Probabilistic forecasting:

Development of novel products for advanced operational needs

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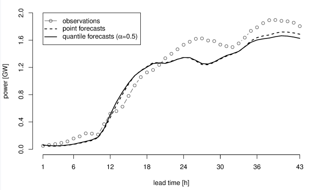
What makes a forecast probabilistic?

All forecasts actually are probabilistic!

The probabilistic forecasts we are used to

Point forecasts

A single-value per lead time

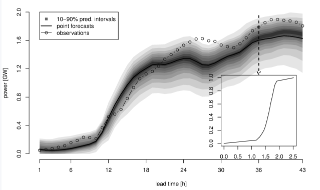


In practice:

- ▷ conditional expectaction
- ▷ quantile forecasts

Interval forecasts

A range of potential outcomes with a given probability

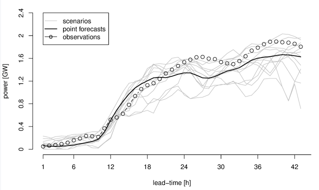


In practice:

- ▷ prediction intervals
- ▷ density forecasts

Scenarios

Alternative plausible realizations



In practice:

- ▷ statistical scenarios
- ▷ ensemble forecasts

And so... what is new with probabilistic forecasting?

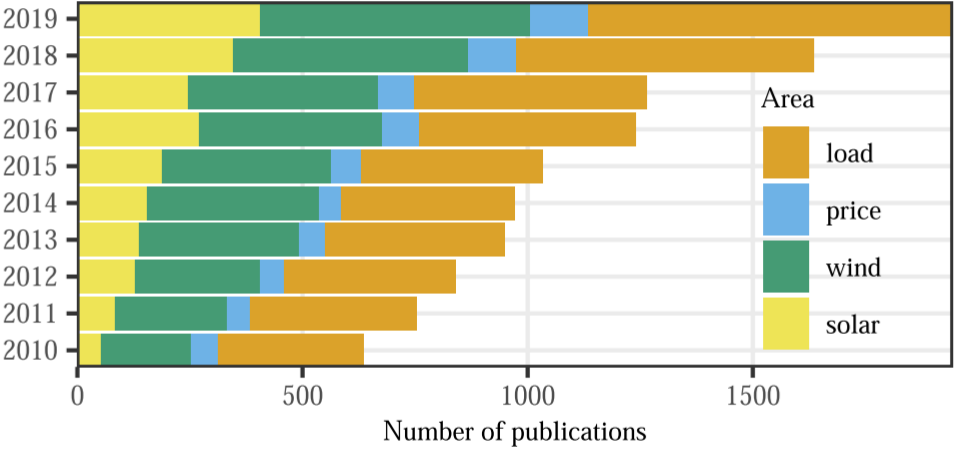
1. Homogenizing the state of the art within energy forecasting

2. Adapting to operational needs

3. Going towards data monetization

1. **Homogenizing the state of the art within energy forecasting**

They are catching up!



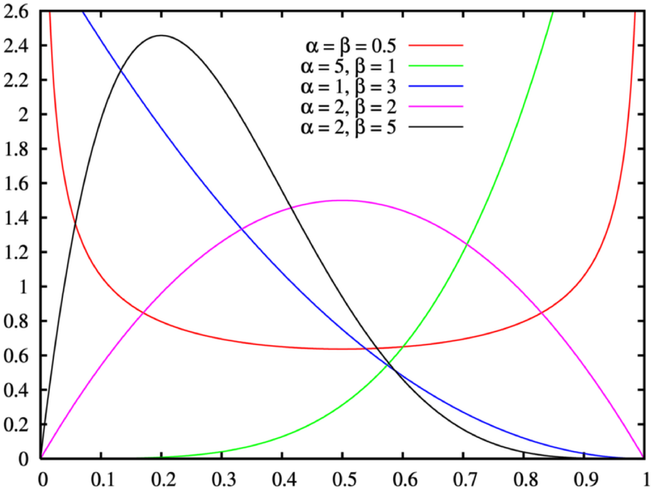
source: Hong *et al* 2020 - "Energy forecasting – A review and outlook"

Also with **new probabilistic forecasting problems** being looked at: DLR, flexibility, etc.

