

Machine-learning aided operation and planning of power systems

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About Málaga



- Over 300 sundays per year (known as Costa del Sol)
- University of Málaga was established in 1972 and currently has 40000 students and 2500 faculty members
- Málaga is becoming the Silicon Valley of the south of Spain
- Andalusia Technology Park includes over 600 companies (Oracle, Ericsson, IBM, TDK, Huawei, Microsoft, Cisco), 20.000 employees and a turnover of 2.000 M€ in 2018

Google To Open A Cybersecurity 'Centre Of Excellence' In Malaga

About OASYS

Optimization and Analytics for Sustainable energy Systems (2018)

- 3 professors
- 2 Postdoc
- 4 PhD students
- 2 research assistants
- 1 support assistant



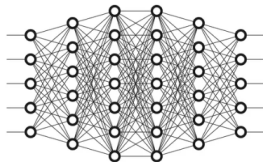
Research topics:

- Mathematical models for decision-making under uncertainty
- Use of large amounts of data for Smart Energy Grids
- Forecasting and optimization for Sustainable Energy Systems
- Algorithms to solve large-scale optimization problems
- Game theory for the analysis of energy markets

More info: oasys.uma.es

Machine learning in power systems

- The blast wave of machine learning has reached power systems
- Most papers propose black-box tools that run as follows:
 - Select a very hard problem to solve (usually NP-hard)
 - Set hyperparameters $\mu, \epsilon_0, \alpha, \beta, \lambda, \dots$ (without explaining how)
 - Train a deep neural network (using available software)



- Discuss the computational savings of the proposed learning-based method with that of solving the original problem

Questions we want to address

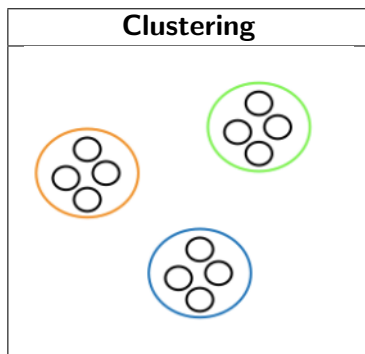
- Are power system problems so complex that any fortuitous learning-based method may involve significant computational savings?
- Do simpler and interpretable learning-based methods perform similarly to complex black-box methods?
- Should black-box methods be benchmarked against simpler methods in power systems applications?

Applications

- Application 1: capacity expansion planning
- Application 2: screening of network constraints
- Application 3: coordination of TSO and DSO
- Application 4: learning unit commitment

Application 1: Capacity expansion planning¹

Capacity expansion problem	
Horizon	1 year
Obj	Min prod+inv cost
Var	Generation capacities Line capacities
Con	Generation = Demand Unit technical limits Line technical limits

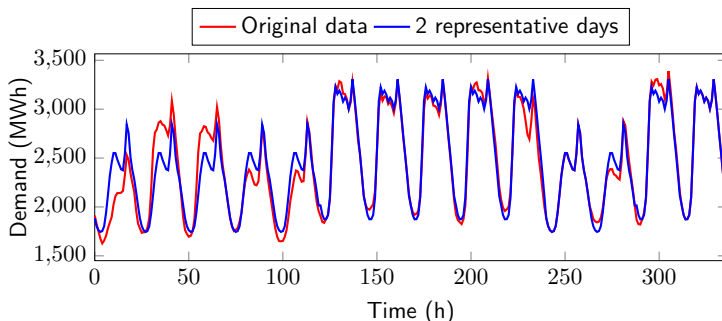


AIM
Reduce the computational burden of capacity planning problems with renewables and storage

