Analyzing Time Period Aggregation Methods for Power System Investment and Operation Models with Renewables and Storage

Authors: Sonja Wogrin, Diego A. Tejada-Arango, Salvador Pineda, and Juan Miguel Morales

October 20-23, 2019.

comillas.edu

Outline

INTRODUCTION

TIME-AGGREGATION METHODS

CASE STUDIES

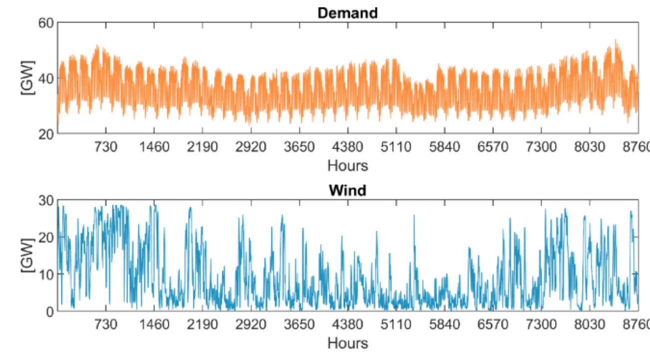
CONCLUSIONS

Computational burden due to time horizon

	OPERATION	PLANNING
Horizon	1 second - 1 week	1 year - 20 years
Decisions	Generation dispach Power flows	Generation investments Line investments
Objective	Min production cost	Min prod. + inv. cost
Constraints	Generation = Demand Unit technical limits Line technical limits	Generation = Demand Unit technical limits Line technical limits
Comput. burden	Medium	Very high

How to overcome computational burden?

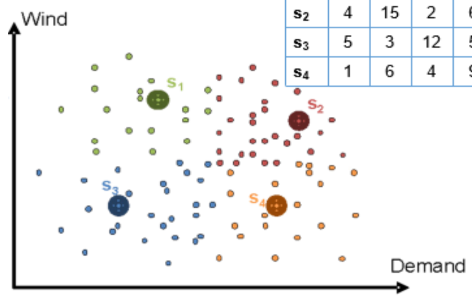
Clustering techniques are applied to reduce the (hourly) temporal representation of data series:



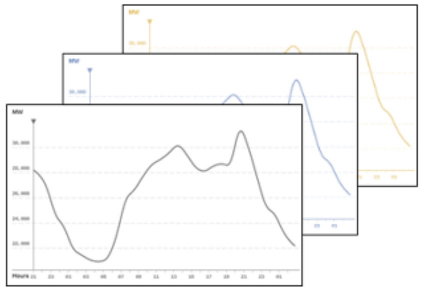
Load Blocks/System States

Transition matrix

	s_1	s_2	s_3	s_4
s_1	9	5	4	0
s_2	4	15	2	6
s_3	5	3	12	5
s_4	1	6	4	9



Representative Periods



Reduce computational complexity

Loss of chronological information! (How to represent technical constraints s.a. ramping, or storage? How to incorporate renewables?)

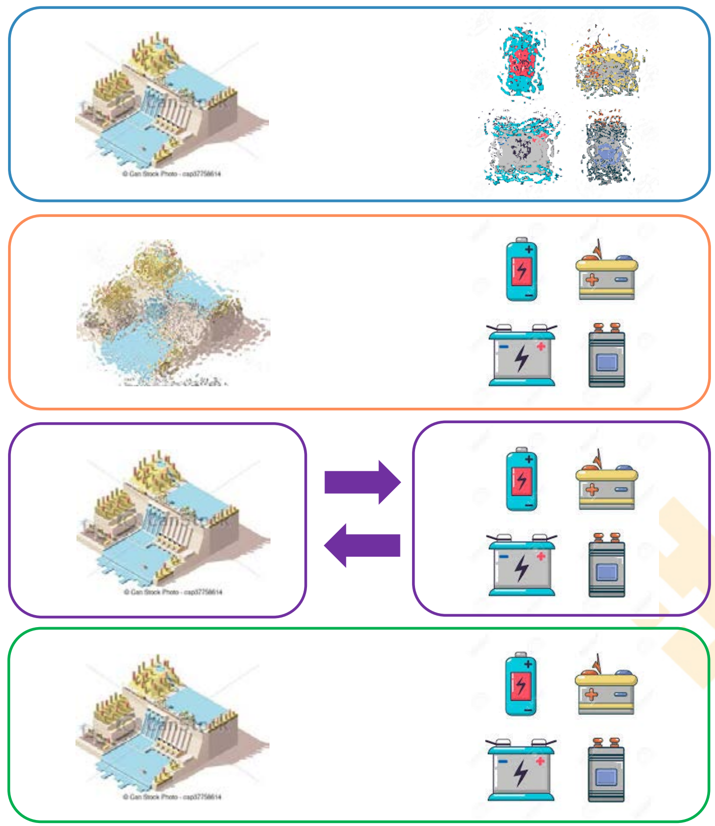
Is it possible to co-optimize short and long term?

