pm), and night (11 pm - 7 am). More importantly, the C-CEM, as its name suggests, sees chronology, and therefore events that occur in a given hour are related to events that occur in the preceding and subsequent hours. The TS-CEM does not link two consecutive time slices with respect to operational constraints. Operationally, C-CEM considers important details associated with thermal generators including: unit commitment decisions, ramping constraints, spinning reserves, quick-start reserves, and start-up costs. In contrast, the TS-CEM omits these details, although spinning reserves are partially taken into account. Lastly, because the C-CEM includes unit commitment decisions, thermal generation expansion decisions are modeled as integer decisions, unlike the TS-CEM which allows for a fractional number of thermal generators to be built.

Both models were implemented in GAMS. The descriptions below were generated using the GAMS utility function `model2tex` as described on the GAMS website. Table 1 lists the section references for key constraints common to both models.

Constraint type	Chronological C-CEM	Time Slice TS-CEM
Load balance	A.5.2	B.5.12
Generator capacity balance	A.5.6–A.5.11	B.5.15
Retirement or retrofit decisions	A.5.12–A.5.13	B.5.16
Annual installation limits	A.5.23–A.5.24	B.5.30
RPS	A.5.25	B.5.24
Capacity planning reserve requirements	A.5.14	B.5.20
System operating reserve requirements	A.5.15	B.5.21
Spinning reserves for thermal generation	A.5.16	B.5.23
Cluster commitment status	A.5.3	NA
Ramping	A.5.4–A.5.5	NA
Power output from generators upper and lower bounds	A.5.19–A.5.20	NA
Minimum turndown	NA	B.5.19

Table 1: Section references to specific constraints

A Chronological Capacity Expansion Model (C-CEM)

A.1 Sets

Name	Domains	Description
t, tt	t	Set of years to be modeled
h, hh	*	Set of time blocks or hours within each dispatch period
d	*	Set of dispatch periods
s, ss	s	Set of nodes. Model represents ERCOT region with a single node
g, gg	g	Set of generator clusters
Wind	g	Set of wind generators - old and new
CSP	g	Set of CSP generators
PV	g	Set of PV generators
Renew	g	Set of renewable generators
ExistingRenew	g	Set of existing renewable generators
NewRenew	g	Set of new renewable generators
Thermal	g	Set of thermal generators
Existingthermal	g	Set of existing thermal generators
Newthermal	g	Set of new thermal generators
Thermalbase	g	Set of thermal generators with non-zero minimum output
ThermalQstart	g	Set of thermal generators contributing to quick start reserves
ThermalSpin	g	Set of thermal generators contributing to spinning reserves

A.2 Parameters

Name	Domains	Description
CapCost	g, t	Annualized investment cost of generator type g in time period t ($ per kW)
LifeExtensionCost	g, t	One time extension cost to extend plant beyond its economic life ($ per kW)
Investmult	g, t	Portion of overnight capital cost of generator type g in time period t that is included in objective
Capmult	g	Technology-specific financial multiplier to account for any applicable differences in depreciation schedule, and tax policies for each generator g >1
FOMCost	g, t	Annual fixed operating & maintenance costs for generator g ($ per kW-year)
VOMCost	g, t	Variable operating & maintenance costs for generator g ($ per MWh)
FuelCost	g, t	Fuel costs for generator type g in time period t ($ per MMBtu)
StartupFueluse	g	Fuel use during startup for each generator type g (MMBtu per MW)
StartUpcost	g, t	Startup cost of generator type g in time period t ($ per MW)
Gridconnect	g, t	Annualized cost of connecting a new generator of cluster g to the grid ($ per kW)

Name	Domains	Description
CarbonTax	t	Carbon tax on emissions from power plants during year t ($ per ton CO2eq)
Ngenexist	g, s	Number of units for each generator cluster at node s at t=0
PTCEligiblePlants	g, s, t	Number of existing wind plants that are eligible for the production tax credit in each year t
Cf	g, s, h, d	Capacity factor for generator type g for each time instance
Heatrate	g, s	Heat rate of generator type g (Btu per kWh)
Pgen	g, s	Assumed size or capacity of an individual type g generator in node s (MW)
Pgenmin	g	Minimum operating capacity of an individual type g generator (MW)
Tlife	g	Lifetime of generator type g (years)
DPdown	g	Maximum ramp down rate for thermal generator between two consecutive time blocks (% of nameplate capacity per hour)
DPup	g	Maximum ramp up rate for thermal generator between two consecutive time blocks (% of nameplate capacity per hour)
Spinfrac	g	Fraction of nameplate capacity that can contribute to spinning reserves for generator type g
Qstartfrac	g	Fraction of nameplate capacity that can contribute to quick start reserves for generator type g
Nmaxgeninstall	g, t	Maximum no. of generators of type g that can be installed at beginning of each year
Emissionf	g	Greenhouse gas (GHG) emissions factor of fuel used by generation type g (kg CO2eq per MMBtu fuel)
CV	g, t	Capacity value or fraction of installed capacity of generator g contributing to planning reserve requirement
Load	s, h, d, t	Demand at node s in block h of dispatch period d in year t (MW)
MaxLoadMW	t	Maximum load to define planning reserve requirement(MW)
Curtailcost		Cost of curtailing generation in $ per MWh
Seasonscale	d	Weight to scale generation in each hour of representative day to d to its contribution to annual generation
RPSfrac	t	Fraction of annual load met by renewables in year t
RPSCapacityMin	t	Minimum renewable generating capacity to exist in each year in MW - included to modeled Texas renewables policy
WindPTC	t, tt	Production tax credit (PTC) for electricity produced from wind plants in period t that were built in periodd tt ($ per MWh) - applies to only first 10 years of operation of each plant
PTCforExistingPlants		PTC credit for each existing wind plant - $23 per MWh
Reservemargin		Reserve margin for planning reserves (% of load)

Name	Domains	Description
ORspin	h, d	Operating spinning reserves for each block h in dispatch period d (%)
ORTot	h, d	Total operating reserve requirement (spinning + non-spinning) for each block h in dispatch period d (%)
DiscountFact		Scalar (between 0 and 1) used to discount future year costs in the objective function to year 1 that allows consideration of inter-temporal trade-offs in the model
Dur	h	Duration of time block h = 1 hour
Yearrel	t	Years considered in the model (relative to t=0)
Opexmult	t	Multiplier to account for discounted operating cost for intermediate years between planning years
Objval_Units		Units in which the objective function value is measured (e.g. 1e9 ==>US$1 billion)

A.3 Variables

Name	Domains	Description
NGenR	g, s, t	No. of renewable generators of type g that are available at node s at beginning of year t
NGenInstallR	g, s, t	No. of renewable generators of type g that are installed at node s at beginning of year t
NGenRetireR	g, s, t	No. of renewable generators of type g that are retired at node s at beginning of year t
NGenRExtend	g, s, t	Number of generators of type g at node s that are extended beyond their economic lifetime at beginning of year t
NGenRInstalledCapTotal	g, s, t	Total number of generators of type g at node s that have not been retired at beginning of year t
AvgPower	g, s, h, d, t	Average power from generator g at node s in block h of dispatch period d in year t (MW)
SpinCap	g, s, h, d, t	Spinning capacity of generator type g located at node s and reserved during block h of dispatch period d in year t (MW))
Curtail	s, h, d, t	Total curtailed generation at each node s during each hour h dispatch period d and year t (MW)
Qstartcap	g, s, h, d, t	Quick start capacity of generator type g located at node s and reserved during block h of dispatch period d in year t (MW))
ObjInvgenTcost	t	Cost of installing new thermal generators in year t (billion $)
ObjInvgenRcost	t	Cost of installing new renewable generators in year t (billion $)
ObjRetrofitcost	t	Cost of extending lifetime of existing generator in year t (billion $)
ObjFOMTcost	t	Fixed operating and maintenance (FOM) cost of thermal generators in year t (billion $)
ObjFOMRcost	t	Fixed operating and maintenance cost of renewable generators in year t (billion $)