¹S. 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, 2018

Application 1: Capacity expansion planning

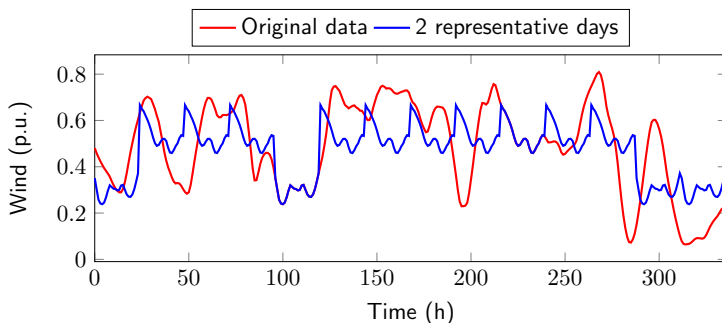
- Electrical demand shows strong daily, weekly and annual patterns and therefore, using representative days works quite well



- Instead of 14 days (336 h), we use 2 representative days (48 h)
- Computational burden is reduced
- Day-to-day chronology information is lost

Application 1: Capacity expansion planning

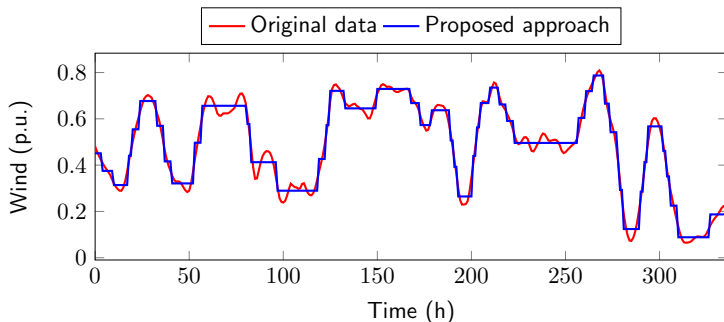
- Some renewables do not present a strong daily pattern



- Energy stored can be used several days later (**seasonal storage**)
- Crucial to overcome the “dark calm” periods in central Europe
- Seasonal storage cannot be modeled using representative days



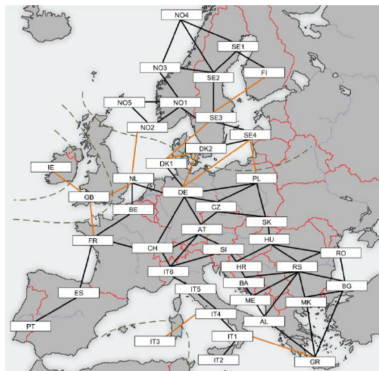
- We propose a new clustering methodology to group **consecutive hours** and maintain chronology
- Wind is approximated more accurately



- Seasonal storage can be properly modeled
- Computational burden is reduced
- Day-to-day chronology information is kept

Application 1: Capacity expansion planning

- Electric power system (28 countries) for 2030 (single target year)
- Investments in conventional and renewable generation, transmission lines and two storage technologies (intraday and interday)
- Greenfield approach (no initial capacities)
- Given renewable penetration target



Application 1: Capacity expansion planning

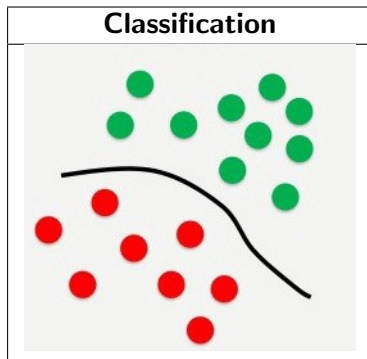
- Average cost increase over all renewable penetration levels.

Approach	Number periods	Av. cost increase	Time
F	8760	0 %	~ 10 h
D-28	$28 \times 24 = 672$	13.1 %	~ 100 s
W-4	$4 \times 168 = 672$	48.1 %	~ 100 s
C-672	672	6.1 %	~ 100 s

- The proposed approach is the closest to the full model

Application 2: Screening of network constraints²

Unit Commitment Problem	
Horizon	24 hours
Obj	Min production cost
Var	On/off status (binary) Power dispatch
Con	Generation = Demand Unit technical limits Line technical limits



AIM
Reduce the computational time of the unit commitment problem by screening out transmission capacity constraints

²S. Pineda, J.M. Morales, A. Jiménez-Cordero (2020), "Data-Driven Screening of Network Constraints for Unit Commitment," IEEE Transactions on Power Systems 35(5):3695-3705.

