How Sampling and Averaging Historical Solar and Wind Data Can Distort Resource Adequacy

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***Abstract*—Capacity planning models and resource adequacy assessments have often relied on averaging and sampling techniques that disregard important reasonably expected interactions of weather-based resources. We provide a method to capture the economic value of information and reliability risk from using inadequate sample data to design sustainable systems with high renewable generation. Analysis of long run portfolio cost and sources of uncertainty shows as much as a 16% system cost increase with a 38-fold increase in expected unserved energy when average renewable outputs are modeled rather than a 10 year hourly coincident sample, which illustrates the pitfalls of averaging data and ignoring temporal interdependencies. Investment recommendations can significantly differ depending on which years and how many years are included in the analysis. We show that selecting the wrong year can increase system costs by over 4% with a 7-fold increase in expected unserved energy, failing to meet planned reliability and renewable design targets. It is possible for a single year of coincident load-wind-solar data to reasonably approximate system characteristics; however, the best year changes with renewable penetration.**

***Index Terms*—Adequacy, composite system forecasting, optimization, power system economics, planning, and reliability, wind and solar power generation.**

I. Introduction

WIND and solar generation are becoming more prevalent in electricity systems. It is increasingly important to accurately capture resource adequacy impacts as weather-dependent generation increases. Adequacy addresses whether the electricity system can always supply customer requirements even during reasonably expected outages [1].

Much of the adequacy literature considers several metrics regarding adequacy, including metrics linked to the number of interruptions and outage duration, likelihood and severity [2]. Most of the classic literature on the topic relies on strong independence assumptions. In particular, the probability of an outage when a unit is needed to serve demand is assumed to be independent of the demand and the status of other units [3]. Assuming independence, system adequacy is assessed using efficient convolution-based techniques. Other widely used deterministic methods remove randomness by assigning parameters including expected values, such as generator capacity adjusted by expected forced outage rates.

Only recently has the literature begun to model weather-dependent generators to estimate their adequacy impacts. Most adequacy literature addressing wind or solar systems relate to improving forecasts of production from individual plants, particularly for short-term applications such as day-ahead operational planning. Another group of literature focuses on different deterministic and probabilistic techniques, without consideration of the data used to validate such methods [4]–[6]. Longer-term studies are generally based on a single year of data or less [7]–[10] or condense long historical records into single year representations/probability distributions or consider weather-based resources and load separately or some combination [4], [6], [11]–[15].

In addition to relying on limited samples of renewable output to estimate probability distributions, most applications of capacity planning models also reduce computational time by relying on data aggregation techniques to form typical load profiles. For instance, rather than use 8760 hours for one or a sample of years, loads for typical weekdays and weekends might be used to represent each month or season [10], [16]. Another well-intended simplification is the consolidation of multiple years of data by averaging across the different realizations, preserving seasonality, day of week, and hourly trends [17]. Both types of data aggregation suppress variability, which may distort the joint distributions of load, wind, and solar profiles.

We have found no study that incorporates multi-year synchronized load, wind, and solar data. Industry planning studies and capacity market designs usually consider relatively brief record lengths, subjecting them to sample error. Although the need for adequate sample size is acknowledged [11], there are no known studies that quantify potential impacts of inadequate samples.

The first contribution of this paper is a new optimization-based method to assess the economic impact of inadequate samples on generation mix. The second contribution includes impact quantifications of inadequate sample sizes and simplified data aggregation procedures, and analysis impact change as

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renewable penetration increases. This paper investigates the necessity of representing load, wind, and solar profiles with their interdependencies to capture simultaneous variations due to weather, time of day and season, along with the potential consequences of not conducting an accurate assessment.

Planning an electricity system generally incorporates both variability and uncertainty. Historical records can capture variability; however, due to parameter estimation error (from using small or unrepresentative samples) and non-stationarities (e.g., economic growth and technology innovation) there is always uncertainty associated with the use of such records. The focus of this paper is on capturing concurrent variability among load, wind and solar. Additional techniques, such as scenario development, are still necessary to capture uncertainties concerning potential non-stationarities.

To investigate data sampling and aggregation techniques and their implications for system cost, resource mix, generation reliability, and renewable targets, this paper is organized as follows. Section II discusses the model and method that is used to simulate the results of planning studies or market outcomes when different data samples are used to approximate long-term system performance. Section III describes the framework for analysis using an example case study. Section IV presents the analysis and results considering systems with and without renewable incentives using each of the data samples, quantifying the cost and reliability distortion resulting from reduced length samples. We also examine interactions of sample size with renewable subsidies in the form of a Renewable Portfolio Standard (RPS) or tax credits. Section V discusses distortions caused by aggregating loads and renewable output across years. Finally, Section VI provides conclusions.

II. Model Formulation and Assumptions

A. Methodology for Testing the Effect of Sampling

To test the system impacts of sample size, we have developed the following multi-step optimization-based methodology to assess how inadequate renewable energy and load samples distort generation mixes.

First, a capacity expansion optimization model is run using a full ten-year sample of actual hourly coincident load, wind, and solar data. The values of the resulting generation investment variables are assumed to reflect the optimal long-term decision given perfect information. We call this solution the “base” investment plan.

Next, other coincident data sets are tested using subsamples of two lengths: 1 year (subsamples Y1-Y10, representing years 1 thru 10) and 5 years (where subsample 5A is Y1-Y5 and 5B is Y6-Y10). In addition, we test a model with an aggregated typical year (AVG). Using each subsample, the optimized installed capacity for each generation type is determined using the capacity expansion model. Then a production cost-only model is used to determine the “true” operating costs. Renewable curtailments and unserved energy for that subsample solution are determined using the full 10 years of operating data. The difference in cost between the base plan and the subsample plan is an indicator of the economic consequences of choosing the wrong generation mix because of sample error. The difference in expected unserved energy (EUE), which captures the magnitude of customer load curtailed in megawatt hours (MWh), is viewed as the reliability impact.

