Federated learning for predictive management of low voltage grids

Ricardo J. Bessa

INESCTEC

ricardo.j.bessa@inesctec.pt

Motivation

Motivation for Federated Learning

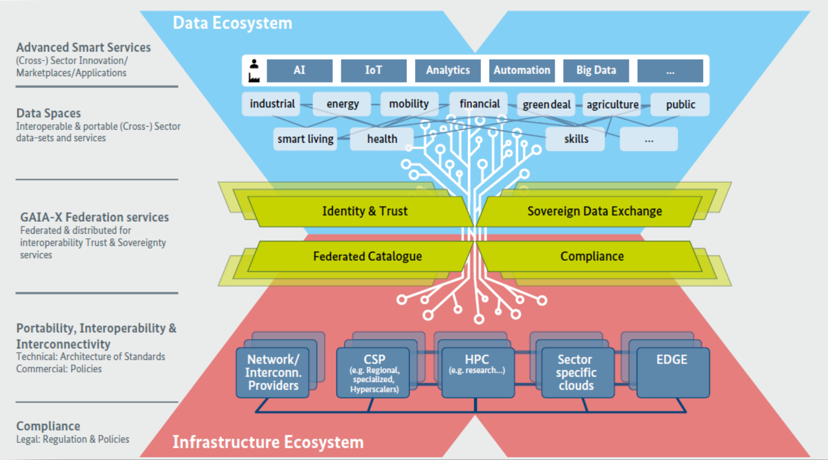
Increasing volume of geographically distributed data

Main Barriers

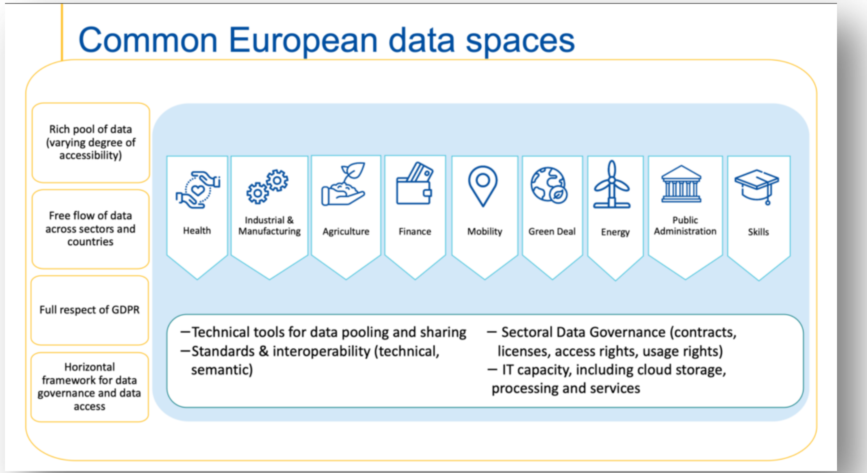
- Data **privacy** and **confidentiality**
- Lack of **monetary and non-monetary incentives** for data sharing
- Lack of **business cases** for collaborative analytics