Application 2: Screening of network constraints

The unit commitment problem can be generally formulated as follows:

$$\min_{p,u} \quad c^\top p \quad (1a)$$

$$\text{s.t.} \quad \mathbf{1}^\top p = \mathbf{1}^\top d \quad (1b)$$

$$u\bar{p} \leq p \leq u\bar{p} \quad (1c)$$

$$-\bar{f} \leq \text{PTDF}(p - d) \leq \bar{f}, \quad (1d)$$

$$u \in \{0, 1\} \quad (1e)$$

We compare six different methods to remove some constraints (1d)

Application 2: Screening of network constraints

Benchmark

- No network constraints are removed (Extremely high time)

Single-bus

- All network constraints are removed (Very fast)

Naive

- It removes line constraints that have not been congested in the past

Constraint generation

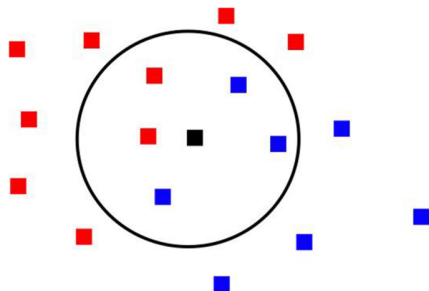
- It solves the single-bus UC and iteratively adds violated constraints

Bounding (optimization-based)

- It computes the maximum feasible flow through all lines
- It only removes redundant constraints

Data-driven method (DD)

- Line congestion is inferred via statistical learning
- No need for solving additional optimization problems
- It removes not only redundant but also inactive constraints
- K -nearest neighbors is used for its simplicity and interpretability
- It can be combined with constraint generation to ensure feasibility



■ → Line is congested

■ → Line is not congested

■ → Line is assumed to be congested

Application 2: Screening of network constraints

- Power system in Texas with 2000 buses and 3206 lines
- Electricity demand at each bus is randomly sampled from a uniform distribution between 0 and twice the nominal demand
- 10% of the lines become congested during the year, and the line that most often gets congested reaches its capacity limit during 4000 hours
- 300 instances for training and 60 for testing

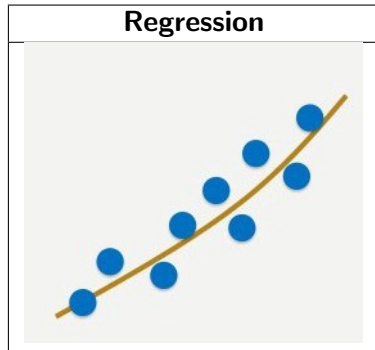
Application 2: Screening of network constraints

Method	Removed(%)	$\Delta\text{cost}(\%)$	Infes(%)	Time(%)
Benchmark	0.0	0.00	0.00	100.0
Single-bus	100.0	-2.17	0.26	0.4
Naive	92.3	0.00	0.00	10.6
ConGen	98.8	0.00	0.00	8.9
Bounding	54.3	0.00	0.00	64.7
Data-Driven	98.6	0.04	0.03	2.3
DD+CG	98.5	0.00	0.00	5.3

- Single-bus approach is fast but provides catastrophic results
- Naive removes 92% of constraints and achieves the optimal solution
- ConGen removes a lot of constraints but requires high time
- Bounding only removes 54% of constraints and limits time reduction
- Data-Driven removes most constraints but involves small infeasibilities
- DD+CG recovers the original solution at lowest time

