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Diurnal, physics-based strategy for computationally efficient capacity-expansion optimizations for solar-dominated grids

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ABSTRACT

Modeling energy storage for a renewables-driven grid using every hour of the year gives more insight and higher accuracy, but can be computationally demanding. In this study, we propose a novel and straightforward Critical Time Step technique, independent of the load and generation profiles, to reduce computational requirements with little loss in accuracy for a solar-dominated system. Using the diurnal cycle, specifically the critical times of an hour after sunrise and an hour before sunset, results in an excellent tradeoff of accuracy and computational complexity compared with fixed-time-step approaches. The accuracy and value of the technique are evaluated by comparing results for three weather years. The technique systematically underestimates the capacity expansion needed but differentiates the three weather years with results correlating well with the hourly simulations. Overall, the results show a high accuracy for the Critical Time Step technique in predicting the power expansion of the resources and the energy rating expansion of the storage system for a grid with more than 35% share of solar in the total operational power. The highest error occurred for storage power buildout but did not exceed 10% relative to the 1-hr-resolution simulation for the studied case.

1. Introduction

As the world is replacing coal and natural-gas power plants with solar and wind generators, modeling of capacity expansion of electrical grids shifts from "how many fossil fuel plants do we need to meet peak demand" to "how can we couple storage with solar and wind electricity to have adequate power for every hour of the year?" Although some studies have concluded that "firm low-carbon electricity" [1] or "cross-sector storage" [2] may reduce need for energy storage, there is interest and value in understanding how energy storage may be used to both keep the lights on at night ("diurnal" storage) [3] and provide power through days, weeks, or months when solar and wind electricity generation are inadequate to meet demand ("long-duration" storage) [4]. When energy storage plays a key role, capacity expansion modeling evaluates *energy* capacity (GWh) in addition to *power* capacity (GW), resulting in the need to study what happens *between* times of peak demand, perhaps requiring study of every hour of the year [5].

Thus, capacity expansion modeling of energy storage may benefit from new strategies. Modeling every hour of the year rapidly increases computational requirements especially when coupled with other requirements for understanding the energy system. Although modern tools are able to complete very complex calculations, an efficient strategy enables modeling the evolution of the capacity expansion over decades [6], repeating calculations for many weather years to minimize the effects of inter-annual weather variability [7,8], optimizing electricity and other use simultaneously [9,10], and exploring a large parameter space (*e.g.* when the cost, duration, and efficiency of storage are simultaneously varied) [11].

Wang et al. [12] found that different strategies for reducing computational intensity could lead to significant differences in the system's design and performance, emphasizing the need to select the strategy according to specific requirements carefully. The strategies may be categorized in two main groups (Fig. 1): the fragmented-year approach (often referred to as "clustering"), where specific hours and/or days from the 8760 h of a year are selected, and the full-year approach, where time steps span the year without gaps [13,14]. Such simplification invariably changes the calculation, resulting in error relative to the hourly simulation. Such errors are observed to increase with higher shares of variable renewable energy resources and lower emission targets [15–17], highlighting the importance of reduced computational intensity to energy storage studies [18].

There are many studies in the literature that deployed fragmented-

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year approaches. Reichenberg et al. [19] found that both the representative-hours and representative-days approaches can predict renewable capacities within a 10% error margin. Frew et al. [20] also noted that using a representative subset of days within a full-year time horizon results in computational savings with a reasonable loss of accuracy. However, they warn that the effect of changing storage balancing constraints on the outputs may not be appropriately captured. Moreover on this deficiency, Holger Teichgraeber and Adam R. Brandt [21] showed that conventionally used fragmented-year approaches often do not perform well when there is a high intra-day variability, especially when the goal is to investigate the storage. Blanford et al. [22] mentioned this weakness for the representative-hours approaches and suggested that one way to address this limitation is to represent the year with a small number of full weeks or days, possibly at slightly less than hourly resolution, and examine the deployment of electricity storage, subject to reservoir constraints, within each of these "representative weeks" or "representative days." However, Green et al. [23] showed that even these clustering methods are not suitable for modeling rare events and their consequences. The novel representative days approach by Paul Nahmacher et al. [24] also cannot sufficiently cover the variability of solar and wind energies under a very low temporal resolution.

On the other hand, the full-year approach as per this definition has the advantage of keeping the chronological order. The number of time steps may be further reduced by prioritizing the critical hours, which may not align with those identified by fixed-time-step downsampling approaches [25]. To address this, Guibert et al. [25] proposed a variable-time-step approach using the residual demand (demand minus solar, wind, and hydropower) to identify the critical times, found great value in the approach, and concluded that further work could be beneficial. For the non-critical times, they used coarser time resolution. By applying their method to the DIETER energy system model, they obtained errors smaller than 2% for solar and wind installed capacities. Still, the obtained error was higher and around −12% to −17% for battery storage power and the chosen variable timesteps depended on the residual demand profile.

It is possible to merge the fragmented-year and full-year approaches by placing representative days (fragmented time elements) in a chronological order (green dashed box in Fig. 1) [26,27], improving accuracy of the results for energy storage. Tejada et al. [28] concluded that including consideration of the chronology to the representative days approach is useful though they found it difficult to simultaneously model short and long time scales and still found errors of 10% or more for some parameters for some implementations. Wogrin et al. [29] proposed a new approach to modeling power systems called "system states" which incorporates chronological information and multiple important system features; however, the "system states" approach may be more complex and require more data to be collected than the traditional load levels approach, as it requires defining and incorporating a transition matrix between states. This data requirement may make it more difficult or costly to implement in practice.

The previously mentioned studies in the literature use one or more outputs from the model, such as the solar, wind, or reduced load after subtracting the solar and wind, as the basis of defining their methods. For studies of energy storage interactions with a complex grid, the community needs a technique that is accurate, computationally efficient, and doesn't use the outputs of the model as inputs.

