Assessing the impact of sampling and clustering techniques on offshore grid expansion planning

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I	Background and motivation
II	Methodology
III	Case study results
IV	Conclusion

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Increasing variability and uncertainty lead to a growing complexity and present computational challenges for power system models

Rise of power systems underlying variability and uncertainty

- Most power systems experience **increasing share of variable and non-dispatchable generation** in their energy mix
- **Traditional power systems** were **primarily subject** to power **demand variations** and **fault occurrences**
- **Adequate models** for both short- and long-term planning **become more complex**

Crucial task of Transmission Expansion Planning (TEP)

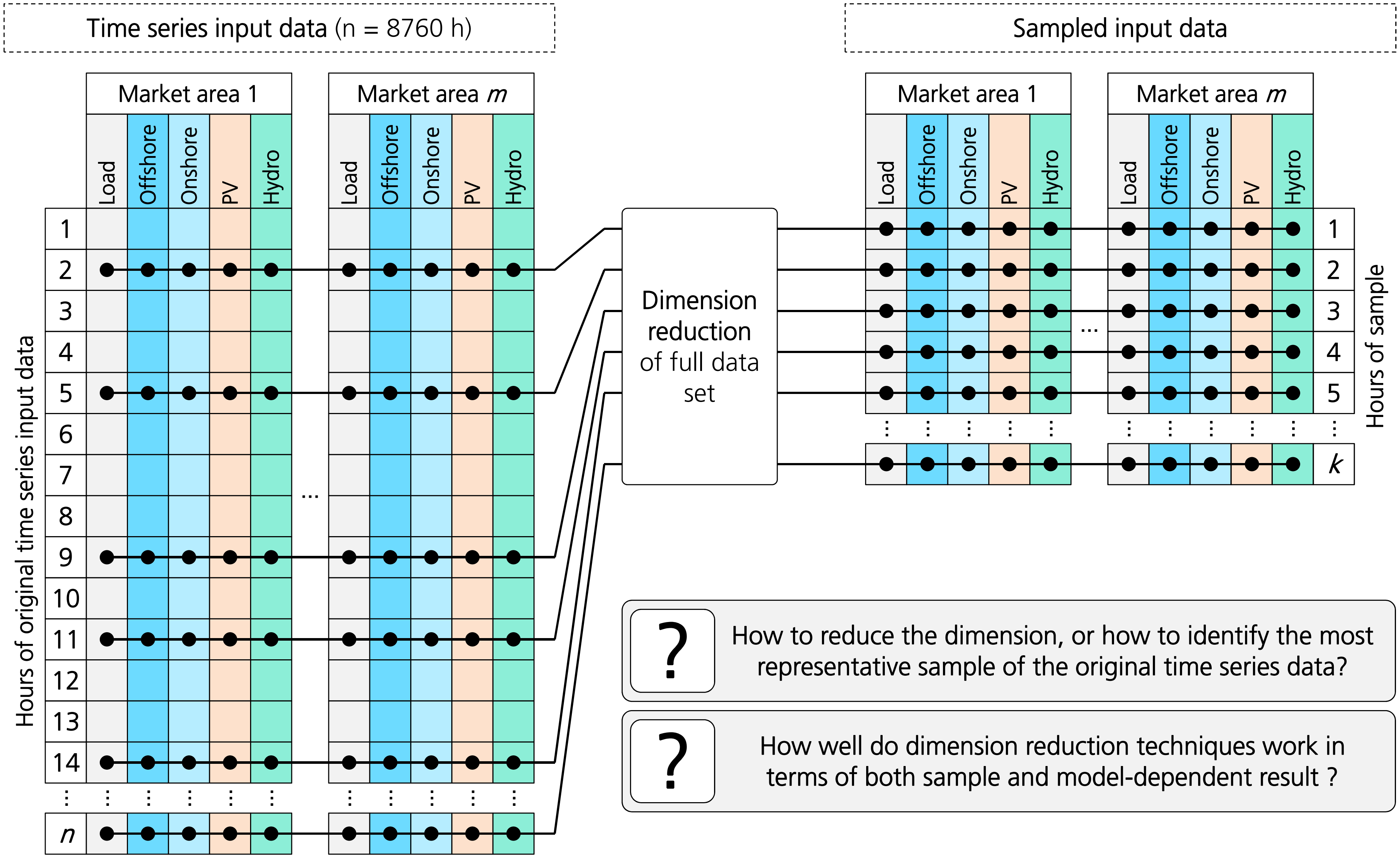
- **Determining** investments in **new transmission lines** or **reinforcements** of the existing transmission network is a **crucial task** in power system planning
- **Long-term** and **capital intensive** decisions having a **long-lasting effect** on expected **market prices** and **power system operation**

Relevance of TEP in European context

- European Union pursuing a **fully integrated internal energy market** in which energy can flow freely across its regions
- **Robust** transmission and distribution **infrastructure, well-interconnected European network** key constituents of a successful integration of renewables
- **Spatial levelling effects** of fluctuating renewable energy resources (incl. offshore wind) **make grid reinforcements attractive**

Recent developments make efficient solutions of long-term TEP problems even more necessary, but at the same time increase their complexity

One approach of dealing with computational challenges is to reduce the dimension of the input data through finding representative samples



? How to reduce the dimension, or how to identify the most representative sample of the original time series data?

