Contextual merit-order dispatch under uncertain supply

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October 2021

Decision making under uncertainty in Power Systems

- Decision making under **uncertainty** plays an important part in **Power Systems**

- Still today one of the most **common practices** is the "**Predict, then Optimize**" framework:

$\{x_i, y_i\}_{i \in \mathcal{N}}$ (data set) $\Rightarrow$ Forecasting model $\Rightarrow$ $\hat{y}$ (estimate) $\Rightarrow$ Optimization problem (deterministic) $\Rightarrow$ $\hat{z}$ (decision)

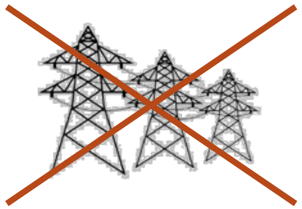
- This is an **approximation** of the **stochastic problem** but is **computationally less expensive**.

- Can be improved if the **forecasting model** <u>takes into account</u> the **optimization problem**.

A two stage electricity market

Demonstrative two-stage electricity market:

Forward market



(Economic Dispatch)

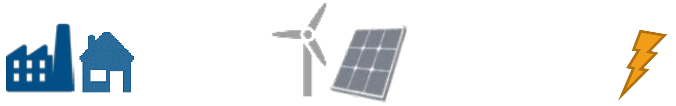
Real-time market

(Pipeline network model)

Demostrative framework characteristic:

- Reserve capacity is free but their use is not
- Max. reserve capacity fixed
- Stylized pipeline network model
- No wind spillage or load shedding
- No ramping or intertemporal constraints
- We consider Net Demand L (**uncertain**)

- The uncertainty is produced by the **unkown Net Demand** L
- This setup resembles some European markets



Demand – Renewable = Net Demand L

Forward and Real-time market models

Forward market model

(Economic Dispatch)

$$\min_{p_g, g\in G} \sum_{g\in G} C_g p_g$$

$$\text{s.t.} \quad \sum_{g\in G} p_g = \boxed{\widehat{L}}$$

$$0 \le p_g \le \overline{P}_g, \quad \forall g \in G$$

$\hat{L}$ is a point estimate

Real-time market model

$$\min_{\Xi} \sum_{g=1}^{G} (C_g^{\mathrm{u}} r_g^{\mathrm{u}} - C_g^{\mathrm{d}} r_g^{\mathrm{d}})$$

$$\text{s.t.} \quad 0 \le p_g^* + r_g^{\mathrm{u}} - r_g^{\mathrm{d}} \le \overline{P}_g, \quad \forall g \in G$$

$$0 \le r_g^{\mathrm{u}} \le R_g^{\mathrm{u}}, \quad \forall g \in G$$

$$0 \le r_g^{\mathrm{d}} \le R_g^{\mathrm{d}}, \quad \forall g \in G$$

$$\sum_{g\in G(b)} (p_g^* + r_g^{\mathrm{u}} - r_g^{\mathrm{d}}) = \sum_{d\in D(b)} L_{di} + \sum_{l:o(l)=b} f_l - \sum_{l:e(l)=b} f_l, \quad \forall b \in B$$

$$|f_l| \le \overline{F}_l, \quad \forall l \in \Lambda$$

Improving the framework

Forward market model

(Economic Dispatch)

$$\min_{p_g, g\in G} \sum_{g\in G} C_g p_g$$

$$\text{s.t.} \sum_{g\in G} p_g = \boxed{\hat{L}}$$

$$0 \le p_g \le \overline{P}_g, \quad \forall g \in G$$

$\hat{L}$ is a point estimate

$\{p_g\}_{g\in G}$ dispatch

Predict, then Optimize:

$\{x_i, L_i\}_{i\in\mathcal{N}}$ ⇨ Forecasting model ⇨ $\hat{L}^F$ ⇨ Economic dispatch (deterministic) ⇨ $\{p_g^F\}_{g\in G}$

historical data set — estimate (i.e. minimize **MSE**) — decision

Our target:

- Learn $\hat{L}$ as a linear function g(x) of the features: $\hat{L} = g(x) = \sum_j q^j x^j$
- When **learning** consider <u>both</u> **forward** and **real-time market** problems
- More specifically, we consider: $\hat{L}^P = \underline{q_0} + \underline{q_1}\hat{L}^F$

We learn the q

Contextual merit-order dispatch model (P-MC)

$$\min_{\mathbf{q},\Upsilon} \frac{1}{N}\sum_{i\in\mathcal{N}}\sum_{g\in G}(C_g p_{gi} + C_g^{\mathrm{u}} r_{gi}^{\mathrm{u}} - C_g^{\mathrm{d}} r_{gi}^{\mathrm{d}})$$

