iea-isgan.org

ISGAN
INTERNATIONAL SMART GRID ACTION NETWORK

# Extracting value from data sharing for RES forecasting

## Privacy aspects & data monetization

Ricardo Jorge Bessa, INESC TEC
Liyang Han, DTU

**December 2020**

ISGAN Academy webinar #25
Recorded webinars available at: https://www.iea-isgan.org/our-work/annex-8/

iea Energy Technology Network

CLEAN ENERGY MINISTERIAL

# ISGAN in a Nutshell

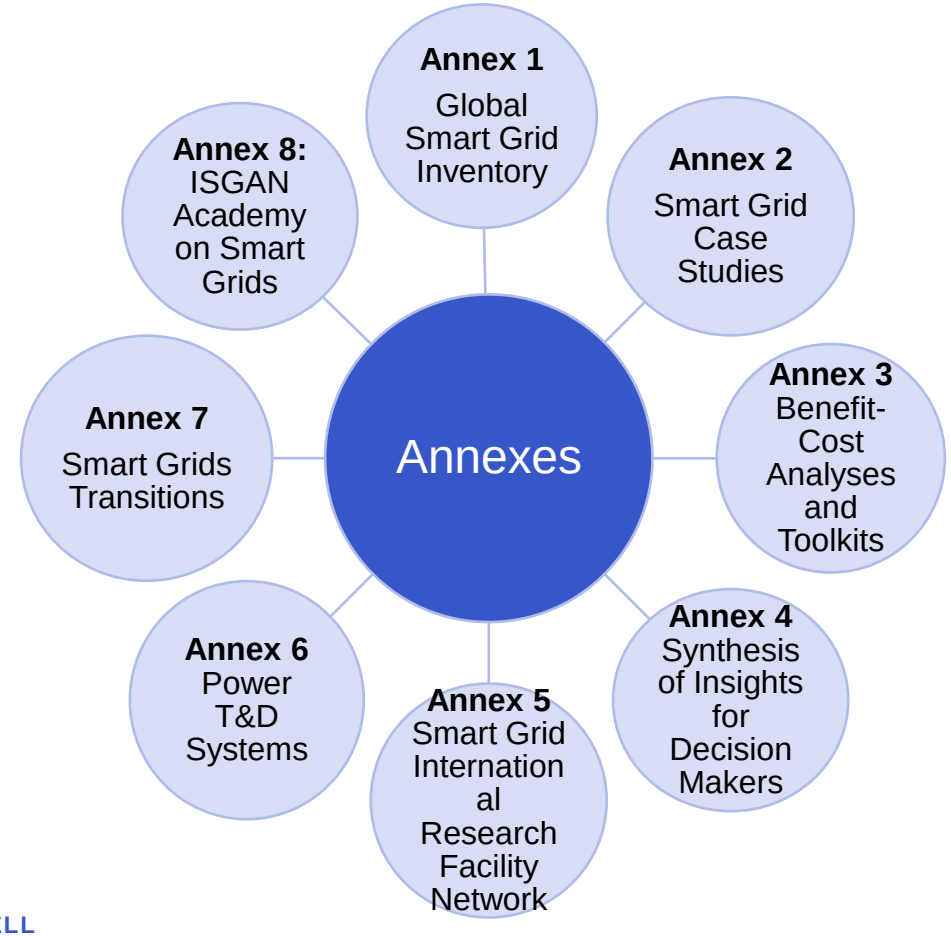
Created under the auspices of:

the Implementing Agreement for a Co-operative Programme on Smart Grids

an initiative of the Clean Energy Ministerial (CEM)

***Strategic platform to support high-level government knowledge transfer and action for the accelerated development and deployment of smarter, cleaner electricity grids around the world***

***International Smart Grid Action Network is the only global government-to-government forum on smart grids.***



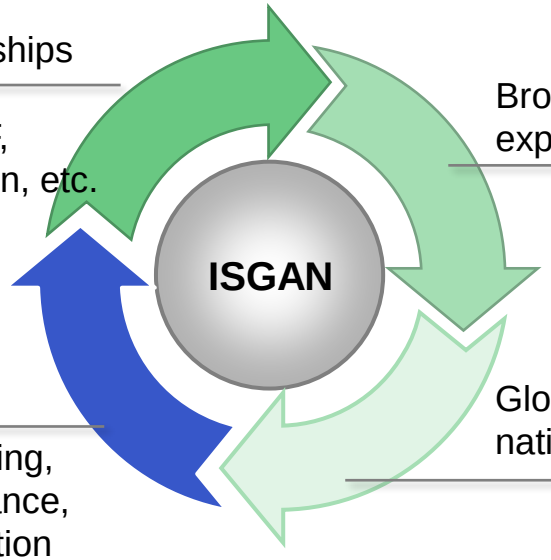
# ISGAN's worldwide presence

ISGAN
INTERNATIONAL SMART GRID
ACTION NETWORK

# Value proposition

Strategic partnerships

IEA, CEM, GSGF, Mission Innovation, etc.




Broad international expert network

Global, regional & national policy support

Knowledge sharing, technical assistance, project coordination

Visit our website:
www.iea-isgan.org

# Agenda

- Smart4RES in a nutshell
- Motivation for data sharing & collaborative analytics
- Collaborative learning for RES forecasting
- Data markets : Basics and Smart4RES proposal

# Smart4RES in a nutshell

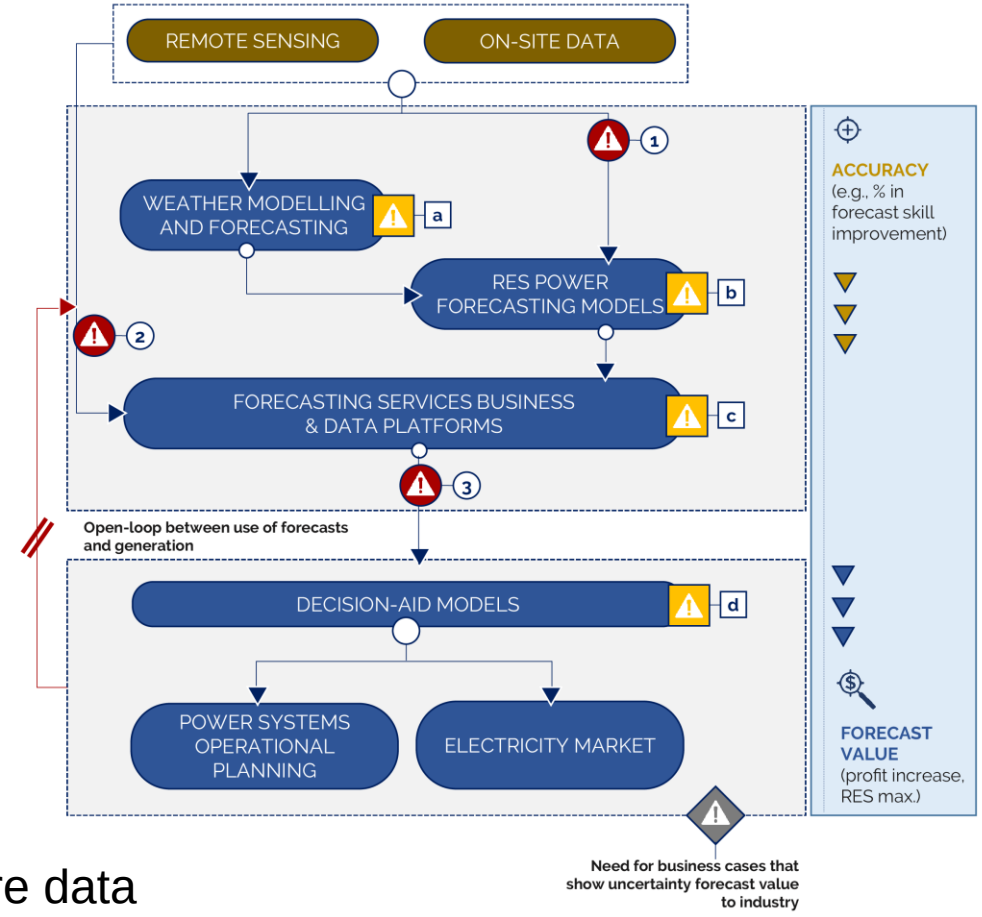
# Smart4RES in a nutshell

## Smart4RES vision

Achieve outstanding improvement in RES predictability through a holistic approach, that covers the whole model and value chain related to RES forecasting

## Improvement from collaborative RES forecasting

Potential for improvement with spatial-temporal approaches up to 20% for 6h ahead for solar energy and up to 15-20% for wind energy




Lack of privacy guarantees and price-based incentives to share data

# Smart4RES consortium

Denmark — DTU

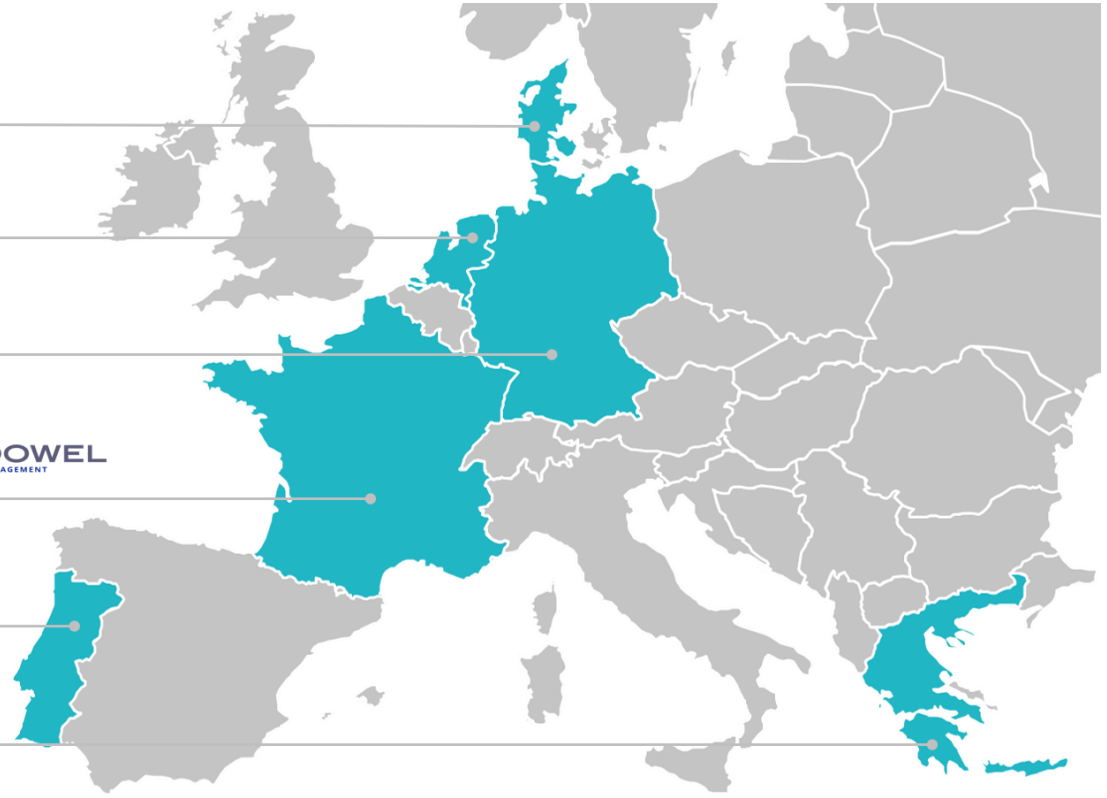
Netherlands — WHIFFLE, DNV·GL

Germany — DLR, energy & meteo systems

France — ARMINES, MINES ParisTech, METEO FRANCE, DOWEL MANAGEMENT

Portugal — INESCTEC, NEW ENERGY WORLD

Greece — HEDNO, ICCS



**6 countries**
**12 partners**

End-users
Industry
Research
Universities
Meteorologists

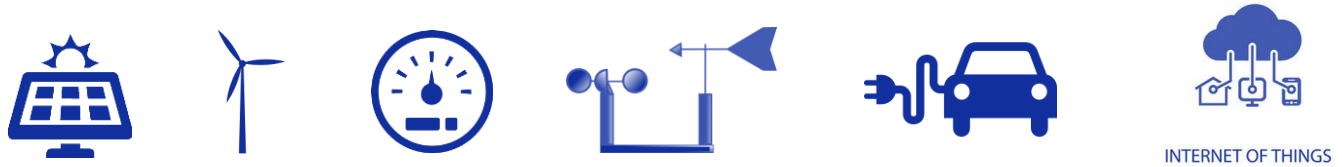
Funds: H2020 programme
Budget: 4 Mio€
Duration: 3.5 years

**11/2019-4/2023**

# Motivation for data sharing & collaborative analytics

# Data Sharing: Motivation

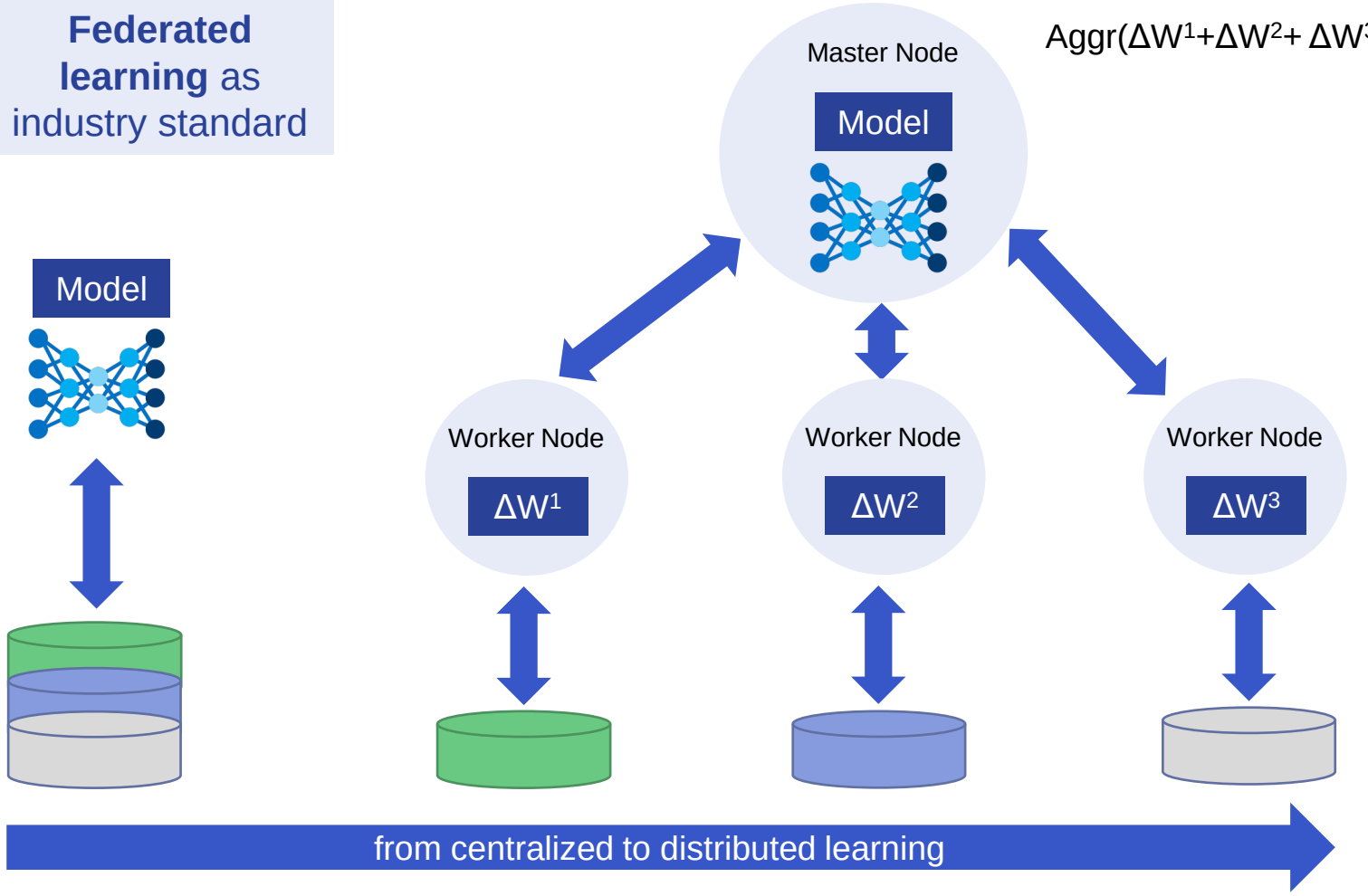
- Increasing volume of geographically distributed data




- Improvement in forecasting accuracy by this data
- Main **barriers**
  - Data **privacy** and confidentiality
  - Lack of **economic signals** for sharing (collaborating with) data
  - Lack of business cases for collaborative analytics

# Collaborative Analytics

**Federated learning** as industry standard

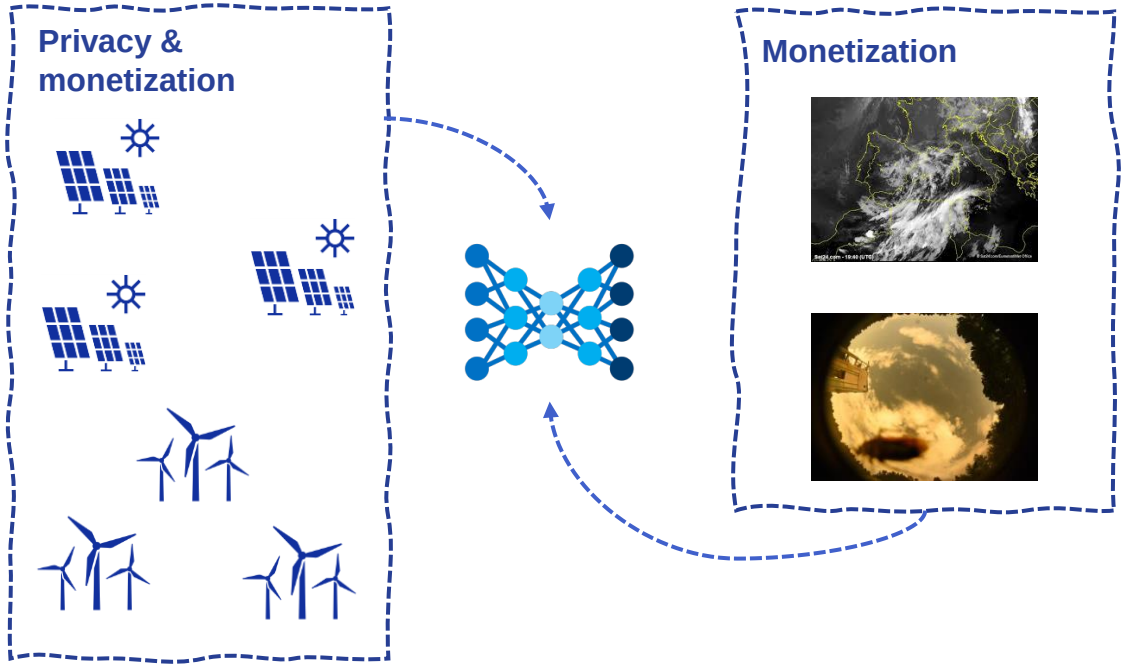



DATA SHARING IN Smart4RES

- Exchange raw data → NO
- Exchange model coefficients → NO (partially)
- Exchange model outputs → YES
- Data divided by features (not by observations)

# Possible Use cases for Data Sharing

## RES Forecasting




**Benefit:** Improve forecasting skill in minutes to day-ahead time horizon & exploit heterogenous data sources

## Weather Modelling

Source: Data Basin

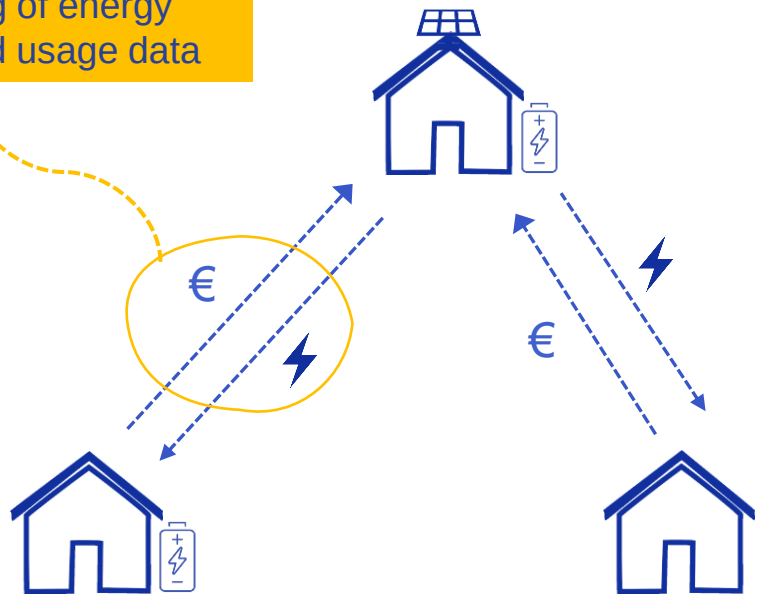
How to price weather data?

**Benefit:** Liberalization of weather data trading → access to large-scale weather data

# Possible Use cases for Data Sharing

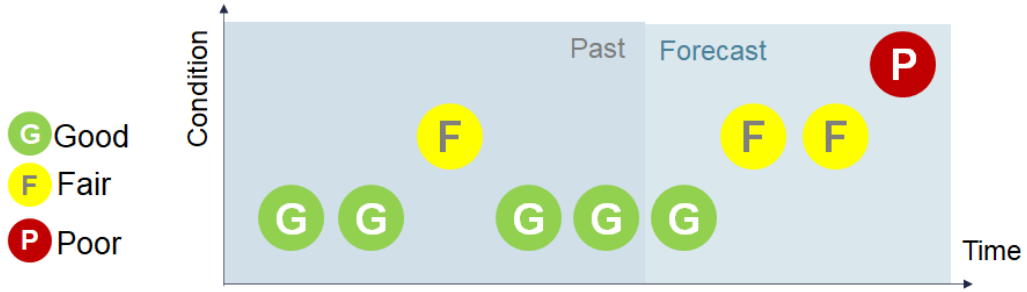
## Peer-to-peer (P2P) Trading

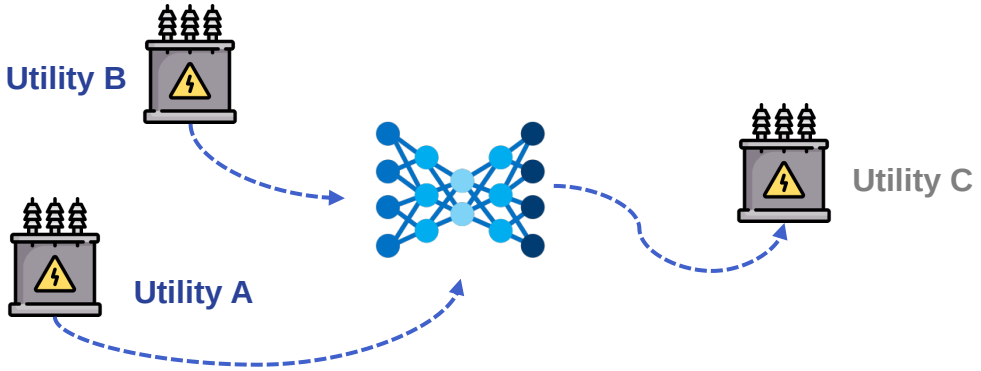
enable sharing of energy transactions and usage data




**Benefit:** Secure analytics with personal data → better decision-making & more trust

## Power Transformer Condition




**Benefit:** Data augmentation (faults, dissolved gas analysis, sensors) → improved maintenance policies

# Collaborative learning for RES forecasting

# RES Collaborative Forecasting
## Formulation

Example for
2 PV sites

forecasted power

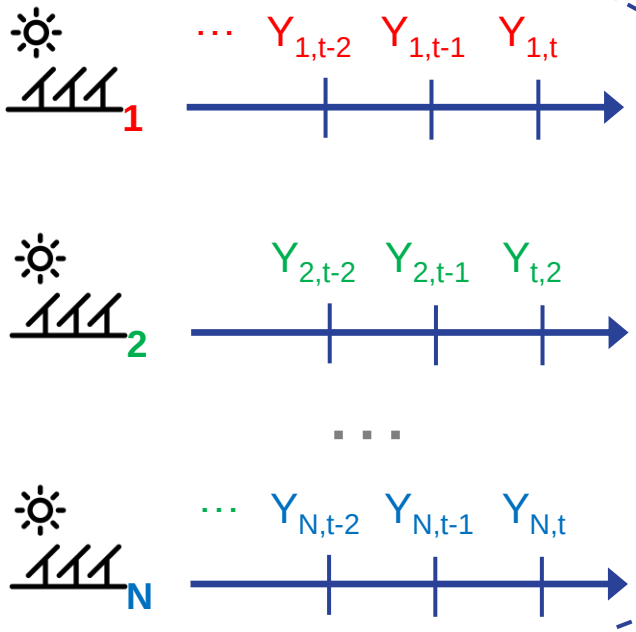
$$[Y_{1,t} \quad Y_{2,t}] = [c_1 \quad c_2] + \begin{bmatrix} B^1_{1,1} & B^1_{1,2} & B^2_{1,1} & B^2_{1,2} \\ B^1_{2,1} & B^1_{2,2} & B^2_{2,1} & B^2_{2,2} \end{bmatrix} \cdot \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{1,t-2} \\ Y_{2,t-2} \end{bmatrix} + [E_{1,t} \quad E_{2,t}]$$

white noise

constant terms **(to estimate)**

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

Z: lagged power observations




Vector Autoregressive Model (VAR)

$$Y = c + BZ + E$$

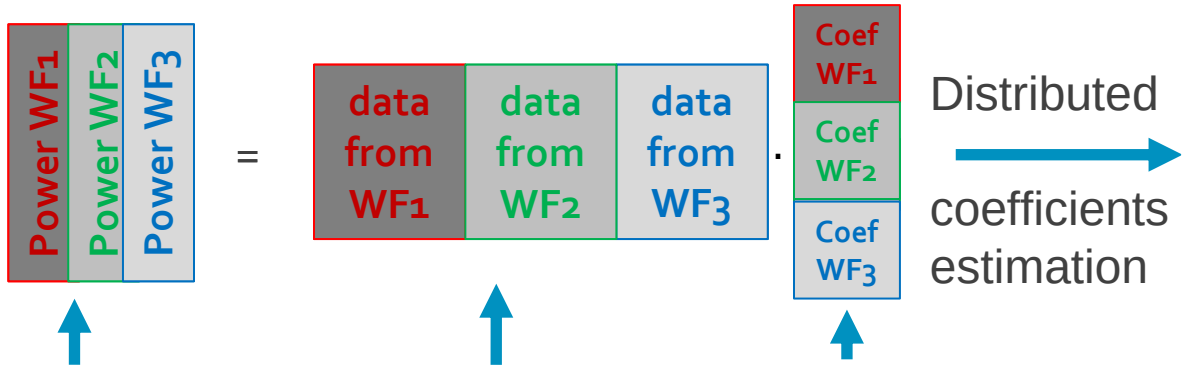
**multivariate linear model**

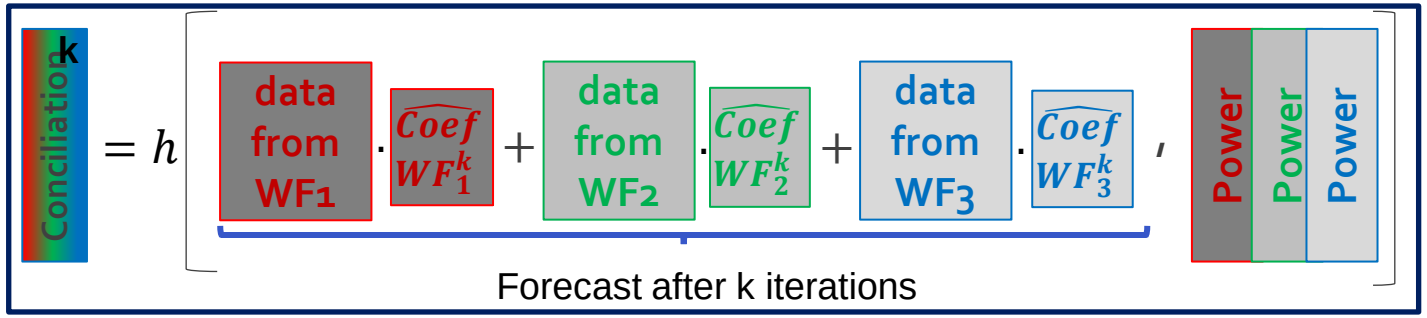
power forecasts for multiple sites **as a function of** past power observations from all sites