B. Model Variables, Objective and Constraints

The models used to investigate the effects of alternative sampling techniques are variations of the model detailed in [18]. The decision variables are installed capacity (x_g) by generator type (g), and the hourly (h) energy dispatch for each generator type ($e_{h,g}$) including the ability to curtail renewables ($ce_{h,g}$) or leave energy unserved (eue_h). The set of generators (G) includes fossil (subset F: coal, natural gas combined cycle (CC), and natural gas combustion turbine (CT)) as well as wind (subset W) and solar (subset S) at different sites.

Parameters include the levelized fixed costs (FC_g), variable costs (VC_g), and wind subsidy forgone during curtailment (WS, equaling the production tax credit (PTC)). EUE is valued at customers' perceived cost of electricity curtailment, known as the value of lost load (VOLL).

The optimal values of the decision variables are found by minimizing the total cost objective (1) subject to market and generator constraints. We showed this to be equivalent to a long-run market equilibrium [18], assuming no market failures.

The capacity expansion model objective is:

$$\begin{aligned} MIN\ \text{TotalCost} &= \text{Fixed} + \text{Variable} + \text{Unserved Energy} \\ &\quad + \text{Lost Wind Subsidy} \\ &= \left[\sum_{g\in G} FC_g{*}x_g\right] + \left[\sum_{h\in H, g\in F} VC_g{*}e_{h,g}\right] \\ &\quad + \left[\sum_{h\in H} eue_h{*}VOLL\right] + \left[\sum_{h\in H, g\in W} WS{*}ce_{h,g}\right] \end{aligned} \tag{1}$$

The model constraints are the same as [18] and include hourly energy balances, generator capacity availability, and simplified operating constraints. Additionally, if an RPS policy is modeled, a constraint is added to ensure the specified renewable energy production as a fraction of total energy consumed is met.

Meanwhile, the production cost-only model's objective is:

$$\begin{aligned} MIN \sum_{h\in H, g\in F} VC_g{*}e_{h,g} &+ \sum_{h\in H} eue_h {*}VOLL \\ &+ \left[\sum_{h\in H, g\in W} WS{*}ce_{h,g}\right] \end{aligned} \tag{2}$$

Although the capacity expansion model includes an RPS constraint to ensure renewable compliance, using subsamples to determine capacity additions can result in renewable investments that fail to comply with the RPS target when the full ten years are considered in the production costing model. For example, if the subsample year has higher than average wind production, the capacity expansion model will yield smaller levels of wind

TABLE I
LOAD, SOLAR, AND WIND CHARACTERISTICS. TOP THREE ROWS SHOW AVERAGE LOAD FACTOR (LF)/CAPACITY FACTORS(CF) DURING THE ANNUAL PEAK HOUR, ANNUAL TOP 10 HOURS, AND ANNUAL TOP 100 HOURS. LAST THREE ROWS SHOW MAXIMUM, AVERAGE, AND MINIMUM LOAD/CAPACITY FACTORS OVER THE 10 YEARS

	Load	S1	S2	S3	W1	W2	W3	Woff
Avg Peak	100%	48.9%	41.1%	80.1%	5.2%	39.6%	8.7%	19.0%
Avg Top 10	98.8%	50.4%	43.8%	73.0%	8.3%	37.0%	8.9%	22.2%
Avg Top 100	95.0%	48.2%	41.6%	71.4%	12.2%	35.2%	13.4%	21.5%
Max LF/CF	58.3%	22.5%	20.4%	29.6%	39.8%	37.9%	44.3%	40.9%
Avg LF/CF	56.2%	21.0%	19.4%	27.6%	36.7%	34.5%	42.3%	38.1%
Min LF/CF	55.0%	19.9%	18.6%	26.2%	31.7%	30.9%	39.4%	33.3%

investment to meet the target. However, production over the full ten-year sample will therefore be lower than that subsample year and fall short of the target. In some jurisdictions, a penalty would be assessed for non-compliance. Therefore, we similarly add to the total cost a non-compliance penalty, post-optimization.

C. Wind, Solar, and Load Data Aggregation Methods

To assess the effect of aggregation, an average year (AVG) was derived using data averaging techniques commonly used by industry [13], [17] to develop separate 8760-hour profiles of load, wind and solar from the ten years of historical data. For wind and solar averaging, the capacity-normalized production values were averaged hourly across the ten years (3) such that the profile produces the annual average amount of energy.

$$W_h = \frac{1}{10} \sum_{y=1}^{10} \text{NormalizedWindProduction}_{y,h},\ \forall h \tag{3}$$

In developing the load profile, instead of matching days of the year as in (3), it was further necessary to match days of the week and holidays, factors that are important to load forecasting [19].

III. TEST CASE FRAMEWORK

A. Wind, Solar and Load Data

To investigate how well differing subsamples of data represent a longer data record, we develop a test case based on the Electric Reliability Council of Texas (ERCOT). Ten years of coincident time-matched hourly demand, wind, and solar data from ERCOT are modeled. The hourly demand data is actual hourly demand [20] for $h = 1 \ldots 8760$ in each year, $y = 1 \ldots 10$, normalized by annual peak and rescaled to create ten different years, each with a peak of 50000 MW:

$$\frac{\text{actual demand}_{h,y}}{\text{max demand}_y} * 50,000MW,\ \forall\ h,\ y \tag{4}$$

This normalization provides a basis for comparing within-year variability across years, keeping the peak demand constant.

Wind generation data is based on four sites using hourly profiles that were developed for ERCOT [21]–[23]. The three onshore sites are chosen due to their diverse geographic and generation characteristics. As shown in Table I, the profile for the first wind site, W_1, has moderate annual energy production with relatively high variation among years, but very little of this energy is produced during high consumer demand periods. The second wind site, W_2, has lower annual energy but high production levels during high load periods. The third wind site, W_3, is in a different region of the state (over 500 miles apart from W_1 and W_2) and produces between W_1 and W_2 during peak demand periods but has the highest annual energy production with the lowest variability among years. The offshore wind site is based on a hypothetical profile. Although offshore wind represents a different geographic region, its output is dominated by W_2 in terms of both peak contribution and annual production while having a much higher investment cost.

