Smart4RES

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Final conference

Paris, 14 April 2023

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

Session 4

Forecasting services and applications

13:30-15:20	**SESSION 4: FORECASTING SERVICES AND APPLICATIONS** Moderator: João Gonçalo Maciel, EDP NEW
	▪ **Towards data markets** P. Pinson (DTU/ Imperial College of London) ▪ **Privacy-preserving data-sharing for energy forecasting** C. Gonçalves (INESC TEC) ▪ **Uncertainty-aware booking of flexibilities in electrical grids** R. Bessa (INESC TEC) ▪ **Optimisation of operation and security assessment of isolated power systems with high RES penetration** D. Lagos (NTUA) ▪ **Trading strategies for RES production** S. Camal (MINES Paris) ▪ **Resilient energy forecasting and prescriptive analytics** A. Stratigakos (MINES Paris)
15:20-15:35	COFFEE BREAK
15:35-16:30	**PANEL – FUTURE CHALLENGES IN RES FORECASTING** Moderator: Gregor Giebel & Georges Kariniotakis
16:30	END OF THE CONFERENCE

AFTERNOON SESSIONS

Smart4RES

Final conference
14 April 2023

Towards Data Markets

Pierre Pinson

Imperial College London, Dyson School of Design Engineering
Technical University of Denmark, DTU Management

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No 864337

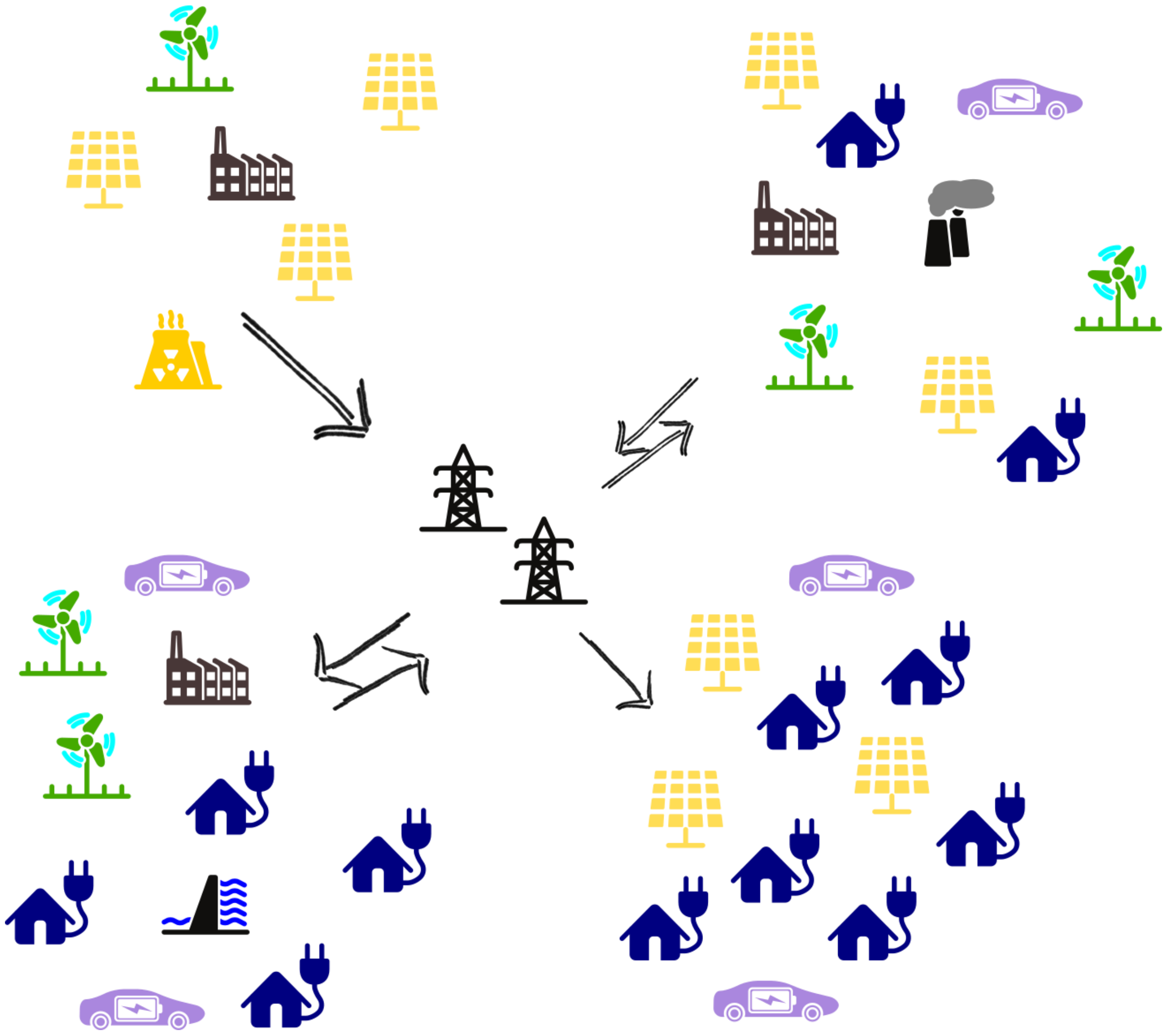
OUTLINE

1. Context
2. Business models for data sharing
3. Data and analytics markets
4. Conclusions and key take-away messages

Additional (main) contributors: Carla Goncalves, Ricardo Bessa (INESC TEC), Liyang Han, Jalal Kazempour (DTU)

Digitalization and energy data

- **Digitalization** is a key component of the energy transition:
  - Data is the raw material
  - Value is generated through analytics
- **Energy data** is naturally distributed
  - geographically, but also…
  - In terms of ownership
- Most often, those who collect and own data are **reluctant to share!**



The million-dollar question…

[source: iStock]

HOW DO WE GET AGENTS OF THE ENERGY SYSTEM TO SHARE THEIR DATA?

- Force every body to share their data with a central entity?
- Impose that all data is open-access?
- Etc.

- Unfortunately, *there may not be a single approach that would work for all types of problems and agents involved*!

- Smart4RES is the first EU project to propose new business models (as well as necessary technical solutions) for energy data sharing

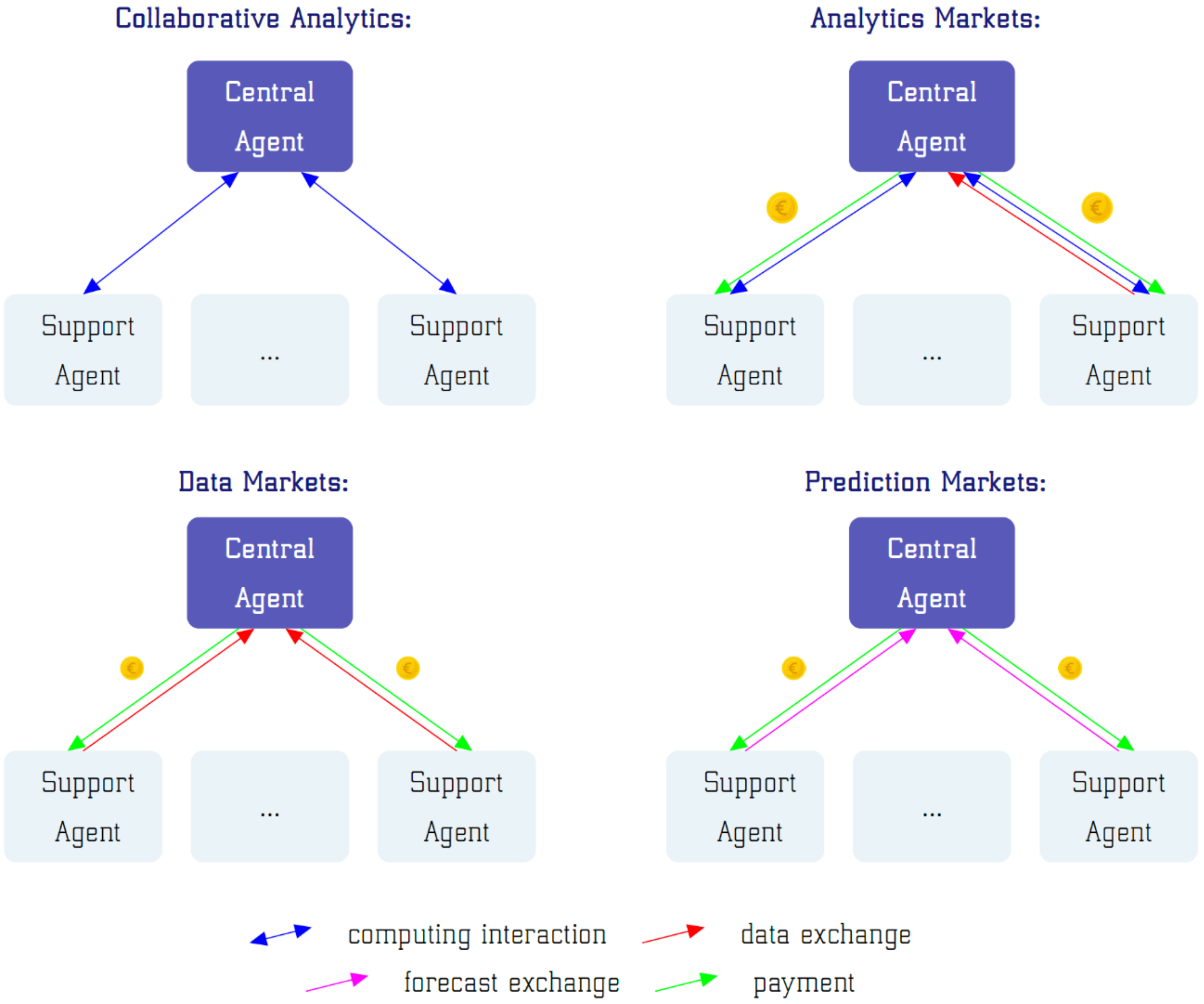
New business models for data sharing

Smart4RES investigates 4 alternative and complementary approaches:

- **Collaborative analytics** (link to presentation by Carla Goncalves)
- **Data markets**
- **Analytics markets**
- **Prediction markets**

Their relevance depends upon the problem at hand and agents involved.

All approach may accommodate a privacy-preserving layer!



Regression markets (1): the regression problem

- Is that possible to monetize data within a regression framework?

Consider a central agent ("**Forecaster**"), with a regression problem as a basis to predict renewable energy generation at a given site (y_{t+k}), and with own features $\omega = \{x_1, \dots, x_m\}$

- The following regression problem can be used as a basis for learning, and eventually forecasting:

$$\boldsymbol{Y}_{t+k} = \beta_0 + \sum_{i=1}^{m} \beta_i \, x_{i,t} + \varepsilon_t, \qquad t = 1, \dots, T$$

- The vector of parameters $\boldsymbol{\beta} = [\beta_0, \dots, \beta_m]^{\mathrm{T}}$ can be estimated as

$$\widehat{\boldsymbol{\beta}} = \operatorname{argmin} S_\omega(\boldsymbol{\beta}), \qquad S_\omega(\boldsymbol{\beta}) = \frac{1}{T} \sum_{t=1}^{T} \rho\Big(y_{t+k} - \big(\beta_0 + \sum_{i=1}^{m} \beta_i \, x_{i,t}\big)\Big)$$

where ρ is any convex loss function (e.g., quadratic, pinball loss, etc.)

- Based on the data available, the minimum loss function value is $S_\omega^* = S_\omega(\widehat{\boldsymbol{\beta}})$

Regression markets (2): regression market task

Forecaster post a regression task on a platform and declares a willingness to pay $\phi = 1$€ per percent improvement in S and per data point

- Two support agents ("**Good data**" and "**Useful features**") bring their features z_1 and z_2 to the platform…
- The overall set of features is now $\Omega = \omega \cup \{z_1, z_2\}$
- The regression problem can be augmented as

$$\boldsymbol{Y}_{t+k} = \beta_0 + \sum_{i=1}^{m} \beta_i \, x_{i,t} + \gamma_1 z_{1,t} + \gamma_2 z_{2,t} + \varepsilon_t, \qquad t = 1, \dots, T$$

- The augmented vector of parameters $\boldsymbol{\beta}^+ = [\beta_0, \dots, \beta_m, \gamma_1, \gamma_2]^{\mathrm{T}}$ can be estimated as

$$\widehat{\boldsymbol{\beta}}^+ = \operatorname{argmin} S_\Omega(\boldsymbol{\beta}^+)$$

$$S_\Omega(\boldsymbol{\beta}^+) = \frac{1}{T} \sum_{t=1}^{T} \rho\Big(y_{t+k} - \big(\beta_0 + \sum_{i=1}^{m} \beta_i \, x_{i,t} + \gamma_1 z_{1,t} + \gamma_2 z_{2,t}\big)\Big)$$

- Based on the data available, the minimum loss function value is $S_\Omega^* = S_\Omega\,(\widehat{\boldsymbol{\beta}}^+)$

Regression markets (3): payments and revenues

- How to define the payment of the central agent and revenues for the support agents?

If the features are valuable, the loss S^*_Ω when using the features of support agents should be lower than S^*_ω. The overall value generated by the mechanism is S^*_ω - S^*_Ω

- The central agent ("**Forecaster**") expressed a willingness to pay per unit improvement of the loss function, and per data point…
- Hence, the payment should be:

$$\pi_c = (S^*_\omega - S^*_\Omega)\, T\, \phi$$

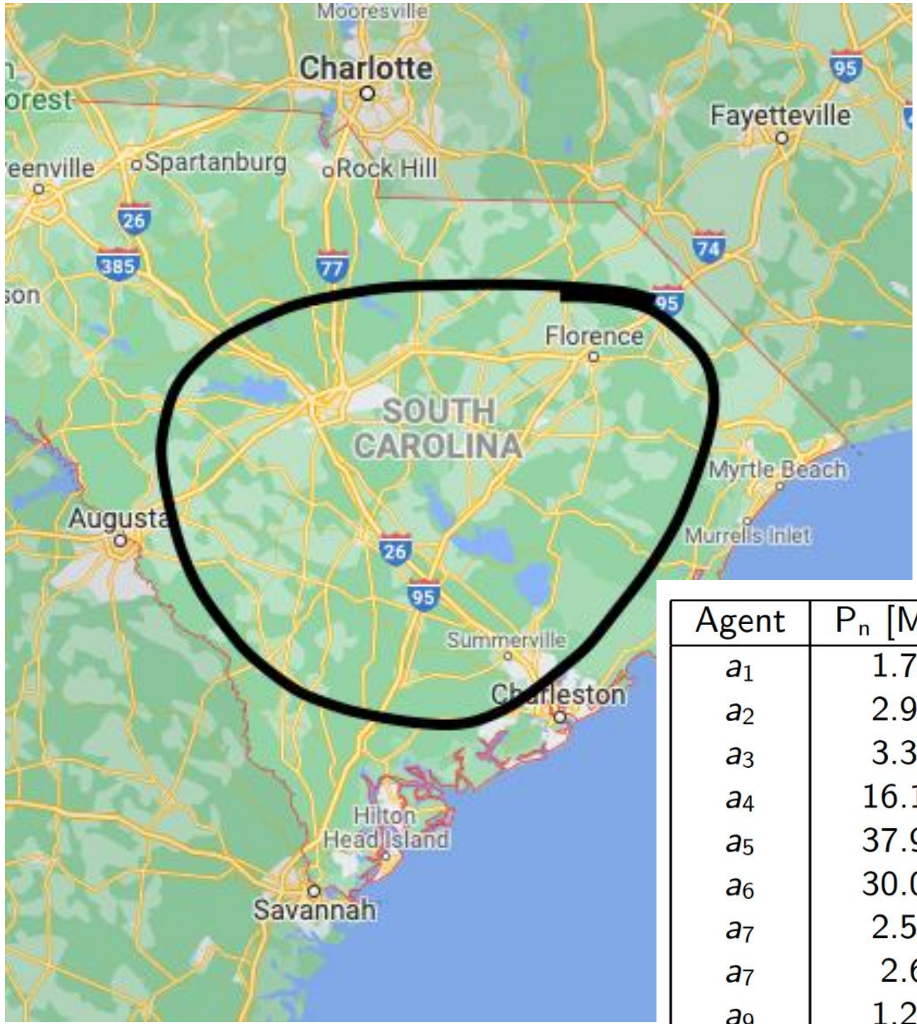
- And, for the support agents ("**Good data**" and "**Useful features**"), they should fairly share that payment…
- Their revenue is then defined as

$$\pi_i = (S^*_\omega - S^*_\Omega)\, T\, \phi\, \psi_i = \pi_c\, \psi_i, \qquad i = 1,2$$

where ψ_i is an allocation policy based on feature valuation (as commonly used in XAI these days, e.g. using Shapley values)

Illustrative application example

- **Case study in South Carolina:**
  - 9 wind farms within 150km radius
  - 7 years of hourly data
  - 1-step ahead forecasts
  - Quantiles with nominal level 0.55
  - AR models with 2 lags for the central agent and 1 lag for support agents
- **Willingness to pay:**
  - 0.2$ per data point per unit decrease in loss function in sample
  - 0.8$ per data point per unit decrease in loss function out of sample



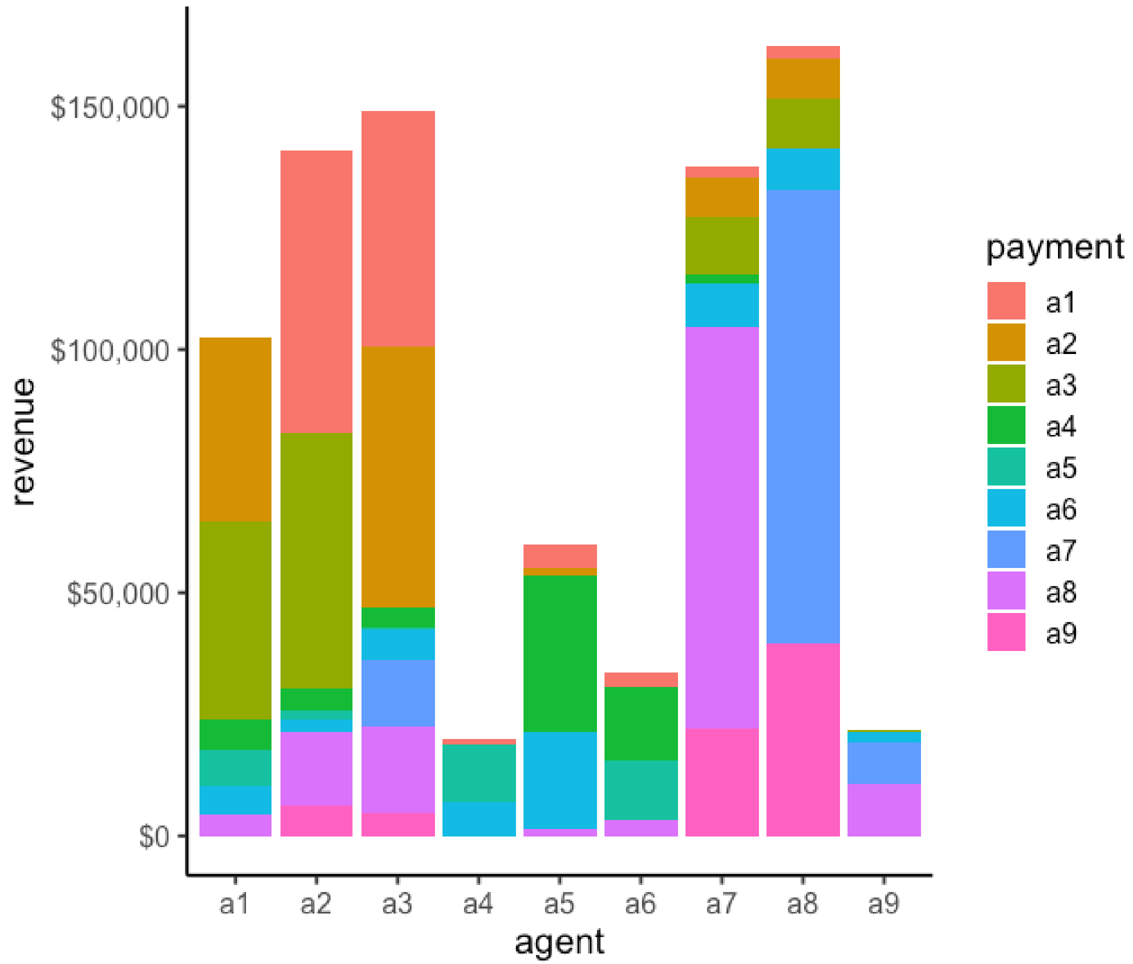
Agent	P_n [MW]	Lat./Long.	County
a_1	1.75	34.248/-79.75	Florence
a_2	2.96	34.02/-79.537	Florence
a_3	3.38	33.925/-79.958	Florence
a_4	16.11	34.732/-82.122	Laurens
a_5	37.98	34.556/-81.889	Laurens
a_6	30.06	34.334/-82.133	Laurens
a_7	2.53	33.136/-80.857	Colleton
a_7	2.6	33.112/-80.665	Colleton
a_9	1.24	32.641/-80.504	Colleton

