Validation of Methods to Select a Priori the Number of Typical Days for Energy System Optimisation Models

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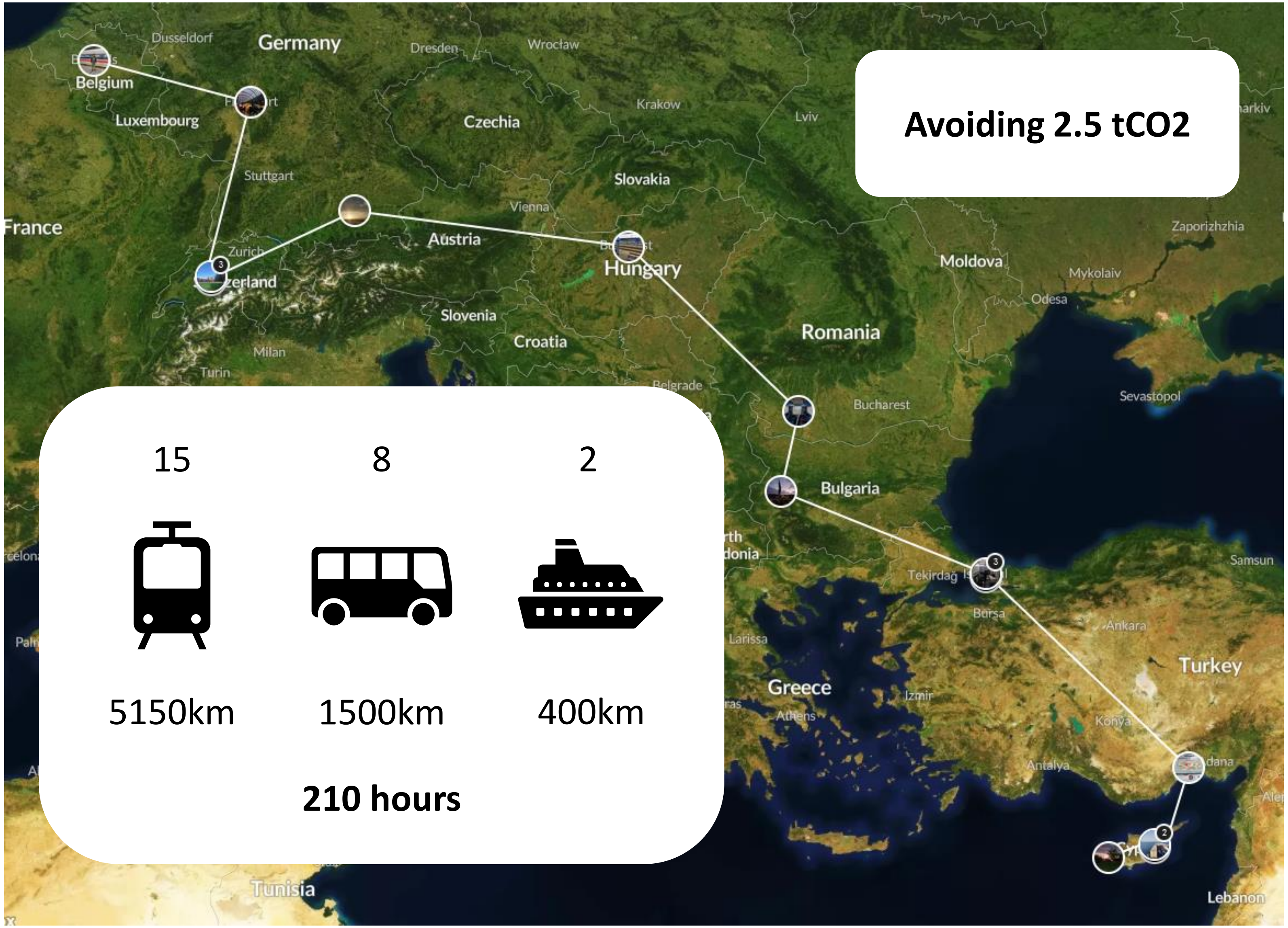
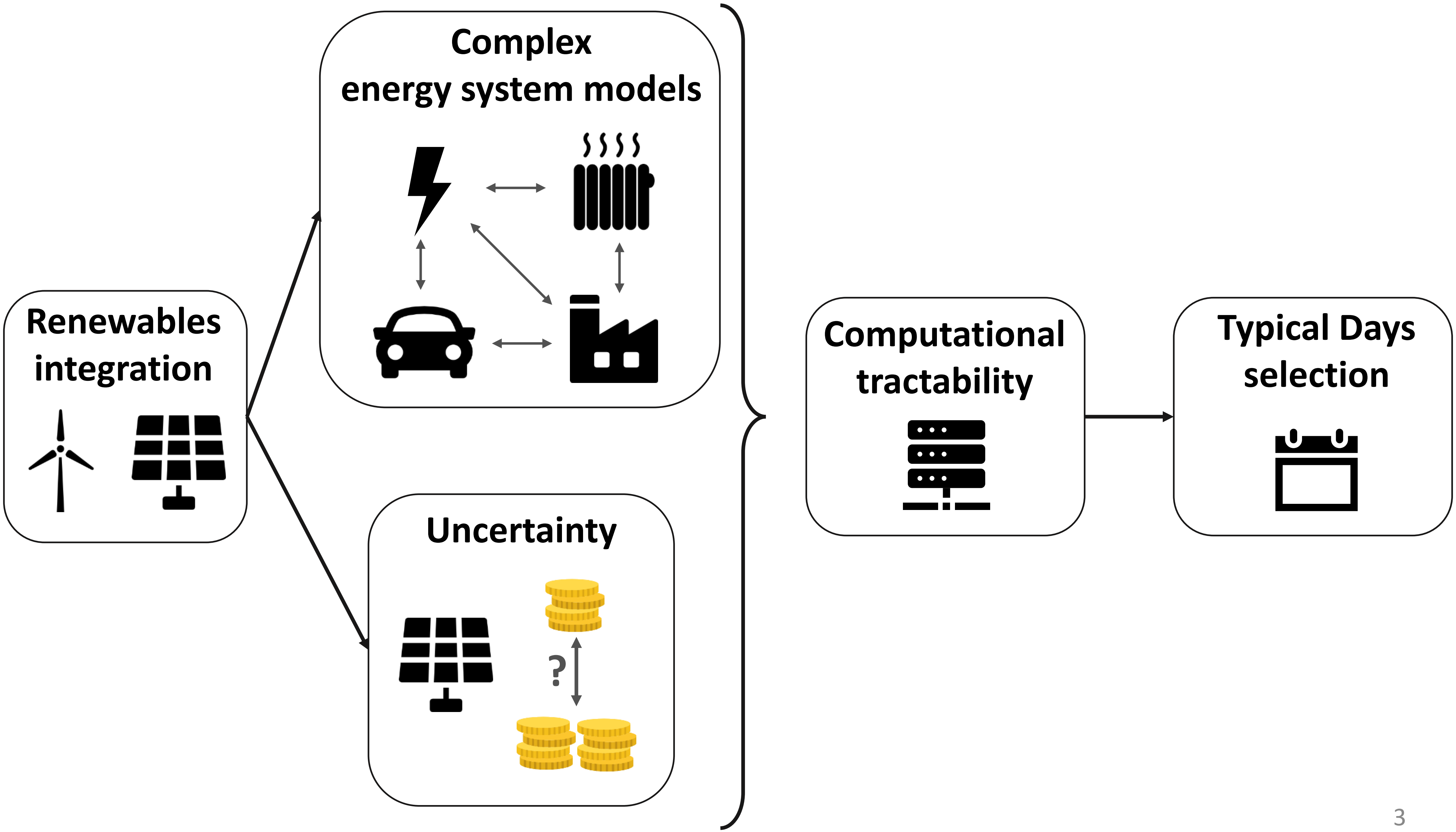
I like complex planning problems…