? How well do dimension reduction techniques work in terms of both sample and model-dependent result ?

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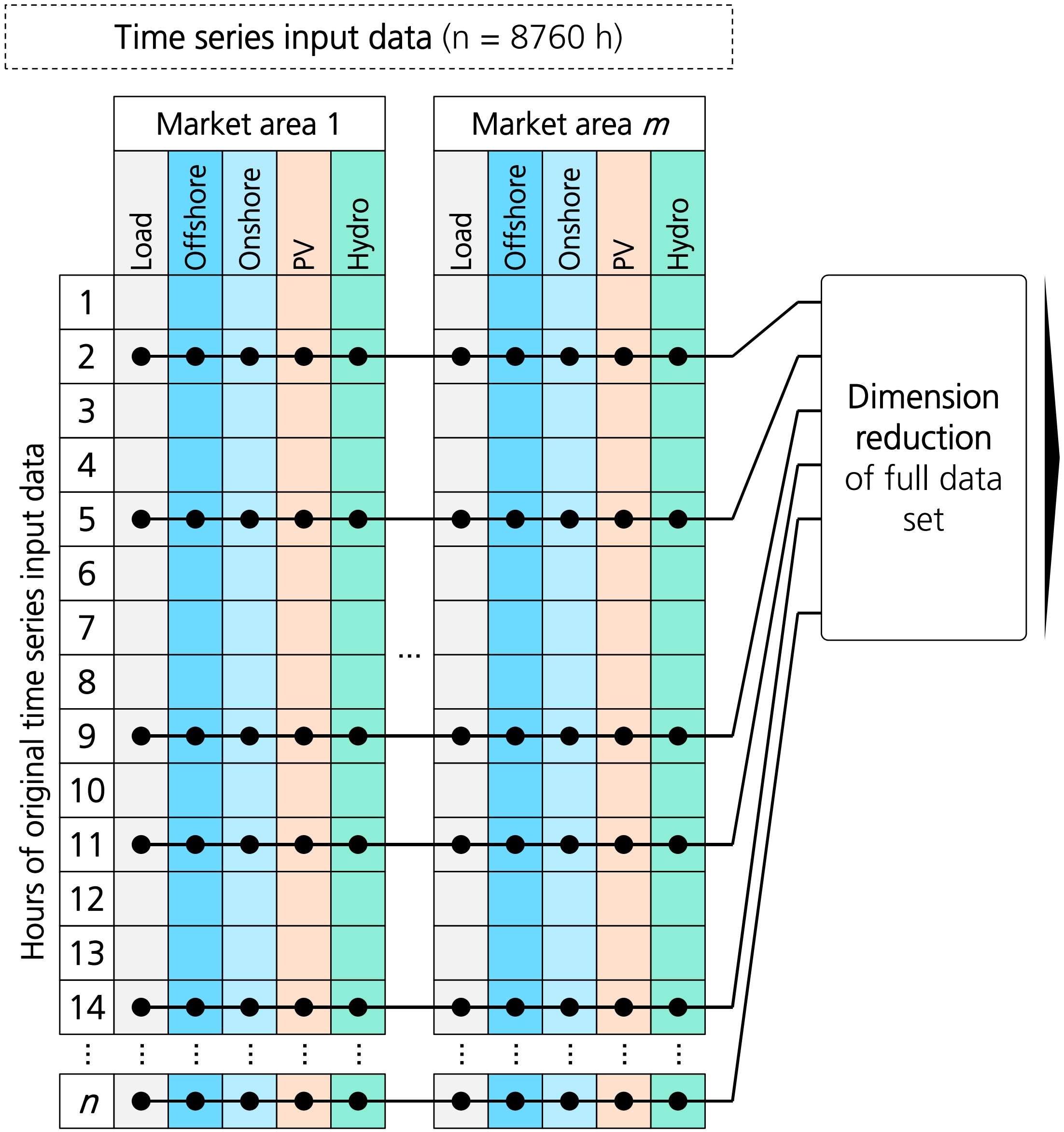
5 different sampling & clustering techniques are employed for the dimension reduct-ion – 2 scaling options & heuristic yield 4 variants for each technique & sample size



Dimension reduction techniques:

