Scenario Reduction for Scalable Stochastic Planning of Energy Storage Resources

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***Abstract*—Long-term and operational uncertainties in generation availability, load growth, and technology costs continue to complicate system planning and reinforce the need for flexible resources such as energy storage. Stochastic capacity expansion planning (SCEP) provides a structured way to represent these uncertainties, but its practical use is often constrained by the large scenario sets required to represent uncertainty with sufficient fidelity. This paper presents a systematic scenario-reduction methodology that enables high-dimensional uncertainty to be incorporated into SCEP more efficiently. Specifically, the proposed approach combines singular value decomposition (SVD) with k-medoids clustering to reduce a large scenario space into a compact set of representative cases while preserving objective function stability. Applied to a 43-zone representation of the Western Interconnection across a 30-year horizon, the stochastic plan yields an estimated $9B benefit relative to deterministic planning, underscoring both the importance of capturing uncertainty and the effectiveness of the proposed reduction technique.**

***Index Terms*—Capacity expansion, energy storage, scenario reduction, stochastic programming, value of stochastic solution.**

I. Introduction and Literature Review

Energy storage (ES) is emerging as a transformative technology for enhancing the flexibility and reliability of the electric power grid [1]. It can provide a wide range of operational and economic benefits, such as energy shifting, frequency regulation, resource adequacy, congestion relief, and capacity charge reduction. [2]. On the other hand, given the upfront capital costs and long investment lifetimes of ES, it is essential to evaluate these resources within long-term planning frameworks such as capacity expansion planning (CEP) [3].

A key challenge for CEP is decision making under long-term and operational uncertainties, including load growth, generator availability, and ES capital costs. Prior work has examined such investment interactions under a limited set of uncertainties and shown that these factors can substantially shift optimal investment [4]. For example, an ES build-out under high ES capital expenditure (CapEx) and low hydropower variability may lead to underutilized, high-cost assets, whereas an ES build-out under low ES CapEx and high hydropower variability may result in highly utilized, cost-effective assets.

The broader literature on stochastic ES planning highlights similar themes. In [5], interval-based stochastic programming is used to analyze uncertainty stemming from generator output and demand forecasts. In [6], uncertainty in generation interconnection queues is incorporated into ES investment decisions. While each study captures a subset of uncertain parameters, system planners ultimately face uncertainty across many dimensions. Representing all uncertainties simultaneously is computationally prohibitive, which is why practical CEP models typically include only those believed to have the strongest impact. This motivates the need for more systematic and scalable approaches for incorporating uncertainty in long-term storage planning.

Uncertainty in system conditions often affects both generation and load in correlated ways, which makes it important to represent these relationships consistently when evaluating long-term investment decisions. Historically, weather data has been incorporated into the development of generation profiles. For example, [7]–[9] have been used to translate weather model outputs into generation profiles. In addition, tools such as those developed in [10] have been applied to incorporate weather data into load profiles. In practice, however, different components of the system are often modeled using disparate data sources or assumptions. Ideally, for any given power system study, generation and load data should be constructed under consistent weather assumptions. Notable progress toward this goal is shown in [3], which analyzes the U.S. grid using generation and load profiles derived from a common weather dataset.

For stochastic capacity expansion planning (SCEP), which evaluates investment decisions across multiple scenarios, planners typically require many distinct sets of weather-consistent generation and load profiles. However, as the number of scenarios increases, SCEP models become increasingly difficult to solve. Decomposition methods offer one approach to reducing the computational complexity of stochastic programming (SP) models. Progressive hedging decomposes SP problems by scenario [11], Benders decomposition decomposes SP models by stage [12], and Danzig-Wolf decomposition [13] exploits the structure of the constraint matrix to construct subproblems based on decision variables with coupling constraints. Although these methods can be challenging to implement in optimization frameworks, they generally allow problems with large number of scenarios to remain tractable.

Nevertheless, it is usually necessary to reduce the full set of scenarios to a smaller representative subset using scenario-reduction techniques. Common scenario reduction methods

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include clustering [14], distance based methods [15], approaches that preserve stochastic properties [16], [17] and expert opinion [18]. In [14], k-means clustering is applied to key generation parameters associated with each scenario. The approach in [15] removes scenarios sequentially by minimizing the Earth Mover's Distance (Wasserstein distance). In [16], Latin Hypercube Sampling is used to construct scenarios, while [17] presents a technique for generating scenarios that preserve the moments of the original distributions. Finally, [18] selects scenarios based on expert assessment tailored to the needs of the study.