Avoiding 2.5 tCO2

15	8	2
5150km	1500km	400km

210 hours


Renewables integration
Complex energy system models
Uncertainty
?
Computational tractability
Typical Days selection

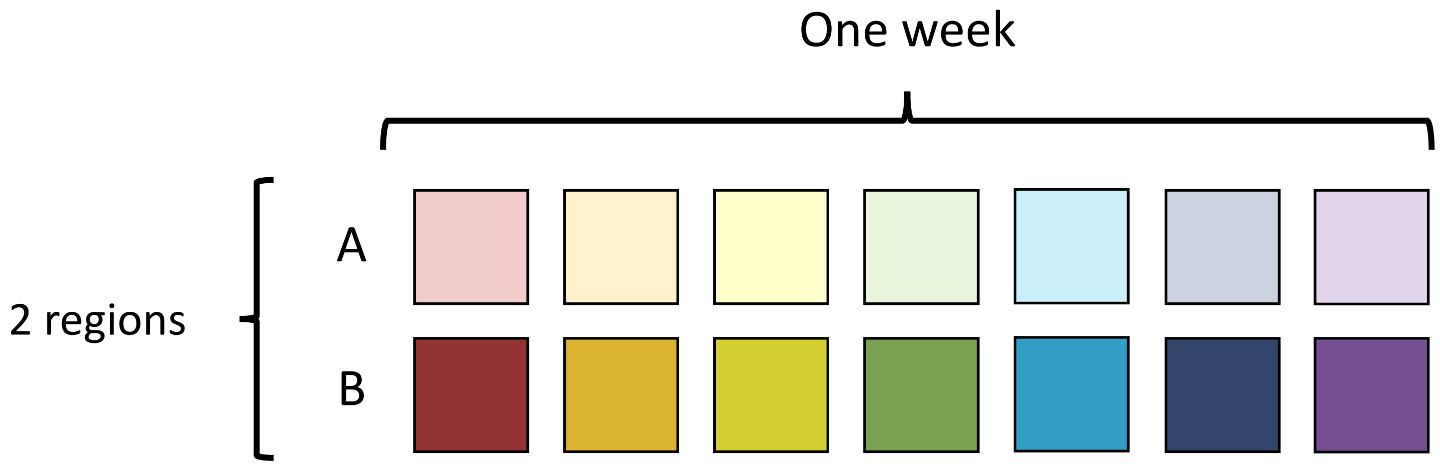
Contents

- Concept of Typical Days clustering for multi-region energy systems
- Case study and model
- How to measure the accuracy of Typical Days clustering?
  - A priori evaluation: clustering error
  - A posteriori evaluation: sensitivity of the energy system strategy
  - Comparison of a priori and a posteriori evaluation