Detailed long-term
Simplified short-term

Detailed short-term
Simplified long-term

Iterative approach between two models

Is it possible to optimize both at the same time?



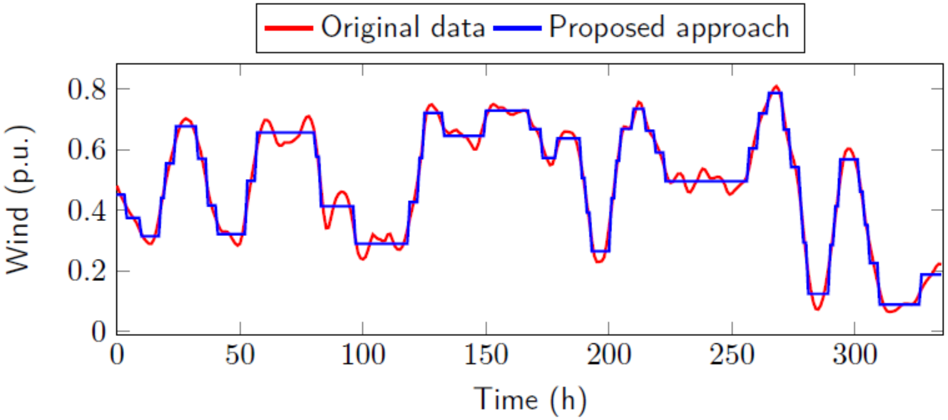
comillas.edu

Outline

TIME-AGGREGATION METHODS

Chronological time-period clustering (CTPC)

- Instead of using representative days, we propose a **new clustering methodology** to group **consecutive hours** and maintain chronology.
- By doing so we can capture the **longer dynamics** of power generation from **renewable** sources such as wind.
- In addition, we can model the **operation of the batteries** more accurately since we maintain the chronology of the data.



Source: *S. Pineda and J. M. Morales. "Chronological Time-Period Clustering for Optimal Capacity Expansion Planning With Storage." in IEEE Transactions on Power Systems. vol. 33. no. 6. pp. 7162-7170. Nov. 2018.*

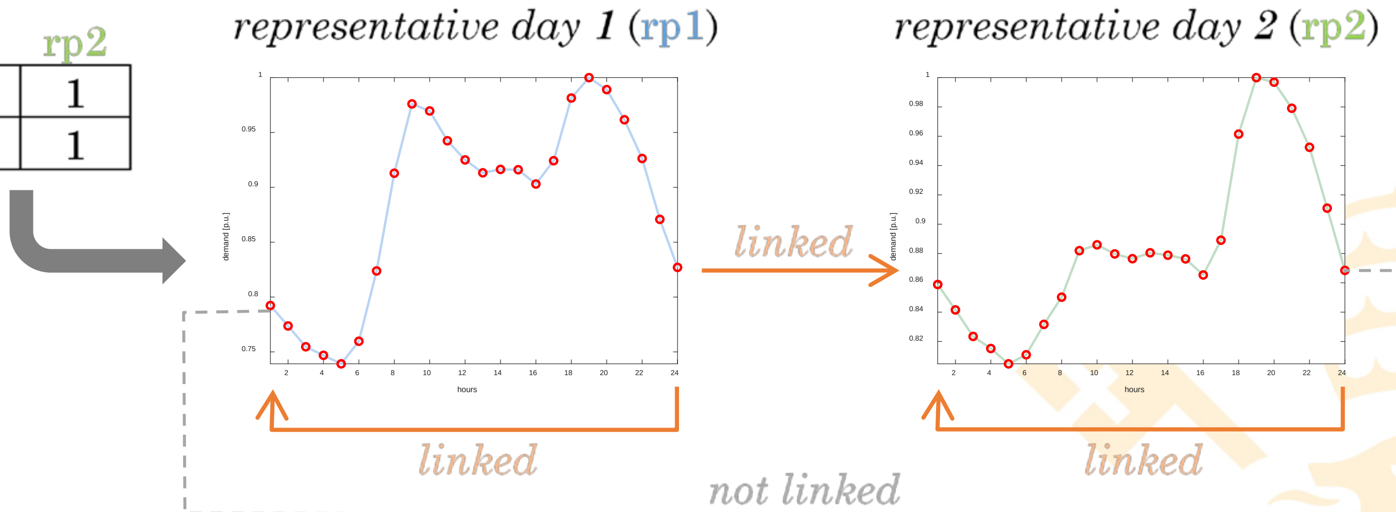
Enhanced Representative Periods (ERP)

