Improving Worst-Case Representative Day Clustering

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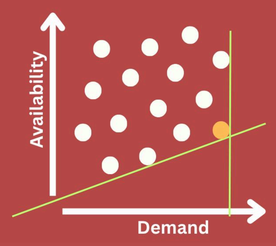
1. Background

Sustainable energy is the future. However, stakeholders need to know in which energy sources to invest. This can be done through the use of historical data on energy availability and demand to understand what investments can satisfy future demand.

The Challenge → Full-scale energy datasets are too computationally heavy for modern optimization.

The Solution → Temporal clustering reduces complexity while preserving critical data characteristics. Information loss should be minimized while maximizing model accuracy.

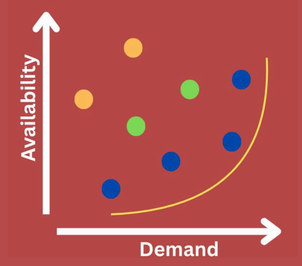
Creating a worst-case data point



The Problem → The Average Trap
Standard clustering algorithms smooth over the extremes that matter most for system reliability.

The Solution → Peak-Aware Clustering
Adjusting algorithms to capture extreme periods → Ensuring grid stability under stress.

Non-dominated sorting → Updating representative points on Pareto-layers capturin extreme days without sacrificing the quality of clusters for common days.

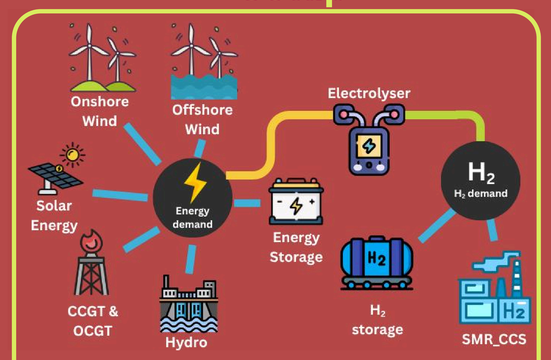


Tulipa Energy Model
The Tulipa energy model is an open-source, multi-regional investment and dispatch optimization tool designed to find the most cost-effective solution for an energy system.

2. Research Question

"How does the embedding of artificial worst-case representative days within existing clustering methods impact the accuracy of energy system model solutions, and the associated computational time?"

3. Experimental Setup



Case Study over 3 years of data

Cluster Data
WCA-K-Means, WCA-K-Medoids & WCA-Hierarchical Clustering + Benchmark Algorithms

A Priori Evaluation

SSE sums the squared distance of every data point (x) to its cluster center (μ) to measure overall compactness

$$\mathrm{SSE} = \sum_{i=1}^{K} \sum_{x \in C_i} \|x - \mu_i\|^2$$

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))}$$

The Silhouette Score measures separation by comparing a point's internal cluster distance (a) to its nearest neighboring cluster distance (b).

Computational Time

Run Energy Model

Posteriori Evaluation
Regret

Aggregated: Energy model aggregated dataset → Lock Investments → Rerun with full dataset (Operational costs)

Benchmark: Energy model full dataset → Optimal total costs → Relative Regret

Loss of Load

When demand > available supply → unserved energy

4. Results

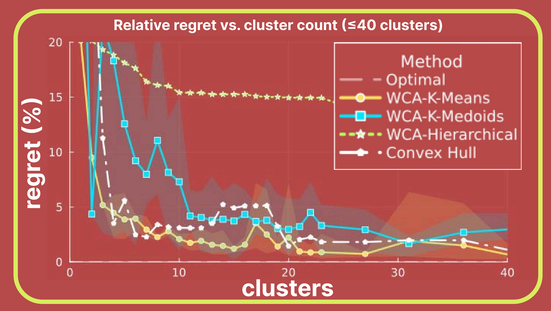
Convex Hull→
From the original benchmarks, the best overall on this dataset

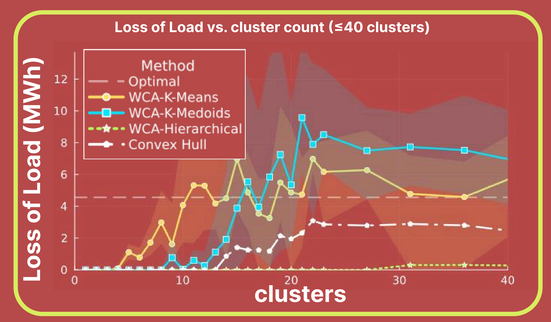
WCA-K-Means →
Able to often outperform both standard Convex Hull and the other worst-case adapted algorithms, with some cluster counts where it is slightly worse. However, its the best at predicting optimal Loss of Load early on.

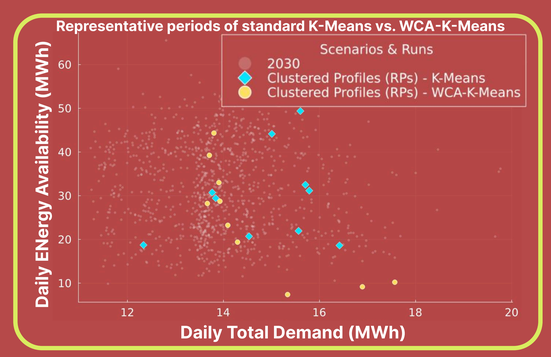
WCA-K-Medoids →
Improvement over standard K-Medoids, but worse than WCA-K-Means

WCA-Hierarchical →
Performs poorly overall

K-Means vs. WCA-K-Means →
Worst-case scenarios are accounted for while normal scenarios are represented as well







5. Conclusion

The Worst-Case Adaptive algorithms integrate synthetic worst-case periods directly into the clustering process to ensure traditional temporal aggregation does not average away critical grid stress events. By leveraging non-dominated sorting to capture multi-dimensional extremes, WCA-K-Means in particular successfully balances grid robustness and computational efficiency.