To satisfy this need, this paper proposes a novel variable-time-step approach, the Critical Time Step (CTS) technique, for modeling solar-dominant energy systems. The distinctive diurnal features of a solar-dominant grid define the CTS with a considerable decrease in computational requirements. Section 2 briefly describes the code for applying the proposed CTS technique, input parameters, and baseline model results when 1-h steps are used to model a full year (8760 h). Then, Sections 2.1 and 2.2 describe how to reduce the modeled times both using fixed and variable time steps. Moreover, section 2.2 describes the selection of 2 critical times for each day and analyzes why and when these provide adequate accuracy based on the physics of the diurnal cycle. The results and discussion section compares the hourly results with those using fixed-time-step sampling approaches for a year in which substantial solar adoption is expected. Finally, the paper tackles the challenge of identifying whether the errors introduced by sampling 2 steps/day instead of 24 steps/day are acceptable by modeling multiple weather years and seeing whether the CTS calculation can correctly differentiate the years (compared with the hourly simulation). To conclude the study, the paper seeks to determine how much solar electricity is needed to reduce errors in the CTS technique. To do this, the years 2030–2045 using policy assumptions that promote the adoption of solar power are simulated, and the change of the errors were examined as the proportion of solar electricity supplied to the grid increased. This identified the threshold below which the model's accuracy declines in solar-dominant grids.

2. Methodology

In order to implement the proposed CTS technique (which is elaborated upon in this section), a code was developed and added to the publicly available Python RESOLVE capacity expansion model, which was developed by Energy and Environmental Economics (E3) (for more information about RESOLVE, see Appendix). The added code replaces the hourly resolution of the input profiles with two-time-points-per-day input profiles (or more time steps, if desired, as for the fixed-time-step approach described below). The code removes other time points and replaces the values for the defined critical hours with the average of that critical data point and all subsequent data points that will be removed

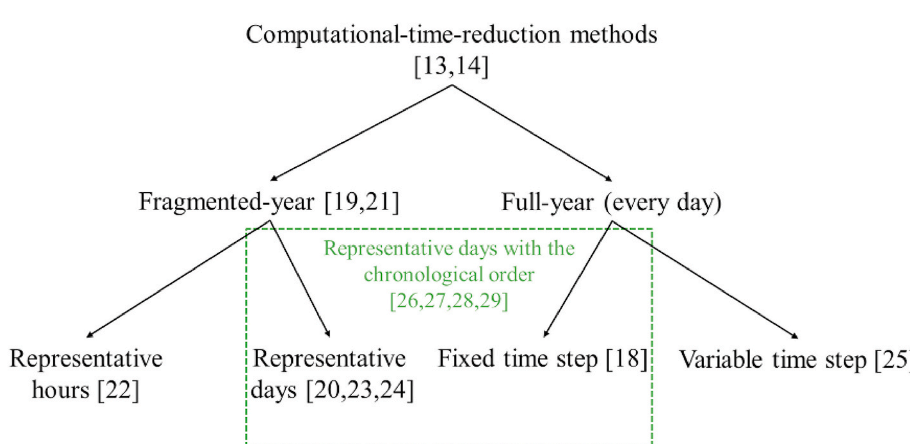

Fig. 1. Examples of computational-time-reduction methods for capacity expansion modeling [13].

before reaching the next critical hour. In the next step, the software uses these newly calculated profiles to do the capacity expansion modeling accounting for the non-hourly time steps when calculating the objective function. E3 plans to release the developed code and the proposed CTS technique in their future package.

Load profiles that match the weather for the three years 2007, 2008, and 2009 were developed and have been used by the state of California for capacity expansion modeling [30,31]. This study used those data from these specific years to benefit from load profiles that reflect actual weather patterns.

For all other generators than solar and wind, RESOLVE optimizes the dispatch using ramping and fuel availability constraints. However, for hydropower, fixed-generation profiles were chosen to represent a dry year. From data reported by Energy Information Administration (EIA) [32] and California Independent System Operator (CAISO) [33] for the years 2019, 2020, and 2021, hourly generation data were selected from the year with the least generation for each balancing area. These generation profiles were used as fixed inputs (the model was not given the option to change the profile of the dispatch).

Fig. 2 shows the operational capacities obtained for an optimization using 1-h time steps (8760 steps), 2045 loads/targets, and generation profiles reflecting 2007 weather. The "Other" resources in this figure include geothermal, natural gas, coal, nuclear, and biomass. The model constraints limit the building of new coal, nuclear, hydro, and biomass capacities. However, some new natural gas plants are built to provide adequate reserve.

In the following, the full-year approaches for reducing computational times used in this study are demonstrated.

2.1. Fixed-time-step calculations

This study uses two fixed-time-step, full-year, computation-time-reduction methods: 1) "snapshots" and 2) "averages." For both methods, the length of the fixed time step was varied by 1 h, 2 h, 3 h, 4 h, …, 12 h. For the "snapshots" approach, the selected hourly values were directly extracted from the full-year input generation and load profiles (8760 h). This approach ignores the input data in between the selected time steps. For the "averages" approach, the data in each time block between time steps were averaged and new input profiles were created (for both generation and loads) for each time step using the code that was described for the critical-time-step technique to average the data in each fixed time step. For both of the fixed-time-step approaches, the starting hour was varied to explore all possible combinations of time-step lengths and start times. For example, in case of a fixed time step of 4 h, the starting hours were selected to be 0:00, 1:00, 2:00 or 3:00.

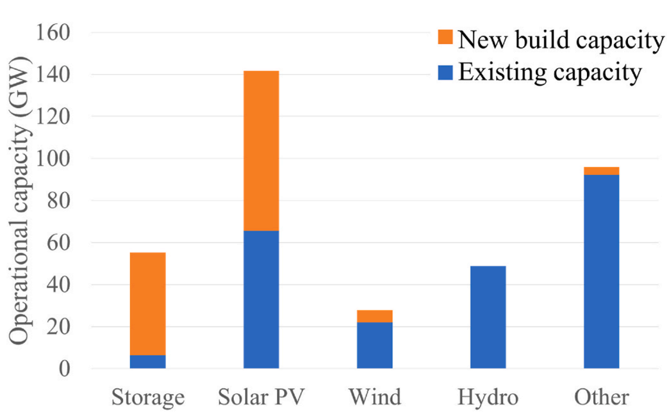

Fig. 2. Operational capacities for 2045 obtained using 1-hr time steps and 2007 weather data.

2.2. Variable-time-step calculations: proposed Critical Time Step technique

When reducing the computational complexity by increasing the length of the time steps, researchers have used many strategies, as described in Fig. 1. Logically, it makes sense to identify the critical times during the year when the system will be most stressed. The identification of those critical times for a grid with a high fraction of solar and wind generators has usually evaluated the times of peak net load (sometimes called residual demand) [25], where the net load is calculated by reducing the load by the variable (*e.g.* solar and wind) renewable electricity generation. This is logical because the model must build enough storage and other generators to deliver the needed power when solar and wind electricity are inadequate. However, the calculation of the net load is an *output* of the model rather than an *input*, creating the need to estimate the result of the calculation before selecting the critical time points. This study undertakes to develop a method that would work well without using the model outputs and that would be independent of the weather characteristics or extreme events in any year.

