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Inter-annual variability of dispatchable generation required for reliable U.S. power systems with substantial wind and solar power

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Abstract—Electric power systems in many parts of the world are undergoing a transformation from relying almost exclusively on dispatchable power (e.g., fossil, nuclear, and large hydropower) toward incorporating more variable non-dispatchable generation (e.g., wind and solar PV). We show for the first time that solar generation can decrease some aspects of variability in the peak residual load in power systems. The electric load minus generation from non-dispatchable resources is known as the "residual load." The maximum or peak residual load provides an estimate of the quantity of dispatchable generation capacity required to supply electric load during all hours. We study the peak residual load as a function of increasing wind and solar generation for three power systems in the U.S.: the PJM system in the Mid-Atlantic, the ERCOT system in Texas, and the NYISO system in New York. We analyze more than a decade of historical data for each region. The introduction of variable renewable power is often thought to increase the variability of most characteristics of power systems. Contrary to this idea, we show the inter-annual variability in peak residual load decreases for all three systems as a function of increasing solar generation. We attribute this effect to correlations between solar generation and peak electric load values. Peak electric load values for all three systems occur during summer heat waves, when air conditioning is used. We find that as solar generation increases, the quantity of dispatchable generation capacity needed to supply the residual load becomes more similar year-to-year. Therefore, in some systems, expansion of variable solar generation can increase predictability of the peak residual load. Thus, an increase in solar generation could ease achievement of certain system reliability targets.

Keywords—residual load, net demand, peak load, resource variability, inter-annual variability

I. Introduction

The electric power industry has developed many metrics of system reliability over the previous decades. Some of these metrics will be challenged by expanding variable and intermittent wind and solar PV (solar) power resources. The North American Electric Reliability Corporation defines "resource adequacy" as the ability of the power system to supply power to meet consumer demands at all times [1]. At the core of resource adequacy is the distinction between dispatchable and non-dispatchable generation technologies. Thermal plants (e.g. fossil and nuclear) and large hydropower facilities can be generally classified as dispatchable generation because they can adjust and ramp their power generation up or down depending on system needs. In contrast, non-dispatchable technologies, including wind and solar power, can not be ramped up or down in the same way. To maintain resource adequacy for all hours, electric load must be less than or equal to the sum of available dispatchable plus non-dispatchable generation. Residual load, or net demand, solves for the needed quantity of dispatchable generation required to ensure resource adequacy,

$$\textit{electric load} - \textit{non-dispatchable} \leq \textit{dispatchable}. \quad (1)$$

At any given moment (1) must be balanced for grid stability. Grouping electric load with non-dispatchable generation combines the two terms with larger seasonal and weather-based dependencies and correlations. Correlations among weather, electric load, and wind and solar availability are preserved when concurrent data from the same geographic region is used for analysis [2].

Researchers study the residual load of systems as a method to estimate the future impacts of wind and solar expansions. Several studies focused on residual load in the context of European power systems [3], [4], [5], [6], while others have focused on power systems in the U.S. [7], and system dynamics in general [8], [9], [10], [11]. Power systems operators are increasingly considering residual load as well in their planning processes [12], [13]. Studies have concluded that, as non-dispatchable generation increases, residual load needs to be taken into account when designing reliability mechanisms for power systems with substantial wind or solar generation [7].

Residual load is illustrated in Fig. 1 for a simulated power system. The figure shows the annual peak load and the peak residual load. The residual load (or required dispatchable generation) is greater during peak residual load than during peak load.

Peak residual load and its use as a proxy for required dispatchable generation has been discussed in many studies [3], [4], [5], [6], [8], [10], [11], [14], [15]. A few studies have added analysis of the inter-annual variability of peak residual load values for power systems studied over many years of data [4], [5], [6]. While the annual peak residual load tells us how much dispatchable generation is needed to supply all electric load for a given year, the inter-annual variability of the annual peak residual load values across multiple years tells us how the needed dispatchable generation capacity can change. If the inter-annual variability is relatively large, any study that aims to forecast future system performance will want to include multiple years of data in their analysis.