Out-of-sample results

- Agents receive a payment as a function of how much their their data allowed others to improve their 1-step ahead quantile forecasts

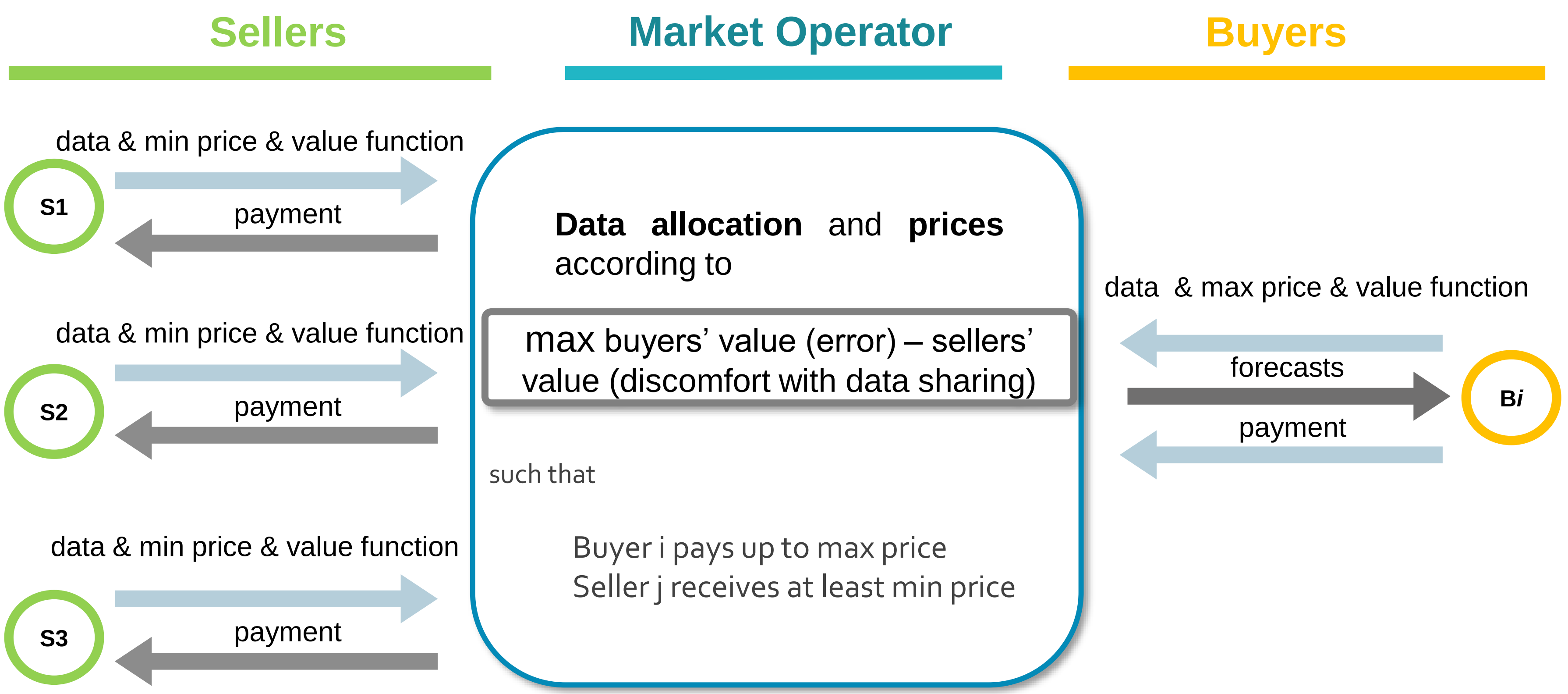
- Not all data is valuable

- One can deduce the value of single data points for each agent, e.g.
  - a4 gets 0.39$ per data point
  - a8 gets 3.26$ per data point



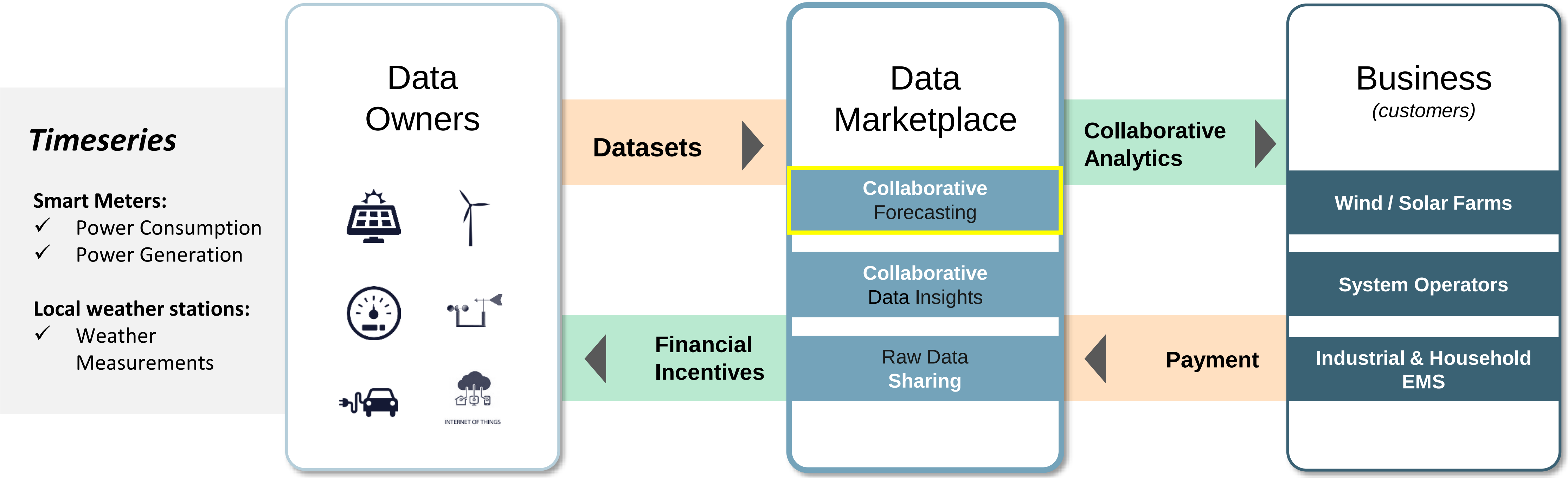
Multiple sellers, multiple buyers

- One can organize a data market where features are allocated and priced following a social welfare maximization approach (as in electricity markets)



Prototype of a data market: Predico

- INESC TEC developed a prototype of a data market platform



- ❑ Data owners **share data** and **receive financial incentives** provided by interested customers
- ❑ **Subproducts created from data owners' information** (e.g., collaborative forecasts), increasing its value and opening new use cases for data sharing

KEY TAKE-AWAY MESSAGES

PROBLEM: There ~~is~~ was no established framework to support and incentivize data sharing within energy system operation

SOLUTION: Data markets allow to bring the necessary incentives, while also defining new revenues streams for the agents of digitalized energy systems

POTENTIAL: We foresee that data markets, analytics platforms, etc., will play a major role in unleashing the value of distributed energy data, and eventually in the management of distributed energy resources

FURTHER READING

- **Public deliverables** (EU project Smart4RES)
  - D4.2 - Data marketplace for RES forecasting
  - D4.3 - Novel business models for data sharing
- **Publications** (selection)

C Gonçalves, P Pinson, RJ Bessa (2020) Towards data markets in renewable energy forecasting, *IEEE Transactions on Sustainable Energy* **12**(1): 533-542

P Pinson (2022) To Share or Not to Share? The Future of Collaborative Forecasting, *Foresight* **67**(7): 8-15

L Han, P Pinson, J Kazempour (2022) Trading data for wind power forecasting: A regression market with lasso regularization, *Electric Power Systems Research* **212**: art. no. 108442

P Pinson, L Han, J Kazempour (2022) Regression markets and application to energy forecasting, *TOP* **30**(3): 533-573

AA Raja, P Pinson, J Kazempour, S Grammatico (2023) A market for trading forecasts: A wagering mechanism, *International Journal of Forecasting*, available online.

Thank you!

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- Jalal Kazempour, DTU: jalal@dtu.dk

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Privacy-preserving data sharing for energy forecasting

Carla Gonçalves

Ricardo Jorge Bessa and Pierre Pinson

INESCTEC
Imperial College London
DTU

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

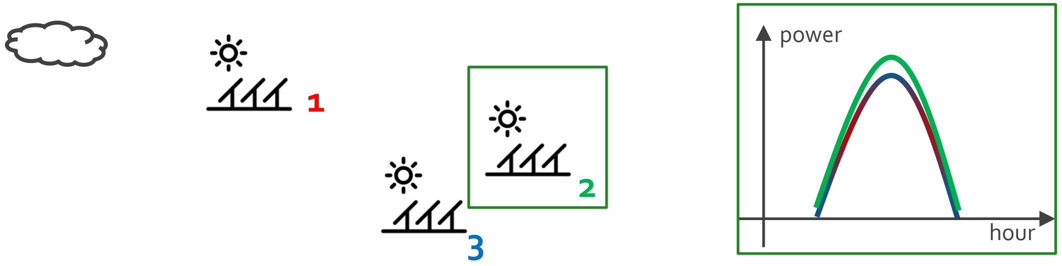
OUTLINE

1. Context
2. Collaborative forecasting model for 6h-ahead
3. Privacy-preserving protocol
4. Extension for 2 days-ahead forecasting
5. Conclusions and key take aways

CONTEXT

Increasing volume of geographically distributed data

- **Combining** data from multiple companies may lead to an **improvement of forecasting skill**
  - due to spatio-temporal dependencies in geographically distributed time series



Main Barriers

Data **privacy** and **confidentiality**

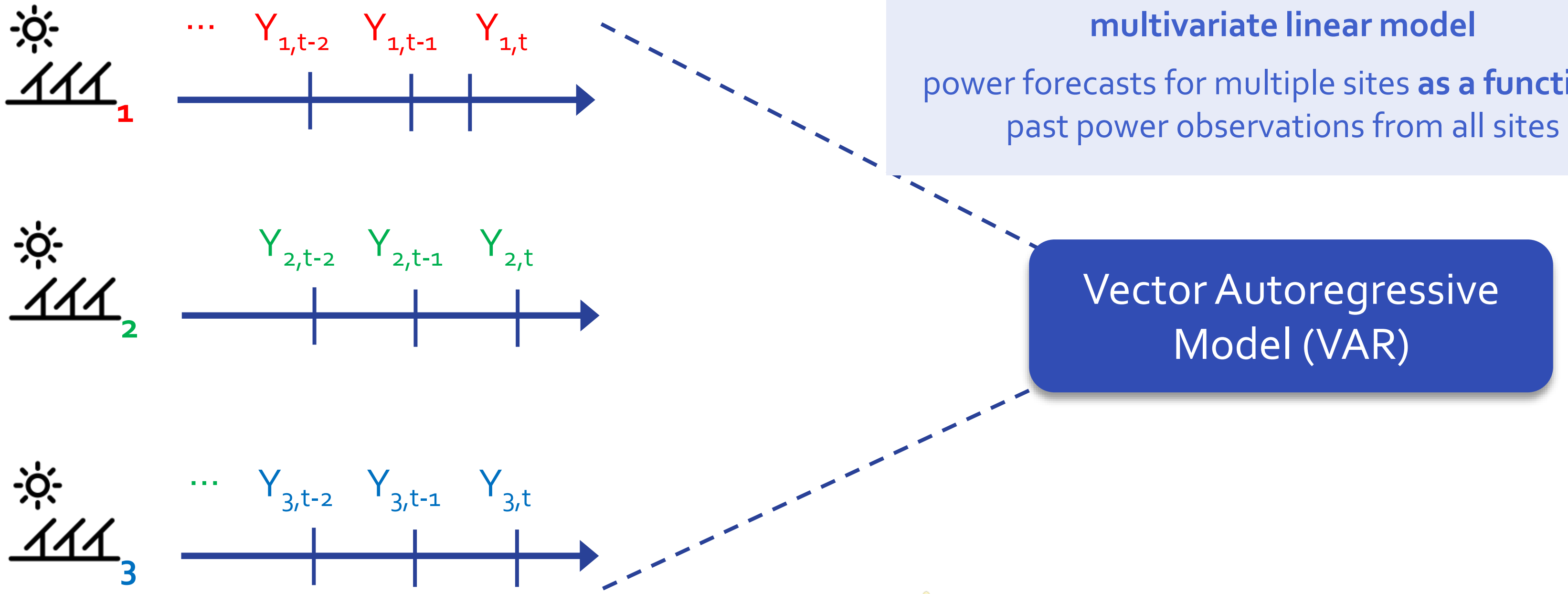
Lack of **monetary and non-monetary incentives** for sharing data

RES COLLABORATIVE FORECASTING

VAR MODEL

multivariate linear model

power forecasts for multiple sites **as a function of** past power observations from all sites



Example: 3 PV sites, 1 lag

These connections are a problem!

$$Y_{1,t} = c_1 + B^1_{1,1} Y_{1,t-1} + \boxed{B^1_{2,1} Y_{2,t-1} + B^1_{3,1} Y_{3,t-1}} + E_{1,t}$$

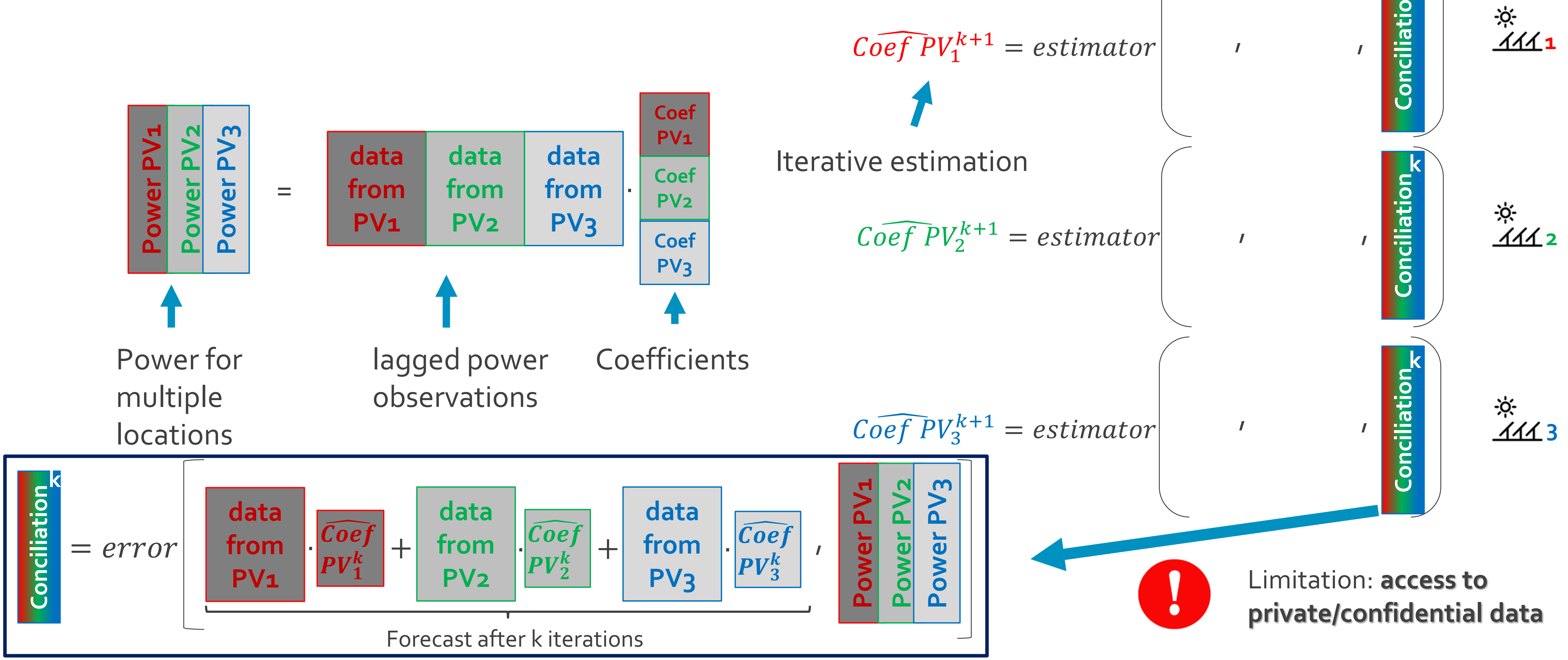
$$Y_{2,t} = c_2 + \boxed{B^1_{1,2} Y_{1,t-1}} + B^1_{2,2} Y_{2,t-1} + \boxed{B^1_{3,2} Y_{3,t-1}} + E_{2,t}$$

$$Y_{3,t} = c_1 + \boxed{B^1_{1,3} Y_{1,t-1} + B^1_{2,3} Y_{2,t-1}} + B^1_{3,3} Y_{3,t-1} + E_{3,t}$$

When compared against AR, VAR has reduced the average error by ~10% (h=1)

