Representative Period Selection for Robust Capacity Expansion Planning in Low-carbon Grids

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***Abstract*—With the increasing urgency to decarbonize power systems, while mitigating extreme weather events, capacity expansion models can play a vital role in reliably planning the expansion of power systems and facilitating the integration of renewable energy (RE) sources. Optimizing capacity expansion generally involves selecting surrogate representative days from forecasts of load and the generation profiles of variable RE resources. To properly select those representative days, we propose a novel input-based approach in combination with the k-means clustering algorithm that utilize three unique operational characteristics: load shedding, renewable curtailment, and transmission congestion. The proposed method allows for more robust and cost-effective capacity planning. The method is validated using a capacity expansion model and a production cost model aligned with California Independent System Operator (CAISO)'s decarbonization goals, and results in significant cost reduction and substantial decreases in load shedding.**

***Index Terms*—Capacity expansion planning, time series clustering, representative period selection, production cost modeling.**

I. Introduction

A. Background & Problem Statement

As both climate change and humanity's response have accelerated in recent years, decarbonization of power grids has emerged as a critical topic within an industry often characterized as slow-moving and cautious. Meeting this challenge requires substantial investments, especially in energy storage and RE generation [1]. As a result, the significance of capacity expansion models (CEMs), which play a pivotal role in ensuring the successful transition toward a cleaner power grid, continues to grow.

CEMs aim to identify optimal generation and transmission investment strategies for future years. These models usually involve two-time scales: one for annual investment decisions and another for hourly generation dispatch simulations. Yet, the complexity of solving the optimization problem increases significantly when attempting to model all 8760 hours in a year, potentially leading to slow or intractable computations.

To mitigate this challenge, one solution is to use representative periods, which can significantly alleviate the computational load. For instance, rather than modeling all 8760 hours annually, one can concentrate on solving for 37 carefully chosen representative days, resulting in a remarkable reduction of almost 90% in the modeled hours. The main goal in selecting these representative days is to capture the essential aspects of the entire yearly system behavior while substantially reducing the computational intricacies involved.

B. Related Work & Paper Contribution

Many studies utilize load, solar generation, and wind generation profiles for clustering. A variety of clustering approaches have been proposed. The performance of several clustering algorithms, including k-means, k-medoids, and dynamic time warping, are compared in [2]. In [3], several questions around this clustering principle are investigated. In [4], fuel use and renewable generation profiles are used for clustering. In [5], a clustering approach that selects extreme days as initial cluster centers is proposed. In [6], the authors propose a clustering approach that requires clusters to consist of a chronologically adjacent set of days. Various methods for reducing the time dimension, including clustering and downsampling, are compared in [7]. In [8], a novel combination of clustering methods is applied to load and generation profiles.

Some works seek to model a year continuously to better model long-term storage [9], [10]. In these works, the temporal reduction is achieved by holding an operating state for multiple hours. However, within the CEM, this approach severely affects ramping modeling. The ramping requirements, particularly those originating from the so-called 'duck curve' due to high solar penetration, are a critical aspect that needs to be modeled. Representative hour approaches have also been proposed [11], [12], but suffer the same loss of chronology and thus the ability to track energy storage and ramping.

There are limited studies that utilize other features for clustering. In [13], clustering based on investment cost is proposed, along with a technique for extreme period selection. The authors in [14] examine the trade-off between temporal and technical modeling detail and propose period selection based on RE variability. A histogram-based approach is used in [15] to ensure the sampled periods accurately represent the loading levels of a full year but misses out on chronology.

While a considerable amount of research effort has been devoted to the representative period selection problem, the majority of it has focused on clustering algorithm design or selection. In contrast, there is not much work dedicated to the selection of power grid features to be used within the clustering algorithm. Indeed, the majority of representative period selection methods use a greenfield approach, assuming no existing capacity, which is an impractical assumption for real power systems. Furthermore, these approaches overlook features highly relevant to capacity expansion planning, such as transmission congestion, renewable curtailment, and load shedding. This work aims to address this research gap by integrating additional operational features into a general time series clustering framework to select representative periods in a manner more suitable for capacity expansion in the presence of high RE penetration and extreme events.