Data Spaces

GAIA-X



European Commission



Enershare
The Energy Data Space for Europe

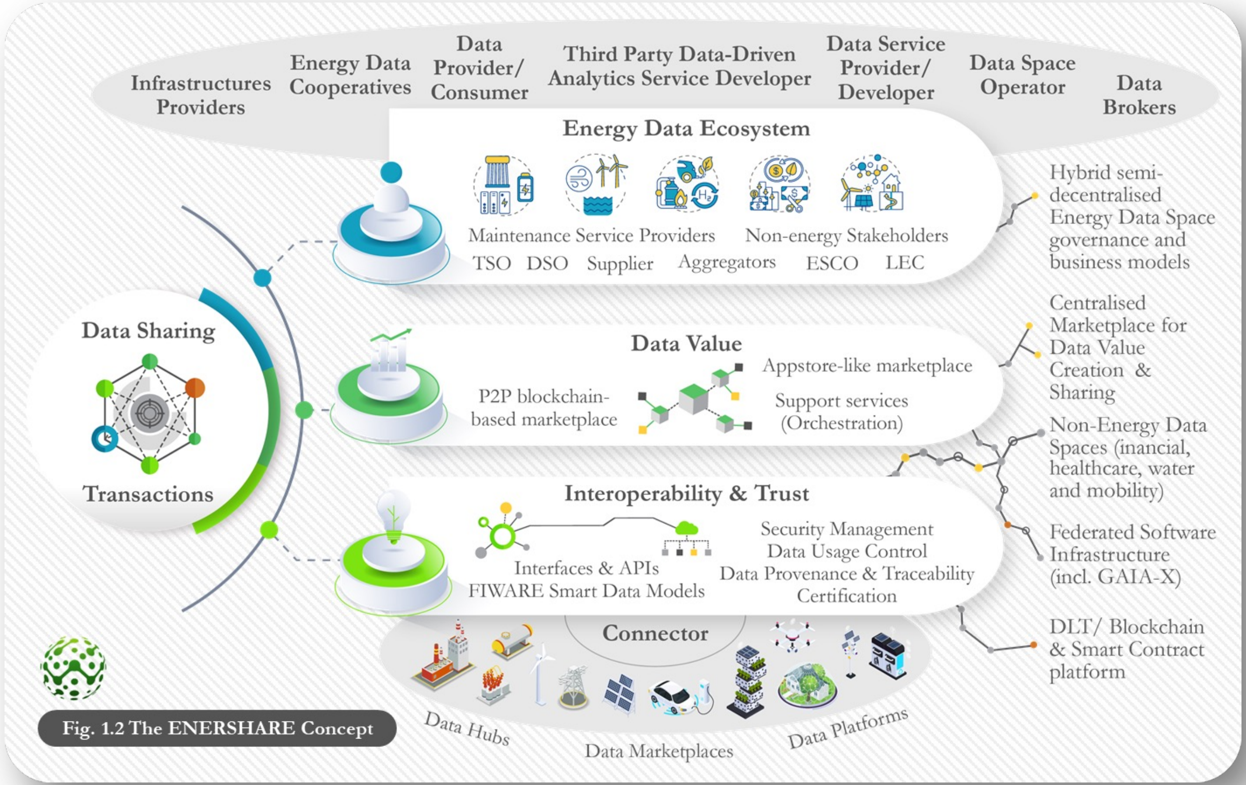


Fig. 1.2 The ENERSHARE Concept

Renewable energy forecasting at the community level

RES Collaborative Forecasting

Example for 2 PV sites

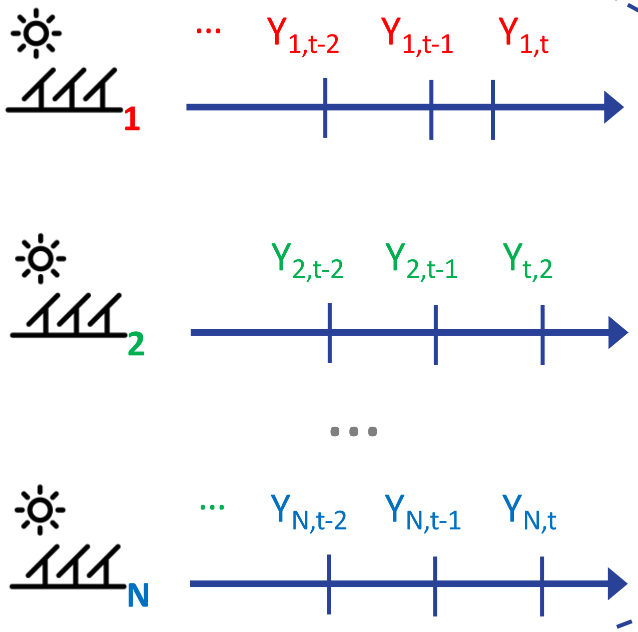
forecasted power

$$[Y_{1,t} \quad Y_{2,t}] = [c_1 \quad c_2] + [Y_{1,t-1} \quad Y_{2,t-1} \quad Y_{1,t-2} \quad Y_{2,t-2}] \cdot \begin{bmatrix} B^1_{1,1} & B^1_{1,2} \\ B^1_{2,1} & B^1_{2,2} \\ B^2_{1,1} & B^2_{1,2} \\ B^2_{2,1} & B^2_{2,2} \end{bmatrix} + [E_{1,t} \quad E_{2,t}]$$

constant terms **(to estimate)**

Z: lagged power observations

B: coefficients matrix **(to estimate)**



Vector Autoregressive Model (VAR)

$$\boldsymbol{Y} = \boldsymbol{c} + \boldsymbol{Z}\boldsymbol{B} + \boldsymbol{E}$$

multivariate linear model

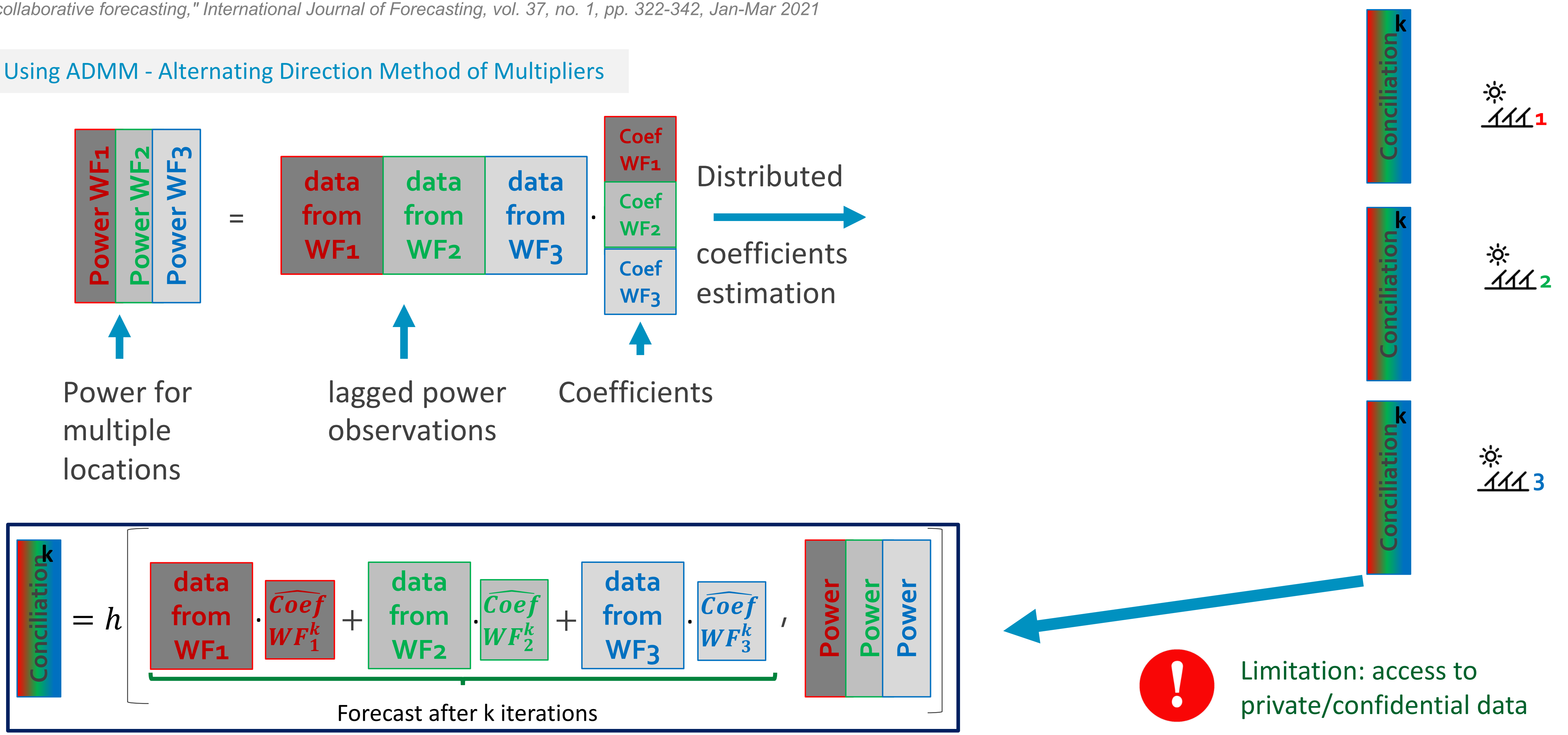
power forecasts for multiple sites **as a function of** past power observations from all sites

