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The Error induced by Using Representative Periods in Capacity Expansion Models - System Cost, Total Capacity Mix and Regional Capacity Mix

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Abstract: Capacity Expansion Models (CEMs) are optimization models used for long-term energy planning on national to continental scale. They are typically computationally demanding, thus in need of simplification, where one such simplification is to reduce the temporal representation. This paper investigates how using representative periods to reduce the temporal representation in CEMs distorts results compared to a benchmark model of a full chronological year. The test model is a generic CEM applied to Europe, equipped with a novel formulation for storage in model versions with reduced temporal representation. We test the performance of reduced models at penetration levels of wind and solar of 90%. Three measures for accuracy are used: (i) system cost, (ii) total capacity mix and (iii) regional capacity. We find that: (i) the system cost is well represented (~5% deviation from benchmark) with as few as ten representative days, (ii) the capacity mix is in general fairly well (~20% deviation) represented with 50 or more representative days, and (iii) the regional capacity mix displays large deviations (>50%) from benchmark for as many as 250 representative days. We conclude that modelers should be aware of the error margins when presenting results on these three aspects.

Keywords: electricity system models; time representation; time reduction methods; representative days

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1. Introduction

The future energy system will have an important impact on several societal goals such as climate change mitigation, energy security, and air pollution. The last few years have seen an increasing number of studies investigating power systems in which the share of variable renewable energy (VRE) may exceed 50%, and sometimes even reach 100% in a large area such as Europe or the US [1-10]. Such studies support policies, either directly [11], or in order to contribute more general knowledge about e.g. cost [12], the dominating generation technologies [12], or about optimal national strategies to transition into a CO2 neutral future energy system [13]. The models underpinning these studies are large and complex and have therefore been subject to simplification, many of them by reducing the temporal representation, e.g. by representing the entire year using a handful of days, such as in references [5, 11, 14].

There is a growing literature that investigates how to best perform this reduction while still preserving an output similar to that of a model with a year's worth of hourly data. The focus in the temporal reduction literature has partly been to compare several methods for finding representative days against each other [15-17], and partly to compare the outputs using reduced time series to outputs with a more extensive temporal representation [15-19]. Regarding the latter branch, the comparison has been done regarding different quantities/metrics: Nahmmacher et al. [19] compared the error of the representative days method for total cost and total VRE capacity in the model EU-LIMES, and found that these two quantities converged at 25 representative days. Reichenberg et al. [15] came to a similar conclusion in a simple 1-node model. Merrick [18] used the L1 metric, which takes into account errors for all the constituents of the objective function, and found that around 150 representative days were necessary to get a prediction within 10%. Pineda and Morales [17] compared wind capacity and cost and found that the cost error with their method was around 6% for an amount of timesteps the equivalent of 28 days. The literature is thus focused on how many time steps that are necessary in order to reasonably duplicate the results of an hourly model, yet the results differ between studies. Moreover, the studies do not systematically investigate if different kinds of questions relating to policy support, such as questions regarding system cost, capacity mix or regional strategies, potentially require diverse levels of detail. In many papers that aim at provding policy support, different numbers of representative days are used [5, 11, 14], and it is not clear whether the time reduction practice in these actually significantly impose distortions in the results and conclusion. In this paper, we seek to address this, by specifically targeting the error introduced by temporal reduction regarding the policy-relevant output from a CEM. Specifically, we address the research question:

What is the relationship between number of time steps and error estimate of

- System cost
- Total capacity mix
- Regional capacity mix

Using the results from our quantitative analysis we discuss the validity of results from energy system models for policy support.

We explore a large range of investment costs to account for a variety of system configurations. We investigate model input with between 24 and 4800 time steps. (i.e. a reduction of a factor of between 1.8 and 365). The time reduction method applied is the representative days method first outline in Nahmmacher [19], which is (i) compatible with most models using only small changes and (ii) versions of which are widely used in CEMs [5, 11, 14].

2. Materials and Methods

We compare the output from a CEM for sets with varying temporal representation drawn from a complete year-long hourly data set of electricity demand and wind and solar output. The results from running the CEM with these differently sized sets, sampled with a method based on clustering, are compared to results from running the CEM using data from the entire year (8760 time steps). The model results are analyzed with three different types of metrics, further described below.

2.1 Sampling method

We use a method based on clustering to find representative days and weight them. The method is similar to that introduced by Nahmmacher et al. [19], and further clarified in Pineda et al. [17]. See Reichenberg et al. [15] for a general discussion of different methods for simplifying the temporal representation in CEMs.