A lot of R&D concentrates on basic problems over which we might have gone too fast in the past, e.g.

- the **bound problem** – power generation and consumption is necessarily double-bounded
- **parametric approaches** – which distributions are most appropriate, and why?
- forecast verification... it is not that easy!
- etc.

Those challenges are common to nearly all energy forecasting problems



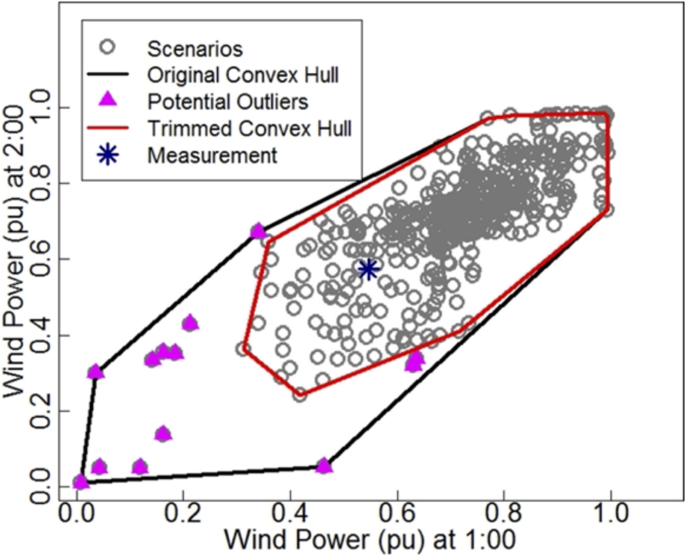
source: wikipedia

2. **Adapting to operational needs**

   (some of the following talks will look into that extensively!)

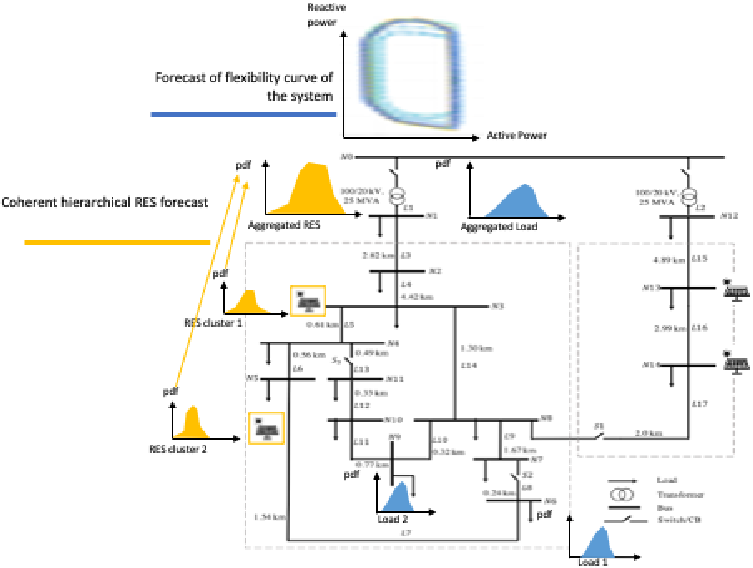
Example 1: ellipsoids and polyhedra

- Today we are used to predictive densities and trajectories...
- That does not mean they are the best input to many modern-days operational problems...
- For some problems (e.g. robust and chance-constrained optimization), it makes sense to have forecasts in the form of ellipsoids and polyhedra.



Example 2: network-aware flexibility forecasts

With distributed RES at distribution grid level, one may need additively consistent forecasts, and projected in the flexibility space...



