Identifying Representative Weeks for the Finnish Power Sector with Time-Series Clustering

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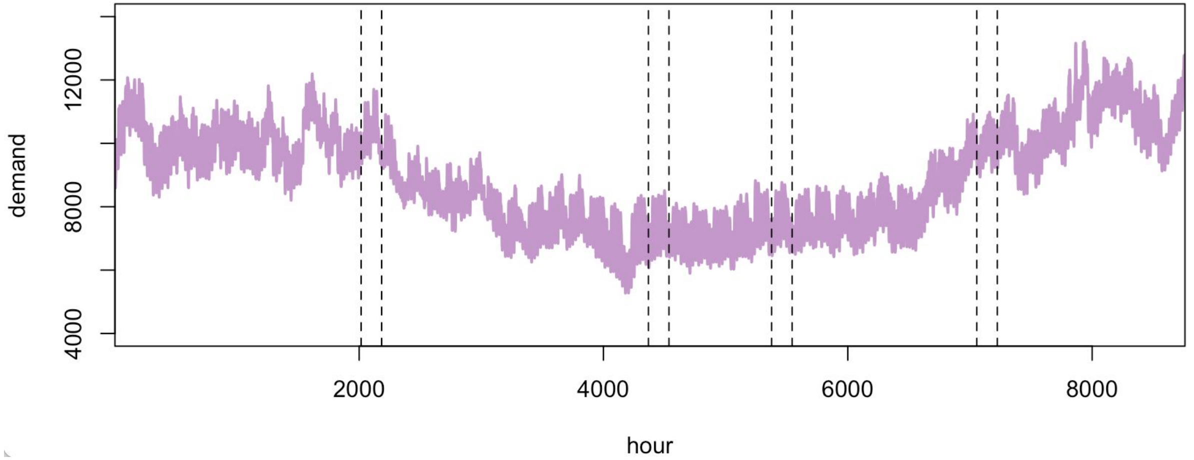
Background

- Power system models can be complex and computationally intractable problem instaces
- To simplify the models, their temporal resolution can be reduced
  - Time series constraints can be simplified by using representative periods instead of full datasets.

Goals

- Apply time-series aggregation techniques to Finnish demand, wind and solar data.
- Compare the results of two different approaches to aggregate data into four representative weeks
    1. Partitional approach
    2. Seasonal approach



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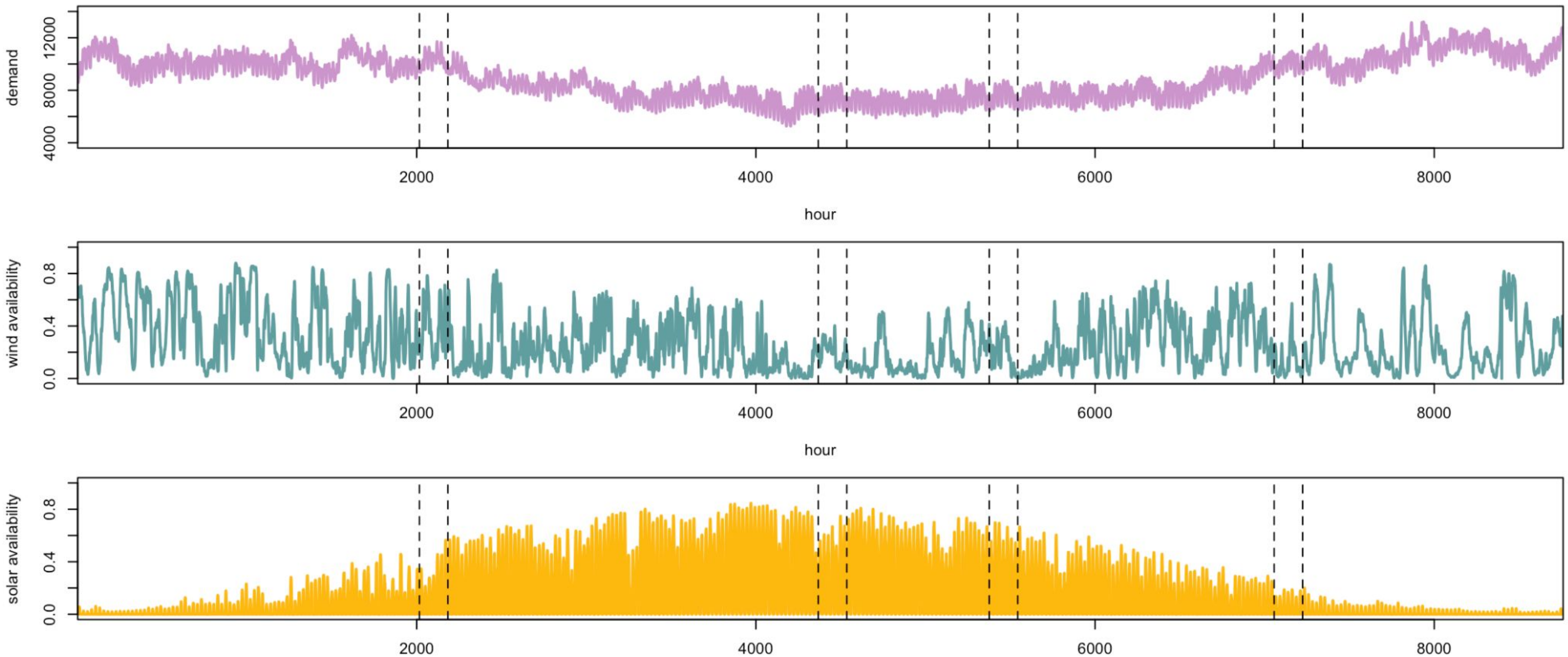
Data

- Hourly time-series for consumption [1] as well as wind [2], and solar [3] availability for 2023