extension with additive models to **capture non-linearities**

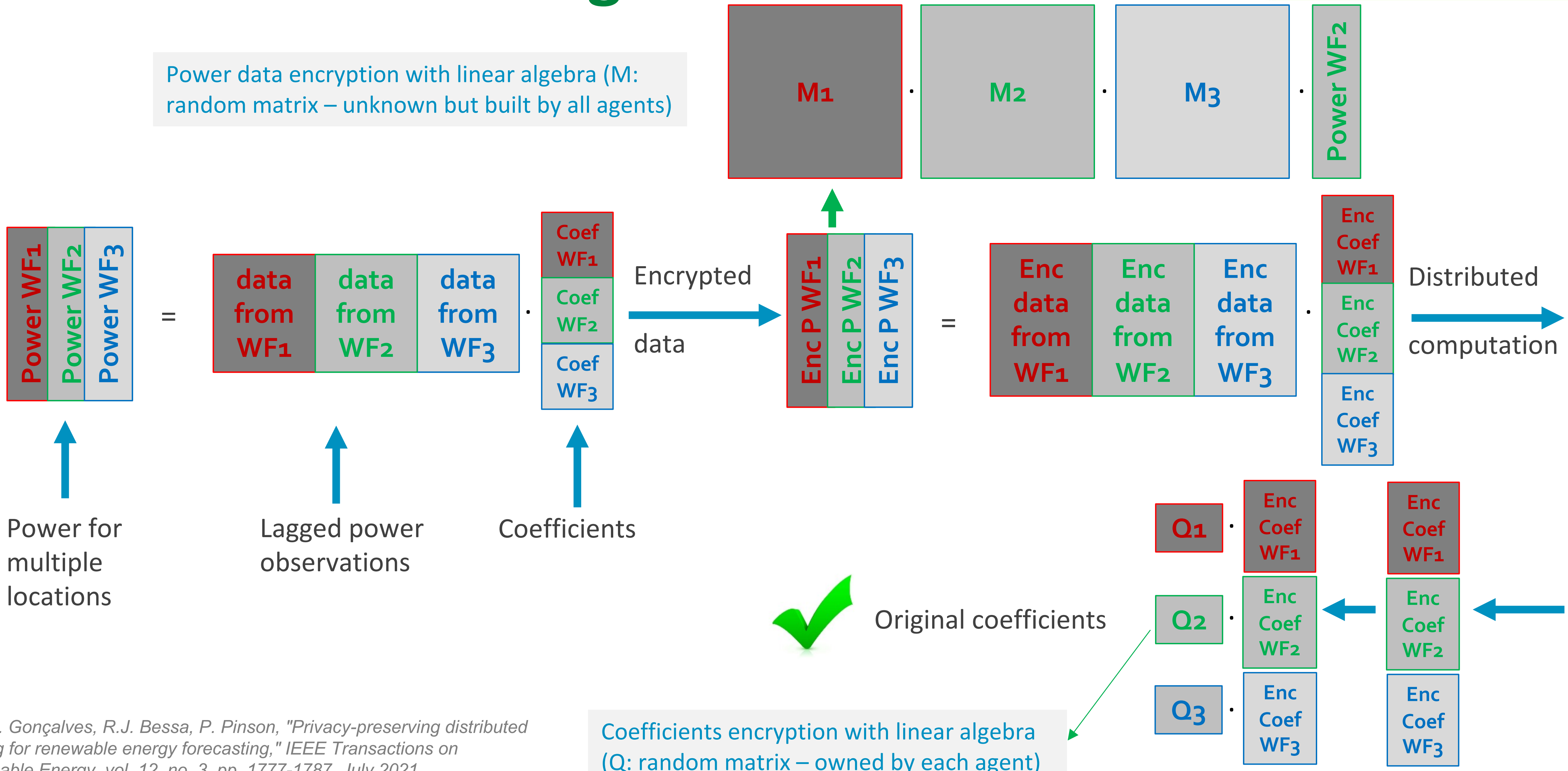
State-of-the Art Limitations

Ref: *C. Gonçalves, R.J. Bessa, P. Pinson, "A critical overview of privacy-preserving approaches for collaborative forecasting," International Journal of Forecasting, vol. 37, no. 1, pp. 322-342, Jan-Mar 2021*

Using ADMM - Alternating Direction Method of Multipliers



Federated Learning Protocol

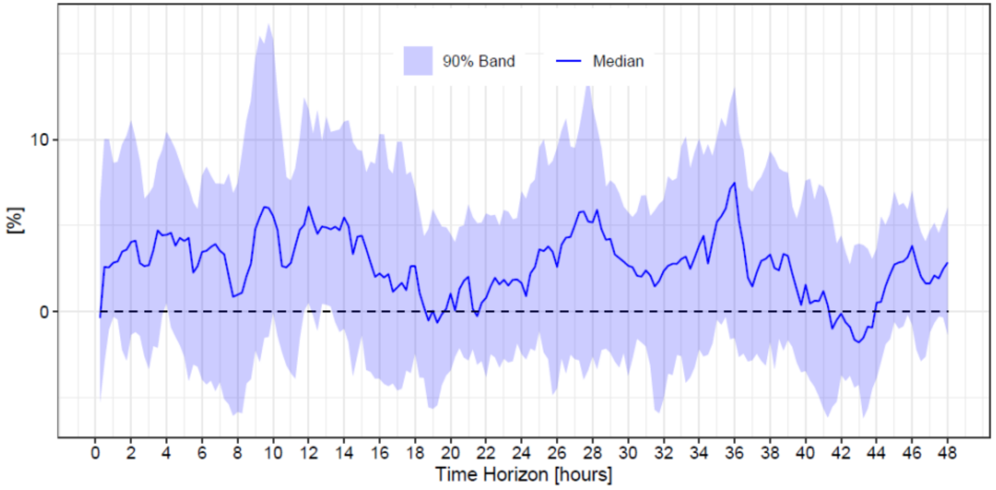


Ref.: C. Gonçalves, R.J. Bessa, P. Pinson, "Privacy-preserving distributed learning for renewable energy forecasting," IEEE Transactions on Sustainable Energy, vol. 12, no. 3, pp. 1777-1787, July 2021.

RES Forecasting Results

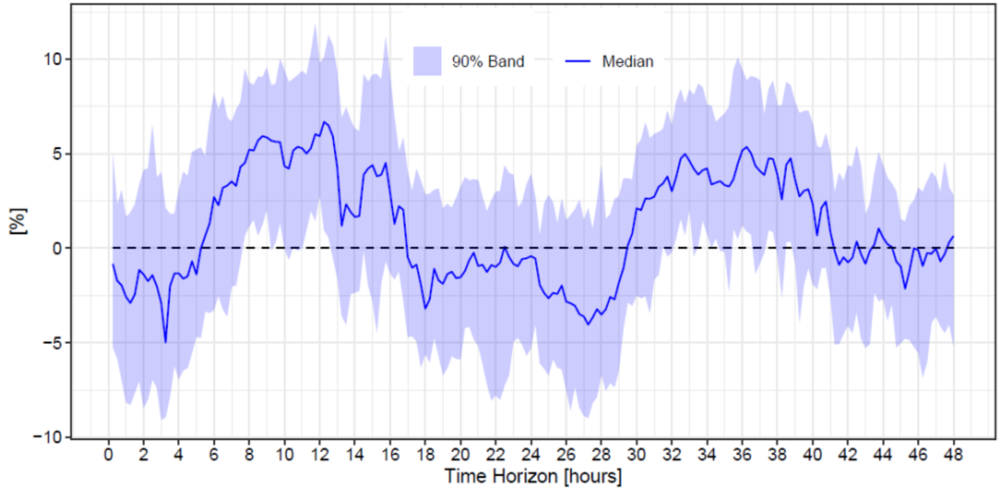
60 wind turbines from 13 wind power plants in France

