Machine-Learning-aided Optimal Transmission Switching

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Outline

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Mathematical Optimization

Machine Learning

Combine knowledge from both worlds

Recent reviews: *Bengio et al. [2021]; Gambella et al. [2021]*

Mathematical Optimization

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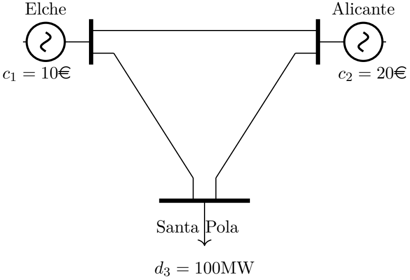
Power Systems Operations

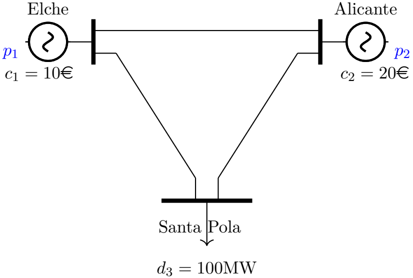
Optimal Transmission Switching (OTS)

Optimal Power Flow (OPF)



Optimal Transmission Switching (OTS)

Optimal Power Flow (OPF)



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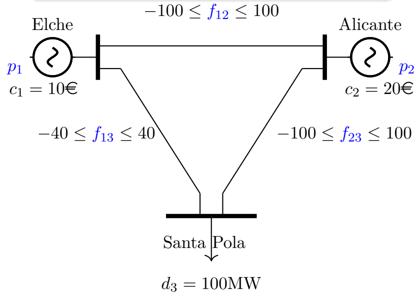

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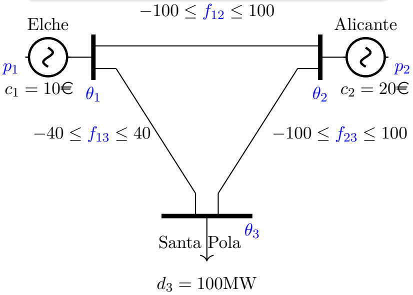

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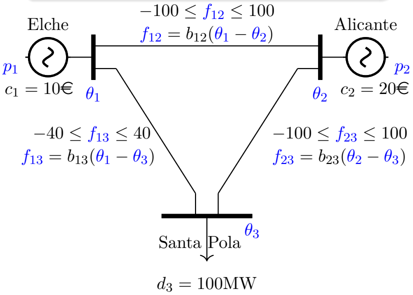

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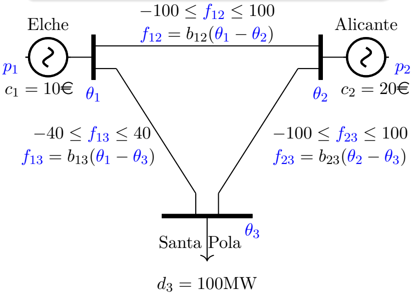

- Balance constraints.
- Assume $b_{nm} = 1, \forall (n, m)$.
- Minimizing costs. $Cost^* = 1800€$.
- $p_1^* = 20$, $p_2^* = 80$.
- $\theta_1^* = 40$, $\theta_2^* = 60$, $\theta_3^* = 0$.
- $f_{12}^* = -20$, $f_{13}^* = 40$, $f_{23}^* = 60$.

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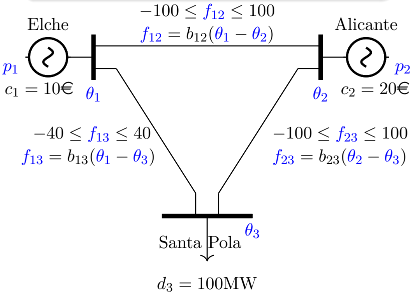

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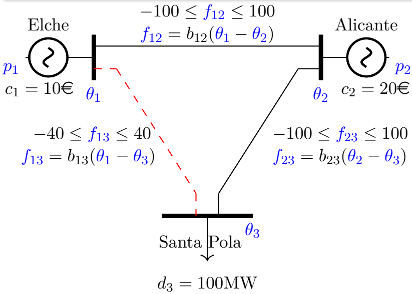
Optimal Transmission Switching