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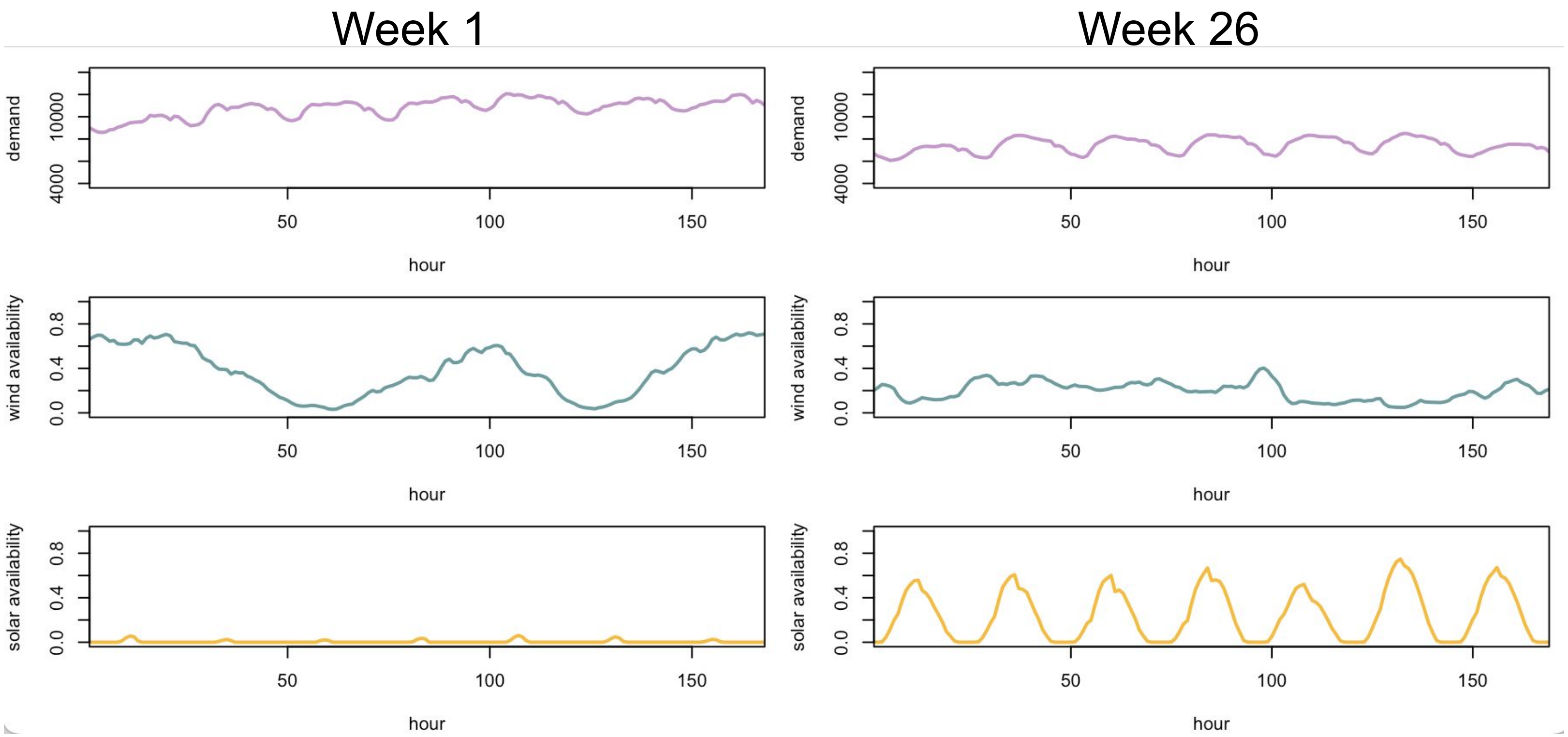
[1] Nord Pool data portal: Consumption, https://data.nordpoolgroup.com/power-system/consumption
[2] Fingrid Open Data, Wind Power, https://www.fingrid.fi/en/electricity-market-information/wind-power-generation/
[3] Fingrid Open data, Solar Power, https://www.fingrid.fi/en/electricity-market-information/solar-power/

Data

- Data are split into 52 168-hour weeks
- The last day is represented by the first 24 hours of the previous week



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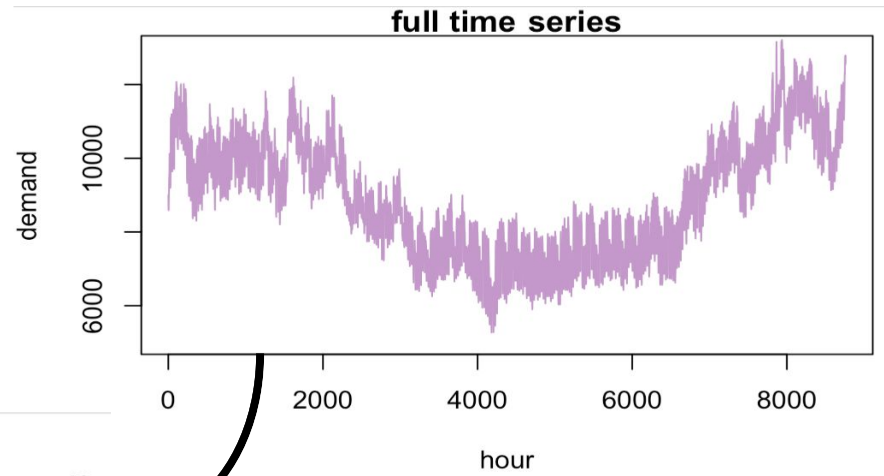
The Two Approaches