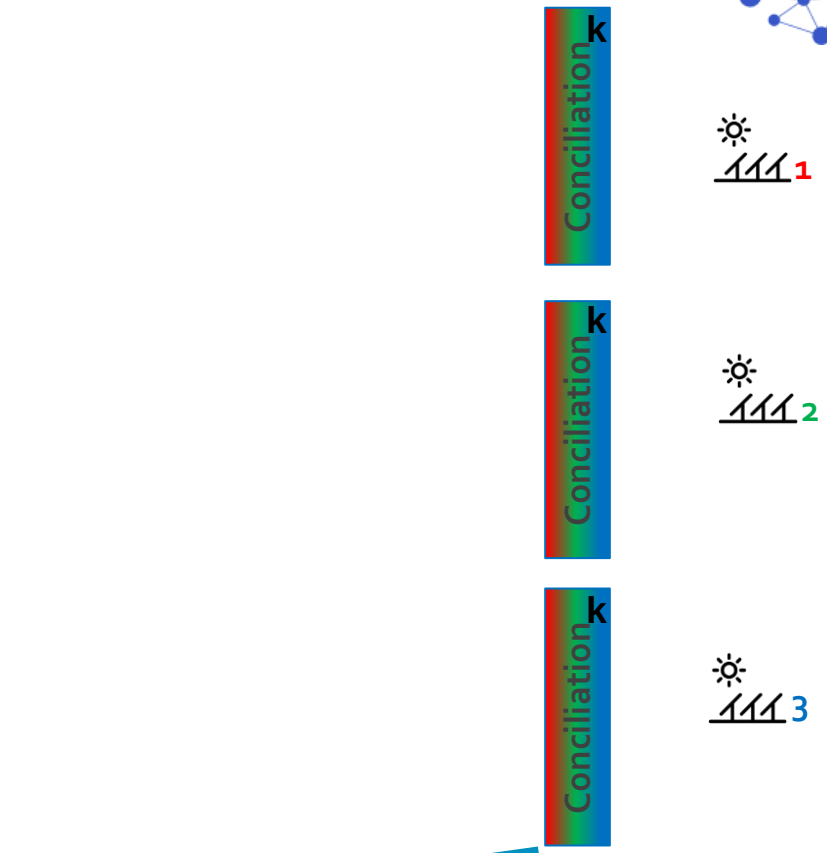
# RES Collaborative Forecasting

## State-of-the-art distributed learning

Distributed learning with ADMM (Alternating Direction Method of Multipliers)



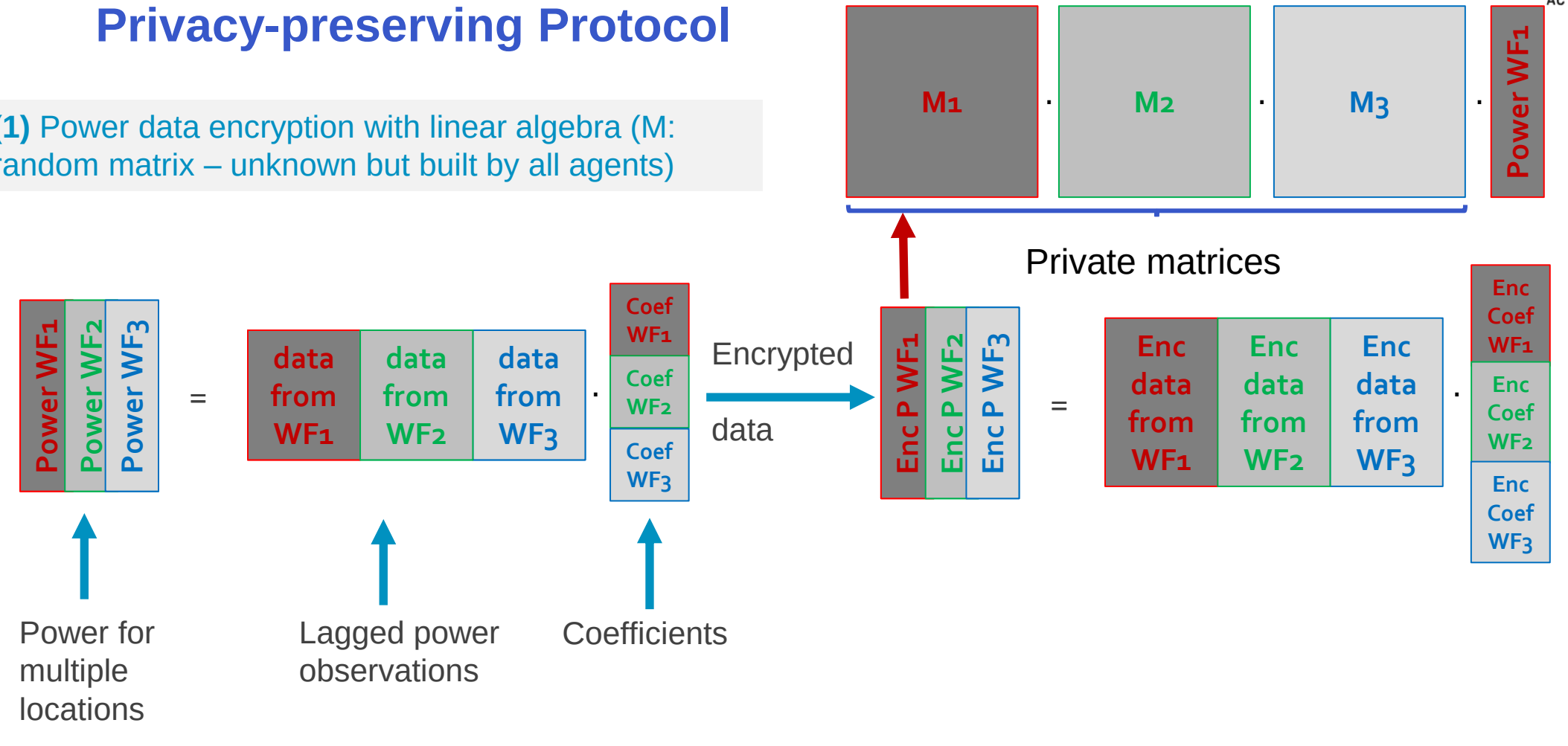




Limitation: access to private/confidential data

# RES Collaborative Forecasting

## Privacy-preserving Protocol

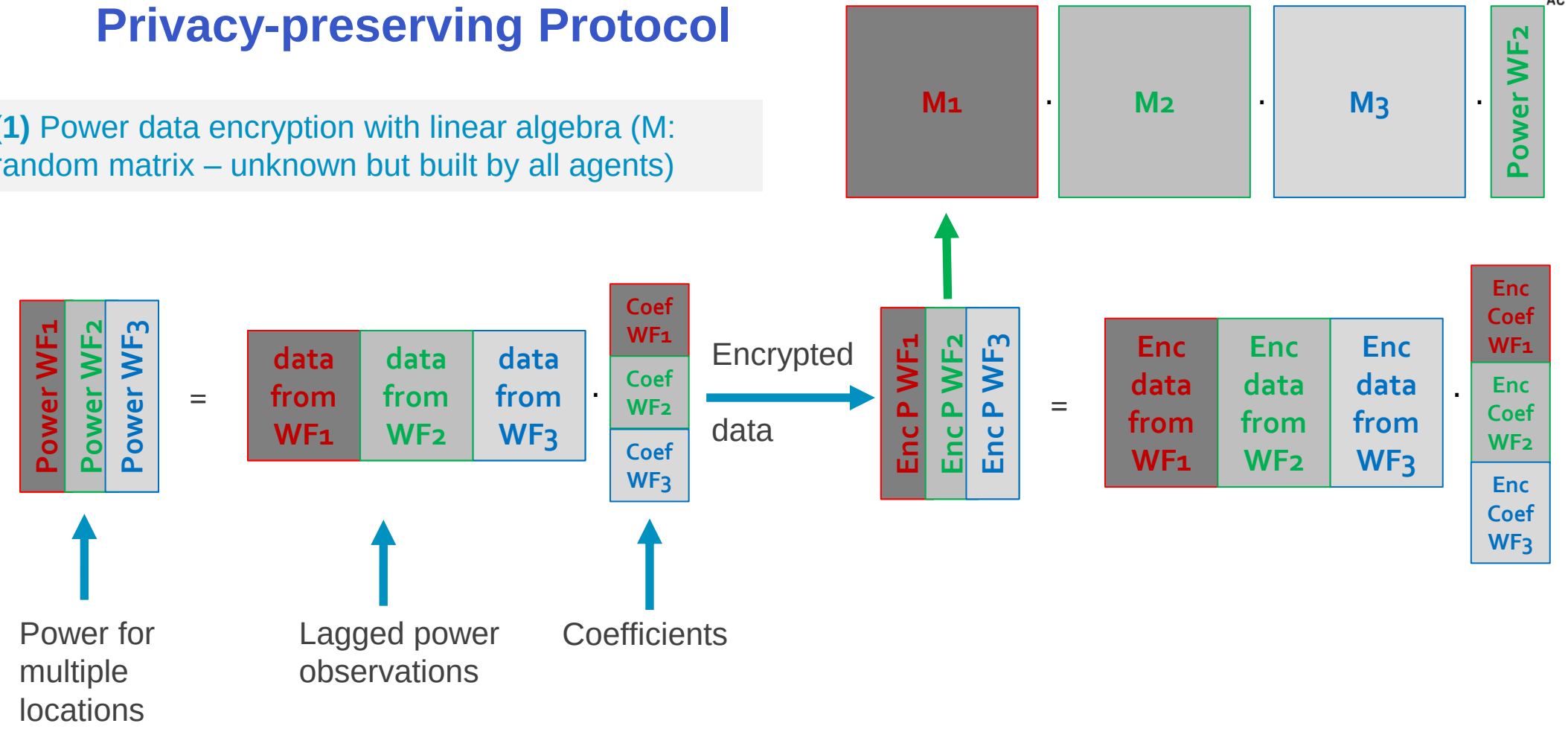
**(1)** Power data encryption with linear algebra (M: random matrix – unknown but built by all agents)



# RES Collaborative Forecasting

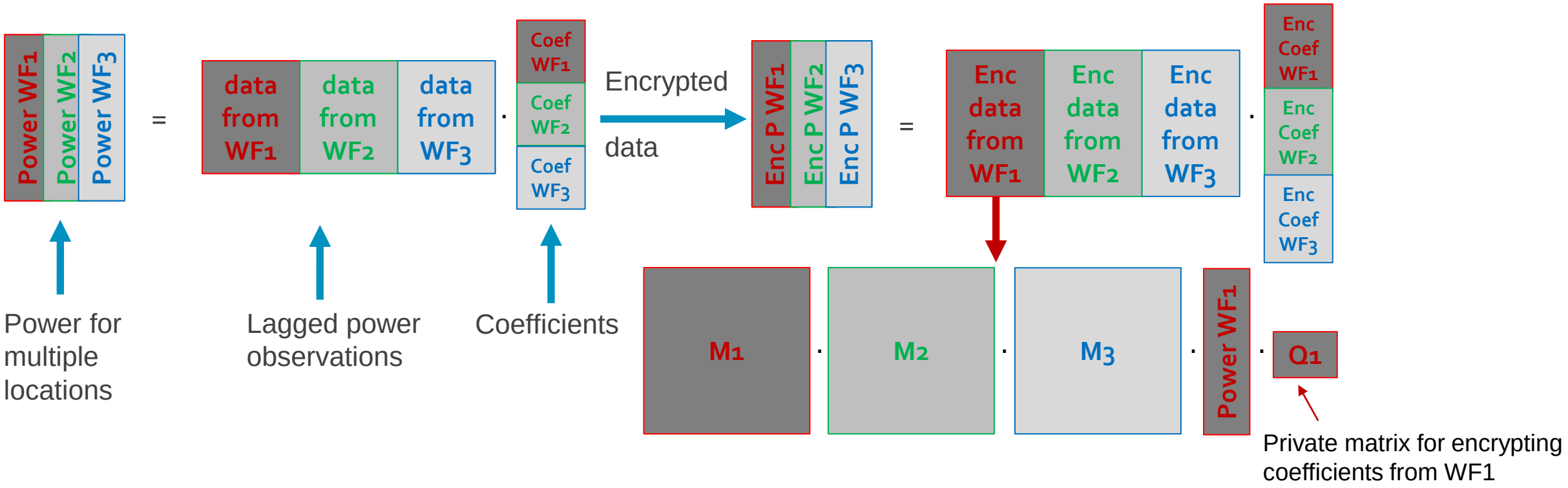
## Privacy-preserving Protocol

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



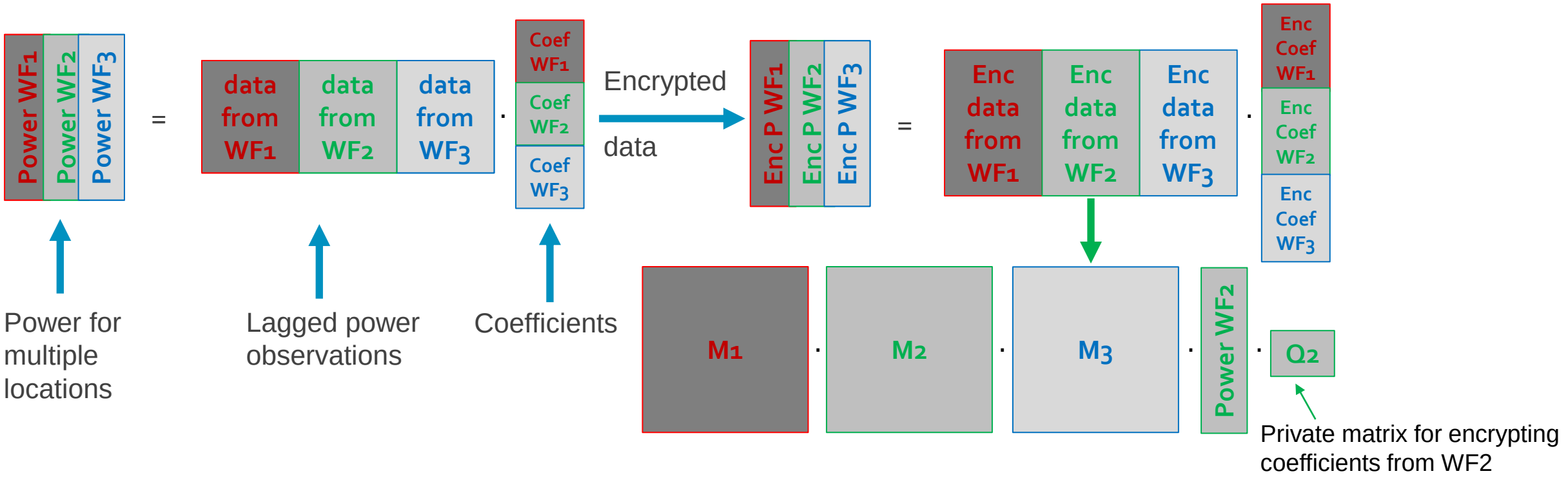
# RES Collaborative Forecasting
## Privacy-preserving Protocol

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



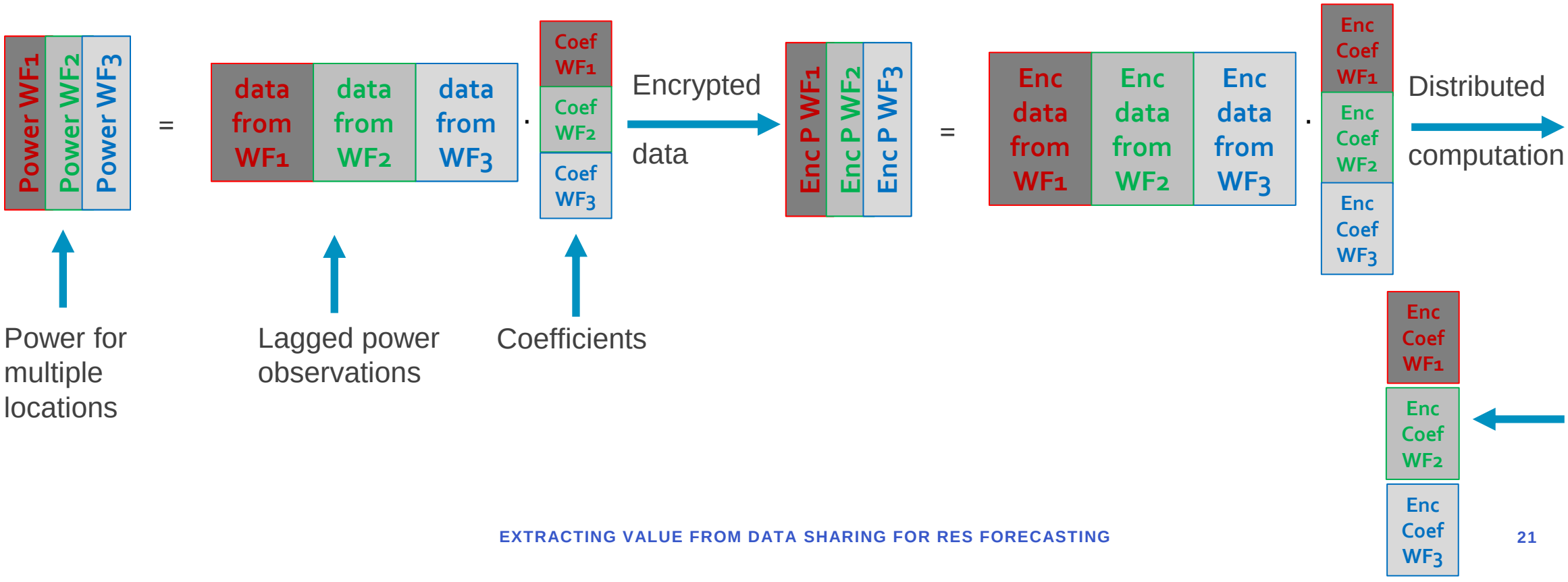
# RES Collaborative Forecasting
## Privacy-preserving Protocol

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



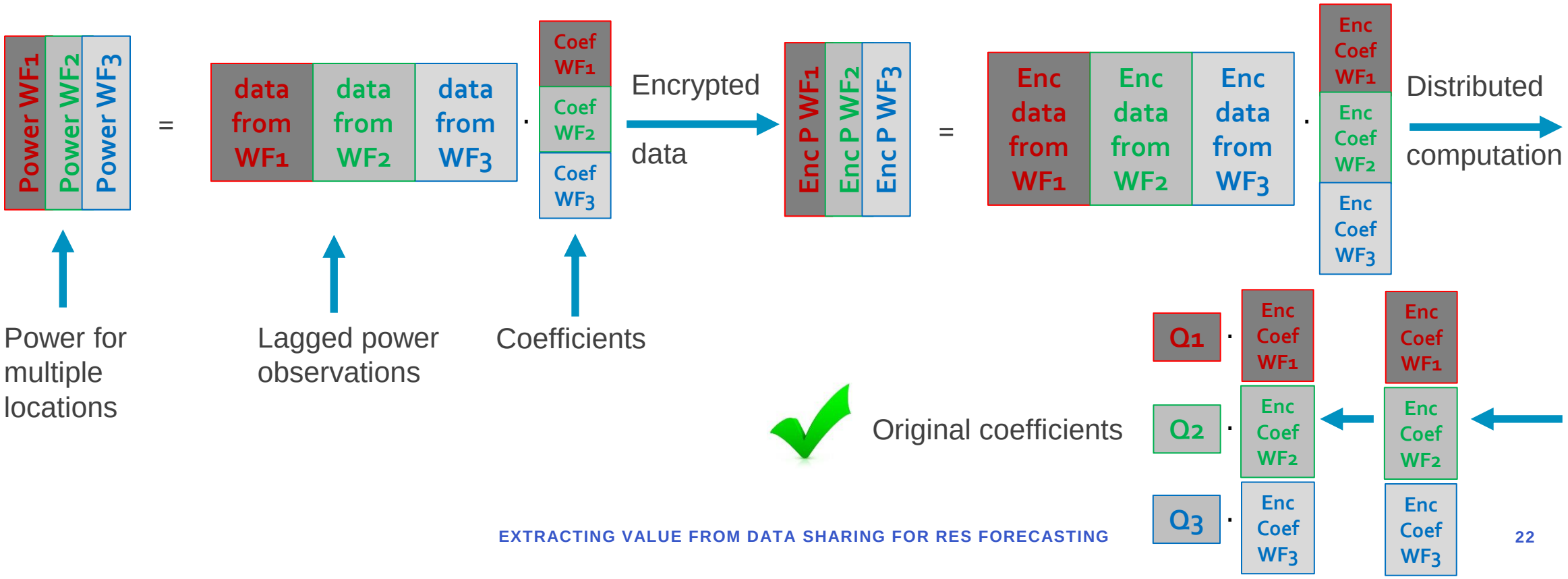
# RES Collaborative Forecasting
## Privacy-preserving Protocol

**(3)** Distributed computation of coefficients with ADMM



# RES Collaborative Forecasting
## Privacy-preserving Protocol

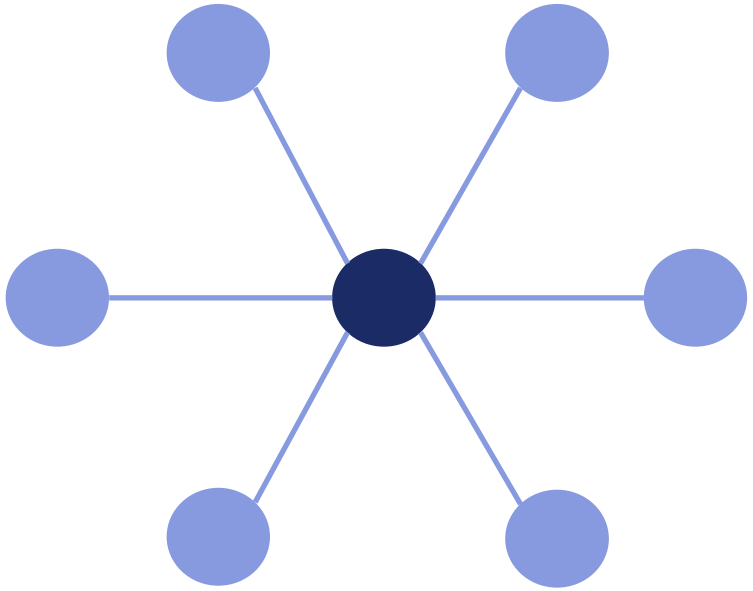
**(4)** Obtain original coefficients with Q matrix (same coefficients with privacy protocol)



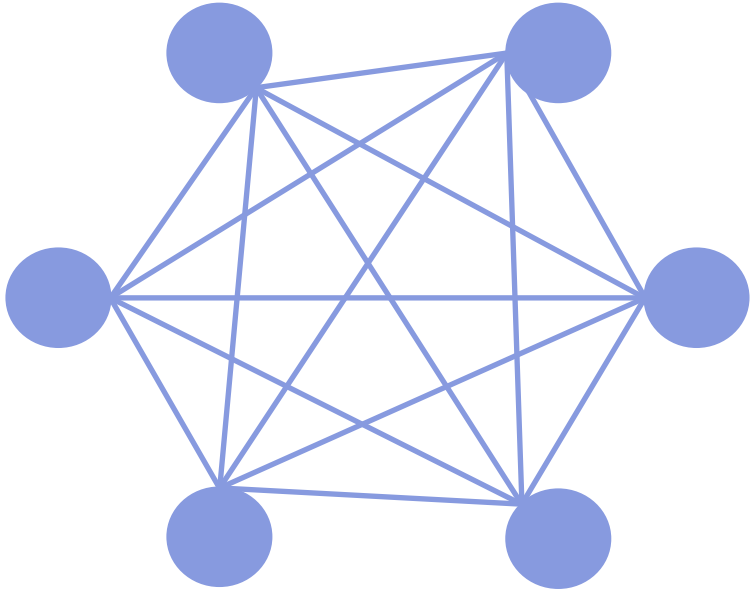
# RES Collaborative Forecasting
## Communication Schemes

Central node (hub)

Agents (RES Producers)