The representative days are found as follows, with the specific choices made here in bold:

1. Define demand, wind, and solar time series to represent each region: **Select the wind sites with annual capacity factor > 25% and solar sites with > 15%; average over these sites.**
2. Normalize the time series S_{rt} of each region so that $\{Max_t\,(S\}_{rt}) = 1,\ \forall r$. This means that each time series (wind, solar, demand) reaches a maximum of 1 for all the regions.
3. Choose a time period for which data will be consecutive. **Here, we use one-day periods, testing five-day periods in the sensitivity analysis.**
4. Form vectors of the time series so that each vector consists of data for the period chosen. This will consist of ordered (normalized according to step 2) wind, solar, and demand (here labeled "resources") data for all regions and the period length chosen. **In the application**

here, the data set consists of a year of hourly data, the period is 1 day, and there are 8 model regions, so that there are 365 vectors, each of which consists of (#resources)*(#representative days)*(#time steps per day)*(#regions)=3*1*24*10=720 elements.

5. Cluster the vectors into the desired number of clusters (**here using hierarchical clustering with between 1 and 200 clusters for the case of one-day periods.**).
6. Find the cluster centroid and pick the vector closest to the centroid as the cluster representative. Weight the vector according to the cluster size.

This procedure results in a subset of the original time steps, $T' \in T$, for which there are weights, , ω_t, assigned. The sum of the weight equals the original number of time steps, $\sum \omega_t, = 8760, \; t \in T'$.

2.2 Model

We use a CEM for Europe with 8 regions, see [20] and *Figure 1* in the Supplementary material. We use a greenfield approach (i.e. no existing transmission-, storage- and generation capacity), and investments are done overnight. The mathematical formulation of the model and a map of the region boundaries may be found in the supplementary material. The input data and details are explained further in the supplementary material.

It is a zonal model, where resulting transmission capacities are interpreted as Net Transfer Capacity (NTC) values, or as capacities in an HVDC (High Voltage Direct Current) network. This model treats electricity as it would other goods, i.e., without taking Kirchhoff's laws into account. The decision variables (see Section 1.3 in the Supplementary material) are:

- investments in generation technologies: wind, solar, and three thermal technologies;
- dispatch of generation technologies;
- investments in and dispatch of generic storage;
- investments in transmission and dispatch of trade.

The model minimizes annualized investment and operation costs for one year (Section 1.4 in the Supplementary material). The model does not include hydropower, nor does it allow investment in offshore wind power. These are excluded because hydropower may obscure the effects on investment in storage, and offshore wind power would further differentiate regions. However, offshore wind power would not introduce new dynamics that would alter the qualitative results.

The model is run in:

- a benchmark version, with a full year of hourly data, i.e., 8760 time steps;
- versions with fewer time steps, in which representative periods of one day (or periods of five day for the sensitivity analysis) are selected.

The reduction is explored for temporal reductions of a factor of between 1.8 (4800 time steps) and 365 (24 time steps). In addition, the model is run with a constraint on minimum VRE penetration of 90%, thus creating systems with a heavy dependency on VRE.

The model formulation of the full and reduced models can be found in the Section 1 in the Supplementary material, but here we highlight some aspects.

The dispatch variables for generation, export and storage represent the generation during one hour, and are related to the capacity variables in the same way as for a full time model:

$$p_{i,r,t} \leq c_{i,r}, \forall\, i \in I_{disp} \cup I_{VRE}, t \in T', r \in R \qquad (1)$$

$$e_{r,r\prime,t} \leq a_{r,r\prime}, \forall t \in T', r \in R \qquad (3)$$

$$l_{i,r,t} \leq c_{i,r}, \; i \in I_{stor}, \forall\, t \in T', r \in R \qquad (4)$$

, where $p_{i,r,t}$ is the electricity generated by technology i in region r during time step t; ω_t [1] is the weight for time step t; $c_{i,r}$ is the capacity of technology i in region r; $e_{rr',t}$ is the energy exported from region r to region r' during time step t; $a_{rr'}$ is the transmission capacity between regions r and r', $l_{i,r,t}$ is the storage reservoir level of storage type I in region r at time step t.

The storage level is the sum of discharge during a period, where the period is made up by the set of time steps in that period, $T'_p, p \in P$, where P is the set of periods.

[1] The weights sum up to 8760, the number of hours in a year.

$$\sum_{t'=1}^{t}(1-\lambda_i)m_{i,r,t'} - o_{i,r,t'} = l_{i,r,t}, \forall\ i\ \in I_{stor}, t \in T'_p, r \in R \qquad (5)$$

where λ_i is the loss factor for round-trip storage operation; $m_{i,r,t'}$ is the charge of storage; $o_{i,r,t'}$ is the discharge of storage.