RES COLLABORATIVE FORECASTING

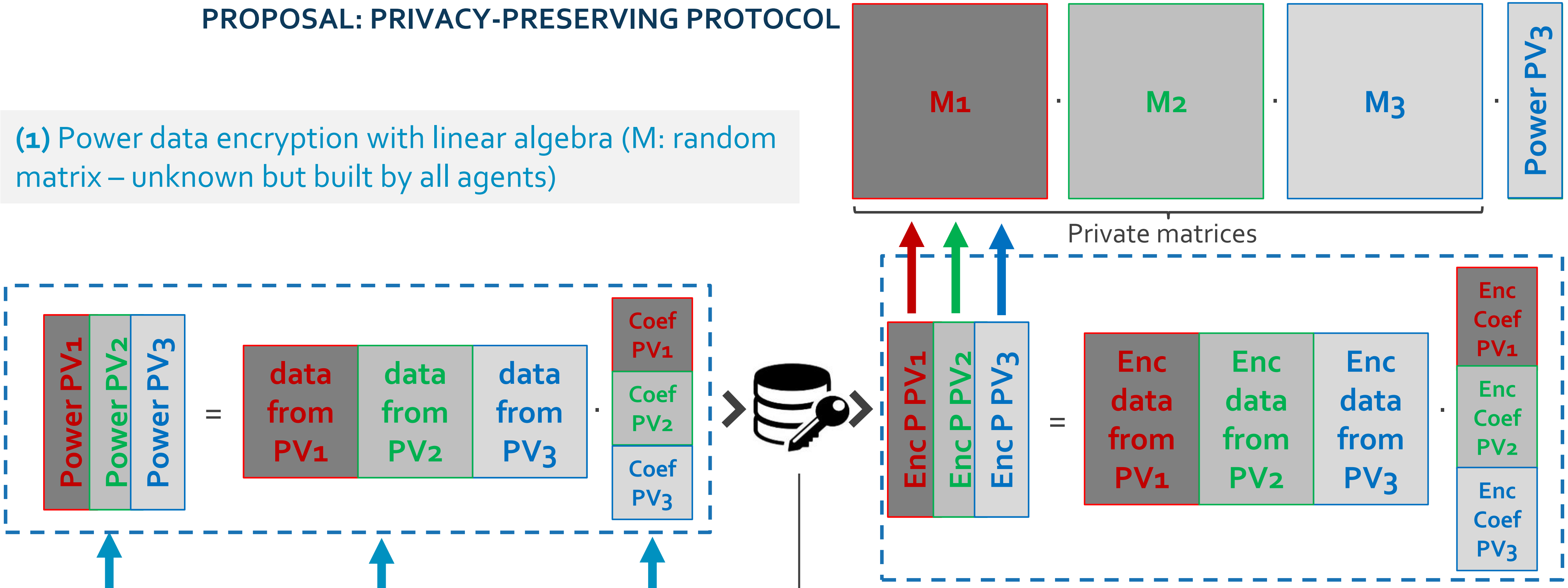
TRADITIONAL APPROACH



RES COLLABORATIVE FORECASTING

PROPOSAL: PRIVACY-PRESERVING PROTOCOL

(1) Power data encryption with linear algebra (M: random matrix – unknown but built by all agents)



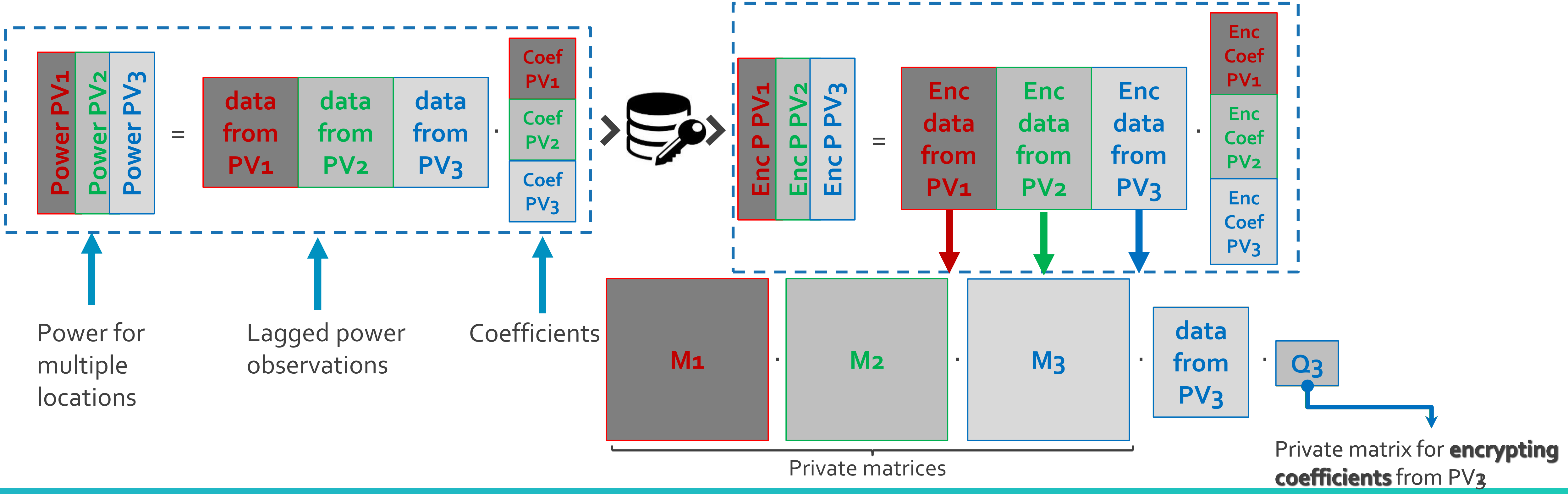
MAIN IDEA

- Transform data without trust third parties
- Ensure data transformation does not affect the model's performance (data transformation preserves data relation)

RES COLLABORATIVE FORECASTING

PROPOSAL: PRIVACY-PRESERVING PROTOCOL

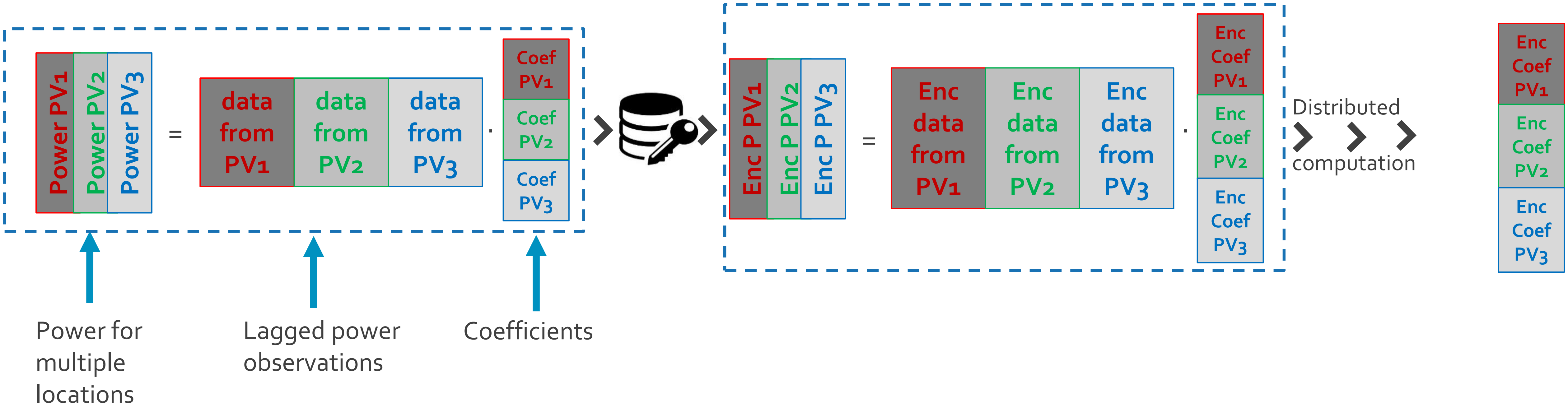
(2) Coefficients encryption with linear algebra (Q: random matrix – own by each agent)



RES COLLABORATIVE FORECASTING

PROPOSAL: PRIVACY-PRESERVING PROTOCOL

(3) Distributed computation of coefficients

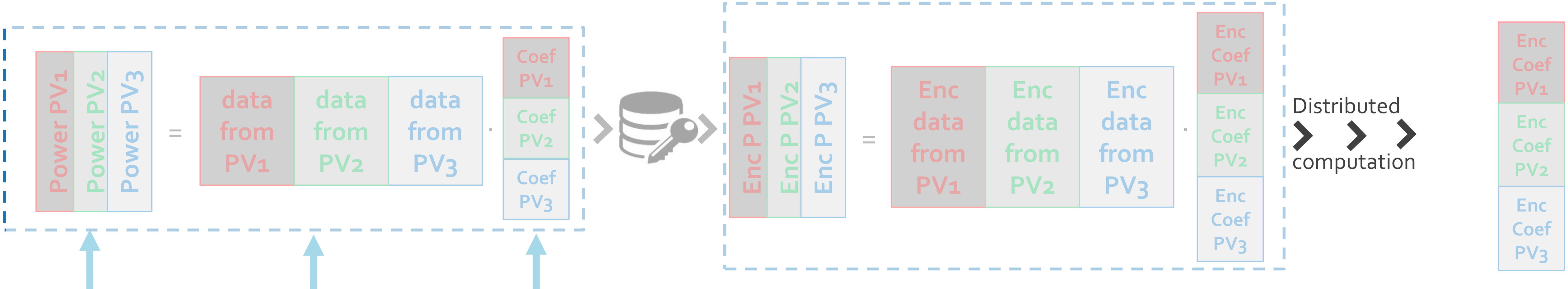


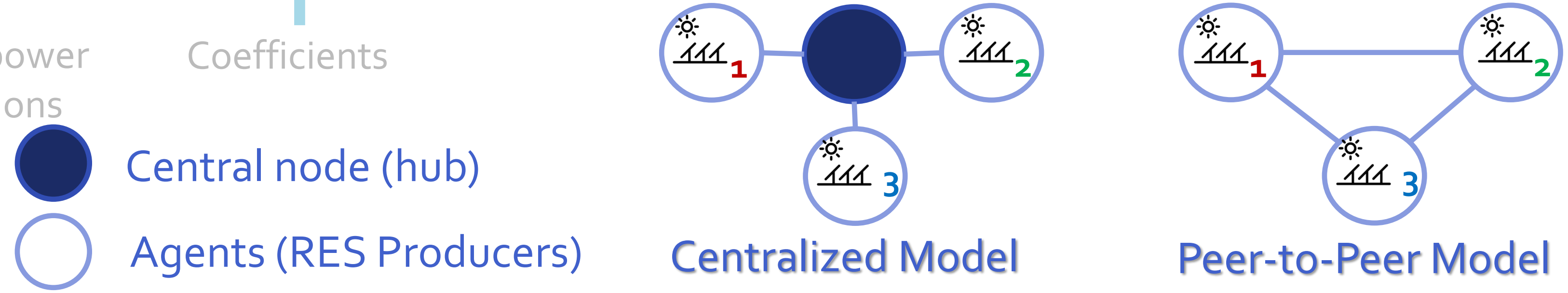
RES COLLABORATIVE FORECASTING

PROPOSAL: PRIVACY-PRESERVING PROTOCOL

(3) Distributed computation of coefficients

Formulation flexible enough to allow **centralized** and **peer-to-peer** model's estimation

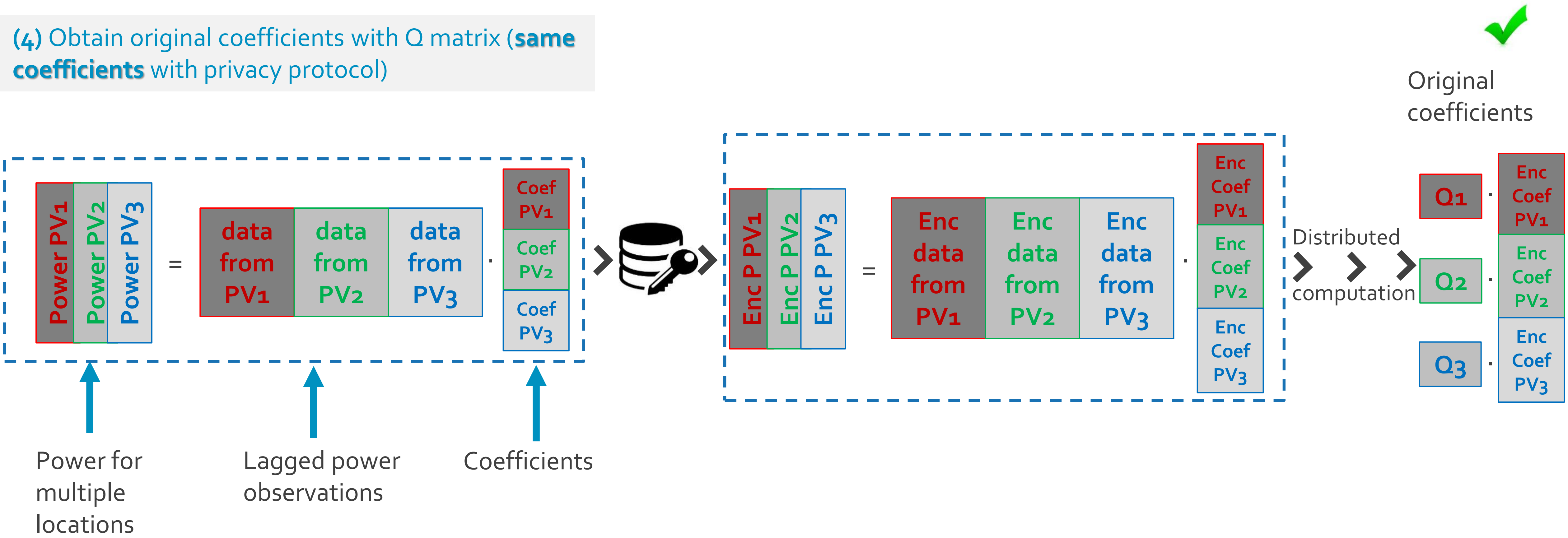




RES COLLABORATIVE FORECASTING

PROPOSAL: PRIVACY-PRESERVING PROTOCOL

(4) Obtain original coefficients with Q matrix (**same coefficients** with privacy protocol)

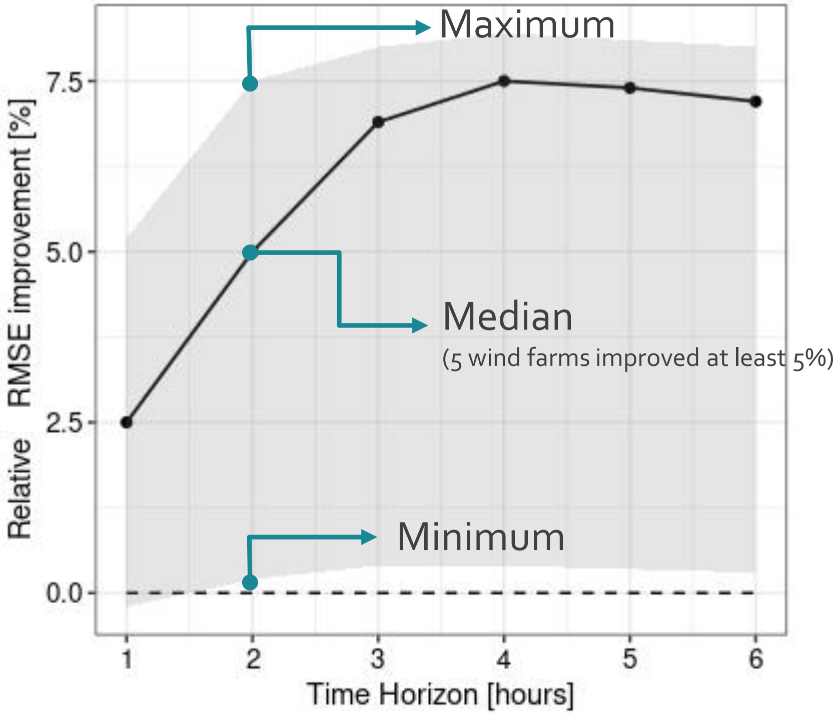


CASE-STUDIES

COMPARISON WITH AN AUTOREGRESSIVE MODEL (MODEL CONSIDERING ONLY OWN LAGS)

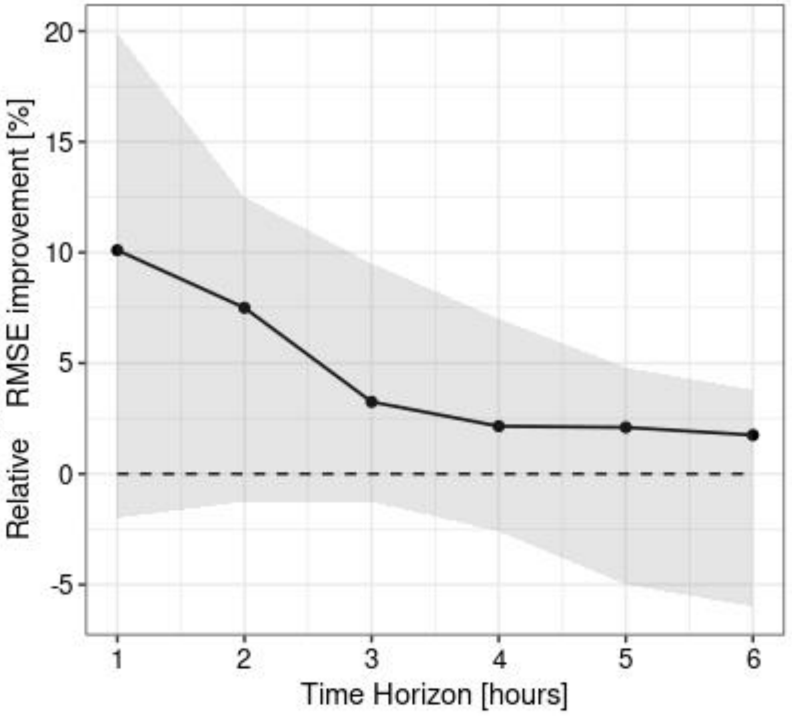
Wind power dataset (10 wind farms located in Australia)

- Jan2012 – Nov2013
- 6 most recent power values
- Sliding window 1 month test/12 months train



Solar power dataset (44 micro generation units located in Portugal)

- Fev2011 – Mar2013
- 2 most recent power values + 24h lag
- Sliding window 1 month test/12 months train



- ✓ Data is protected without changing the model accuracy
- ✓ For each horizon more than 70% of the power plants improved their forecasts
- ✓ Improvement depends on spatial distribution of the power plants

EXTENSION TO DAY-AHEAD FORECASTING

Vector Autoregressive Model (VAR)

Effective up to 6h-ahead

Easy solution: add weather forecasts to the model

1

2

3

$$Y_{1,t} \approx c_1 + B^1_{1,1} \; Y_{1,t-1} + B^1_{2,1} Y_{2,t-1} + B^1_{3,1} Y_{3,t-1}$$

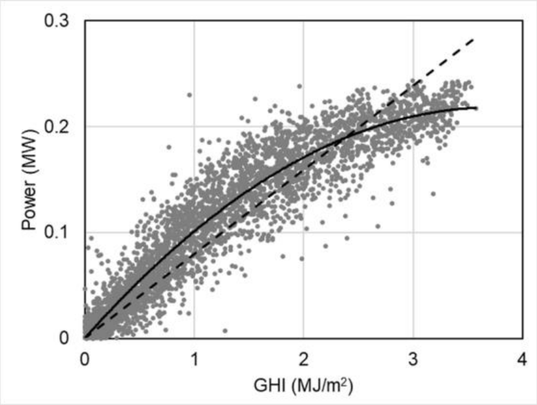
$$Y_{2,t} \approx c_2 + B^1_{1,2} \; Y_{1,t-1} + B^1_{2,2} Y_{2,t-1} + B^1_{3,2} Y_{3,t-1}$$

$$Y_{3,t} \approx c_1 + B^1_{1,3} \; Y_{1,t-1} + B^1_{2,3} Y_{2,t-1} + B^1_{3,3} Y_{3,t-1}$$

Inclusion of weather forecasts is essential for larger forecasting horizons

Global Horizontal Irradiance (GHI)

Non-linear relation between power and weather variables!