Centralized Model



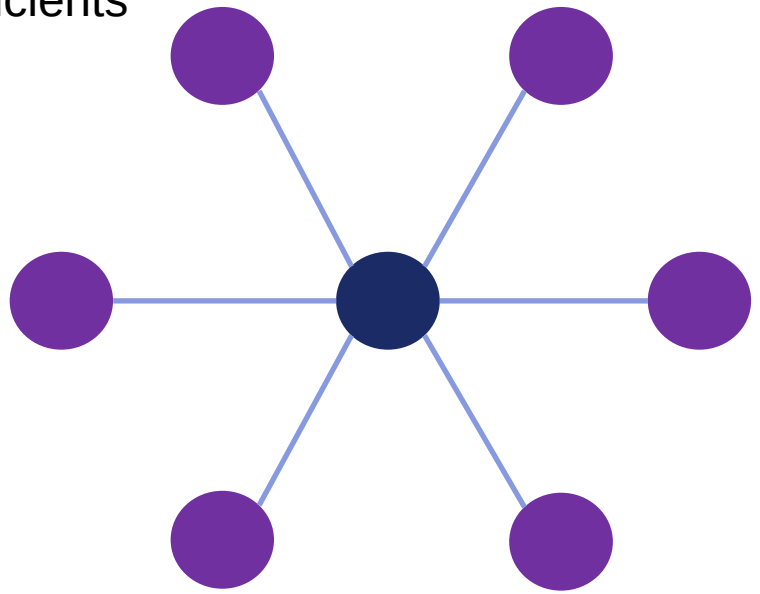
Peer-to-Peer Model

# RES Collaborative Forecasting
## Communication Schemes

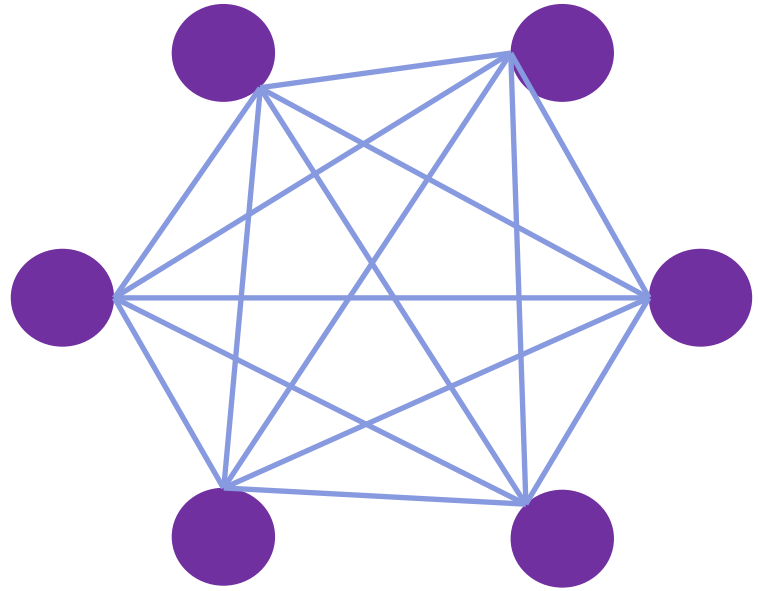
**Step 1.**
Agents compute their encrypted coefficients

$$\widehat{Enc\ Coef}_j^{k+1} = g(\text{Enc Pj}, \text{Enc data from agent } j, \text{Conciliation}^k)$$

Initialized with zeros



Centralized Model

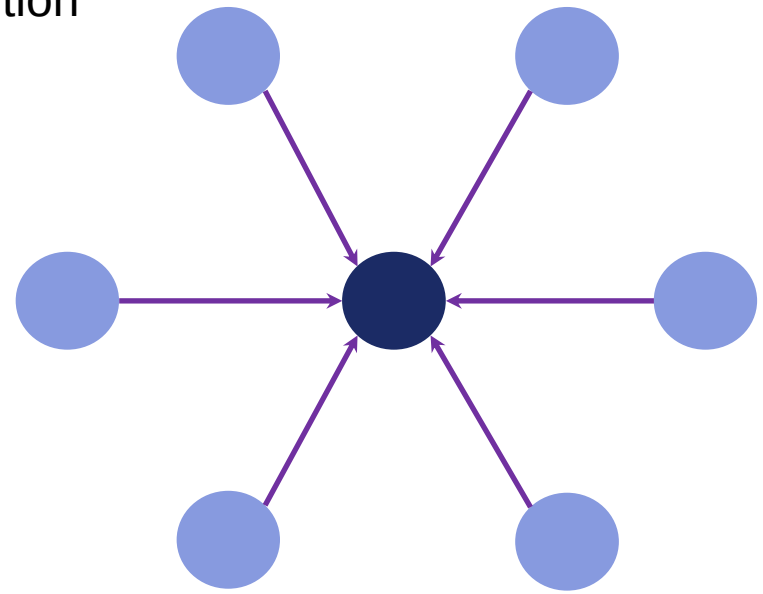


Peer-to-Peer Model

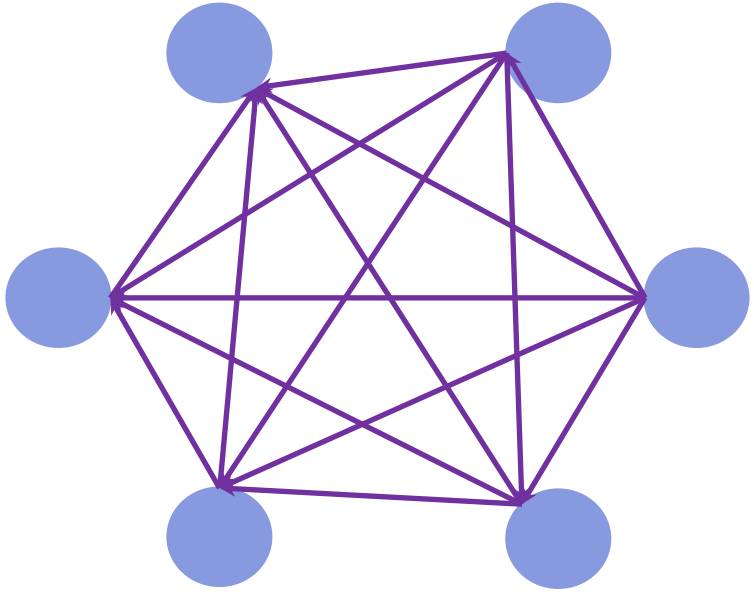
# RES Collaborative Forecasting
## Communication Schemes

**Step 2.**
Agents share their encrypted contribution

Enc data from agent $j$ . $\widehat{Enc}\ Coef\ WF_j^k$



Centralized Model

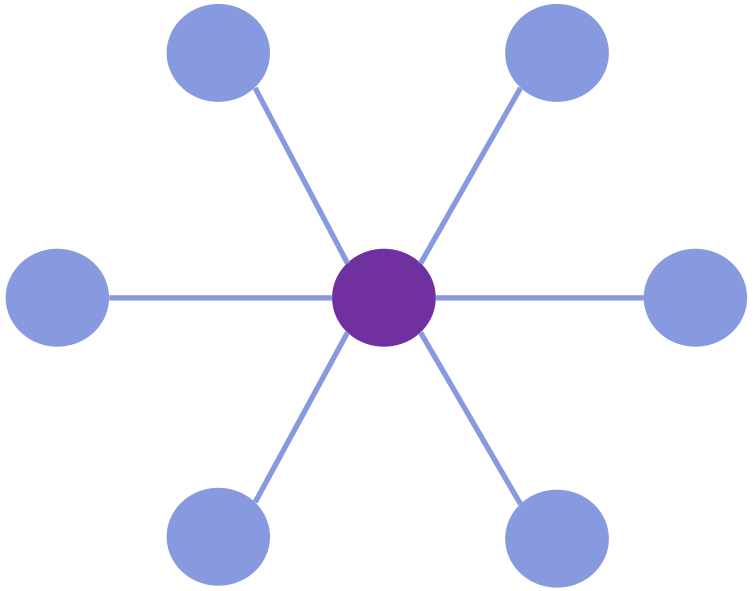


Peer-to-Peer Model

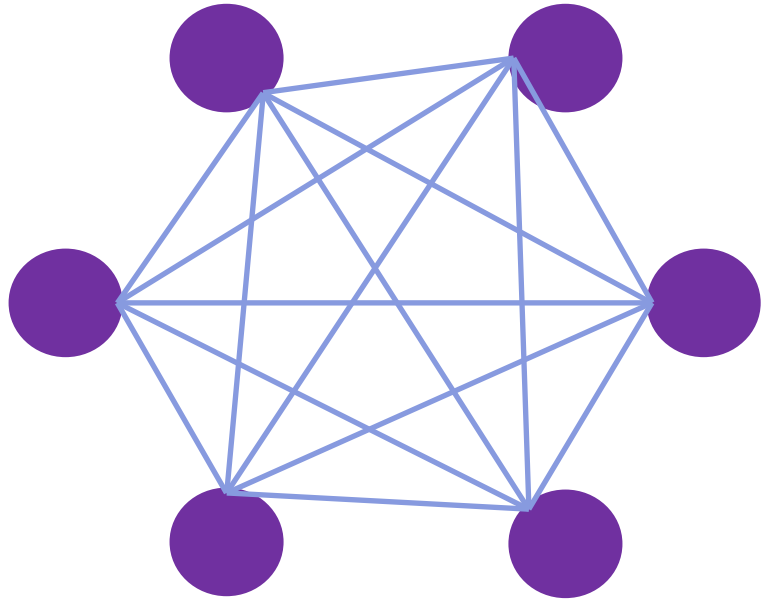
# RES Collaborative Forecasting
## Communication Schemes

**Step 3.**
Computation of

$$\text{Conciliation}^{k+1} = h\left[\left[\sum_j \text{Enc data from agent } j \cdot \widehat{Enc\ Coef\ WF_j^k}\right], \ldots\right]$$



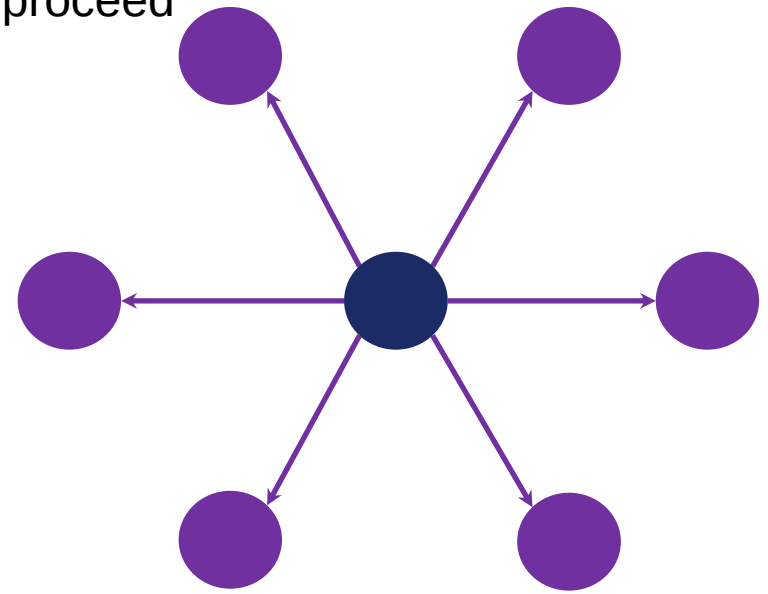
Centralized Model



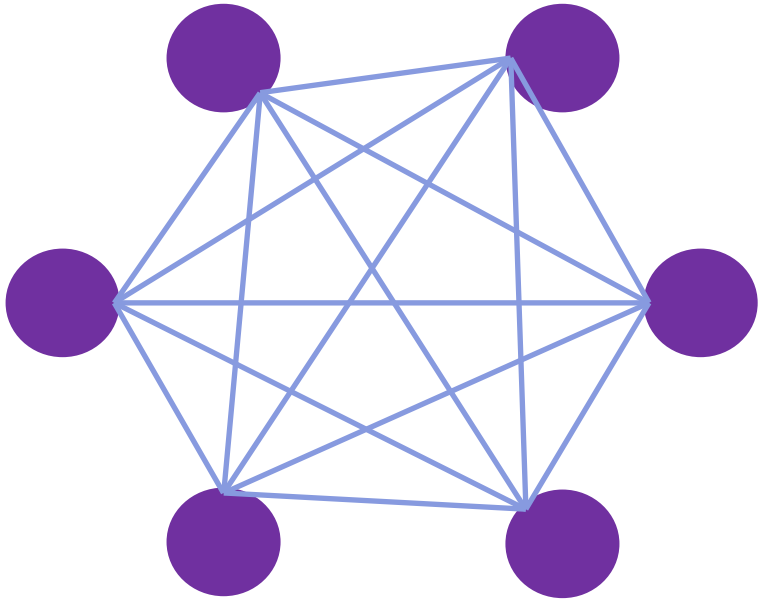
Peer-to-Peer Model

# RES Collaborative Forecasting
## Communication Schemes

**Step 4.**
Agents obtain conciliation matrix and proceed to **Step 1**



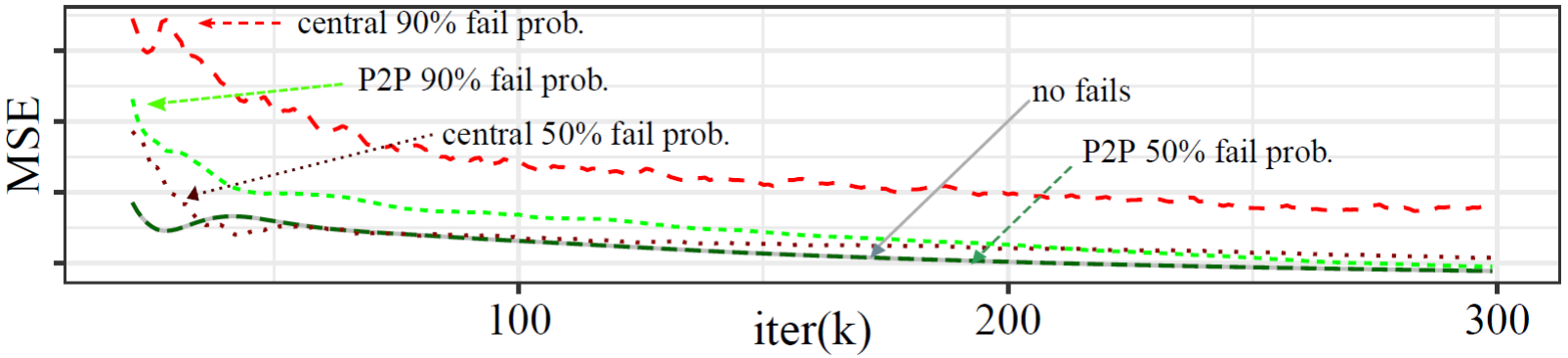
Centralized Model



Peer-to-Peer Model

# RES Collaborative Forecasting
## Results for Évora PV Dataset

Asynchronous communication: equal failure probabilities are assumed for all agents

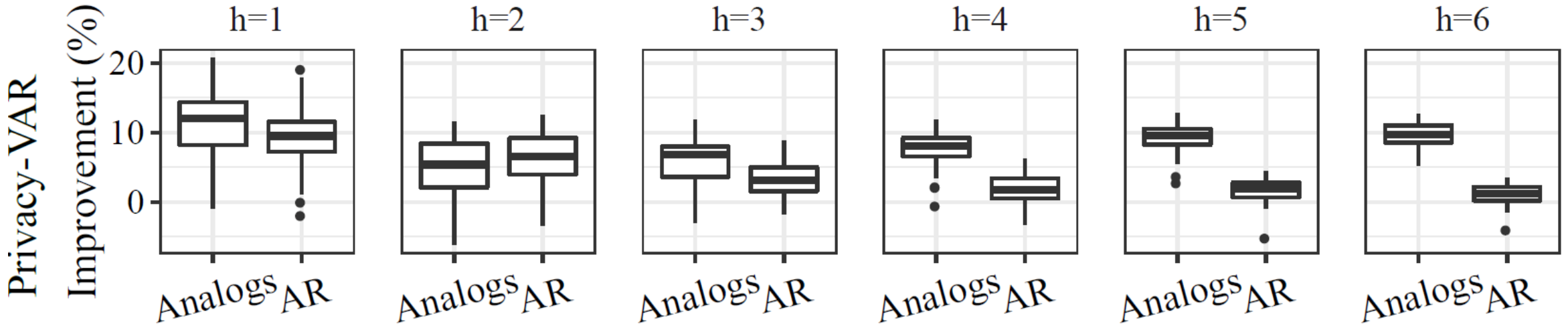



**44 Domestic PV**

- Better performance of the P2P scheme
  - *Centralized*: if one agent fails the algorithm proceeds without its information
  - *P2P*: agent communicates its contribution to some peers → probability of information lost is smaller
- Computational performance
  - Privacy protocol: 65.5s
  - 0.05s (centralized) and 0.12s (P2P) for model fitting

# RES Collaborative Forecasting
## Results for Évora PV Dataset

RMSE improvement of Privacy-VAR over **AR** (autoregressive) & **Analogs search** (collaborative w/ privacy)




Some data owners contribute to improve competitors' forecast without getting the same benefit (error improvement)

↓

**Even if privacy is ensured, such agents may be unwilling to collaborate → data monetization (data markets)**

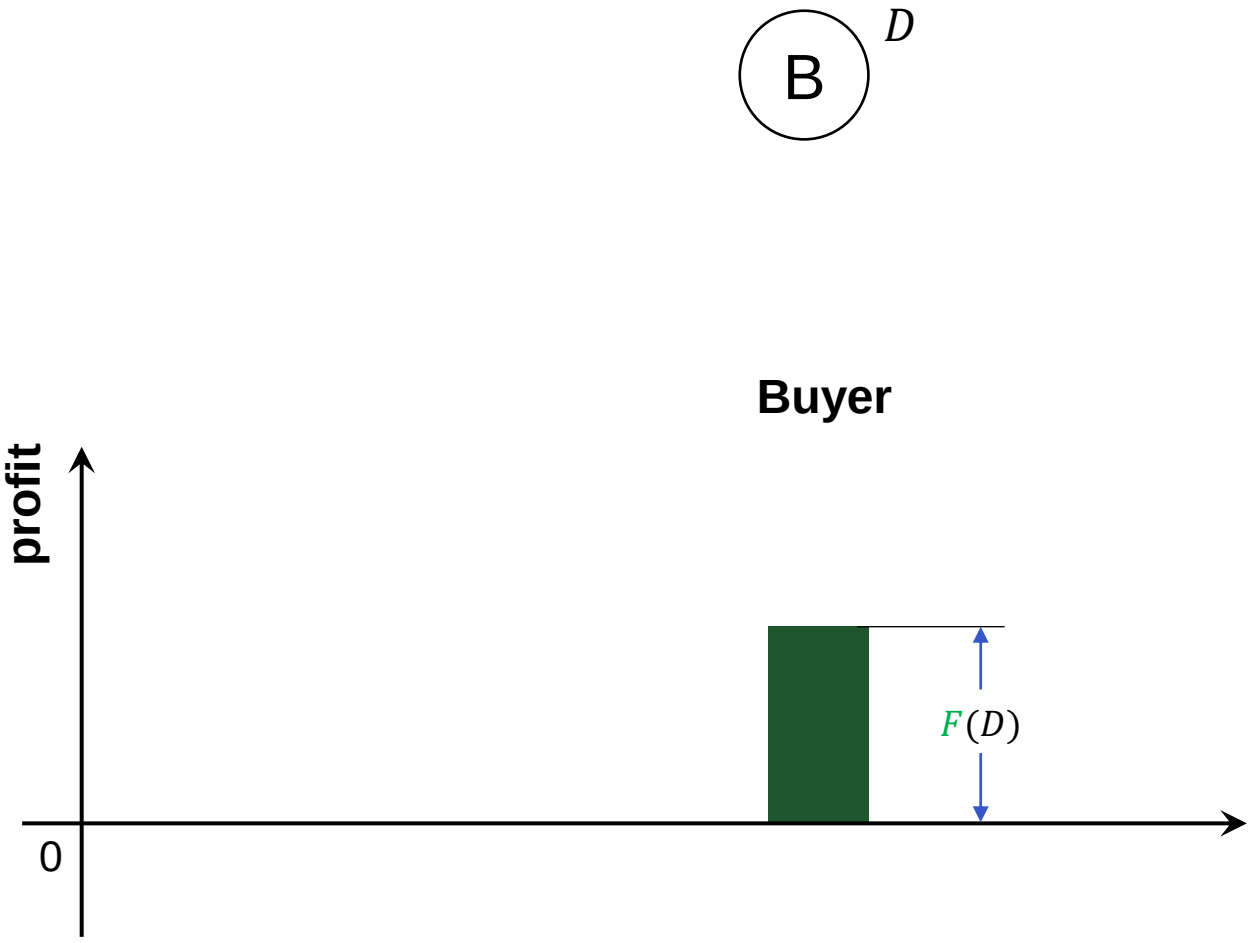
# Data Markets

# Data Market Basics

- Market components
  - Key players
    - Data buyer(s)
    - Data seller(s)
  - Monetary Values
    - Seller’s cost of offering data
    - Buyer’s profit
    - Data payment
- Market procedure

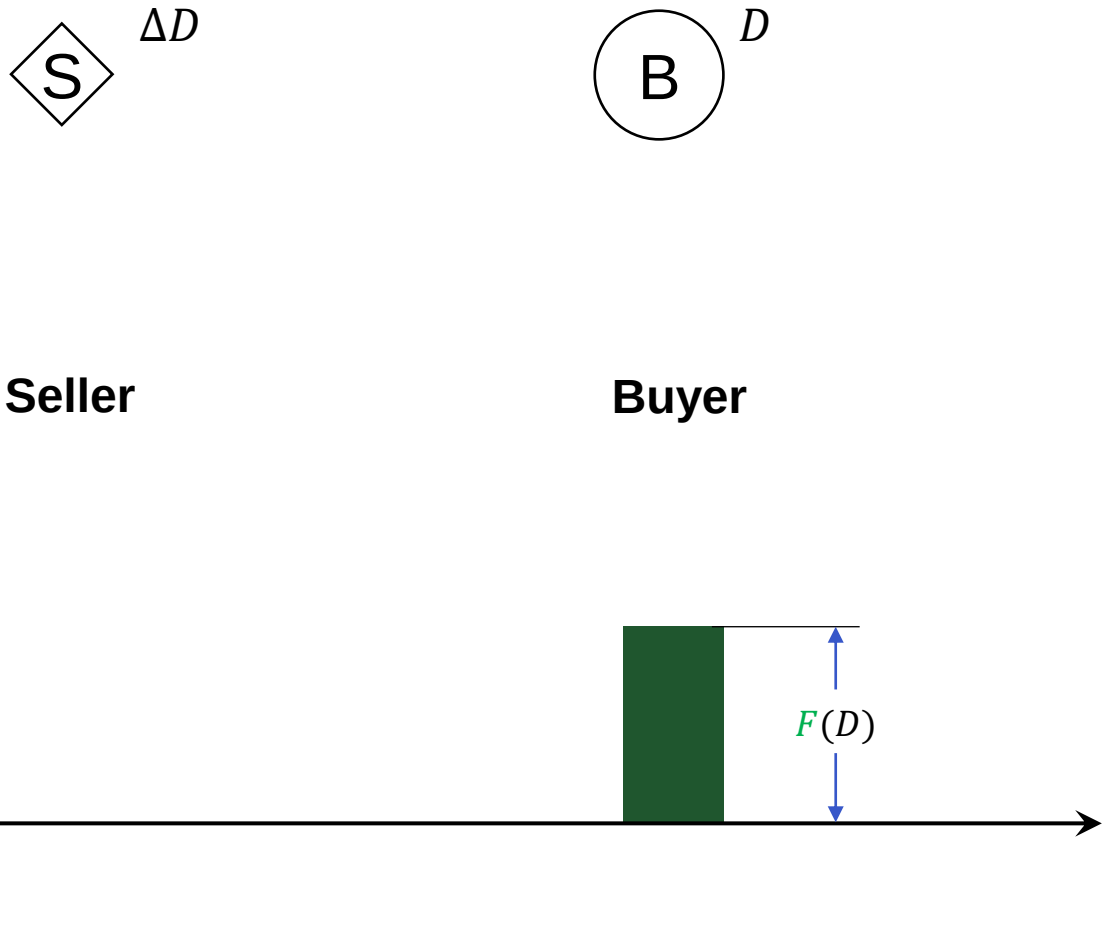
# Data Market Basics

- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s)
  - Monetary Values
    - Seller's cost of offering data
    - Buyer's profit $F(D)$
    - Data payment
- Market procedure



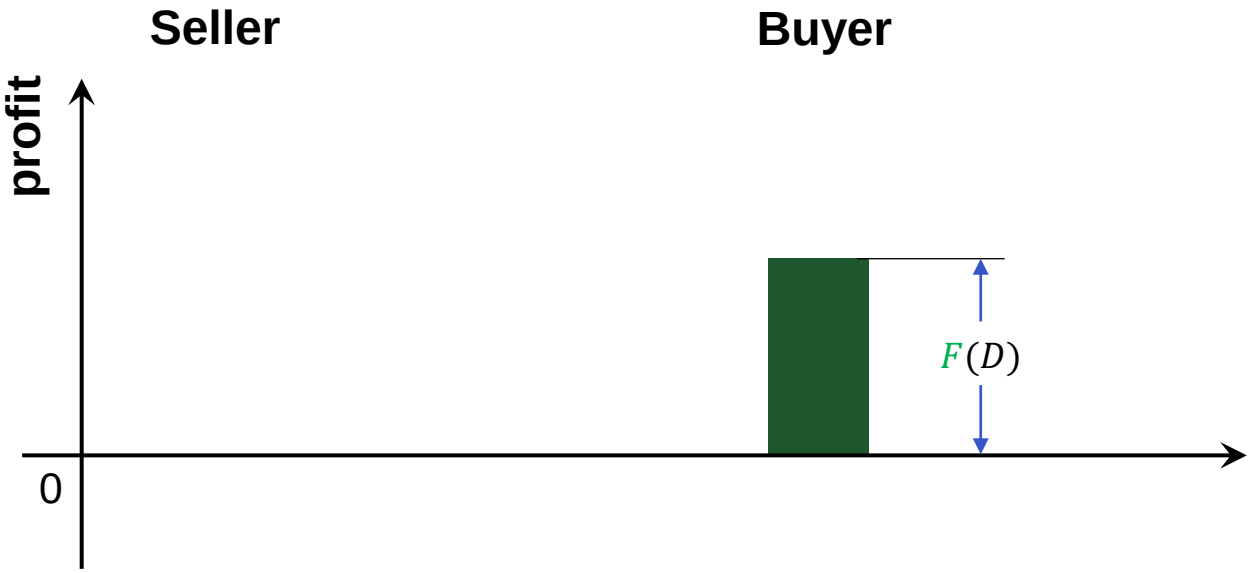
# Data Market Basics

- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data
    - Buyer's profit $F(D)$
    - Data payment
- Market procedure