Name	Domains	Description
ObjVOMTcost	t	Variable operating and maintenance (VOM) cost of thermal generators in year t, excluding fuel costs (billion $)
ObjFuelTcost	t	Fuel costs of thermal generators in year t (billion $)
ObjEnvgencost	t	Environmental policy costs of generation in year t (billion $)
ObjStartupcost	t	Startup cost of thermal generators in year t (billion $)
ObjCurtailcost	t	Cost of curtailment for each year t
ObjVOMRcost	t	Variable operating cost of renewable generators in year t, (billion $)
ObjCredits	t	Production and investment tax credits for renewable generation in year t
NGenT	g, s, t	Integer number of generators of type g at node s that are before their economic lifetime and at beginning of year t
NGenTExtend	g, s, t	Integer number of thermal generators of type g at node s that are extended beyond their economic lifetime at beginning of year t
NGenTInstalledCapTotal	g, s, t	Integer number of thermal generators of type g at node s that have not been retired at beginning of year t
NGenInstallT	g, s, t	Integer number of thermal generators of type g at node s installed at beginning of year t
NGenRetireT	g, s, t	Integer number of thermal generators of type g at node s that are retired at beginning of year t
NShutD	g, s, h, d, t	Integer number of generators of type g at node s that are shutdown at beginning of block h of period d in year t
NStartUp	g, s, h, d, t	Integer number of generators of type g at node s that are started at beginning of block h of period d in year t
NGenOn	g, s, h, d, t	Integer number of generators of type g at node s that are on during block h of period d in year t
objval		Objective function value

A.4 Equations

Name	Domains	Description
ObjectiveFunction		Objective function minimizing total annualized cost
Loadbal	s, h, d, t	Load balance at each node and time instance
NGenOndef	g, s, h, d, t	Defining number of generators that are turned on
Rampdownlim	g, s, h, d, t	Defining Ramp down limits for thermal generators
Rampuplim	g, s, h, d, t	Defining Ramp up limits for thermal generators
Gencapexistdef	g, s, t	Tracking total existing thermal generation capacity
Gencapnewdef	g, s, t	Tracking total new thermal generation capacity
NewThermalendoflife	g, s, t	Determining end of lifetime state for new thermal generators

Name	Domains	Description
NGenTInstalledCapTotaldef	g, s, t	Total thermal generation capacity either in extended condition or pre-retirement condition
Renewcapexistdef	g, s, t	Tracking total existing renewable generation capacity
Renewcapnewdef	g, s, t	Tracking total new renewable generation capacity
Newrenewendoflife	g, s, t	Determining end of lifetime state for new renewable generators
NGenRInstalledCapTotaldef	g, s, t	Total renewable generation capacity either in extended condition or pre-retirement condition
Planningreservedef	t	Planning reserve requirement for the entire region for each year t
TotalOpreservedef	h, d, t	Total operating reserve requirement for the entire region for each time instance
Spinningreservedef	h, d, t	Spinning reserve requirement for the entire region for each time instance
Qstartfracdef	g, s, h, d, t	Fraction of generation capacity allocated to quick start reserves
Spinfracdef	g, s, h, d, t	Fraction of generation capacity allocated to spinning reserves
OpcapUB	g, s, h, d, t	Operating capacity upper bound for thermal generators
OpcapLB	g, s, h, d, t	Lower bound on operating capacity for thermal generators when ON
RenewoutputUB	g, s, h, d, t	Upper bound on renewable energy output for each hour
NGenOnUB	g, s, h, d, t	No. of generators turned on at any period cannot exceed total number of installed generators
NGenInstallTUB	g, t	Upper bound on number of thermal generators installed of type g in a year based on annual installation limits
NGenInstallRUB	g, t	Upper bound on number of renewable generators installed of type g in a year
RPSconstr	t	Minimum renewable penetration constraint for entire region
RPScapacityconstr	t	Constraint on minimum generating capacity of renewable resources as per policy requirements for Texas region
ObjInvgenTcostdef	t	Defining investment cost of thermal generators
ObjInvgenRcostdef	t	Defining investment cost of renewable generators
ObjRetrofitcostdef	t	Cost of extending lifetime of existing thermal generators
ObjFOMTcostdef	t	FOM cost of thermal generators
ObjFOMRcostdef	t	FOM cost of renewable generators
ObjVOMTcostdef	t	VOM cost of thermal generators, excluding fuel costs
ObjFuelTcostdef	t	Fuel cost of thermal generators
ObjVOMRcostdef	t	VOM cost of renewable generators -excludes fuel
ObjEnvgencostdef	t	Environmental policy cost of generation
ObjStartupcostdef	t	Startup cost and shutdown costs of thermal generators
Objcurtailcostdef	t	Cost penalty for curtailing renewable generation

Name	Domains	Description
ObjCreditsdef	t	Production and investment tax credits for renewable generation

A.5 Equation Definitions

A.5.1 ObjectiveFunction

$$\text{objval} = \sum_t \left(\frac{1}{(1+\text{DiscountFact})^{(\text{Yearrel}_t-1)}} \cdot (\text{ObjInvgenTcost}_t + \text{ObjInvgenRcost}_t + \text{ObjRetrofitcost}_t + \text{ObjFOMTcost}_t + \text{ObjFOMRcost}_t + \text{ObjVOMTcost}_t + \text{ObjFuelTcost}_t + \text{ObjVOMRcost}_t + \text{ObjEnvgencost}_t + \text{ObjStartupcost}_t + \text{ObjCurtailcost}_t - \text{ObjCredits}_t)\right)$$

A.5.2 $\text{Loadbal}_{s,h,d,t}$

$$\sum_g (\text{AvgPower}_{g,s,h,d,t}) = \text{Load}_{s,h,d,t} + \text{Curtail}_{s,h,d,t} \qquad \forall s,h,d,t$$

A.5.3 $\text{NGenOndef}_{g,s,h,d,t}$

$$\text{NGenOn}_{g,s,h,d,t} = \text{NGenOn}_{g,s,h--1,d,t} + \text{NStartUp}_{g,s,h,d,t} - \text{NShutD}_{g,s,h,d,t} \ \forall g,s,h,d,t \mid \text{Thermalbase}_g$$

A.5.4 $\text{Rampdownlim}_{g,s,h,d,t}$

$$\text{AvgPower}_{g,s,h--1,d,t} - \text{AvgPower}_{g,s,h,d,t} \leq (\text{NGenOn}_{g,s,h,d,t} - \text{NStartUp}_{g,s,h,d,t}) \cdot \text{DPdown}_g \cdot \text{Pgen}_{g,s} \cdot \text{Dur}_h + \max((\text{DPdown}_g \cdot \text{Dur}_h), \text{Pgenmin}_g) \cdot \text{Pgen}_{g,s} \cdot \text{NShutD}_{g,s,h,d,t} - \text{Pgenmin}_g \cdot \text{Pgen}_{g,s} \cdot \text{NStartUp}_{g,s,h,d,t} \ \forall g,s,h,d,t \mid \text{Thermalbase}_g$$