Each period has τ time steps (e.g. $\tau = 24$ for one-day periods), and the storage level is constrained so that it is the same in the last time step as in the first:

$$l_{i,r,\tau} = l_{i,r,1}, \forall\ i\ \in I_{stor},\ \ r \in R \qquad (6)$$

The (weighted) energy balances are then formulated for every time step by summing generation, import, and export and constraining that sum to be greater or equal to the (weighted) demand in that time step:

$$\omega_t\left(\sum_{i\in I_{disp}\cup I_{VRE}} p_{i,r,t} + \sum_{r}(1-\lambda_{rr'})e_{r'r,t} - \sum_{r} e_{rr',t} + \sum_{i\in I_{stor}}(1-\lambda_i)o_{i,r,t} - m_{i,r,t}\right) \geq \omega_t\Delta_{rt}\forall r, r' \in R, t \in T$$

where Δ_{rt} is the demand (inelastic; parameter value taken from statistics) in hour t for region r.

In the objective function, the weights, ω_t, are part of the running costs for each time step:

$$\min_{i,r,t} \sum_{i\in I}\sum_{t\in T'}\sum_{r,r'\in R} \kappa_i n_{i,r} + \omega_t v_i p_{i,r,t} + 0.5\ \kappa_a \theta_{r,r'} a_{r,r'} \qquad (7)$$

where κ_i denote the annualized investment costs for generation- and storage capacity; κ_a the annualized investment cost ([€/MW km]) for transmission; and v_i are the running costs.

2.3 Data

The input is regional demand and wind and solar time series and is generated using the methodology described in Mattsson et al. [20]. Table 1 shows the fixed- and operational costs used as input to the model. The costs are annualized into fixed costs ([$€/MWh * yr$]) using a social discount rate of 5% and running costs ([$€/MWh$]), which is comprised of fuel costs and O&M costs. The specific costs are less relevant for this study, since the focus is not to describe or predict any energy system in particular, but rather to compare methodological choices. The costs for wind, solar PV and batteries were varied to generate a total of 27 cost combinations. This serves the purpose of generating an ensemble of system configurations, in order to explore more possible outcomes regarding deviations from the benchmark results.

Table 1 The costs and technical data that are input to the model. There are three sets of costs for wind, solar PV and batteries, which gives rise to a total of 27 cost combinations.

Technology	Investment cost [€/kW]	Variable O&M costs [€/MWh]	Fixed O&M costs [€/kW/yr]	Fuel costs [€/MWh fuel]	Lifetime [yr]	Efficiency/ Round-trip efficiency/loss
Natural gas GT	380	0.7	50	30	30	0.4
Natural gas CCGT	760	0.8	50	30	30	0.7
Coal	1400	0	80	8	35	0.4
Wind	800,1000,1200	0	44 [21]	n/a	25	n/a
Transmission	750 (€/MW*km)	0	0	n/a	40	0.05
Batteries	75,150,225 (€/kWh)	0	0	n/a	10	0.85
Solar PV	300,600,900	0	19 [21]	n/a	25	n/a

2.4 Sensitivity analysis

The period length, which was set to 1 day (24 hours) in the base case, was prolonged to five days (120 hours). This would possibly reveal some error introduced by that the storage level is constrained to be the same at the beginning and the end of a period (Equation 6). By extending the period from one to five days, this constraint limits storage operation to a lesser extent, and may reveal whether a large part of the discrepancy is in fact due to this constraint, at the same time as providing a basis for a decision for future modelers regarding the length of the period (e.g. one day, one week etc.).

3. Results

This paper focuses on the outputs system cost, total capacity mix, and regional capacity mix. The reason for the breakdown into these three categories is that energy system studies are often focused on any or all of these, see the Discussion section of this paper. As it turns out, the accuracy that may be achieved, given a certain number of representative periods, differ substantially between these three categories. The accuracy is measured as deviation (in percent) from the value obtained by the benchmark version (8760 chronological time steps) of the model. The results were computed for several cost combinations, in order to explore a possibly wider range of deviations from benchmark.

3.1. System cost

Figure 1 shows the deviation from the benchmark system cost (sample system cost/benchmark system cost) induced by using the sample representative days method for between 1 and 200 days. Each colored line represents one of 27 cost scenarios. As the figure shows, the system cost deviation results for the scenarios align rather well, especially for 40 representative days and over. This means that the accuracy of the time reduction depends only to a very small degree on the assumptions on cost. An accuracy of 10% is achieved already at ~10 representative days, while ~50 days and above ensure a system cost discrepancy of a mere few percent.