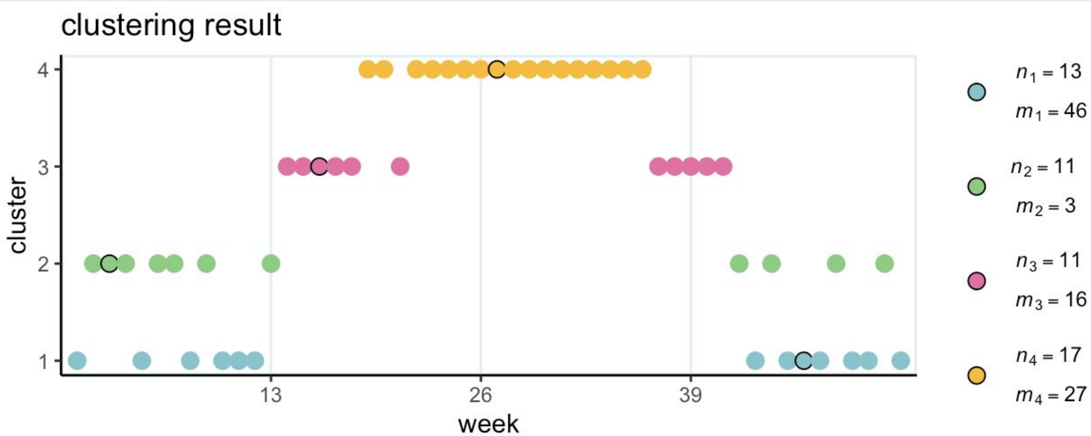
- Two different aggregation approaches for the data were compared
- Partitional approach
  - Use a clustering algorithm to determine groups in the data.
  - Choose a representative week as the medoid of each cluster.
- Seasonal approach
  - Take predetermined groups in data
  - Choose representative weeks in terms of a test statistic

Partitional Approach

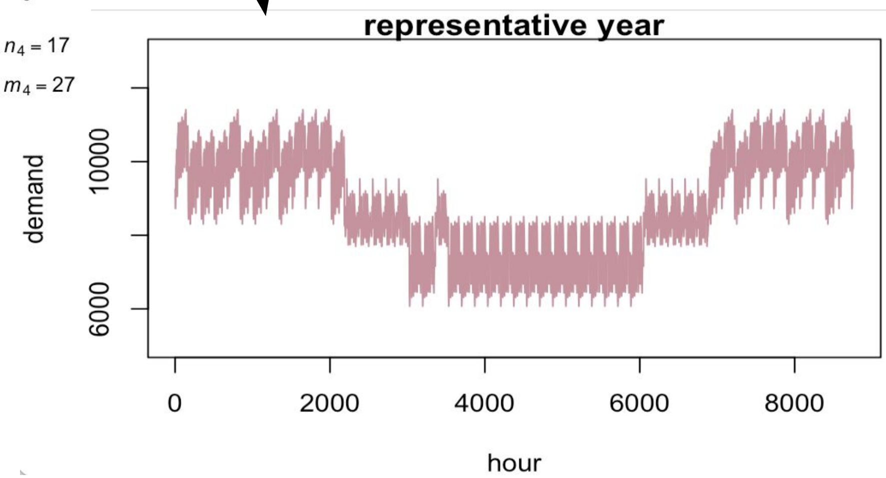
The clustering algorithm assigns each week to a cluster



distances between pairs of normalised weeks are computed



a representative year is formed for each variable

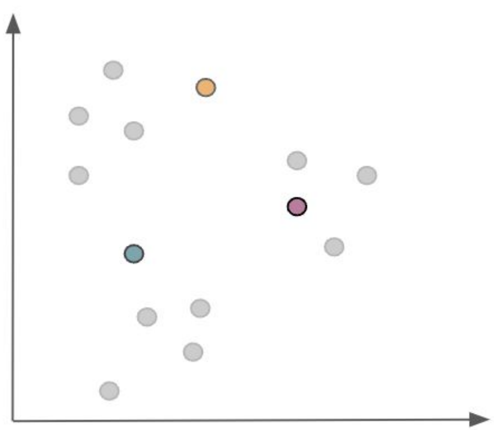


each week w is represented by the medoid m_c of the cluster c it is assigned to

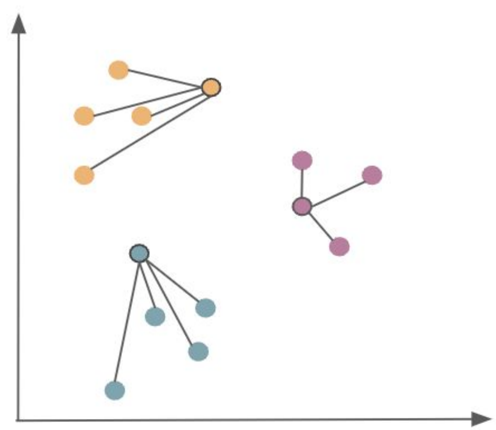
Partitioning Around Medoids (PAM)

- Partitional clustering algorithm, implemented with R-package “cluster” [4]
- Chosen because
  1. Medoids are real objects (weeks) and can be directly chosen as the representative weeks
  2. Greedy selection of starting points leads to semi-deterministic outcomes.