A.5.5 $\text{Rampuplim}_{g,s,h,d,t}$

$$\text{AvgPower}_{g,s,h,d,t} - \text{AvgPower}_{g,s,h--1,d,t} \leq (\text{NGenOn}_{g,s,h,d,t} - \text{NStartUp}_{g,s,h,d,t}) \cdot \text{DPup}_g \cdot \text{Pgen}_{g,s} \cdot \text{Dur}_h + \max((\text{DPup}_g \cdot \text{Dur}_h), \text{Pgenmin}_g) \cdot \text{Pgen}_{g,s} \cdot \text{NStartUp}_{g,s,h,d,t} - \text{Pgenmin}_g \cdot \text{Pgen}_{g,s} \cdot \text{NShutD}_{g,s,h,d,t} \ \forall g,s,h,d,t \mid \text{Thermalbase}_g$$

A.5.6 $\text{Gencapexistdef}_{g,s,t}$

$$\text{NGenT}_{g,s,t} = \text{NGenT}_{g,s,t-1} - \text{NGenRetireT}_{g,s,t} - \text{NGenTExtend}_{g,s,t} + \text{Ngenexist}_{g,s}[(\text{ord(t)} = 1)] \ \forall g,s,t \mid \text{Existingthermal}_g$$

A.5.7 $\text{NGenTInstalledCapTotaldef}_{g,s,t}$

$$\text{NGenTInstalledCapTotal}_{g,s,t} = \text{NGenT}_{g,s,t} + \sum_{tt \mid (\text{ord(tt)} \leq \text{ord(t)})} (\text{NGenTExtend}_{g,s,tt}) \ \forall g,s,t \mid \text{Thermal}_g$$

A.5.8 $\text{Gencapnewdef}_{g,s,t}$

$$\text{NGenT}_{g,s,t} = \text{NGenT}_{g,s,t-1} + \text{NGenInstallT}_{g,s,t} - \text{NGenRetireT}_{g,s,t} \qquad \forall g,s,t \mid \text{Newthermal}_g$$

A.5.9 $\text{Renewcapexistdef}_{g,s,t}$

$$\text{NGenR}_{g,s,t} = \text{NGenR}_{g,s,t-1} - \text{NGenRetireR}_{g,s,t} - \text{NGenRExtend}_{g,s,t} + \text{Ngenexist}_{g,s}[(\text{ord(t)} = 1)] \ \forall g,s,t \mid \text{ExistingRenew}_g$$

A.5.10 NGenRInstalledCapTotaldef$_{g,s,t}$

$$\text{NGenRInstalledCapTotal}_{g,s,t} = \text{NGenR}_{g,s,t} + \sum_{tt|(\text{ord(tt)} \leq \text{ord(t)})} (\text{NGenRExtend}_{g,s,tt}) \ \forall g, s, t \ |\text{Renew}_g$$

A.5.11 Renewcapnewdef$_{g,s,t}$

$$\text{NGenR}_{g,s,t} = \text{NGenR}_{g,s,t-1} + \text{NGenInstallR}_{g,s,t} - \text{NGenRetireR}_{g,s,t} - \text{NGenRExtend}_{g,s,t} \ \forall g, s, t \ |\text{NewRenew}_g$$

A.5.12 NewThermalendoflife$_{g,s,t}$

$$\sum_{tt|(\text{ord(tt)} \leq \text{ord(t)})} (\text{NGenRetireT}_{g,s,tt}) \geq \sum_{tt|(\text{Yearrel}_{tt} \leq (\text{Yearrel}_t - \text{Tlife}_g))} (\text{NGenInstallT}_{g,s,tt})$$
$$\forall g, s, t \mid ((\text{Tlife}_g \leq (\text{Yearrel}_t - 1)) \wedge \text{Newthermal}_g)$$

A.5.13 Newrenewendoflife$_{g,s,t}$

$$\sum_{tt|(\text{ord(tt)} \leq \text{ord(t)})} (\text{NGenRetireR}_{g,s,tt} + \text{NGenRExtend}_{g,s,tt}) \geq \sum_{tt|(\text{Yearrel}_{tt} \leq (\text{Yearrel}_t - \text{Tlife}_g))} (\text{NGenInstallR}_{g,s,tt})$$
$$\forall g, s, t \mid ((\text{Tlife}_g \leq (\text{Yearrel}_t - 1)) \wedge \text{NewRenew}_g)$$

A.5.14 Planningreservedef$_t$

$$\sum_{s,Thermal_g} (\text{NGenTInstalledCapTotal}_{g,s,t} \cdot \text{Pgen}_{g,s}) + \sum_{s,Renew_g} (\text{NGenRInstalledCapTotal}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot$$
$$\text{CV}_{g,t}) \geq (1 + \text{Reservemargin}) \cdot \text{MaxLoadMW}_t \qquad \forall t$$

A.5.15 TotalOpreservedef$_{h,d,t}$

$$\sum_{s,ThermalSpin_g} (\text{SpinCap}_{g,s,h,d,t}) + \sum_{s,ThermalQstart_g} (\text{Qstartcap}_{g,s,h,d,t}) \geq \text{ORTot}_{h,d} \cdot \sum_s (\text{Load}_{s,h,d,t})$$
$$\forall h, d, t$$

A.5.16 Spinningreservedef$_{h,d,t}$

$$\sum_{s,ThermalSpin_g} (\text{SpinCap}_{g,s,h,d,t}) + \geq \text{ORspin}_{h,d} \cdot \sum_s (\text{Load}_{s,h,d,t}) \qquad \forall h, d, t$$

A.5.17 Qstartfracdef$_{g,s,h,d,t}$

$$\text{Qstartcap}_{g,s,h,d,t} \leq (\text{NGenTInstalledCapTotal}_{g,s,t} - \text{NGenOn}_{g,s,h,d,t}) \cdot \text{Qstartfrac}_g \cdot \text{Pgen}_{g,s} \ \forall g, s, h, d, t \mid \text{ThermalQstart}_g$$

A.5.18 Spinfracdef$_{g,s,h,d,t}$

$$\text{SpinCap}_{g,s,h,d,t} \leq \text{NGenOn}_{g,s,h,d,t} \cdot \text{Spinfrac}_g \cdot \text{Pgen}_{g,s} \qquad \forall g, s, h, d, t \mid \text{ThermalSpin}_g$$

A.5.19 OpcapUB$_{g,s,h,d,t}$

$$\text{AvgPower}_{g,s,h,d,t} + \text{SpinCap}_{g,s,h,d,t} \leq \text{NGenOn}_{g,s,h,d,t} \cdot \text{Pgen}_{g,s} \qquad \forall g, s, h, d, t \mid \text{Thermal}_g$$

A.5.20 $\textbf{OpcapLB}_{g,s,h,d,t}$

$$\text{AvgPower}_{g,s,h,d,t} \geq \text{NGenOn}_{g,s,h,d,t} \cdot \text{Pgenmin}_g \cdot \text{Pgen}_{g,s} \qquad \forall g,s,h,d,t \mid \text{Thermalbase}_g$$