The remainder of this paper is organized as follows. Section II develops the proposed feature selection and clustering approach. Section III presents the numerical study and results while Section IV provides study conclusions.

II. Technical Method

A. Feature Selection

In practice, CEMs do what the name suggests: determine optimal strategies for adding energy resource capacity. The current resource fleet within a system might be sub-optimal or insufficient for future years, as a result of a variety of drivers including the following examples. Environmental regulations may limit the use of gas-fired generators. Increasing loads could necessitate additional capacity. High fuel costs for gas-fired generators may also make it more economically viable to invest in additional energy storage or renewable resources. Therefore, it is crucial to consider the characteristics of the existing capacity when selecting representative days. While existing methods for representative period selection have disregarded this aspect, our objective is to incorporate the attributes of the existing capacity into the process of choosing representative days.

To this end, we propose including features that encode the existing capacity, but are typically not considered during clustering. This section identifies these features and justifies their inclusion. These features are referred to as operational features, as they are outputs of system operation, in contrast with demand and generation, which are inputs to operation. Namely, these features are load shedding, transmission congestion, and renewable curtailment.

Load shedding, sometimes known as rolling blackouts, refers to interrupting some portion of loads, generally as a last resort for load balancing. Load shedding events are increasingly associated with extreme weather events, like heat waves or cold snaps. Load shedding is associated with considerable economic cost, as well as potential loss of life, as evidenced by the 2021 Texas power crisis [16]. Load shedding is a key metric for resource adequacy and can be avoided with proper planning. Inclusion of this feature in representative day selection could help select periods that stress the existing resource fleet, thus leading to more robust capacity sizing.

Curtailment refers to disconnecting RE generation to prevent overgeneration. Curtailment occurs when renewable generation exceeds demand, and this excess cannot be exported or used to charge energy storage systems. By including curtailment, the selected representative days will better account for days where renewable capacity is already sufficient, as well as select periods which demonstrate the value in expanding storage capacity.

Congestion refers to a $/MWh transmission cost. Congestion exists when there is more demand for transmission capacity than there is physical capacity. Including this feature should help select periods which would be relevant to expanding transmission capacity by identifying periods with excess RE generation which could be exported to other areas.

Each of these operational features can be readily obtained from the output of a production cost model (PCM). Because these features can be obtained by running a PCM in discontinuous days, the computational complexity associated with long timescales that necessitates the use of representative days in the CEM is irrelevant.

B. Dimensionality Reduction

Often, capacity expansion models consider wide geographic areas. Thus, there are load forecasts at many nodes, as well as renewable generation profiles at different locations. Each time step further inflates the dimensionality of each sample. Attempting to cluster without reducing the spatial dimensionality of these features could produce sub-optimal results. For load, renewable generation profiles, and congestion, this is done in the straightforward method of averaging the time series over the spatial dimension. Some operational features should be highly sparse. In particular, curtailment should be zero in most hours, and load shedding should be even less common. For this reason, the spatial dimension of these features is reduced by taking the maximum. Each feature is normalized to zero mean, unit variance before it is clustered.

C. Extreme Events

The goal of representative day selection is to find a subset of days that best capture the annual behavior of load and generation. However, this goal conflicts with the need to simulate extreme periods. Extreme weather events may only occur for a small fraction of days each year, and thus is unlikely to be selected during typical representative period selection. Within power system planning, extreme events are an extremely important consideration. If enough generation capacity is not held, the reliability of the system during extreme weather patterns could be compromised. Similarly, if there are periods of abnormally low renewable generation, the system could struggle to cope with demand. With climate change and an increasing push for decarbonization, these extreme events will become even more important. Several works have proposed methods for selecting extreme events based on peak load, peak ramping, or other features [5], [13]. Through the numerical study, we will show that inclusion of operational features in clustering implicitly selects these representative periods. In particular, the inclusion of load shedding as a feature in representative period selection effectively captures the inadequacy of existing capacity.

