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Publication Date
2022-05-01

DOI
10.1016/j.segy.2022.100074

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Smart Energy 6 (2022) 100074

Contents lists available at ScienceDirect

Smart Energy

journal homepage: www.journals.elsevier.com/smart-energy

Metrics to describe changes in the power system need for demand response resources

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ARTICLE INFO

Article history:
Received 23 December 2021
Received in revised form
12 April 2022
Accepted 6 May 2022
Available online 11 May 2022

Keywords:
Demand response
Power system planning and operation
Grid decarbonization

ABSTRACT

Grid decarbonization efforts can benefit significantly from demand response (DR) resources. However, system-level changes that affect the net-load such as increased variable renewable energy (VRE) generation and widespread deployment of energy efficiency (EE) also affect the type, magnitude and timing of DR required to support the grid. In this study, we use publicly available system-level data to define seven metrics to assess how these changes affect system-level shed and shift DR needs. Specifically, there are four metrics for grid conditions when DR has the highest system value and three metrics for DR program design that were developed by considering the magnitude and temporal distribution of net-load. We also develop three stylized load shape profiles illustrating EE measure impacts and one high VRE generation profile to demonstrate the application of these metrics. The results confirm the robustness of the metrics to identify complex interactions between demand-side and supply-side resources that can affect the DR need. Widespread application of our metrics can help system planners and operators be cognizant of such interactions and identify the DR need for the system in a way that can be most valuable.
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1. Introduction

Increasing deployment of variable renewable energy (VRE) and broader decarbonization goals are transforming U.S. power system planning and operations. Grid integration of VRE requires more flexible resources that can respond to short-timescale variability in renewable generation, as well as unforeseen supply and demand imbalances [1]. Conversely, technologies that can provide flexible demand (e.g., heat pumps, electric vehicles, storage) can support a higher integration of VRE [2,3]. Load flexibility in the power sector is an integral part of a smart energy system as it allows for an efficient cross-sectoral integration [4]. For example, widespread heating and transportation electrification may increase system load and change the magnitude and timing of peak demand [5]. Demand response (DR), which is the change in electricity consumption in response to price or incentive signals [6] can be a significant resource to improve power system operations through load shifting and shedding and thereby contributing to grid and economy-wide decarbonization goals [7].

Notwithstanding the potential benefits, how the system need for DR evolves over time is driven by several factors, including VRE penetration levels and interactions with other demand-side resources. For example, increased solar generation in California has led to higher ramps in the system net-load (i.e., load net of VRE generation) increasing the need for load flexibility [8,9]. Likewise, certain energy efficiency (EE) measures can reduce the need for DR resources via persistent peak load reductions or load shifting from peak to off-peak periods, while other EE measures that preferentially save energy during off-peak periods and steepen net-load ramps can increase the need for DR resources [6]. Determining how the system need for DR changes can inform the strategic deployment and design of DR programs, as well as assist decision-makers with developing load flexibility targets.

Prior work has largely focused on characterizing DR capabilities and quantifying DR potential but without accounting for the system need for DR. For example, one meta-analysis of building flexibility potential [10] found prior studies focused on specific technological characteristics or capabilities at the building-level but not system-level. Furthermore, studies that quantify demand response potential typically consider the technical potential and whether or not customers will adopt enabling technologies or respond to price and incentive signals [11], but are often irrespective of the system need for the load shedding or shifting (e.g., Ref. [12]).

A limited number of studies have either implicitly or narrowly

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https://doi.org/10.1016/j.segy.2022.100074
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explored the system need for DR. For example, Shah et al. [13] developed metrics for the building's demand flexibility capability and compared to grid need implicitly through marginal energy cost proxies meant to represent demand and supply. Existing utility resource planning approaches implicitly quantify the system need for load shedding DR by characterizing its impacts on coincident peak demand as the primary metric [14] or seasonal peak reductions [15] but fail to account for the value of DR to mitigate other system conditions, like steep ramps. Finally, more explicit discussion and consideration of the system need for DR has either been conceptual without developing quantifiable metrics [6] or required detailed modeling and sometimes speculation in the case of more novel types of DR like load shifting [8].

In this study, we develop metrics to quantify the change in the system need for DR. Specifically, we identify three sets of metrics - one each for load shedding, load shifting, and program design - using the net system-level load (i.e., net of wind and solar generation) that can help inform the change in magnitude and timing of system need for DR. Furthermore, the metrics to quantify the change in the system need for load shifting is based on ramp rates. We modify the definition of ramp rate to reflect the need for ramping from the demand side rather than the existing generators' ramp rates that reflect ramping capabilities from the supply side (e.g., Ref. [16]). We also demonstrate application of the metrics in two sets of illustrative cases. First, we study how EE can change the system need for DR using prototypical EE measure savings shapes that are intended to illustrate the impacts of EE on the system need for DR and are not meant to provide a realistic representation of specific EE measures. Second, we study how increasing VRE penetration can change the system need for DR. In addition to these example cases, our metrics could also be applied to study the impact of other factors (e.g., building weatherization, electrification of transport and industrial processes, storage) on the system-level net-load and hence, the system-need for DR.

Several key boundaries apply to our study. First, we consider two types of DR that are typically called upon for events lasting from one to a few hours, namely load shedding and load shifting. Short-term load-modulation DR and long-term (e.g., diurnal) load-shifting are not considered. Second, although we acknowledge that the DR needs in a system can change when characteristics of the generation portfolio changes, we develop the metrics to assess changes based on changes to the net-load only. Third, the metrics we developed should be used to assess changes in the need for DR relative to a reference scenario, and not in absolute terms. The absolute system-level need for DR is complex to assess, requires detailed optimization modeling of the generation stack, and depends on the time frame being considered (see, e.g., Refs. [17,18]). We expect that assessing changes in the system load alone can indicate whether the need for DR is growing or shrinking, and by how large a factor; our goal in this study is to develop metrics that allow a simple assessment of evolving DR needs. However, these metrics can be calculated using the outputs of capacity expansion and production cost dispatch models. Finally, because we are only considering changes in system DR needs, we do not explicitly account for the incremental costs of EE or DR as is a typical practice in utility integrated resource planning for selecting resources.