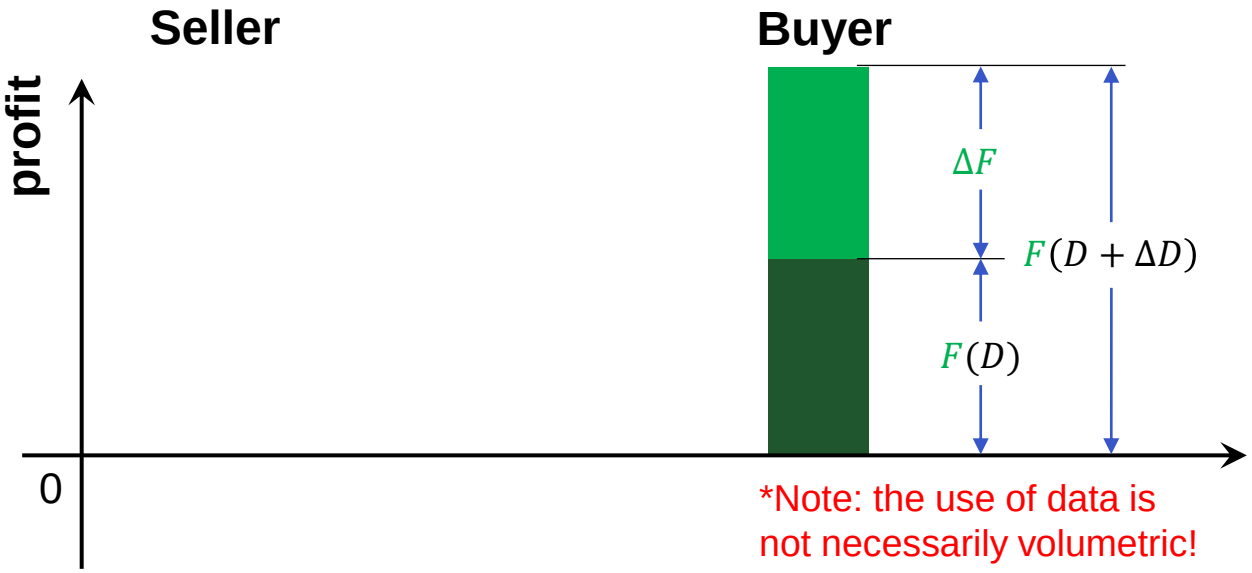
# Data Market Basics

- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data
    - Buyer's profit $F(D)$
    - Data payment
- Market procedure



# Data Market Basics

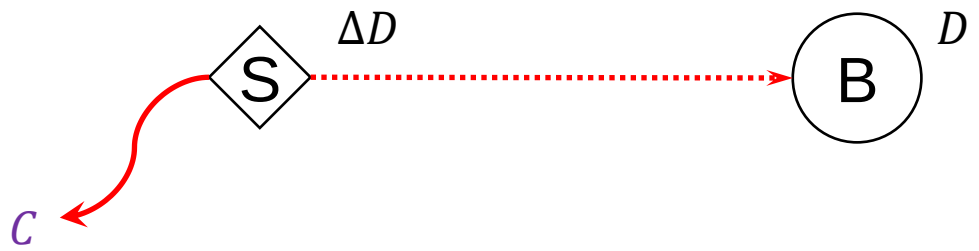
- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data
    - Buyer's profit $F(D) < F(D + \Delta D)$
    - Data payment
- Market procedure
  1) **Buyer can profit from seller's data**

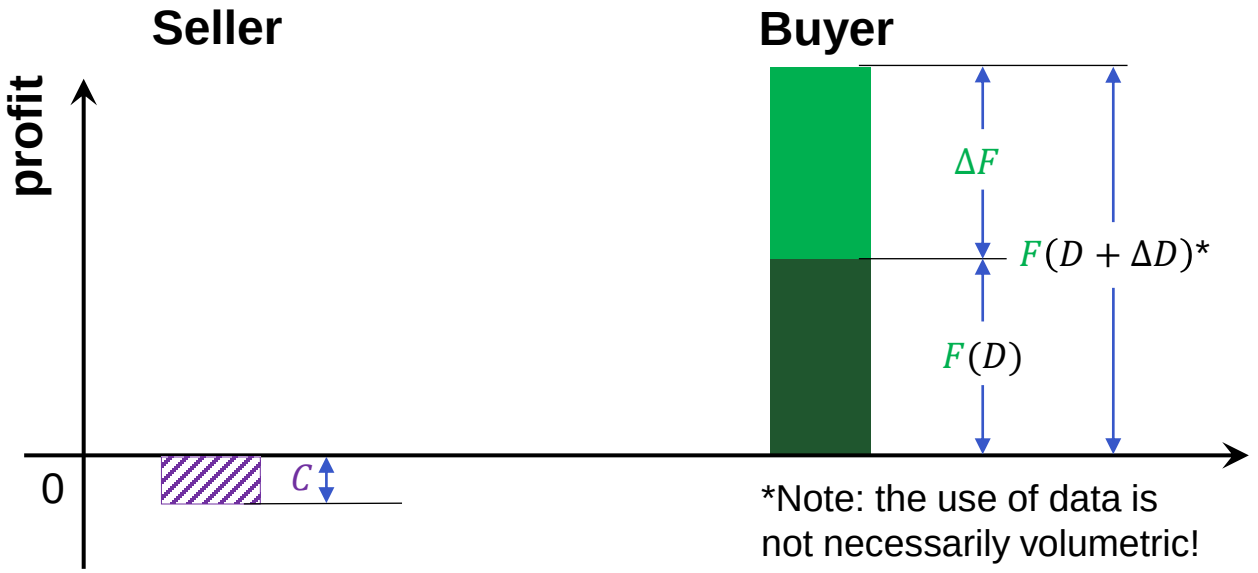



*Note: the use of data is not necessarily volumetric!

# Data Market Basics

- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data $C(\Delta D)$
    - Buyer's profit $F(D) < F(D + \Delta D)$
    - Data payment
- Market procedure
  1) **Buyer can profit from seller's data**

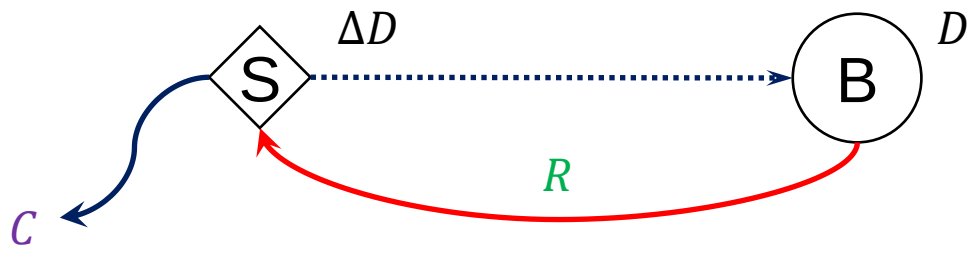


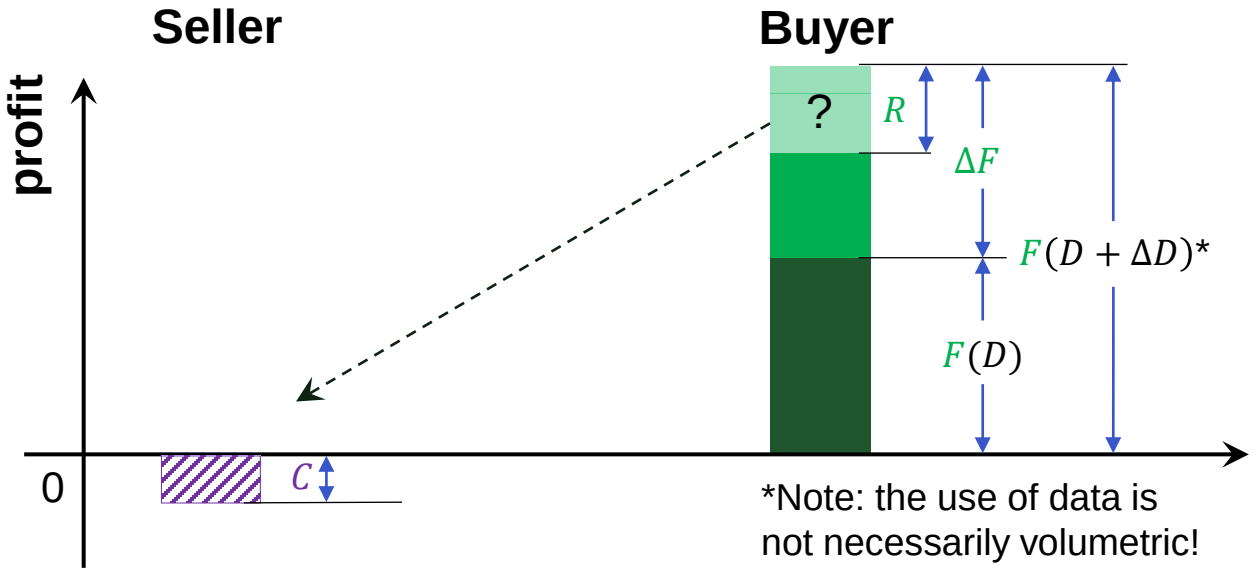




*Note: the use of data is not necessarily volumetric!

# Data Market Basics

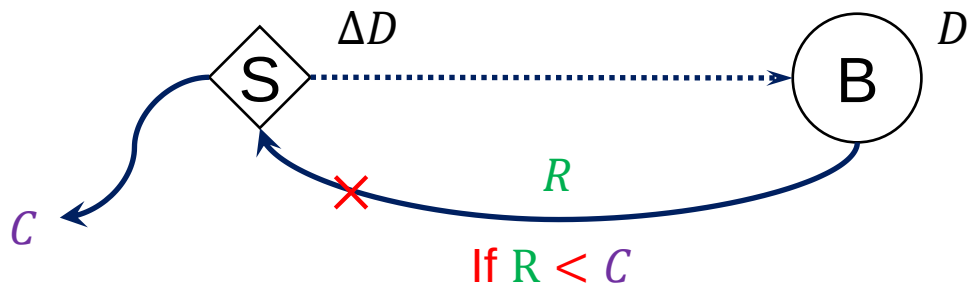
- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data $C(\Delta D)$
    - Buyer's profit $F(D) < F(D + \Delta D)$
    - Data payment $R < \Delta F = F(D + \Delta D) - F(D)$
- Market procedure
  1) Buyer can profit from seller's data
  2) **Buyer offers seller monetary rewards**

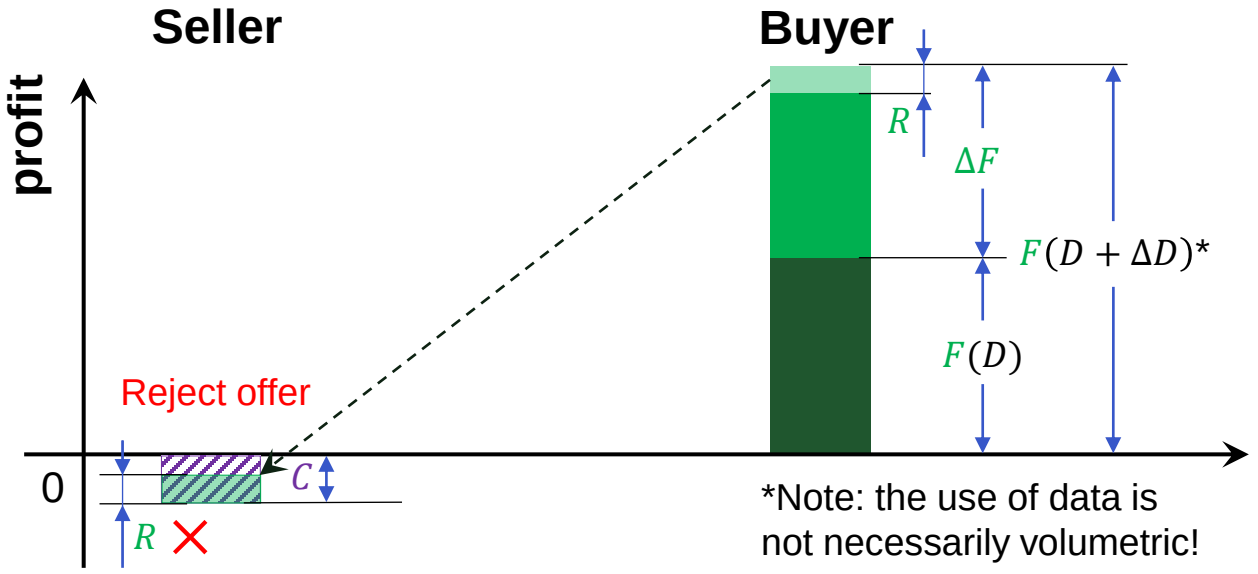


# Data Market Basics

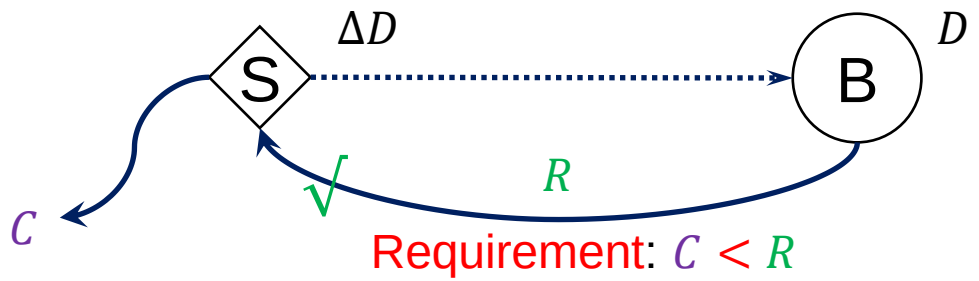
- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data $C(\Delta D)$
    - Buyer's profit $F(D) < F(D + \Delta D)$
    - Data payment $R < \Delta F = F(D + \Delta D) - F(D)$
- Market procedure
  1) Buyer can profit from seller's data
  2) Buyer offers seller monetary rewards
  3) **Seller either rejects or accepts offer**

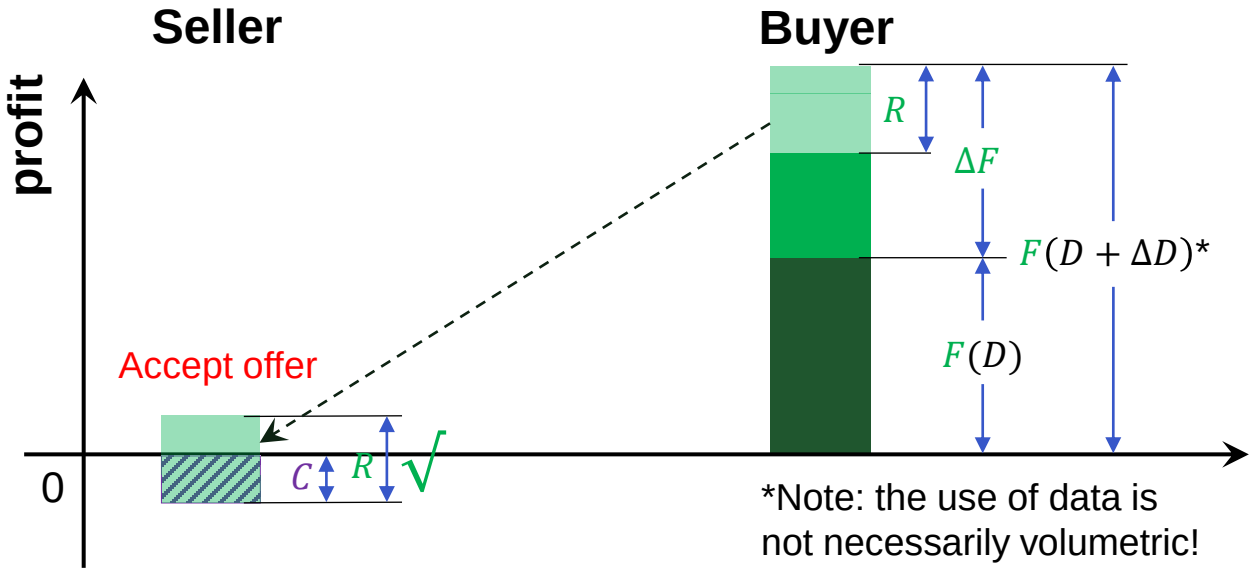


# Data Market Basics

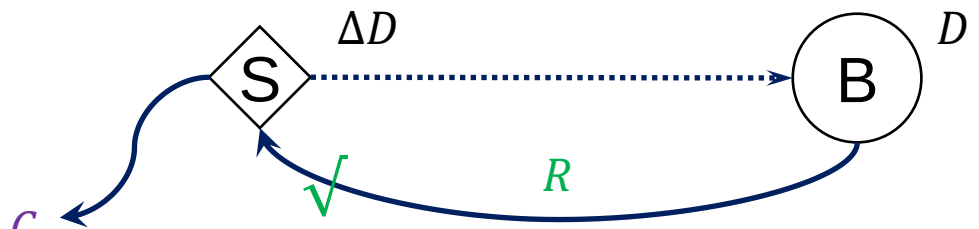
- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data $C(\Delta D) < R$
    - Buyer's profit $F(D) < F(D + \Delta D)$
    - Data payment $R < \Delta F = F(D + \Delta D) - F(D)$
- Market procedure
  1) Buyer can profit from seller's data
  2) Buyer offers seller monetary rewards
  3) **Seller either rejects or accepts offer**



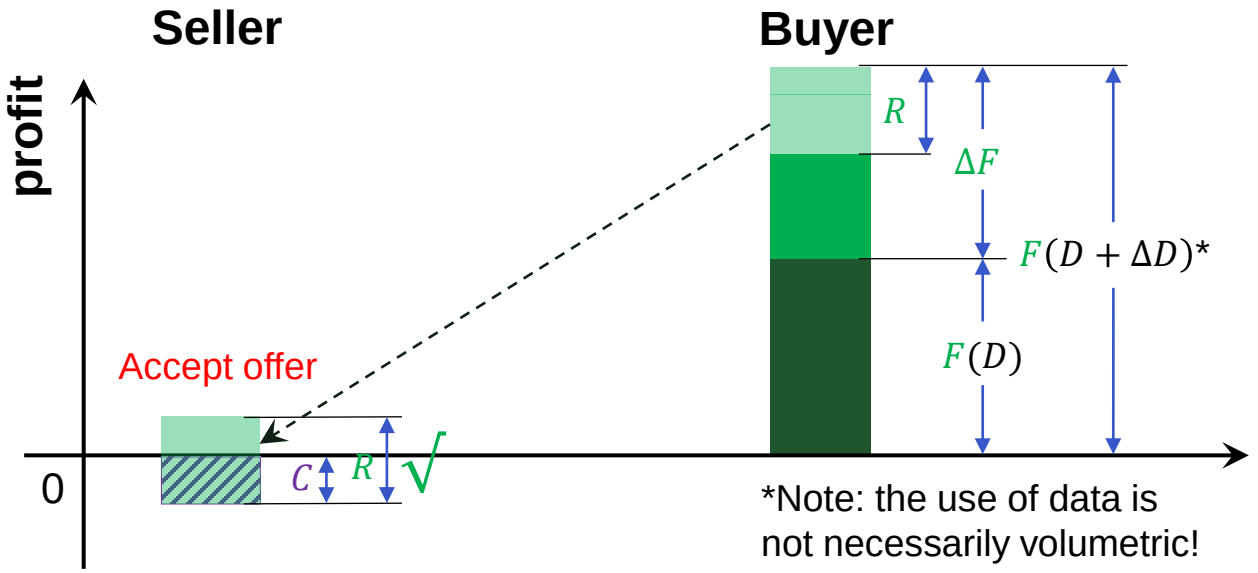
# Data Market Basics

- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data $C(\Delta D) < R$
    - Buyer's profit $F(D) < F(D + \Delta D)$
    - Data payment $R < \Delta F = F(D + \Delta D) - F(D)$
- Market procedure
  1) Buyer can profit from seller's data
  2) Buyer offers seller monetary rewards
  3) **Seller either rejects or accepts offer**




Requirement: $C < R$

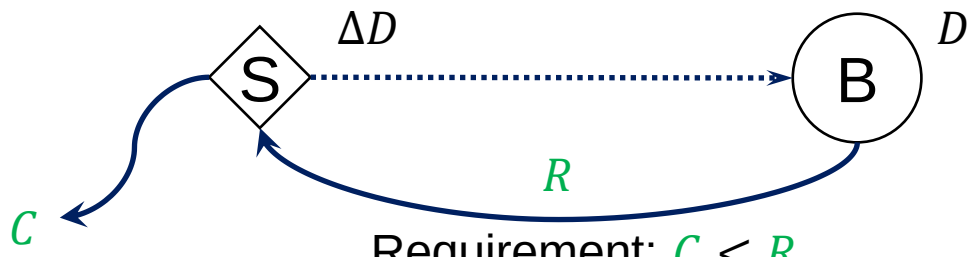
($C$ includes the value of privacy)




*Note: the use of data is not necessarily volumetric!

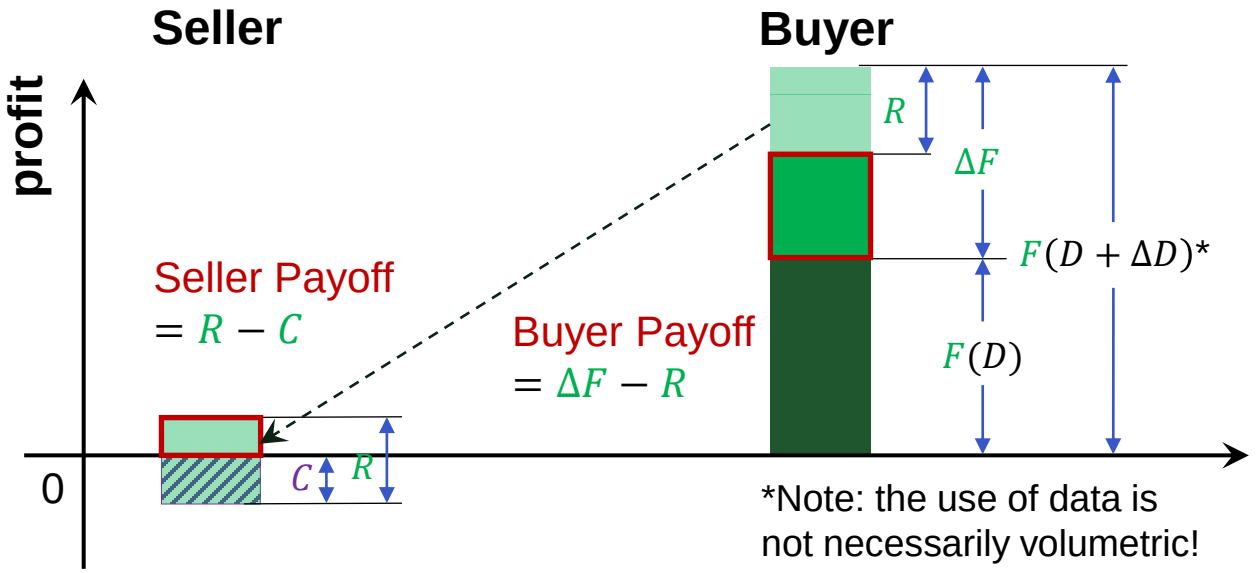
# Data Market Basics

- Market components
  - Key players
    - Data buyer(s) B with known data $D$
    - Data seller(s) S with data $\Delta D$
  - Monetary Values
    - Seller's cost of offering data $\boldsymbol{C}(\Delta \boldsymbol{D}) < \boldsymbol{R}$
    - Buyer's profit $\boldsymbol{F}(\boldsymbol{D}) < \boldsymbol{F}(\boldsymbol{D} + \Delta \boldsymbol{D})$
    - Data payment $\boldsymbol{R} < \Delta \boldsymbol{F} = \boldsymbol{F}(\boldsymbol{D} + \Delta \boldsymbol{D}) - \boldsymbol{F}(\boldsymbol{D})$
- Market procedure
  1) Buyer can profit from seller's data
  2) Buyer offers seller monetary rewards
  3) Seller either rejects or accepts offer




Requirement: $C < R$

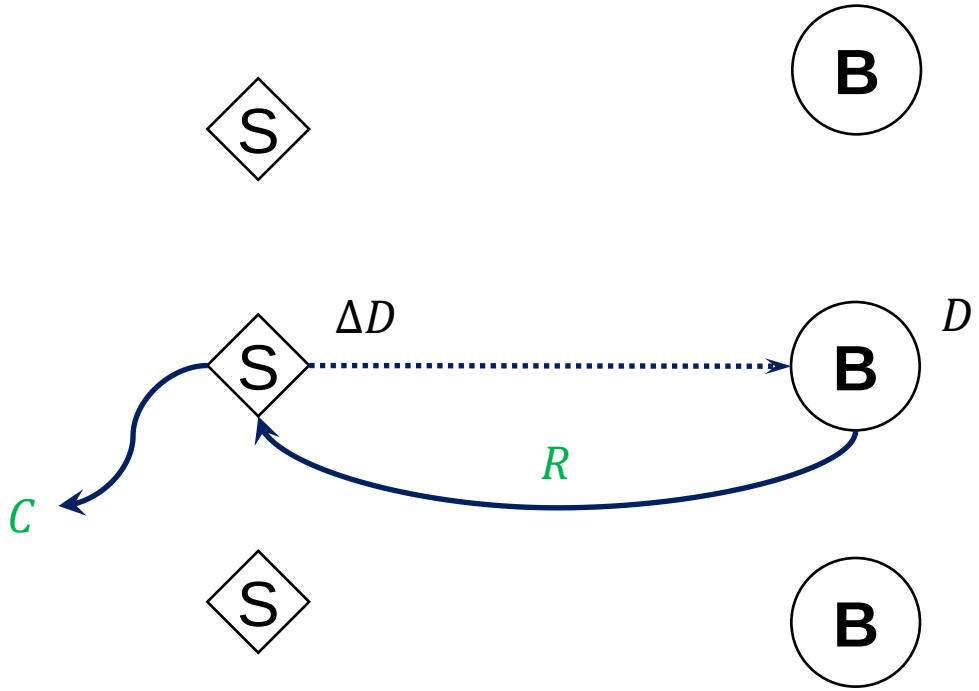
($C$ includes the value of privacy)




*Note: the use of data is not necessarily volumetric!