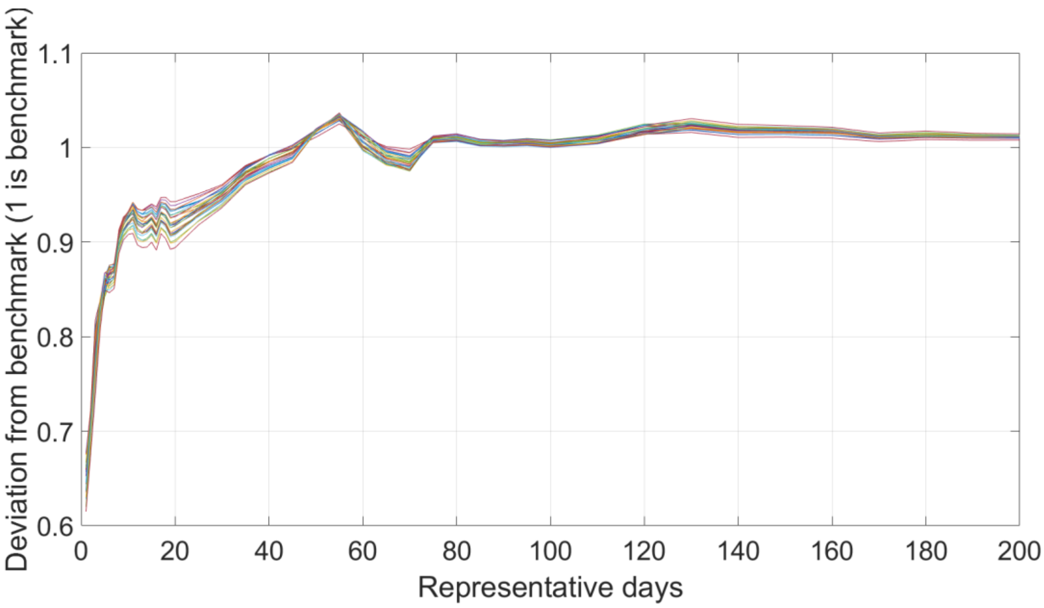


Figure 1 Deviation from the benchmark value for system cost, using 1-200 representative days (1-day periods). Each line represents one technology investment cost combination, see the Method section. All scenarios are highly renewable with a VRE penetration of 90%.

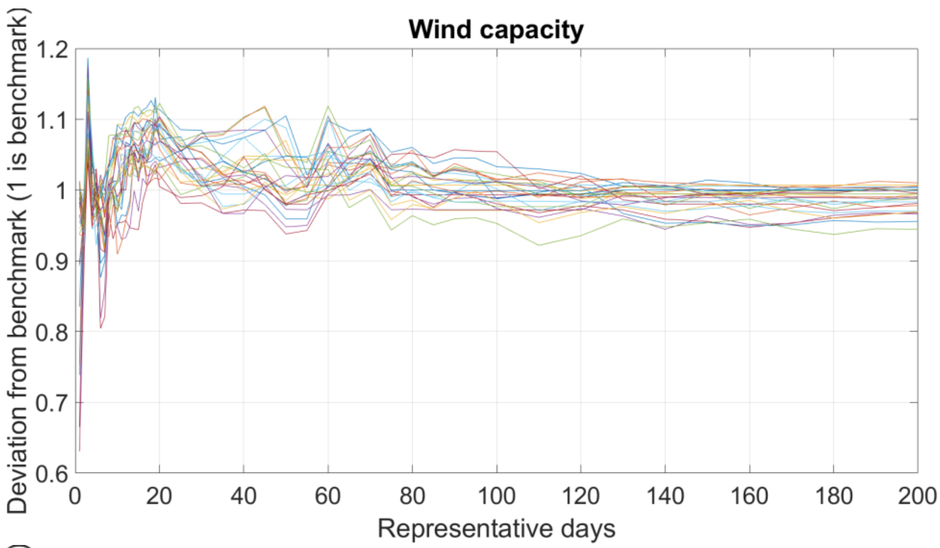
The results demonstrate that models with a reduced temporal representation may over- or underestimate system cost, but underestimates seem more prevalent, especially for cases with few representative days.

3.2 Total capacity mix

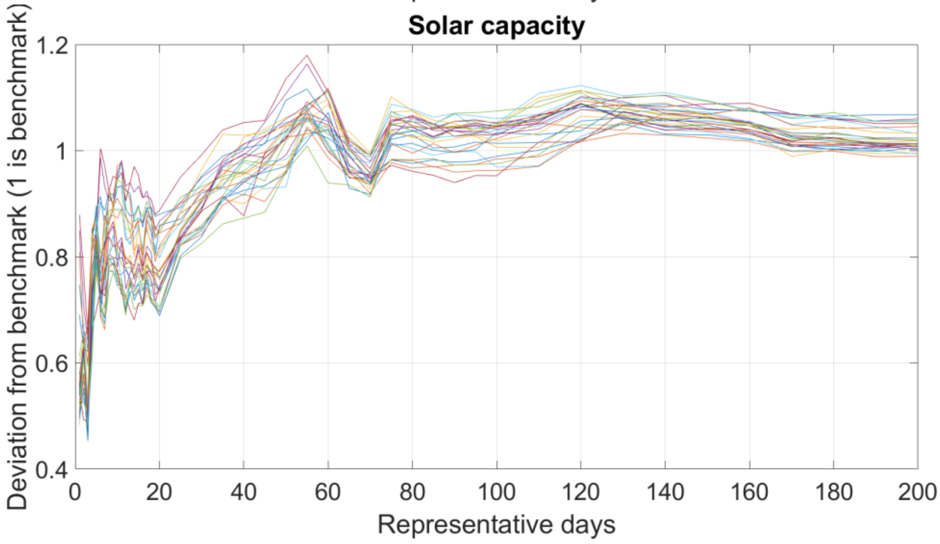
Figure 2 shows the deviation from benchmark capacity for wind power (*Figure 2a*), solar power (*Figure 2b*), battery storage (*Figure 2c*) and transmission (*Figure 2d*) capacity at a penetration level of VRE of 90%. The capacities are the totals for all of Europe.

