A Symmetric Block Resampling Method to Generate Energy Time Series Data

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***Abstract*—Energy modeling frequently relies on time series data, whether observed or forecasted. This is particularly the case, for example, in capacity planning models that use hourly production and load data forecasted to occur over the coming several decades. This paper addresses the attendant problem of performing sensitivity, robustness, and other post-solution analyses using time series data. We propose an efficient and relatively simple method, which we call the *symmetric block resampling* method, a non-parametric bootstrapping approach, for generating arbitrary numbers of time series from a single observed or forecast series. The paper presents and assesses the method. We find that the generated series are both visually and by statistical summary measures close to the original observational data. In consequence these series are credibly taken as stochastic instances from a common distribution, that of the original series of observations. We find as well that the generated series induce variability in properties of the series that are important for energy modeling, in particular periods of under- and over-production, and periods of increased ramping rates. In consequence, series produced in this way are apt for use in robustness, sensitivity, and in general post-solution analysis of energy planning models. These validity factors auger well for applications beyond energy modeling.**

***Index Terms*—energy modeling, bootstrap, time series data, sensitivity analysis, robustness analysis, post-solution analysis, synthetic data, time series generation**

I. Introduction

Time series data are used pervasively in engineering design applications (examples to follow), as well as for forecasting in economics, finance, and sales, and for applications in pattern recognition, bench marking, and quality control, among others.

A single observational series, however, does not afford sensitivity analysis, robustness analysis, and other forms of post-solution analysis of models ("robustness analysis" for short) [1]. For that, multiple observational series are needed or else a generating model whose variability can be employed to probe the performance of a designed object or system. We explore the latter approach in this paper. Our interest has been motivated by modeling related to the energy transition, as we explain below. First, however, we discuss two areas of application quite distinct from energy modeling but which present the problem of generating time series data in much the same form as is present in the energy context, and which may benefit from the generating method proposed in this paper.

It is a standard practice to design buildings to a specified performance level using historical weather data. What is typically used are dry bulb and wet bulb temperatures that are higher (for cooling, lower for heating) than a majority (typically 99.6%) of the historical temperature observations over a year period. Put otherwise, threshold temperatures are used that have a probability of exceedance of not more than 0.004. Then, a safety or over-sizing factor of 15–25% is typically used to size heating and cooling equipment. To illustrate, if X tonnes of air cooling per hour are needed for the threshold temperature of the historical data (e.g., hotter than 99.6% of the observed temperatures), then the space cooling system will be designed with a capacity of, say, $1.2 \times X$ tonnes per hour. (See the "ASHRAE Fundamentals" for one widely-used source of data and standards [2].)

Building energy performance is commonly modeled (simulated) during design and afterwards using *typical meteorological year* (TMY) data. "TMYs contain one year of hourly data that best represents median weather conditions over a multiyear period" [3]. The obvious problem with modeling a building to a TMY, when the building will last for more than 50 years, is that the building's performance is being assessed over a range of conditions (the median) that is less varied than is likely to occur. Also obvious is that a reserve buffer is at best a blunt instrument for dealing with stochastic variability and may often result in over-configuration of the building with attendant extra costs. In both cases, it would be much better to have sufficient data to provide an accurate estimate of the variability that is likely to occur over, say, the next 50 years. Such data are often unavailable, thus the recourse to TMYs.

Infrastructure projects, such as bridges and roadways, are typically built to withstand a 100-year flood (storm, etc.) event, a flood (storm, etc.) level expected to be exceeded only once in 100 years [4]). When the requisite data are available, the 100-year (generally, n-year) event criterion supports probability assessments that can be used to balance risks and outcome consequences. Even so, these risks would potentially be better evaluated were replications of n-year data series available. The occurrence of the most severe event in the last 100 years is a random variable for which we have at best one observation, making it impossible to estimate its distribution absent further information. Alas, this is rarely if ever possible with observational data.