Application 3: coordination of TSO and DSO³

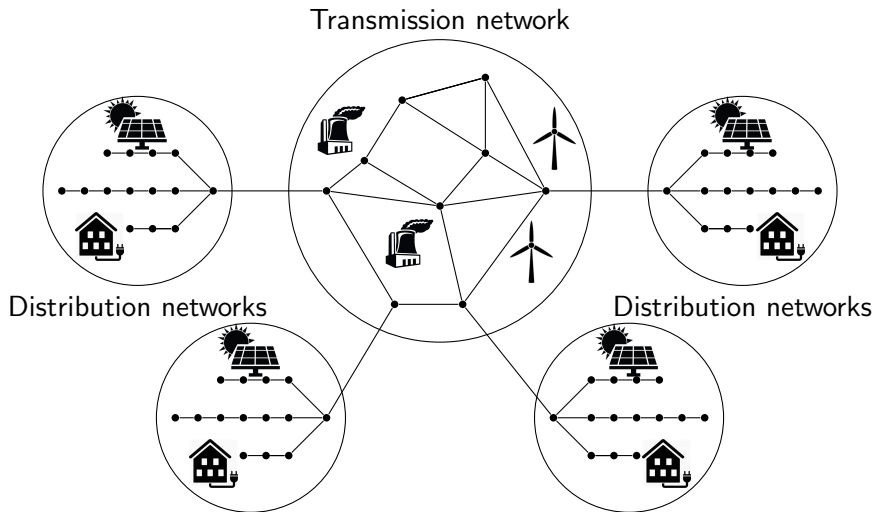
TSO-DSO coordination	
Horizon	1 hour
Obj	Min production cost
Var	Power dispatch Substation operation
Con	Generation = Demand Unit technical limits Line technical limits



AIM
Facilitating TSO-DSO coordination by learning the response of distribution networks using contextual information

³J. M. Morales, S. Pineda, Y. Dvorkin, "Learning-based Coordination of Transmission and Distribution Operations" IEEE Transactions on Power Systems, 2022.

Application 3: coordination of TSO and DSO



Application 3: coordination of TSO and DSO

Benchmark

- Full representation of transmission and distribution networks.
- A single entity treasures all the info.
- Very high computational time.

Single-bus approach (SB)

- All network constraints of DNs are ignored.
- Very low computational time.
- Good results only for uncongested DNs.

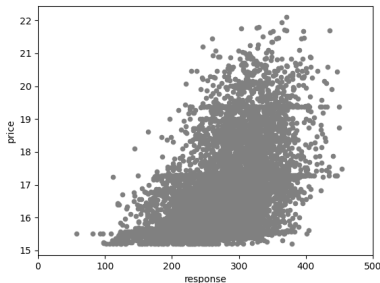
Price-agnostic approach (PAG)

- It assumes that the response of DNs is independent of price.
- It forecasts the expected response of DNs under the current context.
- Good results only for inflexible distributed generators and consumers.

Application 3: coordination of TSO and DSO

Contextual price-aware approach (PAW)

- 1) For each DN, we have access to price-response historical data



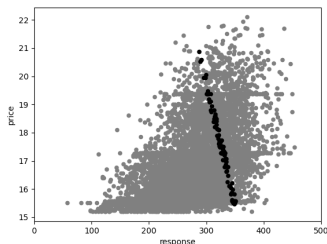
- 2) For a given context, we select the closest price-response pairs
- 3) We approximate the data using a step-wise non-increasing function
- 4) We operate the TN using the step-wise functions

Application 3: coordination of TSO and DSO

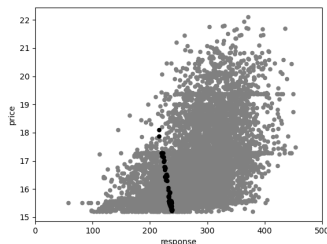
Contextual price-aware approach (PAW)

- 1) For each DN, we have access to price-response historical data
- 2) For a given context, we select the closest price-response pairs