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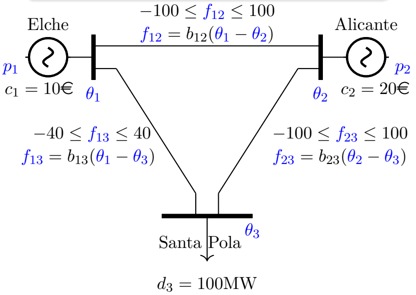

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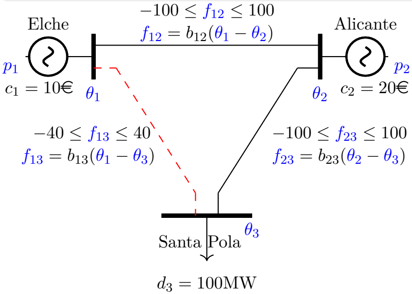
Optimal Transmission Switching



- Switchable lines, $\mathcal{L}_S$.
- Binary variables $x_{nm}, \forall (n,m) \in \mathcal{L}_S$.
- Minimizing costs. $Cost^* = 1000€$.
- $p_1^* = 100$, $p_2^* = 0$.
- $\theta_1^* = 200$, $\theta_2^* = 100$, $\theta_3^* = 0$.
- $f_{12}^* = 100$, $f_{13}^* = 0$, $f_{23}^* = 100$.

Optimal Transmission Switching (OTS)

$$
\begin{cases}
\min\limits_{p_n, f_{nm}, \theta_n, x_{nm}} & \sum_n c_n\, p_n \\
\text{s.t.} & \underline{p}_n \leq p_n \leq \overline{p}_n, \quad \forall n \in \mathcal{N} \\
& \sum_{(n,m)\in\mathcal{L}_n^-} f_{nm} - \sum_{(n,m)\in\mathcal{L}_n^+} f_{nm} = p_n - d_n, \quad \forall n \in \mathcal{N} \\
& f_{nm} = x_{nm} b_{nm}(\theta_n - \theta_m), \quad \forall (n,m) \in \mathcal{L}_\mathcal{S} \\
& -x_{nm}\overline{f}_{nm} \leq f_{nm} \leq x_{nm}\overline{f}_{nm}, \quad \forall (n,m) \in \mathcal{L}_\mathcal{S} \\
& f_{nm} = b_{nm}(\theta_n - \theta_m), \quad \forall (n,m) \in \mathcal{L} \setminus \mathcal{L}_\mathcal{S} \\
& -\overline{f}_{nm} \leq f_{nm} \leq \overline{f}_{nm}, \quad \forall (n,m) \in \mathcal{L} \setminus \mathcal{L}_\mathcal{S} \\
& x_{nm} \in \{0,1\}, \quad \forall (n,m) \in \mathcal{L}_\mathcal{S} \\
& \theta_1 = 0
\end{cases}
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& x_{nm} \in \{0,1\}, \quad \forall (n,m) \in \mathcal{L}_{\mathcal{S}} \\
& \theta_1 = 0
\end{cases}
$$

- MINLP because $x_{nm}(\theta_n - \theta_m)$.
- NP-hard problem.

Optimal Transmission Switching (OTS)

Original constraint

$$f_{nm} = x_{nm} b_{nm}(\theta_n - \theta_m)$$

Reformulation using big-Ms

$$b_{nm}(\theta_n - \theta_m) - \overline{M}_{nm}(1 - x_{nm}) \leq f_{nm} \leq b_{nm}(\theta_n - \theta_m) - \underline{M}_{nm}(1 - x_{nm})$$

Optimal Transmission Switching (OTS)

How to compute bigM values?

$$\underline{M}_{nm} \leq \underline{M}_{nm}^{\text{OPT}} := b_{nm} \times \min_{x_{nm}=0} (\theta_n - \theta_m)$$

$$\overline{M}_{nm} \geq \overline{M}_{nm}^{\text{OPT}} := b_{nm} \times \max_{x_{nm}=0} (\theta_n - \theta_m)$$

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- Computing optimal bigM values is as hard as solving the original problem, [Fattahi et al., 2019].
- We have to be happy with bounds.
- **Objective:** Find good bounds for bigMs.