Energy modeling presents demands for data that in many ways exceed those for building and infrastructure design. There are two principal reasons. First, electricity grids are operated and need to be controlled in (near) real time. This leads to temporal requirements on data to be granular at the hour or shorter duration. Second, while maximums and minimums of supply and demand certainly matter for electricity systems (as they do for infrastructure), *duration* of sub- and supra-supply and demand also matter greatly as does rapidity of change in generation. This is notably the case for the problem of integrating variable renewable energy (VRE, principally wind and solar) to the grid. There the concern arises of prolonged under-generation and how it can be accommodated, given the high expense of longer duration storage. Varieties of forecast plus reserve margin planning have been, and continue to be, used operationally in the electricity industry. Finding richer forms of data to support planning would surely be useful. For planning decades into the future, with the attendant high uncertainties, it is imperative. An extensive literature exists that proposes such models. A recent review [5] identifies 180 such "deep decarbonization" studies, most or all of which do not report robustness analysis based for the forecasted production and demand, even 30 years or more into the future, due to absence of means to obtain alternative series.

The need for a high number of production and demand time series in the electricity sector can be categorized by two main analyses. On the one hand, a high number of time series are necessary to analyse generation adequacy. The load in the electricity grid has to be balanced over short intervals, therefore the system has to be prepared for different load and electricity generation situations. This task becomes more difficult as the share of VRE increases. Since they are not dispatchable and they cause additional difficulties in balancing electricity demand and production. To prepare a robust electricity system, the system should be tested using a large number of time series, reaching hundreds of electricity demand and production scenarios. In these studies, analysts create scenarios that probe the energy system, such as very low electricity production from renewable energy sources (RES, including VRE as well as storage and other services) and high electricity demand. If a design is not robust in these situations, there is concomitant risk of system outages.

On the other hand, the time series are necessary to analyse the uncertainties, e.g. to quantify the flexibility requirements of the system. Due to fluctuations in electricity generation from RES, short-term flexibility options such as batteries and pumped storage power plants are used to compensate for the fluctuations over short periods of time, e.g. one day. For this reason, the data generated should consider both aspects and include different extreme cases, while maintaining the probability distribution and short-term variability of the original time series.

Markov chains [6], [7] are one of the most popular methods of generating wind power data. As mentioned above, these time series are especially used as input for energy system models. Therefore, Brokish et al. [8] use an energy system model to assess the quality of the time series generated by Markov chains. The results show that synthetic wind energy time series using Markov chains lead to lower storage requirements. The study concludes that Markov models correctly reflect the probability density function of wind data, but are not necessarily suitable for quantifying storage requirements. They can be used to a limited extent, especially for the generation of wind time series with time steps of less than 40 minutes [9]. Unfortunately, neither the level of fluctuation nor characteristic trends can be correctly presented in the generated time series.

ARMA or ARIMA models [10] [11] [12] are another widely used approach in this field to generate electricity production time series from wind. However, these models do not reliably maintain the probability distribution of the original data [8].

Usaola [13] uses a bootstrap method to generate time series for electricity generation from wind for the Spanish peninsula. However, the study mainly generates time series to carry out sequential Monte Carlo-based studies on generation adequacy. A new annual series is synthesised by taking random blocks of successive values, each sample block containing a few days. The transition between successive blocks is then also smoothed, so that the difference between the last value of one block and the first value of the next block does not have a large difference. In contrast to that study, we use a more flexible approach, which allows a more detailed and flexible sampling, rather than using the long sequence of time series. As a result, our approach does not generate time series only for analyses of generation adequacy, but also for the quantification and analysis of short-term flexibility requirements and for sensitivity analyses of the energy models.

Our efficient and relatively simple method largely preserves the original distribution of data. In addition, we provide metrics to quantify the level of variation in the time series generated. With this approach, the amount of fluctuation to be induced on the time series can be determined by a parameter. We focus on cases for which sufficient multiple observational data series are not effectively available, implying that a time series generator model of some kind must be used. Among generator models we choose to investigate non-parametric methods, and among them bootstrapping.

Our bootstrapping approach can be applied to different types of time series. However, in order to demonstrate our results, we focus here mainly on the times series of electricity production from VRE and electricity demand. Due to page limitations, we present here only a few of our results, which are representative of our broader findings.

The paper is organized as follows. Section II presents our algorithm for implementing our proposed symmetric block resampling method for generating time series data. It resembles, but is distinct from, prior art discussed in this section and can be generalized to cases beyond those addressed specifically in this short paper. Section III presents our results. We find that our proposed approach indeed generates series that should be useful for the analyses of short-term flexibility requirements and robustness studies and as such complements and extends existing literature (e.g., [1], [14]–[18]). To use these profiles in generation adequacy studies may, subsequent to further investigations, credibly reproduce the observational distribution. The paper concludes in section V with a discussion of the results and of opportunities for future research.