The first observation is that the capacities display greater deviation from benchmark than does cost. While <10% deviation for cost was achieved at ~10 days, capacities do not stabilize at <10% deviation until 80 days or more. (Other capacities, such as transmission, do not stabilize at <10% deviation even for 200 representative days, which was the maximum number tried here.) With the previously proposed [15, 19] sufficient number of representative days, ~25 days, the errors in total capacity are ~10% (wind), ~25% (solar, transmission, storage), see *Figure 2*.

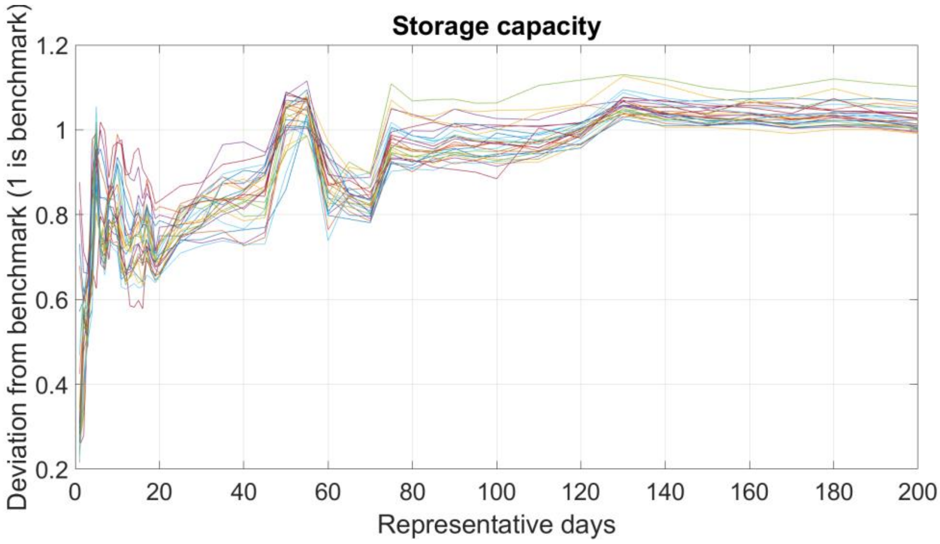
The second observation is that capacities are not equally volatile: solar capacity deviates by more than wind, and storage- and transmission capacity by even more. The fact that wind capacity results are more stable than are solar results may be because that the total wind capacity is greater, so for some cost combinations, the solar capacity is rather low, and thus a small nominal change induces a larger percentage change for solar than it does for wind.


Wind capacity
Deviation from benchmark (1 is benchmark)
1.2
1.1
1
0.9
0.8
0.7
0.6
0 20 40 60 80 100 120 140 160 180 200
Representative days

a)


Solar capacity
Deviation from benchmark (1 is benchmark)
1.2
1
0.8
0.6
0.4
0 20 40 60 80 100 120 140 160 180 200
Representative days

b)


Storage capacity
Deviation from benchmark (1 is benchmark)
1.2
1
0.8
0.6
0.4
0.2
0 20 40 60 80 100 120 140 160 180 200
Representative days

c)