This study uses the unique features (associated with sunrise and sunset) of a solar-dominant energy system to select the critical time points that are the key element of the proposed 2-point CTS method. When solar is a primary source of electricity, it is expected that surplus electricity during the day will charge the storage, reaching the maximum state of charge around sunset. As an example, Fig. 3 shows the total power generation, the power provided by each generator type, the electrical load, and the dis/charging for all storage elements for each hour of the solstices and equinoxes obtained using the 1-h-time-step calculation described in Section 2. Fig. 3 shows how the storage starts charging around sunrise and discharging around sunset, as could be expected. More precisely, roughly an hour after sunrise and an hour before sunset correspond to the extrema of the storage state-of-charge, with little variation from season to season. For modeling of CAISO, sunrise and sunset times for latitude 34.1 ° and longitude −118.2 ° were used, representing a central California location. Each time was rounded to the nearest hour before adding or subtracting an hour. The state-of-charge curves are somewhat flat near the extrema, reducing the need to pinpoint the exact time of the extrema for every day of the year. Modeling of areas more than one time zone wide may require modification to this approach for selecting the critical time points, but the approach of identifying the hours of the extrema can be extended to such situations. As we are evaluating the implementation of CTS technique for designing a future grid, section 3.2.2 explores how well it may work starting in the year 2030.

The two key elements of the proposed 2-point CTS technique are to 1) use an hour after sunrise and an hour before sunset (labeled as "selected" in Fig. 3) as two critical time points for each day and 2) use the averages approach so that the charging and discharging of the storage will be appropriately tracked for all hours. Relative to a full-year, hourly optimization, using 2 time points per day reduces the number of time points by a factor of 12, which may reduce solving time by a factor of 100 or more. Using 2 time points per day could do well at estimating the needed size of the storage in terms of energy capacity, but identifying the hour at which the net load is the greatest each day in order to reduce errors in determining builds of the other generators may also be needed. Surprisingly, using 2 time points per day also did reasonably well at selecting the builds of all generators. Next, the reason why 2 time points per day give so much information will be discussed (see Table 1) with the intent that this understanding will help to identify when 2 time points per day may be adequate or inadequate.

In addition to quantifying the *total* energy storage capacity, the model may be used to simultaneously quantify the energy storage in storage resources with a range of properties. Fig. 4 shows the energy storage system state-of-charge throughout 8760 h of the year obtained from running a 1-h optimization for 2045. By selecting 2 time points for *every* day of the year, it is not needed to identify which days of the year

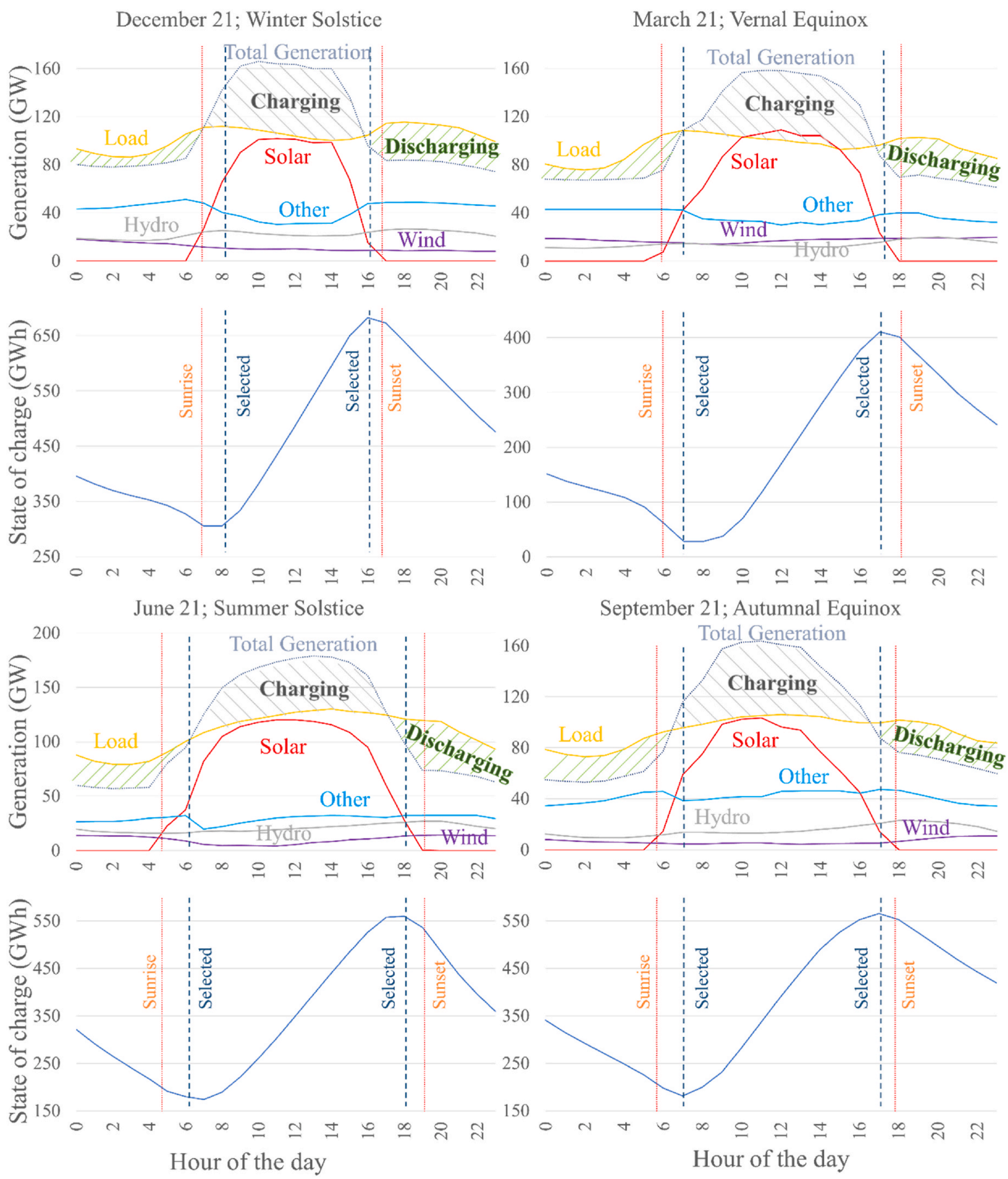

Fig. 3. Generation profiles and storage state of charge versus the daily datapoints obtained for solstices and equinoxes from a 1-h-time-step simulation of 2045.

will require the most diurnal storage, and which will require use of long-duration storage. Fig. 4 illustrates how capturing daily variations of the storage state-of-charge will define both the needed diurnal energy storage, and the needed long-duration storage (including seasonal and cross-day storage).