One study using data from the Great Britain power system estimated the inter-annual variability in annual peak residual load [4]. They showed that inter-annual variability initially decreased as a function of increasing installed wind capacity. This is interesting because wind resources in Europe have substantial inter-annual variability [16], [17], [18]. The change in inter-annual variability in the Great Britain study was explained in a study that assessed the meteorological conditions associated with peak residual load [5]. When no wind generation is present in their modeled system, annual peak residual load occurs during hours of extreme low winter temperatures, and these hours correlate with available wind resources. By increasing wind generation, the most extreme peak residual load values are reduced and made more similar to the annual peak residual load values in other years, thereby decreasing the inter-annual variability of the annual peak residual load values.

There is an intuitive and positive relationship between solar generation and summer peak electric load in regions where peak load is driven by heat wave induced cooling demand [19]. In our study, we set out to answer two questions: how does the inter-annual variability of the annual peak residual load change as a function of wind and solar generation in regions where peak electric load is associated with heat wave induced cooling?, and is there a solar-based equivalent to the relationship observed in studies of Great Britain, where peak winter load correlated with the presence of wind resources, and deploying more wind resources reduced the inter-annual variability of the annual peak residual load?

To answer these questions, we analyze three geographically distinct power systems in the U.S.: the PJM system in the Mid-Atlantic, the ERCOT system in Texas, and the NYISO system in New York. More than a decade of electric load data is retrieved from each region with concurrent wind and solar availability data sets derived from weather reanalysis data. We study the wind and solar generation as a function of total generation ranging from contributing 0% up to generating power equivalent to 100% of the annual load. We construct residual load profiles for each region, for each wind and solar mix, and for each year of data in the region. This allows us to study well populated statistical distributions that show the annual peak residual load across many years and its variability. We specifically study the inter-annual variability, comparing peak residual load values across the years of data. Estimates of peak residual load and its variability could aid planners in understanding how their systems may evolve as a function of wind and solar generation.

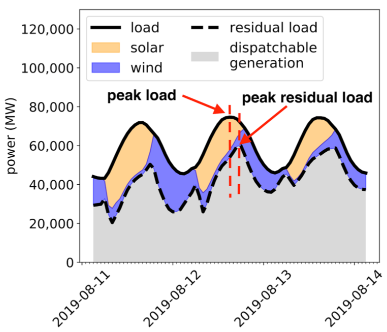

Fig. 1. An example of residual load is shown using historical ERCOT load data and is centered on the annual peak load hour from 2019. The solar and wind generation profiles are synthetic. Dispatchable generation supplies power to meet the residual load.

II. Methods

When analyzing probabilistic distributions, the length of data records matters. Many studies that discuss inter-annual variability in wind or solar resources or electric loads use multi-decadal data sets [5], [6], [17], [20]. One of these studies concluded that less than 10 years of load and resource data are insufficient to provide robust results [4]. Multi-decadal data sets of wind and solar resource availability can be calculated for any region with modern weather reanalysis data [16], [19], [21].

Historical hourly electric load data is downloaded directly from PJM [22], ERCOT [23], and NYISO [24] (Fig. 2). We choose to use the data that requires the least cleaning necessary to make it usable: PJM 2006 through 2019, ERCOT 2003 through 2019, and NYISO 2004 through 2019. In some cases, older data is available, but not used. By limiting analysis to these years, our data cleaning is limited to adjusting the timestamp for daylight savings transitions in some data, and linear interpolation of at most two consecutive missing hours.