Systematic Sampling	■ Selects every k^{th} element, k depends on sample size and #observations ■ Straight-forward but efficient method
k-means clustering	■ Data-partitioning clustering approach ■ Subset centroid mean of all measurements
k-medoids clustering	■ Approach very similar to *k*-means ■ Centroids are actual data points (medoid) of the subset
Hierarchical clustering	■ Agglomerative form of hierarchical clustering analysis ■ Ward’s linkage (minimum variance)
Moment-matching	■ Sample selection through minimizing a predetermined criterion ■ Correlation, mean, standard deviation

Two scaling options:

1 Technology-specific scaling

2 Scaling by the highest occurring value

Heuristic:

Moving average heuristic is included as a further variant to capture extreme values (after sampling)

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Long-term Transmission Expansion Planning model (PowerGIM) is used for a North Sea offshore grid case study to assess the sampled and clustered input data

Long-term TEP model ("PowerGIM")

- **Two-stage stochastic program** (MILP) co-optimizing investment decisions and market operation in a power system consisting of several market areas
- **Integer variables** used to make **transmission infrastructure investment decisions** (first-stage)
- **Linear program (LP)** reflecting **generator capacity investment** and **market operation** (second-stage)

Case study

- **Offshore grid expansion in the North Sea region**
- **2030 scenario** based on ENTSO-E's **Vision 4**
- **Investment options include combined HVAC and HVDC grids** (both radial- and meshed structures)
- **Considered market areas** are Norway, Great Britain, Denmark, Belgium, Germany and the Netherlands
- Economic investment **lifetime 30 a, 5% discount rate**
- **CO_2-price** of **30 €/tCO_2** is assumed

Mathematical formulation

$$TC = \min_{x} c^T x + E_{\xi}[\min_{y(\omega)} q(\omega)^T y(\omega)]$$

s.t.

$$Ax \leq b$$

$$T(\omega)x + Wy(\omega) \leq h(\omega), \quad \forall \omega \in \Omega$$

$$x = (x_1, x_2) \geq 0$$

$$x_1 \in \{0, 1\}, x_2 \in \mathbb{Z}^+$$

$$y(\omega) = (y_1(\omega), y_2(\omega)) \geq 0, \quad \forall \omega \in \Omega$$

Premise

- **Static, deterministic version** of stochastic MILP **is used** for comparison study
- **Inter-temporal constraints are not taken into account** by the model (e.g. storage continuity of hydro reservoirs) - allows for an easier sampling of the input data since the **chronological order of occurrence can be omitted**