Cluster Index

days →	d1	d2	d3	d4	d5	d6	d7
representative days →	rp1	rp1	rp1	rp1	rp1	rp2	rp2

Transition Matrix

	rp1	rp2
rp1	4	1
rp2	0	1



Source: *D.A. Tejada, M. Domeshek, S. Wogrin, E. Centeno. Enhanced representative days and system states modeling for energy storage investment analysis. IEEE Transactions on Power Systems. vol. 33, no. 6, pp. 6534-6544, Nov 2018*

ERP - continued

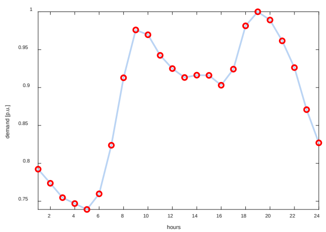
Cluster Index

	d1	d2	d3	d4	d5	d6	d7
days →	d1	d2	d3	d4	d5	d6	d7
representative days →	rp1	rp1	rp1	rp1	rp1	rp2	rp2

h=1   h=168

Intra-day balance equations

representative day 1 (rp1)



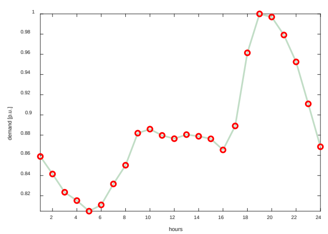
$$storage_{rp1\_1} = storage_{rp1\_0} + charge_{rp1\_1} - discharge_{rp1\_1}$$

$$storage_{rp1\_2} = storage_{rp1\_1} + charge_{rp1\_2} - discharge_{rp1\_2}$$

$$\vdots$$

$$storage_{rp1\_24} = storage_{rp1\_23} + charge_{rp1\_24} - discharge_{rp1\_24}$$

representative day 2 (rp2)



$$storage_{rp2\_1} = storage_{rp2\_0} + charge_{rp2\_1} - discharge_{rp2\_1}$$

$$storage_{rp2\_2} = storage_{rp2\_1} + charge_{rp2\_2} - discharge_{rp2\_2}$$

$$\vdots$$

$$storage_{rp2\_24} = storage_{rp2\_23} + charge_{rp2\_24} - discharge_{rp2\_24}$$