This paper presents a methodology for including correlated weather uncertainties within a SCEP model. A central component of the approach is a structured scenario-reduction technique that enables comprehensive characterization of high-dimensional variability while maintaining computational tractability. The framework supports a broader and more coherent treatment of uncertainty than is typically represented in long-term planning studies. The main contributions are summarized as follows:

- The proposed scenario-reduction procedure employs singular value decomposition (SVD) and k-medoids clustering to efficiently reduce datasets characterized by high feature dimensionality and limited scenario availability.
- The proposed method is applied to forty scenarios to enable comprehensive analysis of ES investment decisions under jointly varying load and generation uncertainty, and to quantify the value of the stochastic solution (VSS).

The rest of this paper is structured as follows. Section II describes the SCEP optimization formulation and reduction methodology using SVD and k-medoids. Section III details the scenario data and system under study. Section IV reports the case study findings, and Section V presents the conclusions.

II. Methodology

This section describes the SCEP model, beginning with the scenario reduction algorithm in II-A and the formulation in II-B. Uncertainty is modeled in a two-stage SP problem where first stage "here and now" investment decisions are made in 2030, and second stage "wait and see" decisions are made in 2040 and 2050, as illustrated in Fig. 1. Additionally, a delay of 10 years is modeled between the project's development initiation and project's availability for operation.

As is characteristic of two-stage SP, parameter values in the first stage are identical across all scenarios, reflecting present-day decisions that can only have one realization. Second stage parameters vary by scenario to represent uncertainty in future system operational conditions.

A. Scenario Reduction Algorithm

Uncertainty is represented by weather (i.e., load and generation profiles) and energy storage capital costs. The reduction proposed in this work is only applied to the weather scenarios given that a small characteristic set of capital cost trajectories for energy storage prices already exist (Figure I). A data matrix is constructed with 40 rows corresponding to individual

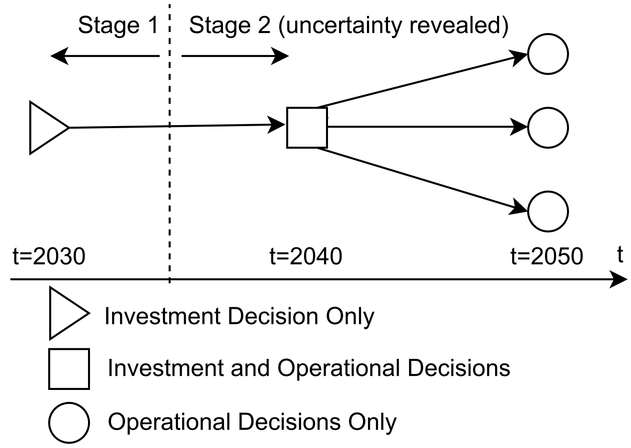

Fig. 1. SP investment and operational decisions structure

weather years and N columns which represent the hourly zonal load, hydropower, and other generation profiles across 43 zones and 8,760 hourly time steps per year, yielding a high-dimensional dataset in which the number of features (columns) far exceeds the number of points (rows). High-dimensional data can pose challenges for clustering algorithms, as distance metrics become less informative [19]; therefore, dimensionality-reduction techniques such as principal component analysis (PCA) or SVD are commonly applied prior to clustering. In this work, SVD is applied to reduce the feature dimension to 10, producing a 40×10 feature matrix. The choice of 10 is a practical heuristic that yields a low-dimensional feature space suitable for clustering, with fewer retained features than weather-year observations, and remains well below the maximum rank of 40. The k-medoids clustering algorithm is then used to select a representative sample of weather years from the data matrix. Additional details on the implementation of the reduction are given in Section III.

B. Formulation

A generic two-stage SP formulation, sometimes referred to as the recourse problem (RP), takes the form of (1)-(4) (adapted from [20], [21]). The SCEP used in this work is no different. Here $\mathbf{x}$, $\mathbf{y}$ are vectors of decision variables, where $\mathbf{x}$ represents first stage "here and now" decisions with cost coefficients c^T, and $\mathbf{y}$ represents second stage "wait and see" decisions with cost coefficients $q(\omega)^T$. ξ represents a random variable that is discretized into N values with each value representing a different scenario ω with probability of $p(\omega)$ of occurring. Equation (2) represents first stage only constraints, where constraint coefficients A and intercepts $\mathbf{b}$ have no dependence on ξ. Equation (3) represents second stage constraints which may have direct dependence on the first stage decisions $\mathbf{x}$. The constraint coefficients $T(\omega)$, $W(\omega)$ and intercepts $\mathbf{h}(\omega)$, vary with the discretized realizations ω of the random variable ξ.