Afternoon



Night

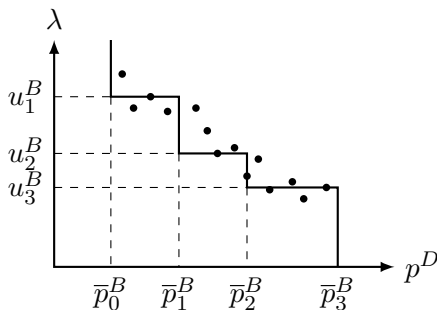


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Application 3: coordination of TSO and DSO

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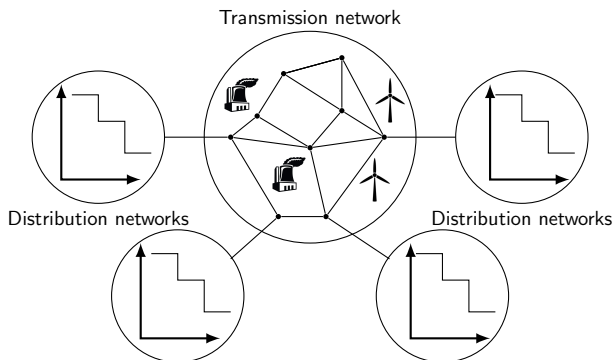
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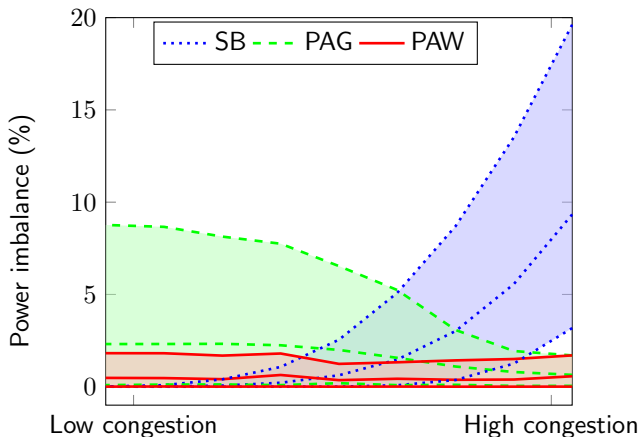
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Application 3: coordination of TSO and DSO

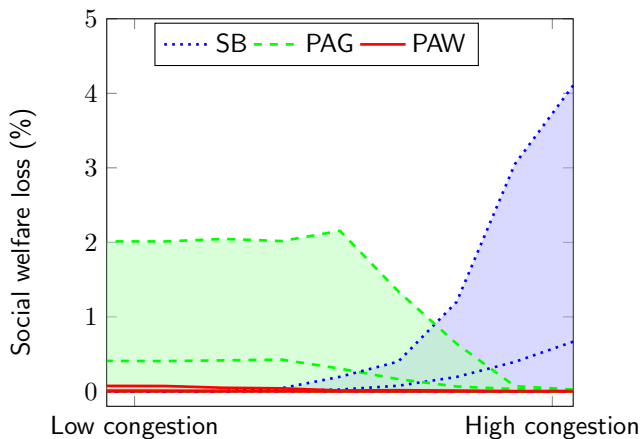
- Transmission network with 118 buses and 186 lines.
- 91 distribution networks with 32 buses and 32 lines each.
- DN include flexible consumers and solar power units.
- DN parameters are varied to simulate different congestion levels.
- 8760 hours for training and 100 hours for testing.