The load data are affected by many factors that include economic and population growth, and weather events such as heat waves and winter storms. A linear regression shows an annual growth of approximately 1.4% for JPM, 2.1% for ERCOT, and -0.25% for NYISO. We remove the leading

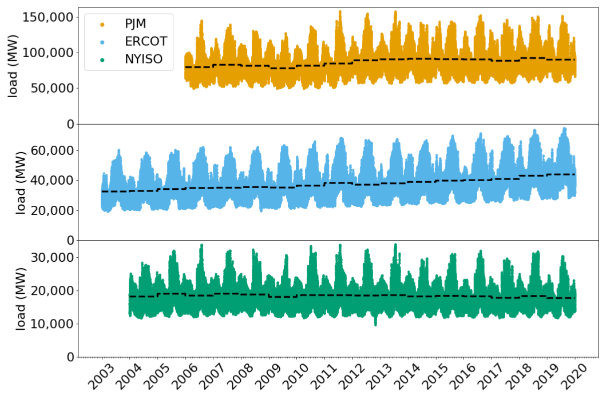

Fig. 2. Hourly electric load data for the PJM, ERCOT, and NYISO regions. The annual mean electric load is shown as black dashed lines. In the analysis, the electric load for each year is normalized by dividing by the annual mean load to remove the leading effects of economic growth and population changes.

impacts of economic and population growth on the demand data by normalizing the data by their annual mean values. Each year of data for each region is normalized by dividing the original values by the mean annual load for that year. This allows comparison of the peak hours across all years with respect to mean annual load, and can be used to extrapolate results based on estimates of future load growth.

To account for correlations between electric load and weather, we use concurrent historical weather data to derive hourly wind and solar resource availability for each region. Specifically, we use wind speed and solar irradiance information from the MERRA-2 data set [21]. The MERRA-2 data has a resolution of 0.625° longitude by 0.5° latitude. For each region and for both wind and solar availability, we calculate the mean resource capacity factor for each 0.625° by 0.5° cell with more than half its area falling within the geographic bounds of the power system territory. We then select the 25% of cells with the highest mean capacity factors to construct an aggregate hourly capacity factor profiles for each region. Wind and solar cells are selected independently.

We are interested in studying the residual load profiles for each region across a range of wind and solar mixes. The mean capacity factors across all years analyzed for the wind and solar profiles are denoted as CF_{wind} and CF_{solar} and are region specific (Table 1). The wind and solar mixes are defined based on the average amount of generated power from wind and solar relative to the normalized electric load. For example, we define a 10% wind and 0% solar mix as a scenario capable of generating enough wind power to supply 10% of the normalized electric load. (We define this case as $f_{wind} = 0.1$, $f_{solar} = 0.0$, where f_{wind} and f_{solar} represent the fraction of total electric load potentially supplied by wind or solar, respectively.) Therefore, to convert to the normalized nameplace installed capacity of wind, we divide f_{wind} by CF_{wind}; assuming ERCOT values (Table 1): 0.10/0.43 = 0.23 (of normalized electric load). This definition of wind and solar mixes does not incorporate the shape of the electric profile; hours where generation is greater than load still contribute their full generation to this calculation.

The normalized residual load profiles are calculated as:

$$normalized\ residual\ load = normalized\ electric\ load - \frac{f_{wind} * wind\ profile}{CF_{wind}} - \frac{f_{solar} * solar\ profile}{CF_{solar}} \quad (2)$$

We study characteristics of the 20 peak residual load hours from each of the annual residual load profiles. The choice to study 20 hours balances selecting fewer hours that more precisely characterize the exact peak system demands versus selecting more hours to have a more statistically robust sample. The sensitivity of our result to the number of peak residual hours selected each year was checked. The trends presented in the Results section hold from selecting a single hour each year to selecting upwards of 50 hours per year for almost all cases. The exception is that the inter-annual variability for NYISO remains approximately constant as solar generation increases when selecting fewer than 5 peak hours (see Fig. 5 in Results section).

TABLE I. WIND AND SOLAR MEAN CAPACITY FACTORS ACROSS ALL YEARS ANALYZED FOR THE PJM, ERCOT, AND NYISO REGIONS.