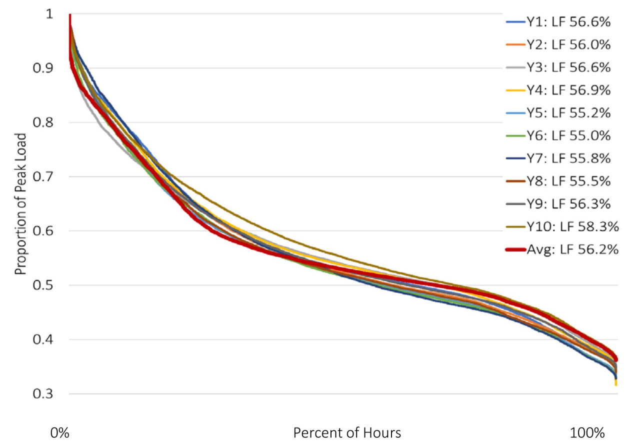

Fig. 1. Normalized Load Duration Curves: Years 1-10 and Average.

Three solar sites were selected mixing geographic location and technology [24], [25]; however, S_3 representing Midland, Texas single-axis tracking has both the highest irradiance (and thus production), best peak load correlation, and lowest cost; hence, since we do not consider transmission, it is the most cost-effective solar site in the model.

B. Model Parameters

Generator cost data are based on [26]. Coal capacity can be selected only up to an existing installed amount with retirement indicated by less. The value of lost load is set at \$10000/MWh [27]. If used, the wind subsidy is a \$23/ MWh PTC [28] and the solar subsidy is a 30% investment tax credit (ITC) [29]. If used, an RPS is the percent of total customer demand met by renewable generation. A \$75/MWh penalty is conservatively added to any portfolios that were renewable deficient when a PTC is present, and a \$50 MWh penalty if no tax credits.

C. Wind, Solar, and Load Data Aggregation Assumptions

Although it is known that averaging reduces variability, the practical importance of that fact in planning needs to be tested. For this data set, the mean consumer demand in both cases is 56.2% of peak load (the system load factor). The full ten-year data has a standard deviation of 13.6% while the averaged data has a standard deviation of 12.4%. When examining the load duration curves of the full ten-year dataset and the aggregated average year (Fig. 1), the curves look similar. If the generation screening curve method [30] was to be used to choose a cost-minimizing mix of thermal generating capacity, one might expect the technology mix to be relatively unchanged despite the slight variation reduction.

The ERCOT-specific data set has lower than average wind production during higher demand periods and correspondingly more wind at lower demand periods; therefore, we anticipate potential investment changes compared to either a screening curve approach or a data averaging model. Since current industry methods typically average consumer demand, wind, and solar facilities separately, we expect greater distortions.

D. Renewable Policy Case Development

The effect of sample error is investigated under five alternative renewable policies:

A) No renewable policy
B) Subsidies in the form of PTC and ITC
C) 40% RPS
D) 40% RPS combination with PTC and ITC subsidies
E) 60% RPS

Following our methodology, for each case the system is optimized using (1) with the full ten-year sample to establish a base investment plan. Then each of the one- or five-year subsamples is optimized. Once the investment mix has been determined for the subsample, the operation of that system is optimized by (2) using the full ten-year data. Economic and reliability distortions due to sample selection are determined by comparing subsample results to the base solution. The total system cost includes market costs shown in (1), including the reliability cost associated with unserved energy. The total system cost also includes costs outside the market, including renewable tax credits and RPS non-compliance payments. Non-monetized externalities are not included. Model size depended on the case but ranged from over 100,000 to over 1 million decision variables for the 1-year and 10-year models respectively. Solution times varied depending on the case and computer used but were on the order of under 30 minutes to several hours on a standard desk-top, with higher renewable penetrations taking longer.

IV. Sample Error Analysis

A. Case A: No Renewable Policy

In this initial set of runs, the model chooses the optimal capacity investment mix without renewable policies. Renewable generation is included in the investment mix if it is cost-effective compared to other generation technologies.

Fig. 2 shows the capacity investment mix and ten-year increased cost when optimizing on each subsample compared to the full sample (portfolio 10Y, indicating that 10 years of wind, solar, and load data were considered), sorted by total cost. The total cost over ten years for the base plan is $153.7 Billion. Unserved energy is 35.1 GWh. Renewable energy is 1.63% of total energy demand with no renewable curtailments.

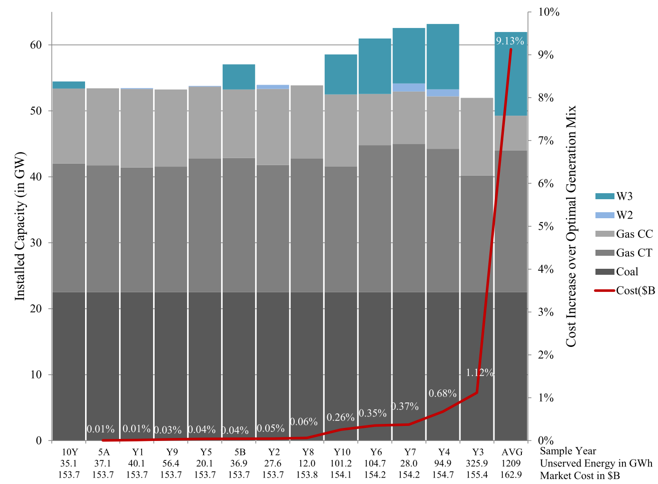

Fig. 2. Case A: Comparison of installed capacity, cost increase, and unserved energy by sample with no renewable incentives.

The amounts of gas-fired and renewable capacity in the optimized portfolios are quite different depending on the sample used.

Some individual years, such as Y1 and Y9, were reasonably good approximations of the base plan from an overall cost perspective, however, are less reliable and create disincentives to wind. With low renewable penetration, the individual years that have similar load factor and peak load hour profiles to the full sample (i.e., Y1 and Y9) result in a generation mix closest to the base solution. This is also true of subsample 5A whose load factor is closer to the 10-year values than that of 5B.