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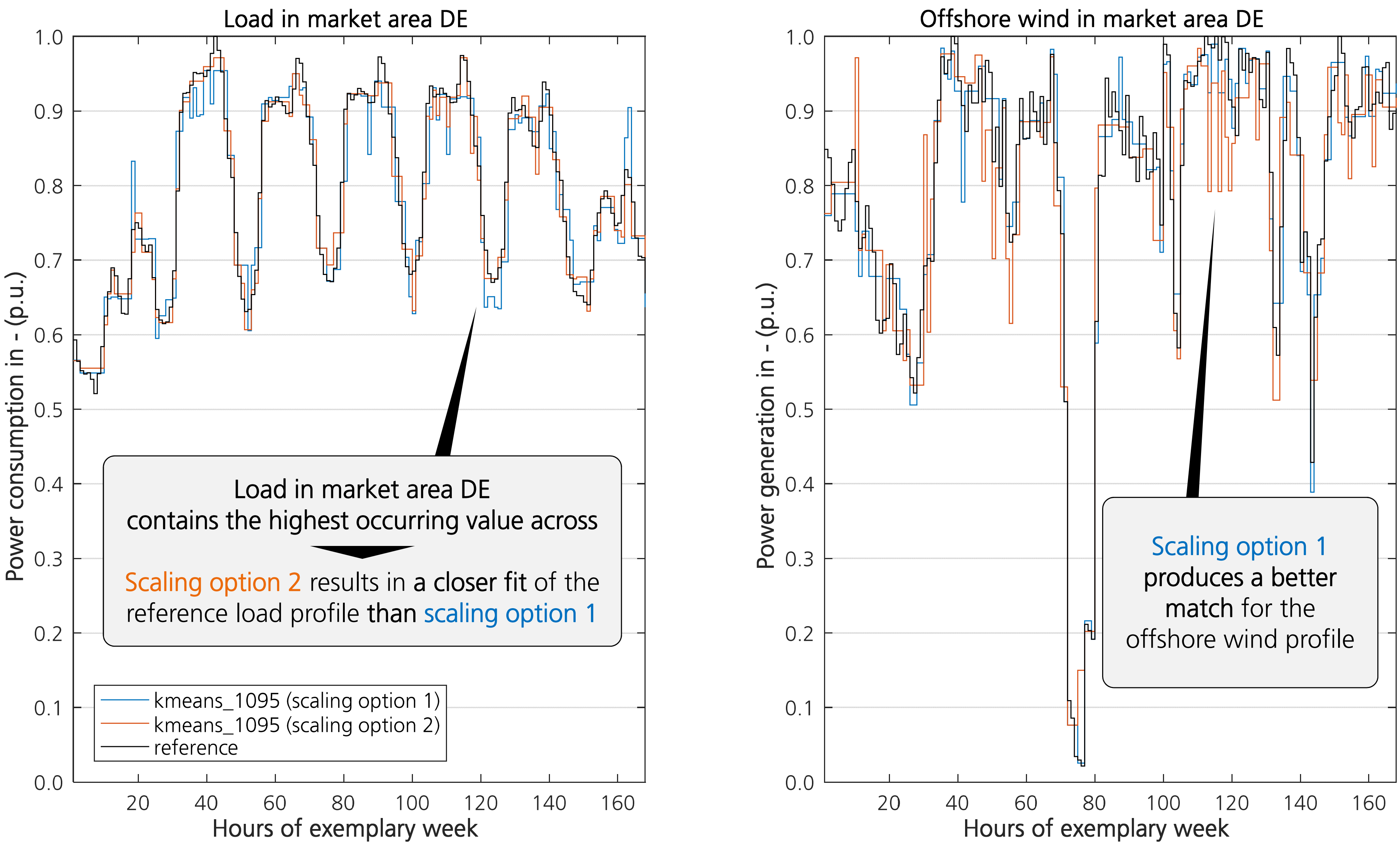
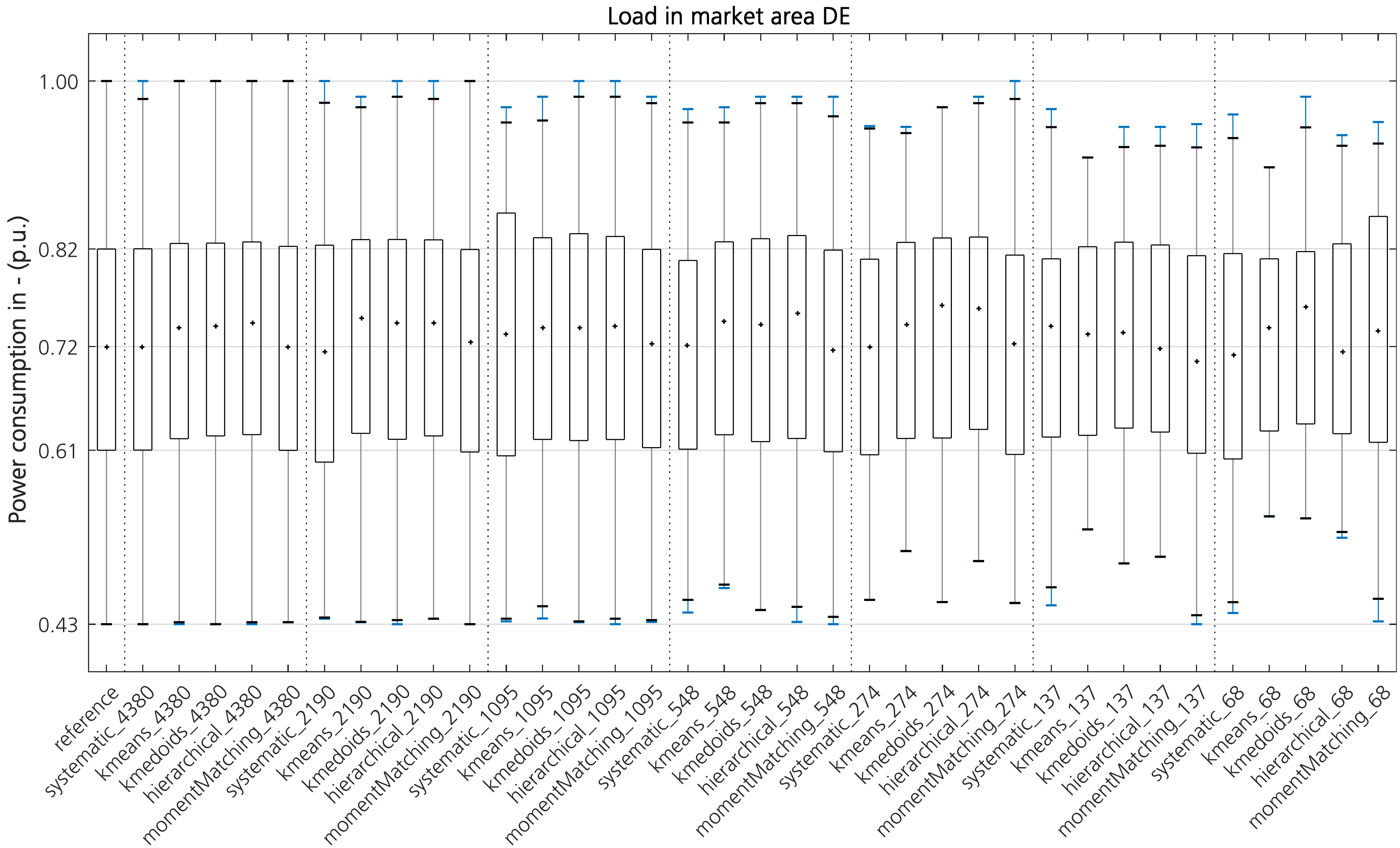