Inter-day balance equations

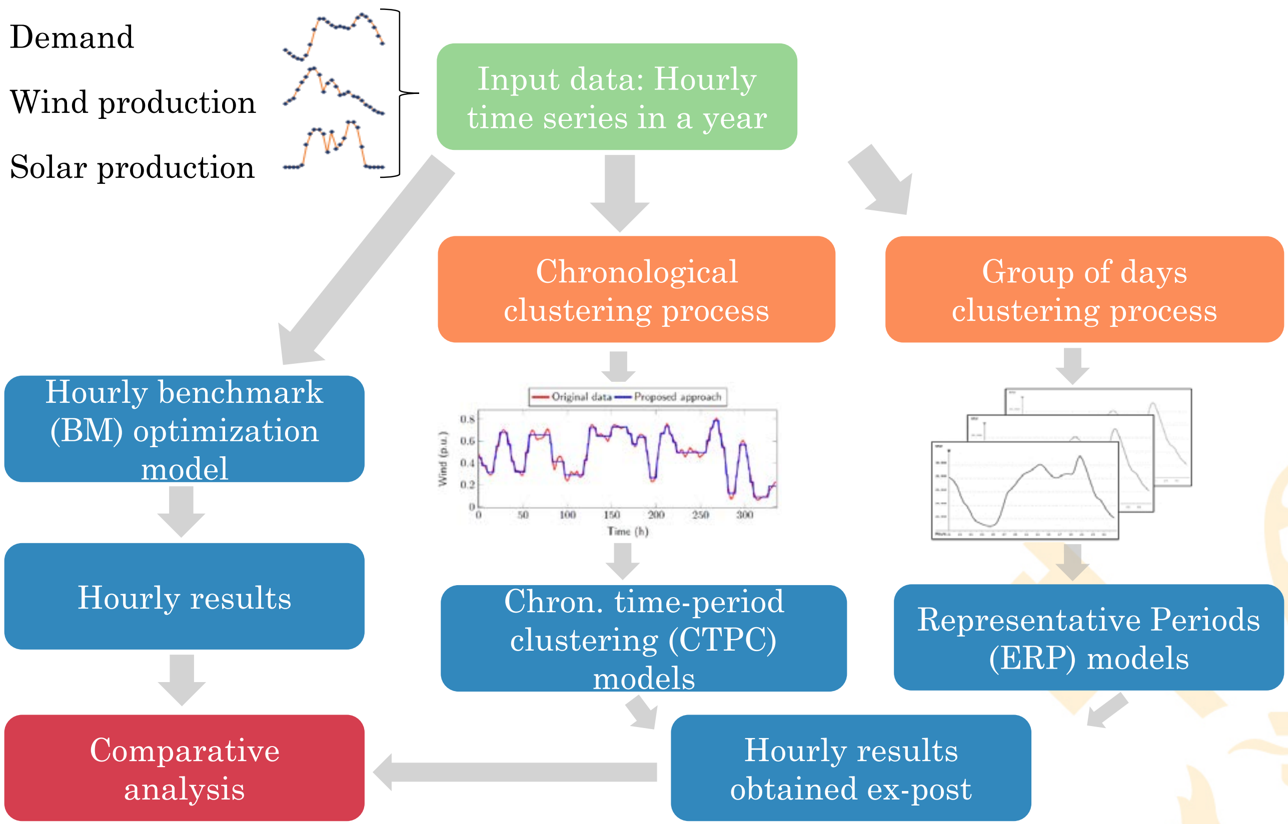
$$storage_{h=168} = storage_{h=0} + 5\sum_{i}^{24}(charge_{rp1\_i} - discharge_{rp1\_i}) + 2\sum_{i}^{24}(charge_{rp2\_i} - discharge_{rp2\_i})$$

$$storage_{h=336} = storage_{h=168} + \cdots$$

Outline

CASE
STUDIES

CTPC versus ERP



Case Data

- Stylized version of Spanish power system
- Thermal technologies (nuclear, coal, CCGTs, OCGTs, fueloil)
- Storage technologies (hydro, BESS)
- Renewable technologies (wind 25%, solar 12%) 37% of total demand
- Time horizon: 1 year (8760 hours)
- ERP and CTPC approximate the hourly benchmark (BM) with same number of binaries.

General comparison

- BM takes **6 hours**, and CTPC/ERP only **minutes**
- Objective function is approximated with **-1.8% (CTPC)** and **2.8% (ERP)** error

	BM	CTPC	ERP
Obj. function [M€]	673.77	685.87	655.43
CPU time (s)	21605.11	842.48	47.10

Total generation per technology

	BM	CTPC	ERP
Nuclear	6586.38	6319.40	6740.70
FuelOilGas	0.00	0.00	0.00
BESS	376.21	142.52	336.74
Wind	7773.73	7734.73	7813.55
Solar	3907.78	3834.41	3921.87
Coal	329.68	99.38	74.38
CCGT	11314.56	11836.96	11331.04
OCGT	153.16	230.70	182.13
Hydro	1545.15	1545.15	1545.15

ERP observes no renewable spillage since it does not consider all individual hours. CTPC captures this.