# Data Market Models

Data ⟶ Money

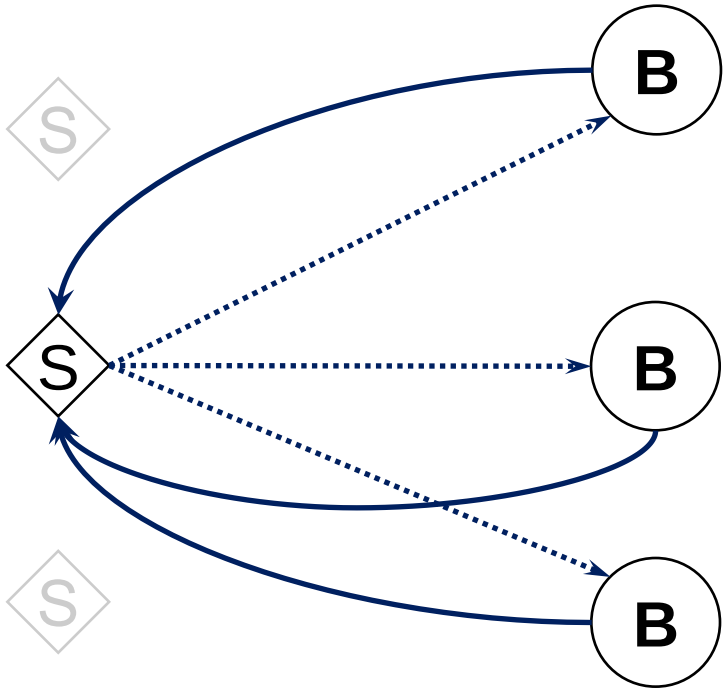



**Data Market Models:**

**Data Seller(s)** **Data Buyer(s)**

# Data Market Models

Data → Money




Data Seller(s) Data Buyer(s)

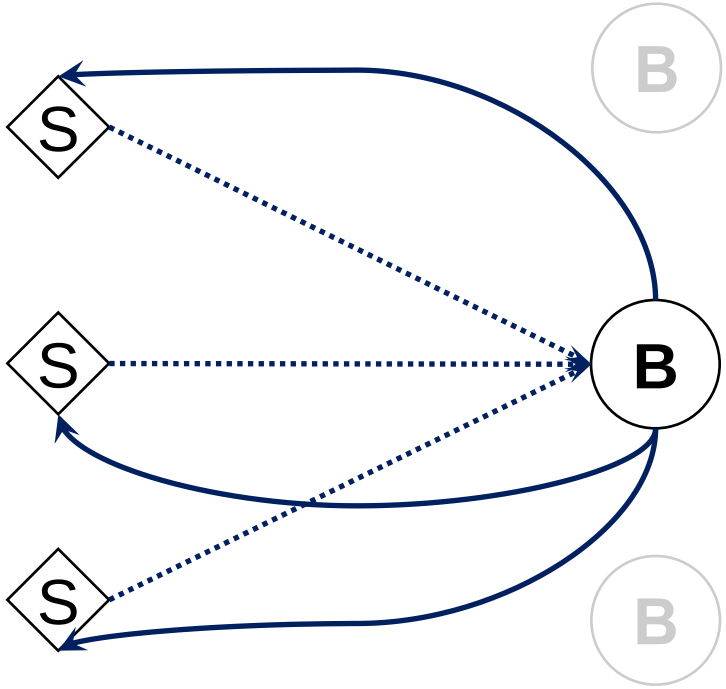
**Data Market Models:**

- Monopolistic Data Seller

# Data Market Models

Data

Money



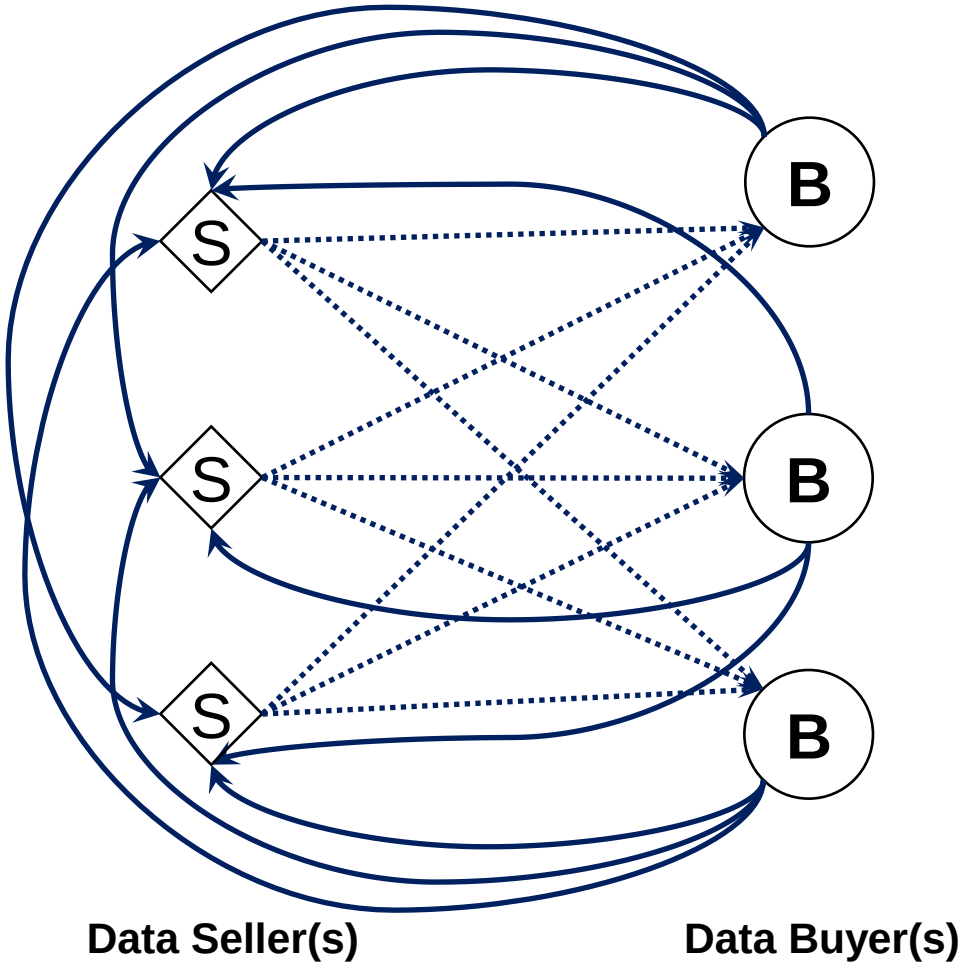

**Data Seller(s)** **Data Buyer(s)**

**Data Market Models:**

- Monopolistic Data Seller
- Monopolistic Data Buyer

# Data Market Models

Data Money

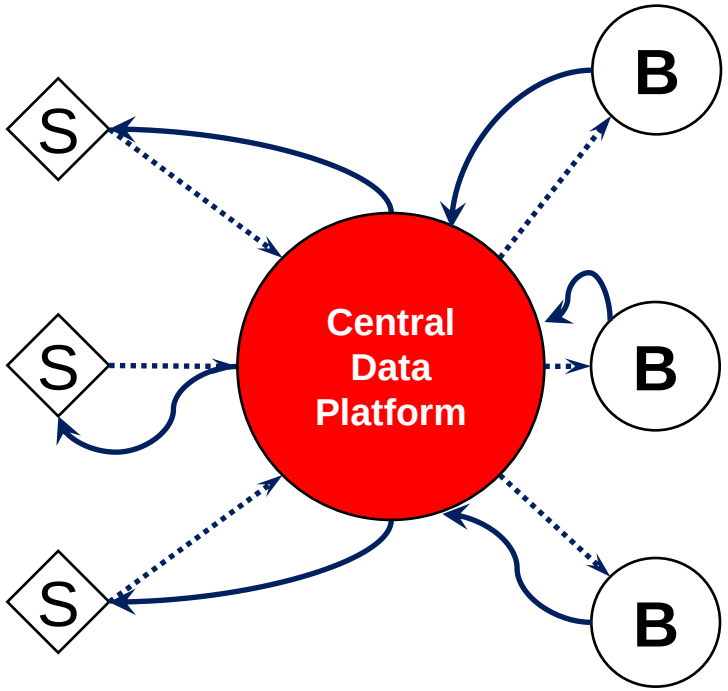



**Data Market Models:**

- Monopolistic Data Seller
- Monopolistic Data Buyer
- Peer-to-Peer Multi-Seller Multi-Buyer

# Data Market Models

Data Money



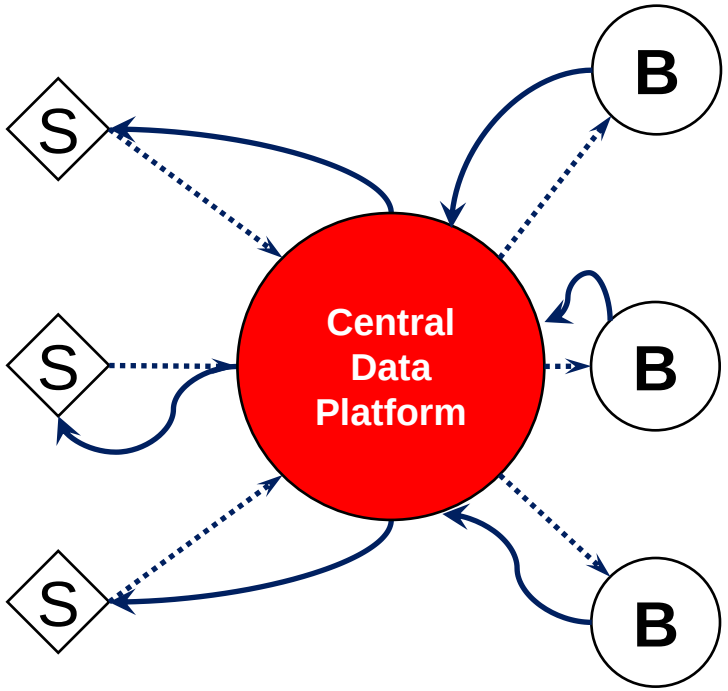

**Data Market Models:**

- Monopolistic Data Seller
- Monopolistic Data Buyer
- Peer-to-Peer Multi-Seller Multi-Buyer
- Centralized Model

# Data Market Models

Data ⟶ Money

How can this be applied to Smart4RES in an energy market?



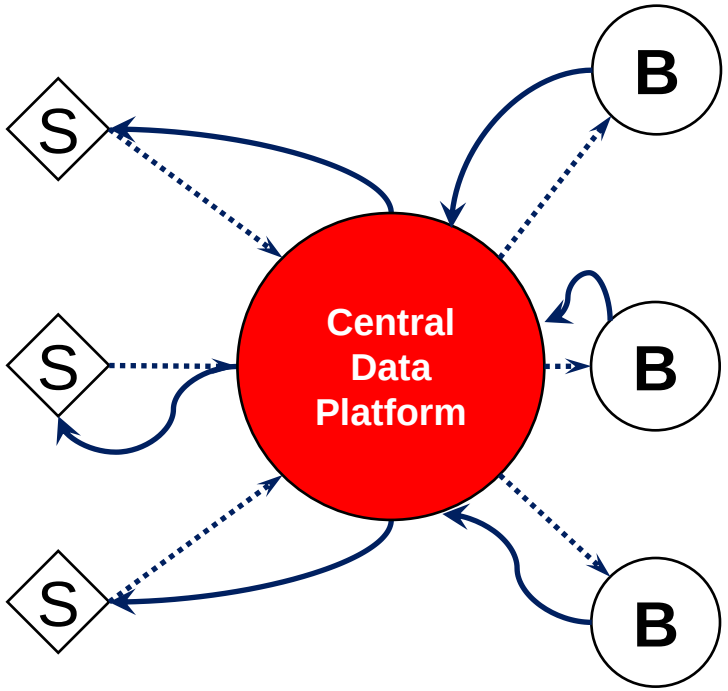

**Data Market Models:**

- Monopolistic Data Seller
- Monopolistic Data Buyer
- Peer-to-Peer Multi-Seller Multi-Buyer
- Centralized Model

# Data Market Models

Data ⟶ Money

How can this be applied to Smart4RES in an energy market?




**Data Seller(s)** **Data Buyer(s)**

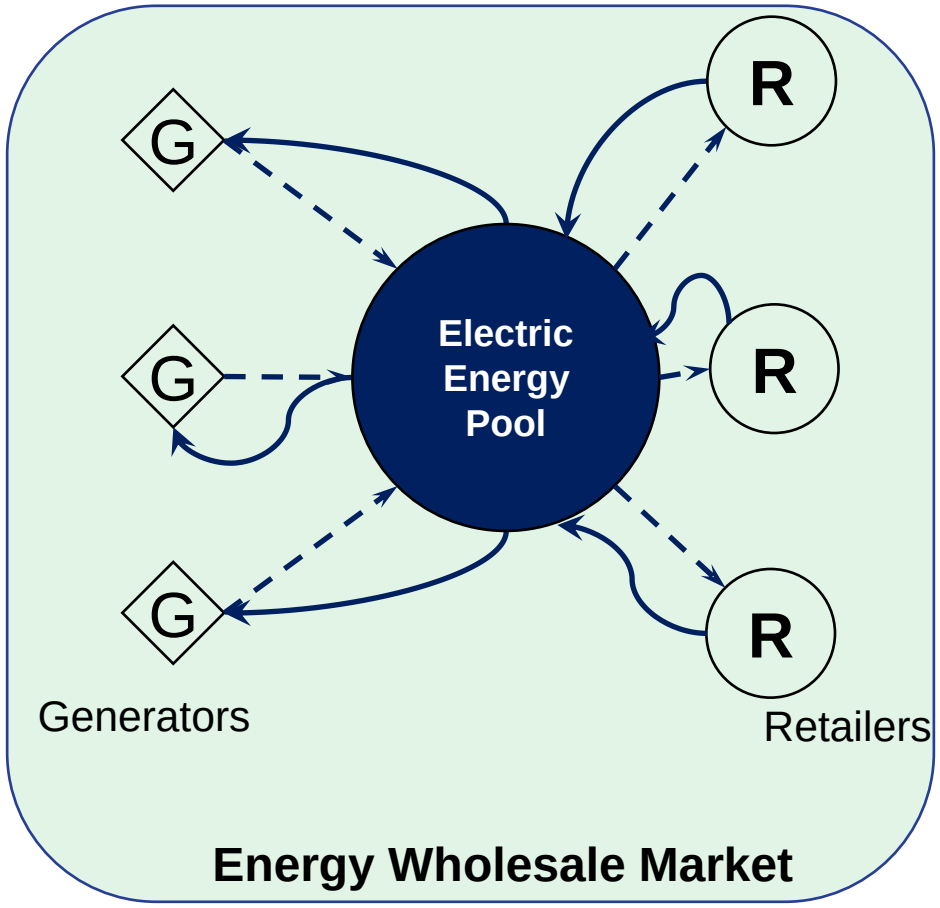
**Data Market Models:**

- Monopolistic Data Seller
- Monopolistic Data Buyer
- Peer-to-Peer Multi-Seller Multi-Buyer
- Centralized Model

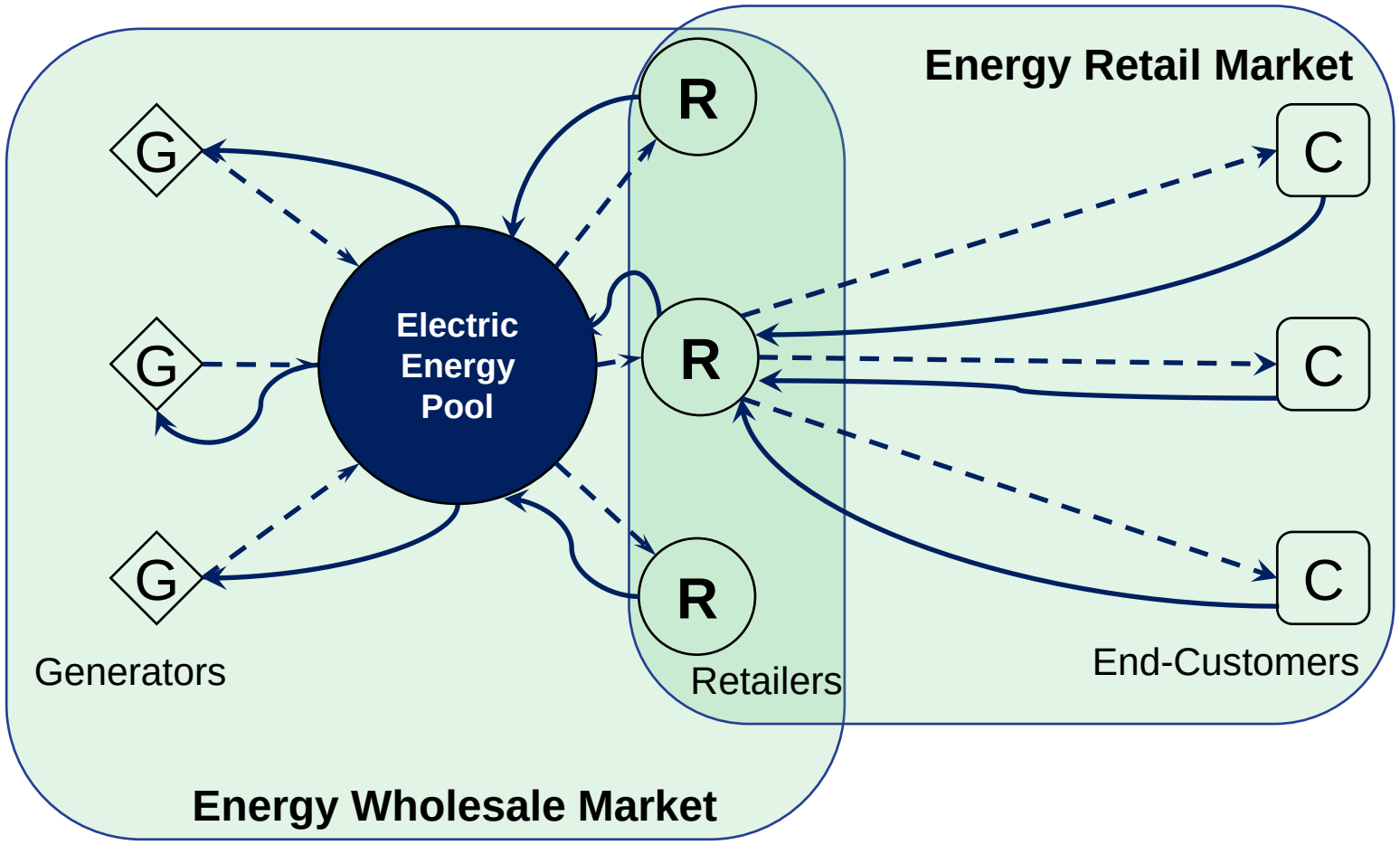
Similar to an **energy wholesale market!**