Other individual years, such as Y4 and Y7 result in an over-installation of wind (14-17% as compared to under 2%) and higher portfolio costs. Both samples had higher wind capacity factors than the full ten years of data, making the wind resource appear more valuable. The higher costs are due to both having the wrong mix of generation and having higher unserved energy because the over installation of wind led to an under installation of other generation types. Y3 performed the worst of the ten single years. This is attributed to that year having fewer critical load hours, as shown by the steeper drop-off in Fig. 1. Y3 builds less capacity since there is a perceived smaller exposure to unserved energy in peak hours; however, when this investment mix is operated for the full ten years, more critical high load hours together with under-investment in generation results in a high amount of unserved energy.

The unserved energy in Fig. 2 shows the impact on system adequacy when using different subsamples of data. Portfolios based on samples Y2, Y7, and Y8 have less unserved energy than the base plan (10Y), thus were more reliable; however, this comes at an increased cost above the customers' willingness to pay for reliability. Meanwhile, portfolios based on samples Y3, Y4, Y6, and Y10 had both increased unserved energy and increased cost –clearly inferior capacity mixes from both the reliability and economic perspectives. Sample selection is becoming complex with interactions between the load and the renewable generation sources even at low renewable levels.

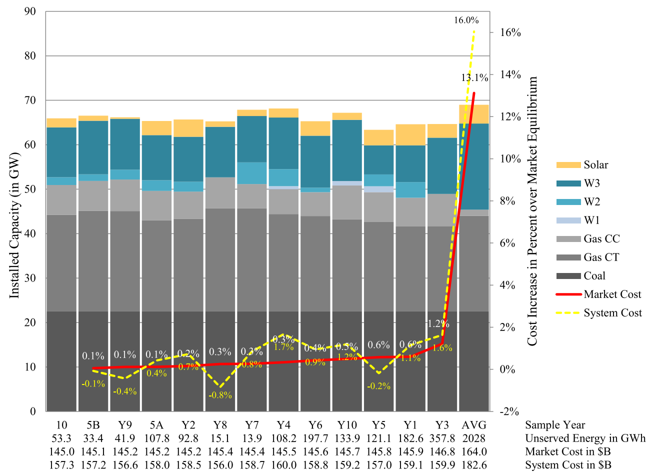

Fig. 3. Case B: Comparison of installed capacity, cost increase, and unserved energy by sample with renewable tax credits.

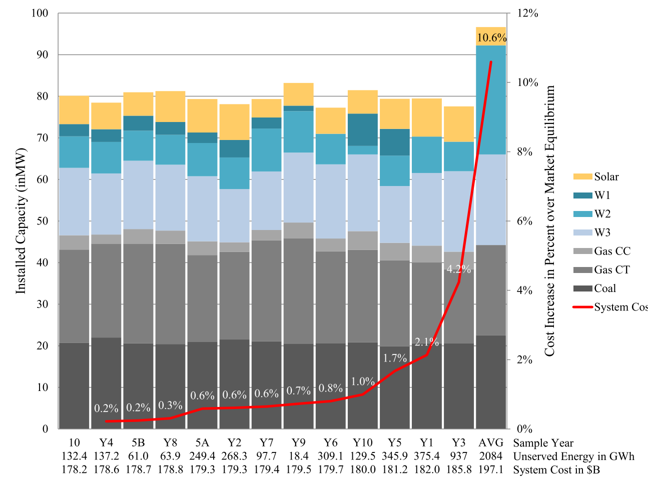

Fig. 4. Case C: Comparison of installed capacity, cost increase, and unserved energy by sample with a 40% RPS.

B. Case B: Renewable Tax Credits- PTC and ITC

The first renewable policy considers tax credits that are administered outside of the electricity market, so although subsidies impact the decision to construct, their levels are not optimized within the market, creating distortions as discussed in [18]. Fig. 3 shows the optimal portfolio mix for this policy, along with subsample price and reliability distortions. The tax credits increased the average renewable energy among the portfolios from under 2% in Case A to approximately 21% with a small (0.6%) level of curtailment. Market costs decreased because of the subsidies; however, if the subsidies are added back in, the overall system cost increased 2.4% compared to Case A to \$157.3 billion. This is partially due to the decrease in reliability, with 53.3 GWh unserved energy occurring, a 52% increase. Cost also increased because the greater renewable generation decreased reliance on more efficient combined-cycle plants in favor of greater installation and operation of costly, higher emitting combustion turbines.

The results show that the individual sample years that provide the best approximation/least distortion are different than the best sample years without tax credits. More complex interactions between load, wind and solar must be considered. As an example, Y1 provided the *best* single year approximation in Case A, where no renewable policy was used and renewable penetration was low; however, Y1 is among the *worst* when subsidies induce over 20% renewable generation. This shows that increasing renewable generation increases the impact of sample error, making it more imperative to select long-term representative data in planning.

When considering tax subsidies, some portfolios perform better than the base plan from a system cost perspective. This occurs when fewer renewables are developed. Y8 is an example where less solar is planned because its performance is 10 percentage points less during the top load hours than shown in Table I for the full ten years. Higher summer evening load in Y8 made solar investment less desirable, thus lowering the tax credits dispersed and the resulting system cost. Portfolio 5B has a similar lower overall cost due to the renewable mix. Although the base plan and 5B have roughly the same amount of renewable production, more of the energy in 5B comes from wind which receives a lower subsidy than solar. The differing tax credit amounts introduce a distortion among renewable generators (the solar credit under our modeling assumptions is equivalent to \$35/MWh PTC).

C. Case C: 40% RPS

The second renewable policy considered is a 40% RPS. This policy results in about twice as much renewable energy production as the ITC and PTC case. The model optimizes renewable choices based on the benefits they provide to the system in terms of serving customer demand. Each technology receives the same implicit subsidy (price per MWh of renewable energy credit). All costs are optimized within the market which internally creates a price for renewable energy credits via the shadow price of the RPS constraint.