The remainder of the study is organized as follows. Section 2 describes the data sources and analytical approach to identify the various indicators of system need for DR and briefly explains how we modeled EE and VRE scenarios to demonstrate the application of our metrics. Section 3 explains how DR can support a power system using proxy indicators. Section 4 defines each metric and shows how to interpret it broadly. Section 5 provides the results of applying the metrics to the EE and VRE scenarios and illustrates how the system need for DR changes under these scenarios. Finally, section 6 concludes with broader implications of this study and how it can be useful to various stakeholders.

2. Approach

The study's analytical approach follows three sequential steps. First, we use actual power system data[1] to indicate grid conditions when DR has the highest system value. Specifically, we use hourly system load [19], VRE generation [16], wholesale electricity prices [20–22], and individual generator's hourly generation dispatch values [23] from three U.S. state and regional power systems that reflect diversity in generator resource portfolio, VRE deployment level, seasonal peaks, and marginal costs. We use 2016 data from California,[2] which is representative of a summer peaking system with high levels of solar penetration, Texas (i.e., the ERCOT system), which is representative of a summer peaking system with high levels of wind generation, and New England (i.e., the ISO-NE[3] system), which is representative of a system with a summer peak and a secondary winter peak and low levels of VRE penetration. The choice of the year 2016 was largely due to the comprehensive data available on load, generation, and weather.

We use the indicators of system value for DR as proxies for the system need for DR. Generally, DR is used by system operators to avoid high electricity costs or to maintain power system reliability. DR dispatch, therefore, tends to occur during high-price events driven by the use of expensive, marginal peaking generation. In addition to system net-load we use three indicators for DR dispatch events. Specifically, probability of peak generator dispatch, wholesale electricity prices that indicate periods of high marginal costs, and heat rates of dispatched generators that indicate high production costs. High heat rates also typically indicate high emissions intensity that could be avoided by dispatching DR.

Second, by exploring how these system indicators correlate with different features of the net-load, we assess how and when changes in net-load will affect the need for DR. We use the correlation between these indicators and the net-load to identify appropriate and reasonable cutoffs that form the basis of our metrics definitions.

In this study we focus on two types of DR, namely shed and shift DR. Shed DR dispatches customers to reduce their electricity demand to address extreme system demand. We determine the system need for shed DR using the highest hourly system net-load values. Shift DR, on the other hand, involves shifting of energy consumption from periods of high system demand to adjacent periods of low demand. We define the system need for shift DR using three-hour net-load ramp rate values. These definitions of shed and shift DR are consistent with other literature (e.g., Refs. [8,24–27]).

Third, we develop and apply the metrics to examine the change in the system need for DR using the California system since it has the highest VRE deployment level compared to the other two power systems we explore. Therefore, application of the metrics, especially at higher assumed VRE deployment levels, are likely to more clearly demonstrate the possible ways that system need for DR can change.

To demonstrate the application of our metrics to the impacts of EE, we develop three stylized hourly savings profiles that illustrate different types of EE measure impacts: a profile with constant

[1] Public data was extracted using ABB Ventyx (last accessed 18 February 2021).

[2] Comprising of the following balancing authorities – California Independent Service Operator (CAISO), Los Angeles Department of Water and Power (LADWP), Balancing Authority of Northern California (BANC) and Imperial Irrigation District (IID).

[3] The ISO-NE system includes the states of Vermont, New Hampshire, Massachusetts, Connecticut, Maine and Rhode Island.

savings fraction across all hours (e.g., lighting upgrades), a profile with preferential on-peak savings (e.g., building envelope improvement), and a profile with preferential off-peak savings (e.g., commercial heating upgrades). To demonstrate the application of our metrics to a system with higher VRE penetration, we also consider a scenario that doubles the actual 2016 VRE generation. In each case, we use the actual 2016 load data from California as the baseline scenario. The modeled scenarios are intentionally designed to have large impacts on system load, to more clearly illustrate the use of our metrics; they are not intended to be realistic. Fig. 1 shows the comparison of average daily net-load profiles for each EE and VRE scenario with the baseline (see the Supplemental Information for methodology used to characterize hourly EE and VRE impacts). In particular, EE measures with flat savings and on-peak savings can significantly reduce the evening net-load ramp whereas high VRE generation and EE measures with off-peak savings can worsen the duck curve by reducing the midday net-load and steepening the ramp.

3. Indicators of DR value and the system need for DR

Power system planning and operations are largely driven by temporal needs, namely the balancing of supply and demand on an annual, seasonal, hourly, and/or sub-hourly basis. As such, the system need for DR should be defined on a temporal basis and focus on the narrow time periods when DR has highest system value (e.g., to avoid peaking generation dispatch). Therefore, we use indicators of DR value to the system as proxies for the system need for DR. As discussed earlier, shed and shift DR have different uses; therefore, we describe indicators and define metrics for shed and shift DR separately.

3.1. Shed DR indicators

Shed DR is defined as the reduction in load that is typically dispatched during events of extremely high system demand. These events are typically infrequent and have durations of a few hours (e.g., one to four hours). Consequently, the metrics representing the system need for shed DR should reflect the characteristics of load during such peak hours. Although there is no firm definition of what load levels qualify as "peak hours", previous studies have defined the peak hours in a year ranging from the top-40 [28] to top-250 [8] hours. In this study, we choose the top-100 hours (which is within the aforementioned range) as an initial threshold in the indicators to capture a qualitative change in the system conditions across all three regions. The net-load in these hours (i.e., roughly top 1% of load hours) can be served by shed DR or by peak generation resources such as combustion gas turbines that are often characterized as low efficiency, high emissions, and high-cost generators. Hence, the value of shed DR is derived from its ability to reduce the need for such peak generation resources and their associated high costs [25].