As mentioned, Figs. 3 and 4 show how the choice of the 2 critical time points per day facilitates accurate calculation of the needed energy storage. Fig. 3 also shows how the selected time points separate times of solar generation from almost no solar generation, enabling use of the selected time points to facilitate the model's selection of solar vs wind generators. To further aid the discussion, the reason that the very complex calculation done by RESOLVE may succeed in quantifying other elements of the capacity expansion has been analytically demonstrated.

Neglecting the efficiency losses for the energy storage system, the discharging and charging of the storage can be estimated by the difference between the load and the generation as in Eqs. (1) and (2):

$$Discharging = \sum_{t=SS-1}^{SR+1} \left[Load(t) - (Wind(t)) \right] - (SS - SR - 2) * Other\ D \quad (1)$$

$$Charging = \sum_{t=SR+1}^{SS-1} \left[Wind(t) + Solar(t) - Load(t) \right] + (SS - SR - 2) * Other\ C \quad (2)$$

where *Discharging* and *Charging* are the total discharge or charge in one

Table 1
Step-by-step analysis of information provided by 2-point CTS technique.

Modeled element	Equation or Figure	Description
Diurnal energy storage capacity	Fig. 4	Sampling the extrema for energy storage state-of-charge for each day sizes the diurnal storage by comparing the difference between the state-of-charge in the morning and evening on adjacent days
Long-duration energy storage capacity	Fig. 4	Sampling the extrema for energy storage state-of-charge for each day sizes the long-duration storage by comparing the difference between the minima and maxima over the entire year
Power capacity of components other than wind and solar	Fig. 3	The choice to build out other components depends less on the selected time points (these other generators provide fairly constant power) and more on the cost optimization and emissions restrictions
Wind power capacity	Eq. 1	Determined by the difference between the nighttime load (predefined) and the average power needed from the diurnal storage (already determined) and other generators (already determined in the previous step)
Solar power capacity	Eq. 2	Determined by the energy needed to charge the storage during the day (already determined) after accounting for the difference between the load (predefined) and wind power generation (determined in the previous step) plus other generation (already determined)

daily cycle, respectively, *Load(t)* is the total load for each hour *t*, *Wind(t)* is the wind generation for each hour *t*, *Solar(t)* is the solar generation for each hour *t*, *SR* and *SS* are the hours of sunrise and sunset, respectively, and *Other D* and *Other C* approximate the electricity generation by the other generators during times of discharging and charging, respectively. In Eqs. (1) and (2), *Other D* and *Other C* are assumed to be independent of hour *t*, so are multiplied by the number of hours rather than being included inside of the summation. The equations are written in this way to make the point that, for the scenarios that are being explored (in which the generation by *Other D* and *Other C* varies little during the day) the choice of time points does not need to consider the profiles for *Other D* and *Other C*. However, strictly speaking, these are not constants, and, in other scenarios, *Other D* and *Other C* may be important in determining the critical time points, so understanding their role in determining the outcome is discussed next.

The *Other C* generators are high-capacity-factor generators including nuclear, coal, geothermal, biomass, and hydropower generators. In general, these generators are selected by the model according to cost rather than according to whether they can be dispatched to meet a peak load. Because these generators run almost constantly (relative to solar and wind), their contribution is constant, and the selection of "critical" times is meaningless for them. In Fig. 3 the traces labeled "Other" and "Hydro" are fairly constant (at least compared with the solar and wind profiles), suggesting that for this simulation, the assumption of these being constant is reasonable. The *Other D* generators include the *Other C* generators as well as dispatchable natural gas generators. Because the simulation limits their total use by limiting the emissions of carbon dioxide, the use of these generators will be determined mostly by the emissions restriction along with the cost. Thus, the accuracy of the 2-point CTS technique may be anticipated by inspecting "Other" and "Hydro" traces in Fig. 3. If these showed significant variability over the day, then it might be beneficial to add additional critical time points accordingly. For example, it is anticipated that a hydropower plant that is being used as a dispatchable generator to meet peak demands might benefit from adding additional time points.

For systems that have relatively constant use of "other" generators, at a high level, Eqs. (1) and (2) show how the model has the needed information from the 2-point aggregation to identify the optimal capacity expansion. The left side of Eqs. (1) and (2) are calculated as part of the optimization by the model. The load summation term is predefined by the inputs. Equation (1) then determines the model's optimized choice of wind generators from the relative costs of building and operating wind vs Other D generators to make the right side of Eq. (1) equal the left side. Then the needed amount of solar generation is roughly determined by Eq. (2) with all other terms being either predefined or defined by Eq. (1).

Equations (1) and (2) are a simplification of the full calculation; they are meant to give the reader insight into why and when the 2-point CTS