Outline

Strategy 1, BEN

- Exact approach.
- Benchmark.
- Shortest path problem (Dijkstra).
- [Fattahi et al., 2019].

$$-\underline{M}_{nm} = \overline{M}_{nm} = b_{nm} \sum_{(k,l)\in \mathrm{SP}_{nm}} \frac{\overline{f}_{kl}}{b_{kl}}, \quad \forall (n,m) \in \mathcal{L}_{\mathcal{S}}$$

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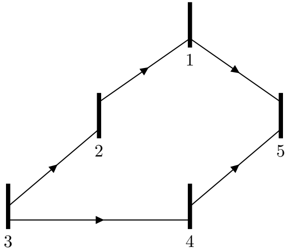

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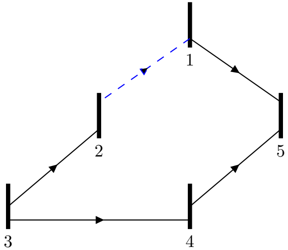

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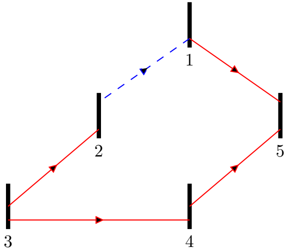

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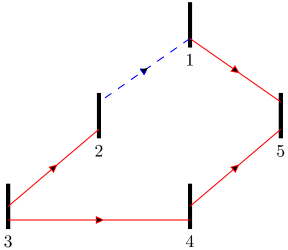

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$$f_{23} \leq \overline{f}_{23} \implies b_{23}(\theta_2 - \theta_3) \leq \overline{f}_{23} \implies (\theta_2 - \theta_3) \leq \overline{f}_{23}/b_{23}$$

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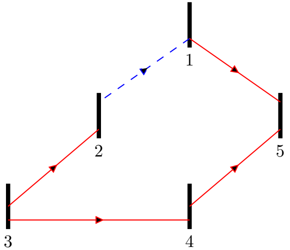

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$(\theta_2 - \theta_1) \leq \overline{f}_{23}/b_{23} + \overline{f}_{34}/b_{34} + \overline{f}_{45}/b_{45} + \overline{f}_{51}/b_{51}$

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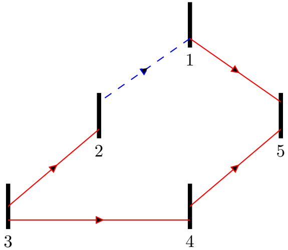

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$$(\theta_2 - \theta_1) \leq \overline{f}_{23}/b_{23} + \overline{f}_{34}/b_{34} + \overline{f}_{45}/b_{45} + \overline{f}_{51}/b_{51}$$

$$\overline{M}_{21} \geq b_{21}(\overline{f}_{23}/b_{23} + \overline{f}_{34}/b_{34} + \overline{f}_{45}/b_{45} + \overline{f}_{51}/b_{51})$$

Strategy 2, Knn-D

- Data-driven approach (Knn).
- Naive approach. Learning this problem is a challenge.

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Algorithm

1) Training set $\mathcal{T} = \{(\mathbf{d}^t, \mathbf{x}^t)\}$ for $\forall t$.

2) For a given test demand $\mathbf{d}^{\hat{t}}$, compute K closest neighbors, $\mathcal{T}_K$.

3) Binary $\mathbf{x}^{\hat{t}}$ as the rounded mean of the binary decision values from $\mathcal{T}_K$ to the closest integer.

4) Solve an LP from the OTS by fixing variables.

Strategy 3, Knn-BM

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- One of our proposals.

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4) The bigM values of the remaining variables are updated using the shortest path.

5) Solve the resulting MILP.

Strategy 4, Knn-B$\widehat{M}$

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$$\overline{M}_{nm} = b_{nm} \times \max_{t \in \mathcal{T}:\, x^t_{nm}=0} (\theta^t_n - \theta^t_m)$$

$$\underline{M}_{nm} = b_{nm} \times \min_{t \in \mathcal{T}:\, x^t_{nm}=0} (\theta^t_n - \theta^t_m)$$

5) Solve the resulting MILP.