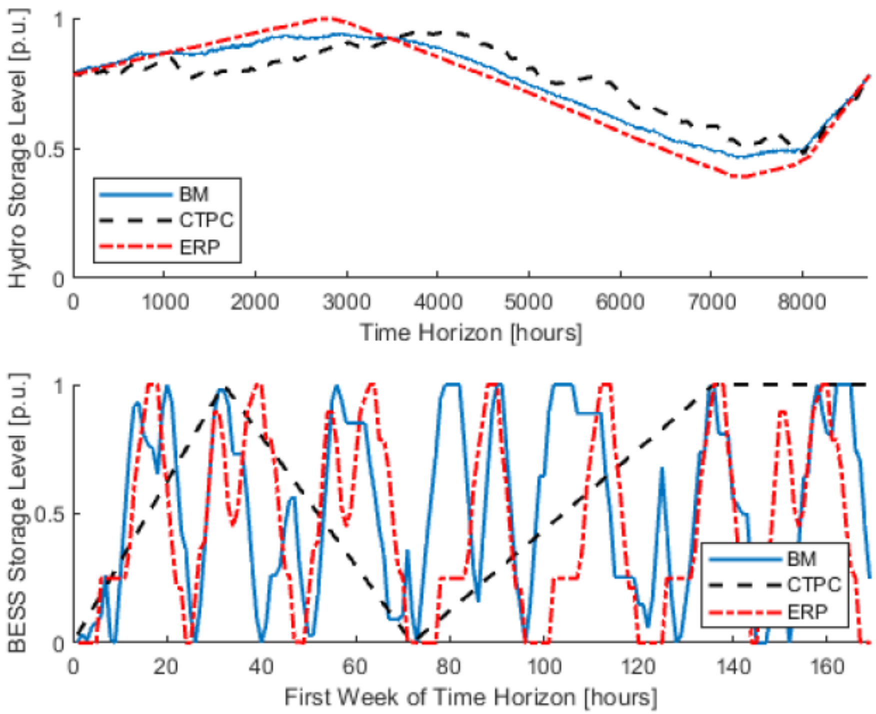
Thermal base load is approximated well by both.

Coal and OCGT have higher error (happens fewer hours).

BESS is approximated well by ERP.

comillas.edu

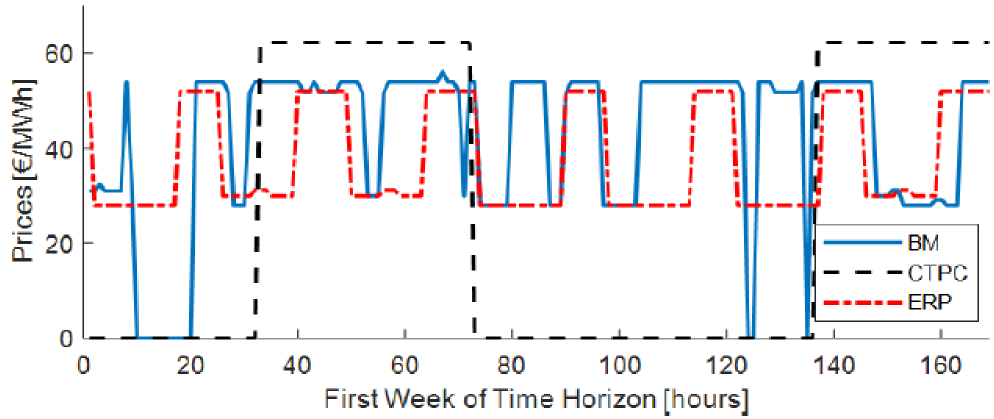
Storage results



- **Hydro** is approximated well by CTPC and ERP
- **BESS** has 10% error with ERP, and 60% with CTPC.
- These results depend on the length of **storage cycle**.

Price results

Since CTPC does not mimic daily patters its MSE is higher.