Minimize the total cost over the training set of N samples

Forward market

$$\text{s.t.} \quad \sum_{g\in G} p_{gi} = \widehat{L}_i, \quad \forall i \in \mathcal{N}$$

Forecast

$$\widehat{L}_i = q_0 + q_1 \boxed{\hat{L}_i^F}, \quad \forall i \in \mathcal{N}$$

Forward Energy balance

Real-time market

$$0 \le p_{gi} + r_{gi}^{\mathrm{u}} - r_{gi}^{\mathrm{d}} \le \overline{P}_{gi}, \quad \forall i \in \mathcal{N}, \quad \forall g \in G$$

$$0 \le r_{gi}^{\mathrm{u}} \le R_g^{\mathrm{u}}, \quad \forall i \in \mathcal{N}, \quad \forall g \in G$$

$$0 \le r_{gi}^{\mathrm{d}} \le R_g^{\mathrm{d}}, \quad \forall i \in \mathcal{N}, \quad \forall g \in G$$

Reserve constraints

True value

$$\sum_{g\in G(b)} (p_{gi} + r_{gi}^{\mathrm{u}} - r_{gi}^{\mathrm{d}}) = \sum_{d\in D(b)} \boxed{L_{di}} + \sum_{l:o(l)=b} f_{li} - \sum_{l:e(l)=b} f_{li}, \forall i \in \mathcal{N}, \forall b \in B$$

$$|f_{li}| \le \overline{F}_l, \quad \forall i \in \mathcal{N}, \quad \forall l \in \Lambda$$

Network constraints (pipeline)

$$u_{gi}\overline{P}_g \le p_{gi} \le u_{(g-1)i}\overline{P}_g, \quad \forall i \in \mathcal{N}, \quad \forall g \in G : g > 1$$

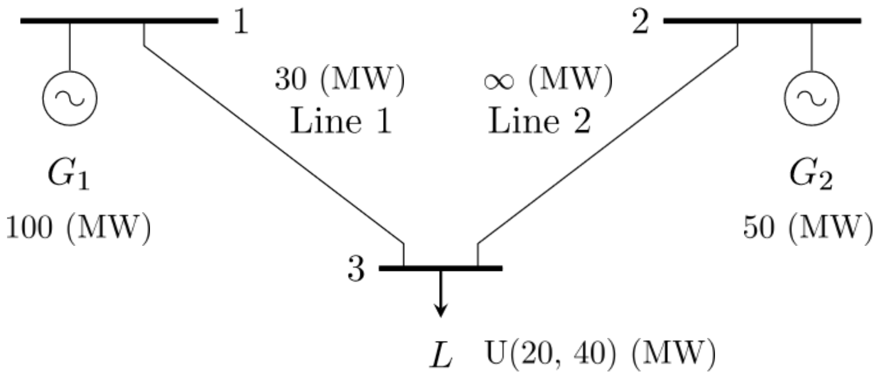
$$u_{gi}\overline{P}_g \le p_{gi} \le \overline{P}_g, \quad \forall i \in \mathcal{N}, \quad g = 1$$

$$u_{(g-1)i} \le u_{gi}, \quad \forall i \in \mathcal{N}, \quad \forall g \in G : g > 1$$

$$u_{gi} \in \{0,1\}, \quad \forall i \in \mathcal{N}, \quad \forall g \in G$$

Generator's merit order (cheaper first)

Toy example (I) introduction



	C	C^{u}	C^{d}
G_1	5	30	-20
G_2	15	20	10

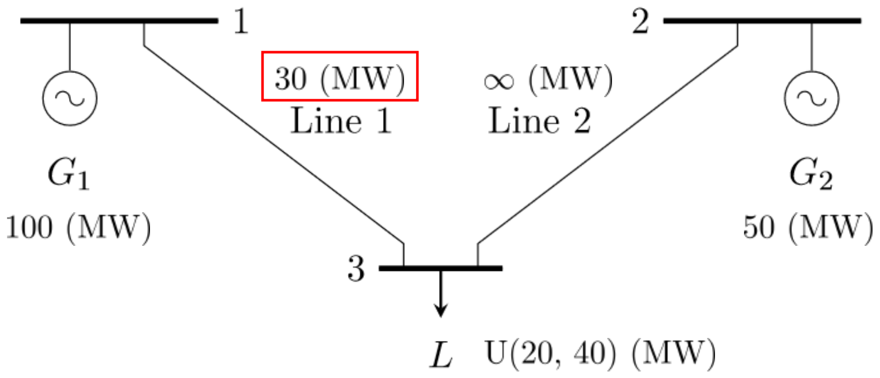
(€/ MW)