II. Method

Bootstrapping (a form of resampling data (sampling with replacement)) is an established and theoretically sound way to generate data for purposes of statistical testing [19]–[21]. In a prototypical case, a confidence interval for a statistic for a given collection of data (e.g., mean, median) is estimated by using resampling to generate multiple synthetic instances of the original data and estimating the statistic's confidence range by recalculating it in each of the generated samples. Because bootstrapping is a non-parametric method it is especially attractive in cases such as renewable energy generation and use of language where finding a credible parametric distribution is problematic [22].

As discussed in the literature review, there is ample precedent for using bootstrap sampling on time series data, although results are mixed or thin in the case of energy time series. There are many ways in which bootstrapping principles can be applied to time series data, depending upon the purpose to hand, and there is no theoretically dictated or even preferred method. Instead, investigators use intuition to propose sampling methods and then empirically test their efficacy, where possible. We proceed in the same mode, proposing a simple and intuitive method, then investigating its performance. To our knowledge, our proposed *symmetric block resampling* method for time series (see below for details) is original, at least for energy-related data. Time series modeling is typically undertaken for purposes of prediction based on recent observations. Given that purpose, it is inappropriate to use observed data arising *after* the data occurring in the target slot. Hence, it is inappropriate to use, as we do, a *symmetric* block of data, centered on the target slot. Our purpose is somewhat different. We wish to produce credible series of hourly data of length of at least one year. We are not interested in predicting any single hour. Instead we seek series that are credibly drawn from whatever process generated the observational data and that exhibit important properties for design of energy systems. Given this purpose, a symmetric window is quite appropriate.

We express the observations in an energy time series as $o_1, o_2, \ldots, o_N$. We use a window w_i with a size of $1+2n$. Window i is centered on a single observation, o_i, with i called the *focal slot*. The window contains n observations before and after the observation o_i, and hence is symmetric. For each observation, o_i, we define the window, w_i, as the observations $o_{i-n}, \ldots, o_{i-1}, o_i, o_{i+1}, \ldots, o_{i+n}$.

For each observation, o_i, we collect the most similar p windows in a pool, $\mathcal{P}_i$ the pool of p (p = pool size) windows. These elements are most similar to w_i. We measure the similarity by calculating mean square deviation between the window w_i and all the other windows. We created a pool, $\mathcal{P}_i$, of p elements for each observations for each focal slot, i. In the results we report here, p is set to 100 and to 20.

We generate a time series by randomly selecting one element from each pool of $\mathcal{P}_i$ and using the element in the middle of this selected window as o'_i. In this way we generate a time series with the elements $o'_1, o'_2, \ldots, o'_N$.

As already noted, we use a symmetrical window, i.e., when we create a window for an observation o_i, we create a window around the observation itself by including n other elements before and after the observation o_i. Also as already mentioned, the window w_i for an observation o_i consists of $o_{i-n}, \ldots, o_{i-1}, o_i, o_{i+1}, \ldots, o_{i+n}$. This allows us to add elements in our pool $\mathcal{P}_i$ with similar fluctuations before and after the observation o_n. If we had only included the observations to the window w_i before or after the observation o_i, we would prioritise the fluctuations after or before the observation we want to analyse. However, having a two-sided window allows us to consider the fluctuations on the both sides equally. (The sampled series is treated as circular, e.g., o_1 succeeds o_N which in tern precedes o_1.)

Finally, note that this approach affords generation of very large numbers of series, p^N. In our application this is N = 8760 hours per year and p = 100, a very large number indeed (excluding rare duplication).

III. Results

We use different years and regions in our data. We apply our algorithm to the time series of hourly electricity production from wind and PV and electricity demand for the PJM market region in the United States for the year 2019 [23] and for Germany for the year 2017 [24]. Figure 1 shows the first two days of wind production from 10 exemplary generated profiles and the historical profile in Germany. Only the first two days have been selected for the illustration so that the reader can clearly see the fluctuations in the generated data.