Concept illustration

Typical days clustering for **multi-regional** energy systems

A simple example of the selection of 3 TDs to represent a week

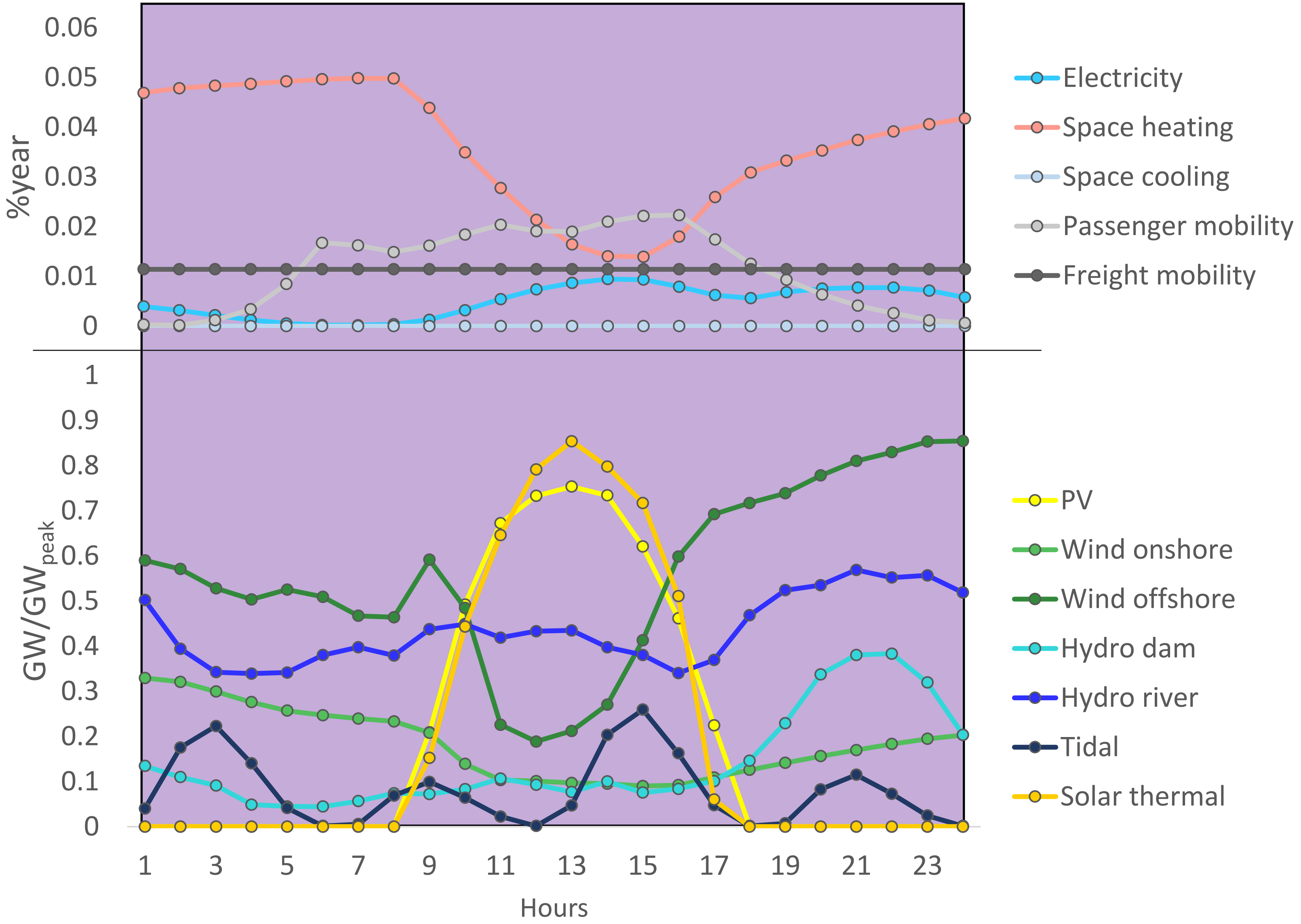


Each day is represented by a color and each region by a row

For each day in each region, 9 time series give the value of the time dependant input data

Variable demand

Variable production



The distance between 2 days is computed as a ponderated sum accross time series

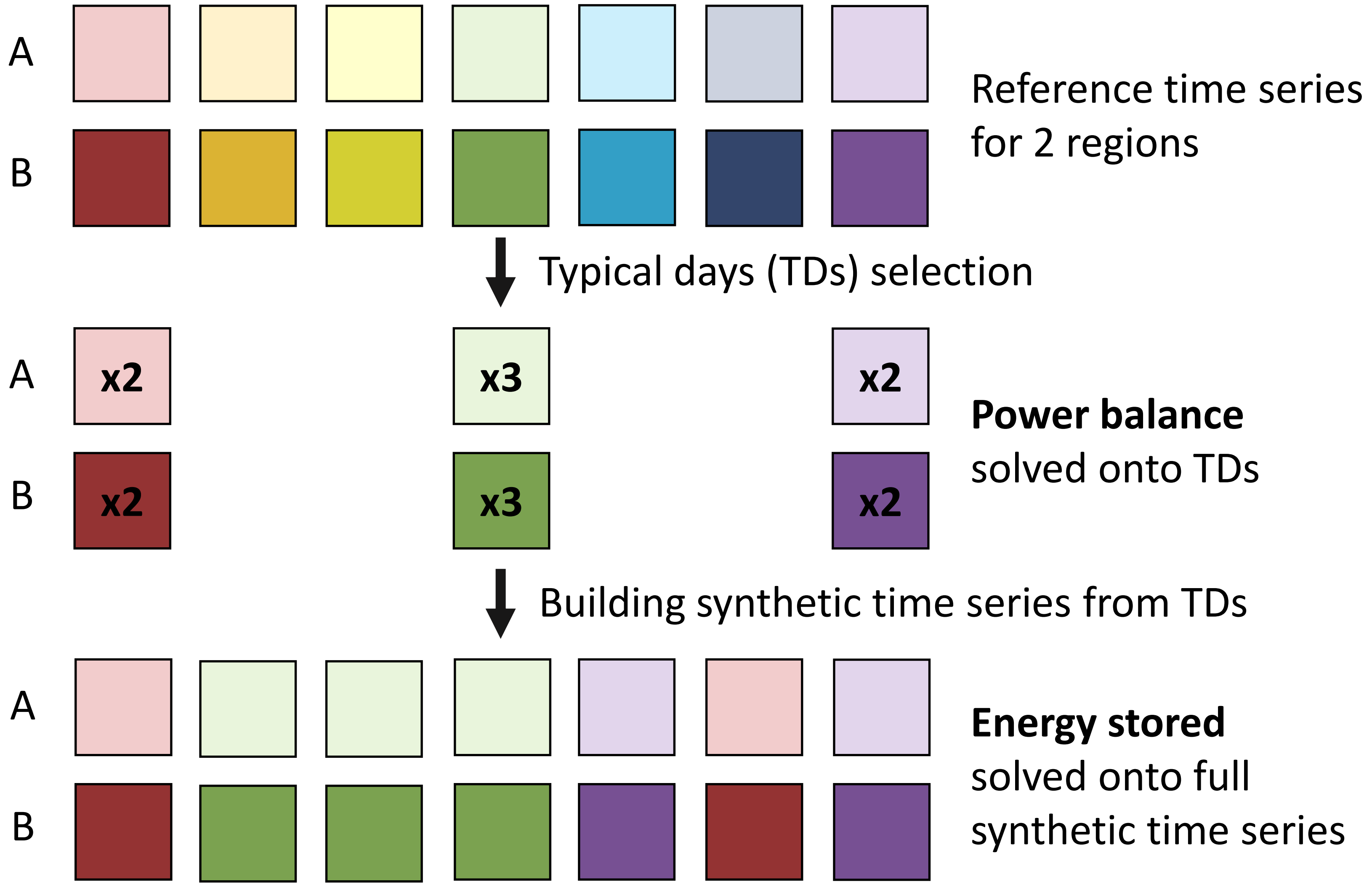
Number of time series

$$Dist(i,j) = \sum_{p=1}^{N_{ts}} \omega_p \sum_{h=1}^{24} |ts(p,h,i) - ts(p,h,j)|$$

