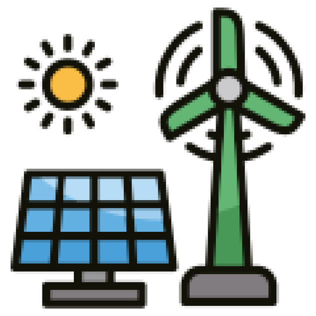
Experimenting with Blended Weights and Extreme Representative Periods for Energy System Optimization

1. Motivation



Planning future energy systems requires deciding which power plants to build, where, and when. Energy system optimization models answer these questions, but solving them on full temporal data is intractable.

Clustering methods can reduce the input year to a small set of representative periods (RPs), but they capture only typical conditions, missing the extreme days that drive investment decisions.

Including worst-case RPs alongside typical ones can fix this, but raises two key questions: How to include them and how much weight should each receive?

Blended weights provide a more flexible weighting approach potentially balancing typical and extreme conditions more accurately.

"How can we combine **blended weights** with the **worst-case** and other clustering methods, and how does this affect **performance** of the model?"

2. Background and Methodology

We can construct a **worst-case RP** that captures extreme conditions by taking the highest demand and the lowest availability/demand ratio for all timesteps across all periods in the dataset. Two strategies are considered (*Fig. 1*):

Global: cluster to find k-1 RPs and then add an artificial worst-case RP built from the full dataset.

Local: cluster to find $k/2$ RPs, and add artificial worst-case RPs built only from the data of each cluster → This way we can capture cluster-specific extremes more accurately.