A.5.21 $\textbf{RenewoutputUB}_{g,s,h,d,t}$

$$\text{AvgPower}_{g,s,h,d,t} = \text{NGenRInstalledCapTotal}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot \text{Cf}_{g,s,h,d} \qquad \forall g,s,h,d,t \mid \text{Renew}_g$$

A.5.22 $\textbf{NGenOnUB}_{g,s,h,d,t}$

$$\text{NGenOn}_{g,s,h,d,t} \leq \text{NGenTInstalledCapTotal}_{g,s,t} \qquad \forall g,s,h,d,t \mid \text{Thermal}_g$$

A.5.23 $\textbf{NGenInstallTUB}_{g,t}$

$$\sum_s (\text{NGenInstallT}_{g,s,t}) \leq \text{Nmaxgeninstall}_{g,t} \cdot (\text{Yearrel}_{t+1} - \text{Yearrel}_t)[(\text{ord(t)} < |t|)] +$$
$$\text{Nmaxgeninstall}_{g,t} \cdot (\text{Yearrel}_t - \text{Yearrel}_{t-1})[(\text{ord(t)} = |t|)] \qquad \forall g,t \mid \text{Newthermal}_g$$

A.5.24 $\textbf{NGenInstallRUB}_{g,t}$

$$\sum_s (\text{NGenInstallR}_{g,s,t}) \leq \text{Nmaxgeninstall}_{g,t} \cdot (\text{Yearrel}_{t+1} - \text{Yearrel}_t)[(\text{ord(t)} < |t|)] +$$
$$\text{Nmaxgeninstall}_{g,t} \cdot (\text{Yearrel}_t - \text{Yearrel}_{t-1})[(\text{ord(t)} = |t|)] \qquad \forall g,t \mid \text{NewRenew}_g$$

A.5.25 $\textbf{RPSconstr}_t$

$$\sum_{s,h,d,Renew_g} (\text{AvgPower}_{g,s,h,d,t} - \text{Curtail}_{s,h,d,t}) \cdot \text{Seasonscale}_d \geq \text{RPSfrac}_t \cdot \sum_{s,h,d} (\text{Load}_{s,h,d,t} \cdot \text{Seasonscale}_d)$$
$$\forall t \mid (\text{RPSfrac}_t > 0)$$

A.5.26 $\textbf{RPScapacityconstr}_t$

$$\sum_{s,Renew_g} (\text{NGenRInstalledCapTotal}_{g,s,t} \cdot \text{Pgen}_{g,s}) \geq \text{RPSCapacityMin}_t$$
$$\forall t \mid (\text{RPSCapacityMin}_t > 0)$$

A.5.27 $\textbf{ObjInvgenTcostdef}_t$

$$\text{ObjInvgenTcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \sum_{s,g,Validloc_s,Newthermal_g} (\text{NGenInstallT}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot (\text{Capmult}_g \cdot$$
$$\text{Investmult}_{g,t} \cdot \text{CapCost}_{g,t} \cdot 1000 + \text{Investmult}_{g,t} \cdot \text{Gridconnect}_{g,t} \cdot 1000)) \qquad \forall t \mid \text{ActiveVarSet}_t$$

A.5.28 $\textbf{ObjInvgenRcostdef}_t$

$$\text{ObjInvgenRcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \sum_{s,NewRenew_g} (\text{NGenInstallR}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot (\text{Capmult}_g \cdot \text{Investmult}_{g,t} \cdot$$
$$\text{CapCost}_{g,t} \cdot 1000 + \text{Investmult}_{g,t} \cdot \text{Gridconnect}_{g,t} \cdot 1000)) \qquad \forall t$$

A.5.29 ObjRetrofitcostdef$_t$

$$\text{ObjRetrofitcost}_t = \frac{1}{\text{Objval\_Units}} \cdot (\sum_{s,Thermal_g} (\text{NGenTExtend}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot \text{Investmult}_{g,t} \cdot \text{LifeExtensionCost}_{g,t} \cdot 1000) + \sum_{s,Renew_g} (\text{NGenRExtend}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot \text{Investmult}_{g,t} \cdot \text{LifeExtensionCost}_{g,t} \cdot 1000)) \qquad \forall t$$

A.5.30 ObjFOMTcostdef$_t$

$$\text{ObjFOMTcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{s,Thermal_g} (\text{NGenTInstalledCapTotal}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot \text{FOMCost}_{g,t} \cdot 1000) \qquad \forall t$$

A.5.31 ObjFOMRcostdef$_t$

$$\text{ObjFOMRcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{s,Renew_g} (\text{NGenRInstalledCapTotal}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot \text{FOMCost}_{g,t} \cdot 1000) \qquad \forall t$$

A.5.32 ObjVOMTcostdef$_t$

$$\text{ObjVOMTcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{s,h,d,Thermal_g} (\text{AvgPower}_{g,s,h,d,t} \cdot \text{Dur}_h \cdot \text{VOMCost}_{g,t} \cdot \text{Seasonscale}_d) \qquad \forall t$$

A.5.33 ObjFuelTcostdef$_t$

$$\text{ObjFuelTcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{s,h,d,Thermal_g} (\text{AvgPower}_{g,s,h,d,t} \cdot \text{Dur}_h \cdot \frac{\text{Heatrate}_{g,s} \cdot \text{FuelCost}_{g,t}}{1000} \cdot \text{Seasonscale}_d) \qquad \forall t$$

A.5.34 ObjVOMRcostdef$_t$

$$\text{ObjVOMRcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{s,h,d,Renew_g} (\text{AvgPower}_{g,s,h,d,t} \cdot \text{Dur}_h \cdot \text{VOMCost}_{g,t} \cdot \text{Seasonscale}_d) \qquad \forall t$$

A.5.35 ObjEnvgencostdef$_t$

$$\text{ObjEnvgencost}_t = \frac{\text{Opexmult}_t}{\text{Objval\_Units}} \cdot (\sum_{s,h,d,} (\frac{\frac{\text{AvgPower}_{g,s,h,d,t} \cdot \text{Dur}_h \cdot \text{Seasonscale}_d \cdot \text{Heatrate}_{g,s}}{1000} \cdot \text{Emissionf}_g \cdot \text{CarbonTax}_t}{1000}) + \sum_{s,h,d} (\frac{\text{NStartUp}_{g,s,h,d,t} \cdot \text{Pgen}_{g,s} \cdot \text{FuelCost}_{g,t} \cdot \text{StartupFueluse}_g \cdot \text{Seasonscale}_d \cdot \text{Emissionf}_g}{1000} \cdot \text{CarbonTax}_t))$$

$\forall t$

A.5.36 ObjStartupcostdef$_t$

$$\text{ObjStartupcost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{s,h,d,Thermalbase_g} (\text{NStartUp}_{g,s,h,d,t} \cdot \text{Pgen}_{g,s} \cdot \text{StartUpcost}_{g,t} \cdot \text{Seasonscale}_d + \text{NStartUp}_{g,s,h,d,t} \cdot \text{Pgen}_{g,s} \cdot \text{FuelCost}_{g,t} \cdot \text{StartupFueluse}_g \cdot \text{Seasonscale}_d) \qquad \forall t$$

A.5.37 Objcurtailcostdef$_t$

$$\text{ObjCurtailcost}_t = \frac{\text{Opexmult}_t}{\text{Objval\_Units}} \cdot \text{Curtailcost} \cdot \sum_{s,h,d} (\text{Curtail}_{s,h,d,t} \cdot \text{Dur}_h \cdot \text{Seasonscale}_d) \qquad \forall t$$