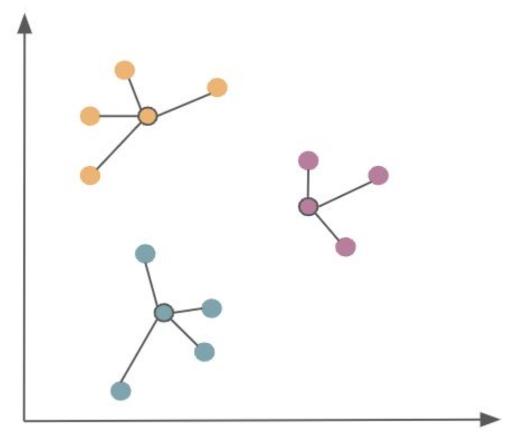
1. Greedy selection of initial medoids



2. Assign each remaining object to its nearest medoid



3. Swap medoids until total sum distances cannot be further minimised



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[4] Martin Maechler, Peter Rousseeuw, Anja Struyf, Mia Hubert, and Kurt Hornik. cluster: Cluster Analysis Basics and Extensions, 2023a. R package version 2.1.6

Measuring Dissimilarity of Weeks

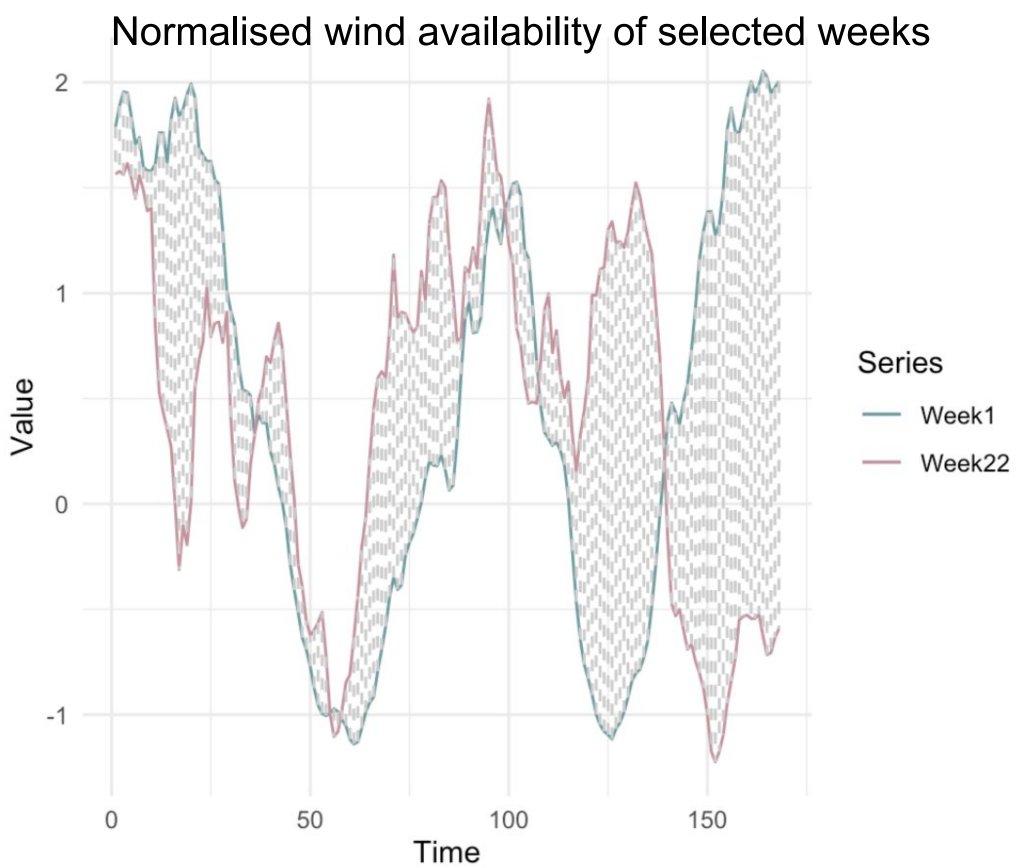
- Each time step *t* of week x is compared to the same time step of week y.
- L2 = Euclidean distance

$$d_{L2}\left(\overline{x},\overline{y}\right) = \sqrt{\sum_{t \in T} \left(x_t - y_t\right)^2}$$

- L1 = Manhattan distance

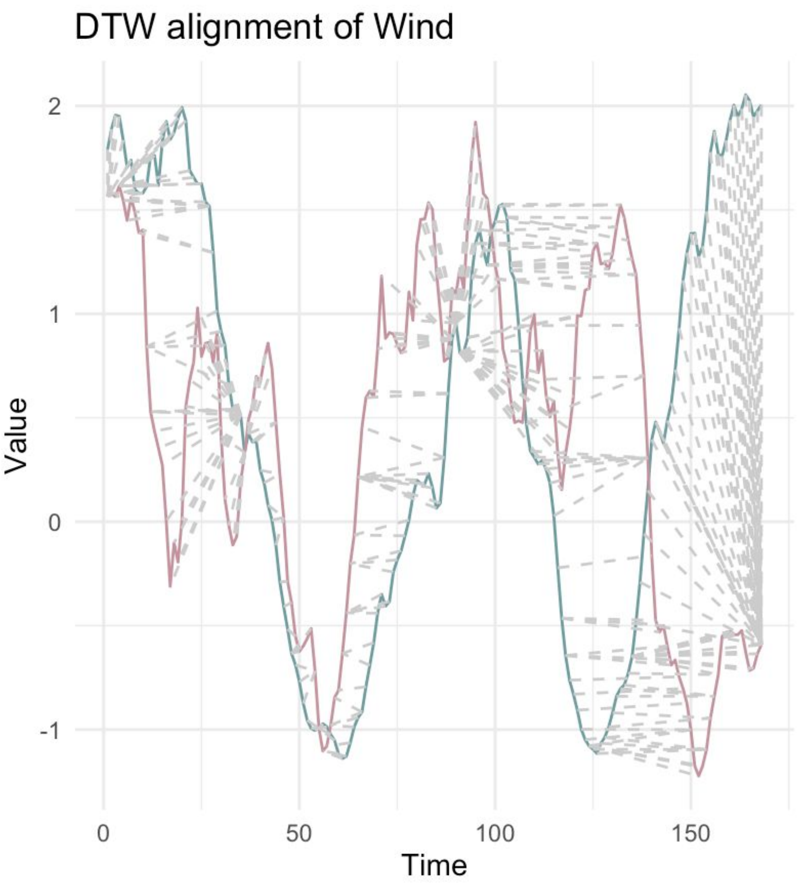
$$d_{L1}\left(\overline{x},\overline{y}\right) = \sum_{t \in T} \left|x_t - y_t\right|$$

