Decision-making in energy markets under uncertainty: human-in-the-loop

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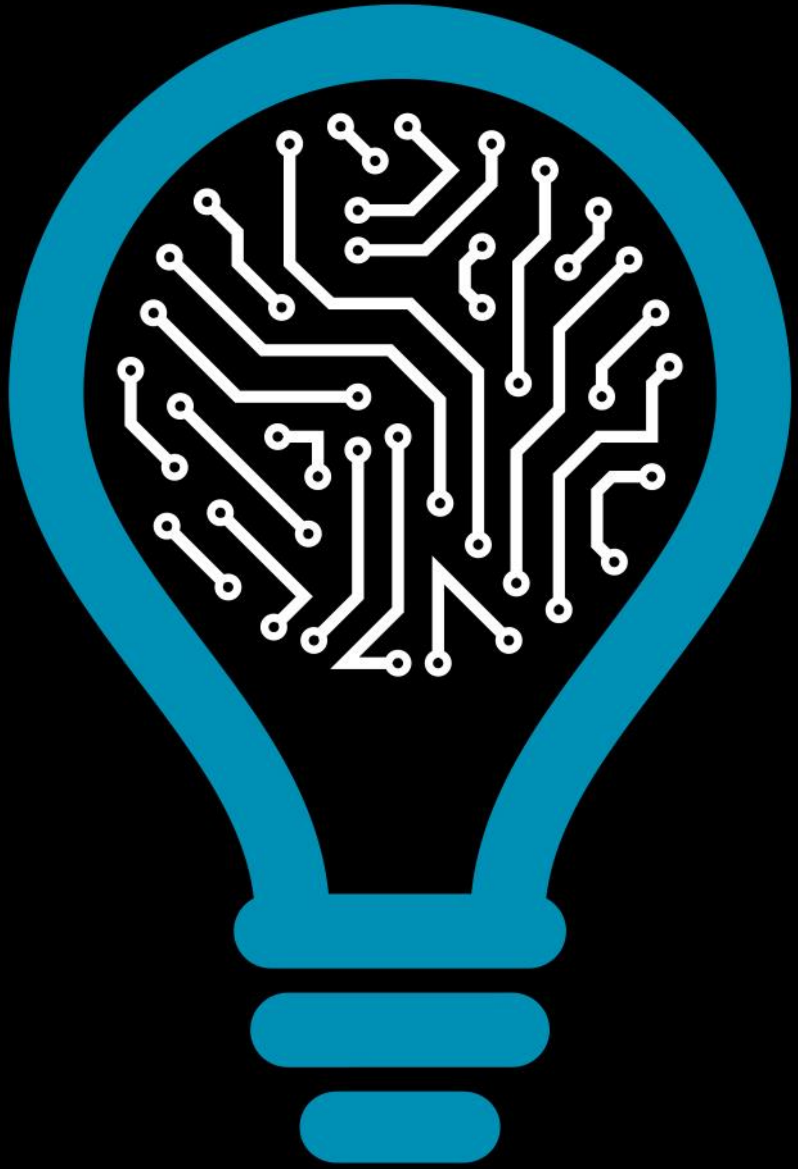

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- **Human-in-the-loop decision-making:** challenges
- **Classical paradigms** and market bidding
- **Human understanding** of forecast uncertainty value
- **Human interpretability** in energy trading
- Towards **new decision paradigms**
- Concluding remarks