$$\text{RP} = \min\ z(\mathbf{x}, \mathbf{y}, \xi) = \min\{\mathbf{c^T x} + \sum_{\omega=1}^{N} p(\omega)\mathbf{q}(\omega)^T\mathbf{y}\} \quad (1)$$

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$$A\mathbf{x} \leq \mathbf{b} \quad (2)$$

$$T(\omega)\mathbf{x} + W(\omega)\mathbf{y} \leq \mathbf{h}(\omega) \quad (3)$$

$$\mathbf{x}, \mathbf{y} \geq \mathbf{0} \quad (4)$$

The SCEP used in this work minimizes generation, transmission, and storage capital and operational costs subject to typical operational and physical constraints, which includes:

1) Capacity update constraints for investment and retirements; including generation, transmission and storage;
2) Power balance constraint;
3) Kirchoff's current law and Ohm's law for DC power flow for existing branches;
4) Kirchoff's current law for candidate branches;
5) Operational generation, transmission, and storage limits;
6) Planning reserve margin and policy constraints.

First-stage decisions $\mathbf{x}$ represent investment and operational choices made in 2030, while second-stage decisions $\mathbf{y}$ represent investment and operational choices made in 2040 and beyond. In this work, uncertainty ξ is represented by two random components: energy-storage CapEx costs and weather, the latter is propagated into load, hydro, and other generation profiles. The full mathematical formulation is described in [4], [22].

A key performance metric, VSS [20], is commonly used to quantify the value of planning for uncertainty as opposed to planning deterministically. This is done by first solving the expected value (EV) deterministic problem represented by (1)-(4) with a single scenario ω where $p(\omega) = 1$ and ω represents the average value of ξ, or $\bar{\xi}$.

$$\text{EV} = \min\ z(\mathbf{x}, \mathbf{y}, \omega = \bar{\xi}) \quad (5)$$

Next the first stage EV solution $\mathbf{x} = \mathbf{x}^*(\bar{\xi})$ is fixed into the original RP problem (1)-(4) to form what is called the expectation of the expected value (EEV) solution defined as:

$$\text{EEV} = \min\ z(\mathbf{x}^*(\bar{\xi}), \mathbf{y}, \xi) \quad (6)$$

The VSS is then defined as:

$$\text{VSS} = \text{EEV} - \text{RP} \geq 0 \quad (7)$$

where, $EEV \geq RP$ is always true as the EEV's feasible region is just a subset of RP's feasible region. The EEV formulation is identical to RP formulation with the exception that $\mathbf{x}$ has been fixed to $\mathbf{x}^*$ in (1)-(4).

III. System and Scenarios

The proposed SCEP model is applied to a 43-zone representation of the Western Interconnection (WI). Existing ES, generation and transmission resources are aggregated at the zonal level from the WECC ADS [23]. Candidate ES and generation resources are drawn from [24], [25], and [26], and candidate transmission is taken from [27]. Generation technologies include inverter-based resources, natural-gas combined-cycle units (NGCC), natural-gas combustion turbines (CT), and three ES technologies with distinct duration capabilities. Additional modeling details are provided in [22]. The ES formulation optimizes both power capacity and energy duration.

TABLE I
Energy Storage Overnight CapEx (adapted from [4]).

Parameter	1-4 Hr	10-24 Hr	100-200 Hr
CapEx 2030 ($/kW)	293.87	1,763.24	2,204.06
Low CapEx 2040 ($/kW)	141.43	848.56	1,060.70
Base CapEx 2040 ($/kW)	231.61	1,389.66	2,048.79
High CapEx 2040 ($/kW)	291.54	1,749.24	2,186.55
CapEx 2030 ($/kWh)	227.49	56.87	28.44
Low CapEx 2040 ($/kWh)	151.37	37.84	18.92
Base CapEx 2040 ($/kWh)	137.92	34.48	23.28
High CapEx 2040 ($/kWh)	274.79	68.70	34.35

TABLE II
Scenario Set Reflecting Joint ES Cost and System Conditions Uncertainty.