$$T = \{\mathbb{Z} \cap [1,168]\}$$



Alignments

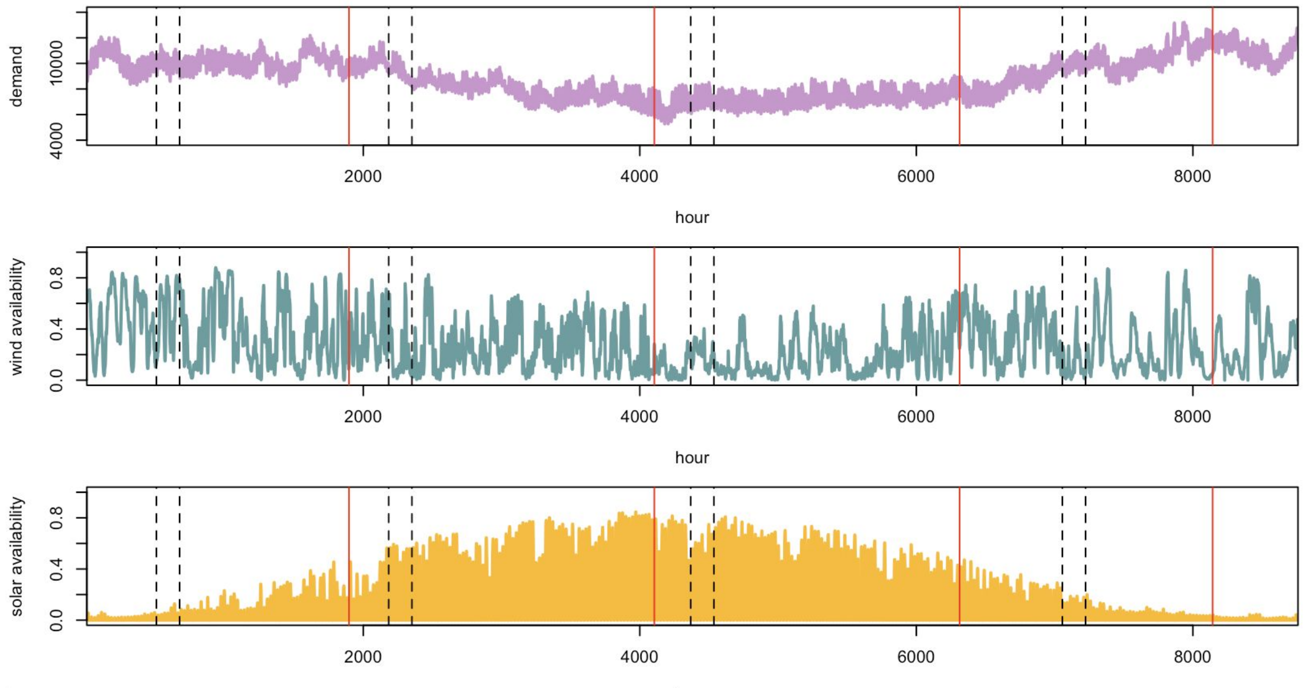
- In addition to pointwise comparison of time steps, Dynamic Time Warping (DTW) is also considered
  - Implemented with R-package "dtw" [5]
- Wind production is very stochastic
  - The peaks in generation do not necessarily align like for demand and solar
- Tests were done both and without a constraint on how far time can be warped
  - Itakura parallelogram defines a window for time warping [5]



[5] Toni Giorgino (2009). *Computing and Visualizing Dynamic Time Warping Alignments in R: The dtw Package*. Journal of Statistical Software, 31(7), 1-24

Seasonal Approach

- Representative weeks are chosen from predetermined equal-sized seasons
- Implemented with a modified version of the GAMS script used in [6]



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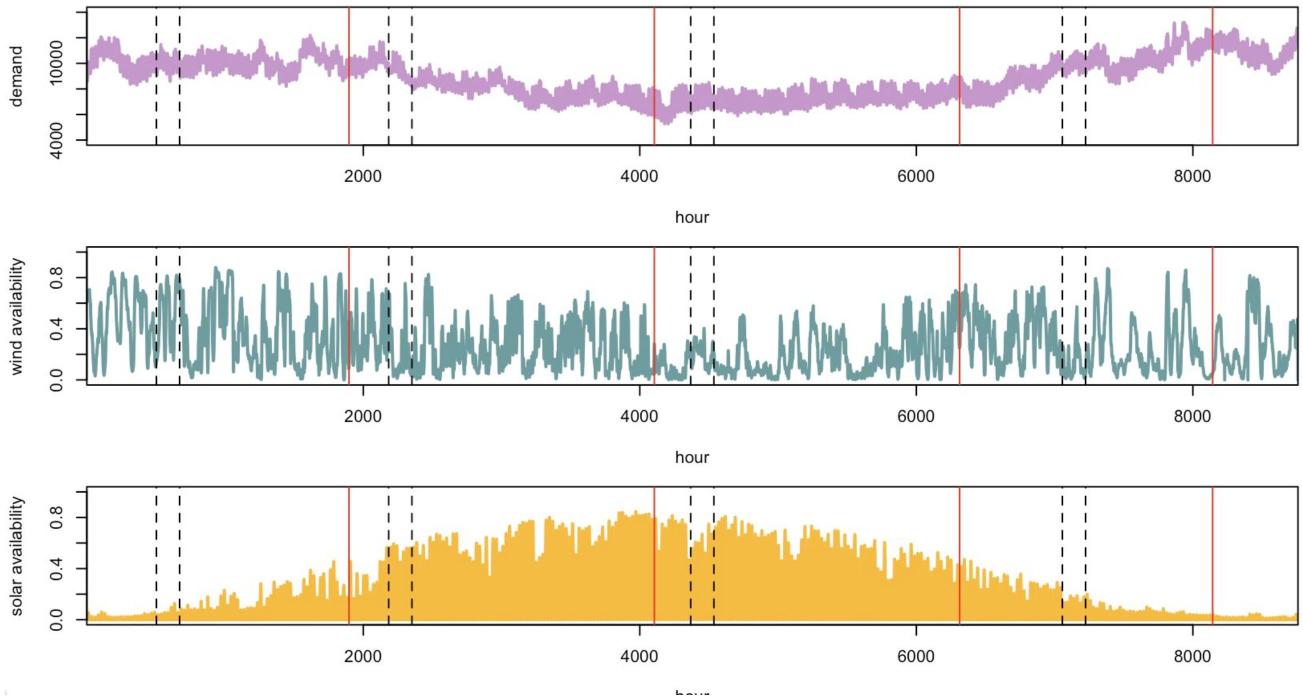
[6] Farzad Hassanzadeh Moghimi, Hanna Ek Fälth, Lina Reichenberg, and Afzal S. Siddiqui. Climate policy and strategic operations in a hydro-thermal power system. The Energy Journal, 44(5):67–94, 2023