EXTENSION TO DAY-AHEAD FORECASTING

PROPOSAL

Vector Autoregressive Model (VAR)

1

2

3

$$Y_{1,t} \approx c_1 + B^1_{1,1}\,Y_{1,t-1} + B^1_{2,1}Y_{2,t-1} + B^1_{3,1}Y_{3,t-1} + B^{GHI}_{1,1}\widehat{GHI}_{1,t} + B^{GHI}_{2,1}\widehat{GHI}_{2,t} + B^{GHI}_{3,1}\,\widehat{GHI}_{3,t}$$

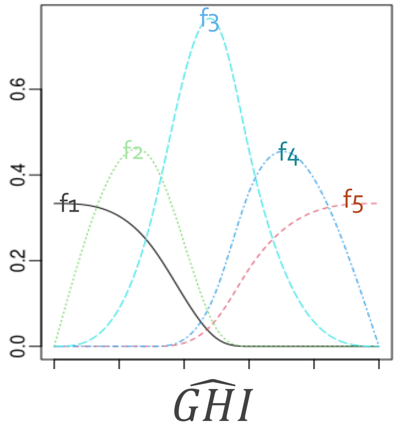
$$Y_{2,t} \approx c_2 + B^1_{1,2}\,Y_{1,t-1} + B^1_{2,2}Y_{2,t-1} + B^1_{3,2}Y_{3,t-1} + B^{GHI}_{1,2}\widehat{GHI}_{1,t} + B^{GHI}_{2,2}\widehat{GHI}_{2,t} + B^{GHI}_{3,2}\,\widehat{GHI}_{3,t}$$

$$Y_{3,t} \approx c_1 + B^1_{1,3}\,Y_{1,t-1} + B^1_{2,3}Y_{2,t-1} + B^1_{3,3}Y_{3,t-1} + B^{GHI}_{1,3}\widehat{GHI}_{1,t} + B^{GHI}_{2,3}\widehat{GHI}_{2,t} + B^{GHI}_{3,3}\,\widehat{GHI}_{3,t}$$

Global Horizontal Irradiance (GHI)

extension with additive models (natural cubic splines) to **capture non-linearities**

$$\widehat{GHI}_{1,t} \begin{cases} f1(\widehat{GHI}_{1,t}) \\ f2(\widehat{GHI}_{1,t}) \\ f3(\widehat{GHI}_{1,t}) \\ f4(\widehat{GHI}_{1,t}) \\ f5(\widehat{GHI}_{1,t}) \end{cases} \quad \widehat{GHI}_{2,t} \begin{cases} f1(\widehat{GHI}_{2,t}) \\ f2(\widehat{GHI}_{2,t}) \\ f3(\widehat{GHI}_{2,t}) \\ f4(\widehat{GHI}_{2,t}) \\ f5(\widehat{GHI}_{2,t}) \end{cases} \quad \widehat{GHI}_{3,t} \begin{cases} f1(\widehat{GHI}_{3,t}) \\ f2(\widehat{GHI}_{3,t}) \\ f3(\widehat{GHI}_{3,t}) \\ f4(\widehat{GHI}_{3,t}) \\ f5(\widehat{GHI}_{3,t}) \end{cases}$$



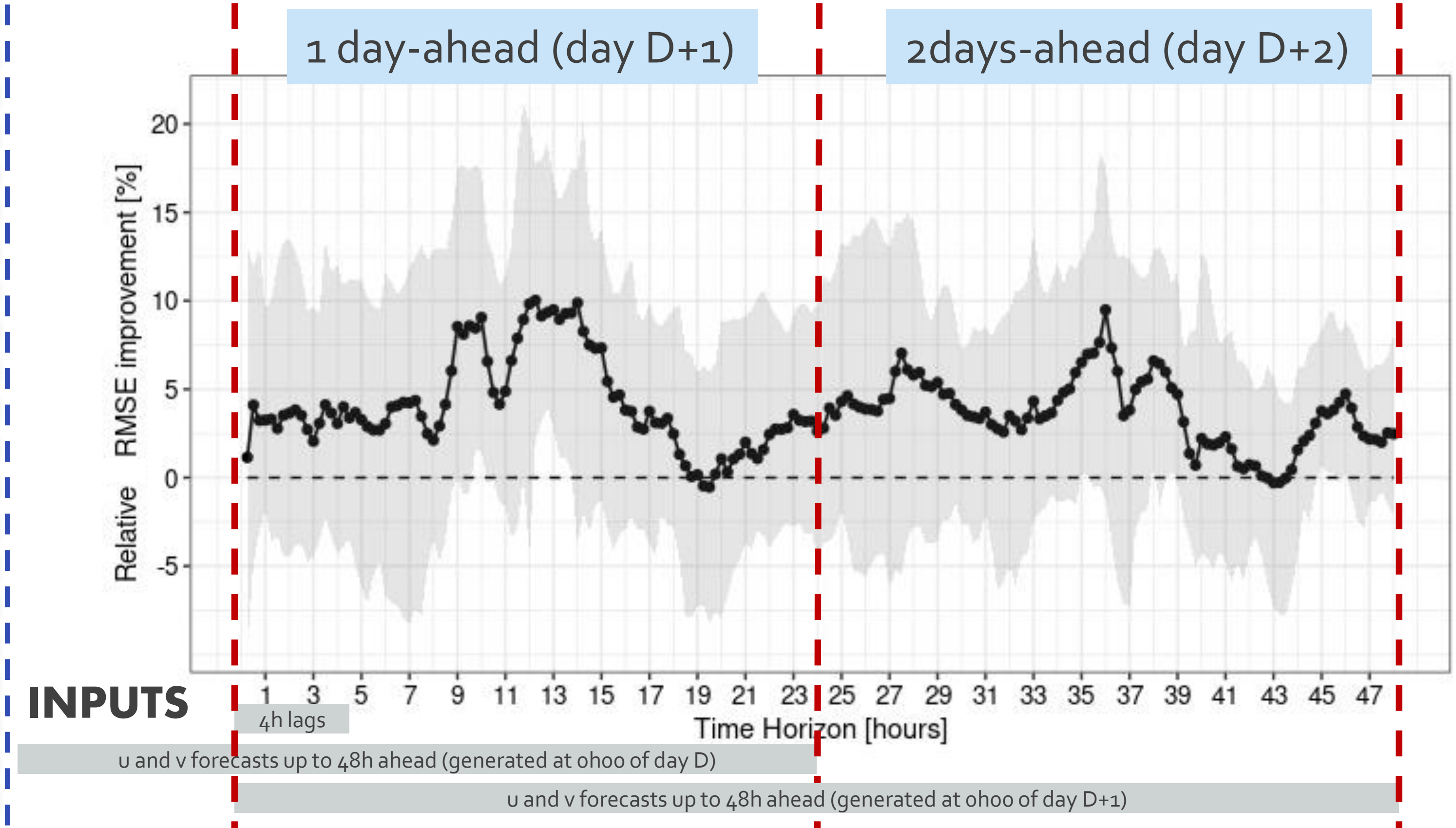
Example of natural cubic spline functions

CASE-STUDY

COMPARISON WITH AN ADDITIVE MODEL CONSIDERING ONLY LOCAL DATA

Wind power dataset (60 wind turbines located in France)

- Oct2018 – Sept2020 (15mins resolution)
- Sliding window 1 month test/12 month train



✓ Data is protected without changing the model accuracy

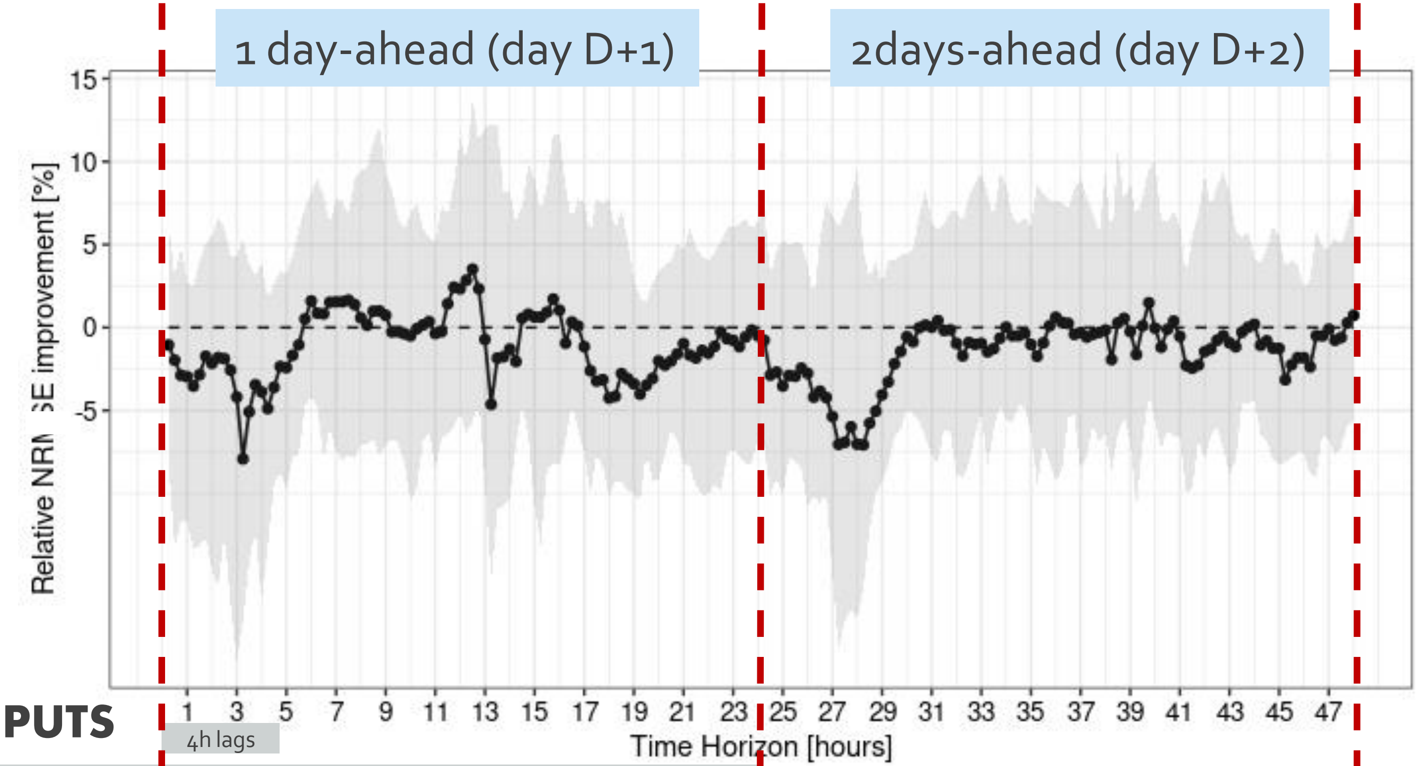
✓ In general, more than 50% of the wind turbines benefit when using the collaborative model

CASE-STUDY

COMPARISON WITH GRADIENT BOOSTING TREES (NON-LINEAR MODEL WITHOUT DATA PRIVACY!)

Wind power dataset (60 wind turbines located in France)

- Oct2018 – Sept2020 (15mins resolution)
- Sliding window 1 month test/12 month train



INPUTS

4h lags

u and v forecasts up to 48h ahead (generated at 0h00 of day D)

u and v forecasts up to 48h ahead (generated at 0h00 of day D+1)

✓ Data is protected without changing the model accuracy

✓ Competitive accuracy when compared with a non-linear collaborative model

KEY TAKE AWAYS

- Combining data may improve forecasting accuracy
- **Data privacy is a requirement** for companies to cooperate
- Existing methods have limitations when applied to spatio-temporal time series data
- A **protocol** was proposed **to encrypt data** such that, when using a **linear model**:
  - original relation between data is not affected
  - computation of the model's coefficients may be performed in a centralized or peer-to-peer way
- **Extension** to capture non-linear relations is possible **with additive models** (splines)
- **Future work:** explore other non-linear models and online estimation

FURTHER READING

- Public deliverables (D4.1)
  - https://www.smart4res.eu/wp-content/uploads/2023/01/Smart4RES_D4.1.pdf

- Publications

1. C. Gonçalves, R. J. Bessa, and P. Pinson. "A critical overview of privacy-preserving approaches for collaborative forecasting." International journal of Forecasting 37.1 (2021): 322-342.
2. C. Goncalves, R. J. Bessa, and P. Pinson. "Privacy-preserving distributed learning for renewable energy forecasting." IEEE Transactions on Sustainable Energy 12.3 (2021): 1777-1787.

Smart4RES

Thank you!

- Carla Gonçalves, INESC TEC: carla.s.goncalves@inesctec.pt
- Ricardo Jorge Bessa, INESC TEC: ricardo.j.bessa@inesctec.pt
- Pierre Pinson, Imperial College: p.pinson@imperial.ac.uk

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Uncertainty-aware booking of flexibilities in electrical grids

Ricardo Bessa

INESC TEC

INESCTEC

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

OUTLINE

1. Context and motivation
2. Framework and buildings blocks
3. Numerical results
4. Conclusions and key takeaways

CONTEXT

Increasing RES integration across all voltage levels

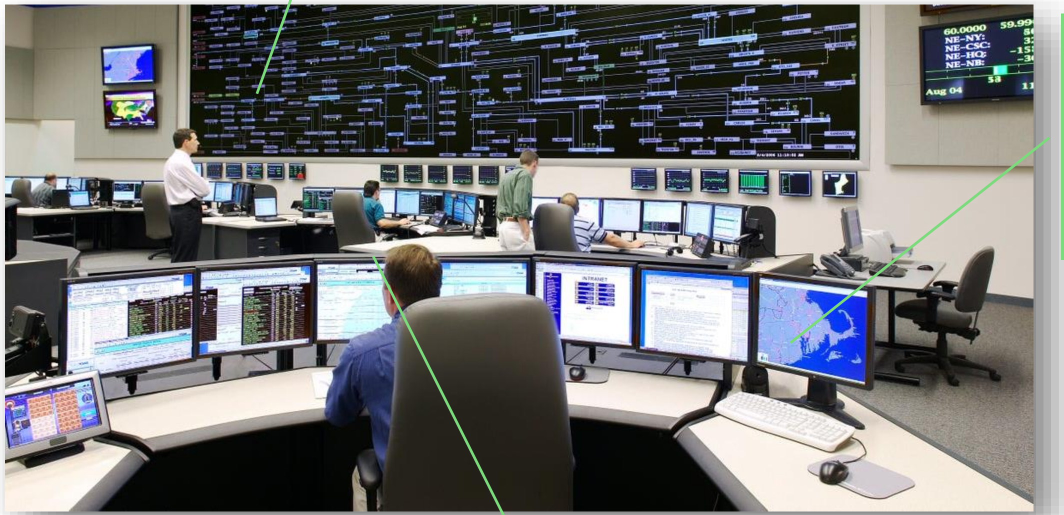
Long-term and short-term flexibility markets are emerging in EU

Need to revisit the traditional power system operating processes & software

USE CASE

Decide procurement and activation of grid and DER flexibility under forecast uncertainty to solve technical problems (voltage / congestion)

MOTIVATION



Uncertainty forecasts for all grid points and with multiple spatial-temporal trajectories

Too much information!

New tools for flexibility procurement and activation under uncertainty

No more new tools please?!

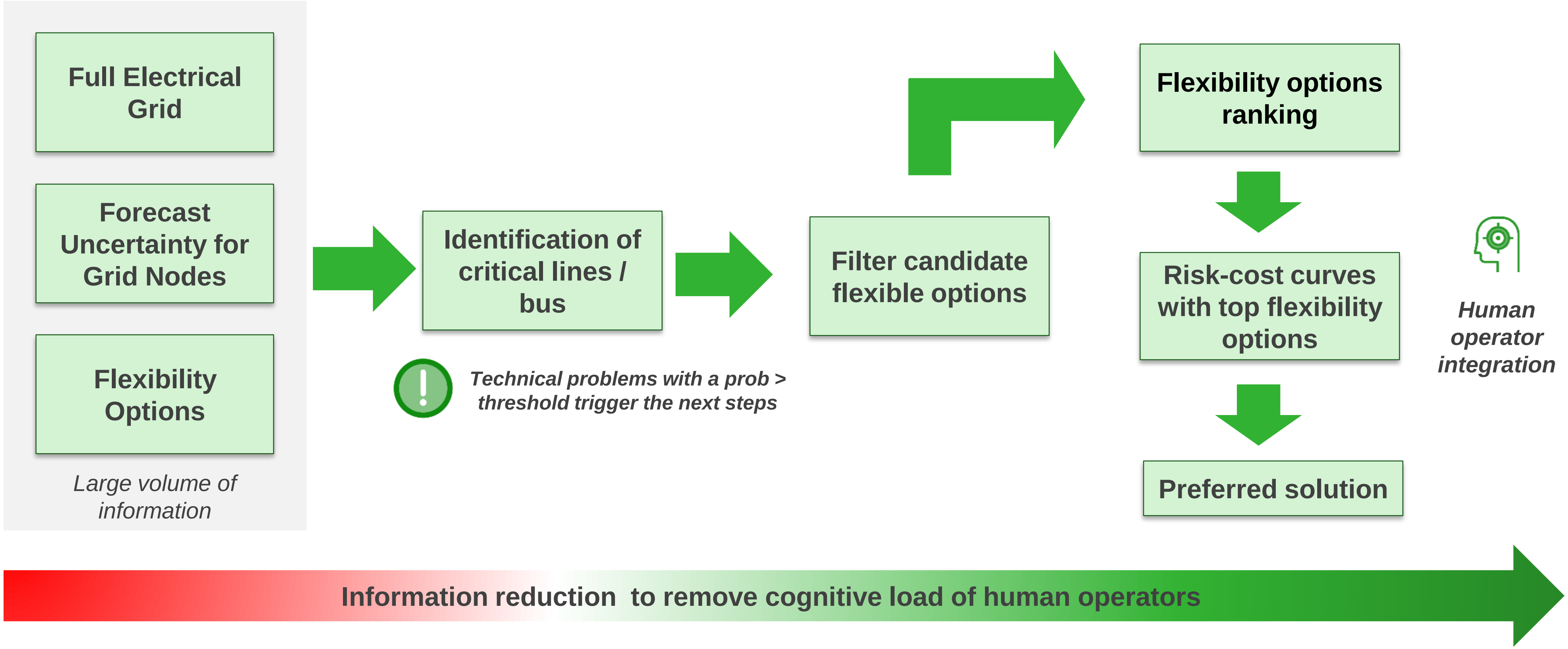
Procure and "reserve" flexibility in the short-term flexibility resources

When to decide? How to rank the different flexibility options?