# Energy-Data Market

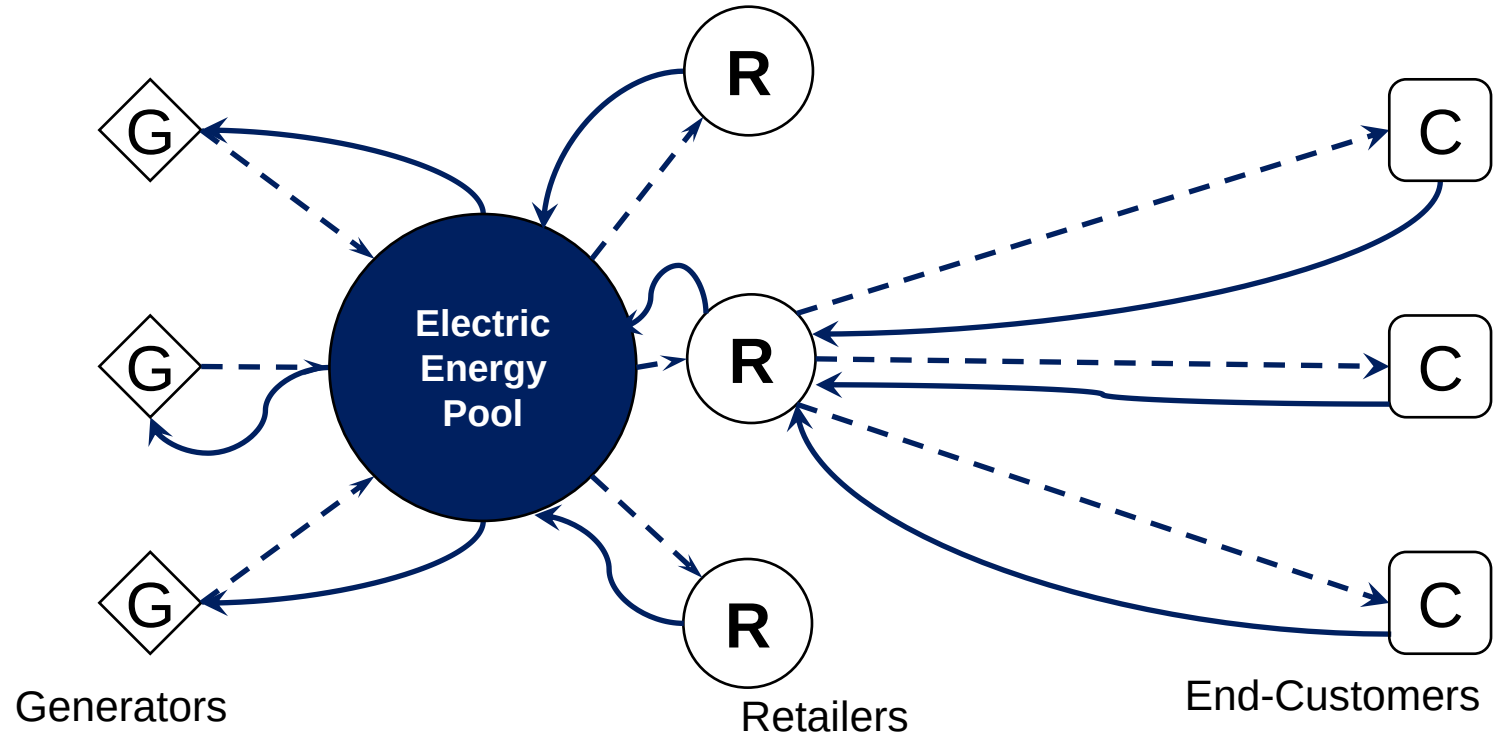
Data
Energy
Money



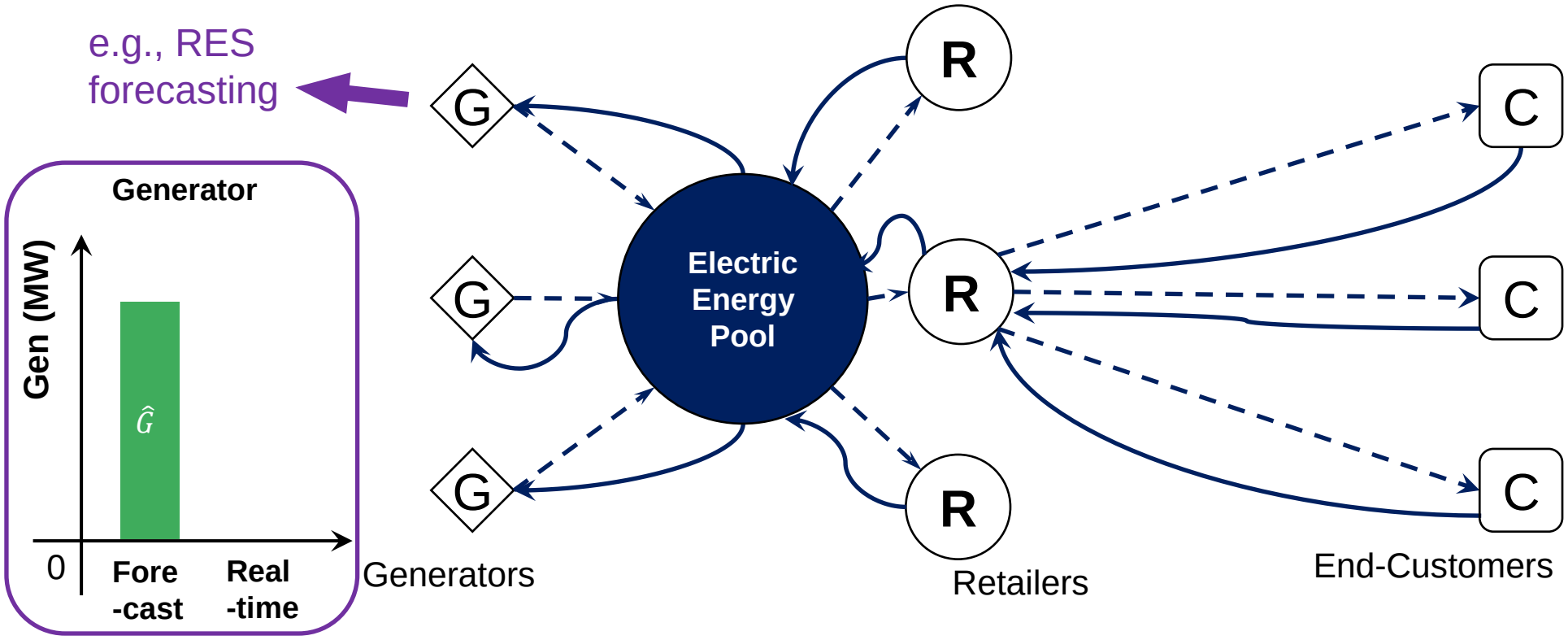
# Energy-Data Market



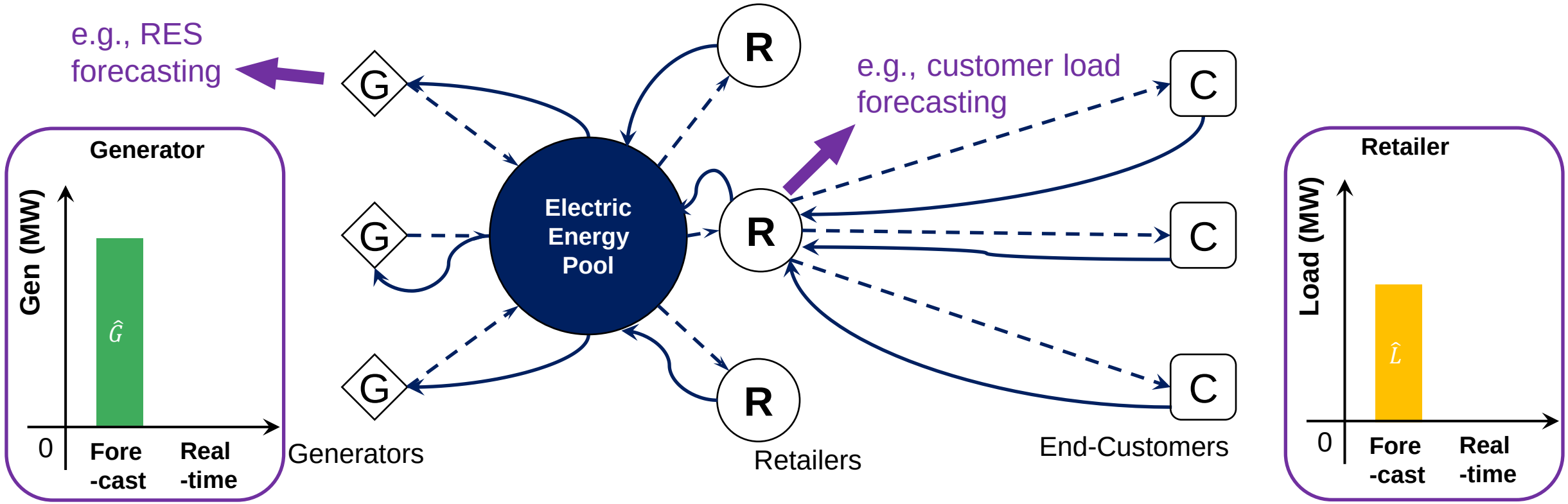
# Energy-Data Market



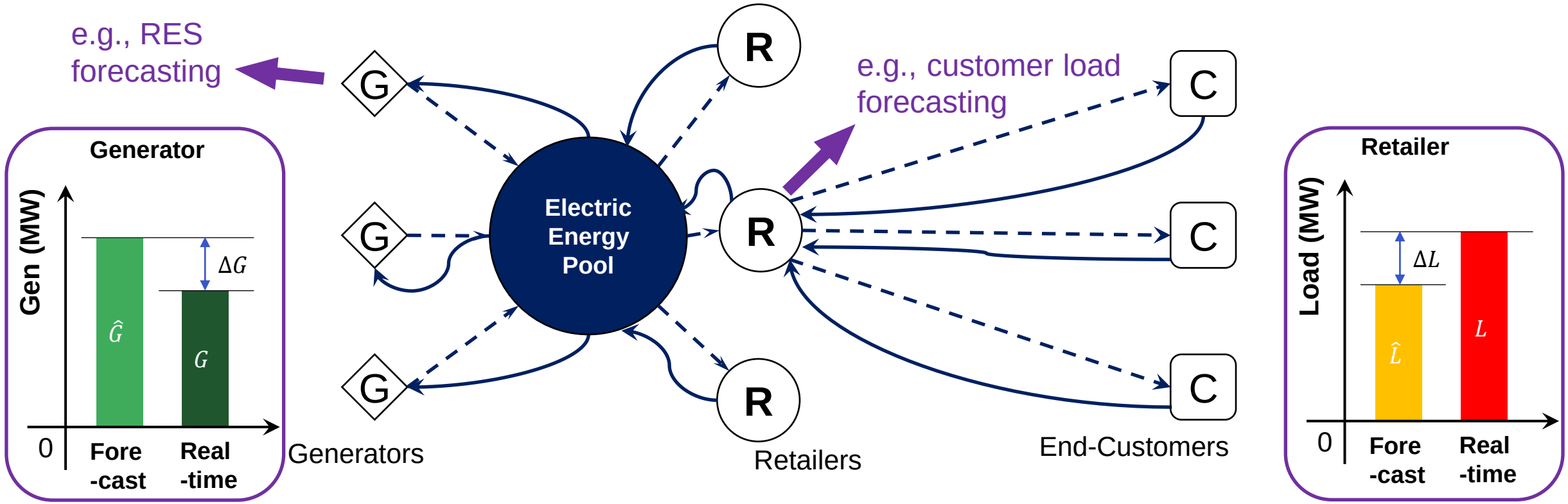
# Energy-Data Market



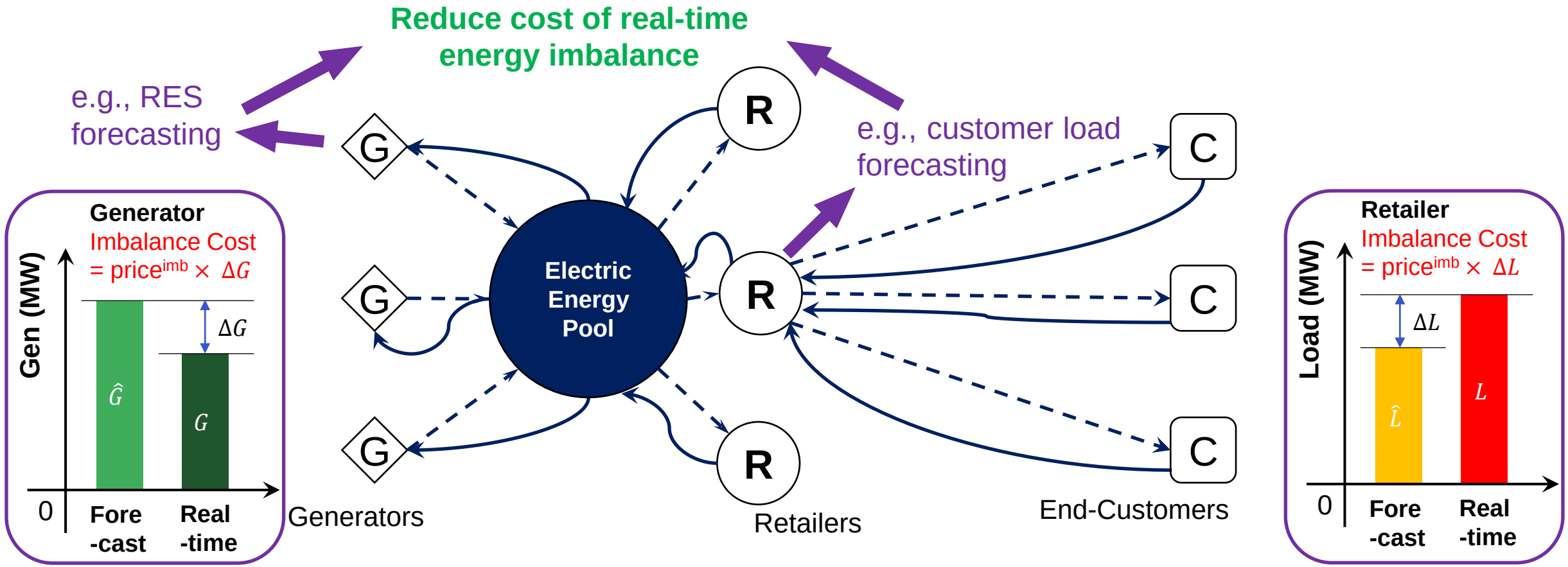
# Energy-Data Market



# Energy-Data Market



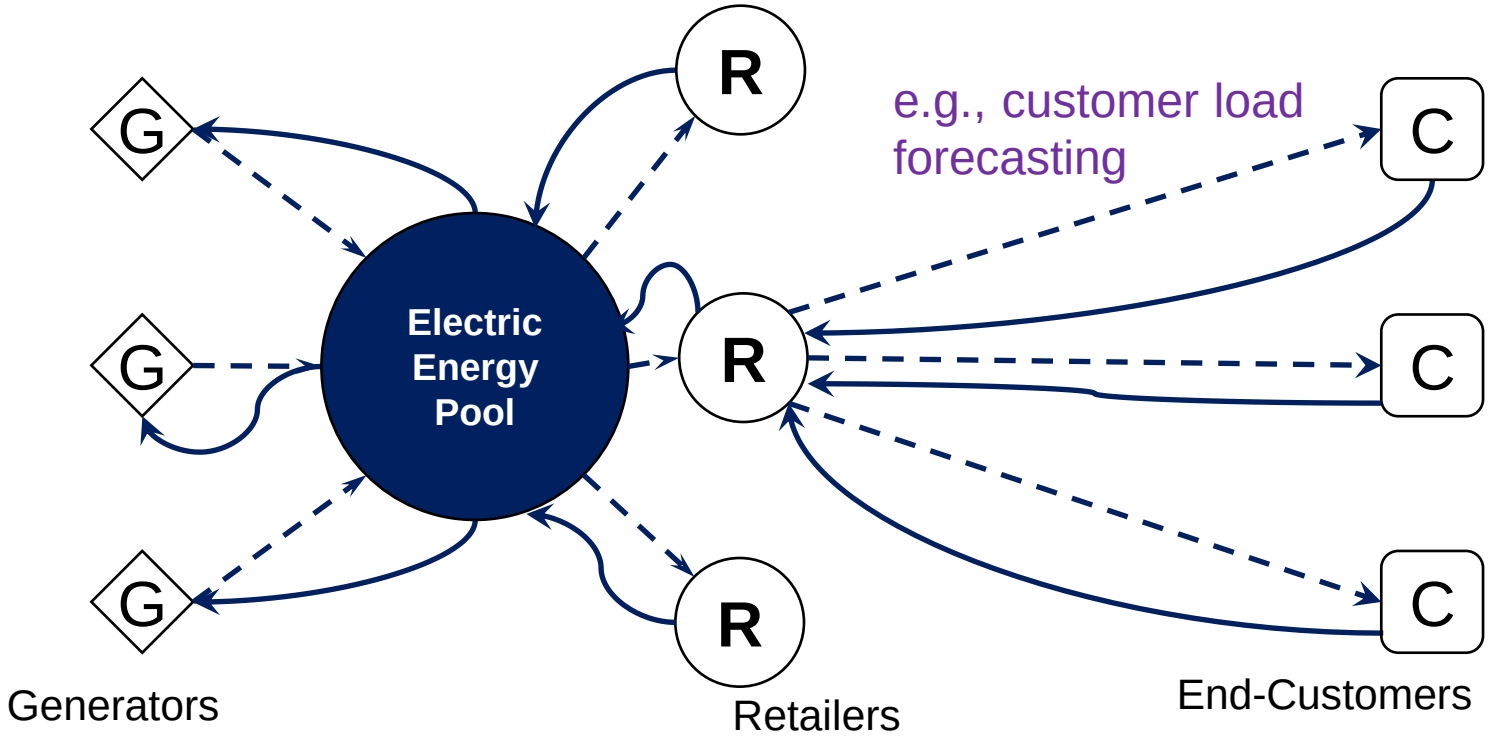
# Energy-Data Market



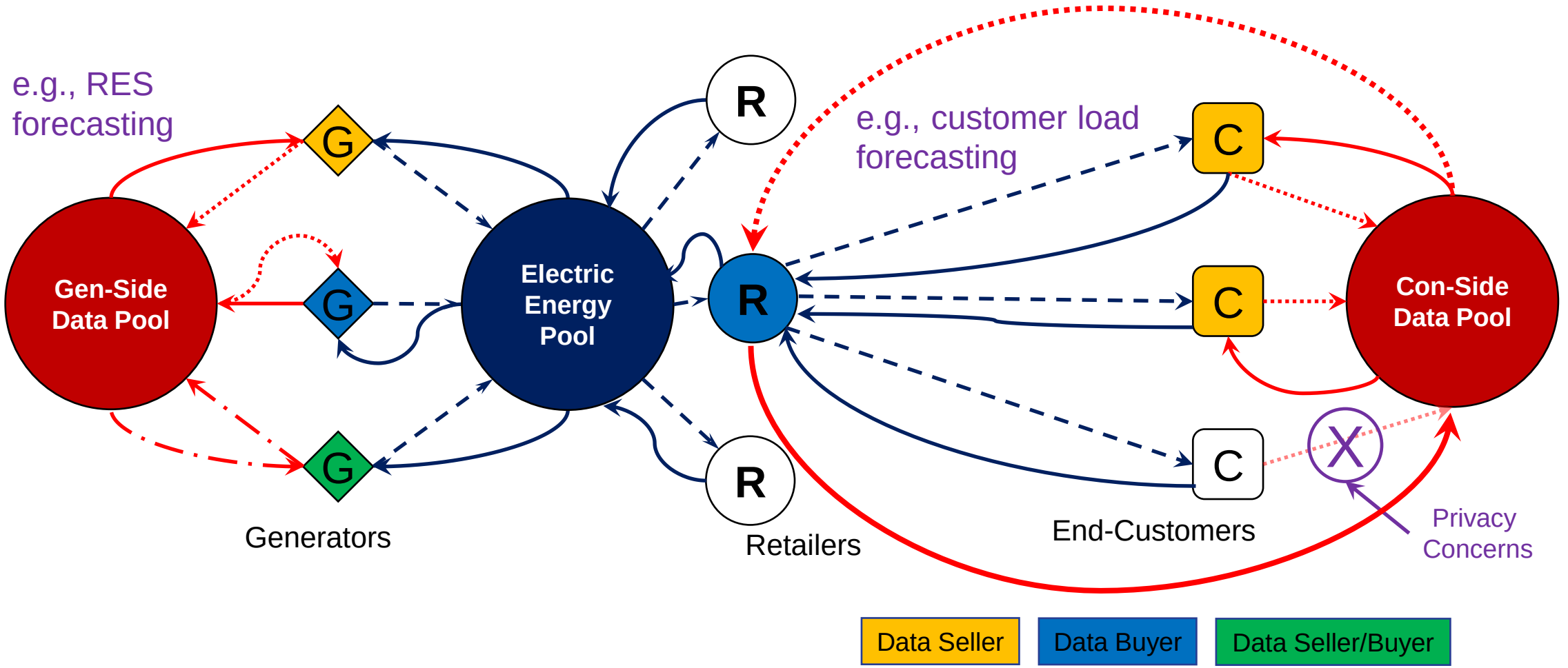
# Energy-Data Market

Data
Energy
Money

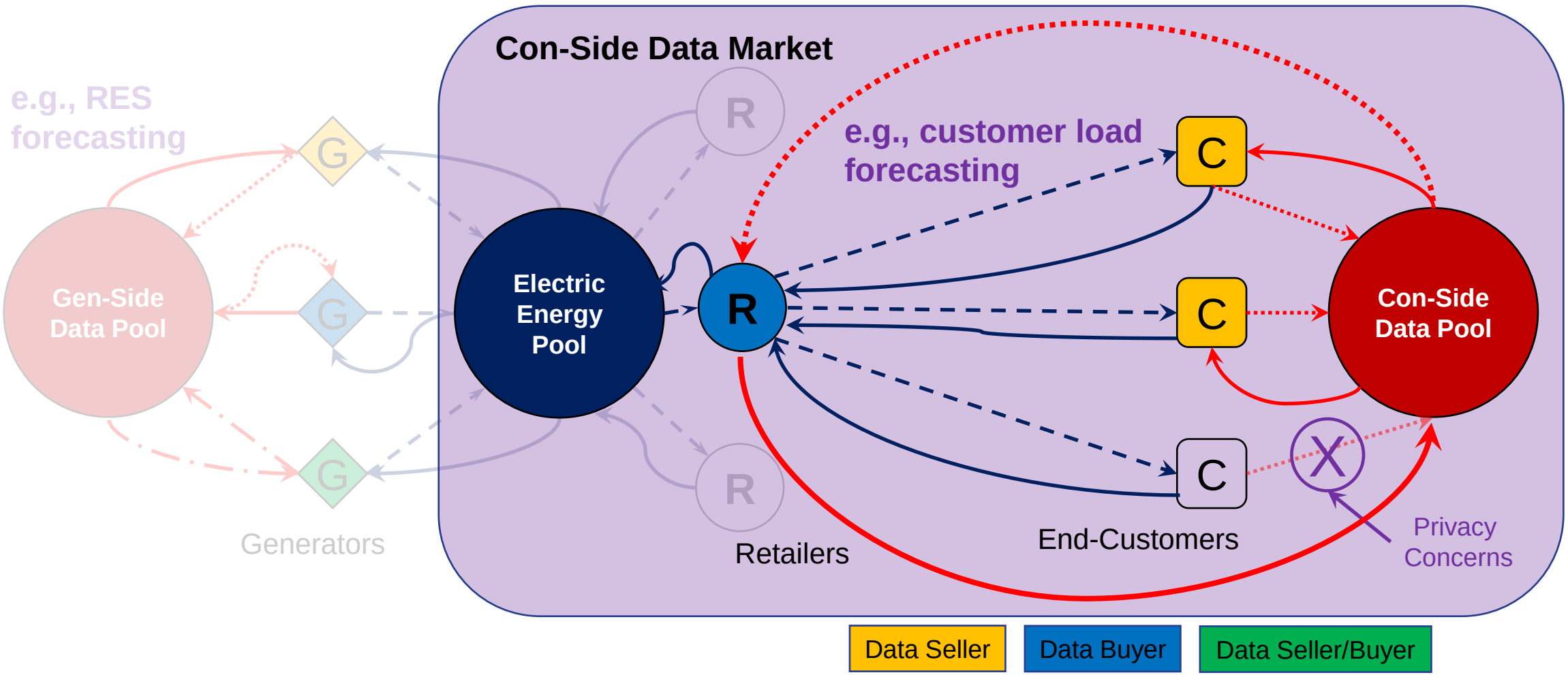
e.g., RES forecasting



# Energy-Data Market

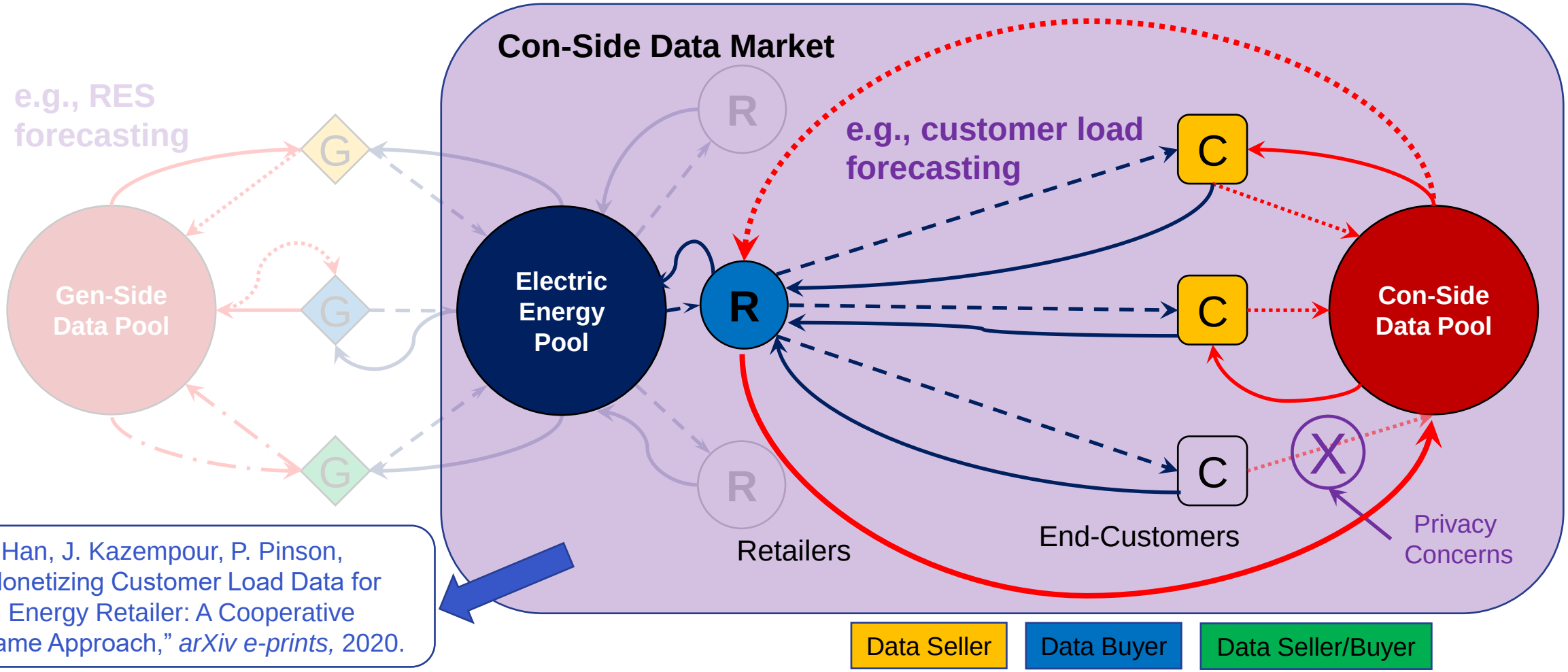


# Energy-Data Market



# Energy-Data Market

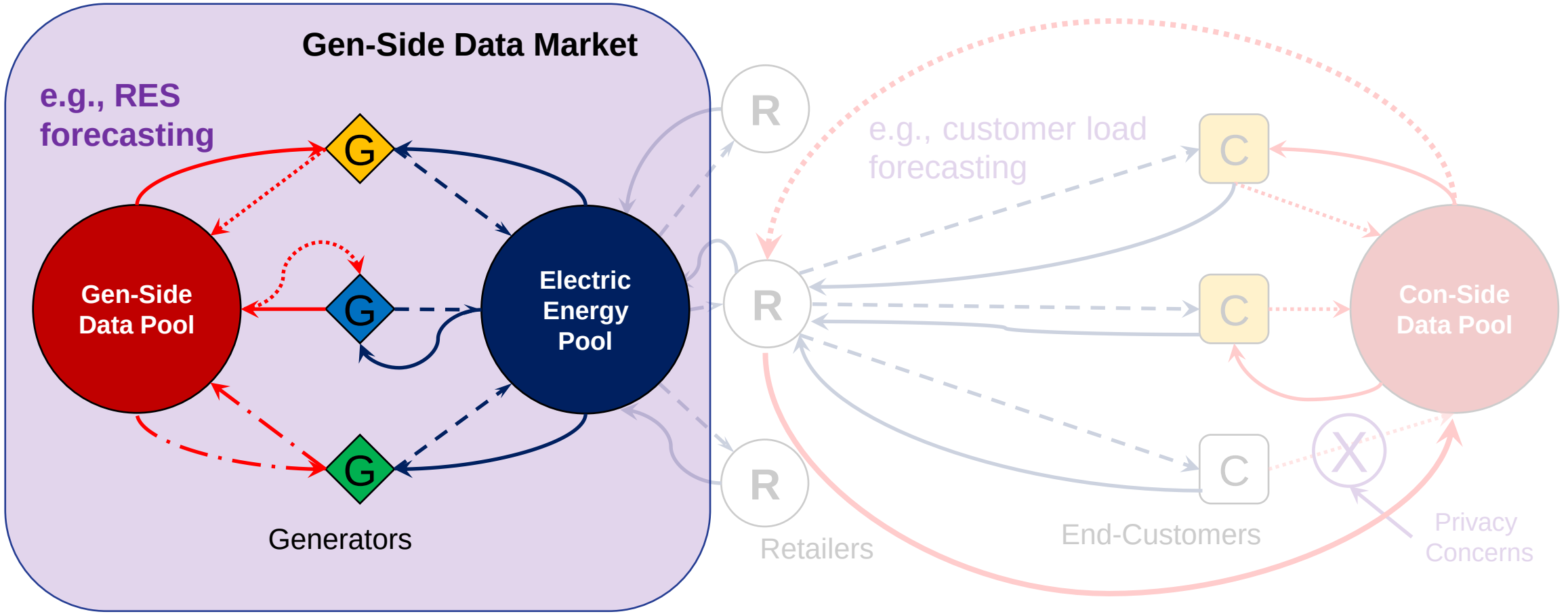
Data
Energy
Money
Data + Money




L. Han, J. Kazempour, P. Pinson, "Monetizing Customer Load Data for an Energy Retailer: A Cooperative Game Approach," *arXiv e-prints,* 2020.