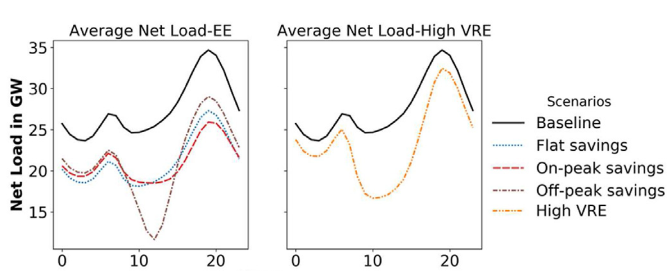

Fig. 1. Average daily net-load profiles of illustrative EE and VRE scenarios using the 2016 data for California as the baseline (black line).

In order to determine the value for shed DR to replace generation capacity, we examine if certain generators are preferentially dispatched during the peak load hours. Fig. 2 shows the probability that peak generation was dispatched in each of the three systems in 2016. We selected five illustrative generators in each region that were dispatched consistently in the top 5% of net-load hours and plotted their dispatch over the entire year as a function of net-load percentile. Across the three power systems, the average probability of dispatching a peaker plant is significantly higher during the highest net-load hours (i.e., from 90% to 100% of the net-load percentile) implying that these generators are typically dispatched to serve high net-loads.

Correspondingly, the top-100 net-load hours typically require the use of expensive generators. Fig. 3 shows the correlation between hourly values of wholesale electricity prices and net-load in 2016 across the three power systems. We observe a clear positive correlation[4] between net-load and the price of electricity in all three regions. Here, a steep trend in the top-100 net-load hours (see blue lines in Fig. 3) is apparent, indicating that peak load is driving the observed high electricity prices. However, in New England, the high prices occurring during relatively low net-load hours is likely driven by other exogenous factors such as high natural gas prices in winter resulting from gas heating demand.

Finally, we examine the average hourly heat rate values of non-nuclear, thermal generators as a proxy for relative production costs and emissions intensity, whereby higher heat rates tend to correspond to higher production costs and emissions rates [29] because peaker plants with low utilization factor are more likely to be dispatched during peak load hours. Nuclear generation is excluded since it serves as a base load generating resource and has uniform impact across all hours. Fig. 4 shows that, although there is variation in heat rate in all hours across the three regions and sometimes we observe a higher heat rate even at low net-loads, the heat rate in the top 100 hours are consistently elevated. This strongly suggests that shed DR, by reducing load in the top net-load hours, could provide significant system value in avoiding high cost and high emissions generation.

3.2. Shift DR indicators

Significant and short-term fluctuations in wind and solar generation can result in an increased need for load flexibility to mitigate steep net-load ramps. Shift DR is defined as the reduction of load during peak hours along with an offsetting increased consumption during adjacent off-peak hours, a strategy to manage these ramps which can otherwise be served by combustion turbines or other flexible generation resources. Shift DR provides an opportunity to avoid high prices and reduce the system stress under capacity constraints, as well as for arbitrage to take advantage of low marginal energy costs in off-peak hours especially in regions with high VRE penetration.

The signature of a low net-load period adjacent to a high net-load period implies that the need for shift DR can be identified by a steep ramp (up or down). In this study, we considered three-hour net-load ramp as an indicator of shift DR and defined as,

$$Ramp = Abs(NetLoad_t - NetLoad_{t-3}) \qquad \text{Eq. (1)}$$

where t is the current hour. This definition of ramp rate reflects the ramping need of a system, which is indicated by changes in power

[4] The values of Spearman correlation coefficients are 0.61, 0.52 and 0.41 for California, Texas and New England, respectively.

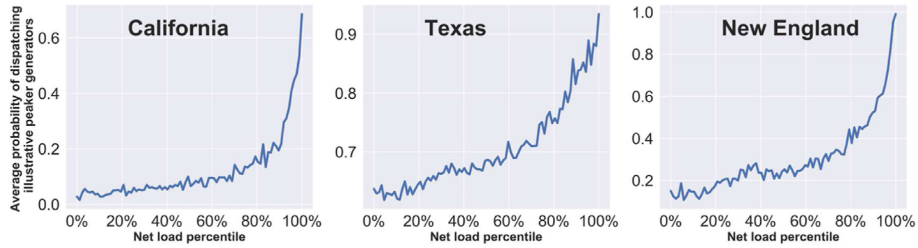

Fig. 2. Probability of dispatching five illustrative peaker generators as a function of net-load percentile in California, Texas, and New England for 2016.

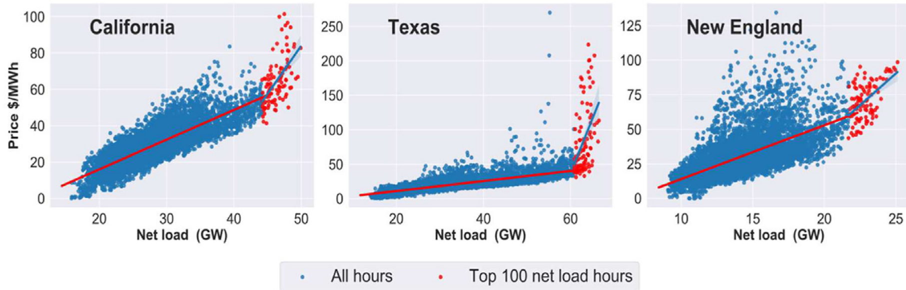

Fig. 3. Relationship between net-load and wholesale electricity prices in California, Texas, and New England in 2016. Top 100 net-loads are shown in red and the rest are blue. For each region, the blue line indicates the best linear fit for the top 100 net-loads and the red line indicates the best linear fit for the remaining net-loads. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

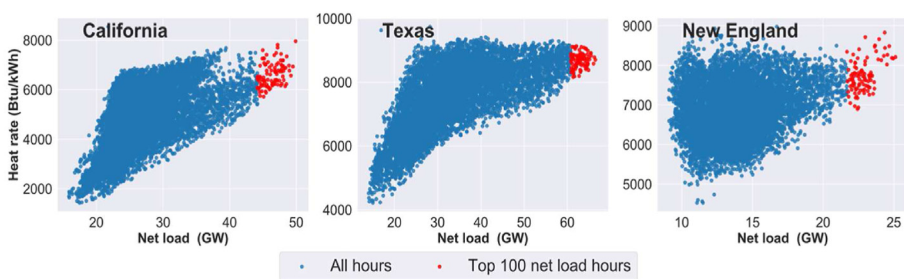

Fig. 4. Relationship between dispatched non-nuclear generation heat rates and net-load in California, Texas, and ISO-NE in 2016. Top 100 net-loads are indicated in red and the rest are indicated in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

system demand, rather than its ramping capability that focuses on the supply-side. The use of a three-hour ramping period definition is consistent with CAISO's requirement [30] for qualifying resources to receive flexible capacity credits and may differ from another ISO/RTO.