Scenario	Storage Capital Cost Maturation Rate	Weather Scenario	Probability
1	Typical maturation of CapEx	43	9.4%
2	Typical maturation of CapEx	40	12.8%
3	Typical maturation of CapEx	49	11.1%
4	Matures to lower CapEx faster	43	9.4%
5	Matures to lower CapEx faster	40	12.8%
6	Matures to lower CapEx faster	49	11.1%
7	Matures to lower CapEx slower	43	9.4%
8	Matures to lower CapEx slower	40	12.8%
9	Matures to lower CapEx slower	49	11.1%

In this study, ES CapEx costs, load, hydro, and other generation profiles are modeled as uncertain parameters in the second stage (2040 and beyond).

- Cost components for ES power and energy are summarized in Table I and are stratified by storage duration. Specifically, 1–4 hour storage has the lowest power cost but the highest energy cost; 10–24 hour storage has moderate power and energy costs; and 100–200 hour storage has the highest power cost but the lowest energy cost.
- For the hourly profiles, 40 historical weather years are used to create 40 weather-synchronized sets consisting of 40 load and 120 generation profiles (120×40). This consistent weather basis reduces the scenario space from $120 \times 40 \times 3 = 7,680,000$ scenarios to $40 \times 3 = 120$ scenarios. The 120 scenarios are further reduced using the method described in Section II-A. In this case study, we select $k = 3$ for the k-medoids algorithm, which classifies the 40 weather years into three groups and identifies each group's centroid. The centroids are selected as the characteristic years, with probabilities given by the number of scenarios in that centroid's cluster divided by 40. These three characteristic weather years are crossed with the three storage-investment cost scenarios to form the nine scenarios listed in Table II.

IV. Case Study

Figure 2 reports cumulative 2040 investments for each of the nine different scenarios under the stochastic programming

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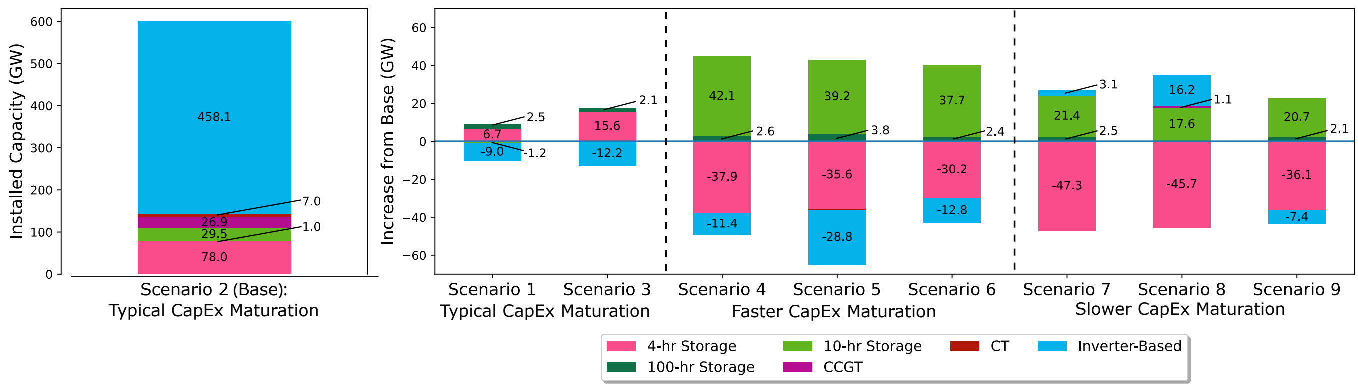

Fig. 2. Cumulative capacity investments by resource type in nine scenarios. The total investments from the representative (medoid) scenario are shown on the left. The right indicates the change in investments from the base case for the remaining eight scenarios.

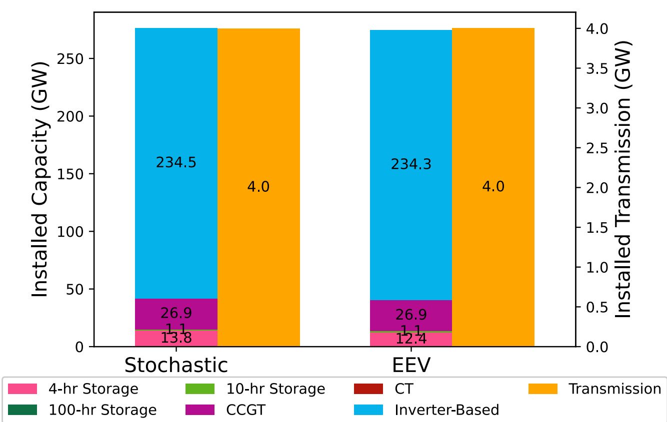

Fig. 3. Investment in 2030 (first stage) RP investment compared to the 2030 (first stage) of EEV (and equivalently EV).