NWP from ECMWF (HRES)



(a) MAE

Relative improvement (%) VAR-X **(collaborative)** over AR-X **(univariate)**



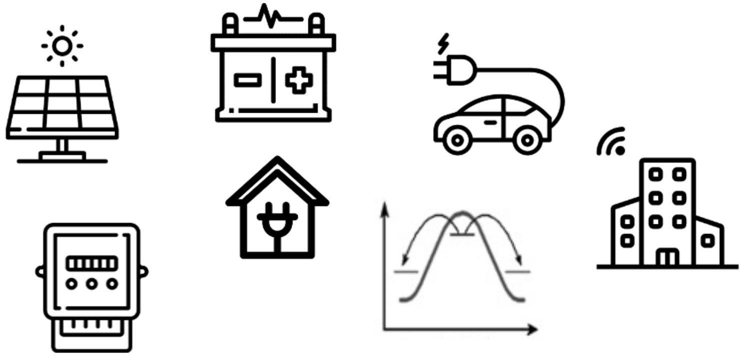
(a) MAE

Relative improvement (%) VAR-X over Gradient Boosting Trees

Extension to low voltage control

Challenges for LV grid operation

New Challenges



LV grids are the major bottleneck in DER integration and require a paradigm shift in terms of monitoring & control

"Real-world" Challenges

- ❑ Lack of accurate information about grid topology and parameters
- ❑ Real-time monitoring of the voltage and active power is not available
  - ❑ ***Ref.:*** *Data-driven state estimation. R.J. Bessa, et al., "Probabilistic low voltage state estimation using analog-search techniques," PSCC 2018*

Data-driven Voltage Control (DdVC)

Considering a linear relationship between the observed values and the explanatory variables

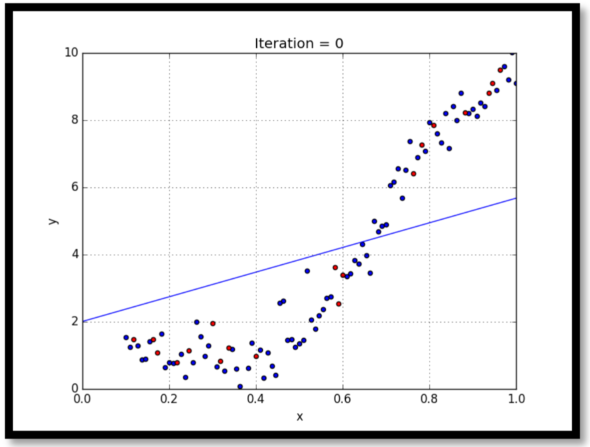
$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_n x_{in} + \varepsilon_i, \qquad i = 1, \ldots, t.$$

Can the voltage magnitude at a given node be expressed as a linear function of the injected power in the remaining nodes?

$$\begin{bmatrix} V_{1,1} & \cdots & V_{1,N} \\ \vdots & \ddots & \vdots \\ V_{T,1} & \cdots & V_{T,N} \end{bmatrix}$$

$$\begin{bmatrix} P_{1,1} & \cdots & P_{1,N} \\ \vdots & \ddots & \vdots \\ P_{T,1} & \cdots & P_{T,N} \end{bmatrix}$$

Regression model



Sensitivity factors

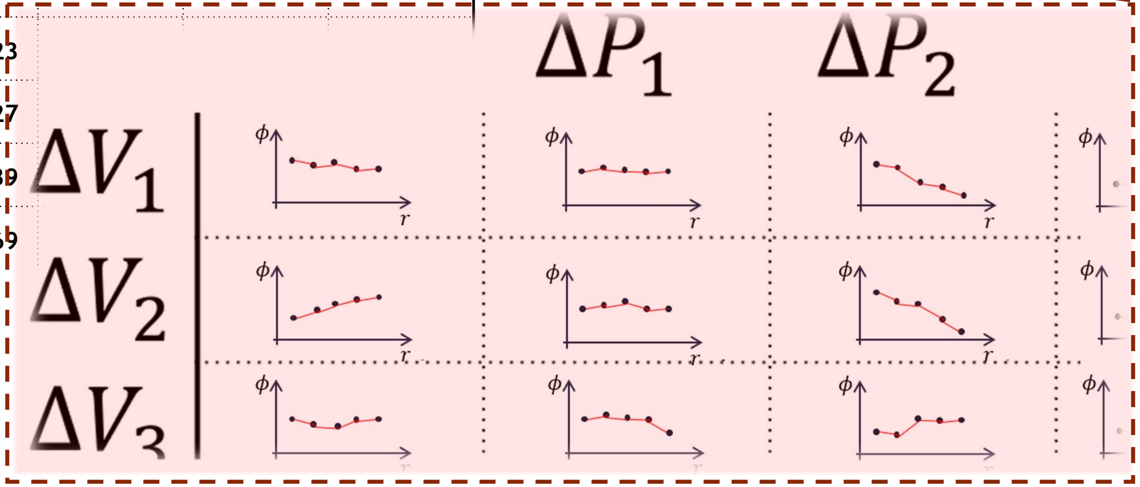
$$\begin{bmatrix} S_{1.1} & \cdots & S_{1.N} \\ \vdots & \ddots & \vdots \\ S_{N.1} & \cdots & S_{N.N} \end{bmatrix}$$

Ref.: *S. Weckx, R. D'Hulst, and J. Driesen, "Voltage sensitivity analysis of a laboratory distribution grid with incomplete data," IEEE Trans. on Smart Grid, vol. 6, no. 3, pp. 1271–1280, May 2015.*

Data-driven Voltage Control (DdVC)