Flexible generators are dispatched to serve ramping needs because of their fast-start and fast-ramp capabilities [31]. The value of shift DR would be to replace such flexible generation units. We chose five generators in California and Texas and three in New England[5] that were dispatched consistently to serve the top 5% of ramps and observed their generation as a function of corresponding system's ramp percentile. Fig. 5 shows that certain flexible generators are preferentially dispatched during high ramping periods (i.e., from 90 to 100th percentile). This indicates that shift DR dispatched over the three-hour ramp periods can offset flexible capacity costs by reducing extreme ramps. In addition to the extreme ramps that would necessitate more episodic and infrequent DR dispatch (e.g., via direct load control), we see that there is a significant probability of dispatching these generators to serve the moderate ramps (just below the top ten percentile). This indicates that shift DR more frequently dispatched as a load modifying or load shaping resource (e.g., via time-of-use rates) can provide significant value in further mitigating the use of such high-cost generators.

Three-hour net-load ramps are also correlated[6] with a corresponding three-hour difference in wholesale price and dispatched generator heat rate, though this correlation is not as strong as the correlation observed between net peak loads and wholesale prices. Fig. 6 shows the relationship between three-hour ramp and three-hour difference in wholesale electricity prices (right) and dispatched generator average heat rates (left) in California in 2016. Here, we can see that large three-hour net-load ramps are associated with concomitant swings in heat rate and wholesale price. Additionally, most of the largest three-hour net-load ramps occur outside of the top 100 net-load hours, suggesting that shift DR has

[5] In 2016 data for New England, most generators' dispatch as a function of ramp percentile was erratic suggesting that New England may not have had significant ramping concerns in 2016.

[6] The values of Spearman correlation coefficients of ramps with three-hour price difference and heat rate difference are 0.90 and 0.71, respectively.

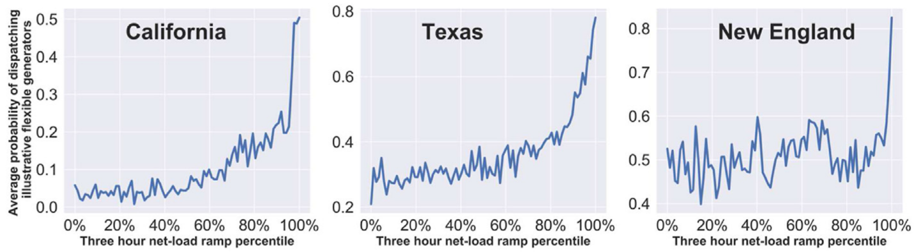

Fig. 5. Probability of dispatching flexible generators during ramping periods in California, Texas, and New England in 2016.

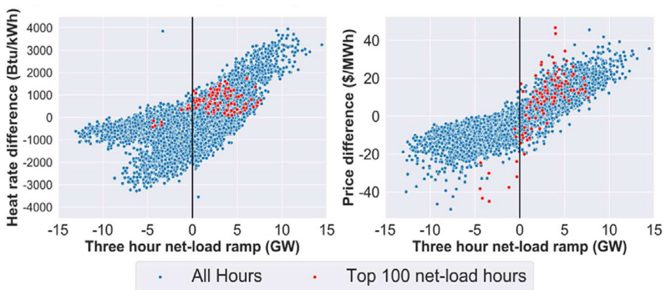

Fig. 6. Relationship between three-hour ramp and three-hour difference in wholesale electricity prices and dispatched generator heat rates in California in 2016. Red dots indicate net-load ramps leading up to the top 100 net-load hours. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

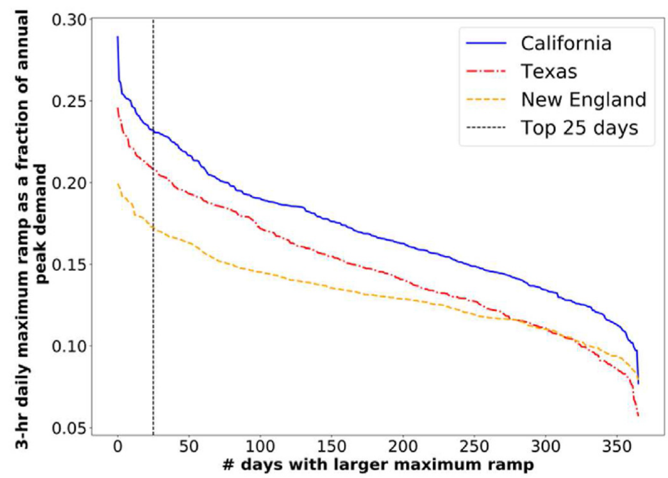

Fig. 7. Ramp frequency curve for California, Texas and New England.

value that is distinct from the value provided by shed DR in peak hours. In Texas and New England regions, these correlations are not as pronounced, suggesting less present-day value for shift DR (see Supplemental Information for figures).

We consider the absolute maximum three-hour net-load ramp rate occurring on each day of the year, and construct a ramp frequency curve by ordering them from largest to smallest. Since California has a high solar penetration, the operational challenges of ramping could arise at sunrise and sunset, meaning that the system could require significant upward and downward ramping. Hence, we consider absolute maximum values. We use the daily maximum instead of each individual ramp value because it indicates the maximum amount of flexible generation required for that day so that the subsequent smaller steep ramps occurring on the same day could be served by the same set of flexible resources. Fig. 7 shows the ramp values as a fraction of each system's annual peak net demand. Ramping issues are more severe in California and are a larger fraction of the system generating capacity than in the other two regions given the higher solar penetration. The most significant ramps also tend to occur on the top-25 days, which also corresponds to the number of days with the top-100 net-load hours in California. Therefore, we use the 25-th highest ramp value as a threshold for defining the metrics for shift DR.