	Capacity factor wind (CF_{wind})	**Capacity factor solar (CF_{solar})**
PJM	0.39	0.23
ERCOT	0.43	0.28
NYISO	0.25	0.21

We analyze two main characteristics of the 20 annual peak residual load hours from each of the profiles. For each region and each wind and solar mix, we calculate the mean peak residual load, μ_{RL}, of the 20 annual peak hours across all years of data. For each region and each wind and solar mix, the inter-annual variability, σ_{inter}, first takes the mean of the 20 annual peak values independently (μ_{yr}), then takes the standard deviation of those values (3), where μ' is the mean of all μ_{yr} and N_{yrs} is the number of years. The σ_{inter} gives a measure of how different the peak residual load values are year-to-year.

$$\sigma_{inter} = \sqrt{\frac{\sum_{yr=1}^{all\ years}\left(\mu_{yr} - \mu'\right)^2}{N_{yrs}}} \quad (3)$$

Examples of μ_{RL} and σ_{inter} can be seen in Fig. 3 for all three regions and two example wind and solar mixes.

We examine a wide range of wind and solar mixes ranging from 0% to 100% wind generation and 0% to 100% solar generation in 1% steps. This arrangement builds a 101 by 101 grid that results in 10,201 wind and solar mixes.

III. RESULTS

The results are split into two sections. The "Peak residual load" section shows how the mean of the 20 annual peak residual load values per year across all years, μ_{RL}, changes as a function of wind and solar generation for the three analyzed power systems. The "Peak residual load" section confirms results seen by many other studies and provides an estimate of the required quantity of dispatchable generation capacity needed to meet peak residual load hours. The "Variability of peak residual load" section analyzes the distribution of σ_{inter} as a function of wind and solar generation and shows the spread of the peak values and provides information to determine the quantity of dispatchable generation capacity needed to supply all peak residual load with a degree of certainty.