Smart4RES GOALS

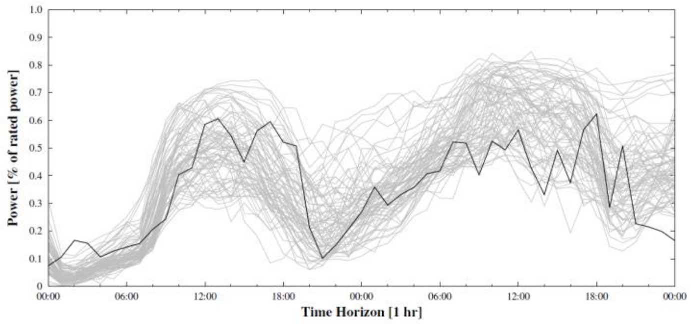
- ❑ Provide information about cause and effect → "**interpretability**"
- ❑ Multi-criteria & **iterative process**
- ❑ Formulate a **time-to-decide** problem: operator decides if "reserve" flexibility now OR wait for the next forecast update

FRAMEWORK FOR RISK-AWARE FLEXIBILTY PROCUREMENT



BUILDING BLOCKS: SCENARIOS & SENSITIVITIES

Spatial scenarios generated with a Gaussian copula and marginal probability distributions



For each scenario compute sensitivity indices relating

P, Q ~ Branch current [(1)]
P, Q ~ Node voltages [(1)]
NTW reconfiguration ~ Branch current (Z-bus + graph theory)

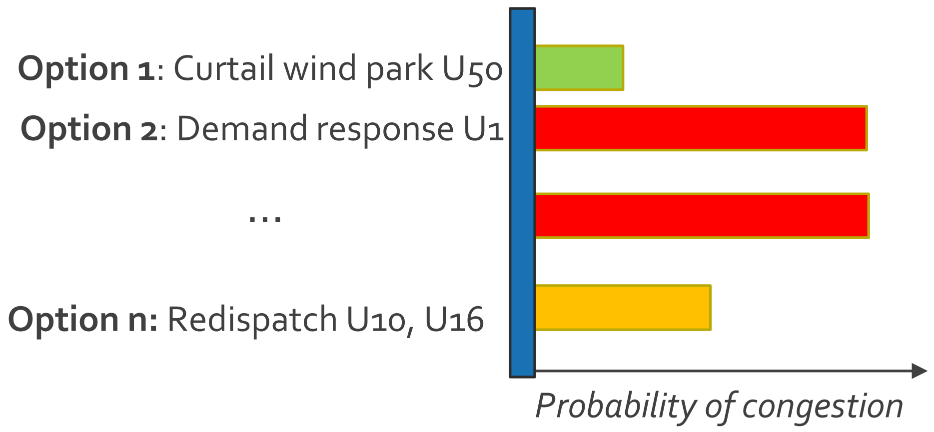
For each flexibility option a set of metrics are computed *to characterize its* ***effectiveness***

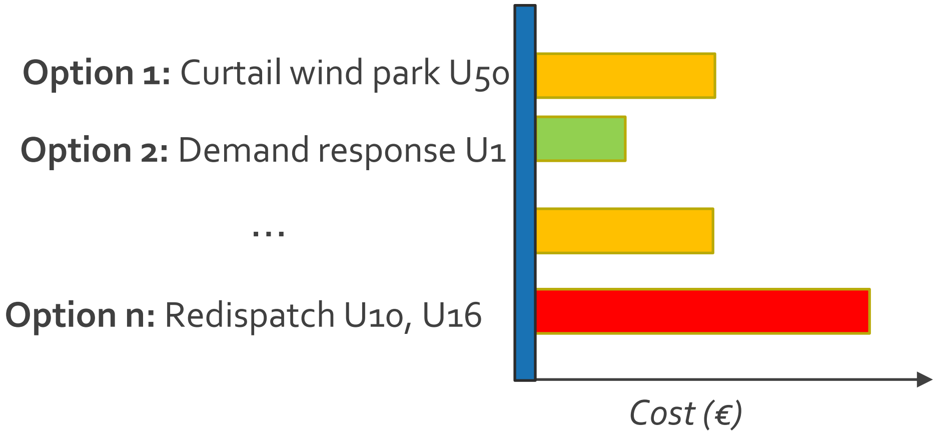
- **Expected flexibility cost**
- **Probability of congestion / voltage problem**
- **VaR of flexibility cost**
- **VaR of severity**
- **Expected severity**

(1) Christakou, K., et al. (2013). Efficient computation of sensitivity coefficients of node voltages and line currents in unbalanced radial electrical distribution networks. IEEE Trans. on Smart Grid, 4(2), 741-750

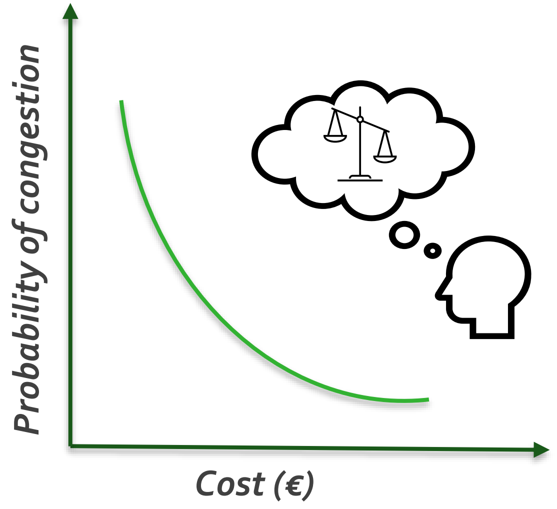
BUILDING BLOCKS: FLEXIBILITY RANKING, RISK CURVES

Flexibility options ranking with TOPSIS(1)





Combine top 3-5 flexibility options

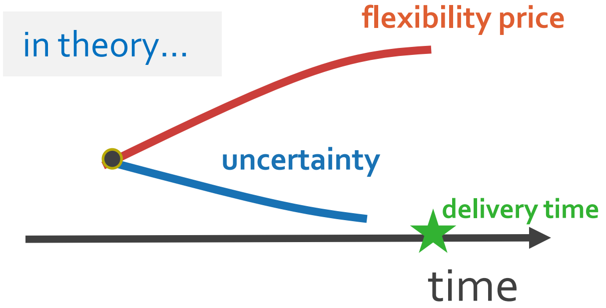


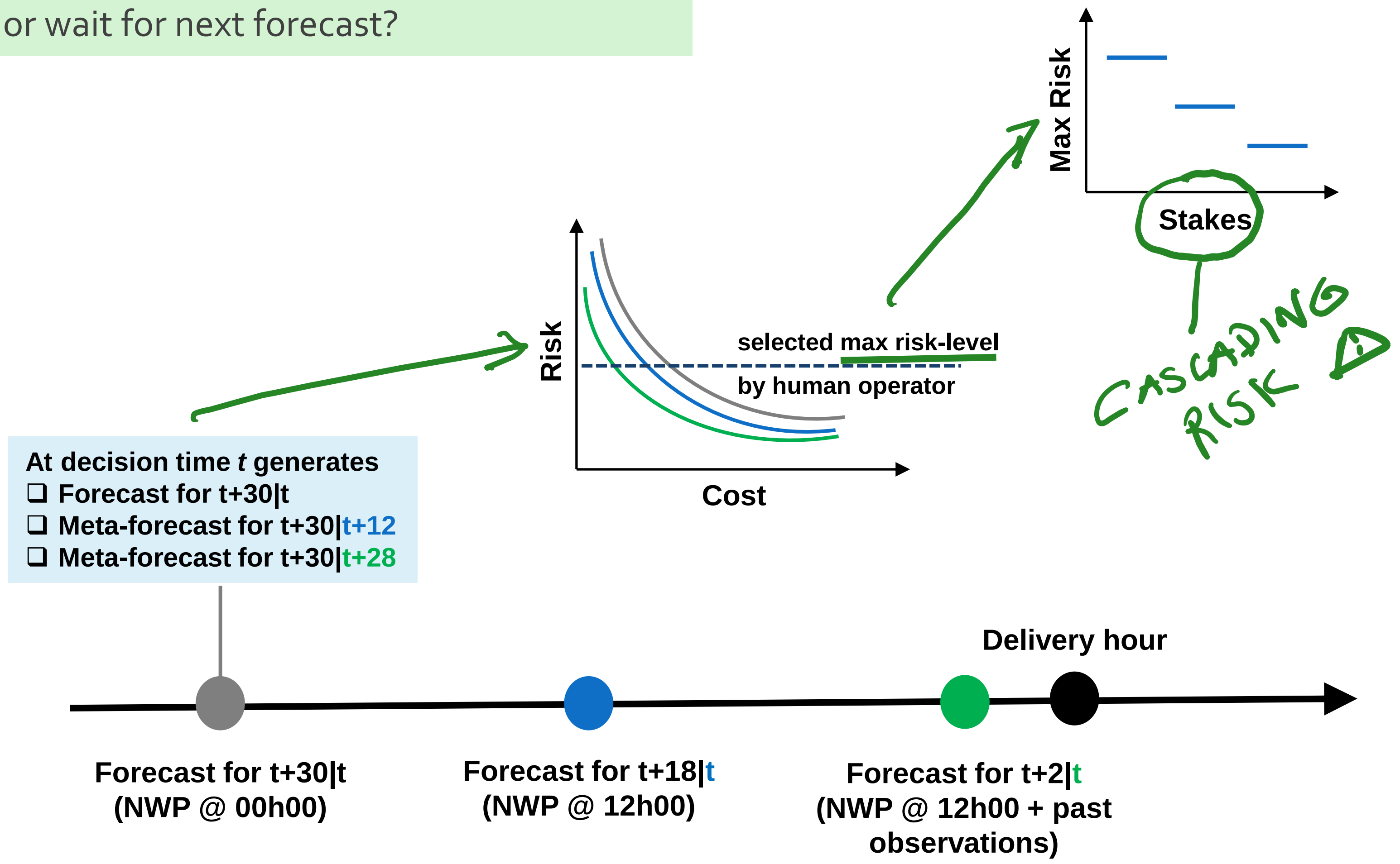
(1) Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

Yoon, K. (1987). "A reconciliation among discrete compromise situations". J. of the Op. Res. Soc. 38: 277–286.

USE OF META-FORECASTS

Probability of a congestion forecasted with NWP for day D+1 (lead time: t+30)
> Decide now ("reserve" a flexibility option) or wait for next forecast?

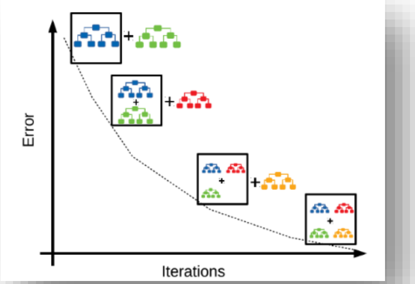




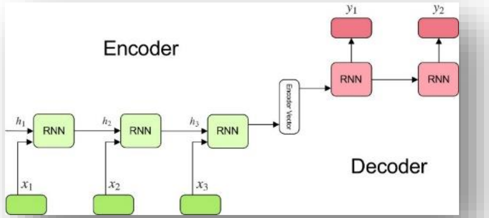
META-FORECASTING MODEL

Forecasted generated with 00h00 NWP
+
Features characterizing level uncertainty (IQR, forecasted quantiles, stdev.)

Gradient Boosting Trees (GBT)



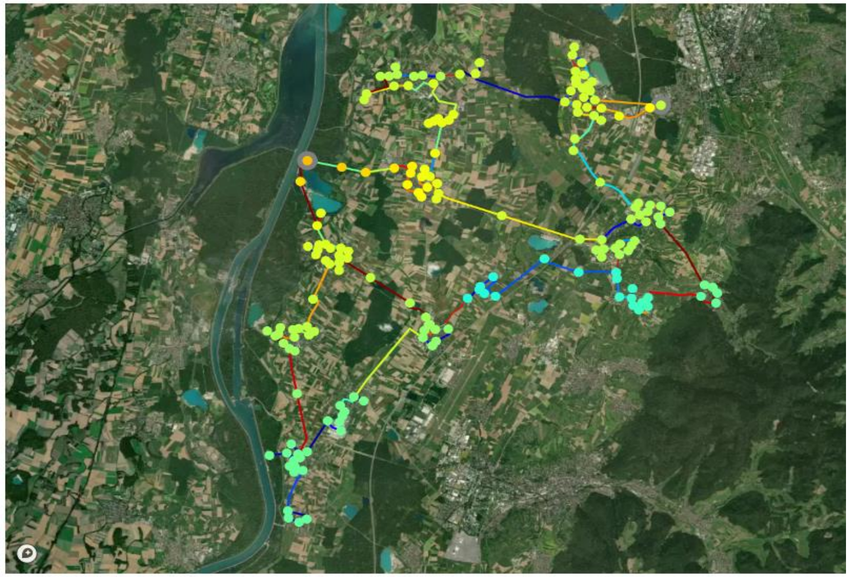
ED-ANN



baseline *model:* ***forecast does not change***

- MAE improvement (**meta-forecast with NWP @ 12h00**) between 13% and 26%
- MAE improvement (**meta-forecast for t+2|t**) between 16% and 31%

CASE-STUDY



- **Modified Oberrhein MV network**
- **Load time series:** Measurements from Iowa Distribution Test Systems[1]
- **RES time series:** French dataset (Smart4RES) + ECMWF NWP data
- Rated power of wind power plants and consumption values adjusted to create technical problems in 1-year of data
- Only wind power forecast uncertainty is used (perfect forecasts for load)
- Flexibility prices computed considered CAPEX and OPEX of resources

EVALUATION METRICS

Confusion matrix

	Congestion occurred	Congestion did not occur
Congestion detected	TP	FP
Congestion not detected	FN	TN

Metric

$$F_\beta = (1+\beta^2) \cdot \frac{Precision \cdot Recall}{\beta^2 \cdot Precision + Recall}$$

Cost-loss matrix

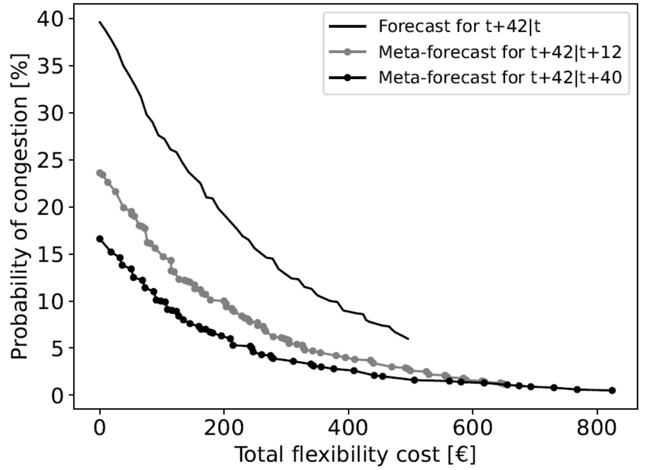
	Congestion occurred	Congestion did not occur
Action taken	Rate of occurrence in % (h) **Flex cost (C) + Loss (L)**	Rate of occurrence in % (m) **Flex cost (C)**
Action not taken	Rate of occurrence in % (f) **Loss (L)**	Rate of occurrence in % (c) **No cost**

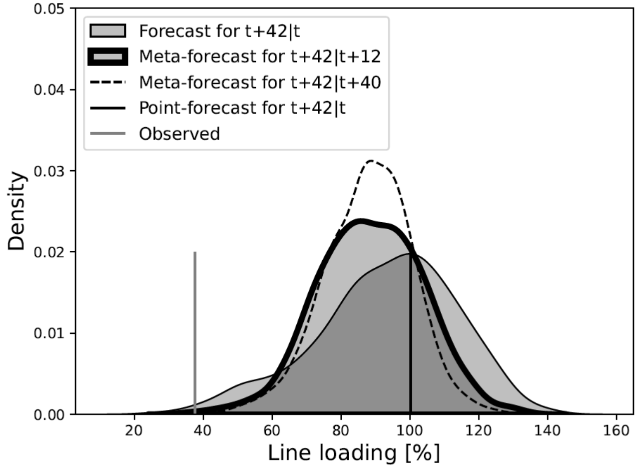
Metric

$$\gamma = (C+L) \cdot h + C \cdot m + L \cdot f + 0 \cdot c$$

EXAMPLE: SOLVE A LINE CONGESTION

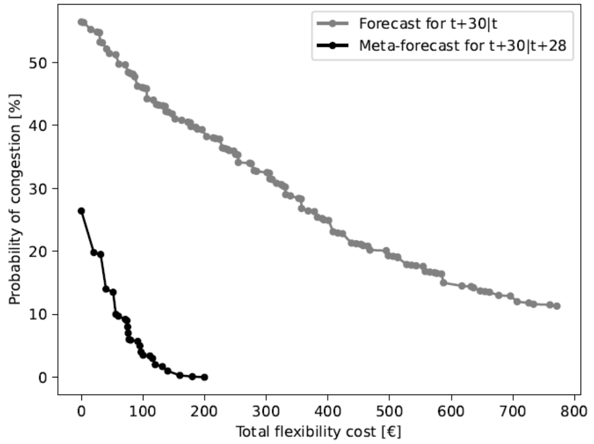
Forecast and meta-forecast launched at 00h00 for t+42|t





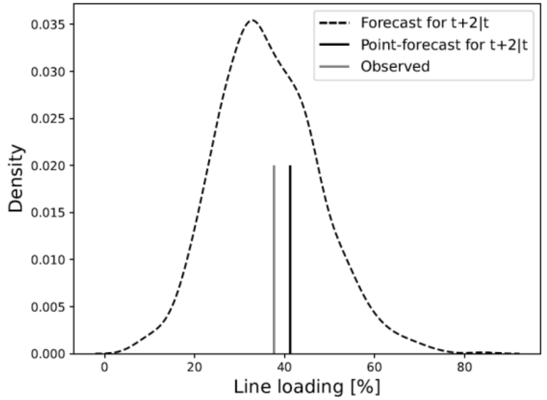
Wait for the next forecast update

Forecast and meta-forecast launched at 12h00



Wait for the next forecast update

Forecast launched for t+2|t



No congestion (no need for flexibility) Saved flexibility cost!

OVERRAL RESULTS

KEY RESULTS

- **Time-to-decide (T2D) approach outperforms deterministic strategies**
  - e.g., F3-score 0.85 (T2D) vs 0.37 (deterministic)
- **T2D outperforms a decision-now strategy** (operator decides to reserve flexibility at the lowest availability cost)
  - Improves in 30% the cost-loss matrix performance metric (γ)

Profiles of different decision/makers

	Stakes (ρ) range		
Decision-making approach	$0 \leq \rho \leq a^*$	$a < \rho \leq 7$	$7 < \rho \leq 10$
DM A: Maximum risk threshold	10	6	3
DM B: Maximum risk threshold	20	15	10
DM C: Maximum risk threshold	25	20	20
DM D: Risk-cost trade-off	30	50	70

- Different **decision-maker profiles lead to distinct results**
  - e.g., F3-score 0.85 (DM A) vs 0.77 (DM C)
  - DM D has a cost-loss matrix performance metric (γ) 20% lower than DM A

KEY TAKE AWAYS

Smart4RES

Main contribution

Methodology to guide the human operator along 1) the different flexibility options available in each hour, ranking them according to their effectiveness under uncertainty, and 2) multiple forecasts updates

Key results

- ❑ Uncertainty forecasts can lead to cost savings when solving technical problems
- ❑ Choosing the best moment to reserve flexibility also leads to cost savings

Avenues of future research

- ❑ Include the look-ahead impact of activating flexibility
- ❑ New metrics to evaluate decision quality under uncertainty
- ❑ Meta-forecasting has room for further improvement & application to other use cases

Smart4RES

Thank you!