A.5.38 ObjCreditsdef$_t$

$$\text{ObjCredits}_t = \frac{\text{Opexmult}_t}{\text{Objval\_Units}} \cdot \Big(\sum_{g,s,h,d,tt|(\text{Wind}_g \wedge \text{NewRenew}_g)} (\text{NGenInstallR}_{g,s,tt} \cdot \text{Pgen}_{g,s} \cdot \text{Cf}_{g,s,h,d} \cdot \text{Dur}_h \cdot \text{Seasonscale}_d \cdot \text{WindPTC}_{t,tt}) + \sum_{g,s,h,d|(\text{Wind}_g \wedge \text{ExistingRenew}_g)} (\text{PTCEligiblePlants}_{g,s,t} \cdot \text{Pgen}_{g,s} \cdot \text{Cf}_{g,s,h,d} \cdot \text{Dur}_h \cdot \text{Seasonscale}_d \cdot \text{PTCforExistingPlants}) \Big) \qquad \forall t$$

Decision variable	**Index domain**
$\text{ObjInvgenTcost}_t \geq 0$	$\forall t$
$\text{ObjInvgenRcost}_t \geq 0$	$\forall t$
$\text{ObjRetrofitcost}_t \geq 0$	$\forall t$
$\text{ObjFOMTcost}_t \geq 0$	$\forall t$
$\text{ObjFOMRcost}_t \geq 0$	$\forall t$
$\text{ObjVOMTcost}_t \geq 0$	$\forall t$
$\text{ObjFuelTcost}_t \geq 0$	$\forall t$
$\text{ObjFuelRcost}_t \geq 0$	$\forall t$
$\text{ObjVOMRcost}_t \geq 0$	$\forall t$
$\text{ObjEnvgencost}_t \geq 0$	$\forall t$
$\text{ObjStartupcost}_t \geq 0$	$\forall t$
$\text{ObjCurtailcost}_t \geq 0$	$\forall t$
$\text{ObjCredits}_t \geq 0$	$\forall t$
$\text{AvgPower}_{g,s,h,d,t} \geq 0$	$\forall g, s, h, d, t$
$\text{Curtail}_{s,h,d,t} \geq 0$	$\forall s, h, d, t$
$\text{NGenOn}_{g,s,h,d,t} \in \mathbb{Z}_+$	$\forall g, s, h, d, t$
$\text{NStartUp}_{g,s,h,d,t} \in \mathbb{Z}_+$	$\forall g, s, h, d, t$
$\text{NShutD}_{g,s,h,d,t} \in \mathbb{Z}_+$	$\forall g, s, h, d, t$
$\text{NGenT}_{g,s,t} \in \mathbb{Z}_+$	$\forall g, s, t$
$\text{NGenRetireT}_{g,s,t} \in \mathbb{Z}_+$	$\forall g, s, t$
$\text{NGenTExtend}_{g,s,t} \in \mathbb{Z}_+$	$\forall g, s, t$
$\text{NGenTInstalledCapTotal}_{g,s,t} \in \mathbb{Z}_+$	$\forall g, s, t$
$\text{NGenInstallT}_{g,s,t} \in \mathbb{Z}_+$	$\forall g, s, t$
$\text{NGenR}_{g,s,t} \geq 0$	$\forall g, s, t$
$\text{NGenRetireR}_{g,s,t} \geq 0$	$\forall g, s, t$
$\text{NGenRExtend}_{g,s,t} \geq 0$	$\forall g, s, t$
$\text{NGenRInstalledCapTotal}_{g,s,t} \geq 0$	$\forall g, s, t$
$\text{NGenInstallR}_{g,s,t} \geq 0$	$\forall g, s, t$
$\text{Qstartcap}_{g,s,h,d,t} \geq 0$	$\forall g, s, h, d, t$

B Time Slice Capacity Expansion Model (TS-CEM)

Notes: The time slice model includes a set of nodes, for a transmission network, and a set of states. Neither are used the study. That is, each set is a singleton.

B.1 Sets

Name	Domains	Description
block, block1, block2	*	Set of blocks associated with time load blocks
g	g	Set of generator types and technologies (existing and potential)
n	*	Set of nodes
t, tt	t	Set of all time periods
state	*	Set of states
fuel_type	*	Set of fuel types
fuel_bin	*	Set of fuel bins for the fuel supply curves
supply_bin	*	Set of supply bins for each resource capacity supply curves
t_ptc	t	Set of time periods (years) in which the production tax credit
g_thermal	g	Set of all (old and new) thermal generators (e.g., Coal, NG, Nuclear)
g_renew	g	Set of renewable generators
g_dispatchable	g	Set of dispatchable generators that can adjust power output on demand and contribute to operating reserves
g_wind	g_renew	Set of wind generators
g_wind_new	g_wind	Set of new wind generators
g_new	g	Set of new generator types
g_itc_eligible	g_renew	Set of ITC eligible generator types

B.2 Parameters

Name	Domains	Description
CapacityFactor	g, n, t, block	The fraction of nameplate capacity that is actually available for generator type g at node n in time period t in time block 'block'
CapacityValue	g	Amount of electrical demand that may be added in each time-slice for an incremental increase in capacity of a given VRRE technology
CapitalMultiplier	g	Capital multiplier associated with generator type g (positive scalar typically between 1 and 2
ExistingInstalledCapacity	g, n	Existing installed capacity of generator type g at node n prior to the planning horizon (MW)
GHG	g	GHG emissions of generator (ton CO2e per MMBtu)
HeatRate	g	Heat rate of generator type g (MMBtu per MWh)
LeadTime	g	Lead time between decision to invest and the time when generator type g is operational (years)
LifeTime	g	Lifetime of generator type g (years)

Name	Domains	Description
MTDF	g	Minimum turndown fraction (as a fraction of nameplate capacity) that a generator must maintain (e.g. for nuclear generators ReEDS assumes this parameter is 1.00 implying that nuclear generators must run at capacity when they are available)
ExtensionCost	g, t	Cost to extend indefinitely the lifetime of generator type g in time period t ($ per MW)
FOMCost	g, t	Annual fixed operating & maintenance costs for generator type g in time period t ($ per MWh)
GridConnectCost	g, t	Cost of connecting new generation capacity of generator type g in time period t to the grid ($ per MW)
Min_Cumulative_MW_To_Extend_Or_Retire	g, t	Minimum capacity (MW) of generator type g to extend or retire by time period t
VOMCost	g, t	Variable operating & maintenance costs for generator type g in time period t ($ per MWh)
FuelTypeCost_Bin	fuel_type, t, fuel_bin	Cost of fuel type fuel_type in time period t in fuel bin fuel_bin at ($ per MMBtu)
GenInstallUB	g, n, t	Upper bound on amount of generation type g that can be installed at node n in time period t (MW)
GenInstallCost_Bin	g, t, supply_bin	Overnight installation capital cost of generator type g in time period t in supply_bin ($ per MW)
LoadMW	n, t, block	Average load at node n in time period t in load block 'block' (MW)
LoadMWh	n, t, block	Average load at node n in time period t in load block 'block' (MWh)
MaxLoadMW	n, t	Maximum load at node n in time period t (MW)
NumHours	block	Number of hours in time period t in load block block (positive integer)
PlanningReserveMargin	n, t	Fraction (e.g., 0.1375) of max load that must be met in the capacity reserve constraints
OperatingReserveMargin		Fraction (e.g., 0.075) of load that must be met by spinning and quickstart reserves
MaxQuickstartReserveMargin		Fraction (e.g., 0.06) denoting the maximum amount of operating reserves that can be supplied from quickstarts
MinSpinningReserveMargin		Fraction (e.g., 0.03) denoting the minimum amount of amount of spinning reserves
ForecastErrorReserve		Fraction
RPS_MIN_GEN_AMOUNT	state, t	Minimum generation (MWh) in state 'state' in time period t required by Renewable Portfolio Standards
BlocksBelongToSameSeason	block1, block2	1 if blocks belong to same season - 0 otherwise
IsFuelTypeGeneratorPair	fuel_type, g	1 if generator type g uses fuel type fuel_type - 0 otherwise (Needed for supply curves)
IsStateNodePair	state, n	1 if node n is in state - 0 otherwise
CarbonPrice	t	Carbon price ($ per ton C02e)
ITC_Fraction	g, t	Investment tax credit fraction (fraction of capital cost) applied to generator type g installed in time period t