Overall, the ten-year optimal (base) portfolio costs \$178.2 billion (\$17.8B/year), a 16.0% increase over Case A (no renewable policy). Reliability continues to decrease with 132.4 GWh of unserved energy, 3.8 times that of Case A. The cost of reducing unserved energy in Case C to the level in Case A exceeds the customers' willingness to pay (assumed to be \$10000/MWh). Renewable curtailments increase to 11.3%. Since 40% renewable energy must be produced, the installed renewable capacity could generate 44.5% of load but a portion was curtailed when there was excess relative to load and system operating constraints. Fig. 4 shows the subsample investment mix, along with unserved energy and costs.

When using a subsample under this policy, the long-term production of renewable energy is inaccurately represented. As a result, portfolios Y2, Y4, Y6, Y7 and 5B are lower cost than the optimal portfolio because their subsample wind capacity factors are higher than the 10-year average, requiring less installed capacity to meet the binding RPS constraint. However, during the

TABLE II
CASE D: COMPARISON OF COST, UNSERVED ENERGY AND RPS BY SAMPLE WITH TAX CREDITS AND A 40% RPS

10	5B	Y4	Y7	Y8	5A	Y9	Y2	Y10	Y5	Y1	Y3	Y6	AVG	Sample year
140.0	77.3	144.3	88.9	67.9	292.9	16.3	307.9	108.9	354.2	412.5	611.8	366.8	2799.4	Unserved energy (GWh)
178.5	178.6	178.7	179.0	179.2	179.7	179.9	180.0	180.1	181.2	182.4	183.6	185.4	203.4	System cost ($B)
	0.1%	0.1%	0.3%	0.4%	0.7%	0.8%	0.9%	0.9%	1.5%	2.2%	2.9%	3.9%	14.0%	Cost incrase over base
40.0%	39.6%	38.1%	38.1%	40.1%	40.4%	40.0%	39.1%	40.3%	41.0%	41.4%	41.2%	35.5%	41.2%	Renewable energy

full ten-year production cost optimization (2), renewables fail to produce at the required RPS levels. To make the comparison with the base plan more appropriate, an alternative compliance penalty was added to these non-compliant portfolios. The resulting system cost and portfolio order are shown on Fig. 4. The ability to comply with an RPS adds another reason that a single year of data is insufficient for planning high penetrations of weather-dependent generation.

Some individual years provide better approximations than others, but these years are different than those performing best under other policies. Y8 is now the best approximation, even though it performed poorly for the previous renewable policies. Y4 and 5B are the best of the non-compliant portfolios, but their relative position compared to the compliant portfolios depends on the assumed level of alternative compliance payment. As shown in Fig. 4, the composition of renewables changes dramatically among sampled years, even though each had the same 40% RPS constraint in (1). Portfolios Y10, Y1, and Y3 have higher costs because their low renewable capacity factors mean that more renewable investment was needed in (1) to meet the RPS; however, this led to greater curtailments, up to 14.5%. Interestingly, the increase in curtailment is not strongly related to increased renewable capacity. Complex interactions between demand and each of the renewable resources makes predicting the optimal mix more difficult.

D. Case D: 40% RPS With ITC and PTC Tax Credits

Next, a case is presented that combines both external tax credits and an internal RPS. The system cost of the base plan is $178.5, 16.1% higher than Case A, and just slightly more than Case C. In Cases C and D, the 40% RPS constraint is binding in (1); however, in Case D the market does not internalize the tax credits and so the investment decision favors solar, building 28% more than Case C in the base plan. The unserved energy is also slightly higher than Case C. Table II shows summary results for each subsample for Case D.

The subsample that provides the best approximation changes yet again. 5B, Y4, and Y7 have the least cost distortion; however, they are not RPS compliant and an alternative compliance payment is applied. Y3 had the lowest single-year renewable capacity factors. This caused a significant overbuild of renewable generation to meet the RPS, leading to higher costs and the need for increased curtailments over ten years.

Fig. 5, further shows the reliability impact of sampling. The planned values on the figure are what the planner believes that the system reliability will be when using subsample optimization. The actual values are those that are realized when the subsample resource mix is operated over the actual ten-year period. The choice of subsample can dramatically impact system reliability.

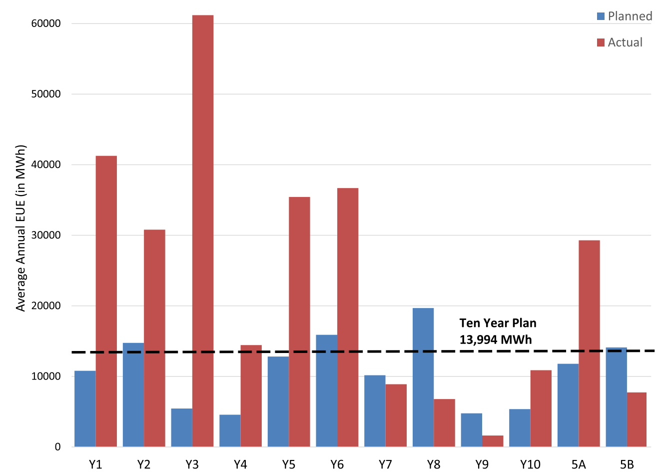

Fig. 5. Case D: Reliability comparison using EUE.

TABLE III
CASE E: COMPARISON OF COST, UNSERVED ENERGY AND RPS BY SAMPLE WITH TAX CREDITS AND A 60% RPS

10	5B	Y8	Y4	Y9	Y2	Y6	Y7	Y5	5A	Y1	Y3	Y10	AVG	Sample year
170.2	128.5	69.6	211.0	73.0	237.9	322.3	62.6	328.5	258.2	288.3	321.9	107.9	3013.6	Unserved energy (GWh
$222.3	$222.6	$222.9	$223.2	$223.5	$223.6	$223.7	$224.3	$227.2	$228.9	$230.0	$230.4	$235.8	$271.6	System cost ($B)
	0.1%	0.3%	0.4%	0.5%	0.6%	0.6%	0.9%	2.2%	3.0%	3.5%	3.7%	6.1%	22.2%	Cost incrase over base
60.0%	59.5%	59.9%	58.0%	60.1%	58.5%	58.3%	57.7%	61.1%	61.6%	61.8%	61.8%	62.8%	49.3%	Renewable energy

For example, subsample 5A will result in over twice as much unserved energy as presumed, while subsample Y3 will have over 4 times as much. Since most capacity expansion modeling is constrained by a reliability constraint, a system can significantly underperform, carrying a much higher risk of not serving load than presumed by the plan.