A. *Peak residual load*

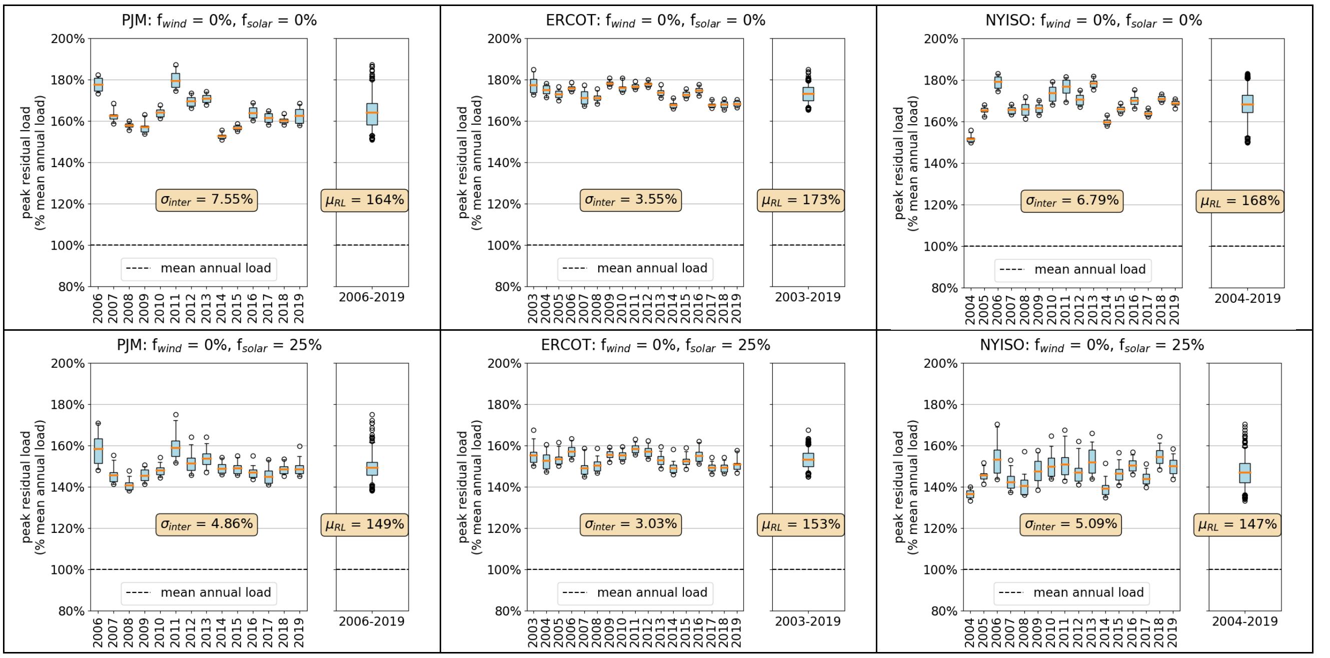

Fig. 3. Examples of the mean peak residual load (μ_{RL}) and inter-annual variability (σ_{inter}) are shown for the PJM, ERCOT, and NYISO regions for two illustrative wind and solar mixes of: 0% wind and 0% solar and 0% wind and 25% solar. The 20 peak residual load values per year are shown split by year in the left sub-panels and aggregated together in the right sub-panels. The calculation of the inter-annual variability incorporates the annual structure (left sub-panels), while the mean peak residual load is calculated based on the aggregate of all annual values (right sub-panels). Boxes show the region containing 50% of the data (with 25% on either side), and whiskers show the region containing 90% of the data (with 5% of the data on either side). The orange bands indicate mean values because mean values are used in the calculation of inter-annual variability.

For each wind and solar mix, the hourly residual load values indicate the quantity of dispatchable power needed to ensure resource adequacy for that hour. The mean of the 20 annual peak residual load values per year across all years, μ_{RL}, can be used as an initial estimate of the dispatchable generation required to meet the average peak hour. Fig. 4 shows μ_{RL} across all considered wind and solar mixes. The gradient shows the relative benefit in reduced μ_{RL} from installing additional wind or solar generation. Some common characteristics for all three regions include:

- The gradient is steepest at the origin (0% wind and 0% solar).
- Wind and solar additions have diminishing returns with respect to reducing the peak residual load.
- When solar generation is relatively small, <10% generation, additions of wind generation bring minimal reductions to peak residual load.
- When solar generation is larger, >10% generation, additions of wind generation bring greater reductions to peak residual load.

The first two bullets are consistent with many previous studies [2], [8], [10], [11], [15], [19], [25].

B. *Variability of peak residual load*

The inter-annual variability, σ_{inter}, (3) of the peak residual load values is shown in Fig. 5. A common feature of the inter-annual variability distributions for all three regions is that, in general, additions of solar generation reduce the inter-annual variability. Depending on the wind generation, after approximately 30% solar generation in ERCOT, the inter-annual variability increases with increasing solar generation, this reverses the common observed trend. The general decrease in inter-annual variability with increasing solar generation shows that the peak residual load values become more similar year-to-year as solar generation expands. This runs contrary to common assumptions about increasing variability as renewable generation increases.

Inter-annual variability increases as a function of wind generation throughout almost all of the wind and solar mixes for the PJM and ERCOT regions. There is less of a