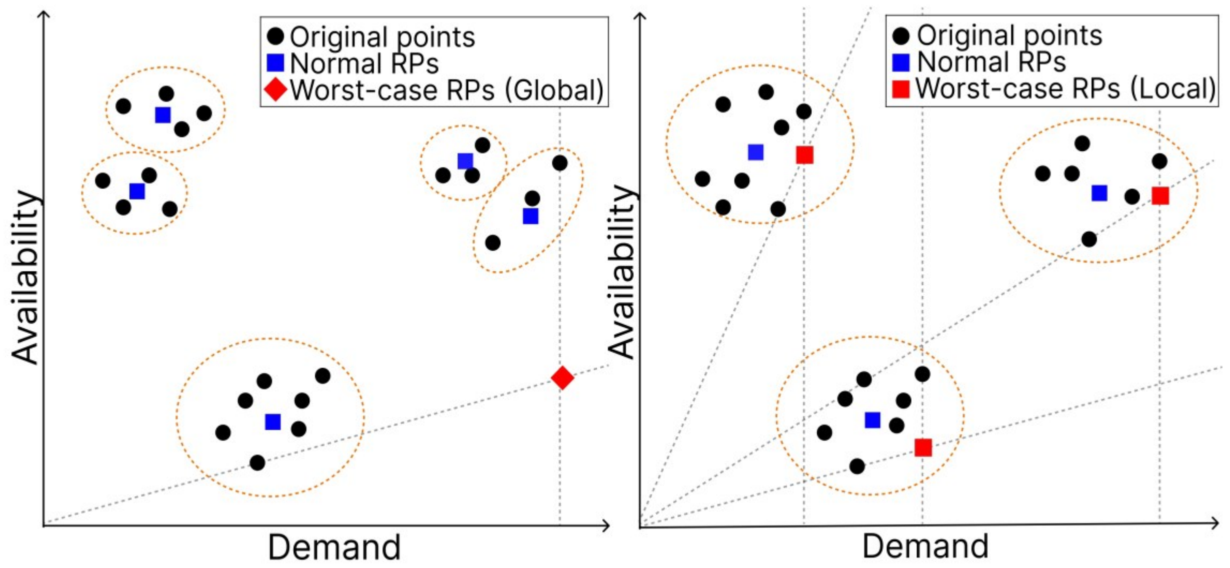


Figure 1: schematic representation of the worst-case construction strategies

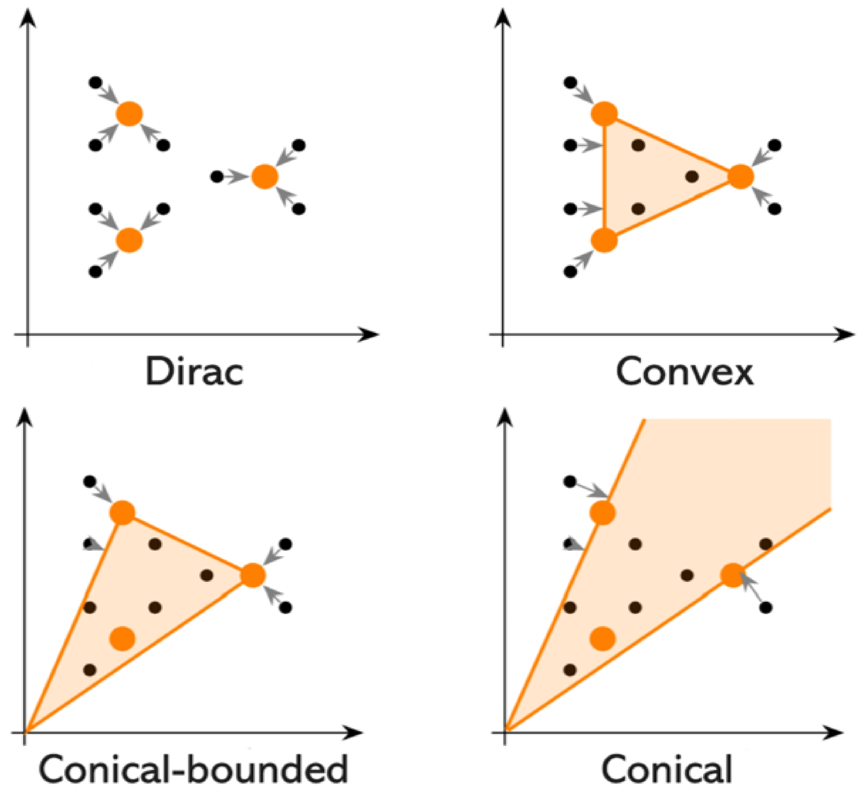


Figure 2: Orange points are RPs, black points are original periods. Shaded area shows which periods can be represented without projection error.

Standard clustering uses Dirac weights, assigning each period to its nearest RP, discarding relationships with all others.

Blended weights express each period as a weighted combination of many RPs by projecting onto a geometric hull (*Fig. 2*). Four variants are considered each imposing different constraints:

- **Dirac**
  full weight to nearest RP
- **Convex**
  non-negative weights summing to 1
- **Conical–bounded**
  non-negative weights summing to at most 1
- **Conical**
  non-negative weights, no sum constraint

3. Experimental Setup

The following metrics are used to evaluate and compare the different combinations:

Relative regret measures solution quality: the percentage cost difference between the reduced model's investment decisions and the true optimal, both evaluated on full data.

Loss of load measures feasibility: the number of timesteps with unmet demand.

All combinations are evaluated across varying number of RPs (k), over 5 random seeds, using k-means and k-medoids, implemented with Tulipa Energy Model and Tulipa Clustering.