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Smart4RES

Final conference
14 April 2023

Optimization of operation and security assessment of isolated power systems with high RES penetration

Dr. Dimitris Lagos

Institute of Computer and Communication Science
National Technical University of Athens

National Technical University of Athens

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

OUTLINE

1. Non-Interconnected islands operating in high RES penetration
2. Dynamic Security Assessment
3. Secure Economic Dispatch considering central Battery Energy Storage Services
4. Key take aways

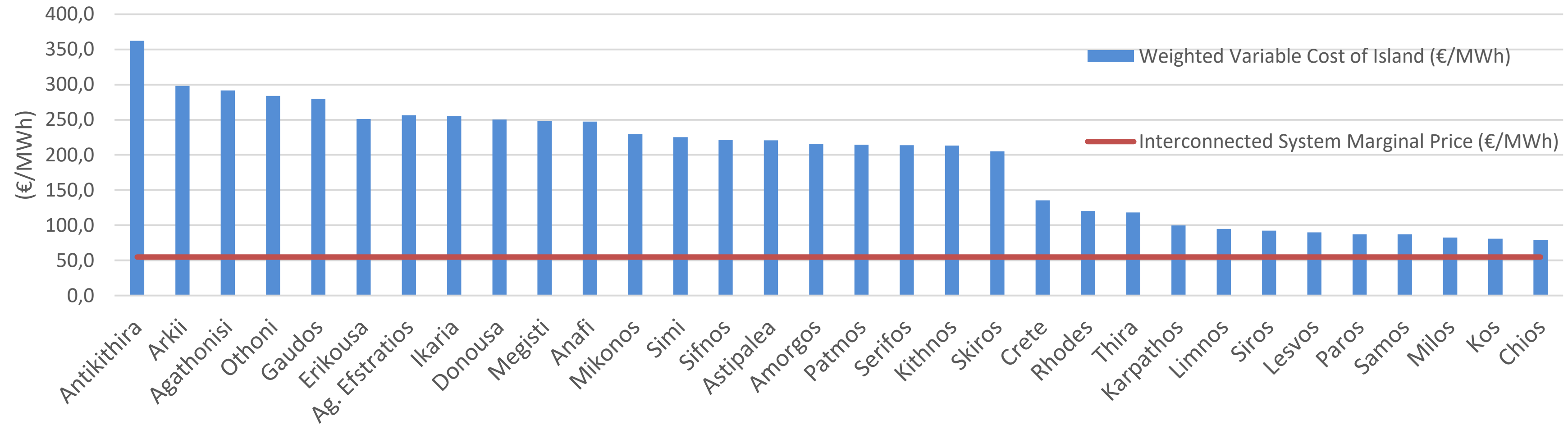
Greek non-interconnected islands

- Host 15% of the Greek population and account for almost 14% of the total national annual electricity consumption.
- High seasonal variability in load demand.
- Supplied by autonomous power stations with diesel Generators (**High Operational Costs**)
- Restricted Penetration of RES for operational security.

"Smart" island projects under development

Utilization of battery storage technologies and smart grid applications to:

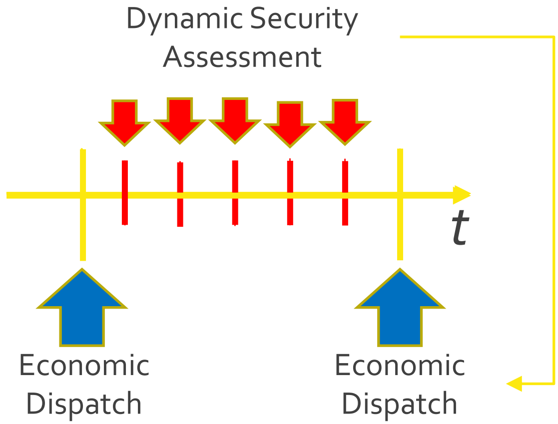
- Increase RES penetration.
- Improve Security of Power Supply under higher RES penetration levels



Data based in 2017

Dynamic Security Assessment

- Module in Energy Management Systems. Run on smaller intervals than economic dispatch.
  - **Goal**: Estimate **accurately** if the existing operating condition is secure or insecure
  - **Algorithm**:
    - Get system state (e.g. generator active/reactive power, load active/reactive power) every x minutes
    - Check if system is secure:
      - Run power flows/dynamic simulations and check if security thresholds are exceeded (e.g. in line loading, voltage levels, frequency nadirs or Rate of Change of Frequency) - **typical approach**
      - Use data driven classifiers - **modern approach (avoid high computational burden of running many simulations)**
  - **Action:** If insecure state computed, further security constraints are added in the economic dispatch to result in secure state (e.g. by curtailing RES, committing extra generators, requesting higher reserve levels, etc.)



Dynamic Security Assessment in Islands

Current Practice

- Frequency Security is the goal in island's dynamic security assessment methods. **How?**
  - Dynamic threshold on RES penetration (e.g. 20-30%).
  - Thermal units Reserves to match N-1 criterion and certain variation in RES output.

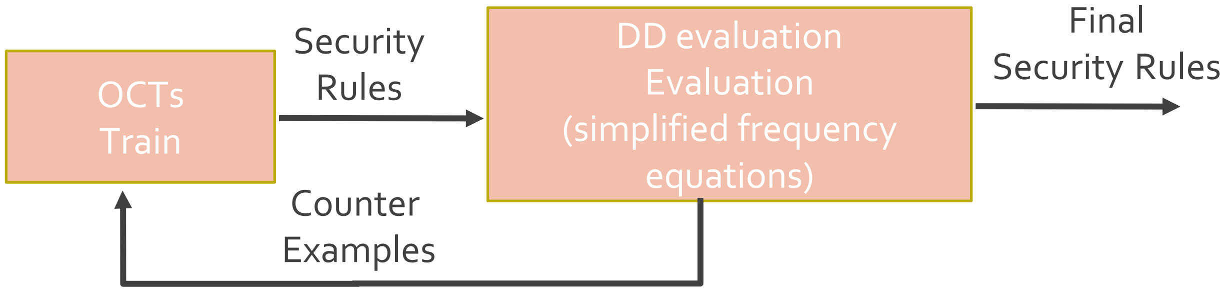
Rules based on operator's experience. **Can be conservative or insecure at certain conditions (no direct link to frequency dynamics).**

- Operation of Dynamic Security Assessment.
  - Read from SCADA the production of generators and check RES penetration and thermal units production.
  - Execution again n minutes (e.g. 5 or 15).

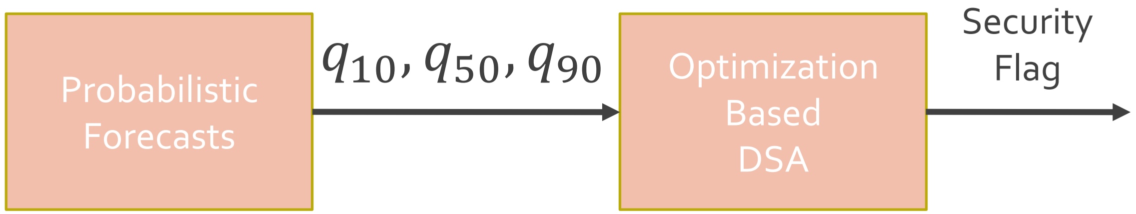
System state changes from a until next execution due to RES, demand variation. **What if it leads to insecure state ?**

Proposed Practice in Smart4RES

- Data Driven security rules trained with Optimal Classification Trees (OCTs) on a **detailed dynamic model**. Validated on physical equations to provide guarantees to the system operator



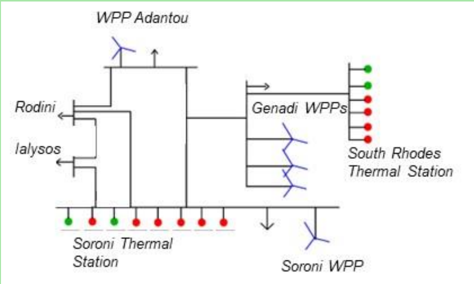
- Formulation of optimization based assessment that uses short term forecasts to find **if possible states in near future are uncertain**.



Test Case – Rhodes Living Lab

Rhodes Power System

System operator SCADA



Local DB

- Detailed Model of Dynamics.
- Run offline for recorded data for evaluation.
- Can **not** model precise dynamics of industrial equipment.

Powerfactory Rhodes Model

Offline Model

Real Time Digital Simulator (Rhodes Digital Twin)

- Detailed Model of Dynamics.
- More **precise** setup (Actual Industrial equipment can be included in the setup)
- Run online for several hours for demonstration (updated every minute).

Frequency Load Shedding Relay (Rhodes Settings)

Living Lab

System State

Frequency Metrics (as actual security indication)

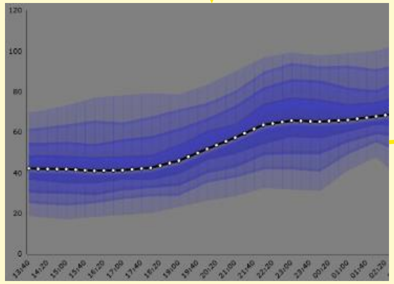
Relay Status (as actual security indication)

System State

Modbus Client

Historical Data

System State



Short Term Probabilistic Forecasts

Timestamp	Security Indication
28-02-2023 13:46:01	Insecure
28-02-2023 13:31:01	Secure

Security Estimation (Secure/Insecure)

Short Term Forecast Module

Dynamic Security Assessment Module

NTUA

Security Assessment Results

- Comparison with **system state as dictated by system operators' economic dispatch and security module.**
- System operator's Security Module is less conservative with load shedding events considered acceptable.
- **Testing period: 15/02/2023 – 31/03/2023**
    - Forecast/Dynamic security module executed online every 1hour/15minutes.
- Evaluation with powerfactory model (every point) and Living Lab demonstration (total of 6 hours, on different days)

PowerFactory

	Secure	Insecure
Estimated Secure	71.8%	2.83%
Estimated Insecure	28.2%	97.17%

Living Lab

	Secure	Insecure
Estimated Secure	89.5%	0%
Estimated Insecure	10.5%	100%

- **High Accuracy in Insecure State Detection. Preventive actions can lead to over 95% Load Shedding Events Reduction.**

Secure Economic Dispatch on Small Islands with RES penetration over 60%

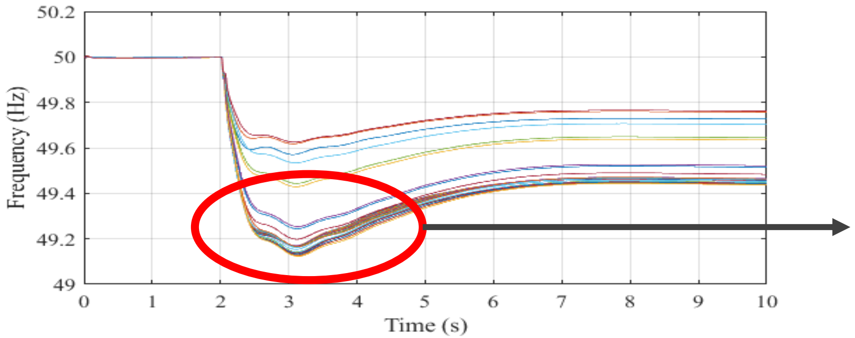
How:

- ➢ Deterministic forecasts. **High Forecast errors can occur in small island systems**.
- ➢ Consider similar response on Battery Energy Storage (BES) and Thermal units frequency containment reserves (FCR).
- ➢ Impact of Frequency Restoration Reserves by the BES on its SoC is **not** considered.

Current Practice

At an unbalance the BES:

- Picks up fast almost all the disturbance.
- **Current limitation** can be activated restricting ancillary services provision



Frequency Transients with current limitation activated on the BES inverter

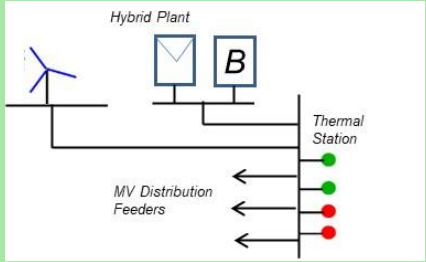
Proposed Secure Economic Dispatch

- ➢ Probabilistic forecasts.
- ➢ Constraints extracted by a dynamic model that includes: BES synthetic inertia and fast frequency containment reserves FCR, thermal units inertia and FCR.
- ➢ Impact of Frequency Restoration Reserves on BES SoC included.

Test Case – Astypalea Living Lab

Astypalea Power System

System operator SCADA



Large RES plants (PV, Wind) not installed (Data from Rhodes used)
BES not installed (simulated)

Local DB

BES Model

Powerfactory Astypalea Model

Offline Model

BES Grid Forming Controller with Ancillary Services

Real Time Digital Simulator (Astypalea Digital Twin)

PV inverter

Living Lab

Power Setpoints, Units Commitment System state

Frequency Metrics, SoC

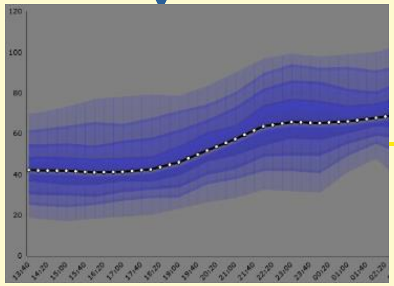
Relay Status, SoC

Power Setpoints, Units Commitment System state

Modbus Client

Historical Data

System State



Short Term Probabilistic Forecasts

$$\min_{x} f(x)$$
$$\text{s.t } Ax \leq B$$

Power Setpoints, Units Commitment

Short Term Forecast Module

Secure Economic Dispatch

NTUA

Secure Economic Dispatch Results

- Comparison between typical and proposed secure economic dispatch.
- **Target**: Reduce load shedding events due to SoC violation and high RoCoF/Frequency Transients.
- **Testing period: 15/02/2023 – 15/03/2023.**
- **Additional predefined Critical Timeseries (high RES/ high Demand scenarios e.g. during summer) (4 hours).**
  - Forecast/economic dispatch executed online every 1h/30min. Real time control every minute to ensure tracking of ED commands
- Evaluation with powerfactory model (all points) and Living Lab demonstration.

Typical	Proposed
• **SoC limits violated at 0.5% of the total testing period.** • **SoC limits can be violated by aFRR activation at 7.17% of the total testing period.** • **120/150 of the predefined critical scenarios in living lab resulted in load shedding (RoCoF islanding detection relay activation)**	• **SoC limits violated at 0.17% of the total testing period.** • **SoC limits can be violated by aFRR activation at 0.69% of the total period.** • **All predefined critical scenarios in living lab are secure.**

- **Proposed Secure ED can lead to reduction of possible Load Shedding Events with a total increase of 0,15% in cost.**

KEY TAKE AWAYS

Non Interconnected Island System Operators apply or consider initiatives (hybrid stations, novel smart grid applications) to increase RES penetration.

Living Labs utilizing real time measurements, real time digital twins and hardware equipment (using HIL approaches) can help build the trust of system operators in novel smart grid applications correlated with dynamic security.

Proposed Smart4RES forecasts and security applications can increase security of operation in islands under those conditions.

FURTHER READING

- D5.1 Joint dispatch of RES and storage technologies towards a multi-service approach
- D5.2 Predictive dispatch of isolated systems to guarantee minimum FCR and system inertia requirements
- D 6.2 Combined software and hardware in the loop tests for distribution grids and isolated power systems with high RES penetration
- D. T. Lagos and N. D. Hatziargyriou, "Data-Driven Frequency Dynamic Unit Commitment for Island Systems With High RES Penetration," in IEEE Transactions on Power Systems, vol. 36, no. 5, pp. 4699-4711, Sept. 2021, doi: 10.1109/TPWRS.2021.3060891.
- D. T. Lagos and N. D. Hatziargyriou, " Comparison of Grid Forming and Grid Following control of a central BES in a island system operating in high RES penetration", in Powertech 2023.

Smart4RES

Thank you!

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Smart4RES

Final conference
14 April 2023

Trading strategies for RES production

Simon Camal

Akylas Stratigakos, Luca Santosuosso
ARMINES – MINES PARIS – PSL University, Centre PERSEE

ARMINES

MINES PARIS | PSL | PERSEE

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No 864337

OUTLINE

1. Context and motivation
2. Trading renewable production in the energy market
3. Adding the provision of ancillary services
4. Conclusions and key takeaways

CONTEXT

Combined operation of RES, storage assets

- **Hybridization and aggregations** ease RES penetration
- **Ancillary Services (AS) needs** expected to grow

Evolutions in short-term markets

- **Energy:** towards single-pricing of imbalances
- **Frequency-control AS:** ongoing harmonization in Europe
- **Sharp rise** in energy prices

USE CASE

Optimize RES trading decisions and storage control (if any) on different short-term markets, considering:

- RES forecasting as input
- Market uncertainties

MOTIVATION

Optimisation of RES Virtual Power plant (VPP) participation in energy + Ancillary Service (AS) markets

Data on RES, storage, markets

Forecast aggregated RES production (1)

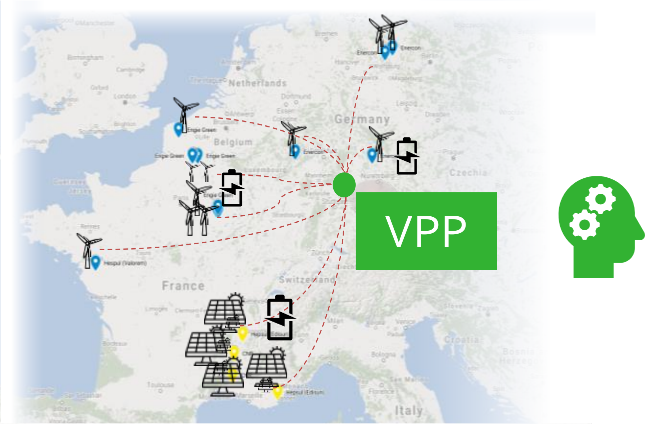
Forecast DA/ID energy market quantities (prices, imbalances) (3)

Forecast AS market quantities (prices, volumes, activation probabilities) (6)

Stochastic optimisation for trading and control decisions (1)

Bids on energy + AS markets

Storage control (if any)



Smart4RES GOALS

- ❑ Develop **uncertainty-aware strategies** for RES trading and control
- ❑ Evaluate the **impact of forecasting performance** on decisions
- ❑ Identify role played by market variables that are **difficult to predict**

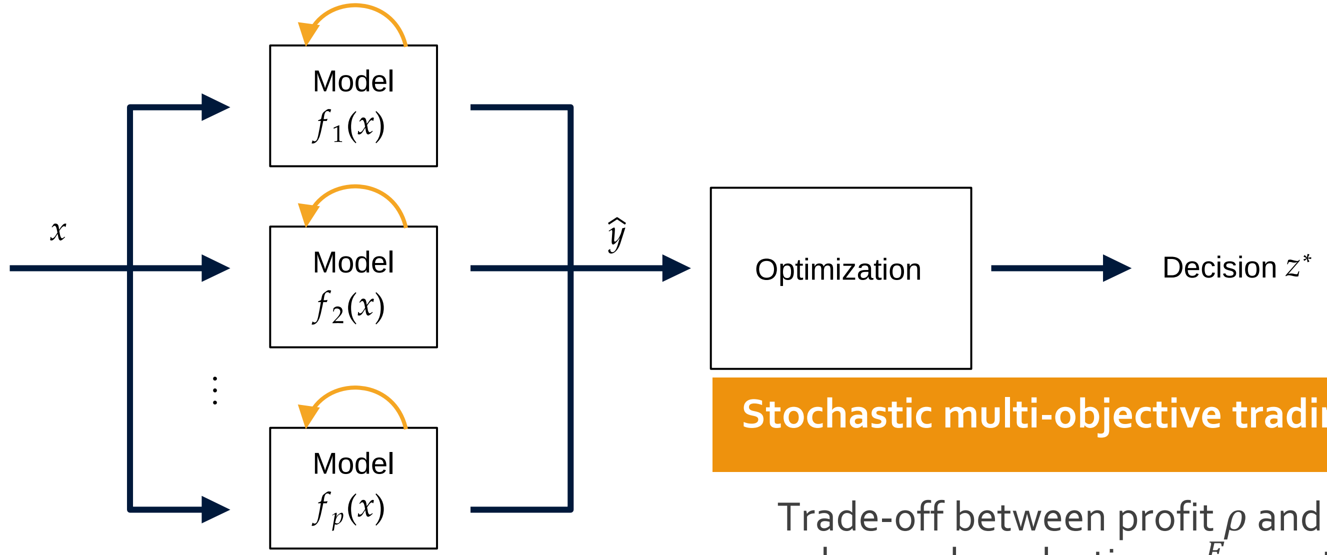
A FORECAST-THEN-OPTIMIZE APPROACH

Forecasting with ML / statistical methods

Data on markets & RES

Market prices (past) & volumes (past, predicted)