	ΔP_1	ΔP_2	ΔP_3	ΔP_4	ΔP_5	ΔP_6
ΔV_1	0.00003	0.952291	0.734143	0.358847	0.425096	0.6365	0.72856
ΔV_2	0.000024	0.483968	0.138431	0.839057	0.121344	0.098726	0.60499
ΔV_3	0.00002	0.203132	0.163509	0.918023			
ΔV_4	0.00003	0.900272	0.224562	0.444027			
ΔV_5	0.00007	0.459594	0.084742	0.431239			
ΔV_6	0.00111	0.791876	0.541225	0.673369			

sensitivity factors are conditioned by external (or exogenous) variables, e.g., transformer loading



smart meter data is classified as personal data

varying-coefficient linear model → coefficients change smoothly with the value of exogenous variables

$$Y = X \cdot B + \varepsilon \longrightarrow Y = X \cdot B(u) + \varepsilon$$

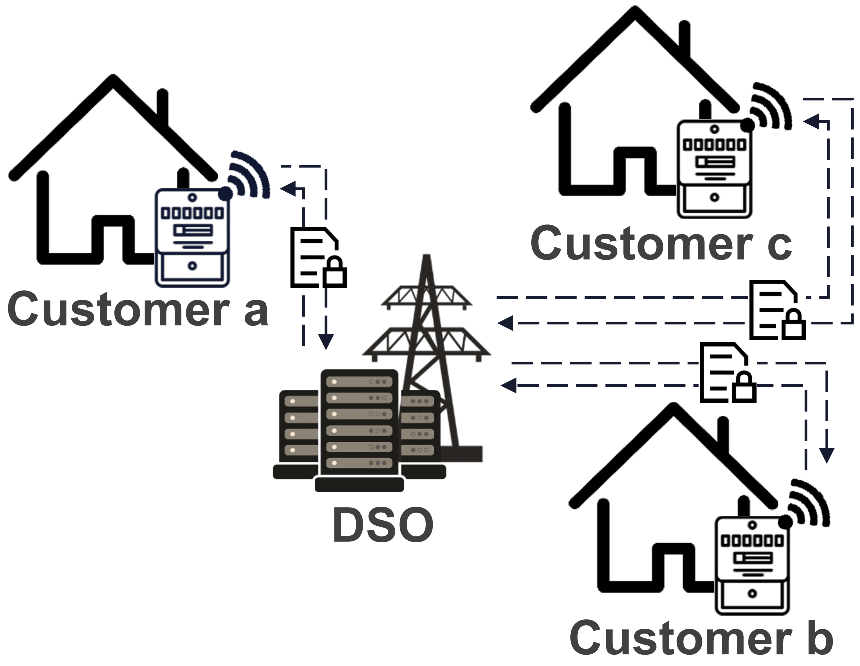
B(u) are estimated by fitting locally a polynomial around *fitting points* e.g. of exogenous variables: MV/LV transformer load or voltage

Ref.: *G. Sampaio, R.J. Bessa, C. Gonçalves, C. Gouveia, "Conditional parametric model for sensitivity factors in LV grids: A privacy-preserving approach," Electric Power Systems Research, vol. 211, 2022.*

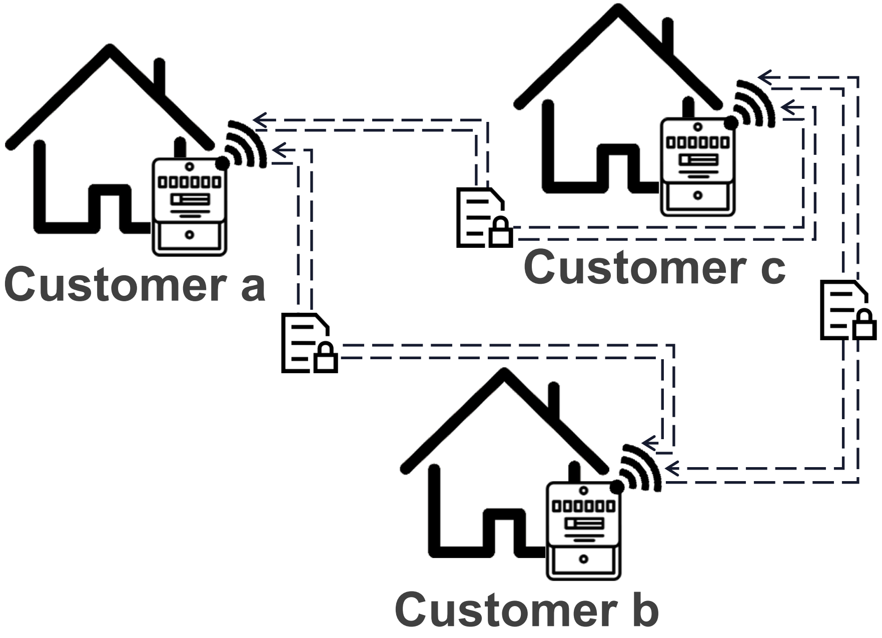
Data Privacy & Federated Learning

Use federated learning protocol to calculate the sensitivity factors using a privacy-preserving data exchange