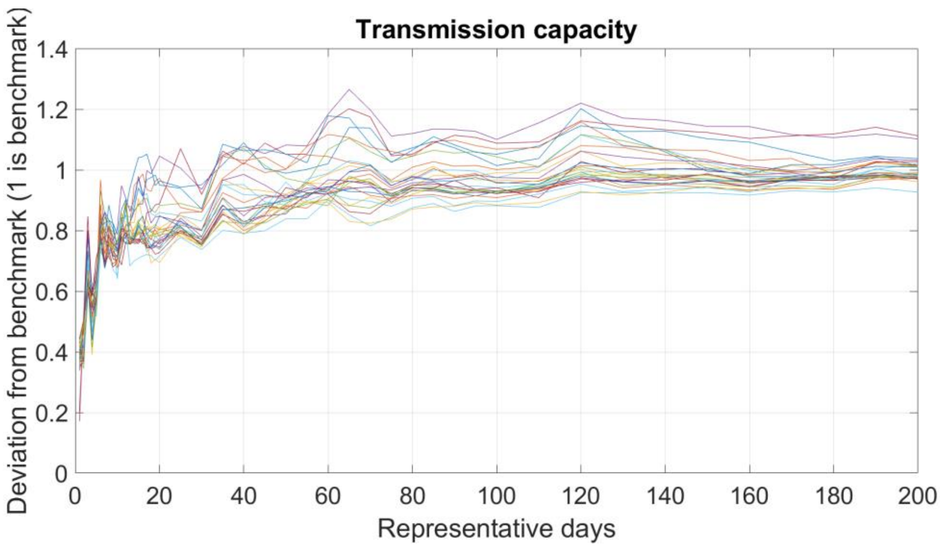
d) 

Figure 2 Deviation from the benchmark value capacity for total a) wind power, b) solar power, c) battery storage and d) transmission capacity. The figures show deviation from the benchmark model results, where 1 means that there is no deviation. Each line represents one technology investment cost combination, see the Method section. All scenarios are highly renewable with a VRE penetration of 90%.

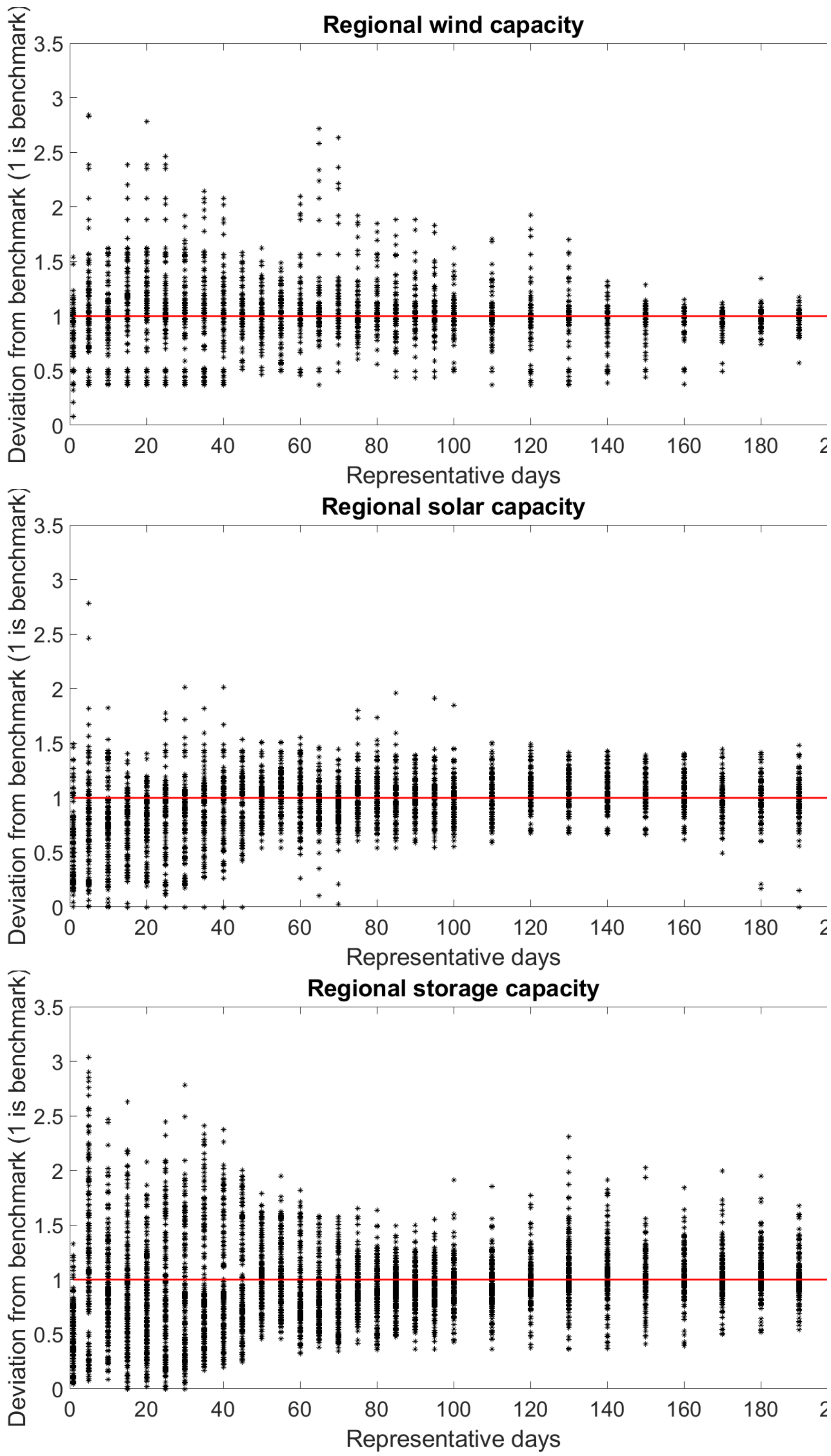
3.3 Regional capacity mix

This section displays results for individual regions, focusing on wind-, solar- and storage capacities, since these, together with transmission, dominate the system with 90% VRE generation.