NWP, past production



Stochastic multi-objective trading optimization

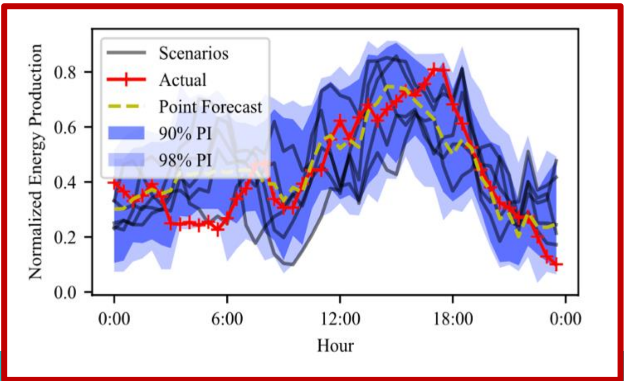
Trade-off between profit ρ and deviation to observed production p^E, controlled by k

$$\min_{p^{\text{offer}}} \quad \mathbb{E}\left[(1-k)(-\rho) + k\left\|p^{\text{E}} - p^{\text{offer}}\right\|_2^2\right],$$

$$\text{s.t.} \quad p^{\min} \leq p^{\text{offer}} \leq p^{\max},$$

Market conditions may be difficult to predict
→ **How to hedge against large profit losses ?**

RES-VPP forecast

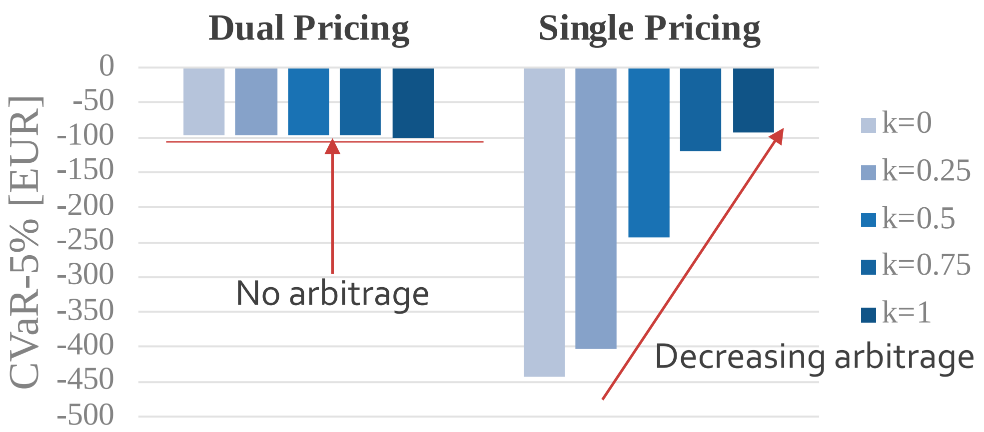


Camal et al., Trading strategies for RES production

TRADING RES ON THE DAY-AHEAD ENERGY MARKET

Case Study: Wind+PV VPP (49 MW), French Market

Evaluation of large profit losses



Improvement in mean profit value $\hat{v}$

$$P = 1 - \frac{\hat{v} - \hat{v}^*}{\hat{v}^{SAA} - \hat{v}^*}$$

- Perfect Foresight ($\hat{v}^*$)
- Naive Sample Average Approximation ($\hat{v}^{SAA}$)

P	Dual Pricing	Single Pricing
k=0	62%	**6%**
k=1	86%	85%

Results

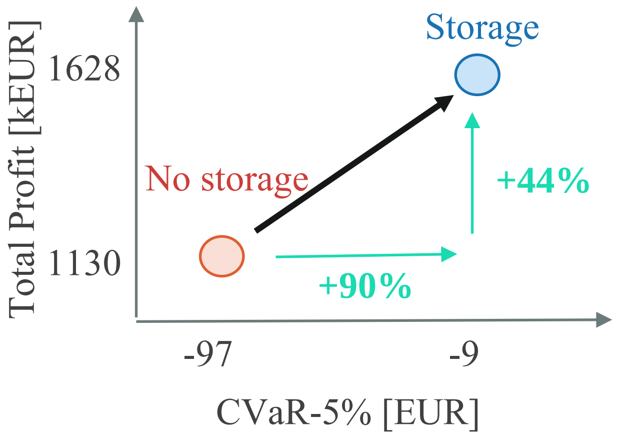
- ❑ Method limits **risk of large profit losses** in dual-pricing and single-pricing
- ❑ **Improvement in mean profit** if no or reduced arbitrage
- ❑ **Barriers in predictability** (e.g. imbalance prices) limit value for risk-prone trading

INTEGRATING STORAGE

Stochastic Optimization + Linear Decision Rules for recourse actions as a function of RES forecast error

Case Study

- Previous 49 MW VPP + 25 MW/12MWh storage
- Dual-pricing, k=0.75



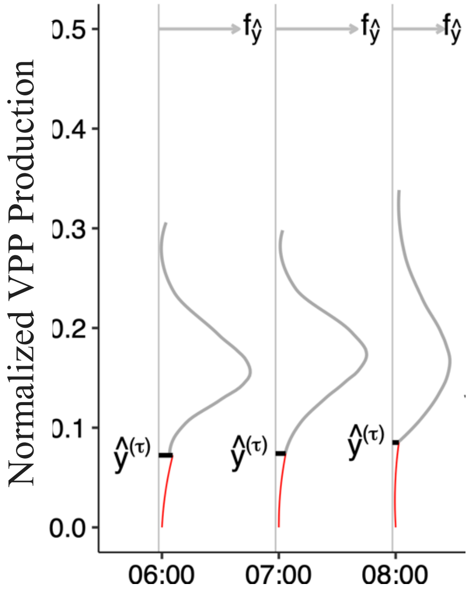
Results

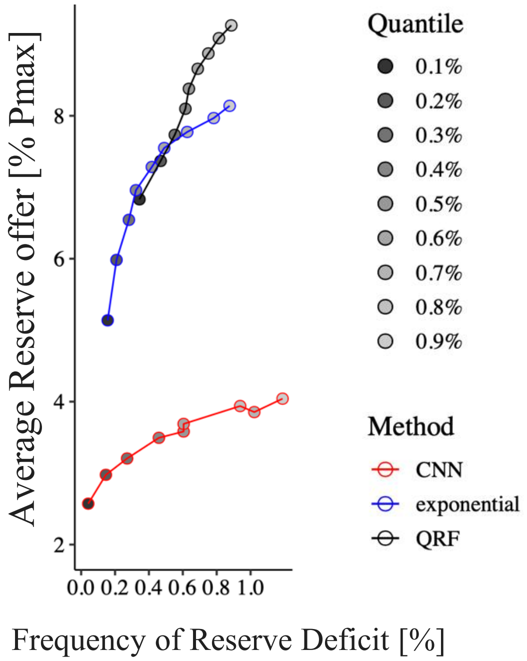
- ❑ **Profit increases**, but payback of storage is long if day-ahead energy only
- ❑ Method adaptable to RES forecasting updates, but limited to track dynamic control signals

TRADING RES-BASED ENERGY + ANCILLARY SERVICES

Provide RES-based energy + reliable AS without storage?

- Predict a low quantile (e.g. $\leq 1\%$) of the expected VPP production (reliability $\geq 99\%$)
- Reserve offer on the AS market (e.g. aFRR) based on this quantile + Energy offer on non-extremal quantiles





Results
- ❑ Trade-off between reliability and reserve volume
- ❑ Without storage, profit increase ~ 4-5 % vs energy only

ENERGY + ANCILLARY SERVICES FROM RES+STORAGE

Smart4RES

A sequential trading -> control framework

Data on RES, markets, storage

Forecasting with
ML / statistical methods

Stochastic optimization
(trading & control)

Day-ahead:
Trading / Scheduling

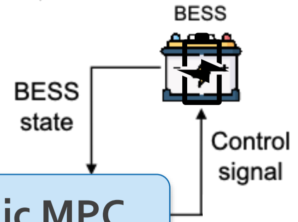
RES Scenarios + Price Scenarios

Trading & Storage
schedule optimization

Simultaneous trading on Energy + AS markets (FCR, aFRR)

Intraday:
Model Predictive Control (MPC)

RES Scenarios + Estimation of AS activation



Economic MPC

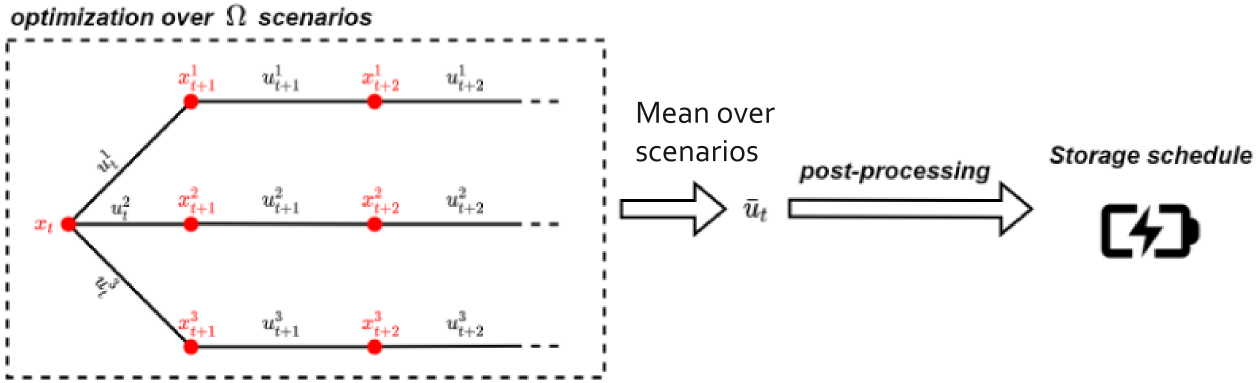
Minimize imbalance costs on energy market & anticipate AS activations

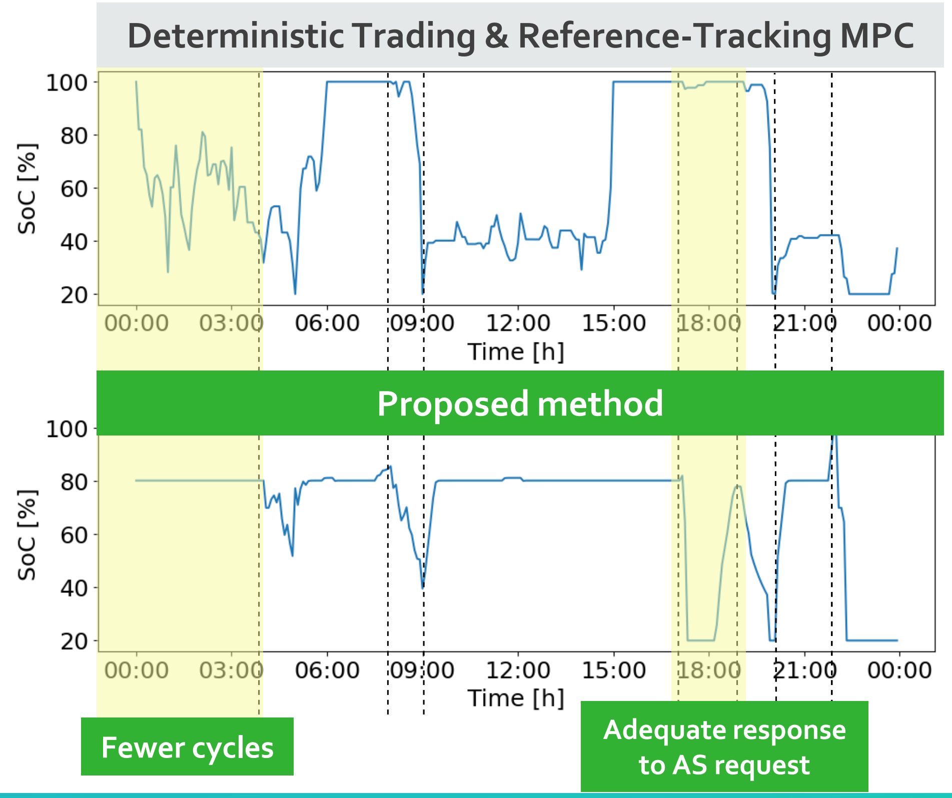
A STOCHASTIC TRADING & CONTROL METHOD

Day-ahead RES scenarios → **Trading** → $\min \mathbb{E}$ (Trading cost Energy + AS + Battery degradation cost)

Offers ↓

Intraday RES scenarios → **Economic MPC** → $\min \mathbb{E}$ (Energy imbalance + AS deficits + Battery degradation cost)



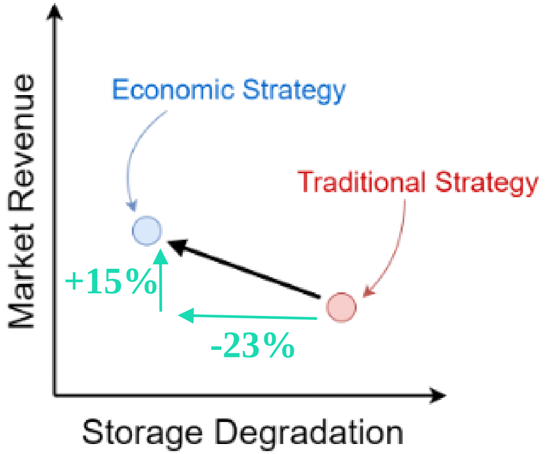


TRADING AND CONTROL WITH ANCILLARY SERVICES

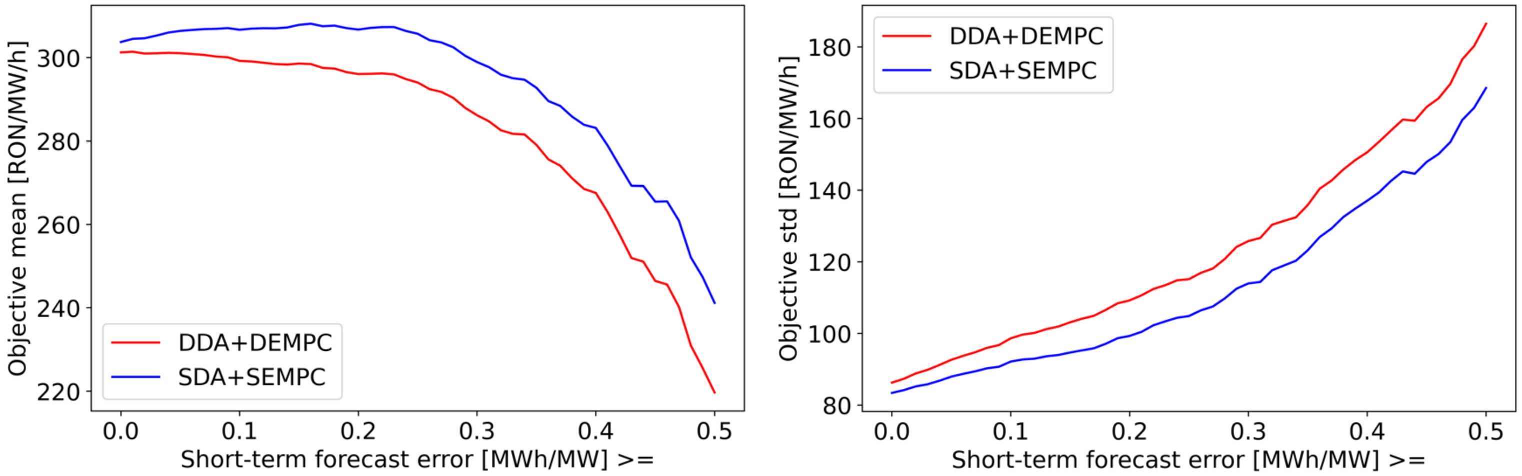
Case Study

- Hybrid system: 26 MW Wind Farm + 1 MW/MWh Storage, Romania
- Day-ahead trading of energy + AS (FCR, aFRR)

Cost Analysis



Impact of RES Forecasting error on objective (trading + degradation)



Results

- ❑ **Economic MPC** enables to increase revenue and reduce degradation
- ❑ Stochastic formulation reduces **sensitivity to RES forecasting error**

KEY TAKE AWAYS

Main contribution

Forecast-then-optimize solutions for trading and control of RES + storage under multiple uncertainties

Key results

- ❑ Stochastic methods improve profitability of renewable-based energy & frequency control
- ❑ Decrease in intraday RES forecasting error reduces costs for storage control

Avenues of future research

- ❑ Value-oriented approach where forecasting models are tuned to improve decision costs
- ❑ Distributionally Robust Optimization to hedge against highly uncertain variables

Thank you!