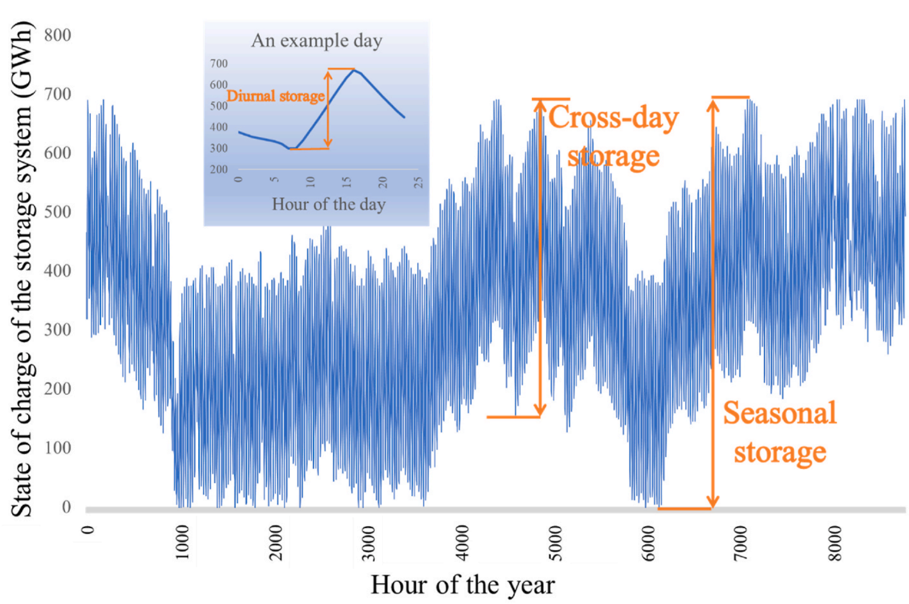

Fig. 4. State of charge of all storage for 1-hr optimization for 2045. The orange arrows show how 2 critical points per day can identify the needed diurnal, cross-day and seasonal storage capacities. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

technique can be fairly accurate. The success of the 2-point CTS technique is evaluated in section 3.

3. Results and discussion

In the previous section, the performance of the CTS technique was analyzed analytically. This section, firstly, will compare the results obtained by the model using the CTS and other fixed-time-step approaches (methods that maintain the chronology; see Fig. 1). Then, some sensitivity analyses will be provided to show to what extent the CTS technique is useful and could be deployed for other grids.

3.1. Fixed-time-step temporal-resolution-reduction approaches vs the Critical Time Step technique

Section 2 showed how selecting the two critical time points per day enables us to accurately model the energy storage rating and the power capacity expansion of the resources. The following will present the results of these metrics for the CTS and fixed-time-step approaches.

3.1.1. Energy storage build (GWh)

Fig. 5 shows the selected energy storage capacity (in GWh) built for the 2045 simulation, comparing the CTS technique with all possible fixed-time-step resolution calculations using both averages and snapshots strategies. The first and second bars in the figure are for the CTS technique and hourly simulation, respectively. For the bars in each fixed-time-step resolution group, the bars differ based on the first selected time point. For example, there are 3 bars for the 3-hrs snapshot calculations, where the first selected time point for the bars are 00:00 a.m., 1:00 a.m., and 2:00 a.m., respectively. According to Fig. 5, the error increases when the temporal resolution is coarser (right side of the figure). Fig. 5 exhibits more variable results for 3-hrs, 4-hrs, 6-hrs, 8-hrs, and 12-hrs temporal resolution cases, where the sampled hours fall at the same hour of the day for every day of the year. On the other hand, the results for those fixed-time-step calculations that capture different hours of the day on different days are more consistent, making the effect of the first selected time point less significant.

The accuracy of each set of calculations in Fig. 5 as a function of the number of sampled time points can be assessed by Fig. 6. For the fixed-time-step calculations, the differences between the biggest and smallest calculated values (depending on the starting hour for the calculation) are indicated by uncertainty bars in Fig. 6, and the mean of the calculated values are shown by circles and diamonds for the averages and snapshots approaches, respectively. Fig. 6 shows that the snapshots approach systematically overestimates the energy storage needed because the selected hours with high net demand will be attributed to all hours in the created time block, resulting in a higher effective net demand. In contrast, the averages approach systematically underestimates

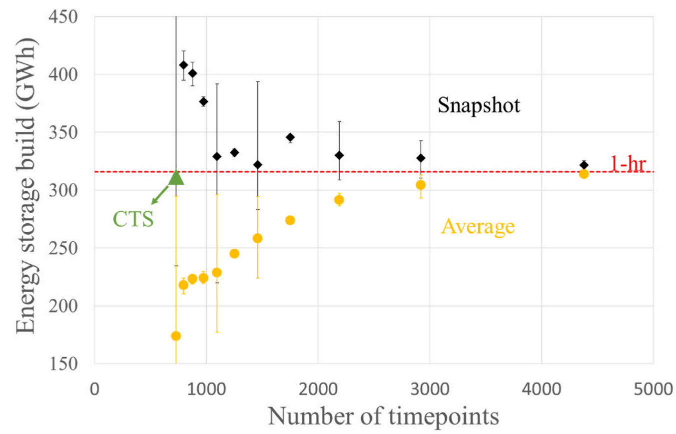

Fig. 6. Total energy storage capacity selected (GWh) versus the number of time points for the fixed-time-step technique and 2-point CTS approach. The uncertainty bars indicate the range of the biggest and smallest calculated values obtained by changing the starting time point for the fixed-time-step cases. The red dashed line indicates the value obtained for the 1-hr calculation. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