- Reserve up and down equals the max. capacity: $\overline{P} = R^{\mathrm{u}} = R^{\mathrm{d}}$
- We have available a **forecast** $\hat{L}^F$ that minimizes the **MSE**.
- We can use this **forecast as** the only **feature**: $x = \hat{L}^F$

Joint distribution $d(L^F, L)$

Probability (%)	L^F (MW)	L (MW)
50%	25	U(20, 30)
50%	35	U(30, 40)

Toy example (II) results



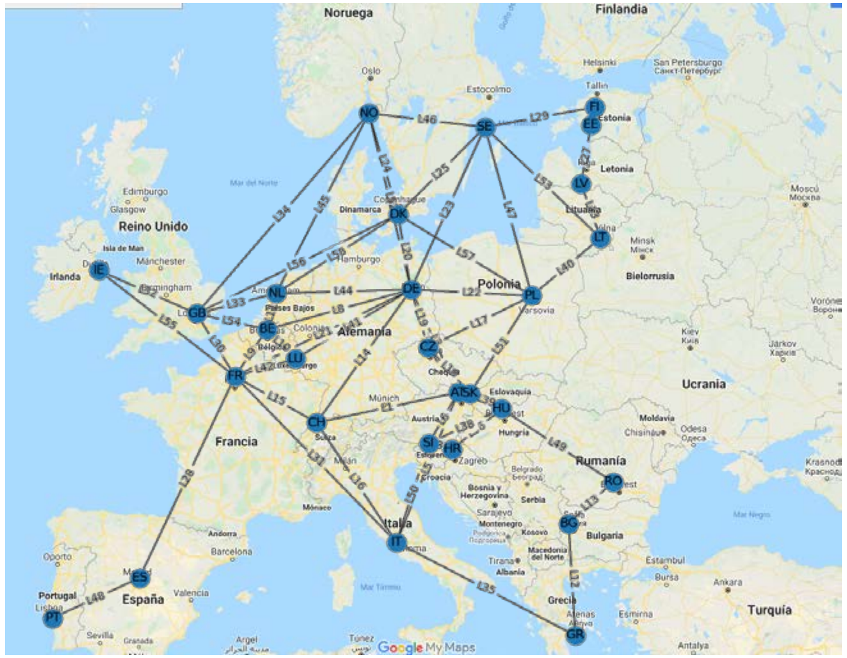
	C	C^{u}	C^{d}
G_1	5	30	-20
G_2	15	20	10

(€/ MW)

Probability (%)	$\hat{L}^F$ (MW)	L (MW)	$\hat{L}^P$ (MW)	Improvement %
50%	25	U(20, 30)	22.8	5.77%
50%	35	U(30, 40)	$\boxed{30.0}$	35.54%

- The minimizer of the **Mean Square Error** <u>is not the best estimator</u> under the "**Predict, then Optimize**" framework
- **P-MC** model produces an estimate L^P <u>tailored</u> to the two-stage market **optimization problem**.

Case study: stylized European network model



- Stylized **European pipeline network model**
- 28 nodes, 1 node per country
- Line and generation capacities from the report (*)
- 1 base and 1 peak dispatchable generator per node
    - **Base**: cheap non-flexible (Nuclear, Hard coal, Oil …*)
    - **Peak**: expensive but flexible (Natural Gas, Waste …*)
- Historical data of demand and renewables from entsoe
- We compute the aggregated net demand of the whole system
- Training / test set 100 / 50 samples, 10 different data sets

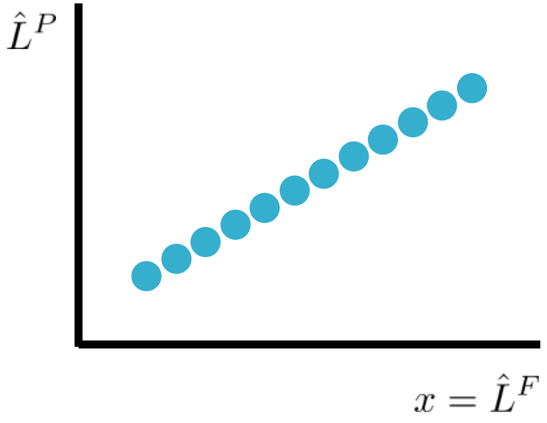
(*) Nahmmacher, P., Schmid, E., & Knopf, B. (2014). *Documentation of LIMES-EU – **A long-term electricity system model for Europe.*** Potsdam Institute of Climate Impact Research (PIK)