Outline

Experimental Setup

- Realistic network, [Blumsack, 2006].
- 118 buses - 186 lines.
- $|\mathcal{L}_S| = 69$.
- 500 instances.
- Demand follows uniform distribution in $[0.9d_n, 1.1d_n]$.
- Gurobi 9.1.2.
- Gap $= 0.01\%$.
- Time limit: 1 hour.
- Github.

Comparison

	# opt	# sub	gap-max	time (s)
BEN	500	0	-	145.44
Knn-D	0	500	14.13	0.0
Knn-BM	500	0	-	12.33
Knn-B$\widehat{\text{M}}$	495	5	0.39	0.7

Table: All approaches ($K = 50$)

Comparison

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Table: All approaches ($K = 50$)

BEN vs Knn-D

- Knn-D has no optimal instances.
- Knn-D is faster.
- Max gap: 14%

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Table: All approaches ($K = 50$)

BEN vs Knn-BM

- All optimal instances
- Knn-BM is faster.
- No gap.

Comparison

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Table: All approaches ($K = 50$)

BEN vs Knn-B$\widehat{M}$

- Knn-B$\widehat{M}$ has almost all optimal instances
- Knn-B$\widehat{M}$ is very fast.
- Small gap.

Comparison

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Table: All approaches ($K = 50$)

Knn-BM vs Knn-B$\widehat{M}$

- Knn-BM is more conservative than Knn-B$\widehat{\mathrm{M}}$ but slower.
- Trade-off decision.
- Competitive against existing approaches.

More details

Learning-Assisted Optimization for Transmission Switching

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Contributing authors: juan.morales@uma.es; asuncionjc@uma.es;

Available at:

S. Pineda, J. M. Morales and A. Jiménez-Cordero, Learning-Assisted Optimization for Transmission Switching, Submitted. Link: `https://www.researchgate.net/publication/370058669_Learning-Assisted_Optimization_for_Transmission_Switching`.

SCAN ME

Outline

Conclusions

- OTS is a challenging problem.
- Useful to reduce costs.
- Find good bigM values for the reformulation.
- Learning strategies.
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Further research

- All switchable lines.
- Other ML approaches.

References

Bengio, Y., Lodi, A., and Prouvost, A. (2021). Machine learning for combinatorial optimization: A methodological tour d'horizon. *European Journal of Operational Research*, 290(2):405–421, doi:10.1016/j.ejor.2020.07.063.

Blumsack, S. (2006). *Network topologies and transmission investment under electric-industry restructuring*. Carnegie Mellon University, Pittsburgh, Pennsylvania.

Fattahi, S., Lavaei, J., and Atamtürk, A. (2019). A bound strengthening method for optimal transmission switching in power systems. *IEEE Transactions on Power Systems*, 34(1):280–291, doi:10.1109/TPWRS.2018.2867999.

Gambella, C., Ghaddar, B., and Naoum-Sawaya, J. (2021). Optimization problems for machine learning: A survey. *European Journal of Operational Research*, 290(3):807–828, doi:10.1016/j.ejor.2020.08.045.

Hastie, T., Tibshirani, R., Friedman, J. H., and Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction*, volume 2. Springer, New Yourk.

Hinneck, A. and Pozo, D. (2022). Optimal transmission switching: improving exact algorithms by parallel incumbent solution generation. *IEEE Transactions on Power Systems*.

Lodi, A. and Zarpellon, G. (2017). On learning and branching: A survey. *TOP*, 25(2):207–236, doi:10.1007/s11750-017-0451-6.

Ruiz, P. A., Goldis, E., Rudkevich, A. M., Caramanis, M. C., Philbrick, C. R., and Foster, J. M. (2016). Security-constrained transmission topology control milp formulation using sensitivity factors. *IEEE Transactions on Power Systems*, 32(2):1597–1605.

Yang, Z. and Oren, S. (2019). Line selection and algorithm selection for transmission switching by machine learning methods. In *2019 IEEE Milan PowerTech*, pages 1–6. IEEE.

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Thank you very much for your attention!

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