Name	Domains	Description
Opexmult	t	Operating multiplier in time period t to account for intermediate model years
PTC	t_ptc	Production tax credit ($ per MWh) to apply for new wind generators installed in time period t_ptc
rel_ord	t	Relative order of time period t e.g. rel_ord('t3') = 3 even if ord('t3') = 2
PTC_constant	t	Constant ($) of production tax credit attributed to wind-old in time period t (computed directly in GAMS)
DiscountFactor		Scalar (Scalar between 0 and 1)
Include_Tax_Credits		Takes value 1 if investment and production tax credits should be included - 0 otherwise
PenaltyUnmetDemand		Penalty for each unit of unmet demand ($ per MWh)
PenaltyExcessGeneration		Penalty for each unit of excess generation ($ per MWh)
Objval_Units		Units in which the objective function value is measured (e.g. 1e9 ==>US$1 billion)

B.3 Variables

Name	Domains	Description
avgPower	g, n, t, block	Average power (capacity in use) from generator g at node n in time period t in load block block (MW)
generation	g, n, t, block	Average generation from g from generator g at node n in time period t in load block block (MWh)
genInstall	g, n, t	Capacity (MW) of generation type g initially installed at node n in time period t
genInstall_Bin	g, t, supply_bin	Capacity (MW) of generation type g installed in time period t in supply bin 'supply_bin'
installedCapacity	g, n, t	Total installed nameplate capacity (MW) of generator type g at node n available to serve load in time period t (after all installation - upgrades - and retirements take place in time period t)
effectiveCapacity	g, n, t, block	Effective or firm capacity (MW) of generator type g at node n available to serve load in time period t
extendedCapacity	g, n, t	Capacity (MW) of generation type g at node n in time period t whose lifetime is extended indefinitely
retiredCapacity	g, n, t	Capacity (MW) of generation type g retired at node n in time period t
spinningReserve	g_dispatchable, n, t, block	Power (MW) of dispatchable generator g available to serve spinning reserves at node n in time period t in block block (MW)
quickstartReserve	g_dispatchable, n, t, block	Power (MW) of dispatchable generator g available for quickstart at node n in time period t in block block (MW)
amountEnergyConsumed	g, t	Amount of energy (MMBtu) consumed by generator type g in time period t

Name	Domains	Description
amountFuelTypeConsumed	fuel_type, t	Amount of fuel type fuel_type consumed in time period t (MMBtu)
amountFuelTypeConsumed InFuelBin	fuel_type, t, fuel_bin	Amount of fuel type fuel_type consumed in time period t in fuel bin fuel_bin (Quad = 1e9 MMBtu = 1e15 Btu)
unmetDemand	n, t, block	Unmet demand (MWh)
excessGeneration	n, t, block	Excess generation (MWh)
ptc_generation	g_wind_new, t_ptc, t	Generation (MWh) from new wind resources in time period t that were built in time period t_ptc
objval		Objective function value
VC_Obj_InstallationCost	t	Auxiliary variable to isolate installation costs
VC_Obj_AnnualFOMCost	t	Auxiliary variable to isolate annual FOM costs
VC_Obj_CarbonTax	t	Auxiliary variable to isolate emissions costs
VC_Obj_ExtensionCost	t	Auxiliary variable to isolate extension costs
VC_Obj_FuelCost	t	Auxiliary variable to isolate fuel costs
VC_Obj_PenaltyUnmetDemand	t	Auxiliary variable to isolate unmet demand costs
VC_Obj_PenaltyExcessGen	t	Auxiliary variable to isolate excess generation costs
VC_Obj_VOMCost	t	Auxiliary variable to isolate VOM costs
VC_Obj_ITC	t	Auxiliary variable to isolate investment tax credit savings
VC_Obj_PTC	t	Auxiliary variable to isolate production tax credit savings

B.4 Equations

Name	Domains	Description
C_ObjectiveFunction		Objective function minimizing generation cost
C_LoadConstr	n, t, block	Load constraint at node n in time period t
C_PowerToGeneration Constr	g, n, t, block	Convert average power (MW) to generation (MWh) in block
C_InstallationCostConstr	t	Redundant constraint to isolate installation costs
C_AnnualFixedOMCost Constr	t	Redundant constraint to isolate annual FOM costs
C_VarOMCostConstr	t	Redundant constraint to isolate VOM costs
C_FuelCostConstr	t	Redundant constraint to isolate fuel costs
C_ExtensionCostConstr	t	Redundant constraint to isolate extension costs
C_CarbonTaxConstr	t	Redundant constraint to isolate emissions costs
C_PenaltyUnmetDemand Constr	t	Redundant constraint to isolate unmet demand costs
C_PenaltyExcessGeneration Constr	t	Redundant constraint to isolate excess generation costs
C_ITC_Obj_Constr	t	Redundant constraint to isolate investment tax credit savings
C_PTC_Obj_Constr	t	Redundant constraint to isolate production tax credit savings
C_InstalledCapConstr	g, n, t	Capacity balance constraint for each generator type g in each time period t
C_EffectiveCapConstr	g, n, t, block	The effective capacity of generator type g in time period t and time block 'block' equals the capacity factor in that block times the installed capacity

Name	Domains	Description
C_RetireCapConstr	g, n, t	Retire or extend capacity that exceeds its lifetime + leadtime to build
C_DispatchableGenCap Constr	g_dispatchable, n, t, block	Dispatchable power plus spinning reserves plus quickstart reserves must not exceed effective capacity
C_RenewableGenCap Constr	g_renew, n, t, block	Average power equals effective capacity
C_MinimumTurndown Constr	g_thermal, n, t, block1, block2	Minimum power level that a generator must satisfy in each time block
C_PlanningReserveConstr	n, t	Planning reserve requirements at node n in time period t
C_OperatingReserve Constr	n, t, block	Operating reserve requirement at node n in time period t in load block block - ReEDS does this for each rs_group
C_MaxQuickstartReserve Constr	n, t, block	
C_SpinningReserveConstr	n, t, block	Spinning reserve requirement at node n in time period t in load block block - ReEDS does this for each rs_group
C_RPS_Gen_Constr	state, t	Requires a minimum generation amount (MWh) from renewable resources in a particular state in time period t
C_AmountEnergyConsumed Constr	g, t	The amount of energy consumed by generator type g in time period t equals heat rate times the generation of g over all time blocks in that period
C_FuelTypeConsumed Constr	fuel_type, t	Equate amount of fuel type fuel_type consumed in time period t with the amount of generation from that same fuel type
C_FuelTypeConsumed SupplyCurveConstr	fuel_type, t	Equate amount of fuel type fuel_type consumed in time period t with amount of fuel type fuel_type consumed in each fuel bin
C_InstallationSupply CurveConstr	g, t	Sum of installations over all supply bins must equal the total amount installed (for each g,t pair)
C_PTC_Constr	g_wind_new, t_ptc, t	Computes the correct amount of ptc eligible generation

B.5 Equation Definitions

Parameters are shown in red. Decision variables are shown in blue.