D. Clustering

To select representative days, the periods are clustered using k-means. Given N samples, the goal of k-means is to generate

K cluster with centers μ_k and assign a cluster label to each sample x_n.

$$\min \sum_{k=1}^{K} \sum_{n=1}^{N} \gamma_{n,k} ||x_n - \mu_i||^2 \tag{1}$$

where $\gamma_{n,k}$ is a binary variable that indicates that sample x_n belongs to cluster k and must satisfy (2),

$$\sum_{k=1}^{K} \gamma_{n,k} = 1, \forall n \in N \tag{2}$$

Although the optimization problem in (1) is NP-hard, computationally efficient heuristics exist, and several are implemented in widely-used Python and Julia packages, such as scikit-learn [17].

Although k-means is a centroid method, clusters will be represented by their medoid in the capacity expansion model. This is necessitated by the dimensionality reduction discussed in Section II-B, making it impossible to accurately map backwards from the low-spatial dimension representation used in clustering to the high-spatial dimension used in the CEM. The medoid is selected after clustering as the sample with the smallest Euclidean distance to the centroid. The weight of each representative period is chosen as the cardinality of the cluster.

III. Experimental Validation

A. Experimental Setup

The proposed clustering technique is validated using a CEM and PCM for the Western Interconnection. Only single-year planning is considered, and the year modeled will be referred to as the target year. First, the PCM is solved for the target year using the existing generation capacity. Then, the features described in Section II are extracted and used within the proposed clustering technique. Finally, these clusters will be used to run the CEM for the target year. To evaluate the performance of the investment decisions made with the representative periods, the PCM is then run again with updated investments. Fig. 1 demonstrates the flow of the numerical study.

The PCM and CEM are based on a MILP adaptation of the formulation and data of E3's RESOLVE power system decarbonization model [18]. Both incorporate a WECC-based zonal model focused primarily on CAISO. Resources include a large fleet of gas generators, wind and solar farms, large hydro, battery and pumped storage, nuclear and small firm resources. Both models share the principal goal of minimizing the cost of serving load. The PCM solves for the operating decisions, primarily scheduling of generation, which minimizes daily operating costs, subject to operating and reliability constraints. A simplified formulation of the model is presented in (3). Operating constraints are resource-specific constraints on the dispatch of that resource. For gas generators, these are unit commitment constraints such as ramping, and minimum up- and down-time. Reliability constraints are those that ensure reliable power supply, including power balance and supply of reserve products.

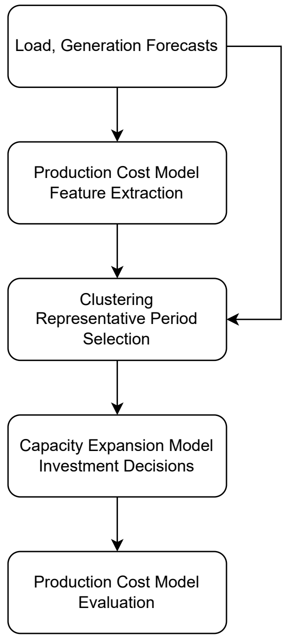

Fig. 1. Flow of proposed numerical validation

$$\begin{aligned} \min \quad & C_{gen} \\ \text{s.t.} \quad & \text{Operating constraints} \\ & \text{Reliability constraints} \end{aligned} \tag{3}$$

The CEM essentially introduces an additional layer to the PCM, solving operational and investment decisions which minimize the cost of generation C_{gen}, maintenance C_{maint} and investment C_{inv} for the year. A simplified formulation is presented in (4). Investment decisions are the retirement of existing gas generators and investment in new resources. Policy constraints include emissions limits and renewable portfolio standards.

$$\begin{aligned} \min \quad & C_{inv} + C_{maint} + C_{gen} \\ \text{s.t.} \quad & \text{Policy constraints} \\ & \text{Operation constraints} \\ & \text{Reliability constraints} \end{aligned} \tag{4}$$

Typically, CEMs include a planning reserve margin (PRM) constraint, requiring that the fleet be able to provide some margin greater than the maximum projected load. As a result, regardless of clustering performance, the investment decisions will produce a fleet that can most likely satisfy all load requirements. In some cases, if this constraint is particularly tight, the final resource investment plan may be predominantly determined by investment costs, thus diminishing the value of improved representative day selection. In other words, system operation may determine the optimal fleet up to some MW of capacity, but any requirement for capacity above that may be determined only by which resource is cheapest per capacity. In the numerical study, results will be shown both with PRM omitted and with a minimal PRM, equal only to the maximum load and not a margin above, as is typical.