Seasonal Approach

- Minimising the seasonal-weekly error in (1) the mean and (2) the standard error within each season
  - i.e. finding the week within each season that has mean and s.e. closest to the average over the whole season



Measuring Representativity

- Benchmark optimisation model
  - A capacity expansion model for Finland the year 2023
    - Modified from [6] and [7]
    - Implemented in GAMS
  - Minimise annual cost of operations, generation, and possible investment
    - Wind, solar and hydro generation has zero cost
    - Cost of thermal generation determined by fuel
  - Hydro reservoir creates dependency across time steps
- Selected statistical values representing the mean and the variance in the time series

[6] Farzad Hassanzadeh Moghimi, Hanna Ek Fälth, Lina Reichenberg, and Afzal S. Siddiqui. Climate policy and strategic operations in a hydro-thermal power system. The Energy Journal, 44(5):67–94, 2023
[7] Tatiana Tassi. Multi-criteria decision analysis for portfolio planning in power generation assessing economic and environmental tradeoffs in the finnish power sector.

Measuring Representativity

- Quality of representative weeks is analysed based on the error in selected statistics
  - Benchmark model - comparison to FTR
    - obj = Objective function value of benchmark model
    - W% = Share of total demand generated with wind power
  - Demand
    - μ_Q = Mean of hourly demand
    - s_Q = Standard deviation of demand
  - Wind
    - μ_W = Mean of hourly wind availability
    - s_W = Standard deviation of wind availability