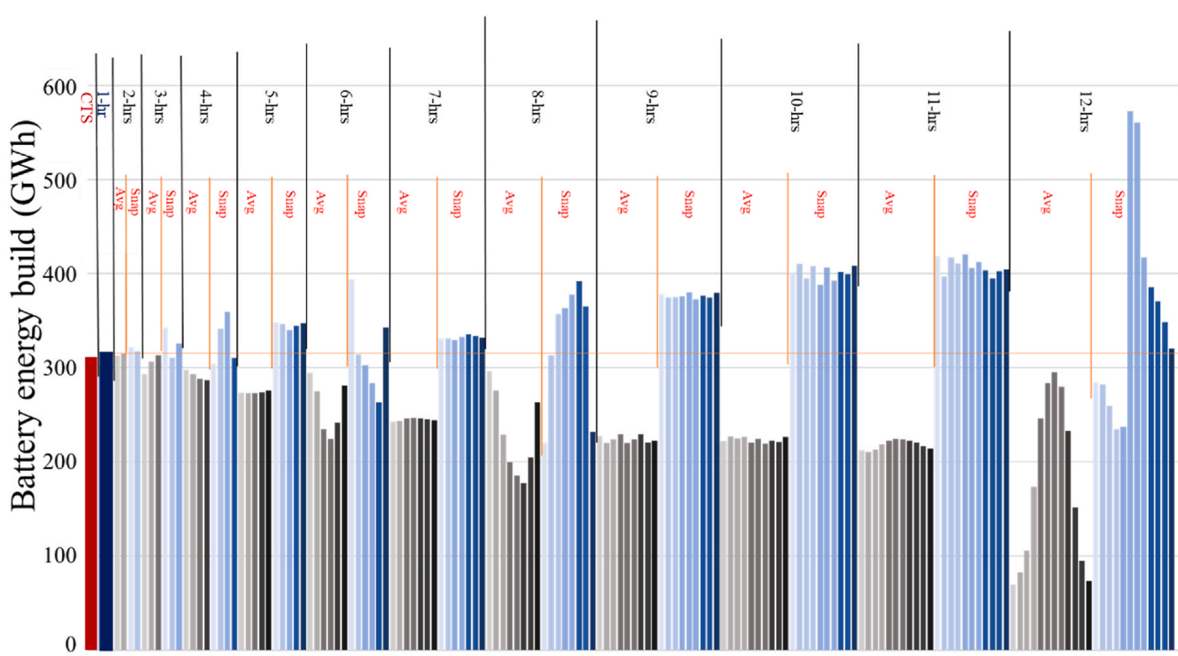

Fig. 5. Selected energy storage capacities (GWh) obtained for the 2045 simulation using fixed time steps ranging from 1 h to 12 h and the 2-point CTS technique (red bar, far left). The top black labels indicate the time interval (in hours) for each set of fixed-time-step calculations. The red labels indicate whether the averages (gray bars) or snapshots (blue bars) approach was used for preparing the input profiles. The horizontal red line indicates the 1-h simulation result; errors are calculated relative to this. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the needed energy storage capacity because the hours with high net demand will merge with the adjacent values in the created time block yielding a smaller net demand value for the time step [25]. Although decreasing the number of sampled hours leads to higher errors for the fixed-time-step calculations, the CTS technique predicts the energy storage rating with only about −1% error relative to the 1-h time step calculation, despite requiring fewer than one tenth of the timepoints.

3.1.2. Power build (GW)

Fig. 7 shows the capacity expansion results for the generators, presented in the same format as Fig. 6. Similarly, Fig. 7 shows larger variations for the capacity expansions for 3-hrs, 4-hrs, 6-hrs, and 8-hrs time intervals calculations when changing the starting hour. In Fig. 7, the fixed time step approaches show a systematically increasing error for the total capacity expansion as the temporal resolution is being reduced. The snapshots approach tends to overestimate, and the averages approach tends to underestimate the total capacity expansion. Again, Fig. 7 shows smaller errors obtained from the CTS technique than the outcomes of the fixed-time-step approaches with similar computational intensity. The results show that, relative to the hourly calculation, the CTS approach calculates storage capacity expansion with −6.1% error, wind plus other resources capacity expansion with −3.4% error, solar expansion with −0.4% error, and total power capacity expansion with −2.7% error. Wind and other resources are considered together in Fig. 7, because they are fairly small compared to the others.

3.2. Sensitivity analyses

Any reduction in computation time is anticipated to change the results. While the capacity expansion model can give an exact result for the problem it is given, the results have uncertainties that reflect the uncertainties in the model inputs as well as other limitations to the model. While Figs. 5–7 demonstrate that the 2-point CTS technique gives more accurate results than fixed-time-step approaches with similar computational intensity, the question is whether the accuracy is good enough to be useful. The required accuracy depends on the question being answered. Section 3.2.1 assesses the accuracy and utility of the CTS technique by asking the question “What effect does the weather year have on the optimal capacity expansion?” Then, Section 3.2.2 considers the range of applicability – how solar dominant does the electricity generation need to be to keep errors small?

3.2.1. Critical Time Step technique ability to detect effects of choice of weather data

As mentioned before, the publicly available inputs for RESOLVE include load and generation profiles reflecting the 2007, 2008, and 2009 weather years. The results in Figs. 5–7 were obtained using 2007 data. Here the 2008 and 2009 weather years are added to assess the accuracy and value of the CTS technique. Figs. 8 and 9 compare the capacity expansion results for the 1-h calculation and the 2-point CTS technique for the three weather years, showing fairly similar results. It is expected that the differences caused by using weather data from different years will have relatively small effects on the results of the simulation, but sometimes the goal is to study those small differences, especially because these differences are anticipated to increase in coming years. The success or lack of success of the CTS technique in detecting those small differences provides a useful assessment of the value of the technique.

Therefore, to quantitatively assess that success, Fig. 10 plots the selected build outs for 2008 and 2009 relative to 2007, with the hourly calculation plotted on the x-axis and the CTS calculation plotted on the y-axis. As the figure shows, the CTS results correlate well with the outcomes of the hourly simulations when changing the weather data. For example, the hourly simulations show that the weather in 2008 and 2009 requires more storage and generators than in 2007. While the CTS approach consistently underestimates the needed build out, the CTS results also conclude that 2008 and 2009 require more storage and generators, demonstrating how the CTS technique can correctly identify even the small differences between weather years.