B.5.1 C_ObjectiveFunction

$$\sum_t (\text{DiscountFactor}^{\text{rel\_ord}_t} \cdot (\text{VC\_Obj\_InstallationCost}_t + \text{VC\_Obj\_AnnualFOMCost}_t + \text{VC\_Obj\_VOMCost}_t + \text{VC\_Obj\_FuelCost}_t + \text{VC\_Obj\_CarbonTax}_t + \text{VC\_Obj\_PenaltyUnmetDemand}_t + \text{VC\_Obj\_PenaltyExcessGen}_t + \text{VC\_Obj\_ExtensionCost}_t - \text{VC\_Obj\_ITC}_t[\text{Include\_Tax\_Credits}] - \text{VC\_Obj\_PTC}_t[\text{Include\_Tax\_Credits}])) = \text{objval}$$

B.5.2 C_InstallationCostConstr$_t$

$$\text{VC\_Obj\_InstallationCost}_t = \sum_{g,supply\_bin} ((\text{CapitalMultiplier}_g \cdot \text{GenInstallCost\_Bin}_{g,t,supply\_bin} + \text{GridConnectCost}_{g,t}) \cdot \text{genInstall\_Bin}_{g,t,supply\_bin}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.3 C_AnnualFixedOMCostConstr$_t$

$$\text{VC\_Obj\_AnnualFOMCost}_t = \text{Opexmult}_t \cdot \sum_{g,n} (\text{FOMCost}_{g,t} \cdot \text{installedCapacity}_{g,n,t}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.4 C_VarOMCostConstr$_t$

$$\text{VC\_Obj\_VOMCost}_t = \text{Opexmult}_t \cdot \sum_{g,n,block} (\text{VOMCost}_{g,t} \cdot \text{generation}_{g,n,t,block}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.5 C_ExtensionCostConstr$_t$

$$\text{VC\_Obj\_ExtensionCost}_t = \sum_{g,n} (\text{ExtensionCost}_{g,t} \cdot \text{extendedCapacity}_{g,n,t}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.6 C_FuelCostConstr$_t$

$$\text{VC\_Obj\_FuelCost}_t = \frac{1}{\text{Objval\_Units}} \cdot \text{Opexmult}_t \cdot \sum_{fuel\_type,fuel\_bin} (\text{FuelTypeCost\_Bin}_{fuel\_type,t,fuel\_bin} \cdot \text{amountFuelTypeConsumedInFuelBin}_{fuel\_type,t,fuel\_bin}) \qquad \forall t$$

B.5.7 C_CarbonTaxConstr$_t$

$$\text{VC\_Obj\_CarbonTax}_t = \text{Opexmult}_t \cdot \sum_{g} (\text{CarbonPrice}_t \cdot \text{GHG}_g \cdot \text{amountEnergyConsumed}_{g,t}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.8 C_PenaltyUnmetDemandConstr$_t$

$$\text{VC\_Obj\_PenaltyUnmetDemand}_t = \text{Opexmult}_t \cdot \sum_{n,block} (\text{PenaltyUnmetDemand} \cdot \text{unmetDemand}_{n,t,block}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.9 C_PenaltyExcessGenerationConstr$_t$

$$\text{VC\_Obj\_PenaltyExcessGen}_t = \text{Opexmult}_t \cdot \sum_{n,block} (\text{PenaltyExcessGeneration} \cdot \text{excessGeneration}_{n,t,block}) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t$$

B.5.10 C_ITC_Obj_Constr$_t$

$$\text{VC\_Obj\_ITC}_t = \sum_{g\_itc\_eligible,supply\_bin} (\text{ITC\_Fraction}_{g\_itc\_eligible,t} \cdot \text{CapitalMultiplier}_{g\_itc\_eligible} \cdot \text{GenInstallCost\_Bin}_{g\_itc\_eligible,t,supply\_bin} \cdot \text{genInstall\_Bin}_{g\_itc\_eligible,t,supply\_bin}) \cdot \frac{1}{\text{Objval\_Units}}$$

$$\forall t \mid \text{Include\_Tax\_Credits}$$

B.5.11 C_PTC_Obj_Constr$_t$

$$\text{VC\_Obj\_PTC}_t = \text{Opexmult}_t \cdot (\text{PTC}_{\texttt{t1}} \cdot \text{PTC\_constant}_t + \sum_{g\_wind\_new,t\_ptc|(\text{ord(t\_ptc)} \leq \text{rel\_ord}_t)} (\text{PTC}_{t\_ptc} \cdot \text{ptc\_generation}_{g\_wind\_new,t\_ptc,t})) \cdot \frac{1}{\text{Objval\_Units}} \qquad \forall t \mid \text{Include\_Tax\_Credits}$$

B.5.12 C_LoadConstr$_{n,t,block}$

$$\sum_g (\text{generation}_{g,n,t,block}) + \text{unmetDemand}_{n,t,block} = \text{LoadMWh}_{n,t,block} + \text{excessGeneration}_{n,t,block}$$
$$\forall n, t, block$$

B.5.13 C_PowerToGenerationConstr$_{g,n,t,block}$

$$\text{generation}_{g,n,t,block} = \text{avgPower}_{g,n,t,block} \cdot \text{NumHours}_{block} \qquad \forall g, n, t, block$$

B.5.14 C_EffectiveCapConstr$_{g,n,t,block}$

$$\text{effectiveCapacity}_{g,n,t,block} = \text{CapacityFactor}_{g,n,t,block} \cdot \text{installedCapacity}_{g,n,t} \qquad \forall g, n, t, block$$

B.5.15 C_InstalledCapConstr$_{g,n,t}$

$$\text{installedCapacity}_{g,n,t} = \text{ExistingInstalledCapacity}_{g,n}[(\text{rel\_ord}_t = 1)] + \text{installedCapacity}_{g,n,t-1} + \text{genInstall}_{g,n,t-\text{LeadTime}_g} - \text{retiredCapacity}_{g,n,t} \qquad \forall g, n, t$$

B.5.16 C_RetireCapConstr$_{g,n,t}$

$$\sum_{tt|(\text{rel\_ord}_{tt} \leq \text{rel\_ord}_t)} (\text{extendedCapacity}_{g,n,tt} + \text{retiredCapacity}_{g,n,tt})$$
$$\geq \text{Min\_Cumulative\_MW\_To\_Extend\_Or\_Retire}_{g,t}[(\text{ExistingInstalledCapacity}_{g,n} > 0)]$$
$$+ \sum_{tt|(\text{rel\_ord}_{tt} \leq (\text{rel\_ord}_t - (\text{LeadTime}_g + \text{LifeTime}_g)))} (\text{genInstall}_{g,n,tt})$$
$$\forall g, n, t \mid ((\text{ExistingInstalledCapacity}_{g,n} > 0) \vee \text{g\_new}_g \wedge ((\text{rel\_ord}_t - (\text{LeadTime}_g + \text{LifeTime}_g)) > 0))$$