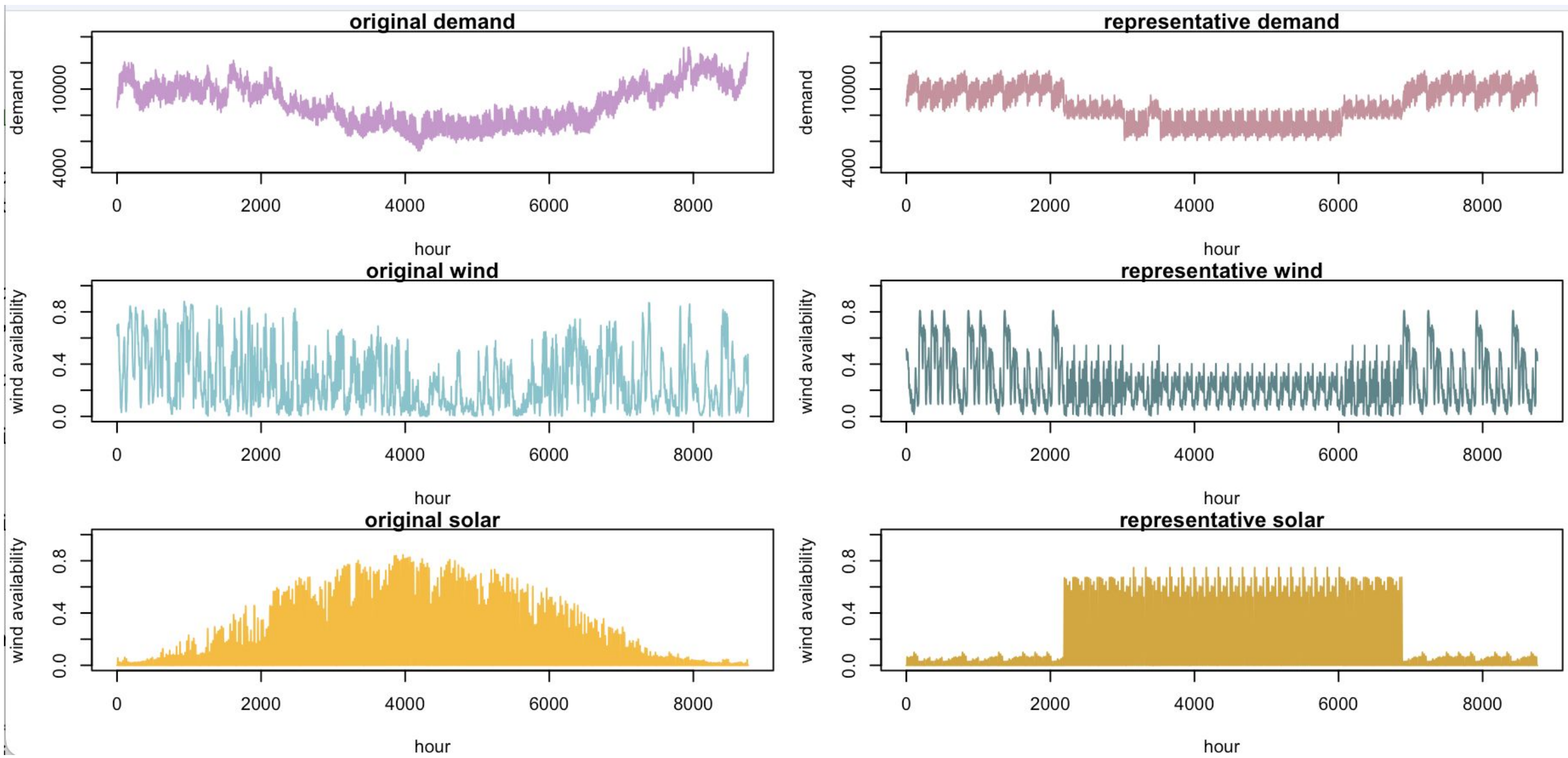
Results with the Partitional Approach

Wind + Demand	obj	W%	μ_Q	s_Q	μ_W	s_W
L2	-2,54 %	-8,12 %	-1,31 %	-7,37 %	-9,39 %	-20,47 %
L1	-0,78 %	-11,05 %	0,33 %	-2,46 %	-11,55 %	-26,51 %
DTW L1	-5,34 %	-1,61 %	-0,74 %	-0,74 %	-3,25 %	-13,95 %
DTW L1 window	-2,38 %	-6,81 %	1,12 %	-10,68 %	-6,86 %	-18,60 %
DTW L2	-5,72 %	-2,16 %	-1,09 %	-1,50 %	-4,33 %	-14,88 %
DTW L2 window	-2,07 %	-6,81 %	1,12 %	-10,68 %	-6,86 %	-18,60 %

- Objective function value lower than FTR for all variants
    - Likely due to lower share of outlier hours in representative weeks than in the original time series

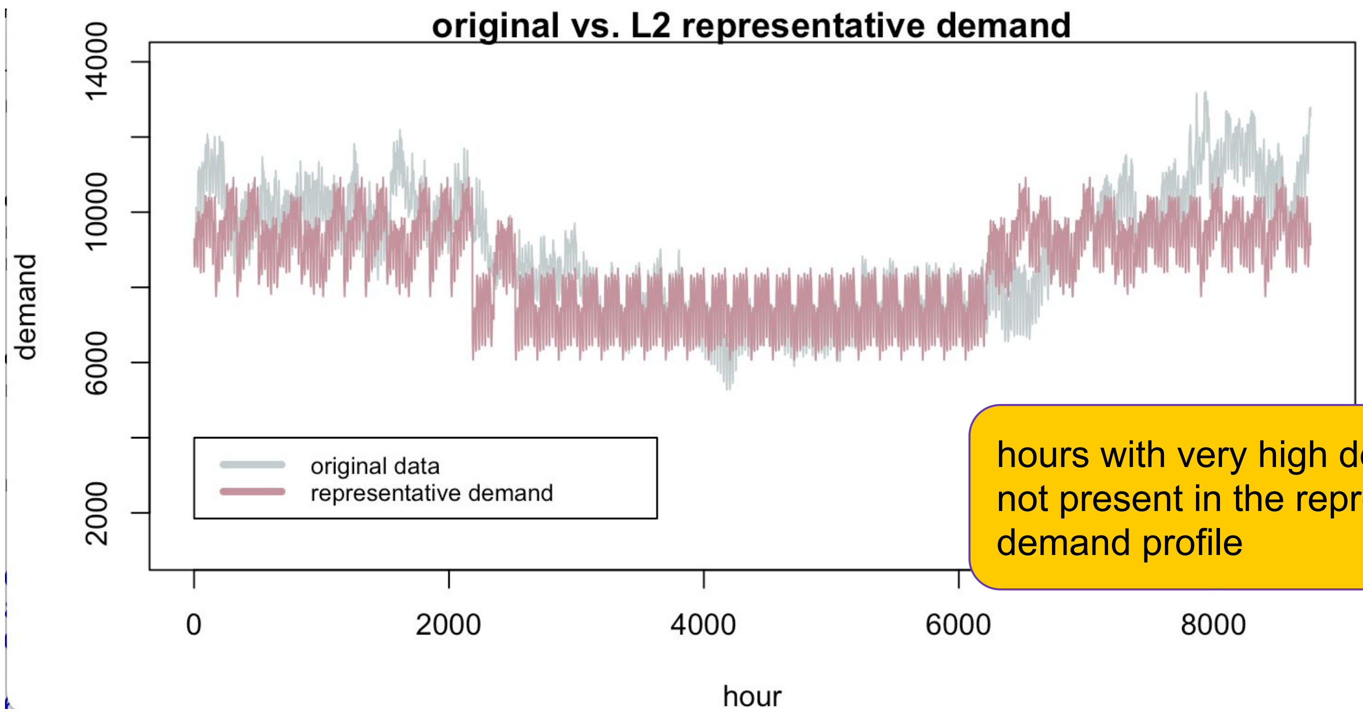
Results with L2 Distance

Wind + Demand	obj	W%	μ_Q	s_Q	μ_W	s_W
L2	-2,54 %	-8,12 %	-1,31 %	-7,37 %	-9,39 %	-20,47 %



Results with L2 distance

Wind + Demand	obj	W%	μ_Q	s_Q	μ_W	s_W
L2	-2,54 %	-8,12 %	-1,31 %	-7,37 %	-9,39 %	-20,47 %