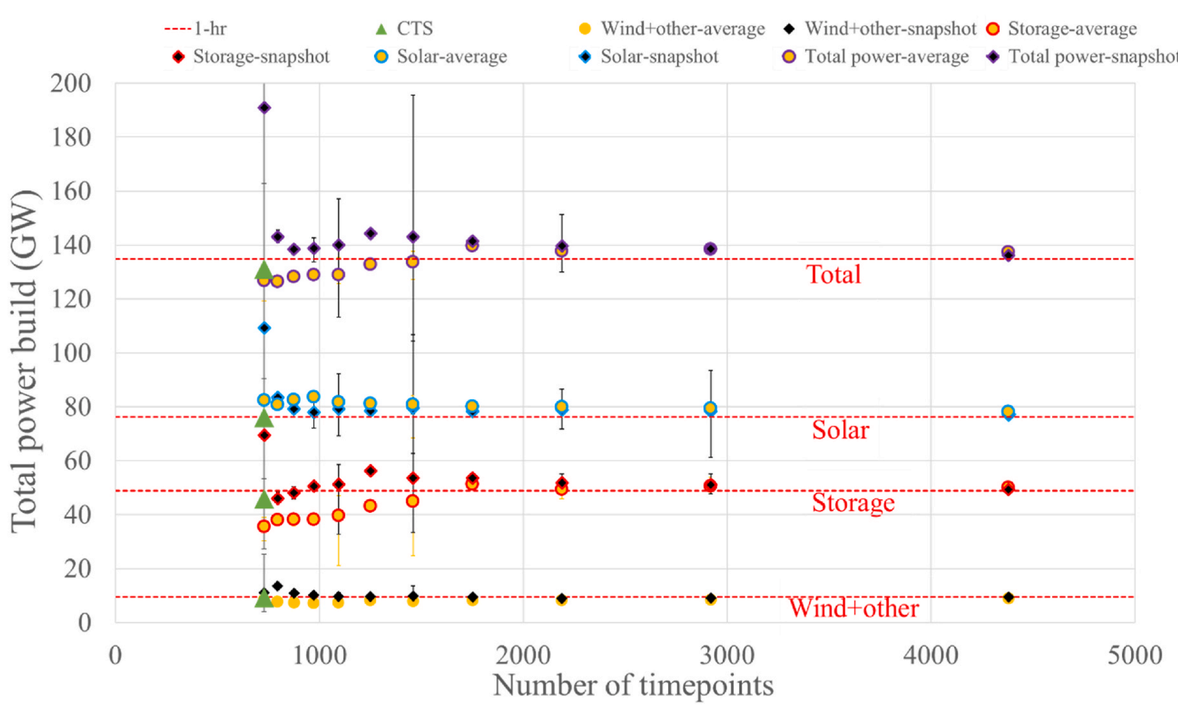

Fig. 7. Optimized capacity (GW) expansions versus number of timepoints for the 2045 simulation using the CTS technique and the fixed-time-step approaches. The 1-h calculation is shown by the red dashed line. The uncertainty bars indicate the range of variation based on the biggest and smallest calculated values obtained by changing the starting time point for the fixed-time-step cases. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

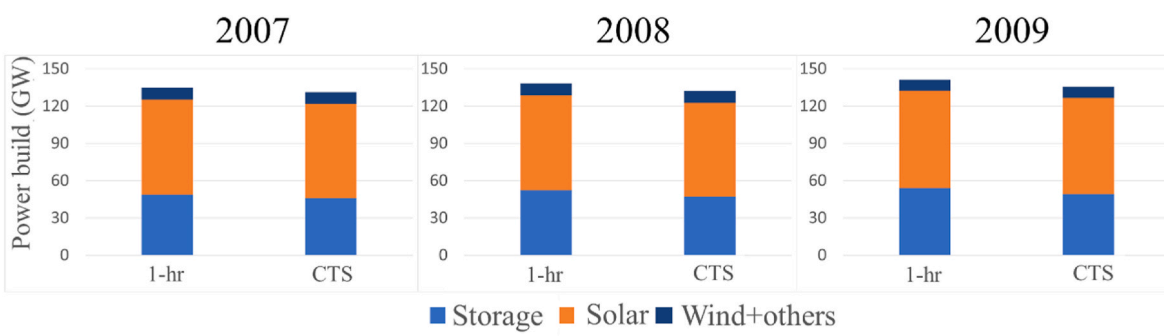

Fig. 8. Capacity expansions (GW) obtained for 1-hr calculation and 2-point CTS technique for weather years 2007, 2008, and 2009. Estimated load growth and policy constraints for 2045 were used.

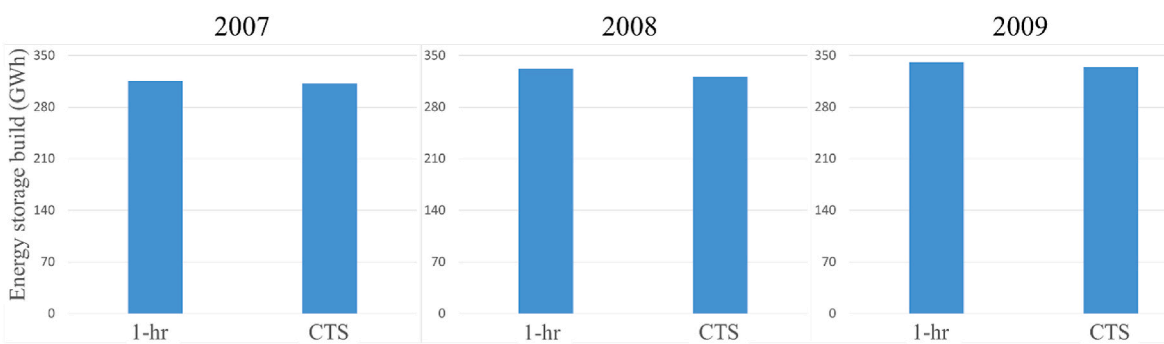

Fig. 9. Energy storage expansion (GWh) obtained for 1-hr calculation and 2-point CTS technique for weather years 2007, 2008, and 2009. Estimated load growth and policy constraints for 2045 were used.

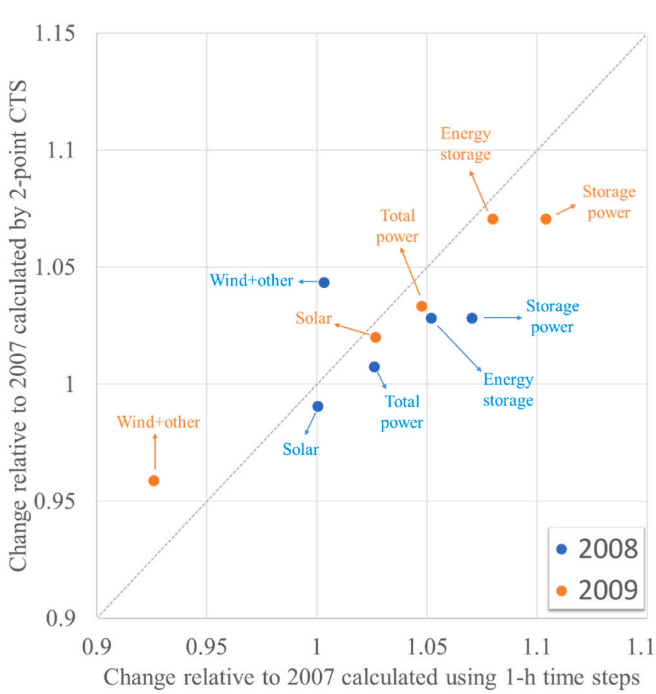

Fig. 10. New build capacities selected by the model for 2008 and 2009 divided by those selected for 2007, comparing the hourly calculation (x axis) with the CTS calculations (y axis).