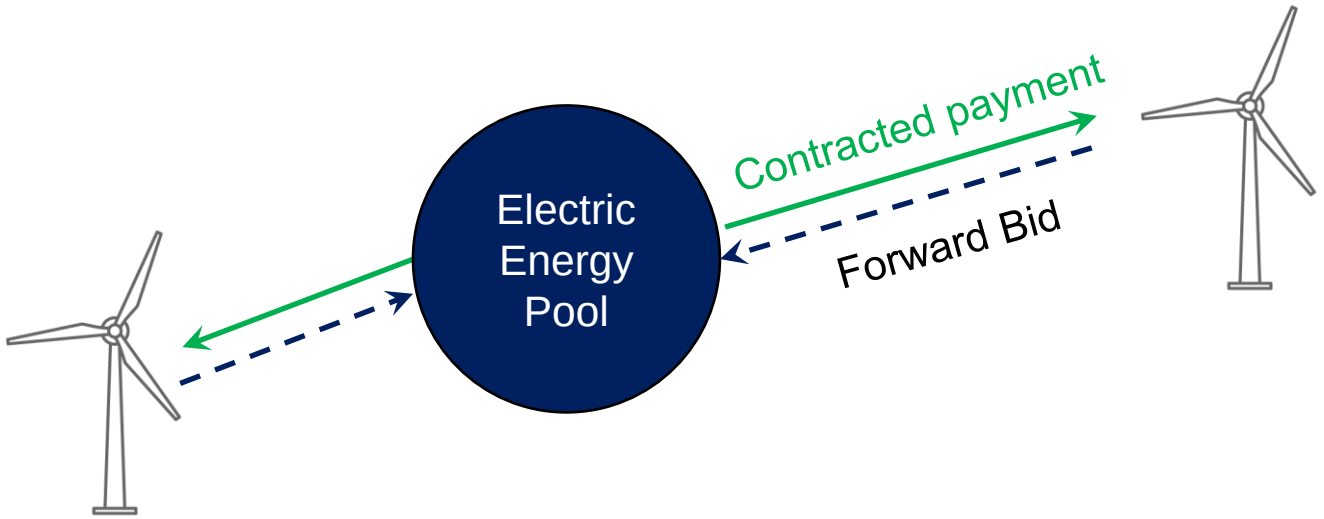
# Energy-Data Market

Data
Energy
Money
Data + Money

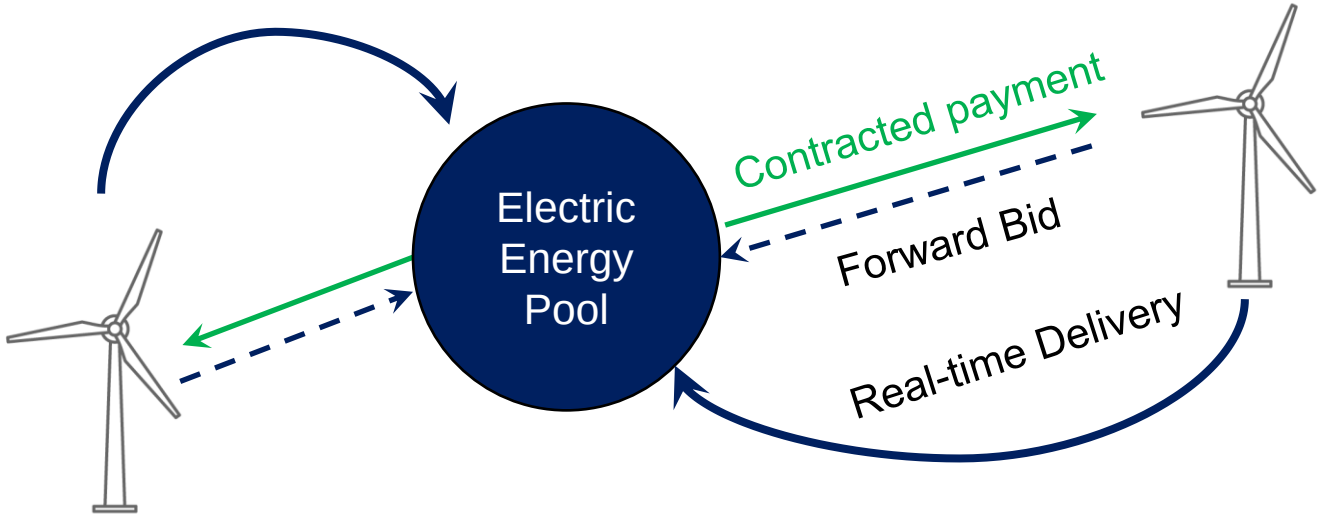



Data Seller
Data Buyer
Data Seller/Buyer

# RES in a Wholesale Market: 2 Agents

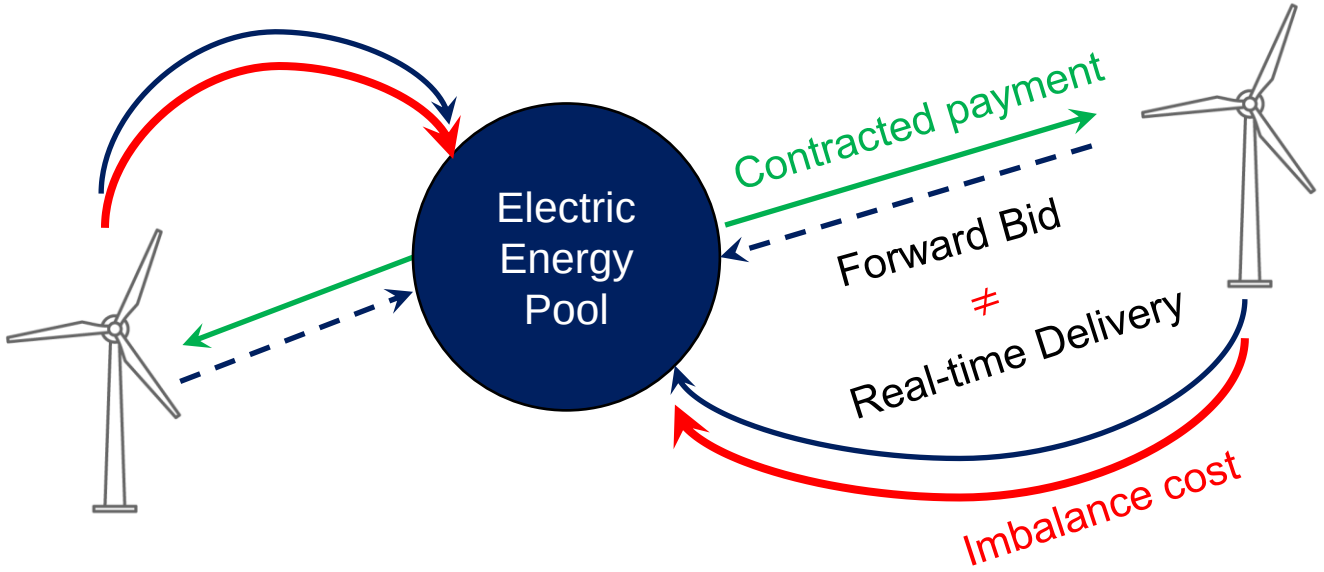


# RES in a Wholesale Market: 2 Agents



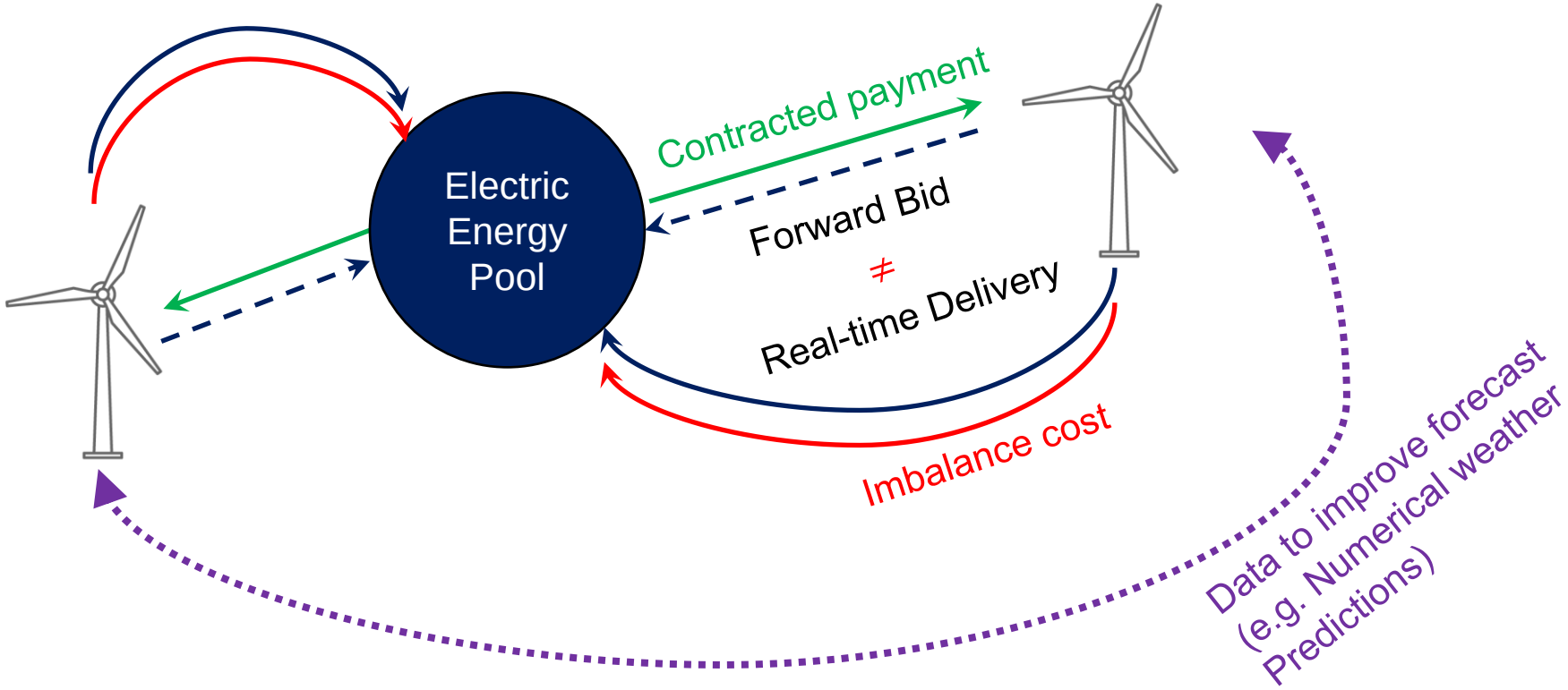
# RES in a Wholesale Market: 2 Agents

Problem 1. RES generation uncertainty leads to **imbalance costs**



# RES in a Wholesale Market: 2 Agents

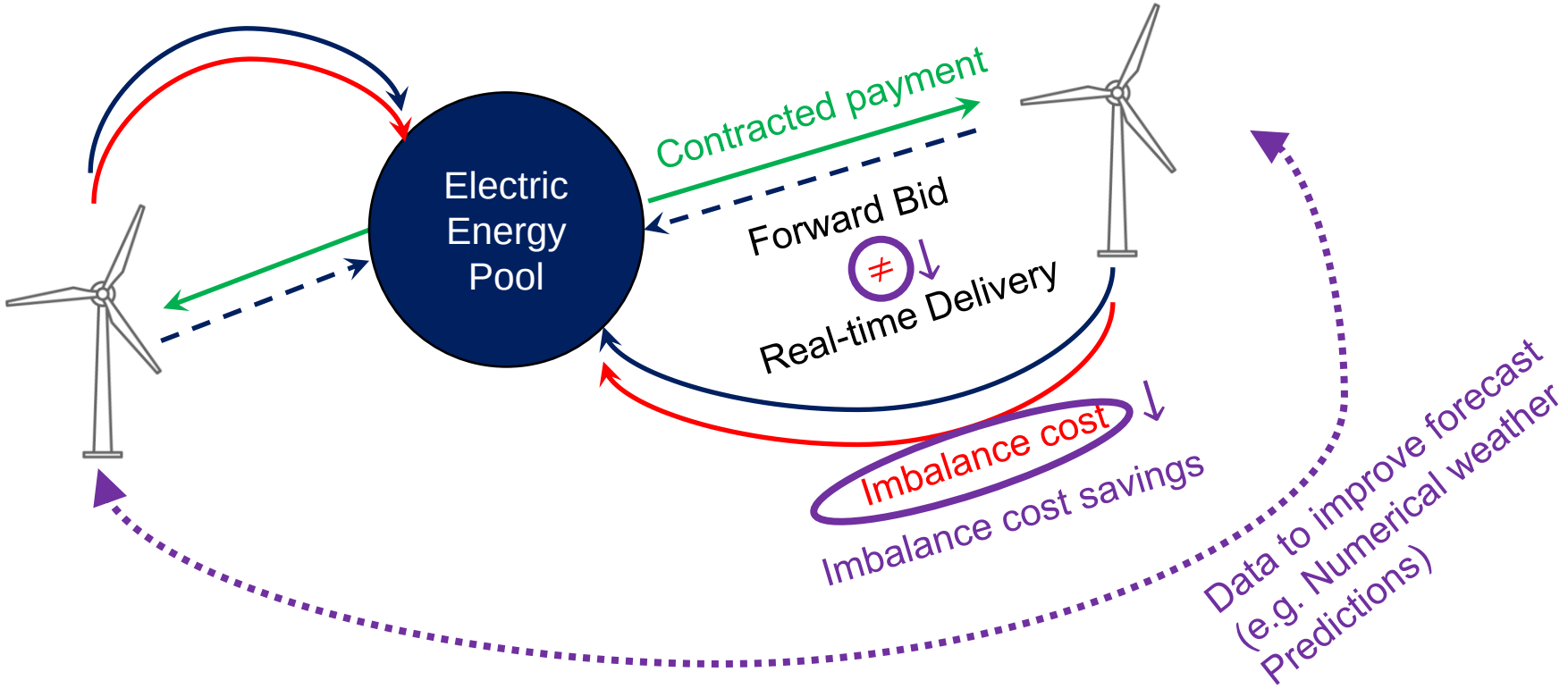
Problem 1. RES generation uncertainty leads to **imbalance costs**



# RES in a Wholesale Market: 2 Agents

Step 1) Data from neighboring plants can help **improve forecasts**, **reducing imbalance costs**

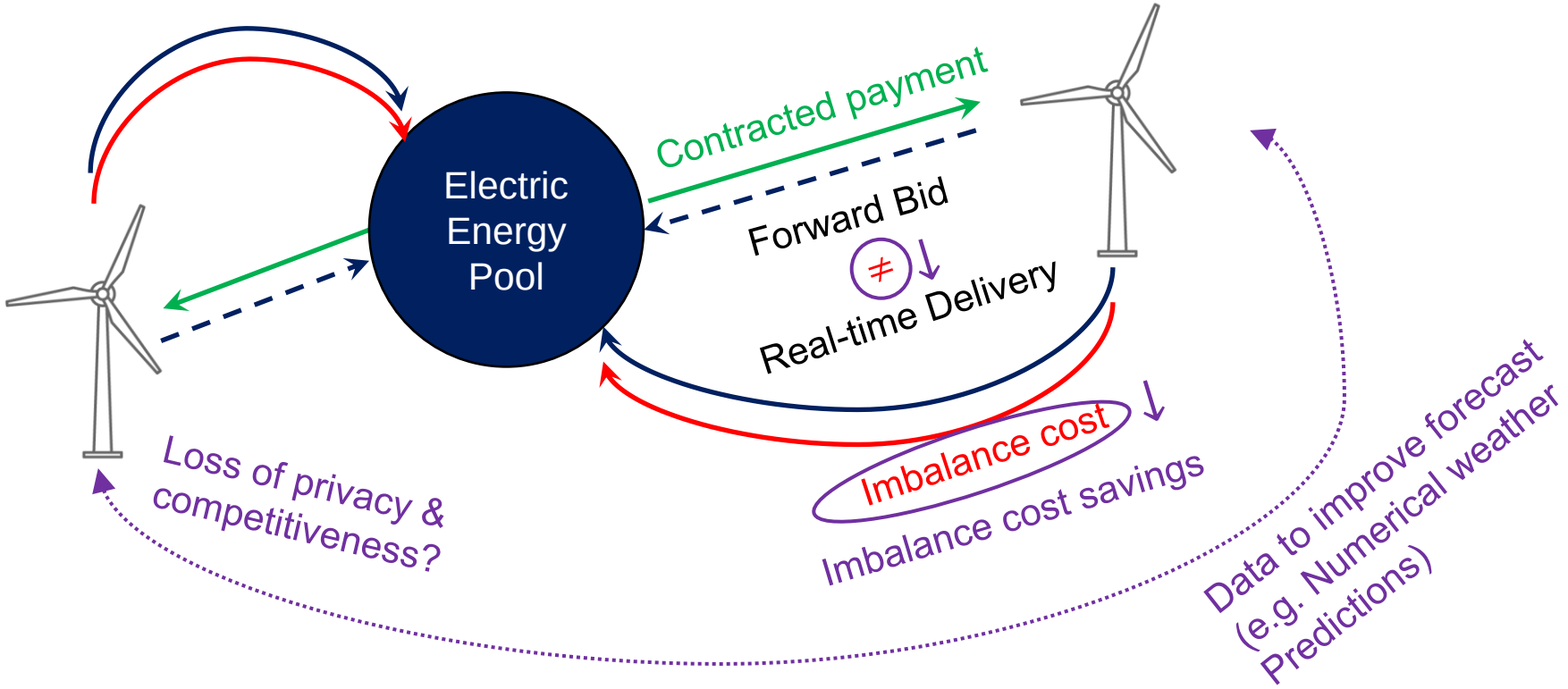
Problem 1. RES generation uncertainty leads to **imbalance costs**



# RES in a Wholesale Market: 2 Agents

Step 1) Data from neighboring plants can help **improve forecasts**, **reducing imbalance costs**

Problem 1. RES generation uncertainty leads to **imbalance costs**

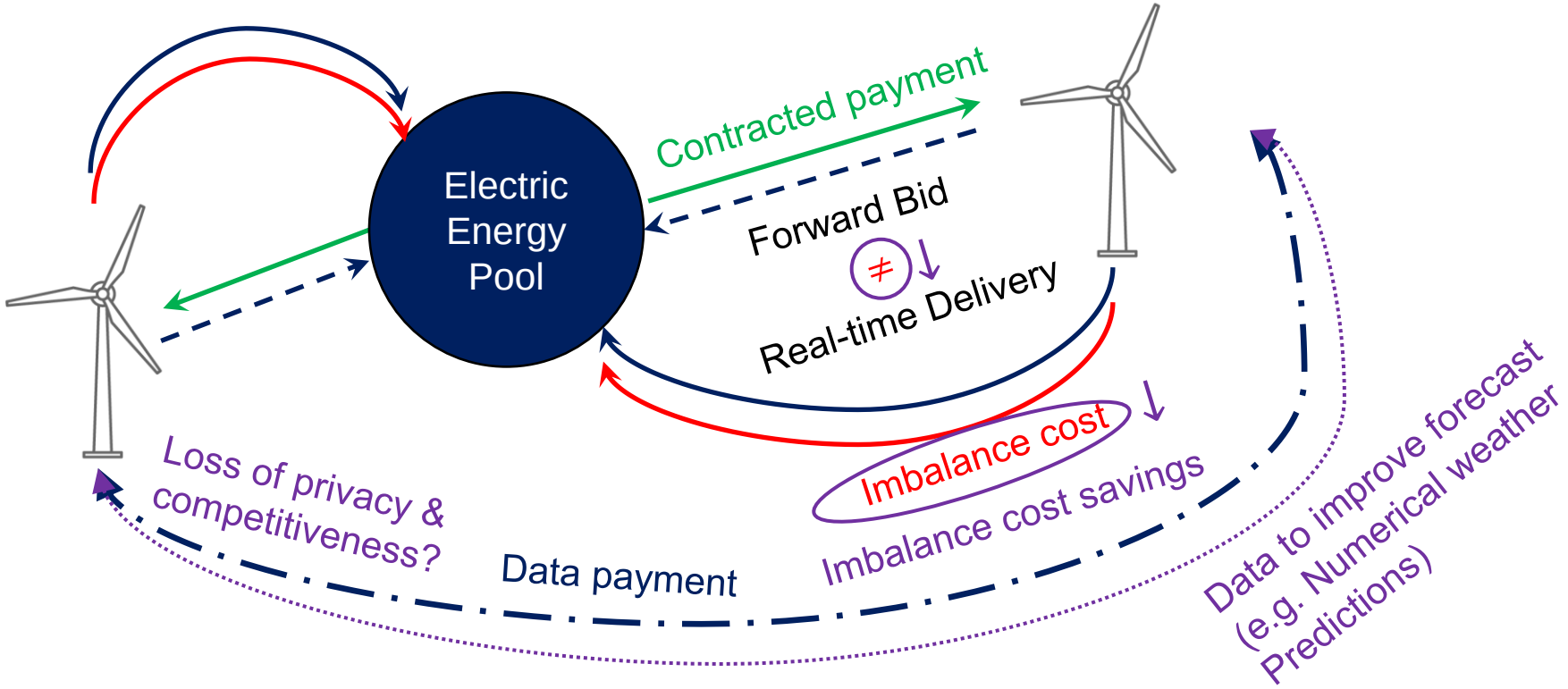



Problem 2. Potential loss of **privacy** and **competitiveness**

# RES in a Wholesale Market: 2 Agents

Step 1) Data from neighboring plants can help **improve forecasts**, **reducing imbalance costs**

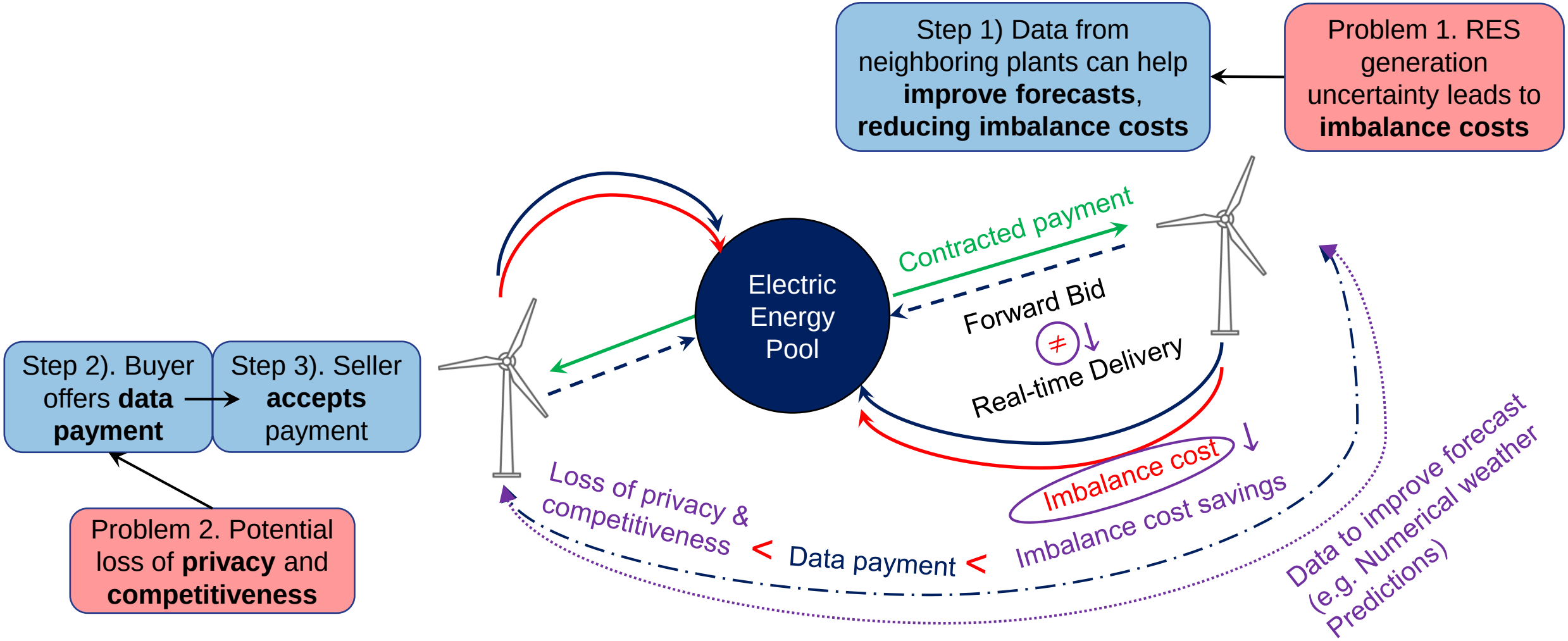
Problem 1. RES generation uncertainty leads to **imbalance costs**