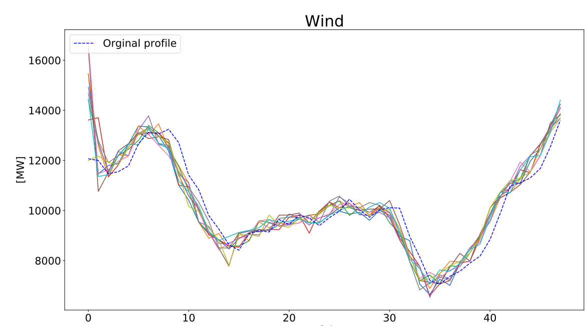

Fig. 1. Generated and historical electricity production profiles from wind using a similar window size, p=20.

Observing the profiles, we can see that the newly generated profiles differ to some extent from the historical wind profile used as input. Nonetheless, these new profiles in general follow the pattern of the historical profile. The amount of fluctuation mainly depends on the number of similar window sizes (number of p). Using a higher number for p results in larger fluctuations in the generated data. Figure 2 shows the generated profiles using the 100 most similar windows instead of 20. These two plots are representative of the behavior of the hundreds of series we have generated: the series track with apparently modest variation the original data.

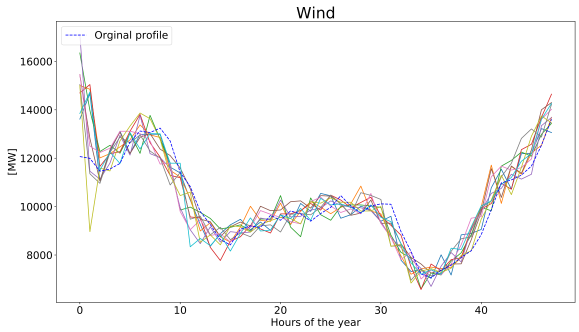

Fig. 2. Generated and historical electricity production profiles from wind with p=100 similar windows.

To analyze the quality of the applied method, we test the assumption of the normal distribution of the residual values. (This assumption is *not* made in our algorithm. We make it in the analysis in order to gain insight into the structure of the generated data.) The residual values are calculated by subtracting the generated profiles from the historical profiles. But here we want to check the normality assumption of the residuals. Figure 3 demonstrates the distribution of the residual values.

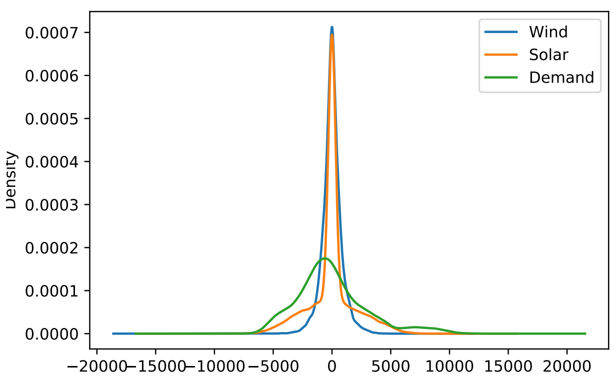

Fig. 3. Distributions of the residuals from wind, solar and demand data with p=20 similar windows.

The residuals appear to have close to a normal distribution. To test precisely whether the generated residuals have a normal distribution, we use Q-Q-Plot. Figure 4 shows the comparison of the distribution of the two quantitative variables. In Figure 4, we can see the results of Q-Q plots. In these diagrams the points are on or near the diagonal. So we can conclude that the residuals of wind data have close to a normal distribution. This further supports the finding that the generated series are not systematically biased to any significant degree. As in the case of plotting, we undertook these analyses to our solar and wind data as well, with similar upshot.

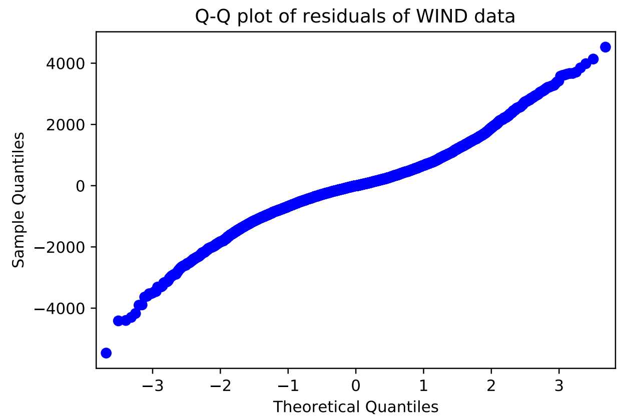

Fig. 4. Q-Q plot of the residuals of wind data with p=20 similar windows.