Day i and j

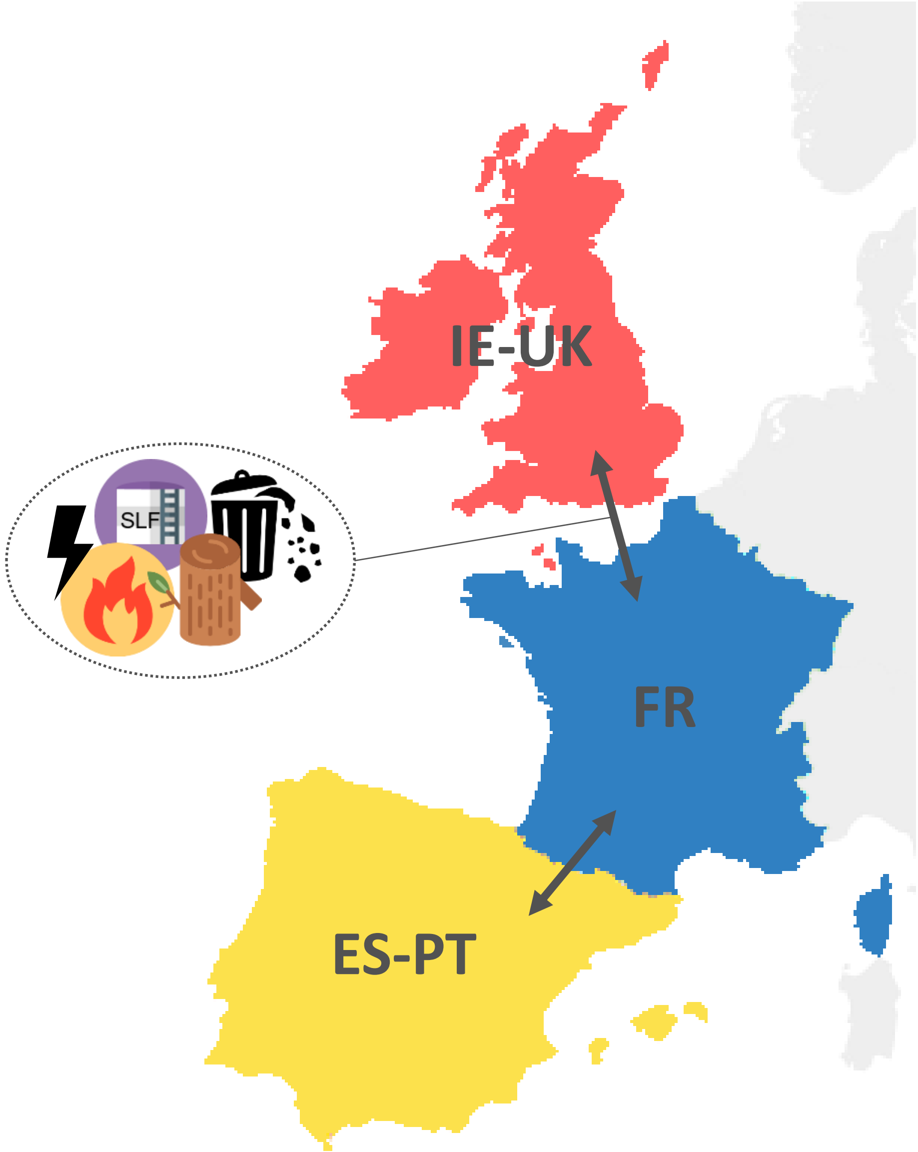
Weight of time series p

Illustration of the selection of 3 Typical Days (TDs) to repepresent 1 week



Case study and model

Case study description : Atlantic EU countries



90% direct emission reduction compared to 1990

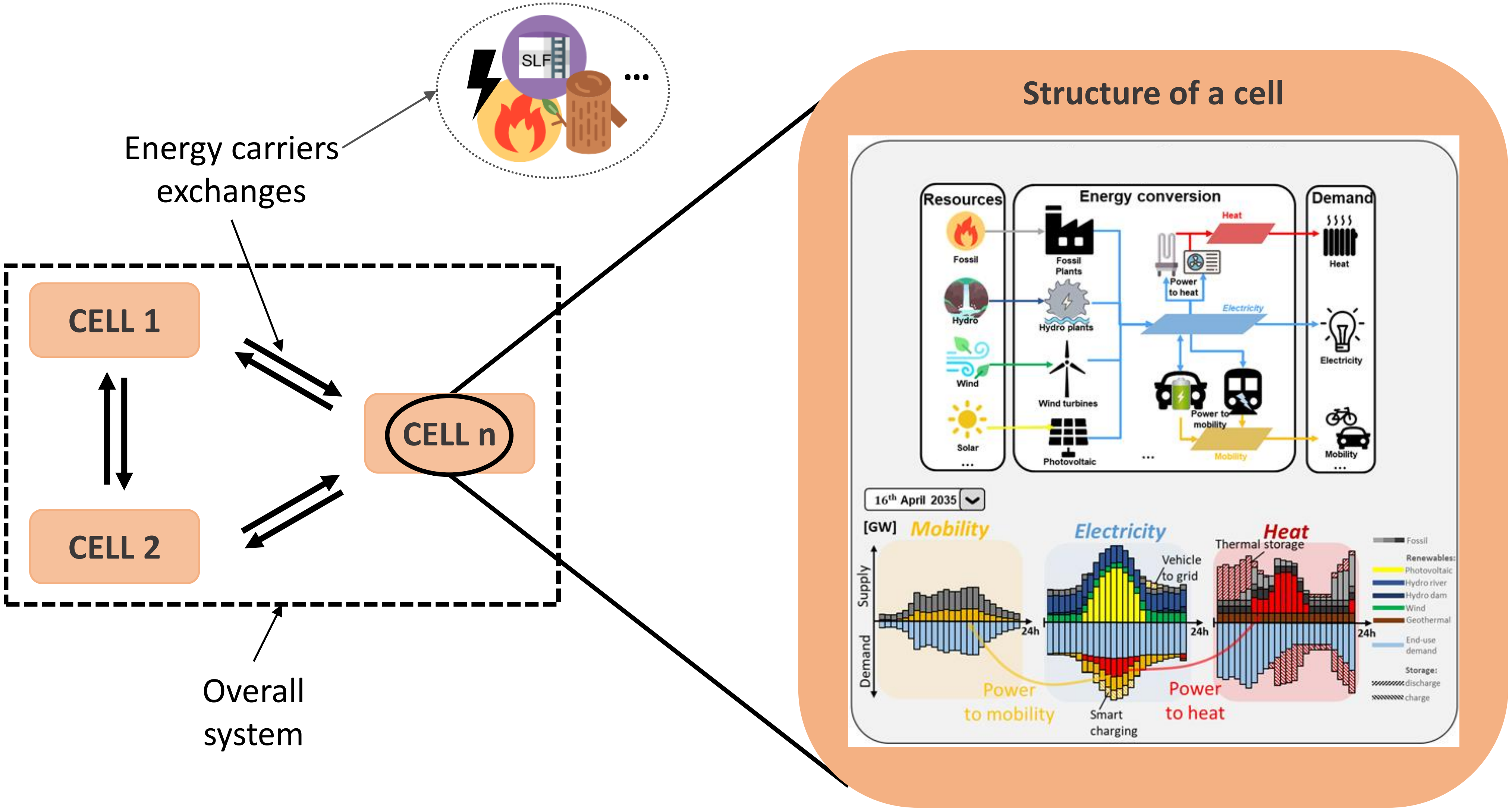
3 macro-cells interconnected through:

- Electricity
- Gas
- Synthetic liquid fuels (SLF)
- Woody biomass
- Waste
- CO_2

Transfer capacities of the network are optimized

Data from [7]

EnergyScope Multi-Cell is a multi-regional whole-energy system optimisation model



Adapted from [2]

How to measure the accuracy of typical days clustering

How to mesure the accuracy of the Typical Days clustering?