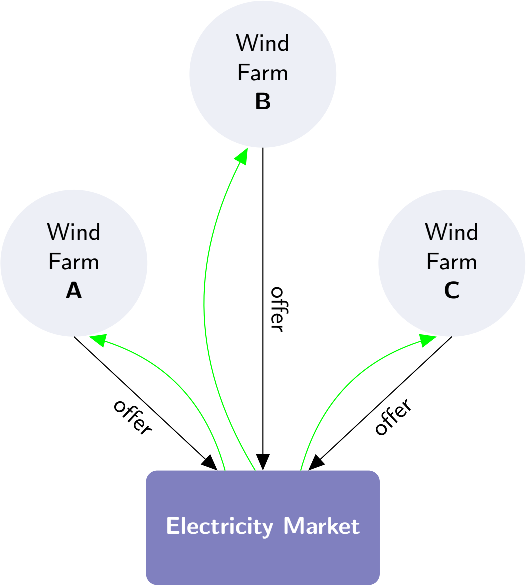
M. Kalantar-Neyestanaki et al. (2020) *IEEE Transactions on Smart Grid* **11**(3): 2464-2475

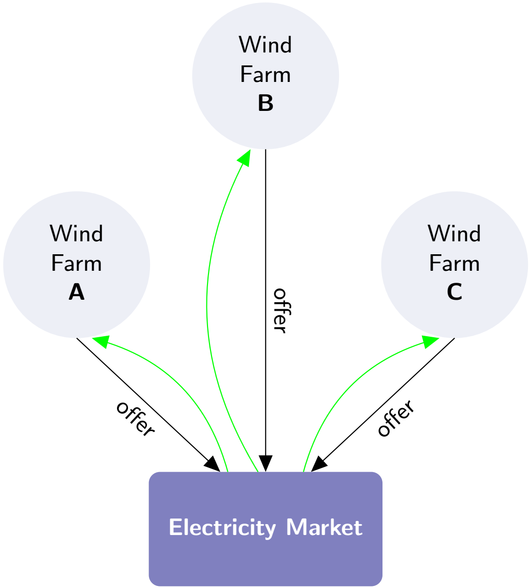
3. **Collaborative and market-based analytics**

A motivating real-world example

Context:

- Wind farms offer in electricity markets based on their individual (probabilistic) forecasts and private information
- Their revenue is affected by their (lack of) forecast accuracy

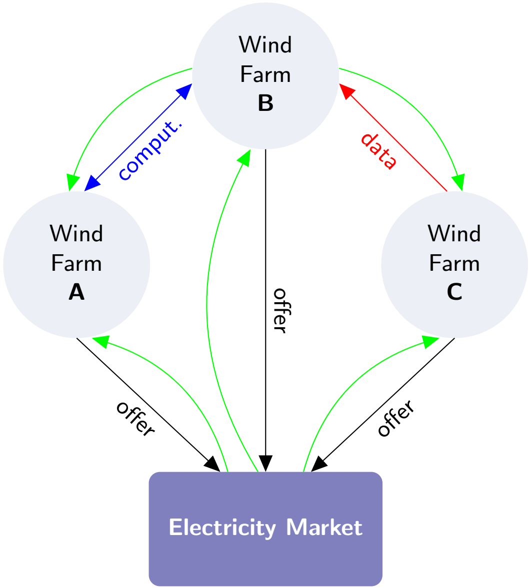




Opportunity: All *could* benefit from some form of collaboration (e.g., information sharing)

Challenge: They have no interest in doing so

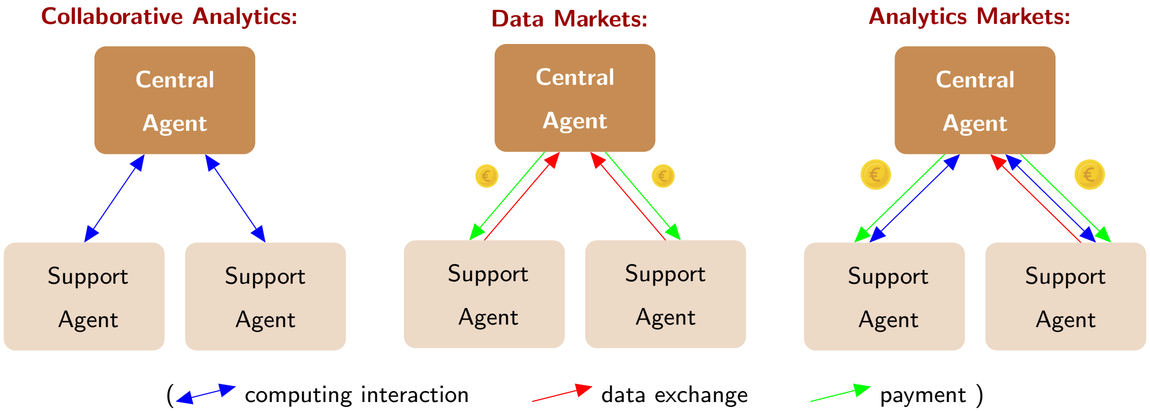
A motivating real-world example



Proposal: Design a framework allowing for all agents to collaborate and benefit from it