We now examine the potential of the synthetic data to create patterns that can be used for sensitivity analysis, robustness analysis, and other forms of post-solution analysis of models [1], particularly energy models. We focus, in this short paper, on two properties of interest for energy modeling. The first is the emergence of patterns of lengthy under-production of variable renewable energy (VRE). We focus on under-production over the period of a week, as this is long enough to challenge existing and anticipated battery storage. Second, we examine the size and frequency of hour-to-hour generation changes because this affects ramping by non-VRE generators or flexibility options (e.g., storage) that must act to balance large changes in generation levels.

We begin with PJM 2019 wind production data with 100 generated series and neighborhood pools, $\mathcal{P}_i$s of size $p = 100$. In the observational series, the mean hourly generation for 2019 is 2,747 MW with a standard deviation of 1,871. The mean for the 100 generated series is 2,743 with a standard deviation of 1,860. This further confirms that the generated series are close to the original data. In the 5,200 weeks modeled (100 synthetic series, extracting 52 weeks from each), we find 1,344 weeks in which the total production is at least 2,747 MW hours (the mean hourly production in the original data) *below* the corresponding series in the original data, and 320 weeks in which the total production is at least 5,494 MW hours (twice the mean) below the corresponding week's production. In one series, this occurs during 8 distinct weeks in the year. Multiple other series are at 7, 6, 5, and so on. Of the 100 series, 17 have at least 5 weeks in which the total production is at least 5,494 MW hours below the corresponding week's production. This indicates a potentially significant production risk against which capacity planning models should be tested.

Ramping behavior (on an hourly basis in our data) is a second property of a series that may change significantly under resampling, and it is an important one for design of electricity systems. Will resampling with our algorithm produce, in some years, increased incidents of larger ramping events, which in general challenge system design? Looking at PJM observed wind data we find the following descriptive pattern: mean 0.0042, std 341.43, min -2706.90, 25% -178.25, 50% -4.90, 75% 176.15, max 1875.80. Taking 1,500 as threshold of a large jump, the original data has 5 instances of jumps larger than 1,500 and 2 smaller than -1,500, for a frequency of 0.00057 on the high side. In the 100 generated series, in total there are 740 instances of jumps larger than 1,500 for a frequency of 0.00084, and 447 jumps smaller than -1,500 for a frequency of 0.00051. Significantly, comparing the 100 generated series, we find that in 42 of them the count of jumps larger than 1,500 is 8 or more, with a maximum of 15. As in the case of weeks of under-production, higher incidences of larger hourly ramps occur in the 100 series produced by resampling with our algorithm, as both should under real random draws from the true distribution. Again, the generated series have produced promising material for sensitivity and post-solution analysis.

We repeated this analysis for wind with the PJM solar data and got similar results. In brief, the mean hourly solar production in the observational data is 275 MW, which doubled is 550. This is our threshold indicator for a significant shortfall (compared to the observed data series) in production over the period of a week. The mean number of weeks in a year of the synthetic data that show a shortfall in excess of 550 is 19.84. In fully 27 of the 100 series, the number of weeks of shortfall this large equals 22 or more, nearly half the weeks in a year.

On ramping behavior, the PJM observed solar data has the following descriptive pattern: mean -0.000502, std 133.679, min -946.1, 25% -11.4, 50% 0.0, 75% 2.2, max 899.8. Taking 500 as the threshold of a large jump, we find 50 such hourly jumps in the original series, for a frequency of 0.0057. In the generated series we find 8 series in which there are 50 or more hourly jumps of at least 500 MW. We find that, as in the case of the wind data, the generated series produce meaningful variation for sensitivity and post-solution analysis.

IV. Discussion

A primary use of our proposed symmetric block resampling method for time series data is, in our view, for sensitivity analysis, robustness testing, and post-solution analysis of models in energy planning and other areas. Methods for these kinds of analysis are well-established in the case of scalar parameters, but much less so for vectors and even less so for time series with all their internal dependencies. Our proposed method affords the possibility of undertaking these kinds of analyses with time series data as parameters. We foresee modeling done as it is at present, based upon observed or forecast time series data, but augmented by probing the model's behavior with alternative time series generated by our method and selected to exhibit certain properties of interest, e.g., times of low production for renewable energy generation. Undertaking studies along these lines in order to test and demonstrate the efficacy of our envisioned use of our proposed method is at the top of the future research agenda. Deep decarbonization models [5] are a primary target, but much can and should be investigated on a smaller scale.