E. Case E: 60% RPS

A final case was run at 60% RPS. The system cost of the base plan is $222.3, 45% higher than Case A. Unserved energy also increases. Table III shows summary results of each subsample. Again, the subsample economic order changes.

F. Summary Comparison of Renewable Policy Cases

As renewable penetration increases, greater distortions occur with inadequate sample sizes. Resource diversity is important in providing energy both overall and during the system critical hours. Eventually, the renewable penetrations saturate to a point where renewable generation, without complementary storage capability, no longer provides marginal capacity benefits. At this point, high capacity factor renewables that minimize curtailments are most economical. Low cost, high capacity factor renewables would also intuitively be the objective if storage is added. Cost and reliability distortions are related primarily to the mix of renewable generation. The renewable resource variations, shown in Table I, reveal in part the cause of increasing distortions at higher renewable penetrations. Fig. 6 shows overall system cost rankings and reliability rankings of the subsamples. A rank of 1 has the least distortion compared to the optimum, while higher ranks are farther from optimal. Using five years of data instead of one may reduce both cost and reliability distortions;

Cost Ranking

Case	A	B	C	D
5A	1	3	4	5
Y1	2	11	11	10
Y9	3	2	7	6
Y5	4	10	10	9
5B	5	1	2	1
Y2	6	4	5	7
Y8	7	5	3	4
Y10	8	9	9	8
Y6	9	8	8	12
Y7	10	6	6	3
Y4	11	7	1	2
Y3	12	12	12	11
AVG	13	13	13	13

Relibility Ranking

Case	A	B	C	D
Y8	1	1	3	2
Y5	2	8	10	9
Y2	3	5	8	8
Y7	4	3	4	4
5B	5	2	2	3
5A	6	6	7	7
Y1	7	10	11	11
Y9	8	4	1	1
Y4	9	7	6	6
Y10	10	9	5	5
Y6	11	11	9	10
Y3	12	12	12	12
AVG	13	13	13	13

Fig. 6. Portfolio rank according to least system cost and most reliable (1 = best, 13 = worst).

TABLE IV
SYSTEM COMPARISONS OF DATA AGGREGATION SOLUTIONS

Scenario	10 Year ($B)	Averaging ($B)	Cost Increase	% Renew	EUE (MWh)	EUE (x base)
No Renewable Generation	$ 157.1	$ 157.2	0.0%	0.0%		
A: No Renewable Subsidy	$ 153.7	$ 167.7	9.1%	18.9%	1,506,592	42.9
B: ITC/PTC	$ 157.3	$ 182.6	16.1%	31.0%	2,028,144	38.0
C: 40% RPS no tax credits	$ 178.2	$ 197.1	10.6%	34.0%	2,084,910	15.7
D: 40% RPS & ITC/PTC	$ 178.5	$ 203.4	14.0%	34.7%	2,799,400	20.0
E: 60% RPS	$ 222.3	$ 271.6	22.2%	49.3%	3,013,608	17.7

however, in those cases distortions are still significant and sample dependent. Single year samples can outperform five-year samples; yet, the best year changes with renewable penetration.

It is also clear that adding an RPS increases reliability distortions measured by unserved energy when a suboptimal sample is chosen. This is caused by the change in the shape of the peak of the net load curve (demand minus renewable generation), which indicates the amount of unserved energy corresponding to a given loss of load probability (i.e., a given number of hours in which load is unserved). The reliability rank of the subsample portfolios depends strongly on the renewable policy, as shown in Fig. 6.

Increasingly renewable penetrations complicate the cost versus reliability tradeoff. Generally, a higher investment results in a more reliable portfolio. However, these results show that higher investments in renewables that do not match load requirements can reduce reliability while also increasing curtailments – clearly an inferior investment plan. Lower EUE occurs primarily in cases where the portfolio includes a greater amount of thermal generation that can be dispatched to match load. Because the subsample portfolios were not optimized in (1) with the full range of data, the model was short-sighted and sometimes chose a generation mix that exceeded the customers' willingness to pay over the long-term.

Overall, very complex interactions are shown among the load, wind and solar variations which lead to different hours of the year being the highest reliability risk depending on the magnitude and type of renewable generation. Consequently, investment in one type or location of renewable can impact the value of others. Accurately understanding these interactions, requires much larger data sets that capture these interactions. Not doing so creates significant distortions that increase with renewable penetration. However, even larger distortions come from the common practice of data averaging.

V. Distortions Due to Data Aggregation

The worst performing portfolio of investments uses a "typical" year constructed based on separately aggregating long-term demand, wind, and solar data. Although this aggregation preserved peak demand and total annual energy, it reduced variability and distorted interactions between weather-dependent demand and renewable generation. Fig. 1 shows that there is no obvious deviation of the average year's load duration curve from the individual years. Figs. 2-4 show the resulting capacity mixes from using the aggregated data, based on the various renewable policies. Overall cost increases range from 9.1% to 22.2% over the optimum base plan respectively, as shown in Table II, or $14-$49 billion additional over ten years for this system. In contrast, the worst individual sample year under the five policies had "true" cost increases of only 6%, or $13.5 billion. Most regional and national scale capacity expansion models reduce data even further (e.g., 17 time slices per year [31]) and are expected to have even larger distortions.

The smoother, less variable demand, wind, and solar profiles resulting from aggregation cause less overall capacity to be installed in model (1), yet increased unserved energy in (2), indicating a significant reduction in system adequacy compared to what planners might expect from the planning model with aggregations (1).