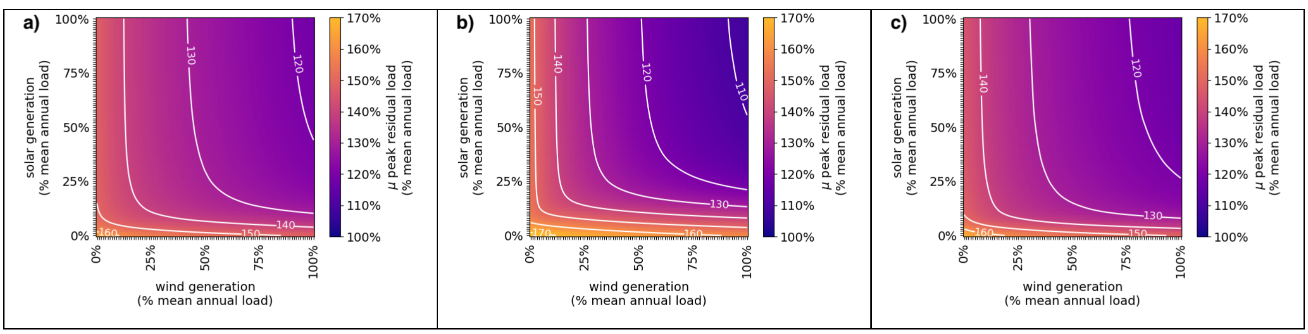

Fig. 4. The mean of the 20 peak residual load values per year across all years is shown in panels (a), (b), and (c) for the PJM, ERCOT, and NYISO regions, and indicates the approximate quantity of dispatchable generation needed to power the system for all hours.

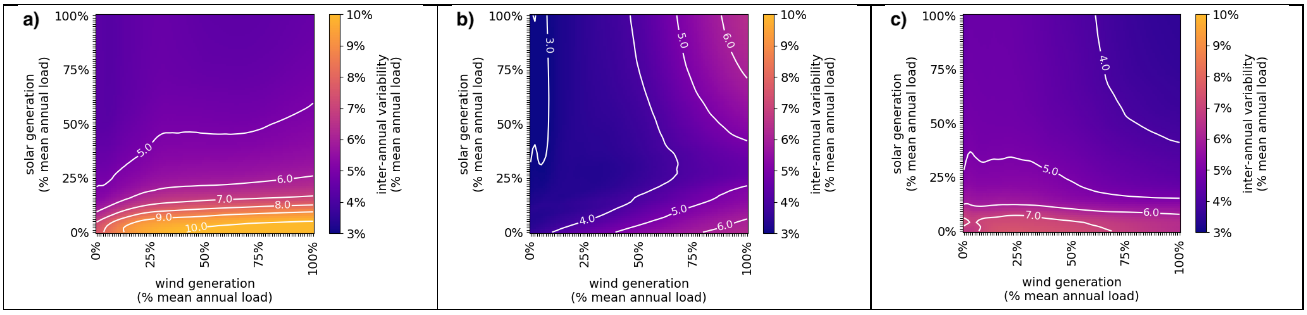

Fig. 5. The inter-annual variability of the peak residual load values, σ_{inter}, is shown in panels (a), (b), and (c) for the PJM, ERCOT, and NYISO

clear trend in the NYISO region, which has a lower annual wind capacity factor of 0.25 compared to 0.39 and 0.43 for PJM and ERCOT, respectively (Table 1).

IV. Discussion

A. *Decreasing inter-annual variability and solar*

Adding solar generation to the three studied electric power systems reduces the inter-annual variability, σ_{inter}, (3) of the peak residual load values in general. This means the peak values become more similar year-to-year. This trend is seen for all three regions and is shown in Fig. 3 and Fig. 5.

All three regions experience their annual peak loads during the summer months on hot days when air conditioning is in use. This analysis is in agreement with previous studies that show summer days on average have substantial solar resources available during their daily peak load hours, as seen in Fig. 6 [2], [11], [15], [19], [25]. This analysis is unique because it demonstrates that this correlation between peak load and solar availability reduces the inter-annual variability of peak residual load values as more solar generation is deployed. The correlation between the peak load hours and solar availability allows added solar generation to reduce the most extreme residual load values year-to-year, and thereby decreases the inter-annual variability. This analysis provides a solar generation complement to the studies of inter-annual variability in Great Britain that showed increasing wind generation could, in certain cases, decrease the inter-annual variability of winter peak residual load [4], [5].

The results shown here may be broadly applicable across much of the U.S. In 2018, approximately 77% of the annual electric load in the contiguous U.S. occurred within the territories of power systems that experience their annual peak load during the summer months (data from [26]). The PJM, ERCOT, and NYISO regions are included in this group.

This is an important result because it shows that some critical characteristics of power systems, such as peak residual load, may become more predictable in systems that expand intermittent and variable solar generation. In power systems with reduced inter-annual variability, more consistent and predictable peak dispatchable generation needs will allow more precise system planning.