DSO as the central node



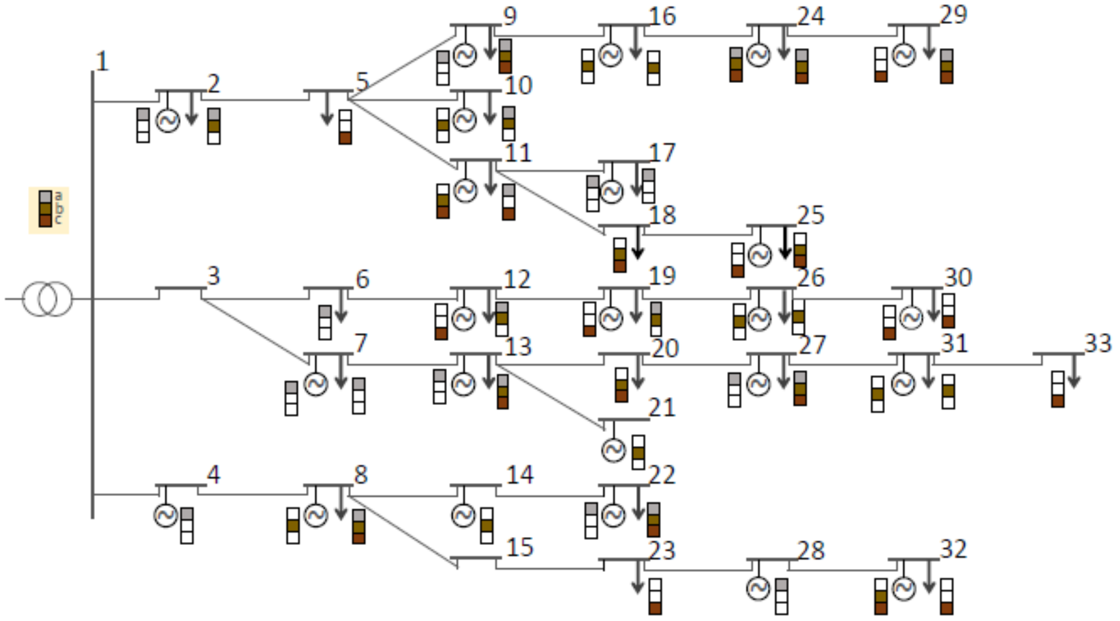
Peer-to-peer



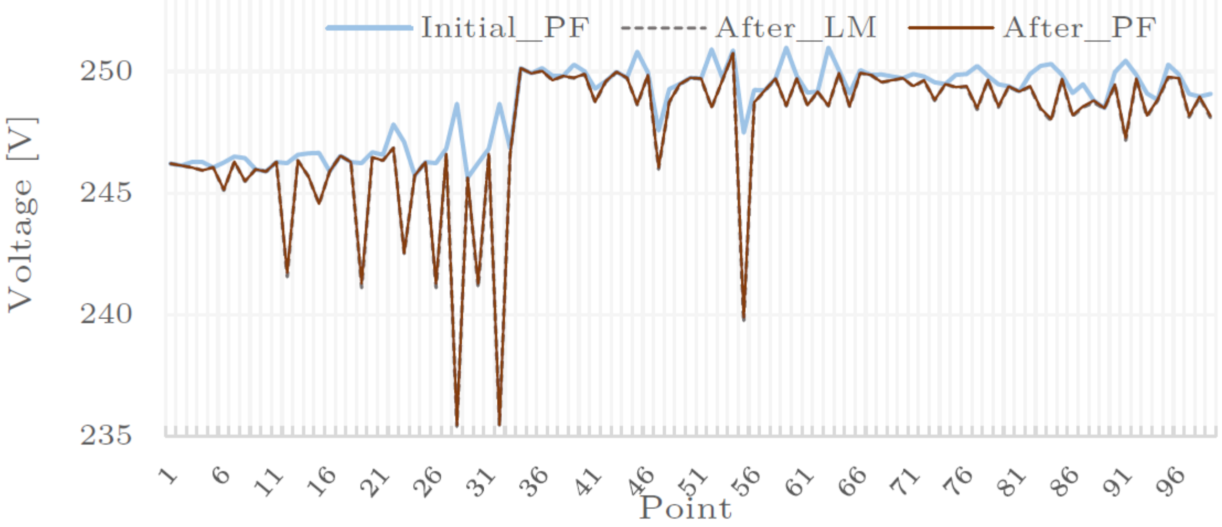
Ref.: *G. Sampaio, R.J. Bessa, C. Gonçalves, C. Gouveia, "Conditional parametric model for sensitivity factors in LV grids: A privacy-preserving approach," Electric Power Systems Research, vol. 211, 2022.*

Accuracy of the Linear Model

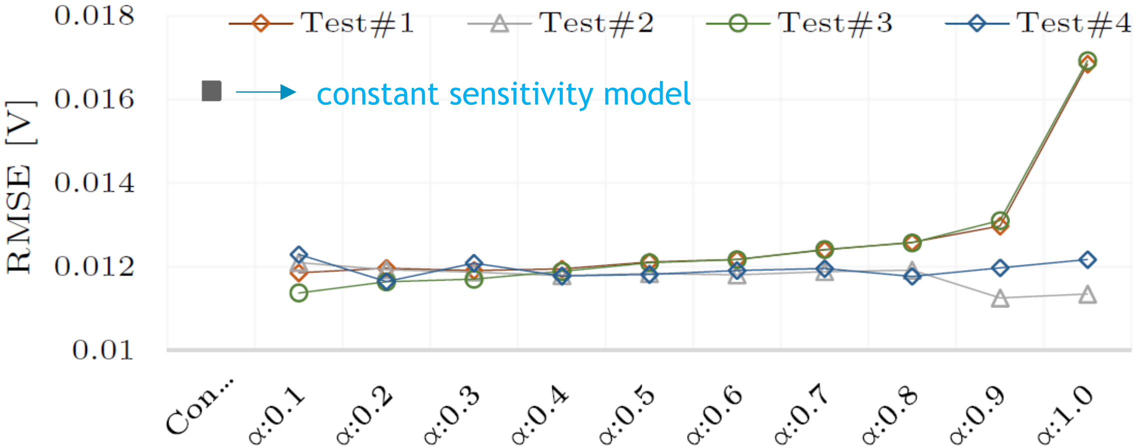
33 node typical Portuguese LV grid



voltage after changing active power injection/consumption



RMSE of constant versus (var. coef.) conditional model



Integration in Low Voltage Control

$$\min\ J = \sum_{i=1}^{n} \Delta P_i^{up} \cdot C_i^{up} - \Delta P_i^{down} \cdot C_i^{down}$$

subject to

$$\begin{cases} 0 \le \Delta P_i^{up} \le \Delta P_i^{max} \\ \Delta P_i^{min} \le \Delta P_i^{down} \le 0 \end{cases}$$

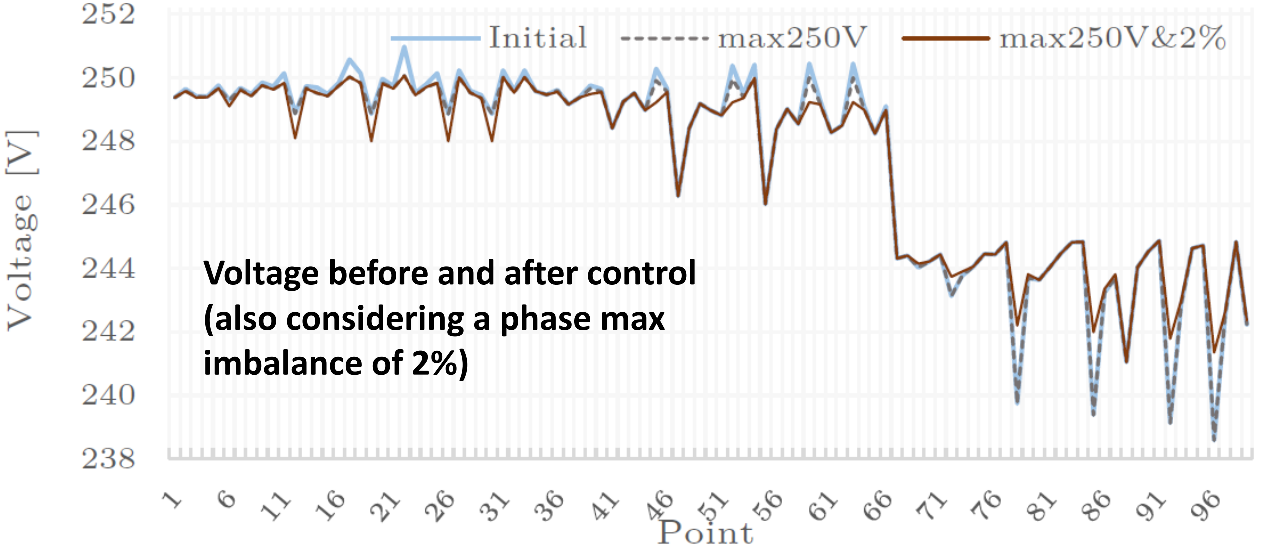
$$V_i^{min} - V_i^{old} \le \Delta V_i \le V_i^{max} - V_i^{old}$$