Figure 3 shows the deviation from the benchmark regional capacity for a) wind, b) solar and c) storage. In order not to give importance to negligible amounts of capacity, data points for regions where the generation wind/solar contributes less than 10% of the total demand are discarded. Similarly, data points for regions with storage capacity less than the equivalent of one hour's regional demand are discarded. For each model version (1, 2, ... 200 representative days), there are thus a maximum 216 data points (27 cost combinations times eight regions) for each technology.

All three capacity types show instances of large deviations, of more than 40%, all the way up to 200 representative days. For 25 days or more, the deviation of regional capacities may be above 200%.

The supplementary material contains similar figures (*Figures 3* and *4* in the Supplementary material), where only data points for which the technology generates more than 40% of the regional demand of wind and solar. Even thus excluding all but the data points representing very substantial parts of the regions' capacity mix, the regional capacity outlay for reduced temporal models is highly erroneous. The overall picture conveyed here is that regional capacities from models with reduced temporal resolution should not be trusted to be correct.



a)

b)

c)

Figure 3 The deviation from benchmark for regional (a) wind power, (b) solar power and (c) storage capacity for VRE penetration of 90%. The figures show deviation from the benchmark model results, where 1 *means that there is no deviation. Each dot represents one data point, where a data point is the deviation for one region in one of the 27 cost scenarios. Data points for regions where the generation wind/ solar contributes less than 10% of the total demand are omitted. Similarly, data points for regions with storage capacity less than the equivalent of one hour's regional demand were omitted. For each model version (1, 2, … 200 days), there is a maximum of 216 data points (27 cost combinations times eight regions).*

3.4 Sensitivity analysis

The model was also run with five-day periods (instead of one-day periods as in the base case). This sensitivity analysis is of interest because it may reveal the error introduced by the storage formulation when the cost of storage is such that it may be assumed to be a vital part of the modeled power system. The results show that the deviation in system cost, for the same number of hours, is slightly higher when using five-day periods, compared to one-day periods (see *Figure 2* in the Supplementary material). Thus, for the range of costs represented in this investigation, it seems that the error introduced by the constraint on the storage operation to 24 hours is smaller than that induced by forcing (five) consecutive days, and thus limiting the representation of variability.

3.5 Sumary of results

Table 2 summarizes the results by measuring the deviation from benchmark results at 25 representative days, as well as the number of days necessary to predict quantities within a 10% deviation from benchmark results. The table shows the worst case, i.e., the deviation for the penetration level with the greatest deviation from benchmark. The comparison shows that models with a reduced temporal representation of 25-100 days predict system cost and total VRE capacities within a range of 10-20% of benchmark. Regional values for wind, solar, transmission, and storage capacities are poorly predicted by models with reduced temporal representation. Using a model with the proposed number of days, ~25 days [19], induces errors so large that little may be said about regional capacities.

Table 2 Summary of results for the three categories discussed here: system cost, total capacity mix, and regional capacity mix. The numbers in the table show the worst-case deviation from benchmark. For regional capacities (rows 6-9), results pertain to all regions with substantial capacities (>10% of the region's electricity demand for wind and solar and the equivalent of one hour or more of average regional demand for storage). The hyphen indicates that either the value is infinity (for the first column, this occurs when there is at least one value for the reduced models that is =0), or the maximum tested reduction (200 representative days) did not yield a value below 10% deviation (second column).

Quantity	Maximum deviation/error for >25 representative days [%]	Days necessary to limit deviation to <10%
System Cost	9%	25
Total capacity		
- **Wind**	12%	65
- **Solar**	25%	160
- **Storage**	41%	200
- **Transmission**	35%	-
Regional capacity		
- **Wind**	270%	-
- **Solar**	-	-
- **Storage**	-	-
- **Transmission**	-	-

4. Discussion

The main finding of this paper is that using a model with reduced temporal representation is a valid method to investigate questions relating to system cost. The fact that the system cost in reduced time models comes close (15-20% for 4-10 days, 2-5% for 30 days or more) to benchmark results should not be surprising: As long as there is some representation of variability, the model is likely to capture the fact that serving demand with VRE generation requires additional flexibility: transmission, storage, flexible thermal, which all generate higher costs than the mere technological LCOE of VRE. In contrast, models using a temporal representation based on averaging may display very large deviations from benchmark even for the system cost [15]. Studies that use the representative days method with at least 30 days and focus on system cost may thus be relatively sure that their estimates are in the right approximate range. However, using 48 time steps as in Knopf et al. [11] or 6 days, as in Osorio et al. [14], may induce much larger errors. This is especially the case, since many studies compare decarbonized scenarios with BaU scenarios, where a lot of thermal generation remain in the mix. Since it is the irregular variation on the generation side, i.e. large share of VRE, that incurs the errors due to temporal representation, this may bias studies to assess renewable scenarios as being less costly than they actually are.