Regarding limitations and future work, we make the following comments and points at a range of generality and abstraction, some large, some small.

1) A notable limitation in our treatment of the observational data series is that we neglect any underlying changes in installed wind and solar capacity. Ideally, the original hourly data observations should be scaled by installed capacity. Any distorting effect on our findings should, however, be minimal. Because we are comparing the generated series on an hour-by-hour (or week-by-week) basis with the original data, any increase (or decrease) in capacity will be reflected in the original data at the time of occurrence and reflected, if imperfectly, in the generated series corresponding to the affected times.

2) Because this is a length-constrained paper we have focused on the poverty case of having just a single series to use for generating new series. How would our proposed method work in the presence of multiple observational series? This is especially pertinent when, as is often the case in energy studies, there are several years of production data available.

If the installed capacity (*pace* the previous point) varies significantly over the historical data, it will be necessary to scale the observational data by installed capacity. Once that issue is resolved, a simple and intuitive extension to our algorithm would be to pick at random one of the historical series, use the symmetric block resampling algorithm to generate the new series, and continue in this fashion until the desired number of new series is generated.

3) Resampling methods cannot introduce values not present in the original sample. In consequence, more extreme values cannot be captured, even though it is believed they would appear in replications of draws from the original distribution. Were a series to be generated from one or more probability distributions, instead of by resampling, it would be possible to realize values beyond the range of the original data. Fitting such distributions, however, is problematic for wind and solar data and to our knowledge has not been proposed for generating multiple series of data. This is in distinction to fitting parametric models for the purpose of near-term prediction. While this has been done successfully, it is not the problem we are addressing and doing it successfully does not solve the problem we are addressing.

Our proposed resampling method can be modified in *prima facie* credible ways to generate values more extreme than those in the observational source data. One way to do this would be to use the p most similar blocks for a given slot as data for fitting a continuous distribution for the slot. For example, the empirical mean and variance of the center of the p most similar blocks could be used to specify a normal distribution for the slot in question. Upon doing individual fitting in this way for each slot in the series, a new series could be generated by assembling independent draws from the distributions associated with each slot. Inevitably, this would lead to draws more extreme than the original data, even assuming that provision would need to be made in the energy case for prohibiting negative amounts of generation. This is an important topic for future research.

4) Given the intended use of our proposed method (for sensitivity analysis, robustness analysis and other forms of post-solution analysis), it would be desirable to have a principled way of increasing variability in the generated series. There are many ways to do this and they should be explored for their usefulness. We have already discussed how using slot-by-slot fitted continuous distributions can lead in a principled way to production of more extreme values than are found in the original series. Maintaining a purely resampling regime, the consideration sets of similar windows, the $\mathcal{P}_i$s, can be increased in size and subjected to non-uniform sampling in a way that favors somewhat less similar candidates. A more radical approach would be to condition generated slot values on the generated series, in addition to the original series. For example, the window portion before the target slot could consist of the generated series values. This would imply a somewhat different consideration set of similar windows and lead to a degree of path dependence in the generated series.

5) Finally, by combining generated series from multiple sources it would be possible to investigate unusual co-occurrences, such as unusually high demand and unusually low production from wind and solar, which are nonetheless crucial for planning.

The overriding research question of this paper is What is the best method (or methods) for generating times series data for purposes of post-solution analysis for energy modeling and other purposes? The question is not specified with enough precision to afford a definitive answer, but in any case a thorough investigation, including comparison of multiple generation methods, is well beyond the scope of a single paper. It has been our ambition to make the case that this is a useful, yet under-explored avenue for research.

V. Conclusion

The paper has proposed a *symmetric block bootstrap resampling* method for generating time series data and it has discussed applications of this method to example load, wind generation, and solar generation data. We find that the generated series are both visually and by statistical summary measures close to the original observational data. In consequence these series are credibly taken as stochastic instances from a common distribution, that of the original series of observations. We find as well that the generated series induce variability in properties of the series that are important for energy modeling, in particular periods of under- and over-production, and periods of increased ramping rates. In consequence, series produced in this way are apt for use in robustness, sensitivity, and in general post-solution analysis of energy planning models. Moreover, these validity factors auger well for applications beyond energy modeling, but this is something to be addressed in future work.

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