Similar to the one-year subsamples, results show that distortion increases with renewable penetration. We considered an additional aggregation scenario that did not allow renewable generation. The results of the No Renewables case are shown in Table IV. This case had very minimal distortion due to averaging. Thus, we conclude that using demand averaging techniques alone does not result in significant changes to resource planning for this test data set; however, incorporating renewable generation together with weather dependent demand creates significant distortions, indicating aggregation should be strongly discouraged with renewable generation.

Renewable compliance is again short of the RPS, but for different reasons. Data averaging preserves the average capacity factor, so the same amount of energy is produced; however, that energy is represented as occurring at incorrect times since the relationships between demand and renewable generation are not preserved. The initial optimization (1) selects the renewable portfolio that is least cost; however, when operated over a full 10-year period in (2), significant amounts of the wind power are being generated at low load periods. Renewable curtailments jump to 17.2% and 24.2% in the 40% and 60% RPS cases respectively. Actual usable renewable production is significantly less than expected. Aggregation also caused a significant shift in which renewable facilities were constructed (Figs. 2-4). The distortions in generation mix were greater than those based on single year subsamples.

VI. Conclusion

We provide a method to capture the economic value of information and reliability risk from using inadequate sample data when designing sustainable systems with high renewable generation. The results show the importance of using coincident time series data and how inadequate sample sizes (one or five years rather than ten years) result in distorted investment plans that, in general, are less reliable and have higher costs. The distortions due to inadequate sample size are larger as weather dependent renewable generation increases. The 60% RPS case yielded the greatest cost distortions. Further, the industry practice of aggregating years using long-term averages (which may initially include more years of data), results in the greatest distortions. Ten years, however, might not be the best record length [32]. It was chosen due to the availability of data and to match a one-day-in-ten historic planning criterion. Increased reliance on weather-based resources may necessitate more data, which can be examined in future research.

The results show that the distortions vary strongly among subsamples, in that some single years' load and renewable profiles are better approximations than others. Factors that most influence the ability of a subsample to accurately reflect the full record include:

- matching the capacity factors of weather-based resources to their long-run values (accurate RPS compliance).
- having a matching number of critical hours in the subsample to put the appropriate weight on the value of system stress.
- assuming the appropriate renewable penetration level due to policy intervention and customer choice.

Each of these factors may be difficult to implement in practice, however, improvements can be made. Models exist that can transform weather data into wind and solar production depending on geographic location and facility layout [33]. Using these models to backcast output from new wind and solar facilities will improve understanding of its contribution to the system including interactions with existing wind and solar facilities. A practical challenge is that our analysis shows that the best choice of a representative sample year will depend on the renewable policy. Unlike the static reliability contributions of thermal generators, weather-based generators have dynamic ratings that are based on the composition of the other weather-based resources on the system including the growing number of behind-the-meter resources.

Production profiles should not be averaged as this practice suppresses important load and renewable variability in the model, resulting in significantly increased system costs and reduced reliability. Using more data may take more effort and increase computational costs; however, this may be a small price to pay as compared to the distortion and cost consequence of a suboptimal portfolio. Since capacity and adequacy studies are long-term in nature, increased computational time is tolerable as compared to short-term operational planning. Our 50 GW test case showed costs of using an inadequate sample could amount to over $4.9 billion/year at a 60% RPS. Five-year samples were not necessarily better than single year data.

When data reduction is required, careful consideration should be given to preserving temporal variability and interactions among demand, wind, and solar or any other weather dependent generation. Importance sampling and clustering may be valuable techniques if critical net peak hours at varying renewable penetrations are the focus. This conjecture would need to be validated.

This study looked at a single system and included simple operating constraints. Unique characteristics will change the value of information for each system, yet the themes in this paper are expected to be valid. Also, increased operational details, such as unit commitment constraints that limit the flexibility of thermal generation, could lead to even larger sample error impacts. This will be subject of future research.

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References

[1] North American Electric Reliability Corporation, "Glossary of terms used in NERC reliability standards," Jan. 2021. Accessed: Feb. 2, 2023. [Online]. Available: https://www.nerc.com/pa/Stand/Glossary%20of%20Terms/Glossary_of_Terms.pdf

[2] A. A. Kadhem, N. I. A. Wahab, I. Aris, J. Jasni, and A. N. Abdalla, "Computational techniques for assessing the reliability and sustainability of electrical power systems: A review," *Renewable Sustain. Energy Rev.*, vol. 80, pp. 1175–1186, 2017.

[3] R. Billinton, R. N. Allan, and L. Salvaderi, Eds., *Applied Reliability Assessment in Electric Power Systems*, New York, NY, USA: IEEE Press, 1991.

[4] P. A. G. M. Amarasinghe, S. K. Abeygunawardane, and C. Singh, "Kernal density estimation based time-dependent approach for analyzing the impact of increasing renewables on generation system adequacy," *IEEE Access,* vol. 8, pp. 13 8661–13 8672, 2020.

[5] E. Tómasson and L. Söder, "Generation adequacy analysis of multi-area power systems with a high share of wind power," *IEEE Trans. Power Syst.,* vol. 33, no. 4, pp. 3854–3862, Jul. 2018.

[6] J. Zhu and Y. Zhang, "A frequency and duration method for adequacy assessment of genration systems with wind farms," *IEEE Trans. Power Syst.,* vol. 34, no. 2, pp. 1151–1160, Mar. 2019.

[7] B. Frew, W. Cole, Y. Sun, J. Richards, and T. Mai, "8760-based method for representing variable generation capacity value in capacity expansion models," NREL, Golden, CO, USA, NREL/PR-6A20-68870, Aug. 2017.

[8] S. Pfenninger, "Dealing with multiple decades of hourly wind and PV time series in energy models: A comparison of methods to reduce time resolution and the planning implications of inter-annual variability," *Appl. Energy*, vol. 197, pp. 1–13, 2017.