3.2.2. *Critical Time Step technique sensitivity to solar ratio*

Section 2.2 concluded that the accuracy of the 2-point CTS technique is likely to depend on the degree of the grid's solar-dominance. Fig. 11 shows the error of the calculated storage energy expansion using the CTS technique relative to the 1-hr simulation versus solar ratio, where the solar ratio is defined as the ratio of the solar operational power to the total operational power. The data were obtained using the inputs described in Section 2 for the target years of 2030–2050 using the three weather years data, i.e., 2007, 2008, and 2009. From 2030 to 2050, the solar ratio increases because of policy requirements to move toward greater use of renewable energy and reduced carbon dioxide emissions. Fig. 11 shows that the CTS accuracy systematically correlates with the solar ratio when the ratios are smaller than 35%. However, for the solar ratios greater than 35%, the CTS errors show no systematic trend but remain small (at most −7%), where the mean value of the errors is −4.1%, quantifying the systematic underestimation of the CTS technique of the capacity expansion. Based on calculations not shown, a grid that adopts more wind is also predicted to benefit from the 2-point CTS technique as long as the solar is enough to cause the storage state-of-charge extrema around sunrise and sunset.

4. Conclusion

In this study, a 2-point Critical Time Step (CTS) technique was proposed, which uses only two daily data points, an hour after sunrise and an hour before sunset, to calculate the optimal capacity expansion for solar-dominant grids. The 2-point CTS technique demonstrates higher accuracy than fixed-time-step techniques with similar temporal resolution and does not need any clustering algorithm to determine representative periods because it relies on solar generation to force the daily extrema of the energy storage system state-of-charge to times near sunrise and sunset. The CTS technique has the advantages of being very easy to use while providing an excellent tradeoff between model accuracy and computational time.

This tradeoff was assessed by comparing the CTS results with a set of calculations that varied the temporal resolution using fixed time steps between 1 h and 12 h and variable starting times. It was found that when

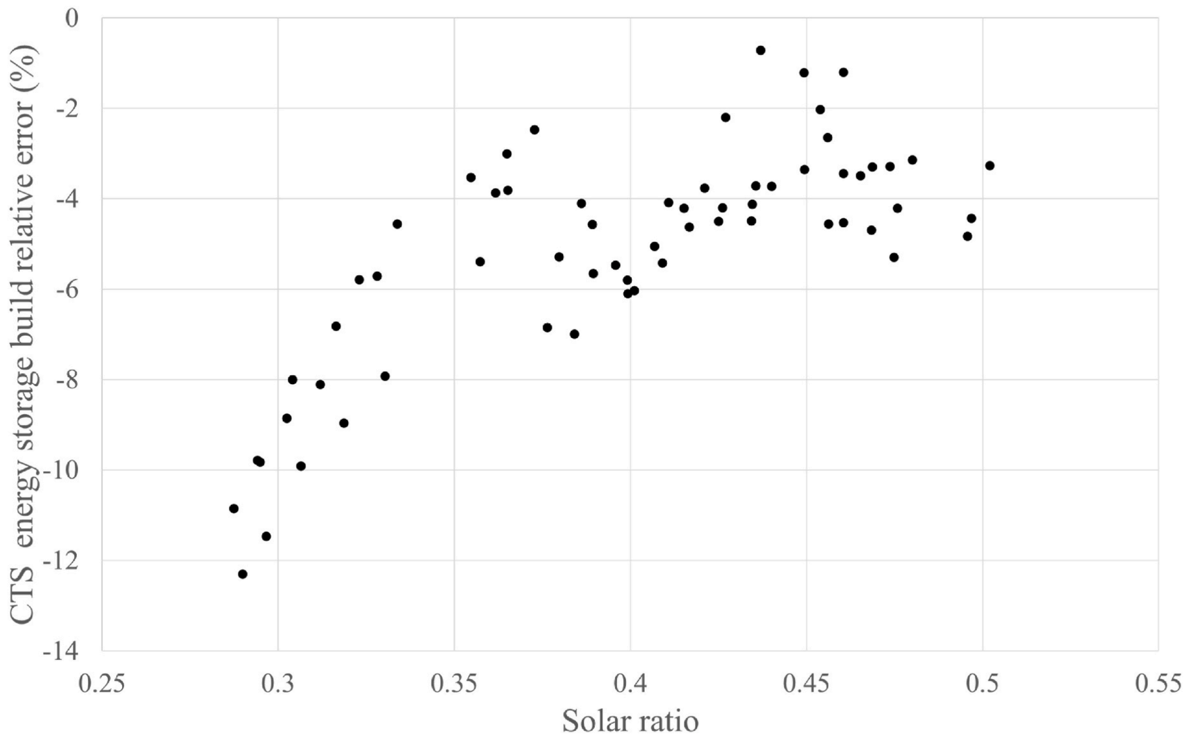

Fig. 11. CTS error in modeling energy storage system expansion relative to 1-h simulation versus solar ratios obtained for target years 2030–2050.

the selected timepoint data were used without consideration of the points in between (snapshots approach), the needed capacity expansion was overestimated relative to the hourly simulation, with the amount of the overestimation increasing as the length of the time step increased. In contrast, if the data for the selected time points were taken as an average of the data in that time interval, the capacity expansion requirements were underestimated by a similar amount. For both approaches, simulations using 3-h, 4-h, 8-h, or 12-h time steps showed large variations in the results, depending on the starting hour. For example, sampling 6:00 and 18:00 each day gave results that varied by a factor of 2 (or 3 in some cases) compared with sampling at 0:00 and 12:00. The CTS technique, which averages the data in each time step (but with time steps of variable lengths), also systematically underestimated the needed capacity expansion, but with substantially less error than for the fixed-time-step calculations that used a similar number of time steps.

The CTS technique's ability to model grids with lower levels of solar electricity was assessed by modeling the capacity expansion starting in 2030. The calculated error increased when <35% of the operational power of the energy system was solar. For solar fractions >35%, the CTS technique gave errors of less than 7%, suggesting that the discussed technique may also work well for a wind-driven grid as long as the solar power is enough to have the maximum and minimum state-of-charge of the storage system around sunset and sunrise. The observed error consistently underestimated the needed capacity expansion, enabling the technique to detect trends when the inputs were varied. Specifically, the changes in the capacity expansions obtained by the hourly simulations identified for three weather years correlated well with the observed changes in the CTS results.

Credit author statement

Farzan ZareAfifi: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, **Zabir Mahmud**: Conceptualization, Methodology, Software, Investigation, Writing – review & editing, **Sarah Kurtz**: Conceptualization, Methodology, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2023.128206.

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