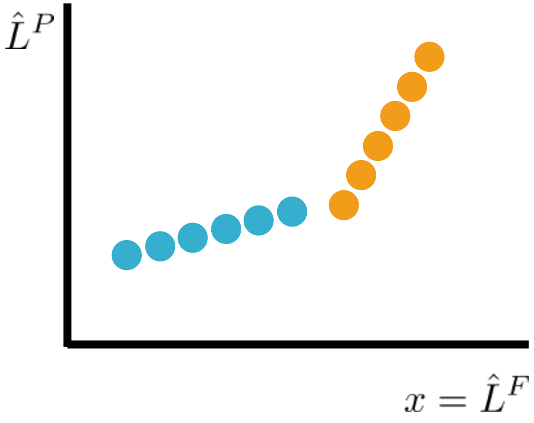
Clustering techniques to improve P-MC

$$\hat{L}_k^P = q_{0k} + q_{1k}\hat{L}^F$$

Technique 1:

K-Means
Euclidian distance



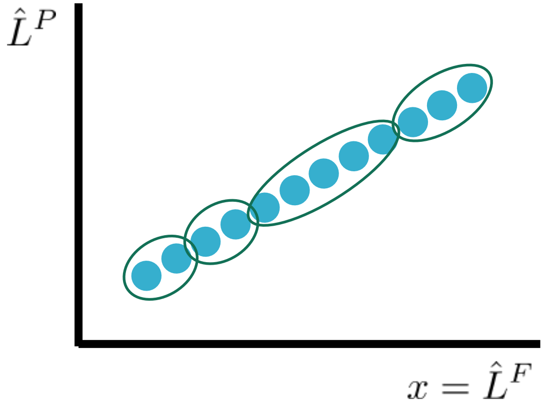


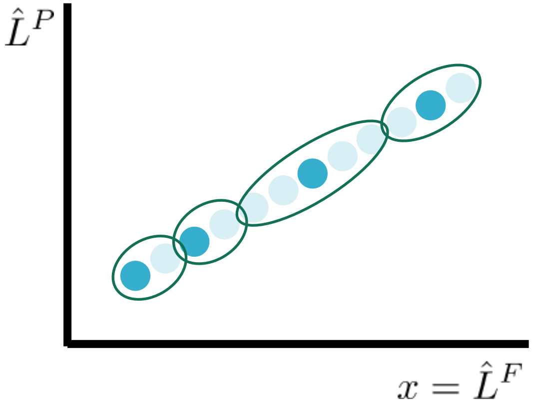
Split the data set in several subsamples

Increase flexibility

Techinique 2:

K-Medoids
PAM





Find the most representative samples

Reduce computational burden

Numerical results

We use as **benchmark** the aggregated forecast (**net demand**) issued by European TSOs (**F-MC**)

Cost saving results (%) (Improvement of P-MC)

k-Means

K		1	2	5	7
r k-Medoids	100%	2.83%	4.29%	4.74%	4.75%
	50%	2.67%	4.23%	4.39%	4.06%
	20%	2.38%	4.12%	4.12%	3.97%

Computational time P-MC (seconds)

1	2	5	7
2127.7	283.7	75.9	28.0
180.0	27.2	7.4	5.5
8.3	3.2	1.1	1.4

K: **number of clusters** the data set is divided in through k-Means

r: **sample reduction** through the k-Medoids technique

We achieve a sustantial cost reduction with respect to the F-MC benchmark

Conclusions

- Our model prescribe the net demand that a two-stage electricity market should clear in order to minimize the expected total cost of the system.
- Our simulations showcase the benefits of using several cluster techniques to face different operating points of the system.
- Numerical experiments conducted on a stylized model of the European electricity market reveal the cost savings implied by this approach are well above 2%.

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THANKS!

uma

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Checkout more at:

Morales, Juan M., **Miguel A. Muñoz**, and Salvador Pineda. *"Prescribing net demand for electricity market clearing."* arXiv preprint arXiv:2108.01003 (2021).

Acknowledgement: M. A. Muñoz is funded by the Spanish Ministry of Science, Innovation and Universities through the State Training Subprogram 2018 of the State Program for the Promotion of Talent and its Employability in R&D&I, within the framework of the State Plan for Scientific and Technical Research and Innovation 2017-2020 and by the European Social Fund.