4. Definition of metrics to quantify change in system need for DR

Decision-makers and utilities in the U.S. have traditionally established DR goals based on reduction of annual system peak demand (e.g., peak demand savings from demand response programs are eligible to count towards compliance with the Arizona Energy Efficiency Resource Standard [32]). Yet, use of a single metric, focused on a single hour of the year, fails to capture the value of DR to mitigate multiple system needs across different system conditions, such as load shifting to mitigate steep ramps.

We define new metrics for the system need for shed and shift DR drawing on the observed relationships between high system costs, heat rates, and load described in Section 3. We also define metrics that capture the frequency and temporal distribution of DR events to inform DR program design and capture the value of DR identified in Section 3. Table 1 summarizes the metrics used to determine the system-level need for DR.

4.1. Shed DR metrics

Given the high system value in reducing the top load periods of the year, we define shed DR metrics within the top-100 annual net-load hours (i.e., top 1% of net-load). Fig. 8 shows two metrics to quantify the system need for shed DR, for an illustrative scenario in which EE upgrades (red) reduce system-level loads from a baseline (blue). The inset panel represents the top 100 net-load values in both scenarios. The first shed DR metric is *peak load* and defined as the maximum value of net-load in a year (i.e., Δ_{peak} in Fig. 8). Assuming a fixed generation stack, a reduction in peak load indicates that, in the short-run, the need for shed DR has reduced due to impacts from an illustrative EE measure. Similarly, an increase in peak load would imply an increased need for shed DR. Hence, Δ_{peak} can indicate the change in the short-run need for shed DR.

In the long-run, we can expect a change in supply-side resources through retirement of old generation units and construction of new ones. Reducing load in the top-100 hours relative to a baseline can result in lower utilization of generation resources that may no longer be economical to operate, as well as reducing the need for DR to serve the highest load hours. At the same time, if the net-load in the top-100 hours increases relative to the baseline, the need for DR or expensive peaking generation increases. The second shed DR

Table 1
Summary of the metrics for system-level need for DR.

Category	Metric name	Metric definition
Shed DR	Peak Load	Maximum hourly system net-load
	Peakiness	Height of system peak net-load above the 100th-highest hourly net-load
Shift DR	Routine ramping	Maximum daily three-hour absolute (upward or downward) net-load ramp in demand, on the day with the 25th-largest such ramp
	Extreme ramping	Size of the maximum annual three-hour absolute (upward or downward) net-load ramp compared to the 25th-highest ramping day
DR program design	Shed event days	Total number of unique days represented within the top 100 hours of annual net demand
	Shed season duration	Duration of the shortest period containing 80 of the top 100 hours of annual net demand
	Shift season duration	Duration of the shortest period containing 20 of the top 25 ramping days

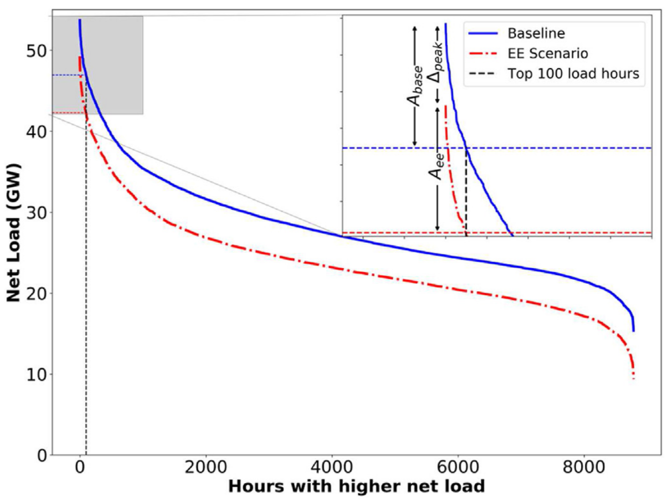

Fig. 8. The change in system-level need for shed DR using load duration curves for an illustrative EE scenario. The inset panel represents the top 100 net-load values of both scenarios used to define the shed DR metrics.

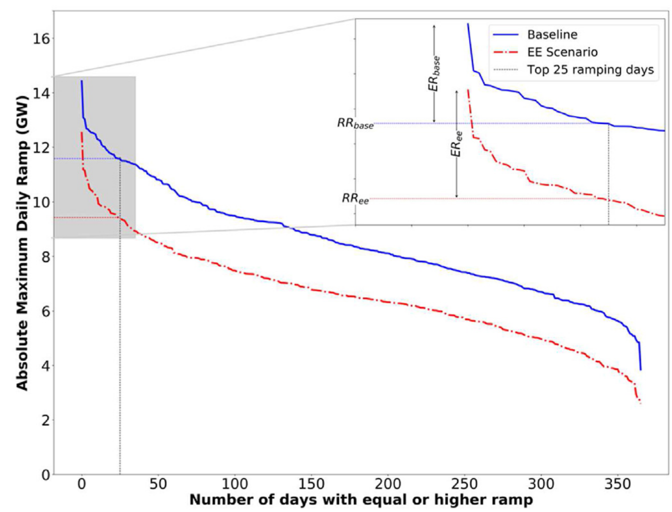

Fig. 9. The change in system-level need for shift DR using ramp frequency curves for an illustrative EE scenario. The inset plot represents the top 25 net-load ramps used to define shift DR metrics.

metric is *peakiness* and defined as the additional net-load required only in the top-100 hours. It is the difference between the peak and 100-th highest net-loads. Fig. 8 depicts the peakiness metric and its change for a representative EE scenario denoted by

$$\Delta_{peakiness} = A_{ee} - A_{base} \quad \text{Eq. (2)}$$

where a smaller value of A_{ee} relative to A_{base} indicates a reduced need for shed DR in the long-run, and vice-versa. Hence, the change in system peakiness, $\Delta_{peakiness}$, can be used as an indicator of how the system's long-run need for shed DR changes.