Input Data

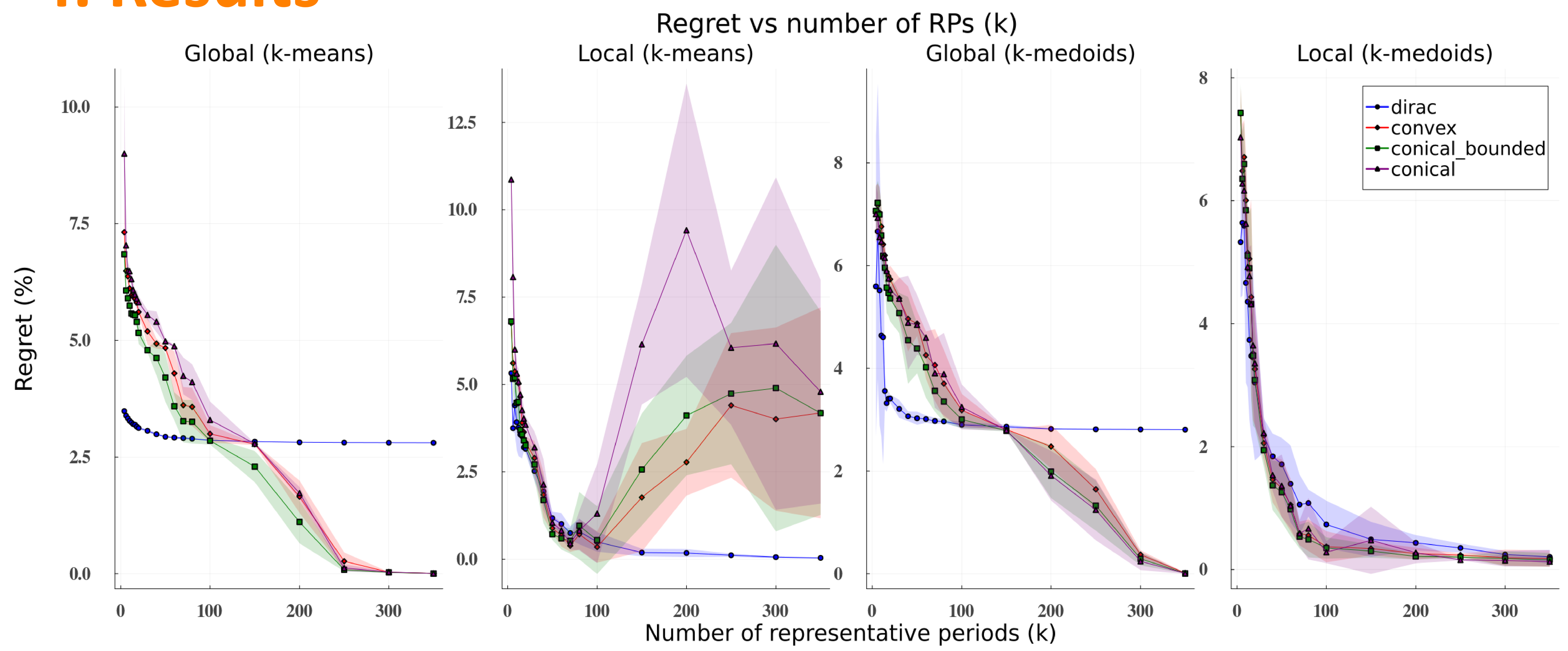
Cluster to find RPs

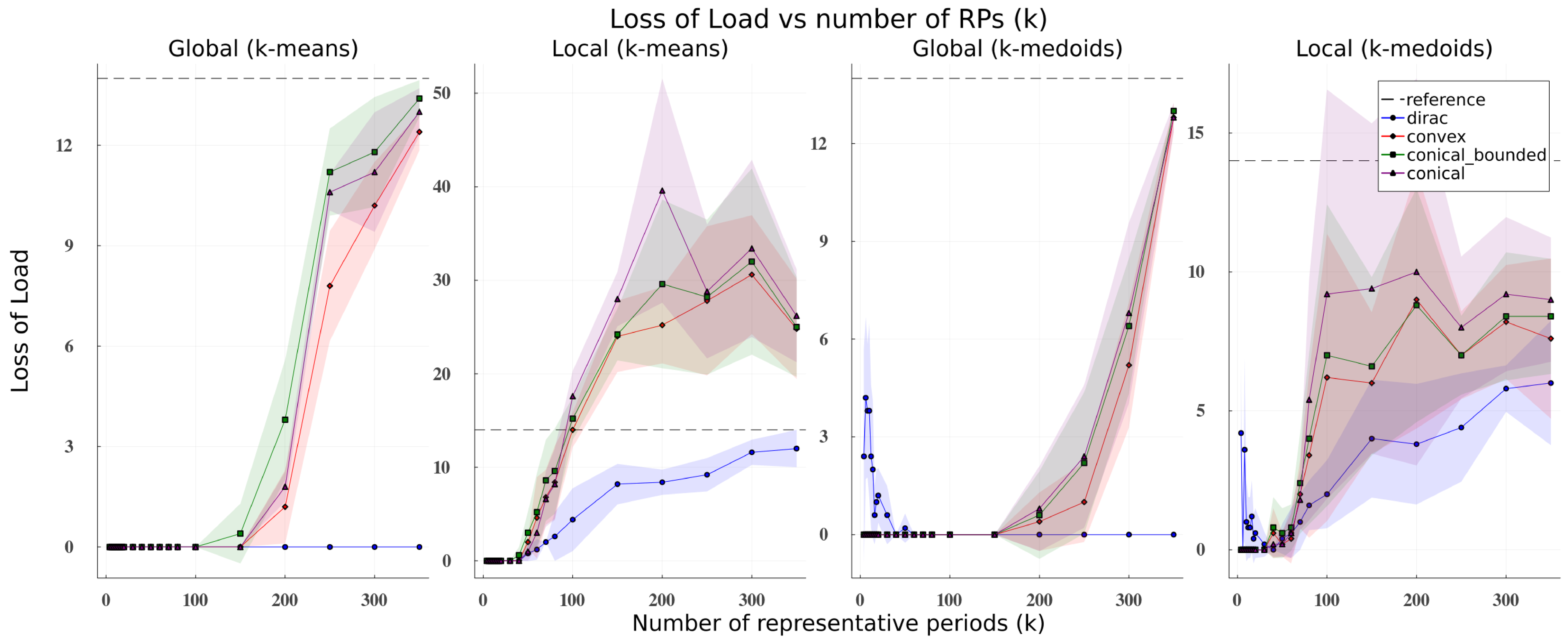
Inject Worst-Case RP(s)

Compute Weights

Solve the reduced problem

4. Results





5. Conclusions

1. **Per-cluster extreme periods are less conservative and more targeted than a global one.** Local worst-case periods outperform Global especially for low k, achieving lower regret while maintaining feasibility.
2. **For Global, blended weights improve over Dirac only at high k.**
   However, for k-medoids, including no worst-case already performs comparably at that point, making the advantage irrelevant in practice.
3. **For Local, blended weights show a visible improvement over Dirac at moderate k.**
   For k-means though, regret spikes at high k, as worst-cases weight decays, becoming too small to influence investment decisions.

While blended weights **show promise** in some settings, they should **not be applied blindly**.

6. Future Work

- Explore how **weighting**, **dataset characteristics**, and **worst-case construction** interact to influence model **performance** in more depth to improve blended weights applications.
- **Generalize findings** on larger and more complex datasets.
- Investigate alternative **distance metrics** like cosine distance.

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