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- Luca Santosuosso, ARMINES / MINES PARIS
- Akylas Stratigakos, ARMINES / MINES PARIS

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Final conference
14 April 2023

Resilient energy forecasting and prescriptive analytics

Akylas Stratigakos

Mines Paris, PSL University, Center PERSEE

MINES PARIS | PSL | PERSEE

ARMINES

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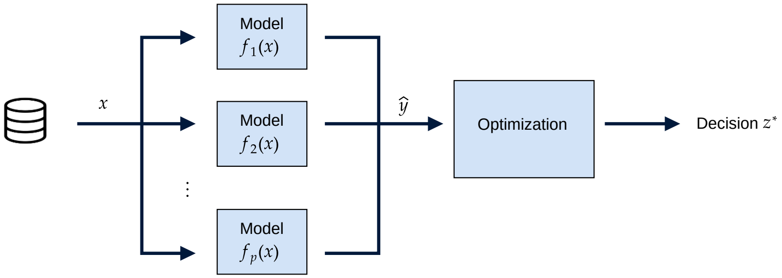
Outline

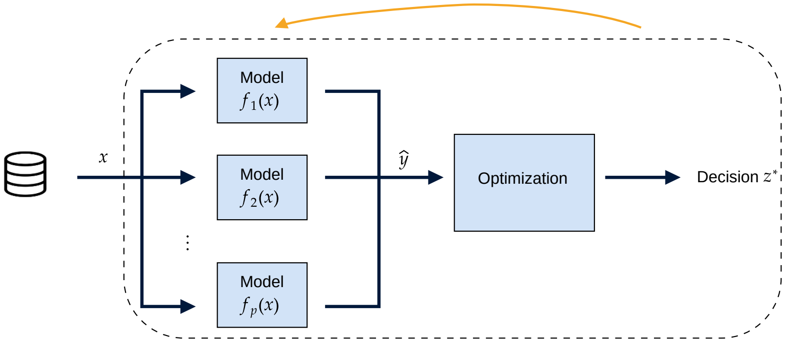
1. Introduction
2. Integrated Forecasting-Optimization
3. Resilient Energy Forecasting
4. Conclusions
5. References

Outline

Moving from data to decisions



Forecast value



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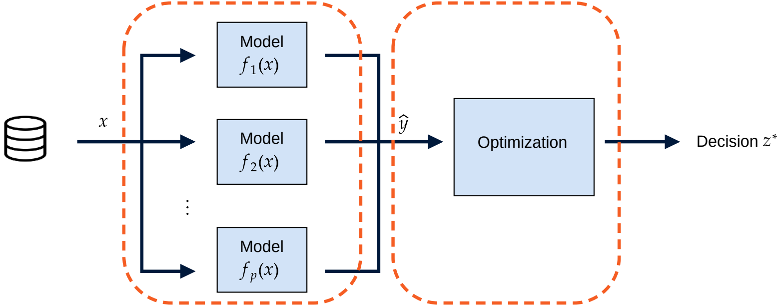
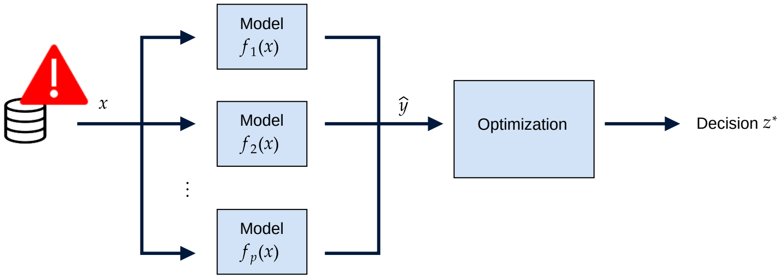
Modeling effort, computational speedup



Challenges

Data-management issues



Goal: Increase value in data-driven decision-making processes via *(i)* value-oriented forecasting, *(ii)* simplification of complex model chains, and *(iii)* enhanced resilience.

RD1: Developing integrated forecasting-optimization tools

1. Improve forecast value
2. Reduce number of models
3. Evaluate the impact of data on decisions

RD2: Enhancing resiliency in energy forecasting applications

1. Consistent performance when data are missing operationally
2. Reduce number of models, maintain practicality

Objectives and Research directions

> **Goal:** Increase value in data-driven decision-making processes via *(i)* value-oriented forecasting, *(ii)* simplification of complex model chains, and *(iii)* enhanced resilience.

RD1: Developing integrated forecasting-optimization tools

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Outline

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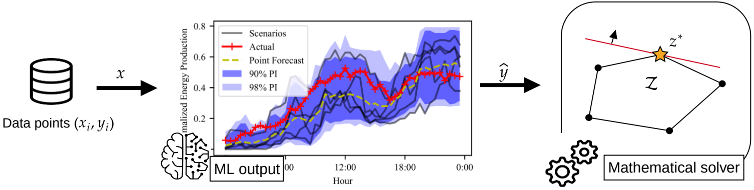
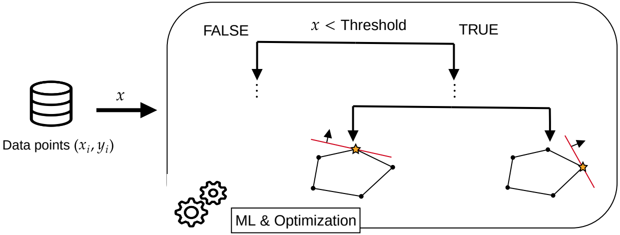
Overview of Methodology

Prescriptive analytics problem: $\min_{z \in \mathcal{Z}} \mathbb{E}_y[c(z; y|x)]$





z: decisions
x : features
y: uncertainty
$c(\cdot)$: cost function
$\hat{\cdot}$: forecast
$\mathcal{Z}$: feasible set

Outline

Proof of concept: RES trading

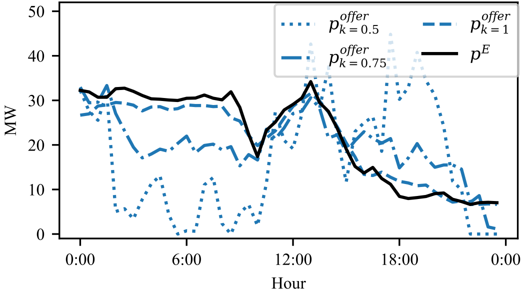
- **Setting**: renewable aggregator participates in a day-ahead market, subject to imbalance penalties
- **Hybrid trading strategy:** balance between expected trading profit (*prescriptive*) and expected forecast accuracy (*predictive*), given by

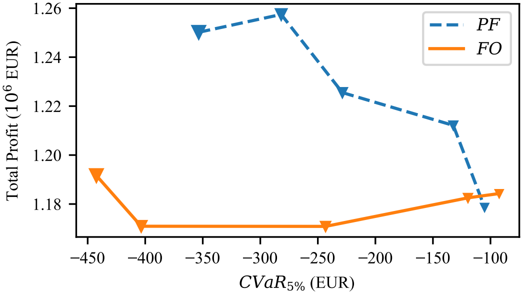
$$\begin{aligned} \min_{p^{\text{offer}}} \quad & \mathbb{E}\left[(1-k)(-\rho) + k\left\|p^{\text{E}} - p^{\text{offer}}\right\|_2^2\right], \\ \text{s.t.} \quad & p^{\min} \leq p^{\text{offer}} \leq p^{\max}, \end{aligned}$$

where ρ is the profit function, k is a design parameter controls the trade-off.

  - $k = 0$: "0-1" or newsvendor loss (depending on market design)
  - $k = 1$: standard regression loss

Illustrative results for a day-ahead market, *single*-price balancing mechanism:





Offers are riskier as k decreases and the producer attempts to arbitrage.

Risk versus reward trade-off for different k. PF: proposed, FO: forecast-then-optimize.

Evaluating Feature Importance

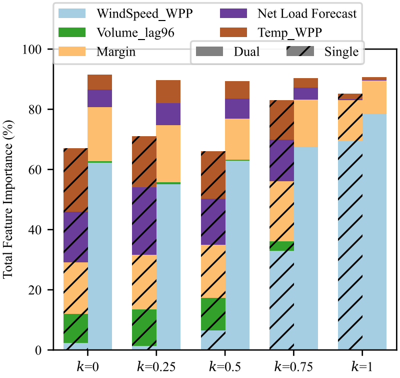
For $k = 1$:

- Offers the expected production.

For $k = 0$, optimal trading offer:

- Single-price: offers either 0 or 1, *only* market quantities matter.
- Dual-price: offers the optimal production quantile given expected market quantities.

Forecasting market quantities is relatively more important in a single-price setting.



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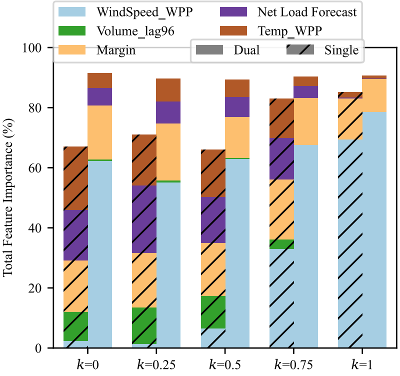


Prescriptive feature importance

Summary

Contributions[1]:

1. Profit increase: 3.82% (single-price market) and 0.62% (dual-price market).
2. 1 model versus 4 forecasting models (renewable production + market quantities).
3. Profit increase associated with each feature.

Other applications:

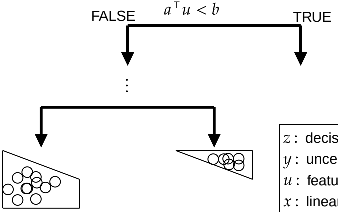
- Co-optimization of renewable trading and storage operation
- Tailored forecasting problems (e.g., shape forecasting)

[1] A. Stratigakos, S. Camal, A. Michiorri, and G. Kariniotakis, "Prescriptive Trees for Integrated Forecasting and Optimization Applied in Trading of Renewable Energy," in IEEE Transactions on Power Systems, vol. 37, no. 6, pp. 4696-4708, 2022.

Extensions

Prescriptive trees that learn a piecewise affine policy [2]:

- Leaves with affine decision rules
- Hyperplane splits encode domain knowledge (**interpretable**)
- Robust optimization to ensure **feasibility**
- Application: learning the DC-OPF solutions



$$\min \mathbb{E}(c(z;y)) = \frac{1}{N_\ell}\sum_{i=1}^{N\ell} c(z;y_i)$$
$$s.t.\ z(u) \in \mathcal{Z},\ \forall u \in \mathcal{U}_\ell$$
$$z(u) = x^\top u$$

z : decisions
y : uncertainty
u : features
x : linear decision rules
$c(\cdot)$: cost funtion
(a, b) : hyperplane parameters
$\mathcal{Z}$: feasible set
$\mathcal{U}_\ell$: polyhedral uncertainty set

[2] A. Stratigakos, S. Pineda, J. M. Morales, and G. Kariniotakis. "Interpretable Machine Learning for DC Optimal Power Flow with Feasibility Guarantees." (2023).

Outline

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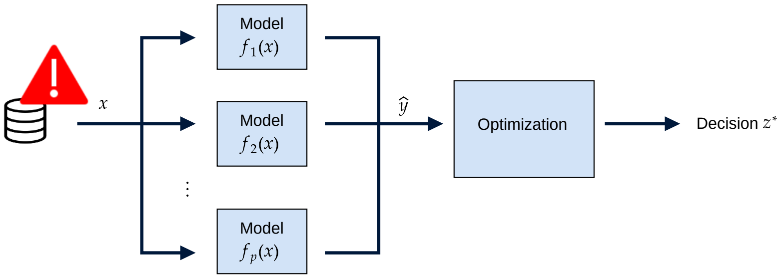
x
Model
$f_1(x)$
Model
$f_2(x)$
Model
$f_p(x)$
$\hat{y}$
Optimization
Decision z^*

Context and Motivation

Forecast performance:

- Depends on data **quality** and **availability**.
- Data-management issues [1] emerge after model deployment.

Missing features in an operational setting:

- Subset of features used for training is unavailable at test time.
- Reasons: network latency, APIs, cyber-attacks, equipment failures...
- Assessment on ENTSO-E's Transparency platform: "for every data domain, fewer than 40% of users reported that data were always there when needed" [2].
- Might not even be possible to model the missingness patterns.

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Dealing with missing data:

- *Impute-then-regress*: computationally costly.
- *Retraining* without missing features: performs well, but it is impractical [3].

Ideally, deployed models should be **resilient** and maintain **consistent** performance without increasing complexity[3].

Design regression models that optimally resilient to missing features at test time

- Requires only solving an LP
- Agnostic to missingness patterns

[3] A. Stratigakos, P. Andrianesis, A. Michiorri, G. Kariniotakis. Towards Resilient Energy Forecasting: A Robust Optimization Approach. 2023.

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Outline

Proposed Robust Formulation

Linear Regression: n observations of target $y \in \mathbb{R}$ and features $\boldsymbol{x} \in \mathbb{R}^p$, estimate parameters $\boldsymbol{w} \in \mathbb{R}^p$ by minimizing loss function l: $\min\limits_{\boldsymbol{w}} \frac{1}{n} \sum_{i=1}^{n} l\left(y_i - \boldsymbol{w}^\intercal \boldsymbol{x}_i\right)$

Modeling Feature uncertainty:

- Use $\boldsymbol{\alpha} \in \{0,1\}^p$ and model features as $\boldsymbol{x}_i \odot (\mathbf{1} - \boldsymbol{\alpha})$, where $\alpha_j = 1$ if the j-th feature is missing.
- $\mathcal{U} = \{\boldsymbol{\alpha} \mid \boldsymbol{\alpha} \in \{0,1\}^p, \mathbf{1}^\intercal \boldsymbol{\alpha} = \Gamma, \boldsymbol{M}\boldsymbol{\alpha} = \mathbf{0}\}$, Γ is the budget of robustness.

Feature-deletion robust regression **(FDRR)**: minimize the worst-case loss when Γ features are missing:

$$\min_{\boldsymbol{w}} \max_{\boldsymbol{\alpha} \in \mathcal{U}} \sum_{i \in [n]} l\left(y_i - \boldsymbol{w}^\intercal\left(\boldsymbol{x}_i \odot (\mathbf{1} - \boldsymbol{\alpha})\right)\right)$$

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Outline

DA Forecasting

Description: Day-ahead horizon (12h-36h ahead), data arriving in batches, point and probabilistic forecasts

Data set	Source	Features
Prices	FR, ENTSO-E	Lags, calendar, net load, system margin
Load* (21 series)	GEFCom 2012	Vanilla model [4] for multiple weather stations
Wind* (10 series)	GEFCom 2014	Wind speed/dir. (10m, 100m), Fourier terms for diurnal patterns
Solar† (3 series)	GEFCom 2014	Numerical Weather Predictions

*: features deleted in groups, †: one model per hour

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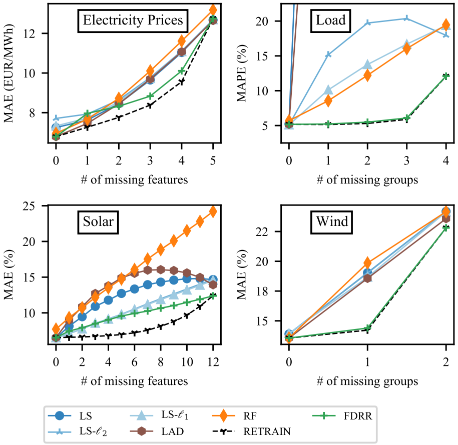
- $\texttt{LS}^*$: a least squares regression with adequate performance.
- $\texttt{LAD}^*$: a least absolute deviations (ℓ_1) regression.
- $\texttt{LS}^*_{\ell_1\backslash\ell_2}$: LS regression with ℓ_1 (lasso) and ℓ_2 (ridge) penalty.
- $\texttt{RF}^*$: a Random Forest.
- $\texttt{RETRAIN}$ [3]: an LAD model retrained for each combination of missing features. A total of $\sum_{k=1}^{p}\binom{p}{k}$ additional models is required (lower bound).
- $\texttt{FDRR}(\Gamma)$: a robust regression with Γ indicating the robustness budget (a different model is trained for each Γ).

* missing data is filled with mean imputation.

DA Forecasting: FDRR versus Benchamarks

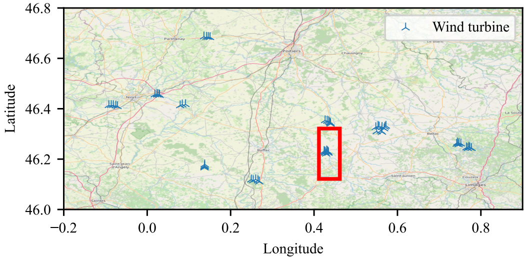
Improvement:

- Point forecasting: 2% for electricity price, 37% for load, 9% for wind, and 5% for solar
- Probabilistic forecasting: 5% for electricity price, 46% for load, 15% for wind, and 21% for solar
- `RETRAIN`: lower bound, but requires **thousands** of separate models.



ID Wind Forecasting

- **Setting**: Wind production forecasting (16MW farm), 30-min ahead, imputation with *persistence*.
- **Features**: Spatio-temporal data from neighboring farms.
- **Improvement**: 23% when data are missing.



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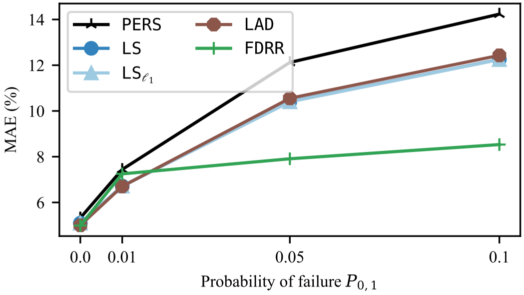
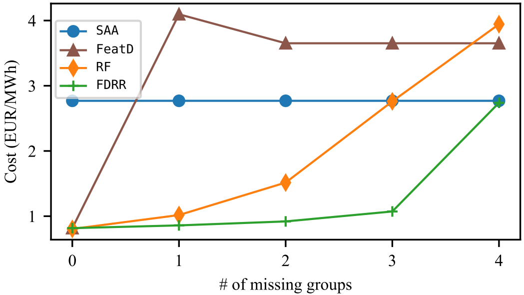


Trading Renewables in DA market

- **Setting**: Forecasting trading decisions (120MW aggregation).
- **Features**: NWPs at several points.
- **Improvement**: 29% smaller trading cost when data are missing.



Outline

Conclusions

Integrated forecasting-optimization (RD1) to improve prescriptive performance:

- 3% improvement in trading performance against forecast-then-optimize
- Reduced modeling effort, evaluation of prescriptive feature importance.

Resilient energy forecasting (RD2) to handle missing data at test time:

- Consistent performance with lower degradation, 20% improvement against benchmarks when data are missing operationally.
- Agnostic to missing data mechanisms, requires only solving an LP problem.

List of publications

Journal publications:

- Towards Resilient Energy Forecasting: a Robust Optimization Approach, in IEEE TSG (*to appear soon*).
  A. Stratigakos, P. Andrianesis, A. Michiorri, G. Kariniotakis
- Prescriptive Trees for Integrated Forecasting and Optimization Applied in Trading of Renewable Energy, in IEEE TPWRS
  A.Stratigakos, S. Camal, A. Michiorri and G. Kariniotakis

Working/under review:

- Optimal Transport for Contextual Stochastic optimization (*working*)
  A. Stratigakos, S. Pineda, J.M. Morales
- Interpretable Machine Learning for DC Optimal Power Flow with Feasibility Guarantees (*under review*)
  A. Stratigakos, S. Pineda, J.M. Morales, G. Kariniotakis

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Conference publications:

- End-to-end Learning for Hierarchical Forecasting of Renewable Energy Production with Missing Values, PMAPS 2022
  A. Stratigakos, D. van der Meer, S. Camal, G. Kariniotakis
- A Value-Oriented Price Forecasting Approach to Optimize Trading of Renewable Generation, 2021 IEEE PowerTech
  A. Stratigakos, A. Michiorri and G. Kariniotakis
- A robust fix-and-optimize matheuristic for timetabling problems with uncertain renewable energy production, IEEE Symposium Series on Computational Intelligence
  A. Stratigakos

Outline

References I

[1] N. Polyzotis, S. Roy, S. E. Whang, and M. Zinkevich, "Data management challenges in production machine learning," in *Proceedings of the 2017 ACM International Conference on Management of Data*, pp. 1723–1726, 2017.

[2] European Commission, "A review of the entso-e transparency platform," 2017.

[3] R. Tawn, J. Browell, and I. Dinwoodie, "Missing data in wind farm time series: Properties and effect on forecasts," *Electric Power Systems Research*, vol. 189, p. 106640, 2020.

[4] T. Hong, *Short term electric load forecasting*. North Carolina State University, 2010.

Thanks!

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Final conference
14 April 2023

PANEL SESSION

Future challenges in RES forecasting

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Gregor Giebel, DTU

Maxime Fortin, RTE
Ana Garcia Gomez, EDP renewables
Ricardo Bessa, INESC TEC
Matthias Lange, EMSYS
Quentin Libois, Météo France

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