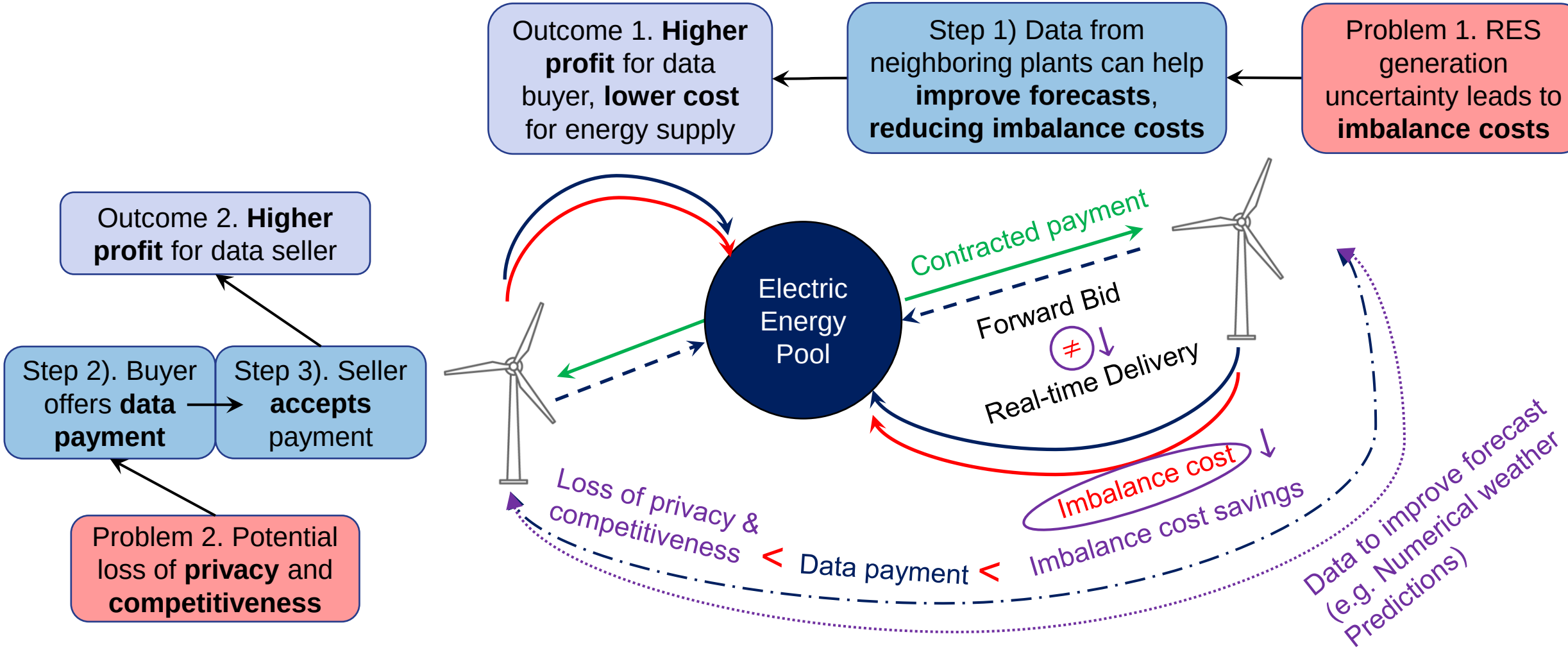

Step 2). Buyer offers **data payment**

Problem 2. Potential loss of **privacy** and **competitiveness**

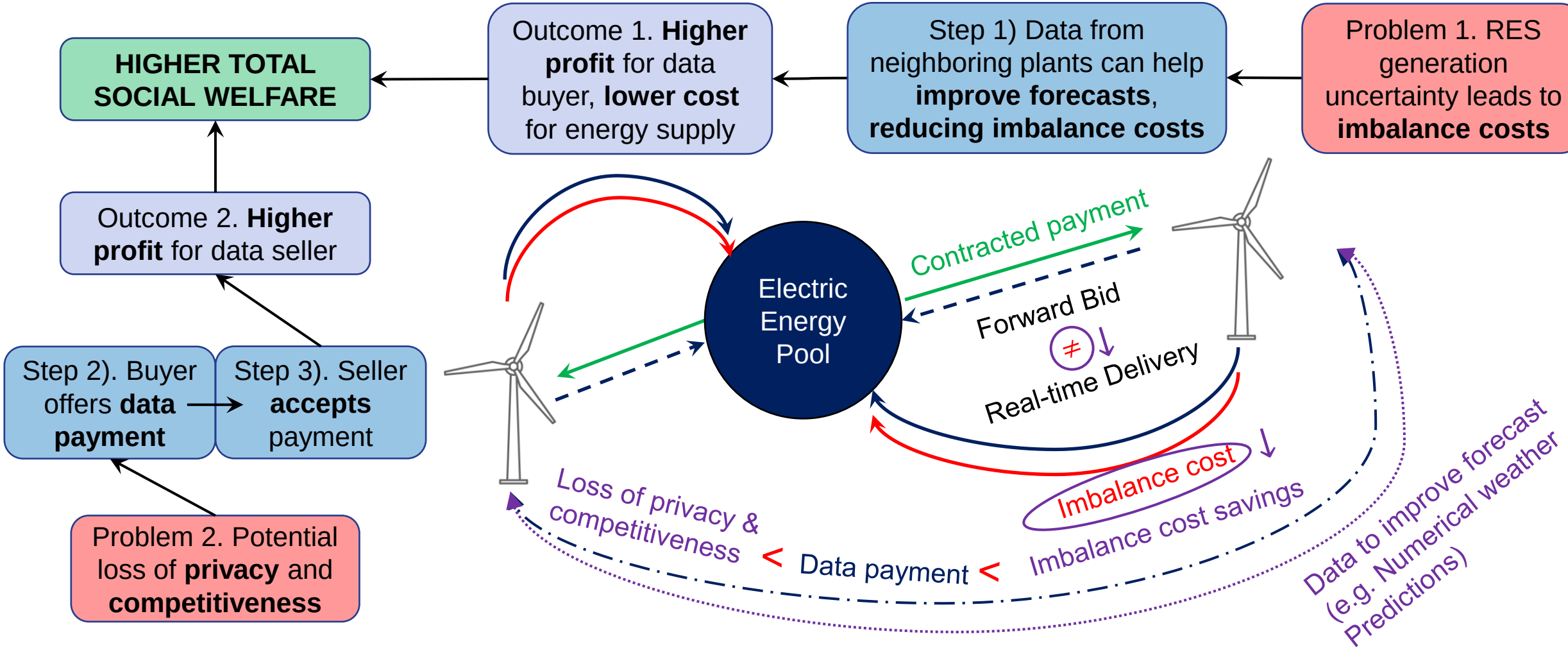
# RES in a Wholesale Market: 2 Agents



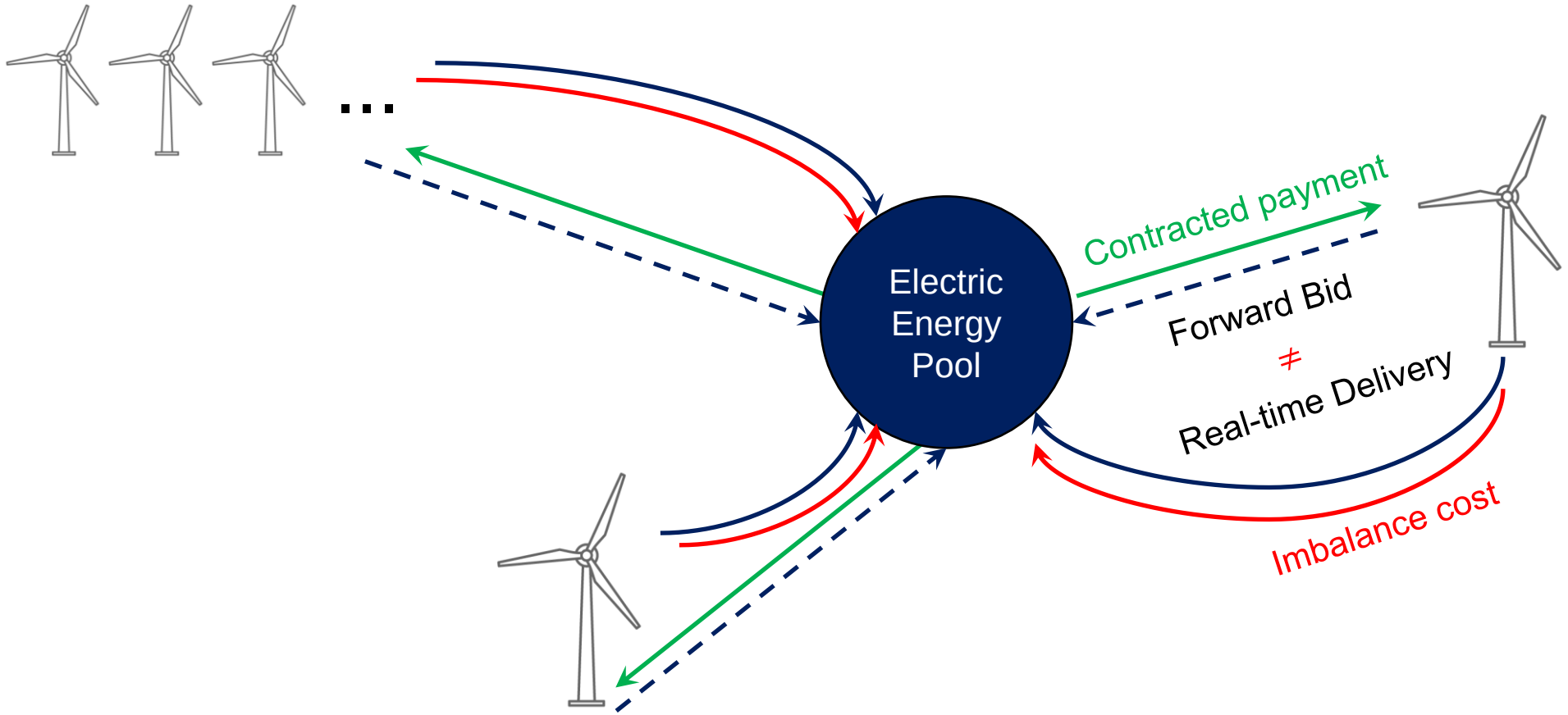
# RES in a Wholesale Market: 2 Agents



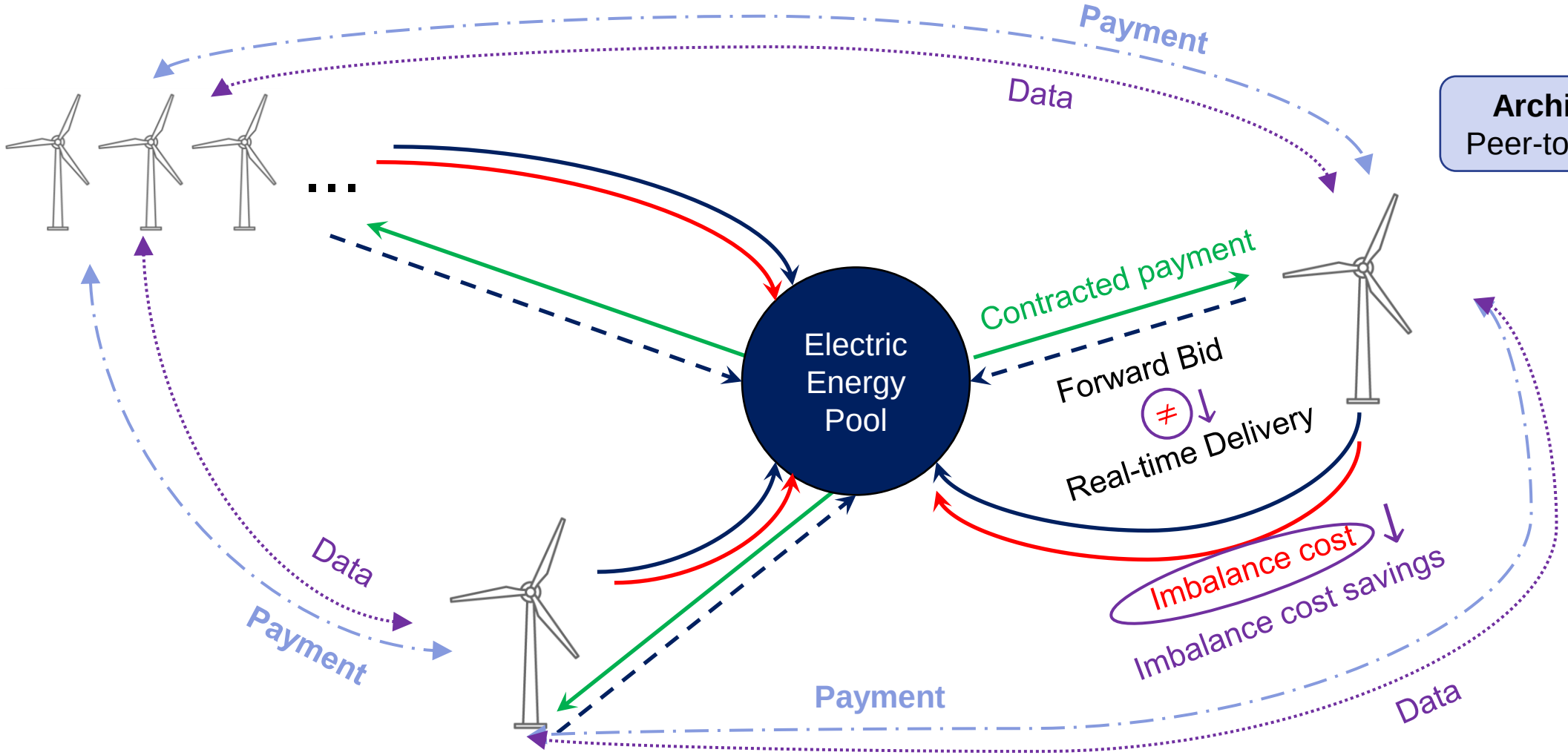
# RES in a Wholesale Market: 2 Agents



# RES in a Wholesale Market: Many Agents

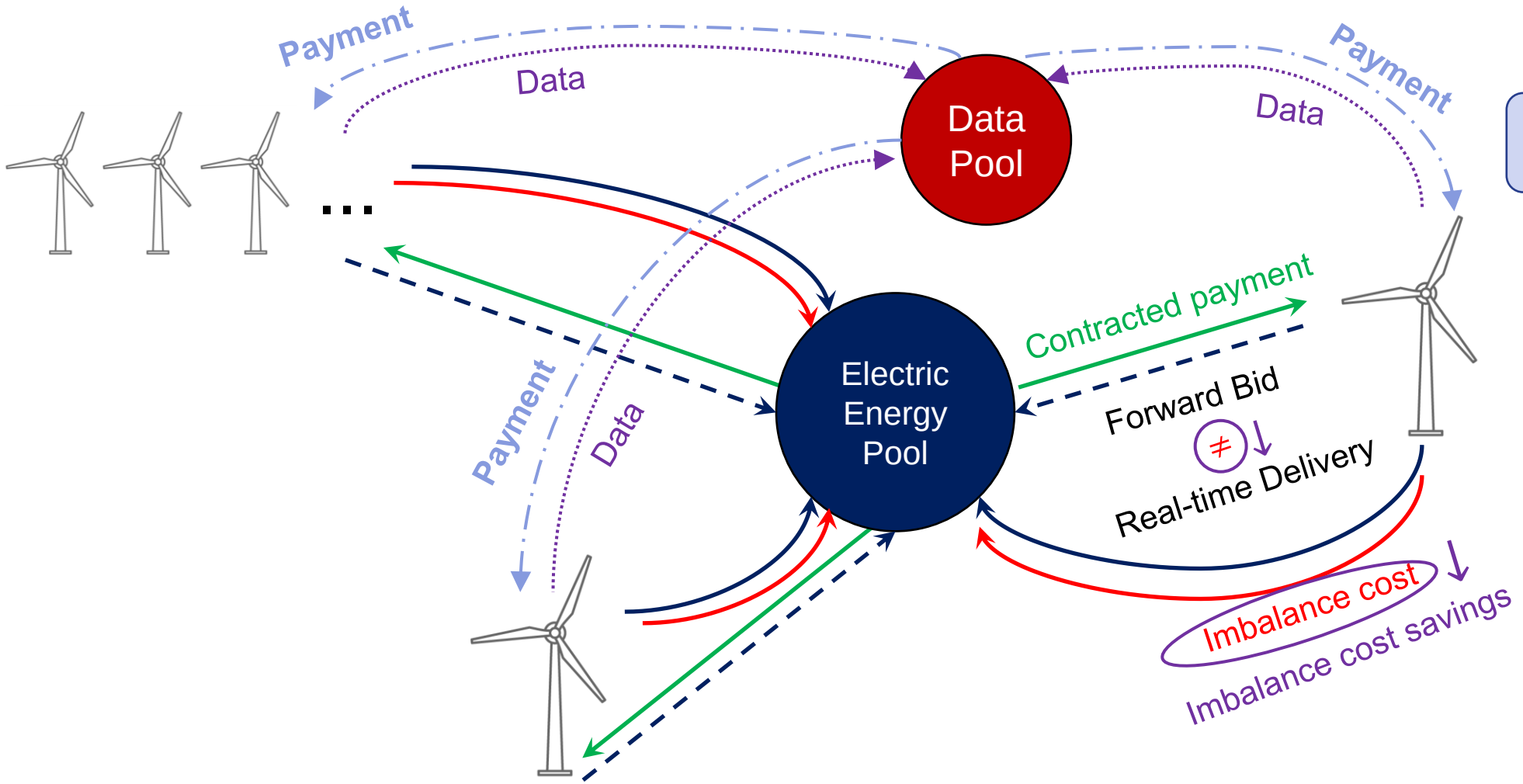


# RES in a Wholesale Market: Many Agents



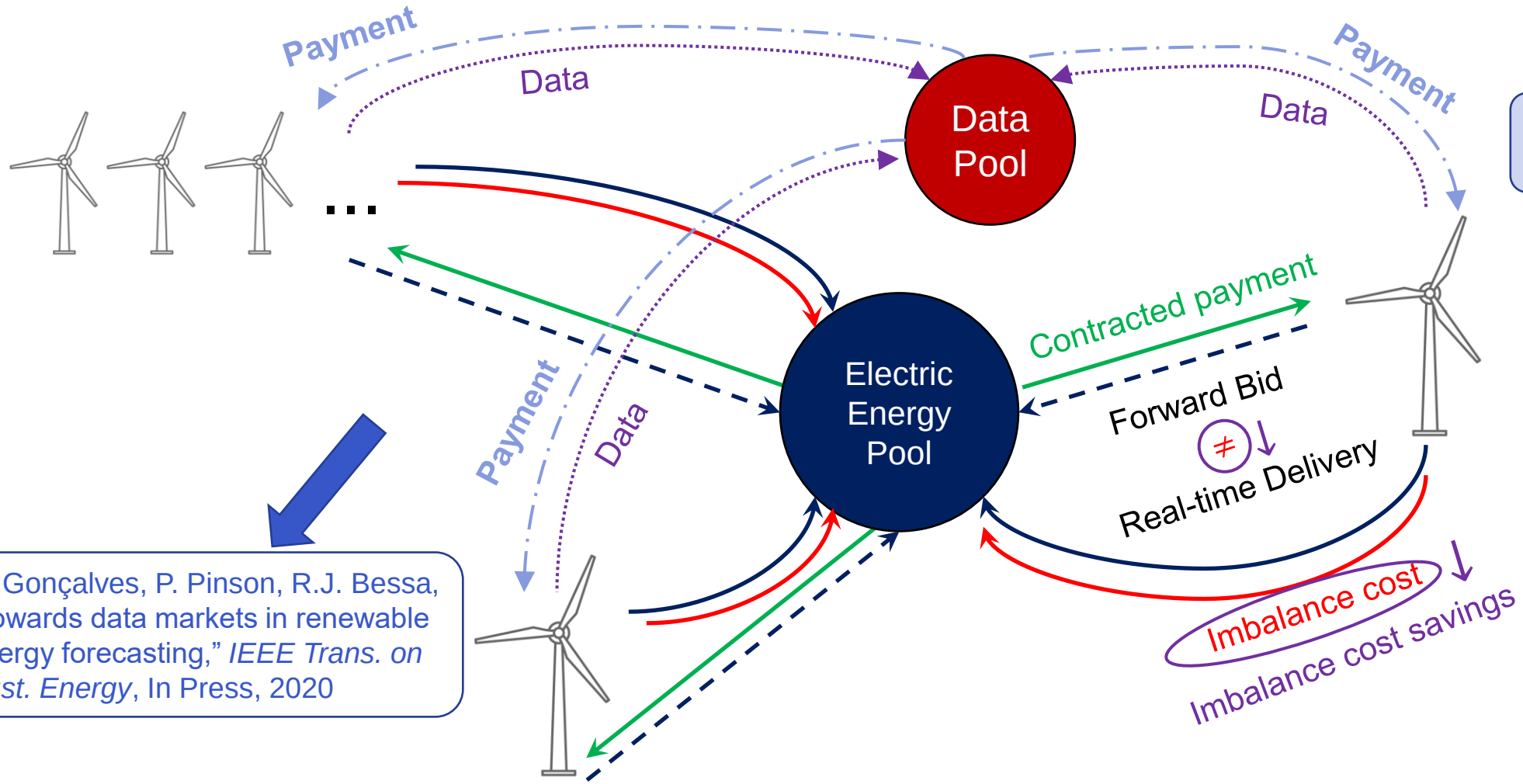

**Architecture 1:**
Peer-to-Peer Model

# RES in a Wholesale Market: Many Agents




**Architecture 2:**
Centralized Model

# RES in a Wholesale Market: Many Agents




**Architecture 2:**
Centralized Model

C. Gonçalves, P. Pinson, R.J. Bessa, "Towards data markets in renewable energy forecasting," *IEEE Trans. on Sust. Energy*, In Press, 2020

# Challenges

- The **cost of privacy** is highly individual and difficult to quantify. As a result, the value of privacy preserving techniques is difficult to quantify as well.
- Data is a unique commodity. The table below compares data and energy*.

| Market | Production and Replication | Value to Buyer | Pricing |
|---|---|---|---|
| **Energy** | Produced at a certain cost, non-replicable | Additive and known | Decided a priori |
| **Data** | Usually a side-product that is **produced at zero marginal costs, Replicable at no extra costs** | **Combinatorial**: the value of a dataset is dependent on all other available data. | Dependent on **buyer's valuation** of the dataset with a certain prediction task |

*Concepts from publication:
A. Agarwal, M. Dahleh, and T. Sarkar, "A marketplace for data: An algorithmic solution," *ACM EC 2019 - Proceedings of the 2019 ACM Conference on Economics and Computation*, pp. 701–726, 2019.

# Conclusion

# Take-Away Messages & Smart4RES Ongoing Research

- Collaborative learning **improves forecast** accuracy, which may yield **additional individual or societal value** in the market.
- Monetizing data promotes data exchanging by **redistributing** the **added value**, helping to **address** concerns about **loss of privacy** and competitiveness.

Smart4RES is planning to

- Design a suitable marketplace for data trading;
- Develop relevant data market concepts and create prototypes to foster awareness to the value of data markets;
- Extend the concept to different use cases from the energy sector;
- Collaborate with other domains, such as IoT, blockchain technologies, etc.

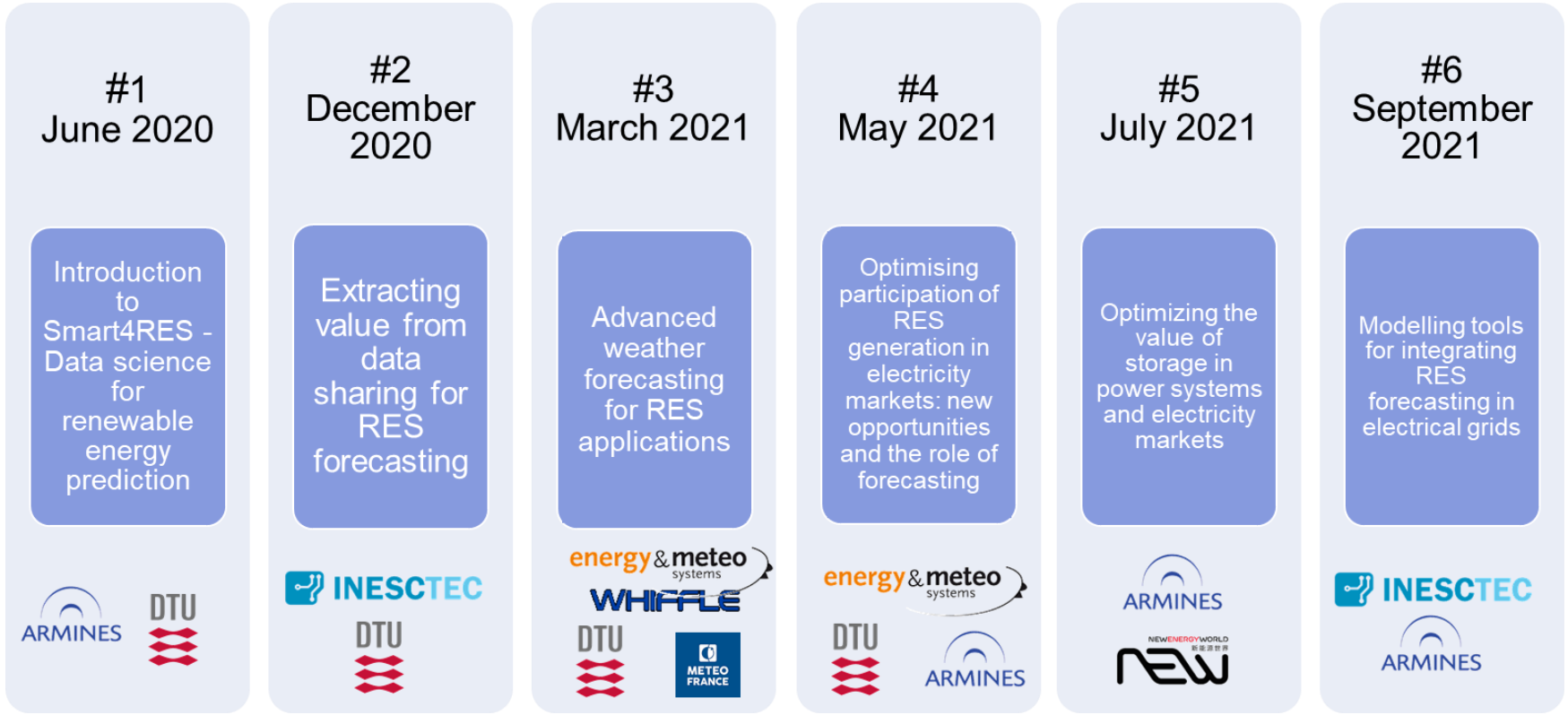
# References


- C. Gonçalves, P. Pinson, R.J. Bessa, “Towards data markets in renewable energy forecasting,” *IEEE Trans. on Sust. Energy*, In Press, 2020.
- C. Gonçalves, R.J. Bessa, P. Pinson, "Privacy-preserving distributed learning for renewable energy forecasting," Working Paper, 2020.
- C. Gonçalves, R.J. Bessa, P. Pinson, “A critical overview of privacy-preserving approaches for collaborative forecasting,” *Int. J. of Forecasting*, vol. 37(1), pp. 322-342, Jan-Mar 2021
- L. Han, J. Kazempour, P. Pinson, “Monetizing Customer Load Data for an Energy Retailer: A Cooperative Game Approach,” *arXiv e-prints*, 2020.
- A. Agarwal, M. Dahleh, and T. Sarkar, “A marketplace for data: An algorithmic solution,” *ACM EC 2019 - Proceedings of the 2019 ACM Conference on Economics and Computation*, pp. 701–726, 2019.

- BESSA, Ricardo Jorge, GONÇALVES, Carla. “Geographically distributed solar power time series [dataset].” 10 September 2020. *INESC TEC research data repository.* https://doi.org/10.25747/gywm-9457

# Smart4RES webinar series

**Season1: Towards a new Standard for the entire RES forecasting value chain**




To stay in touch
https://bit.ly/2Tawgn3

iea-isgan.org

ISGAN
INTERNATIONAL SMART GRID ACTION NETWORK

# Thank you

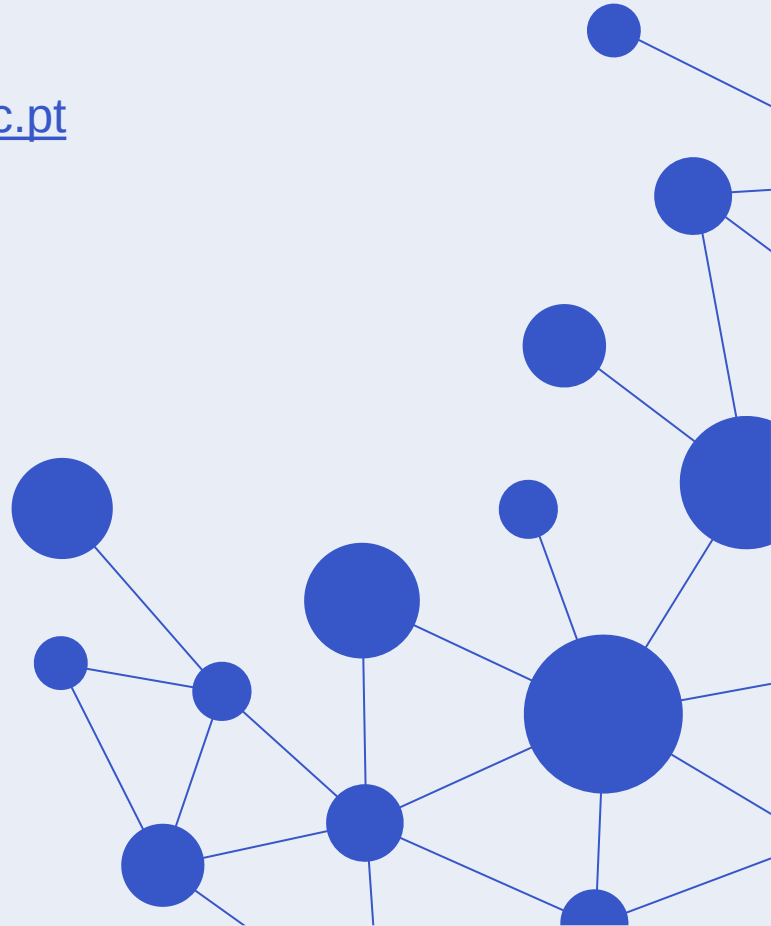
Ricardo Jorge Bessa, INESC TEC ricardo.j.bessa@inesctec.pt

Liyang Han, DTU liyha@elektro.dtu.dk

**info@smart4res.eu**

For more information ☞ **www.smart4res.eu**

Follow us on our social media



iea Energy Technology Network

CLEAN ENERGY MINISTERIAL

ISGAN
INTERNATIONAL SMART GRID ACTION NETWORK

**COPYRIGHT** (except initial slides on ISGAN)

Smart4RES H2020 Project **“**Next Generation Modelling and Forecasting of Variable Renewable Generation for Large-scale Integration in Energy Systems and Markets**”**

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

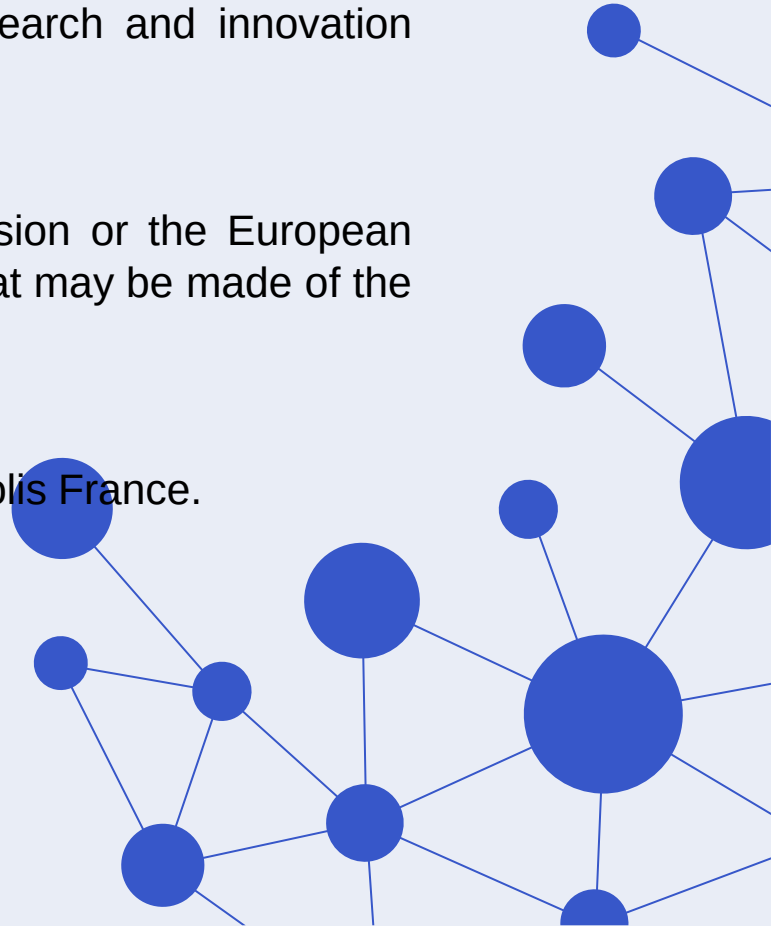
**DISCLAIMER**

The present presentation reflects only the authors’ view. The European Commission or the European Innovation and Networks Executive Agency (INEA) is not responsible for any use that may be made of the information it contains.

**PROJECT COORDINATOR & CONTACTS**

Georges Kariniotakis, ARMINES/MINES Paris Tech, Centre PERSEE, Sophia-Antipolis France.

info@smart4res.eu



iea Energy Technology Network

CLEAN ENERGY MINISTERIAL