4.2. Shift DR metrics

While shed DR provides value during top net-load hours by simply reducing peak demand, one of the most significant opportunities for shift DR is in mitigating steep ramps particularly as the grid continues its transition to increased variable renewable energy deployment [8]. Fig. 9 illustrates two metrics to quantify the change in the system need for shift DR based on a ramp frequency curve constructed as described in section 3.2, for a baseline scenario and a scenario with EE upgrades. The first metric for shift DR is *extreme ramping* and defined as the incremental amount of ramping required in the top 25 days (i.e., the difference between the highest and 25-th highest maximum daily ramp). This metric represents the need for a dispatchable shift DR resource that would be used infrequently to meet the most extreme ramps in net demand. Fig. 9 depicts the extreme ramping metric, where ER_{base} is the extreme ramping in the baseline scenario and ER_{ee} is the extreme ramping for a representative EE scenario. The change in extreme ramping is denoted by

$$\Delta_{ER} = ER_{ee} - ER_{base} \quad \text{Eq. (3)}$$

where an increase in the value of this metric would suggest an increased need for flexible resources, and vice-versa.

The second shift DR metric is *routine ramping* and defined as the size of the 25th highest maximum daily ramp. The metric indicates the need for a more frequently utilized shift DR resource (e.g., load-modifying or load shaping). Fig. 9 depicts the routine ramping metric and a change in routine ramping is denoted by

$$\Delta_{RR} = RR_{ee} - RR_{base} \quad \text{Eq. (4)}$$

where RR_{base} is the routine ramping in the baseline scenario and RR_{ee} is the routine ramping in a representative EE scenario. An increase in routine ramping relative to baseline would suggest an increased need for load-modifying resources to deal with routine ramps, and vice versa.

4.3. DR program design metrics definition

DR programs, typically administered by electric utilities or third-parties (e.g., aggregators), are often defined in terms of

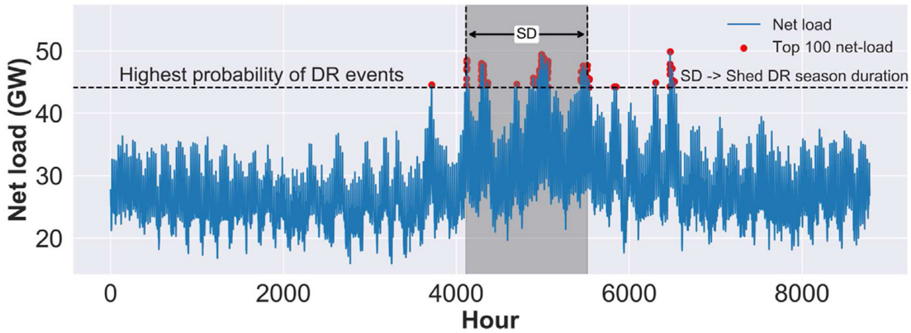

Fig. 10. California's hourly net-load in GW for the year 2016 used to illustrate the temporal distribution of top 100 net-loads (indicated by red dots). Shed season duration is the shortest interval that contains the 80% of the top 100 net-loads. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

number of events and their frequency (e.g., maximum number of events per month), as well as the season during which customers can participate (e.g., summer air-conditioning cycling programs). As the system need for DR changes with increasing penetration of VRE and widespread electrification, DR programs will need to be designed consistent with new seasonality and timing of DR events. Fig. 10 illustrates two metrics for shed DR program design, based on considering the distribution of the top 100 net-load hours throughout the year. The first metric is the *shed DR-event days*, defined as the number of days that contain at least one of the top 100 net-load hours. This metric quantifies the frequency and the duration of shed DR events that a program might call. A lower number of event days indicates that a program would need to call longer shed DR events that occur less frequently, while a higher number of events indicates shorter individual events that would occur more frequently.

The second metric is the *shed DR season duration* and we define this metric as the shortest interval, in days, that contains at least 80% of the top 100 net-load hours. This represents the period in a year where shed DR is most valuable for the system. Computing the duration based on 80% of the top 100 hours yields a more stable metric: we observed that many of the top-100 net-load hours occur over a span of a few weeks or months with the remaining hours scattered throughout the rest of the year, such that one or a few of these hours can be widely separated from the core period. Therefore, limiting the shed DR season duration metric to 80% of the top net-load hours can reduce annual volatility from a few and isolated hours. This is important because customers typically participate in DR programs for several years and make investments in control technologies. Therefore, DR program design should be consistent over several years.

Shift DR program designs will need to evolve with the changing grid characteristics, such as increased VRE penetration or electrification of present-day fossil-powered end uses. Analogous to the shed DR season duration metric, we define a metric for the *shift DR season duration* using the top-25 ramp values by calculating the minimum period, in days, that contains 80% or 20 of the top 25 ramps (see Fig. 12 for graphical representation of shift DR season duration).

5. Application of metrics on EE and high VRE scenarios

We apply the metrics defined above to four sample scenarios — three EE and one high VRE, as described in Section 2— to demonstrate how different drivers of change in the system-level net-load can affect the system need for DR, using California power system data. Table 2 summarizes the results of the impacts for each of the shed DR, shift DR, and DR program design metrics defined in Section 3.

From the system perspective, reductions in the peak load, either via EE savings or increased VRE generation, are beneficial since they reduce the need for shed DR (see inset plot of Fig. 11). The peak load is reduced in all scenarios relative to baseline, however, the degree to which it changes depends on the coincidence of the EE driven load reductions with the system peak-load. This is evident when comparing the on-peak EE savings scenario with greater peak demand coincidence of impacts (24.6% reduction in peak demand) versus the off-peak EE savings scenario (15.5% reduction in peak demand). This implies that the on-peak EE scenario can provide a larger reduction in the need for peaking capacities to meet the peak load. The change in the system peakiness metric across the EE and VRE scenarios further illustrates that more coincident peak reductions (i.e., flat EE and on-peak EE savings scenarios) reduce the incremental amount of load in the top-100 hours, which reduces the need for peaking capacity and shed DR to meet that load. In contrast, scenarios that reduce midday net-load and increase evening net-load (i.e., off-peak EE savings and high VRE) increase the peakiness and need for shed DR.