A priori evaluation: clustering error [2-5]

Time series error → Accurate **value** at each hour of the year for each time serie ?

Duration curve error → Accurate **distribution** for each time serie ?

Correlation error → Accurate **relations** between time series ?

- Intraregional
- Overall

A posteriori evaluation: sensitivity of energy system strategy

Computational time
Objective function (Total cost)
Installed capacity
Resources used
Exchanges

How to mesure the accuracy of the Typical Days clustering?

A priori evaluation

- Time series error
- Duration curve error
- Correlation error
  - Intraregional
  - Overall

A posteriori evaluation

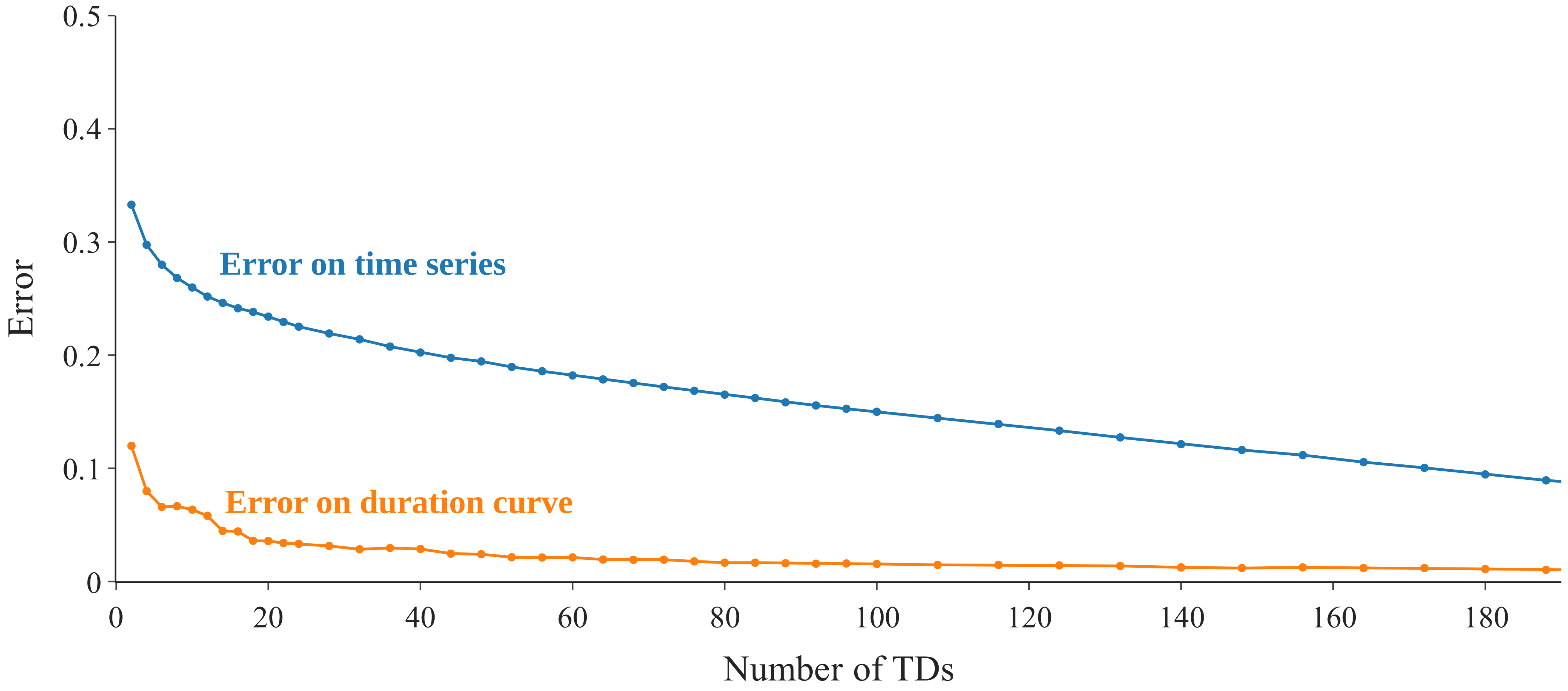
- Computational time
- Objective function (Total cost)
- Installed capacity
- Resources used
- Exchanges