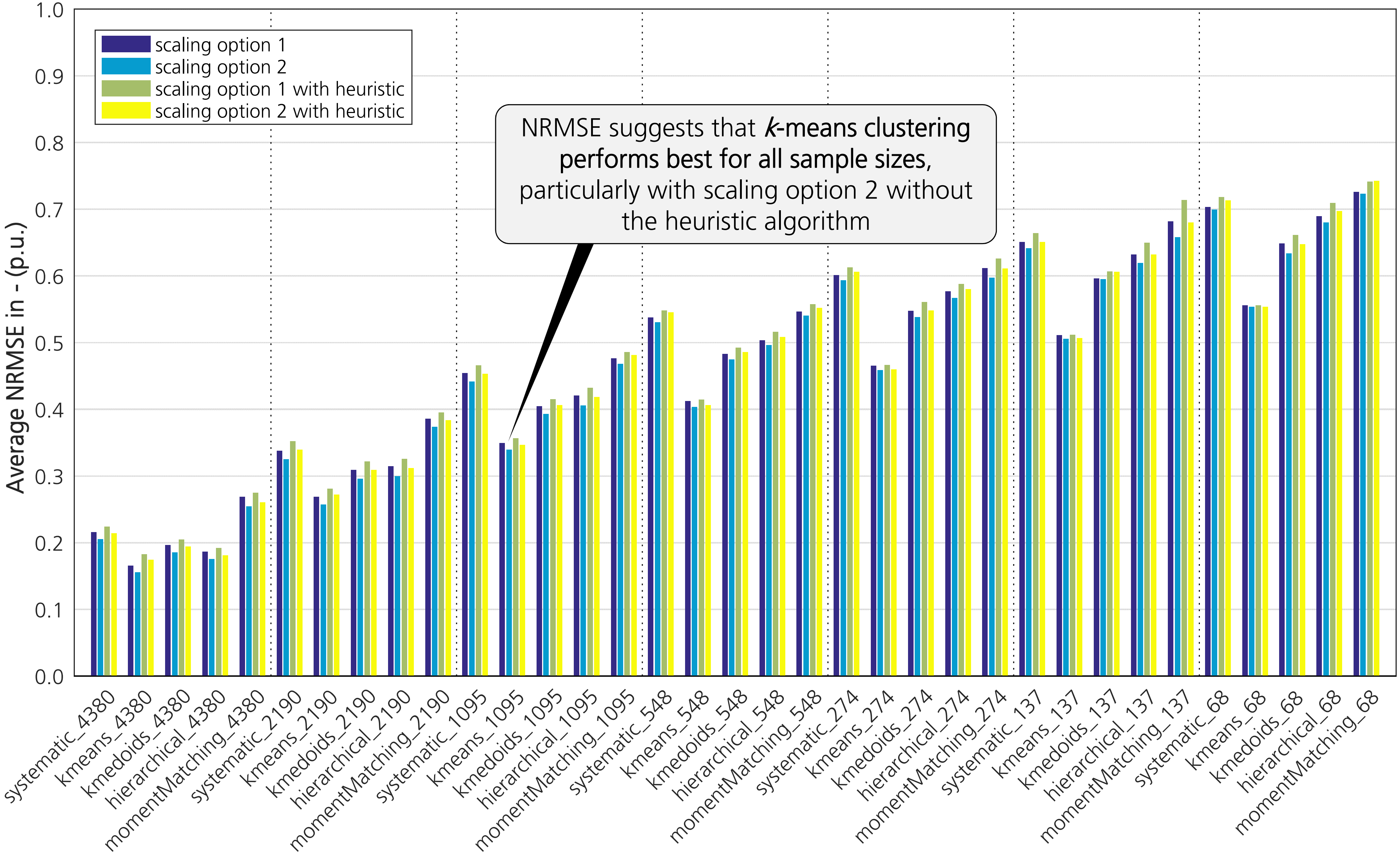
The effect of using the two different scaling options can clearly be seen in the resulting sampling and clustering results