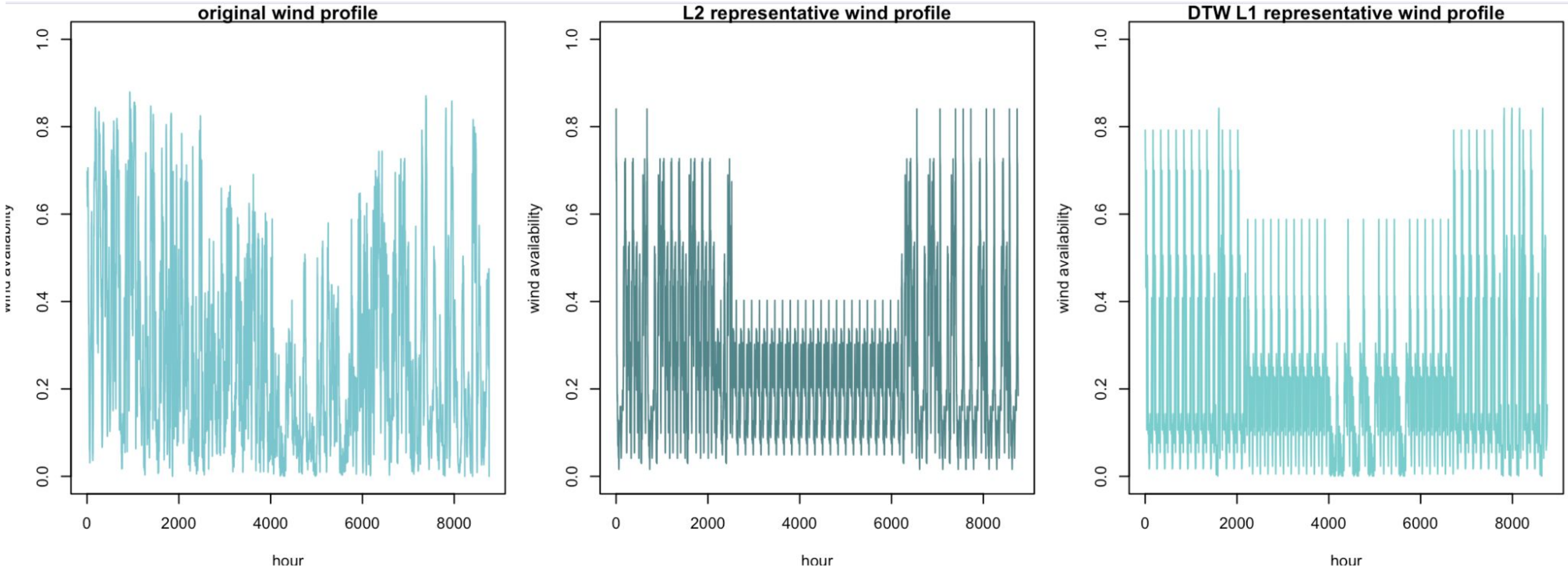
hours with very high demand are not present in the representative demand profile

Results with the Partitional Approach

Wind + Demand	obj	W%	μ_Q	s_Q	μ_W	s_W
L2	-2,54 %	-8,12 %	-1,31 %	-7,37 %	-9,39 %	-20,47 %
L1	-0,78 %	-11,05 %	0,33 %	-2,46 %	-11,55 %	-26,51 %
DTW L1	-5,34 %	-1,61 %	-0,74 %	-0,74 %	-3,25 %	-13,95 %
DTW L1 window	-2,38 %	-6,81 %	1,12 %	-10,68 %	-6,86 %	-18,60 %
DTW L2	-5,72 %	-2,16 %	-1,09 %	-1,50 %	-4,33 %	-14,88 %
DTW L2 window	-2,07 %	-6,81 %	1,12 %	-10,68 %	-6,86 %	-18,60 %

- Mean demand tracked well with all variants
  - Standard deviation however is lower
- Wind mean and generation lower than expected
  - DTW alignments perform better in this regard

Representative Wind Profiles



Wind + Demand	obj	W%	μ_Q	s_Q	μ_W	s_W
L2	-2,54 %	-8,12 %	-1,31 %	-7,37 %	-9,39 %	-20,47 %
DTW L1	-5,34 %	-1,61 %	-0,74 %	-0,74 %	-3,25 %	-13,95 %

Results with the Partitional Approach

Wind + Demand + Solar	obj	W%	μ_Q	s_Q	μ_W	s_W
L2	-4,37 %	-2,31 %	-2,49 %	-5,65 %	-5,05 %	-15,81 %
L1	-1,80 %	-8,61 %	-0,49 %	-5,01 %	-9,03 %	-14,42 %
DTW L1	-1,96 %	-0,59 %	-0,66 %	-2,38 %	-2,17 %	-1,40 %
DTW L1 window	-3,03 %	-0,67 %	-1,28 %	-3,87 %	-2,89 %	-13,02 %
DTW L2	-0,33 %	-11,93 %	-0,98 %	-2,63 %	-13,72 %	-6,98 %
DTW L2 window	-3,03 %	-0,67 %	-1,28 %	-3,87 %	-2,89 %	-13,02 %

- After adding solar
  - Error in the objective function value decreases with the unconstrained DTW alignments and increases with the others

Results with the Seasonal Approach

- Performs well in terms of the variable means
  - Expected as it is a directly in the minimised objective criteria
- However, the error in the objective function value is higher
  - Likely due to the lower obtained variance in the demand
  - Adding a higher weight to consumption (Q) leads to some improvement

Variables	obj	W%	μ_Q	s_Q	μ_W	s_W
Equal weights (WQ, WQS)	-8,14 %	+0,44 %	-0,14 %	-30,40 %	-0,72 %	-2,79 %
1,5xQ, 2xQ and 1xW (WQ)	-3,72%	+0,26%	-1,10%	-12,28%	-1,08%	-5,58%

Conclusions

- No one method clearly outperformed the others
- Both approaches dampen outliers
  - Reflected in the lower objective function values than the FTR
  - Number of representative weeks was fixed at four, which likely aggravated the effect
- Low error in the mean and standard deviation did not guarantee low error in the objective function or vice versa

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