$$\boldsymbol{E} = \frac{|x_{td} - x_{ref}|}{x_{ref}}$$

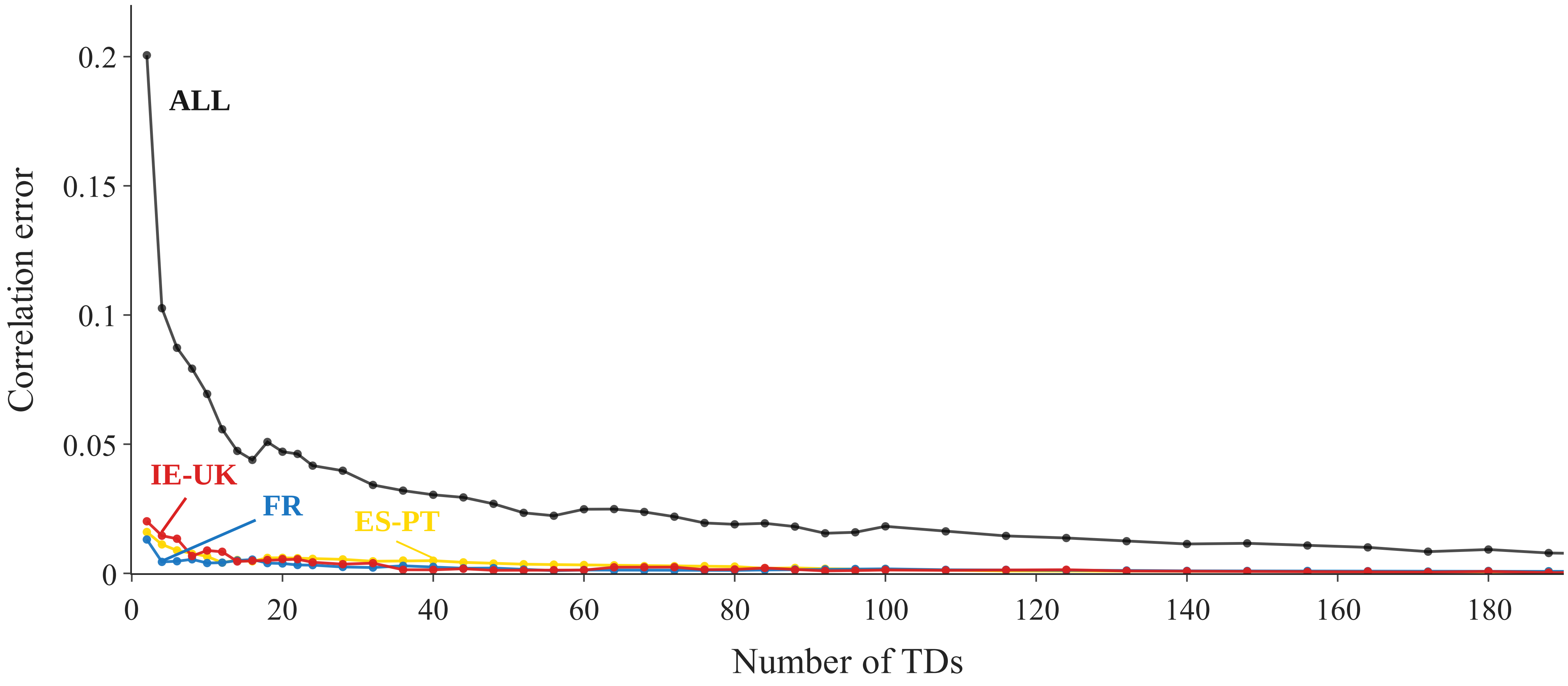
with **x** the variable of interest
td the number of Typical Days to evaluate
ref the reference case with 365 days

A priori evaluation: clustering error

Errors on time series and duration curve decrease rapidly at low number of Typical Days (TDs)

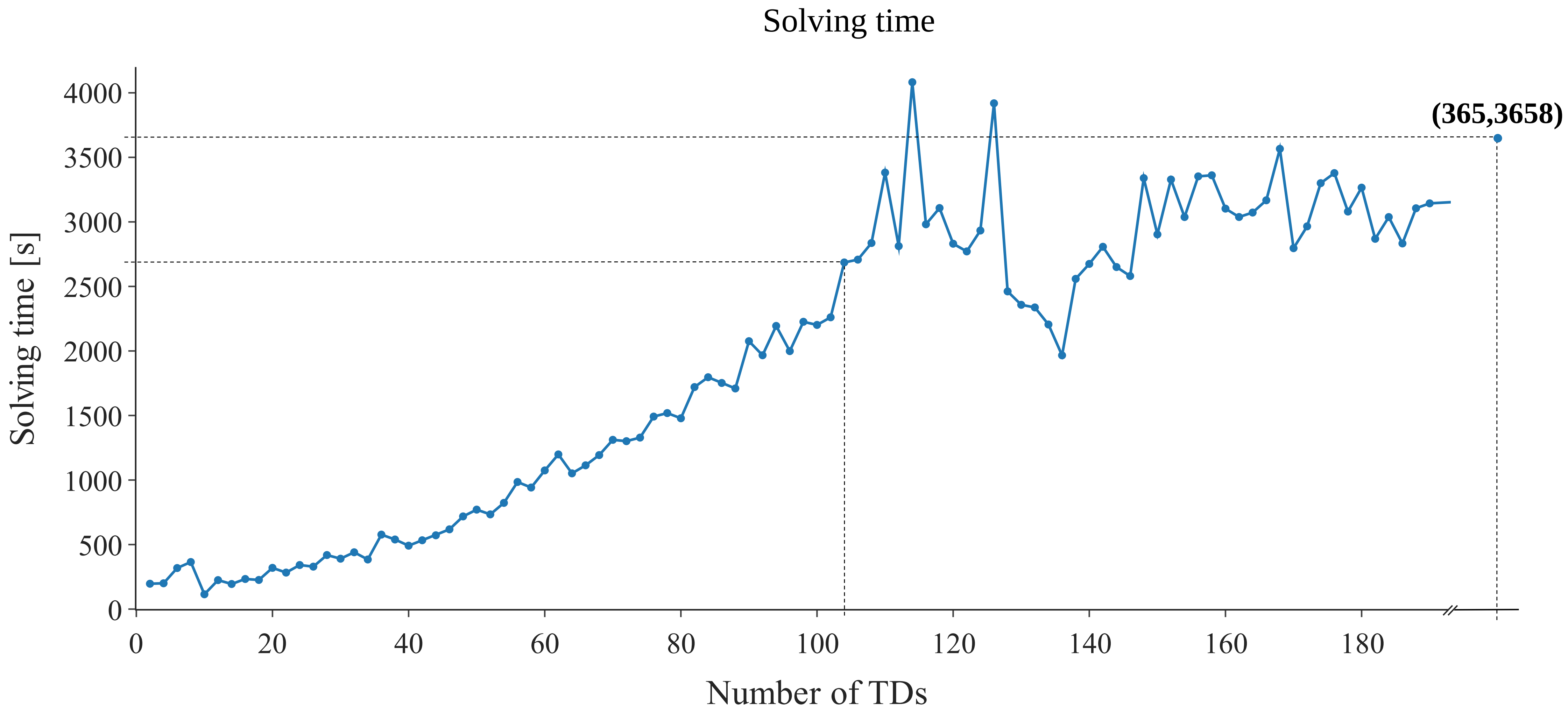


Errors on correlation decrease rapidly at low number of Typical Days (TDs)