	BM	CTPC	ERP
Avg. annual price [€/MWh]	48.04	45.56	43.28
Avg. abs. error [€/MWh]	-	19.79	12.14
Avg. error [€/MWh]	-	2.47	4.76
MSE [$(€/MWh)^2$]	-	23108	22810

Average price and error are better under CTPC

Renewable sensitivity analysis

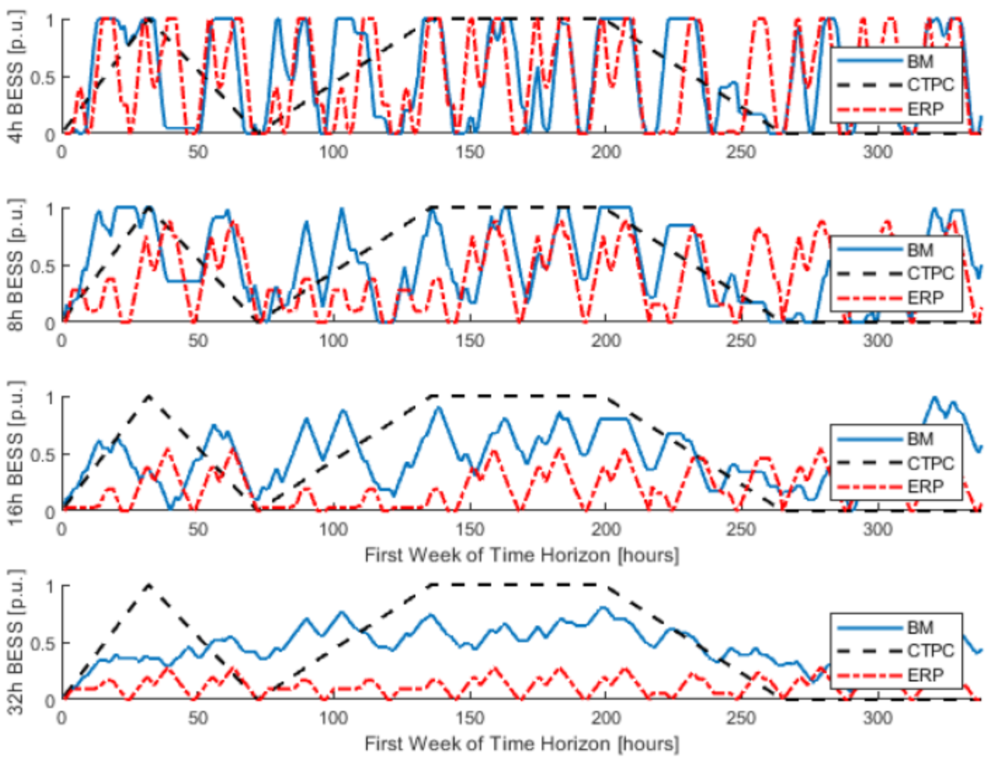
Wind
only case

- CTPC (ERP) slightly over(under)-estimates total system cost
- CTPC under-estimates BESS production
- ERP over-estimates nuclear and CCGT production

Solar
only case

- Solar energy has a strong daily pattern, which is difficult to capture under CTPC

Storage cycle sensitivity analysis



ERP approximates BESS well when the length of cycle is relatively small.

ERP has problems to approximate BESS whose discharge cycle is beyond 24h.

Investment results preliminary (rMIP)

[MW]	BM	CTPC	ERP
BESS	214.03	0.00	164.75
Wind	4891.25	4826.27	5655.20
Solar	947.00	3385.94	765.46
CCGT	3490.65	1752.40	2865.84
OCGT	2699.70	1933.58	373.23

CTPC does not predict BESS investment.

ERP over-estimates Wind investment (no wind spillage).

CTPC grossly over-estimates Solar production.

ERP fails to capture OCGT (due to Wind over-production)

comillas.edu

Outline

CONCLUSIONS

Conclusions and future work

We have compared to time-period approx. methods: CTPC and ERP

ERP is slighly faster and better predicts BESS.

CTPC has slighly better objective function, and obtains better average market prices.

Extend these studies to MIP expansion problems

Develop a hybrid method to combine advantages of both methods.

https://stexem.iit.comillas.edu/

Questions?

Sonja Wogrin
Sonja.Wogrin@comillas.edu

This work was partially supported by project grant ENE2016-79517-R awarded by the Spanish Ministerio de Economía y

GOBIERNO DE ESPAÑA
MINISTERIO DE ECONOMÍA, INDUSTRIA Y COMPETITIVIDAD