B.5.17 C_DispatchableGenCapConstr$_{g_dispatchable,n,t,block}$

$$\text{avgPower}_{g\_dispatchable,n,t,block} + \text{spinningReserve}_{g\_dispatchable,n,t,block} + \text{quickstartReserve}_{g\_dispatchable,n,t,block} \leq \text{effectiveCapacity}_{g\_dispatchable,n,t,block} \qquad \forall g\_dispatchable, n, t, block$$

B.5.18 C_RenewableGenCapConstr$_{g_renew,n,t,block}$

$$\text{avgPower}_{g\_renew,n,t,block} = \text{effectiveCapacity}_{g\_renew,n,t,block} \qquad \forall g\_renew, n, t, block$$

B.5.19 C_MinimumTurndownConstr$_{g_thermal,n,t,block1,block2}$

$$\text{avgPower}_{g\_thermal,n,t,block1} \geq \text{MTDF}_{g\_thermal} \cdot \text{avgPower}_{g\_thermal,n,t,block2}$$
$$\forall g\_thermal, n, t, block1, block2 \mid ((\text{MTDF}_{g\_thermal} > 0) \wedge (\neg(\text{ord}(\text{block1}) = \text{ord}(\text{block2}))) \wedge \text{BlocksBelongToSameSeason}_{block1,block2})$$

B.5.20 C_PlanningReserveConstr$_{n,t}$

$$\sum_{g}(\text{CapacityValue}_{g} \cdot \text{installedCapacity}_{g,n,t}) \geq \text{MaxLoadMW}_{n,t} \cdot (1 + \text{PlanningReserveMargin}_{n,t})$$
$$\forall n, t$$

B.5.21 C_OperatingReserveConstr$_{n,t,block}$

$$\sum_{g\_dispatchable}(\text{spinningReserve}_{g\_dispatchable,n,t,block} + \text{quickstartReserve}_{g\_dispatchable,n,t,block}) \geq \text{LoadMW}_{n,t,block} \cdot \text{OperatingReserveMargin} + \text{ForecastErrorReserve} \qquad \forall n, t, block$$

B.5.22 C_MaxQuickstartReserveConstr$_{n,t,block}$

$$\sum_{g\_dispatchable}(\text{quickstartReserve}_{g\_dispatchable,n,t,block}) \leq \text{LoadMW}_{n,t,block} \cdot \text{MaxQuickstartReserveMargin} + \frac{5}{6} \cdot \text{ForecastErrorReserve} \qquad \forall n, t, block$$

B.5.23 C_SpinningReserveConstr$_{n,t,block}$

$$\sum_{g\_dispatchable}(\text{spinningReserve}_{g\_dispatchable,n,t,block}) \geq \text{LoadMW}_{n,t,block} \cdot \text{MinSpinningReserveMargin}$$
$$\forall n, t, block$$

B.5.24 C_RPS_Gen_Constr$_{state,t}$

$$\sum_{g\_renew,n,block \mid \text{IsStateNodePair}_{state,n}}(\text{generation}_{g\_renew,n,t,block}) - \sum_{n,block \mid \text{IsStateNodePair}_{state,n}}(\text{excessGeneration}_{n,t,block}) \geq \text{RPS\_MIN\_GEN\_AMOUNT}_{state,t} \qquad \forall state, t \mid (\text{RPS\_MIN\_GEN\_AMOUNT}_{state,t} > 0)$$

B.5.25 C_AmountEnergyConsumedConstr$_{g,t}$

$$\text{amountEnergyConsumed}_{g,t} = \sum_{n,block}(\text{HeatRate}_{g} \cdot \text{generation}_{g,n,t,block}) \qquad \forall g, t$$

B.5.26 C_FuelTypeConsumedConstr$_{fuel_type,t}$

$$\text{amountFuelTypeConsumed}_{fuel\_type,t} = \sum_{g|\text{IsFuelTypeGeneratorPair}_{fuel\_type,g}} (\text{amountEnergyConsumed}_{g,t})$$

$\forall fuel\_type, t$

B.5.27 C_FuelTypeConsumedSupplyCurveConstr$_{fuel_type,t}$

$$\text{amountFuelTypeConsumed}_{fuel\_type,t} = \sum_{fuel\_bin} (\text{amountFuelTypeConsumedInFuelBin}_{fuel\_type,t,fuel\_bin})$$

$\forall fuel\_type, t$

B.5.28 C_InstallationSupplyCurveConstr$_{g,t}$

$$\sum_{supply\_bin} (\text{genInstall\_Bin}_{g,t,supply\_bin}) = \sum_{n} (\text{genInstall}_{g,n,t}) \qquad \forall g, t$$

B.5.29 C_PTC_Constr$_{g_wind_new,t_ptc,t}$

$$\text{ptc\_generation}_{g\_wind\_new,t\_ptc,t} = \sum_{n,block} (\text{CapacityFactor}_{g\_wind\_new,n,t,block} \cdot \text{genInstall}_{g\_wind\_new,n,t\_ptc})$$

$\forall g\_wind\_new, t\_ptc, t \mid (\text{Include\_Tax\_Credits} \wedge (\text{rel\_ord}_{t\_ptc} \leq \text{rel\_ord}_t) \wedge (\text{rel\_ord}_t \leq (\text{rel\_ord}_{t\_ptc} + 10 - 1)))$

B.5.30 C_Installation_Limit$_{g,n,t}$

$$\text{genInstall}_{g,n,t} \leq \text{GenInstallUB}_{g,n,t} \qquad \forall g, n, t$$

Decision variable	Index domain
$\text{genInstall\_Bin}_{g,t,supply\_bin} \geq 0$	$\forall g, t, supply\_bin$
$\text{installedCapacity}_{g,n,t} \geq 0$	$\forall g, n, t$
$\text{generation}_{g,n,t,block} \geq 0$	$\forall g, n, t, block$
$\text{extendedCapacity}_{g,n,t} \geq 0$	$\forall g, n, t$
$\text{amountFuelTypeConsumedInFuelBin}_{fuel\_type,t,fuel\_bin} \geq 0$	$\forall fuel\_type, t, fuel\_bin$
$\text{amountEnergyConsumed}_{g,t} \geq 0$	$\forall g, t$
$\text{unmetDemand}_{n,t,block} \geq 0$	$\forall n, t, block$
$\text{excessGeneration}_{n,t,block} \geq 0$	$\forall n, t, block$
$\text{ptc\_generation}_{g\_wind\_new,t\_ptc,t} \geq 0$	$\forall g\_wind\_new, t\_ptc, t$
$\text{avgPower}_{g,n,t,block} \geq 0$	$\forall g, n, t, block$
$\text{effectiveCapacity}_{g,n,t,block} \geq 0$	$\forall g, n, t, block$
$\text{genInstall}_{g,n,t} \geq 0$	$\forall g, n, t$
$\text{retiredCapacity}_{g,n,t} \geq 0$	$\forall g, n, t$
$\text{spinningReserve}_{g\_dispatchable,n,t,block} \geq 0$	$\forall g\_dispatchable, n, t, block$
$\text{quickstartReserve}_{g\_dispatchable,n,t,block} \geq 0$	$\forall g\_dispatchable, n, t, block$
$\text{amountFuelTypeConsumed}_{fuel\_type,t} \geq 0$	$\forall fuel\_type, t$