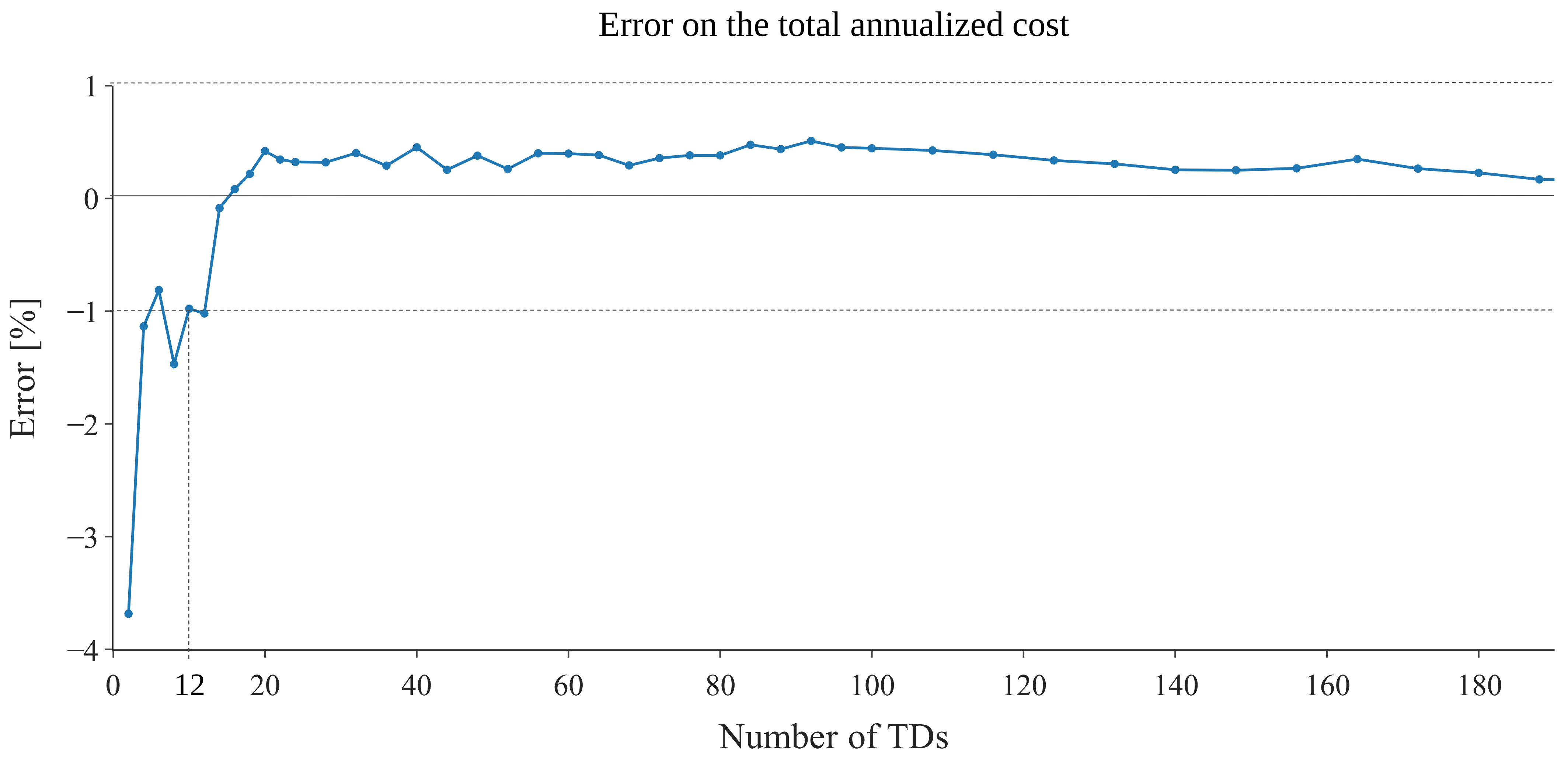


A posteriori evaluation: sensitivity of energy system strategy

The gain in solving time is significative only below 108 Typical Days (TDs)



The total cost is not a good indicator to study the impact of Typical Days (TDs) on the energy system results



Main expected outputs from the model

Sizing of technologies

Primary energy used

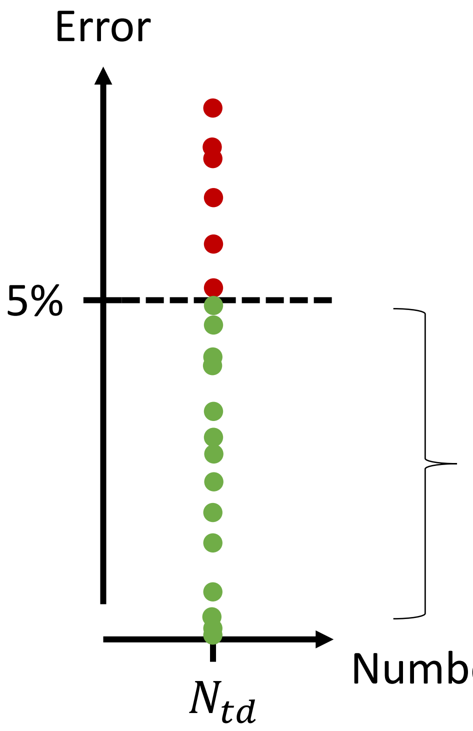
1 element = 1 technology or primary energy

Energy exchanges

Already considered into the other outputs

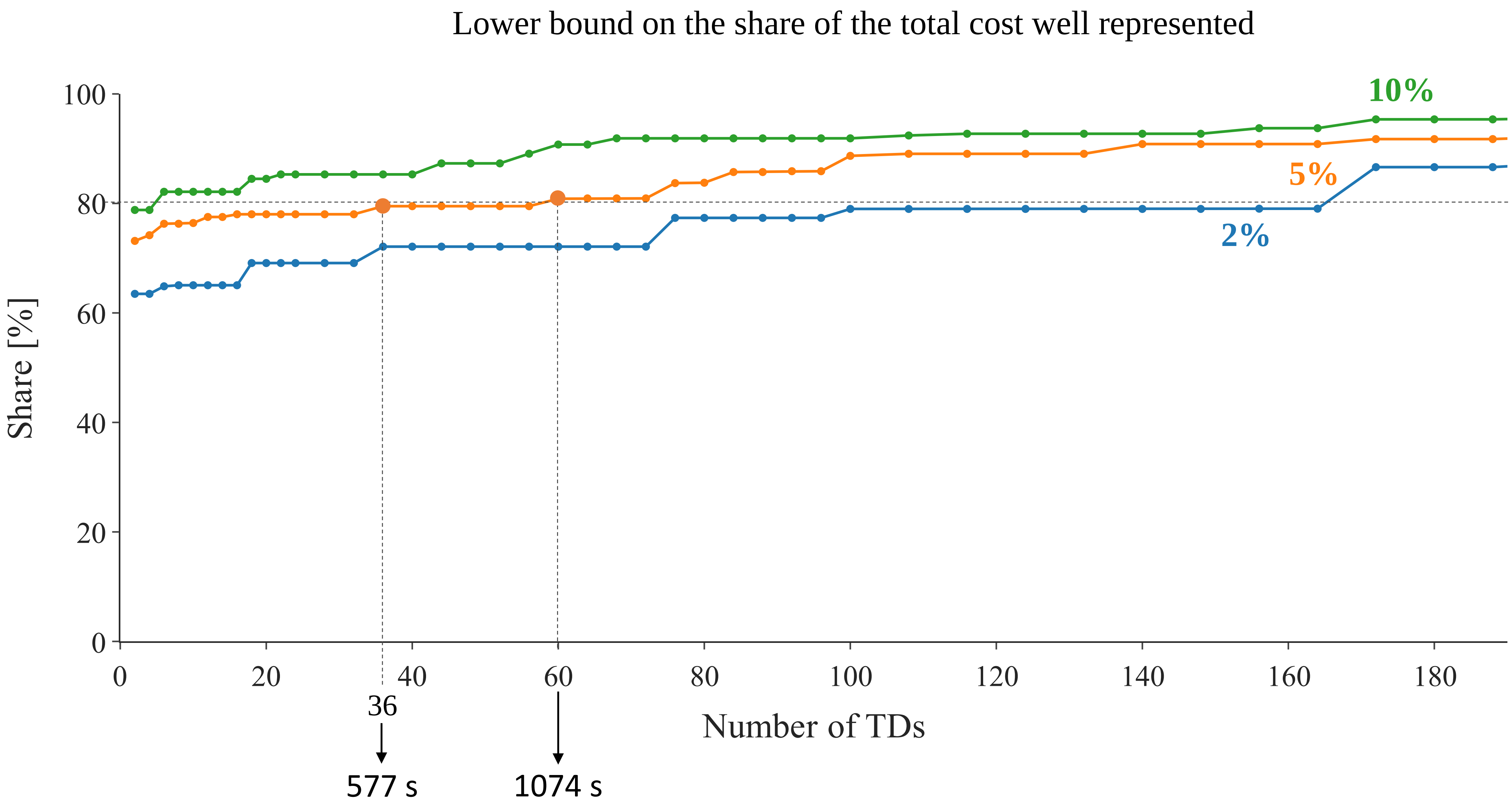
A bottom-up indicator to get a lower bound on the accuracy