The change in the system need for shift DR is dependent on both demand-side and supply-side changes, especially in the California system with a high solar penetration. In the baseline scenario, the 25-highest ramps occur primarily in the late summer and fall seasons (see Fig. 12). California's daily summertime peak demand is generally cooling-driven and also drives ramps in the baseline scenario.[7] EE-driven load reductions that are coincident with the peak (e.g., flat EE savings and on-peak EE savings) tend to reduce the magnitude of ramps overall (see Fig. 12) by reducing the summer peak loads relative to baseline. This reduces the need for DR to serve routine ramps by reducing the size of the 25th highest ramp. The degree to which it declines depends on the coincidence of EE driven load reductions with system peak load (i.e., on-peak EE savings reduce the need for routine ramping by 22.3% whereas flat EE savings reduce it by 13.3%). This implies that deploying strategies to reduce peak demand can also help reduce ramping concerns that may occur on a day-to-day basis. In this particular example from California, such strategies help reduce the severity of ramps occurring in summer season to the extent of eliminating them from the top-25 extreme ramps. Hence, the extreme ramps are shifted towards fall and winter days. Off-peak EE savings are unique in that

[7] This observation is specific to 2016 load in California. The highest ramping needs shifted out of summer months as solar generation increased in subsequent years and mitigated the cooling driven peaks (as observed in the high VRE scenario).

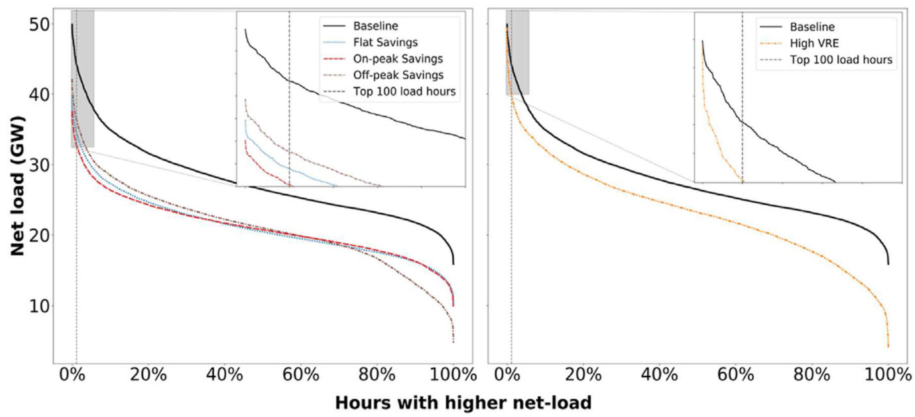

Fig. 11. Load duration curves comparing baseline (black) with EE scenarios (left panel) and high VRE scenario (right panel). The inset plot on each panel represents the top 100 net-load hours, where peak load reduces across all scenarios.

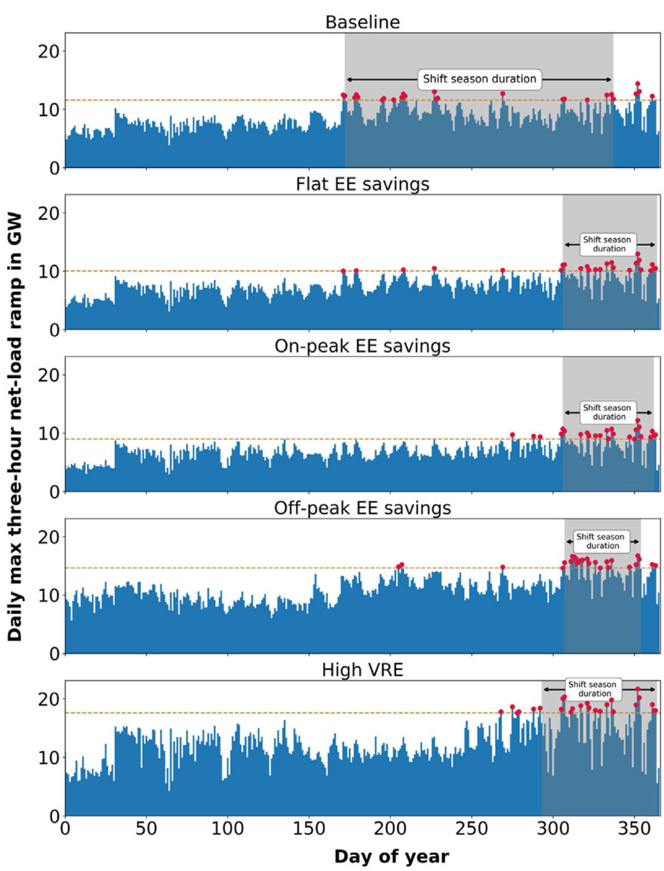

Fig. 12. California's absolute maximum ramp for each day and scenario. The red dots indicate top 25 ramps and the orange line indicates the 25-th highest ramp (Routine Ramp) in each scenario. The shaded region on each panel denotes the shift season duration. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

extreme ramping decreases but the routine ramping increases. The off-peak EE savings reduce the midday net-load and tend to increase the magnitude of ramps overall relative to baseline, thus increasing routine ramping (Fig. 12). However, these effects also tend to increase the top-25 ramps by a similar size thus reducing the difference between the highest ramp and 25th highest and reducing extreme ramping.

In the high VRE scenario, the need for both extreme ramping as well as routine ramping increases. Shift metrics are largely driven by the type of VRE (e.g., wind versus solar) in a given system. In California, significant need for ramping is driven by solar generation [9]. High VRE tends to increase the magnitude of ramps overall since high midday solar generation reduces the net-load, thereby exacerbating the evening ramps and increasing routine ramping (see Fig. 12 bottom panel). High VRE generation also deepens the duck curve in the winter and spring days, causing large evening ramps and hence increasing extreme ramping.

Table 2 presents the change in shed and shift DR program design metrics from the impact of different EE savings and VRE penetration. In every EE and VRE scenario, the frequency of shed DR events (i.e., number of days that constitute the top 100 net-load hours) increases compared to the baseline. Similarly, the shed DR season duration (i.e., the shortest interval in days that contains 80% of the top 100 net-load hours) also increases in the on-peak EE savings, off-peak EE savings, and high VRE scenarios and does not change in the off-peak EE savings scenario. The results suggest that a lower net-load, either via EE savings or higher VRE penetration, emphasizes shoulder or winter peaks (compared to a summer-peaking baseline) thus spreading out the number and timing of shed DR events. More peak-coincident EE savings (i.e., on-peak EE savings and flat EE savings) appear to mitigate this spread resulting in smaller change in shed DR events and shed DR season duration.