$$\frac{\Delta V_k^{max}}{V_k^{avg}} \times 100 \le l$$

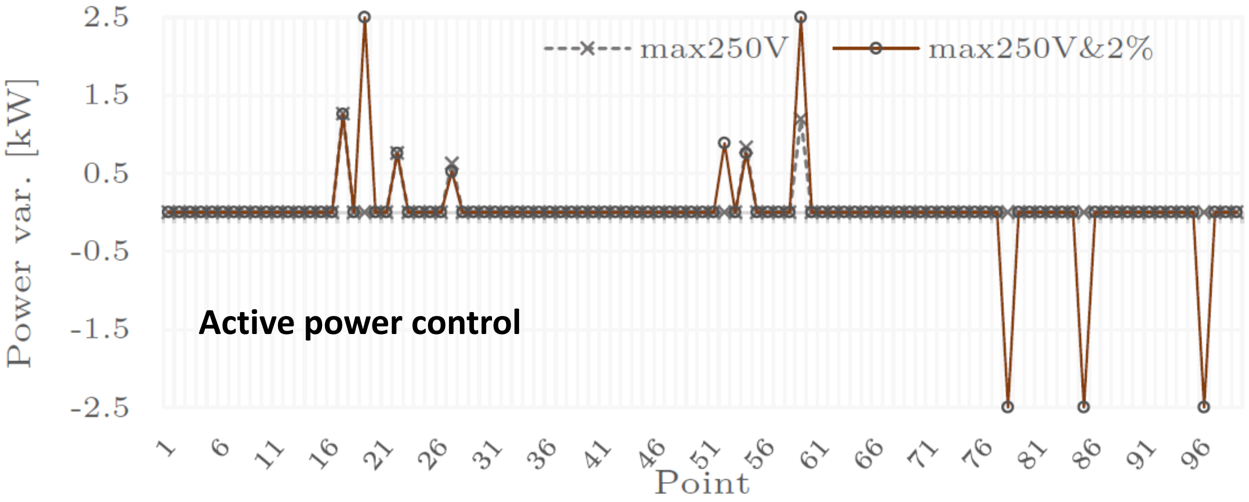
$$V_k^{avg} = \frac{V_{a,k} + V_{b,k} + V_{c,k}}{3}$$

$$\Delta V_P^{max} = \max\{|V_{a,k} - V_k^{avg}|, |V_{b,k} - V_k^{avg}|, |V_{c,k} - V_k^{avg}|\}$$

$$\Delta V_i = \sum_{j=1}^{n} (\Delta P_j^{up} - \Delta P_j^{down}) \cdot S_{i,j}$$



Voltage before and after control (also considering a phase max imbalance of 2%)



Active power control

A glance about Data Markets

Incentive Mechanisms for Data Sharing

Data by Money

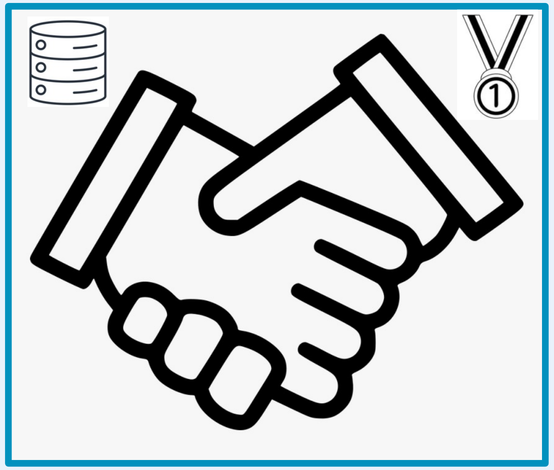
- ✓ **Accurate forecasts** with collaborative forecasting models
- ✓ **Monetary compensation** proportional to the data importance when forecasting the others' data

Data by Data

- ✓ Data owners **provide and receive data** with approximately **the same value**
- ✓ **Value** is measured with metrics such as mutual information, correlation, etc.

Data by Recognition

- ✓ **Recognition** ,e.g., as a climate change mitigator
- ✓ Proportional to the data importance when forecasting the others' data