$$Share_{N_{td}} = \frac{\sum_{tech \in A}[C_{inv_{ann}}(tech) + C_{maint}(tech)] + \sum_{res \in A} C_{op}(res)}{TotalCost}$$



$$A = \{el \mid E(el) \leq 5\%\}$$

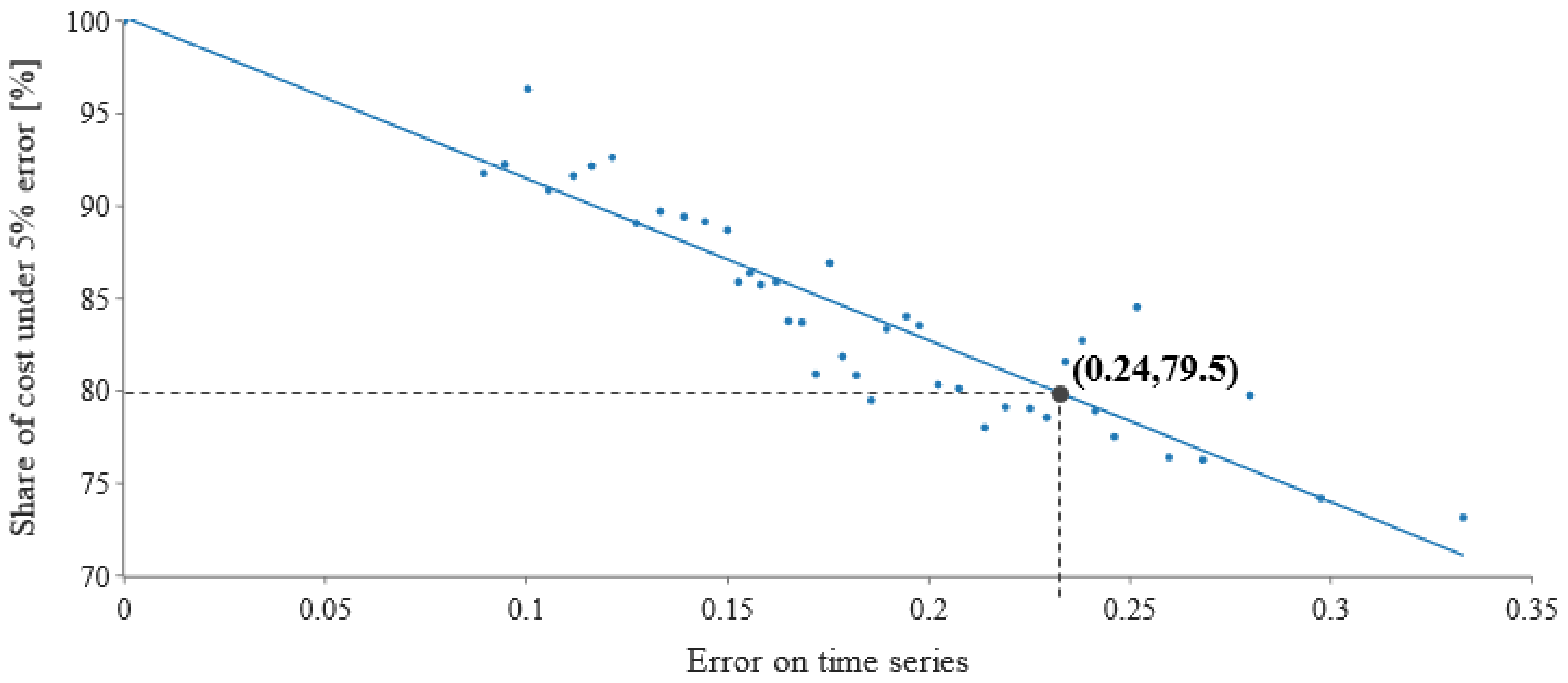
Here, it is easier to compare different trade-off: 36 TDs is better then 60 TDs



Comparison of a priori and a posteriori evaluations

The error on the time series is a good a priori evaluation

	E_{ts}	E_{dc}	$E_{corr,ES-PT}$	$E_{corr,FR}$	$E_{corr,IE-UK}$	$E_{corr,all}$
Threshold of 5%	-0.92	-0.74	-0.82	-0.67	-0.65	-0.70



Conclusions and perspectives

Conclusions

- A simple **bottom-up indicator** to assess the impact of Typical Days clustering on the energy system results has been developped
  - It allows to **select the number of typical days for a new case study**
  - It can be applied in general to **compare energy system results**

- With **36TDs**, we reach at least 79.5% of the elements of the energy system that are well represented.
  - It divides by **6.3** the computational time (577 seconds) → uncertainty analysis

- A correlation of -0.92 is observed between the error on the energy system and the error on time series
  - **Error on time series** can be used to select the number of TDs

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