To demonstrate the performance of the proposed technique, we compare the investment decisions obtained using the proposed clustering method to those using only traditional features, namely the load and renewable generation profiles. The performance of investment decisions is evaluated using two metrics: cost and reliability. Reliability is evaluated using both the number of load shedding events and MWh of load shedding. Cost is the combined cost of maintenance, investment, and operation. Within the PCM, load shedding is available at $50,000 per MWh. Investment costs are amortized to allow for single-year planning.

B. Results

We evaluate the performance of the algorithm through two lenses: load shedding and total cost. We also look to the blend of resources to evaluate how representative day selection affects valuation of one resource group versus another. The proposed method is compared to a base method, in which the clustering step only accounts for load, solar, and wind. To better understand the impacts of the proposed method, results will be shown under several planning scenarios, with several target years. K-means heuristics are not deterministic and are highly dependent on initialization. To address this, most implementations run the algorithm multiple times and choose the result with the lowest cost function. Still, the selected days and weights can vary, so the numerical study is repeated three times for each scenario and averaged. Unless stated otherwise, 20 representative days are selected.

The two PRM scenarios will be shown with target years of 2025, 2030, and 2045. We also show the results for 2025 in which economic retirement is not allowed and for 2045 in which economic retirement is required for 50% of all in-CAISO units. No such constrained retirement will be demonstrated for 2030. The justification for including these scenarios is as follows. Without PRM, the effect of representative day selection on resource adequacy should be more obvious. With PRM, there should be a smaller effect on resource adequacy and a greater effect on system costs.

Table I shows the total cost for each target year with the proposed method and the base method. The base method often requires considerable load shedding, which greatly increases the total cost. To give a point of comparison without this effect, costs are shown both with and without the load shedding penalty component, denoted by 'pen'. Note that for the proposed method, the penalty and no penalty values often are equal as there is no load shedding. In every case with load shedding penalty, the proposed method leads to lower or nearly identical costs. Omitting the load shedding costs, the proposed method generally has comparable costs to the base case. This indicates that the proposed method produces more realistic capacity plans, which, in turn, lead to a reduction in load shedding, with only moderately higher investment costs.

TABLE I
TOTAL COST COMPARISON OF BASE AND PROPOSED METHOD INVESTMENT DECISIONS (MILLIONS $)

Year	Pen	Method	PRM	No PRM	Constrained Retirement
2025	Yes	Base	13,372	13,354	12,468
		Proposed	12,412	12,407	12,442
		Improvement	7.18 %	7.09 %	0.21 %
	No	Base	12,461	12,472	12,466
		Proposed	12,412	12,407	12,442
		Improvement	0.39 %	0.52 %	0.19 %
2030	Yes	Base	14,507	14,666	-
		Proposed	14,503	14,255	-
		Improvement	0.03 %	2.80 %	
	No	Base	14,448	14,141	-
		Proposed	14,470	14,239	-
		Improvement	-0.16 %	-0.69 %	
2045	Yes	Base	23,713	23,649	23,481
		Proposed	23,414	21,323	21,351
		Improvement	1.26%	9.84%	9.07%
	No	Base	23,545	22,011	21,952
		Proposed	23,414	21,323	21,351
		Improvement	0.56%	3.13%	2.74 %

Fig. 2 shows the costs for 2030 without PRM, both with and without load shedding penalty. As expected, the capacity plan resulting from representative days with the base features requires more load shedding in the PCM. This load shedding is a result of lower capacity, which in turn has lower investment costs. However, the capacity plan resulting from the proposed method, has only slightly higher investment costs. With load shedding costs ignored, the total costs are only 0.69% higher for the proposed method. Investment costs are 2.6% higher, but are offset by lower operational costs and much lower load shedding costs. With load shedding costs accounted for, the total cost is drastically lower. Fig. 3 shows components of