For almost all techniques, the average load levels tend to be higher than in the reference case – heuristic can partly capture extreme values



Based on the average normalized root-mean-square error, it stands to reason that *k*-means also yields the most accurate long-term TEP model results



Normalized Root-Mean-Square Error (NRMSE)

Solution time significantly reduced - *k*-means clustering performance not persevering for model-dependent results, Hierarchical and *k*-medoids show good accuracy

	Average reduction in solution time per sample size Solution time as share of full year reference in %							Average cost accuracy Deviation of full year reference in %		
	4380	2190	1095	548	274	137	68	Total (obj.)	Investment	Operation
Systematic	17.83	5.69	2.11	1.03	0.36	0.17	0.09	1.48	0.90	1.51
k-means	23.11	5.75	2.14	0.86	0.62	0.21	0.11	-1.46	-3.36	-1,34
k-medoids	21.23	6.94	2.26	1.05	0.46	0.25	0.09	0.70	-1.63	0.84
Hierarchical	20.52	6.74	2.33	1.16	0.44	0.16	0.09	0.67	-0.23	0.72
Moment-matching	23.47	5.67	2.40	0.83	0.40	0.20	0.10	1.35	2.32	1.29
Reference (abs.)	*2016.1 s*							*473.1 bn€*	*26.9 bn€*	*446.1 bn€*

As expected, **with decreasing sample size** the **average solution time** can be **significantly reduced**

Although showing **best NRMSE, *k*-means clustering** exhibits **poor performance** when looking at investment and total cost deviations