Application 3: coordination of TSO and DSO



- SB works for low congestion since network can be disregarded
- PAG works for high congestion since response is independent of price
- PAW works for low and high congestion. Average imbalance $< 0.7\%$

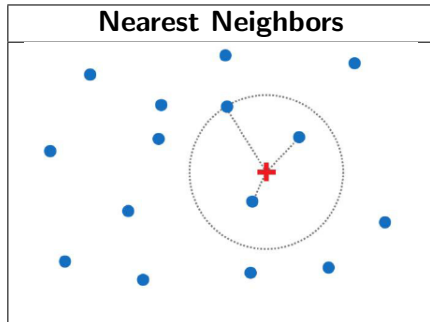
Application 3: coordination of TSO and DSO



- Maximum loss for SB and PAG are 2% and 4%, respectively
- Maximum loss for PAW is 0.1%

Application 4: learning unit commitment⁴

Unit Commitment Problem	
Horizon	24 hours
Obj	Min production cost
Var	On/off status (binary) Generating dispatches
Con	Generation = Demand Unit technical limits Line technical limits



AIM
Leverage past unit commitment solutions to solve new instances of the problem

⁴S. Pineda, J. M. Morales, "Is learning for the unit commitment problem a low-hanging fruit?", Electric Power Systems Research, vol. 207, 2022



We propose a naive K -nearest neighbor procedure:

- Find the K past UC instances that are closest to the new one in terms of the net demand profile.
- Solve K linear problems (LP) obtained by fixing the binary variables to those of the closest neighbors.
- From the K candidate solutions, keep the one with the lowest cost.

Application 4: learning unit commitment

System	Av. error (%)	Max error (%)	< 0.01%	# Infes	Speedup
1888rte	0.0174	0.2394	230	1	116.5x
1951rte	0.0382	0.3759	47	8	150.4x
2848rte	0.0186	0.1332	179	2	132.6x
3012wp	0.0485	0.4864	37	5	188.8x
3375wp	0.1256	0.8073	9	13	215.9x
6468rte	-0.0001	0.0175	498	0	41.2x
6470rte	-0.0016	0.0187	496	0	171.9x
6495rte	-0.0001	0.0481	496	0	41.0x
6515rte	-0.0009	0.0133	497	0	101.7x

- 500 instances, leave-one-out
- $K = 50$
- MIP gap = 0.01%

Application 4: learning unit commitment

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- No need for complicated learning techniques for these systems, as naive strategies involve time reductions with negligible errors.
- For these systems, the naive learning strategy involves errors slightly higher than the set MIP gap, but with substantial time reductions.
- For these systems, the naive approach involves higher errors and some infeasible cases. Thus, other learning approaches may be required.

Application 4: learning unit commitment

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Questions we want to address

- Are power system problems so complex that any fortuitous learning-based method may involve significant computational savings?

Yes, specially in combinatorial problems like UC

- Do simpler and interpretable learning-based methods perform similarly to complex black-box methods?

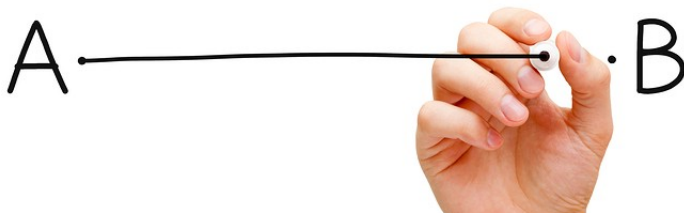
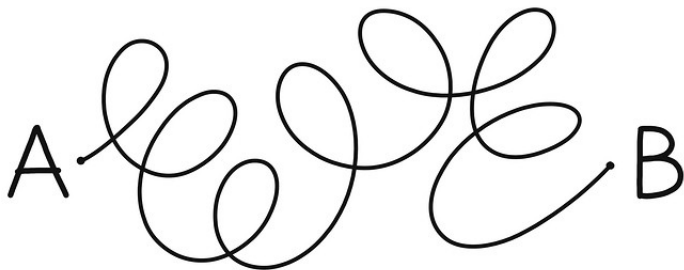
Yes, depending on problem structure and data

- Should black-box methods be benchmarked against simpler methods in power system applications?

Yes. Otherwise, irrelevant publications will continue

Takeaway message

In many cases the simplicity of less is more



Thanks for the attention!

Questions?



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