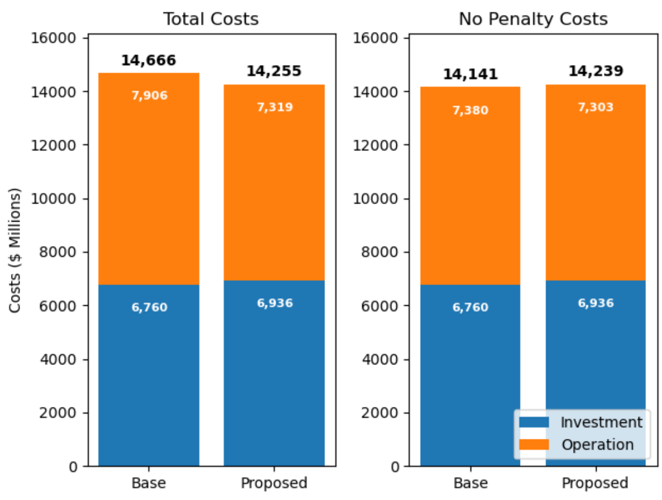

Fig. 2. Operation and capital costs for 2030 without PRM

capacity expansion by resource class for 2030. Intuitively, the scenarios with PRM have increased investment regardless of the representative day selection. The proposed method leads to greater investment in both energy storage and renewable generation. The methods have roughly equal retirement of gas-fired generators. Fig. 4 shows the sensitivity of the number

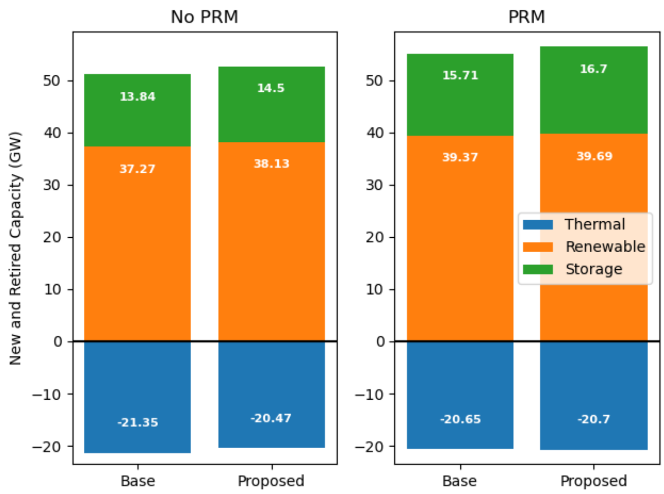

Fig. 3. Capacity expansion decisions in 2030

of representative days for 2030. Regardless of the number of representative days, the proposed method leads to lower load shedding, both in the number of events and the average MWh of shedding per event. As previously suggested, this indicates that the inclusion of the proposed operational features implicitly selects extreme conditions more effectively.

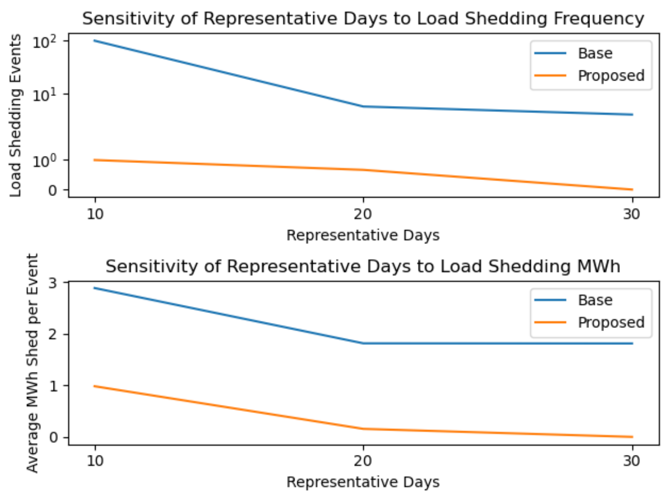

Fig. 4. Sensitivity of number of representative days on load shedding

IV. Conclusion

In this paper, we proposed a novel method to select representative days that can be used in capacity expansion models. The proposed method better accounts for existing capacity by considering key novel operational features during the clustering step. By including these features, the resulting capacity expansion plan exhibits improved load-serving capability and cost savings as compared to the base-feature case. The proposed method was validated on a capacity expansion model based on decarbonization goals in CAISO. Several planning scenarios and horizons were studied. In all scenarios, the proposed method resulted in lower load shedding in the full-space production cost model, as well as lower or comparable costs even when the cost of load shedding is neglected.

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