B. *Expanding to include energy storage*

The residual load profiles, as currently implemented and generally defined in the literature, do not incorporate the benefits of introducing energy storage into a power system. As it is modeled here, the peak residual load values show the quantity of dispatchable generation needed to supply the remaining electric load. In this formulation, energy storage and other distributed energy resources are considered in the dispatchable generation category. Energy storage could be added as a third parameter of interest in addition to wind and solar generation. Simple operational rules could characterize energy storage focused on peak residual load shaving. We suspect that this would substantially reduce the variability by shaving the most extreme values the most. A similar method could also model distributed energy resources as adjustments on top of the residual load profiles.

C. *Limitations of the analysis*

Some concerns should be raised when using historical load profiles for analysis. There is a potential trade-off between using longer electric load data records to capture more years of data and variability versus the possibility that older years no longer reasonably represent the current system. If older years no longer reasonably represent the current system, they are less useful for forecasting. One example of this could be a significant expansion of behind-the-meter (BTM) solar PV. We specifically excluded regions from this analysis that have substantial BTM solar, such as California. In future work, calibrations could be applied to

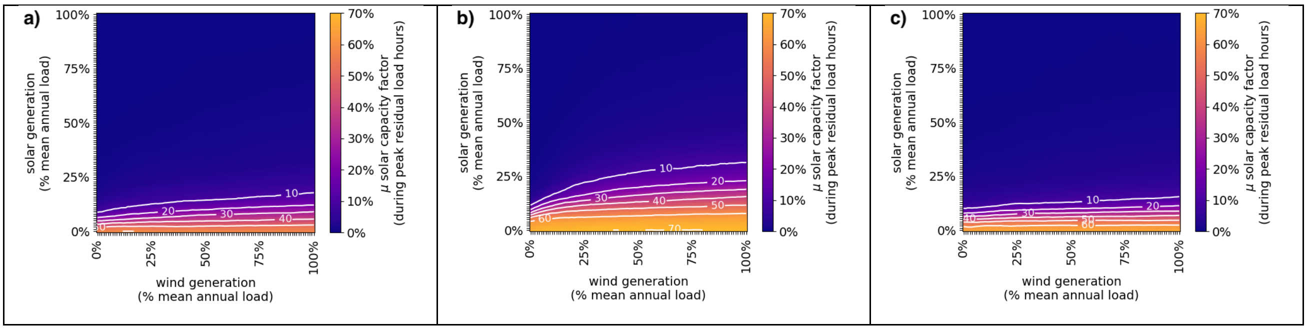

Fig. 6. Mean solar capacity factors during the 20 annual peak residual load hours each year is shown in panels: (a) PJM, (b) ERCOT, and (c) NYISO.

the electric load profile to adjust all years of data to have the same estimated quantity of BTM solar, or remove it entirely. This would create more accurate representations of regions like California.

V. CONCLUSION

This paper analyzes annual peak residual load and its inter-annual variability as a function of increasing solar and wind generation. We study three geographically distinct power systems in the U.S.: the PJM system in the Mid-Atlantic, the ERCOT system in Texas, and the NYISO system in New York. We show that increasing solar generation consistently decreases the inter-annual variability of the annual peak residual load values for all three regions (Fig. 3 and Fig. 5). This result appears to be an exception to the common assumption that an increase in variable renewable capacity in a power system brings an increase in variability of most characteristics of that power system.

These three regions experience their annual peak loads during summer months, on hot days when air conditioning is in use. There are considerable solar resources available during these same peak load hours (Fig. 6). The correlation between the peak load hours and solar availability allows additions of solar generation to reduce the most extreme residual load values year-to-year, and thereby decrease the inter-annual variability. This is an important result because it shows that some critical characteristics of power systems, such as the annual peak residual load, may become more predictable in systems that expand intermittent and variable solar generation. Changes in inter-annual variability will have economic consequences for building and operating dispatchable generation resources to ensure power system reliability.

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