Hierarchical clustering shows **highest accuracy**, followed by ***k*-medoids**

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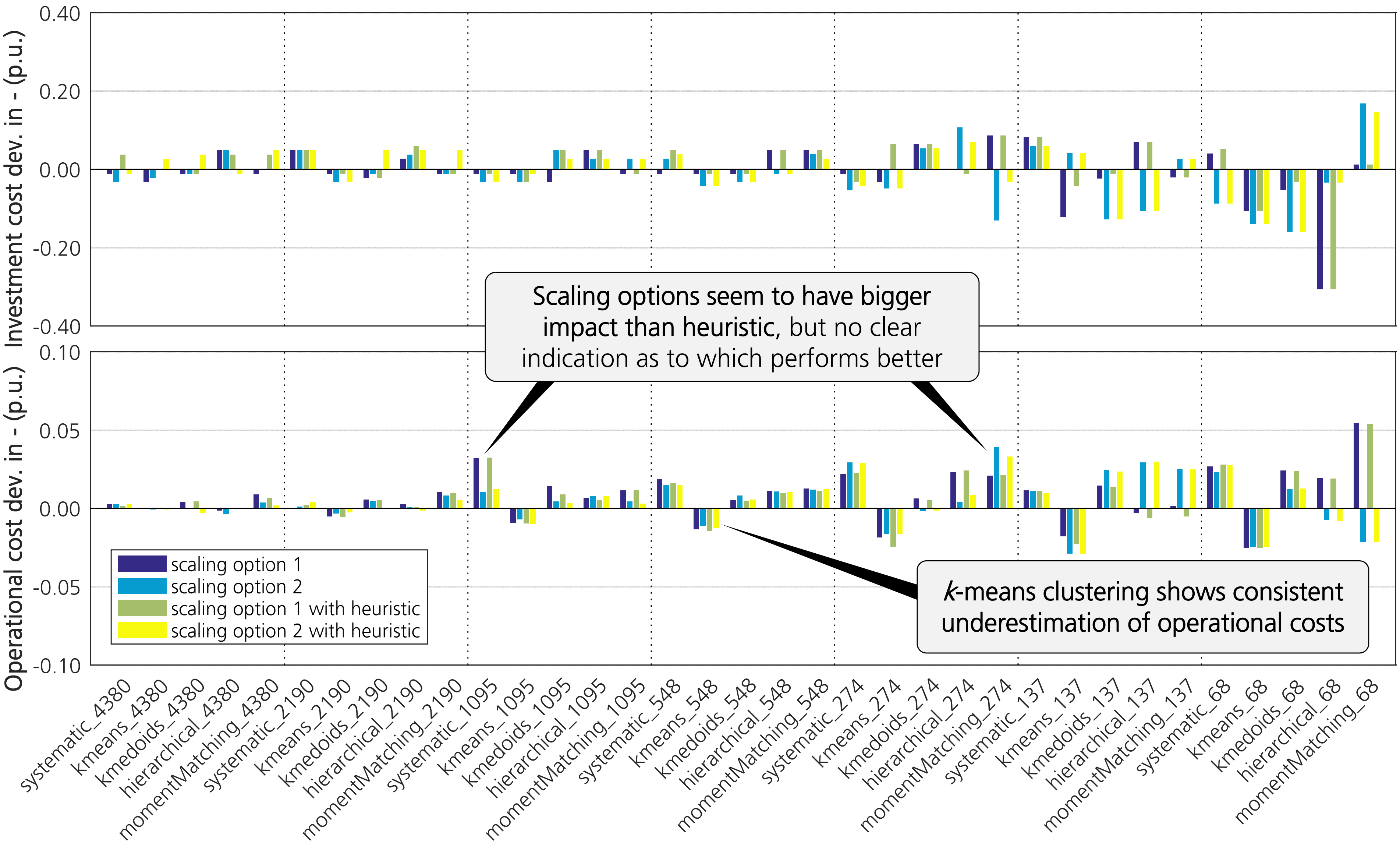
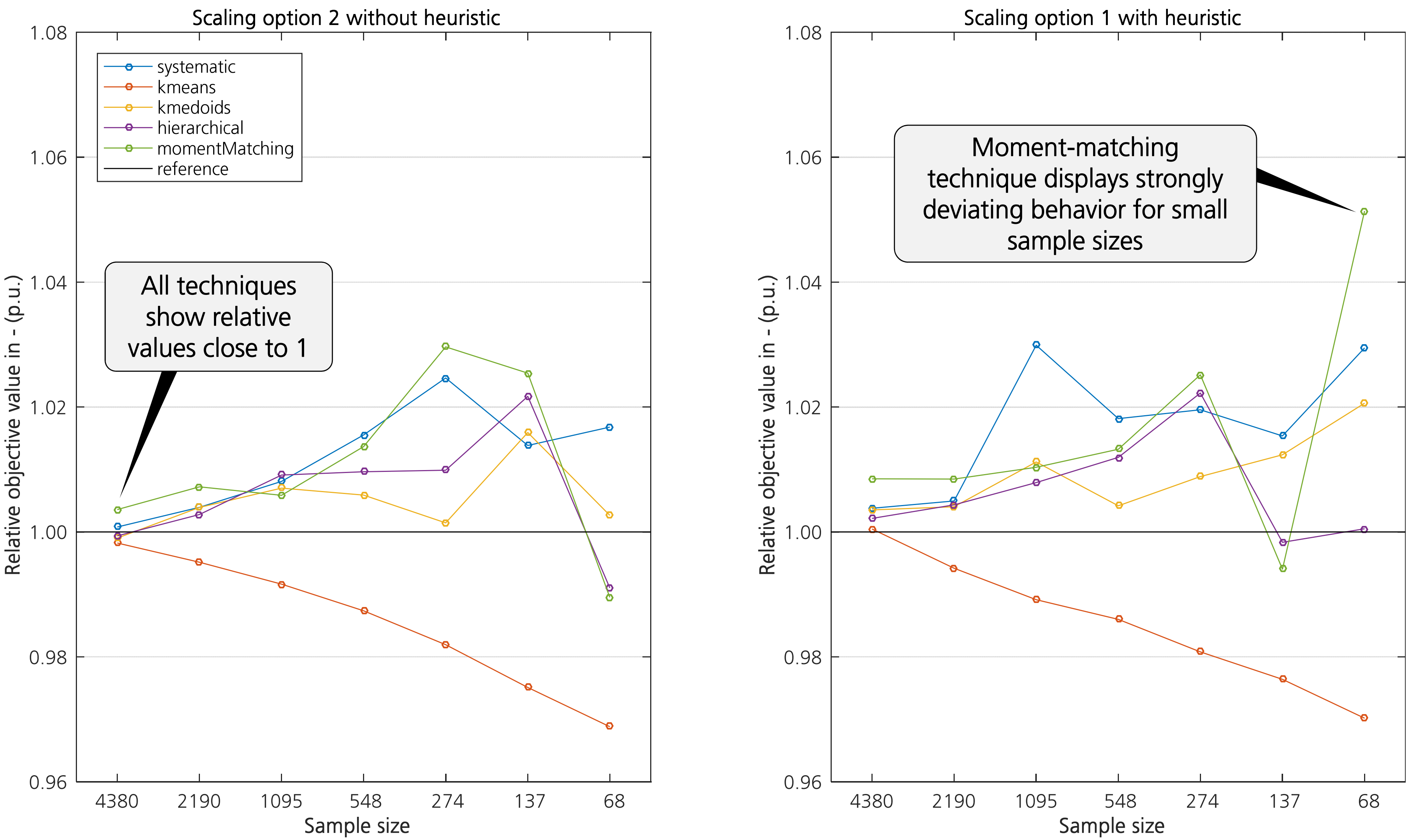
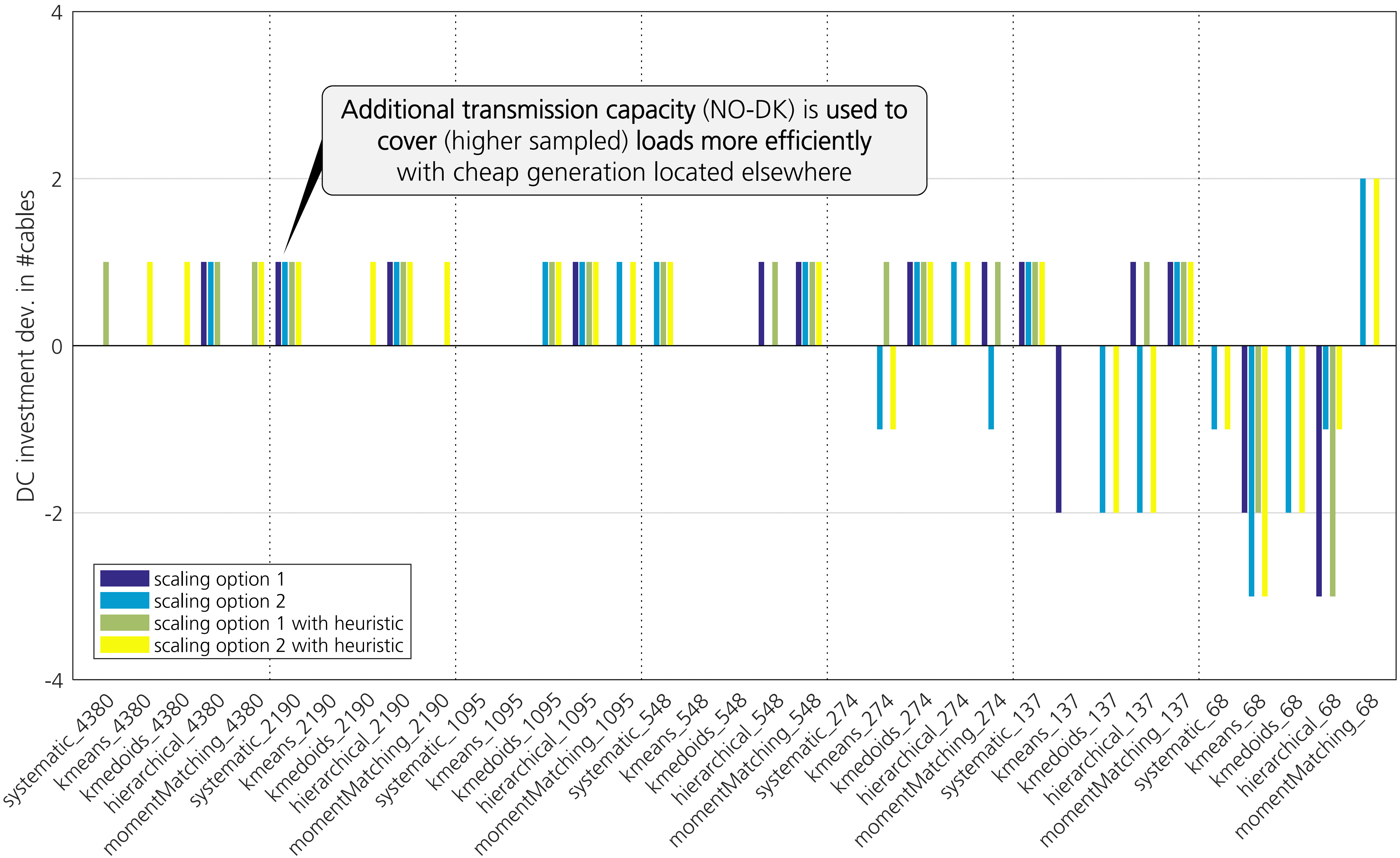
Relative investment and operational cost deviations generally increase with reduced sample size



The convergence results of the relative objective value are in line with the previous findings



Over-investments are mainly limited to one DC cable – under-investments do not occur for sample sizes bigger than 274 h



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Conclusion

Comprehensive comparison of dimension reduction techniques:

Techniques performing well in the sampling process do not necessarily produce reliable results in the large-scale TEP model
which became particularly evident for *k*-means clustering

Agglomerative hierarchical and *k*-medoids clustering show comparatively good results
when quantifying both the NRMSE and the effects on offshore grid expansion decisions in the North Sea case study

Scaling options have a greater impact than the applied heuristic
but no clear indication can be given as to the more suitable choice of either one, careful attention to different scaling options for the original data set seems appropriate

Future work:

Subsequent analysis of dimension reduction techniques can include the use of more sophisticated heuristics
particularly in investment models as they depend on highest occurring values

Ways of incorporating inter-temporal constraints to better capture medium-term dynamics and operational flexibility
either by employing dimension reduction approaches or developing alternative solution strategies involving decomposition for the full year problem

Thank you very much for your attention!

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