various approaches to collaborative and market-based analytics

Agents meet through **analytics platforms** supporting collaborative and market-based analytics



Substantial **methodological research** is needed to obtain such analytics platforms! (e.g. blending mechanism design and statistical/machine learning)

A quantile regression market example

- **Rogue Trading** is a *central agent* that has a quantile regression problem (for generation y_{t+k}), since optimal renewable energy offers generally are quantiles of predictive distributions
- **Rogue Trading** owns a set ω of m features, $\omega = \{x_1, \ldots, x_m\}$

The following (linear) regression problem could be used as basis for eventual prediction,

$$y_{t+k} = \beta_0 + \sum_{i=1}^{m} \beta_i x_{i,t} + \varepsilon_t, \quad t = 1, \ldots, T$$

where the vector of coefficients $[\beta_0 \ \ldots \ \beta_m]^\top$ can easily be learned using a pinball loss function ρ_α (for nominal level α)

$$S_\omega = \frac{1}{T} \sum_{i=1}^{m} \rho_\alpha \left(y_t - (\beta_0 + \sum_{i=1}^{m} \beta_i x_{i,t}) \right)$$

Based on the data available, the minimum loss function value is S_ω^*

- **Rogue Trading** could post the regression task on an analytics platform, to improve model fit
- It declares a willingness to pay of $\phi =$100€ per percent-point improvement in S

Support agents and the augmented regression problem

- Two support agents **Good Data** and **Useful Features** may bring in additional features z_1 and z_2, to be remunerated

The regression problem can then be augmented, as

$$y_{t+k} = \underbrace{\beta_0 + \sum_{i=1}^{m} \beta_i x_{i,t}}_{\text{Rogue Trading}} + \underbrace{\gamma_1 z_{1,t}}_{\text{Good Data}} + \underbrace{\gamma_2 z_{2,t}}_{\text{Useful Features}} + \varepsilon_t, \quad t = 1, \ldots, T$$

where the augmented vector of coefficients $[\beta_0 \ \ldots \ \beta_m \, \gamma_1 \, \gamma_2]^\top$ can be learned similarly, yielding a lower value of the loss function

$$S_\Omega = \frac{1}{T} \sum_{i=1}^{m} \rho_\alpha \left(y_t - (\beta_0 + \sum_{i=1}^{m} \beta_i x_{i,t} + \gamma_1 z_{1,t} + \gamma_2 z_{2,t}) \right)$$

which we denote S_Ω^*

- If z_1 and/or z_2 are informative features, one expects $S_\Omega^* < S_\omega^*$

Revenues, payments and market properties

- How to define **revenues** and **payments** in such a regression market?

For each support agent j ($j = 1, 2$), the revenue is given by

$$\pi_j = \phi(S^*_\omega - S^*_\Omega)\psi_j, \quad j = 1, 2$$

where ψ_j is an allocation policy based on feature valuation (can be obtained with, e.g., leave-one-out or Shapley-based allocation), such that $\sum_j \psi_j = 1$

For **Rogue Trading**, the payment is

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

Such a simple approach actually yields a well-behaving market with a wealth of good properties, i.e.,

- budget balance
- symmetry (or anonymity)
- zero element
- incentive compatibility (and group-strategy-proof)
- thruthfulness and normality, etc.

Closing remarks

- Probabilistic forecasting is a very active field of R&D
- Many developments are oriented towards the needs of forecast users and bringing them optimal value
- Novel approaches are under development to incentivize data sharing, in both collaborative and market-based environments
- Ultimately, the biggest challenge may still be supporting adoption of probabilistic forecasting by forecast users!

Thanks for your attention!