The results regarding both global (sum for all regions) and regional capacities should give pause to modelers using models with reduced temporal representation: For the total capacity mix, we show that the deviation from benchmark results may be large (>20%) for solar, storage and transmission capacity, at 25 representative days. Such a discrepancy is larger than, yet rather close to, the estimate in [17, 19, 22]. For fewer number of days, such as in references [14] (6 days), [5] (4 days) and [11] (48 times steps), [23] (12 days), [24] (12 days) the discrepancy may be 50% or more. Yet, these studies typically do not mention the uncertainty range due to the temporal representation.

Regarding the regional capacity mix, it displays large deviations from benchmark results, even for models with ~100 representative days. This result is more similar to those in reference [18], where the equivalent of ~150 days was necessary in order to come within 10% deviation for the statistical measure used. Even though the measure employed by Merrick [18] differs from the regional capacity mix in this study (Merrick's test model has only one node and thus there is only one region), they both point to the possibility that CEMs with reduced temporal representation are not fit to use for all types of analysis. Thus, one may view the regional capacity mix investigated in this paper as but one example of a volatile output , but volatile outputs are likely not limited to just the regional capacity mix. In addition, a temporal reduction is clearly one source of volatility, but there may be others. In fact, there is reason to believe that the large variation in regional capacity mixes, is due to that there are simply many regional capacity configurations that give rise to near optimal solutions (flat objective function around optimum). If such is the case, many types of perturbations may give rise to a different optimal configuration. Reducing the time dimension may then be viewed as one type of perturbation, but there may be other perturbations that also yield solutions that are near optimal, yet quite different in terms of system configuration. The flatness is investigated in more depth in Neumann and Brown [25]. Another example is Zeyringer et al. [26] who investigated the effect from using different years for the wind- and solar input, and found that system cost is impacted but a few percent, while the optimal regional capacity mix displayed a very large range between the years. A systematic investigation of the effect of different perturbations thus seem essential to find robust regional strategies for renewable power systems. While outside the scope of this study, this issue has been explored for energy system models with different scopes [27].

5. Conclusions

This study assesses the accuracy of CEMs with reduced temporal representation in terms of three different quantities: system cost, total capacity mix, and regional capacity mix. It does so by comparing results from models with reduced temporal representation using 1 to 200 one-day periods, to results from a benchmark model that uses a full year's worth of data.

We show that the number of representative days necessary to use CEMs with reduced temporal representation to predict system cost, capacity mix, and regional capacity mix differs for these three quantities.

- For system costs, the deviation from benchmark results can be kept below 10% by using ~25 days.
- For the total capacity of the most important components of a renewable system (wind, solar, storage, transmission) the same standard requires between 65 and 200 days. 20% accuracy is achieved at ~50 days.
- For the regional capacity mix, not even 250 days were enough to yield a good approximation of benchmark results.

Hence, CEMs with reduced temporal representation of ~25 days may be well-suited to assess, e.g., the cost of a future renewable power system, but less suited to detail the optimal regional allocation of generation technologies in such a system. Still, there are a fair number of studies that have used reduced temporal resolution and analyzed quantities that we have shown they were not apt to analyze. Therefore, researchers and policy makers should exercise care when drawing conclusions regarding a regional capacity mix from CEMs with reduced temporal representation.

We therefore recommend that researchers working with energy system models exercise caution in performing any detailed analysis of the capacity mix, whether regional or total. Regarding the temporal resolution, we recommend using CEMs covering a full year of operation.

Finally, we find it disturbing that a rather small reduction in the temporal representation may create misleading results for regional capacity mixes. Further research is therefore needed to analyze the extent to which other simplifications (for instance cost structure, weather data, etc.) affect results in CEMs. There is a risk that current CEM research presents and analyzes detailed regional results that are essentially noise resulting from simplifications in the models.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure S1: title, Table S1: title, Video S1: title.

Author Contributions: Conceptualization, L.R., F.H.; methodology, L.R.; software, L.R..; formal analysis, L.R., supervision, F.H.; writing—original draft preparation, L.R..; visualization, L.R. All authors have read and agreed to the published version of the manuscript

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