Data Market for Forecasting

Buyers

Objective: Improve forecasting skill

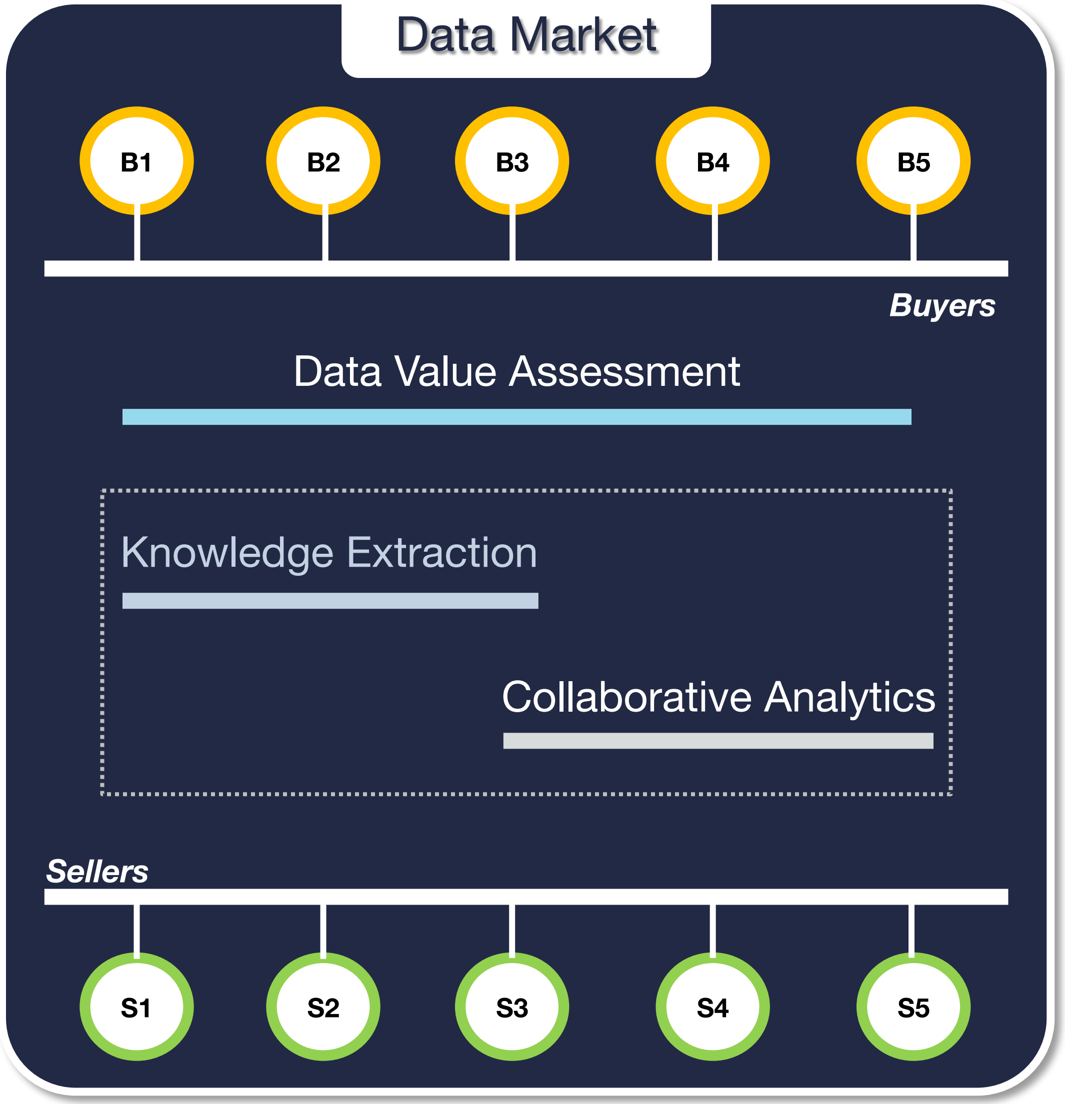
Payment depends on the **gain** obtained by using market **sellers'** data

Data value found through collaborative analytics

Sellers

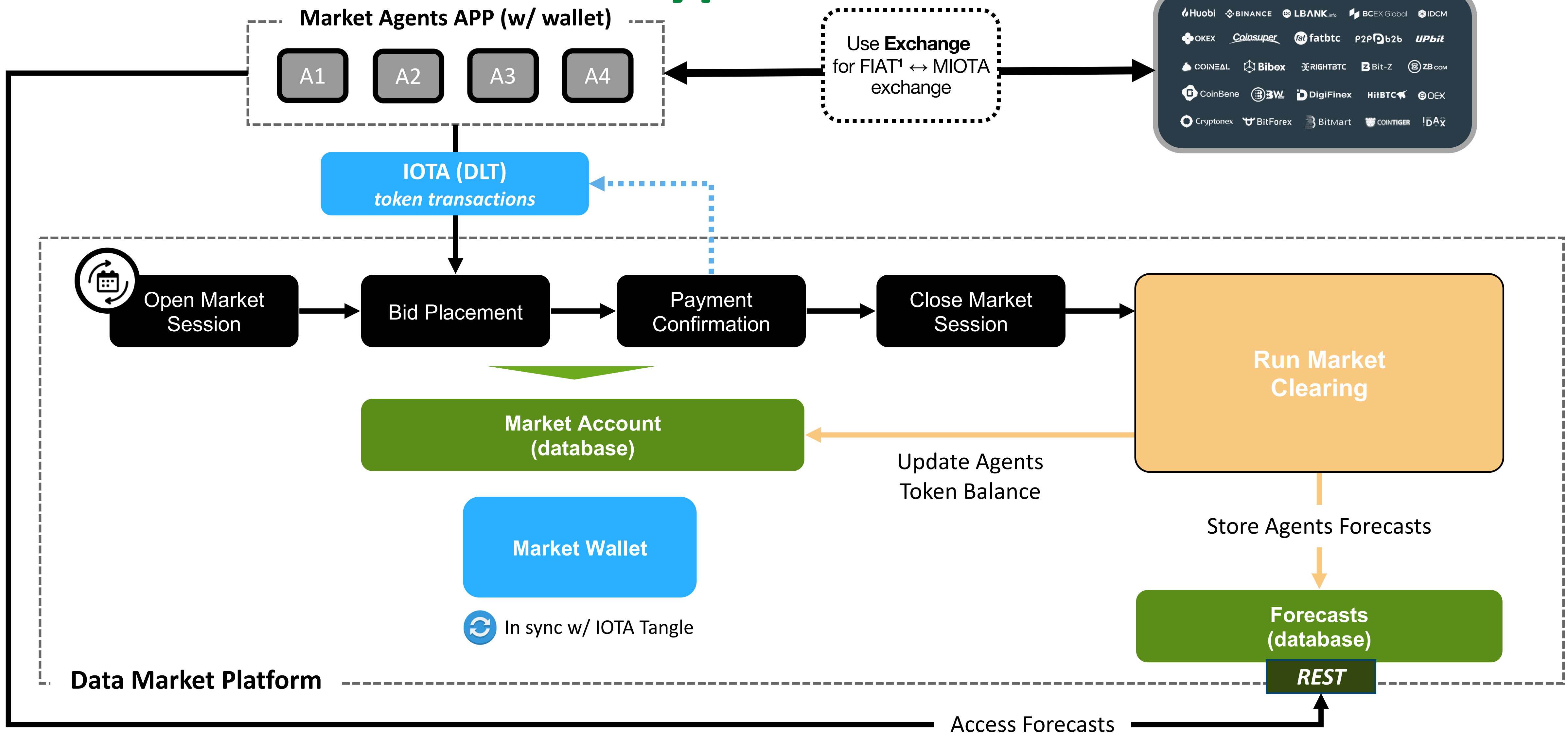
Objective: Monetize their data

Revenue depends on the actual contribution to Buyers forecast skill



Ref.: *C. Gonçalves, P. Pinson, R.J. Bessa, "Towards data markets in renewable energy forecasting", IEEE Transactions on Sustainable Energy, vol. 12, no. 1, pp. 533-542, Jan. 2021.*

Data Market Prototype



1 – FIAT money: government-issued currency that is not backed by a physical commodity , but rather by the government that issued it.

Concluding Remarks

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- We departed from linear models up to non-linear models in a FL framework (different from ANN FL)
- Load/RES forecasting has been the primary use case for FL in energy → new use cases are needed
- Data monetization and other data-sharing mechanisms (e.g., data-by-data) should be complementary to FL
- Energy consumption at the edge should also be a concern (simple models have an advantage)

Acknowledgments

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