There is a dramatic reduction in the shift DR season duration across all the EE and VRE scenarios, with the highest reduction occurring in the off-peak EE scenario (see Table 2). While the EE and VRE impacts to net-load emphasize winter peaks relative to the baseline, the most significant net-load ramps are more concentrated in the winter season. While a few top-25 ramps occur in the summer and fall seasons, they do not affect this metric because of the 80% threshold (see Fig. 12).

6. Discussion and conclusion

DR is a valuable resource for managing loads and reducing costs as the power system transitions towards greater VRE and integrates other decarbonized resources. This study developed new metrics to quantify change in the power system need for shed and shift DR to inform system operators, regulators, policymakers, and other stakeholders about how to maximize the value of existing and future DR programs and technologies. Using historical system load, wholesale prices, and emissions we characterized the system value of DR both in the traditional case of shed DR for peak reduction and

Table 2
Summary of results of applying system need and program design metrics to the scenarios described in section 2. Positive values indicate an increase in DR need as a percentage change relative to baseline, and vice versa.

	Shed DR Metrics		Shift DR Metrics		DR Program Design Metrics		
Scenario	Peak Load (% change)	Peakiness (% change)	Extreme Ramping (% change)	Routine Ramping (% change)	Shed Event days (% change)	Shed season duration (% change)	Shift season duration (% change)
Flat EE Savings	−20.1	−6.2	+3.9	−13.4	+16.6	0	−64.8
On-peak EE savings	−24.6	−13.7	+11.6	−22.3	+20.8	+1.7	−66
Off-peak EE savings	−15.5	+1.3	−25.5	+26.3	+37.5	+1.7	−71.5
High VRE	−0.86	+62.8	+43.6	+51.7	+54.2	+34.5	−56.9

in the more novel case of shift DR to mitigate steep net-load ramps. We then formulated seven metrics to quantify changes in the system-level need for DR that may occur in response to changes in net system load. The metrics considered changes in both the magnitude and the timing of the need for shift and shed DR, to inform both the scale and the design of DR programs. Importantly, the need for DR and its value in reducing high system loads, costs, and emissions was easily identifiable and constrained to limited hours (i.e., top-100 net-load hours) and events (i.e., top-25 ramps). Furthermore, the seven metrics defined in the study can be easily calculated using publicly available hourly load and VRE generation data, which will promote their adoption and utilization by grid planners and DR program administrators.

The study also demonstrated that the metrics can be used to quantify the impact on DR need arising from system-wide changes on both the demand-side (i.e., via the EE scenarios) as well as the supply-side (i.e., via the high-VRE scenario). Additionally, these metrics could also be applied to study the impact of changes in other sectors (e.g., building weatherization, electrification of transport and industrial processes, storage) on a system's net-load and hence, its need for DR. As expected, shed DR metrics that are based on the top-100 load hours are highly influenced by changes that are coincident with peak load. EE measures that produce savings during system peaks (e.g., more efficient building envelopes and air-conditioning for summer peaking systems and more efficient lighting, water heating, and heating for winter peaking systems) are highly effective at reducing the system need for shed DR by decreasing both peak load and peakiness. This suggests a reduction in both short-run and long-run need for shed DR. Off-peak EE savings, however, reduced the peak load but increased the peakiness, suggesting a short-run reduction but a long-run increase in the need for shed DR. While the off-peak EE savings resulted in the largest increase in shed DR events relative to the other EE scenarios, none of the EE scenarios noticeably increased shed DR season duration.

Shift DR metrics, however, are driven by ramping, which is sensitive to changes in load and VRE generation and, therefore, exhibit greater seasonal variation. While more peak-coincident changes can reduce the magnitude of ramps (thus, reducing the routine ramping metric), in some cases, they may also increase the extreme ramping, as well as shift the highest ramps to different seasons. For example, in the case of our on-peak EE savings scenario, the size of the 25th-highest ramp was reduced but the difference between the highest and 25th-highest ramp increased, as well as significantly concentrating the top-25 ramps to the winter season. These results show a change in both the nature and the timing of the system need for shift DR, which suggests a different strategy for load-shifting program design. The shift DR metrics also exhibited sensitivity to the ways in which VRE generation alters the net-load throughout the year, including periods outside the conventional peak season. For example, the high VRE scenario showed an increase in *both* routine and extreme ramping, while also reducing ramps during the peak season and concentrating the need for shift DR into shoulder and off-peak seasons. The changes and interrelationships between gross and net-load (as a result of application of EE and high VRE) determine the variability in system ramps and hence, the shift DR metrics. These results suggest system planners and operators need to be thoughtful about interactions between EE, DR, and VRE in order to avoid unintended consequences on the magnitude and timing of system ramping.

In practice, the metrics that we have developed here for assessing the changes in system-level DR need can be of value for various electricity industry stakeholders. For example, the metrics can help system planning identify the most valuable type of DR resources and inform system operations and dispatch to ensure a robust utilization of DR to meet high load and ramp conditions. The metrics can also inform and improve DR program design by quantifying the seasonality of shed and shift DR events, to facilitate better targeting of customers and end-uses that are aligned with the system need. Finally, these metrics can help inform decision-makers in setting more comprehensive targets or mandates for DR that go beyond simply reducing the annual system peak to also address needs to mitigate seasonal peaks and major ramping events.

Declaration of competing interest

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

Acknowledgements

This work was funded by the US Department of Energy (US DOE)'s Building Technologies Office under Lawrence Berkeley National Laboratory (LBNL) Contract No. DE-AC02-05CH11231. We thank Monica Neukomm (US DOE) for supporting this study. We also thank Joachim Seel and Andrew Mills (LBNL) for inputs and comments on the analysis. Any remaining errors or omissions are our own.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.segy.2022.100074.

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