[9] Y. Wang, V. Vittal, M. Abdi-Khors, and C. Singh, "Probablistic reliability evaluation including adequacy and dynamic security assessment," *IEEE Trans. Power Syst.,* vol. 35, no. 1, pp. 551–559, Jan. 2020.

[10] J. Kwon, Z. Zhou, T. Levin, and A. Botterud, "Resource adequacy in electricity markets with renewable energy," *IEEE Trans. Power Syst.,* vol. 35, no. 1, pp. 773–781, Jan. 2020.

[11] R. Billington, R. Karki, Y. Gao, D. Huang, P. Hu, and W. Wangdee, "Adequacy assessment considerations in wind integrated power systems," *IEEE Trans. Power Syst.,* vol. 27, no. 4, pp. 2297–2305, Nov. 2012.

[12] W. Wangdee, R. Billington, and W. Li, "Adequacy and security measures in integrated intermittent renewable generation systems," in *Reliability and Risk Evaluation of Wind Integrated Power Systems*, R. Billinton, R. Karki, and A. K. Verma, Eds., New Delhi, India: Springer, 2013, pp. 75–89.

[13] R. Ak, Y.-F. Li, V. Vitella, and E. Zio, "Adequacy assessment of a wind-integrated system using neural network-basedinterval predictions of wind power generation and load," *Elect. Power Energy Syst.*, vol. 95, pp. 213–226, 2018.

[14] A. Almutairi, M. H. Ahmed, and M. Salama, “Use of MCMC to incorporate a wind power model for the evaluation of generating capacity adequacy,” *Electric Power Syst. Res.*, vol. 133, pp. 63–70, 2016.
[15] S. Becker *et al.*, “Features of a fully renewable US electricity system: Optimized mixes of wind and solar PV and transmission grid extensions,” *Energy*, vol. 72, pp. 443–458, 2014.
[16] Electric Power Research Institute, “Systems analysis in electric power sector modeling: A review of the recent literature and capacibilities of selected capacity planning tools,” Palo Alto, CA, USA, Rep. 3002011365, 2017.
[17] SPP Supply Adequacy Working Group, “Wind and solar report,” Southwest Power Pool, May 2017. Accessed: Feb. 2, 2023. [Online]. Available: https://www.spp.org/documents/53721/sawg%20approved_wind%20and%20solar%20report.pdf
[18] C. Bothwell and B. F. Hobbs, “Crediting renewables in electricity markets: The effects of alternative definitions upon market efficiency,” *Energy J.,* vol. 38, no. KAPSARC Special Issue, pp. 173–192, Jun. 2017.
[19] PJM, “PJM manual 19: Load forecasting and analysis,” 2017. Accessed: Feb. 2, 2023. [Online]. Available: https://www.pjm.com/~/media/documents/manuals/m19.ashx
[20] ERCOT, “ERCOT hourly load data,” 2015. Accessed: Feb. 2, 2023. [Online]. Available: www.ercot.com/gridinfo/load/load_hist/index.html
[21] ERCOT, “Resource adequacy>wind and Solar>ERCOT 2005-2013 onshore wind generation profiles.” 2021. Accessed: Feb. 2, 2023. [Online]. Available: http://www.ercot.com/gridinfo/resource
[22] AWS Truepower, LLC, “Simulation of wind generation patterns for the ERCOT service area,” Mar. 2015. Accessed: Feb. 2, 2023. [Online]. Available: https://www.ercot.com/files/docs/2017/02/17/MemoReport_AWST_ERCOT_27Mar2015.pdf
[23] ERCOT, “Resource adequacy>wind and Solar>ERCOT 1997-2013 offshore wind generation profiles.” 2021. Accessed: Feb. 2, 2023. [Online]. Available: http://www.ercot.com/gridinfo/resource
[24] ERCOT, “Resource adequacy 2015>Wind and solar>photovoltaic single axis tracking solar data sets,” 2015. Accessed: Feb. 2, 2023. [Online]. Available: http://www.ercot.com/gridinfo/resource/2015
[25] ERCOT, “Resource adequacy 2015>Wind and solar>residential PV solar data sets,” 2015. [Online]. Accessed: Feb. 2, 2023. Available: http://www.ercot.com/gridinfo/resource/2015
[26] U.S. Energy Information Administration, “Levelized cost and levelized avoided cost of new generation resources in the annual energy outlook 2015,” Jun. 2015, Accessed: Feb. 2, 2023. [Online]. Available: www.eia.gov/forecasts/aeo/pdf/electricity_generation.pdf
[27] ECCO International, “2012 ERCOT loss of load study,” 2013. Accessed: Feb. 2, 2023. [Online]. Available: https://www.ercot.com/files/docs/2013/03/08/ercot_loss_of_load_study_2013partii.pdf
[28] International Energy Agency, “Renewable Electricity Production Tax Credit (PTC),” 2017. Accessed: Feb. 2, 2023. [Online]. Available: https://www.iea.org/policies/4797-renewable-electricity-production-tax-credit-ptc
[29] “Federal solar tax credits for businesses,” *Office of Energy Efficiency & Renewable Energy*, 2023. Accessed: Feb. 2, 2023. [Online]. Available: https://www.energy.gov/eere/solar/federal-solar-tax-credits-businesses
[30] S. Stoft, *Power System Economics: Designing Markets for Electricity*. Piscataway, NJ, USA: IEEE Press, 2002.
[31] M. Brown *et al.*, “Regional energy deployment system (ReEDS) model documentation: Version 2019,” NREL, Golden, CO, USA, Tech. Rep. NREL/TP- 6A20-78195, Jun. 2021.
[32] J. Wohland, N. E. Omrani, N. Keenlyside, and D. Witthaut, “Significant multidecadal variability in German wind energy generation,” *Wind Energy Sci.,* vol. 4, pp. 515–526, 2019.
[33] A. P. Hilbers, D. J. Brayshaw, and A. Grandy, “Importance subsampling: Improving power system planning under climate-based uncertainty,” *Appl. Energy,* vol. 251, 2019, Art. no. 113114.