solution. The bar represents the base scenario. This scenario is identified by applying the k-medoids clustering algorithm described in Section III with k=1 to select the most typical weather year, paired with the representative ES CapEx maturation trajectory. The eight bars to the right correspond to the remaining scenarios described in Table II, grouped by ES CapEx maturation rates. Each bar shows the change in installed capacity relative to the base scenario. Under higher ES cost-decline trajectories (Scenarios 4–6), total ES deployment increases, with a notable shift toward medium-duration storage (10-hour, green), offset by reductions in short-duration storage (4-hour, pink). For Scenarios 1–3 with typical ES cost maturation, results exhibit only a modest increase in short-duration storage. Finally, for Scenarios 7–9 with lower ES CapEX maturation rates, there is an overall decrease in storage investment. This consists of a large reduction in short duration ES (4-hour) with a small increase to medium duration ES (10-hour). Despite the variation in ES CapEx across scenarios, the base case exhibits relatively high investment in 4-hour storage and the lowest investment in 10-hour storage. This pattern suggests that weather-driven uncertainty strongly influences ES investment decisions, beyond the effects of cost assumptions alone.

In Fig. 3, the “here and now” stage 1 investment decisions are compared between the stochastic and EEV problems. The bars on the left represent the stochastic solution, in which planners explicitly account for uncertainty when making investment decisions. The bars on the right correspond to the EEV solution, representing investments selected by a planner who optimizes deterministically and then operates in a stochastic world. For the EEV problem, the base scenario was selected as the most representative of system conditions and augmented with an increased planning reserve margin (PRM) to match the highest potential load scenario. Overall, investment levels are broadly similar across the two solutions in Fig. 3. The stochastic solution results in slightly higher total investment, with the largest percent increase observed in 4-hour energy storage capacity (11.3%).

Table III reports the total system costs for the RP and EEV formulations, as well as their difference. The results indicate that planning stochastically yields approximately $9 billion in savings over the 30-year planning horizon. By comparison, [4] reported only $0.24 billion in savings from stochastic planning—an order-of-magnitude smaller benefit. A key distinction with [4] is that it modeled uncertainty only in hydroelectric output and ES capital costs, whereas the present analysis also incorporates uncertainty in demand, and inverter-based resource profiles. Although the system representation in [4] is similar to that used here, other modeling differences may have also contributed to the larger savings observed in this study, including the longer planning horizon and differences in hydro uncertainty modeling.

To evaluate SCEP objective sensitivity to the number of clusters, the analysis is repeated for $k = \{4, 5\}$ (Table IV). The $k = \{4, 5\}$ SCEP objective value differs less than 3% from k=3 case indicating that SCEP objective is relatively insensitive to k for simulations $<$ 11 hours. Simulations used CPLEX v22.1.0 on a dual AMD EPYC 7502 system (32 cores).

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TABLE III
VALUE OF STOCHASTIC SOLUTION NET PRESENT VALUE (NPV).

	Stochastic	EEV	Difference
Investment ($B)	974.67	972.65	-2.02
Operations ($B)	324.01	335.05	11.04
Total NPV ($B)	**1,298.68**	**1,307.70**	**9.01**

TABLE IV
CLUSTERING SENSITIVITY

k	Computational Time	Objective ($B)	Change vs. k=3
3	262 min	1,299	N/A
4	379 min	1,280	-1.46%
5	619 min	1,338	2.99%

V. CONCLUSIONS

This work examined the impact of uncertainty on long-term investment planning over a 30-year horizon, focusing on ES investment decisions. The analysis employed a SCEP model with a scenario-reduction procedure combining SVD and k-medoids clustering to efficiently reduce high-dimensional uncertainty while preserving scenario diversity. The considered uncertainties include ES CapEx trajectories and weather-driven variability in generation, hydro, and load profiles. These uncertainties were found to influence both the total level of ES investment and the mix between short-duration (4-hour) and medium-duration (10-hour) storage technologies. The stochastic solution resulted in greater first-stage ES investment, including an 11.3% increase in 4-hour storage capacity. Over the 30-year horizon, stochastic planning yielded a VSS of approximately $9B, underscoring the economic benefit of explicitly representing multiple sources of uncertainty. Future work will further analyze the scenario reduction methodology by investigating how the number of SVD vectors and k-medoids clusters chosen impact the reduction algorithm's ability to accurately represent the full uncertainty space.

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