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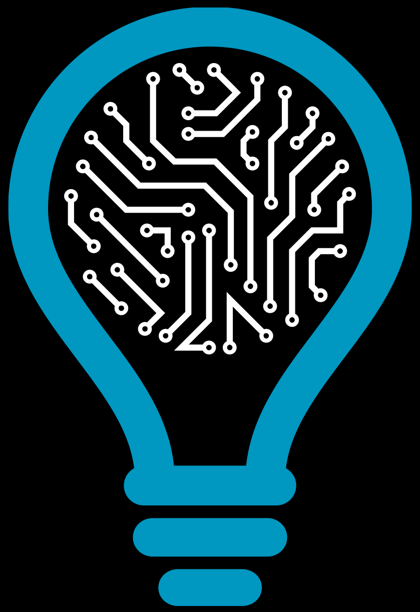
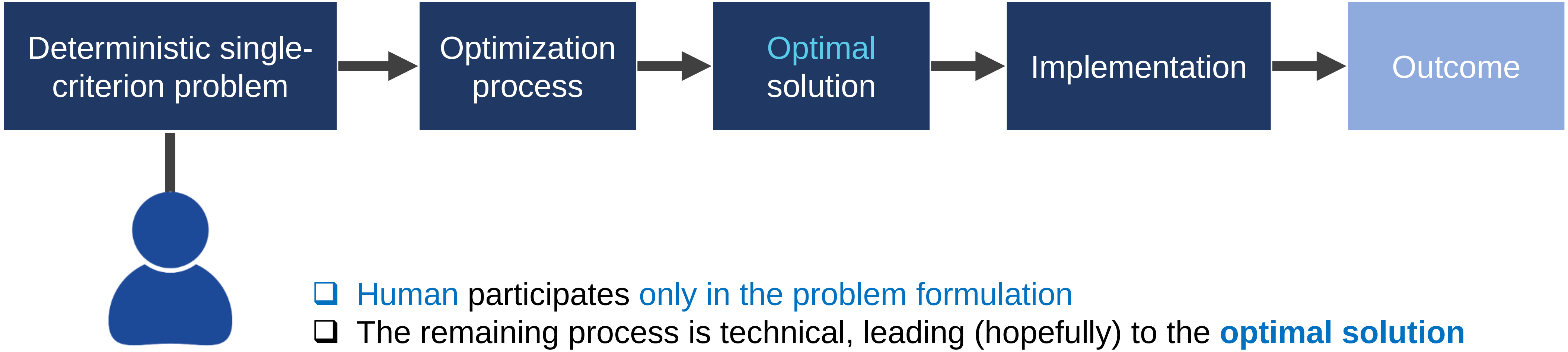
Human-in-the-loop decision-making: challenges



Decision-making: single criterion



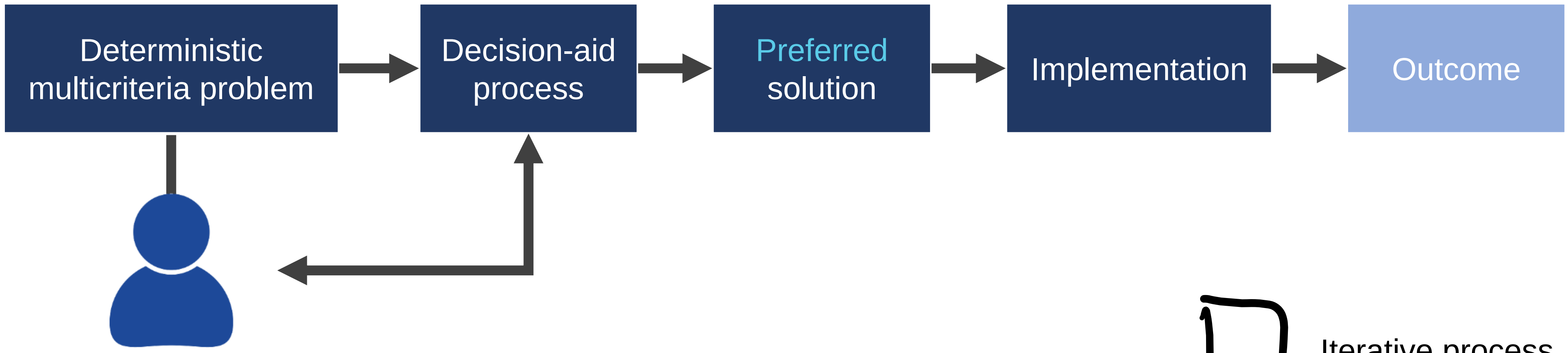
- Human participates only in the problem formulation
- The remaining process is technical, leading (hopefully) to the **optimal solution**
- Decision is embedded in the problem formulation ("somehow" is a **black-box** for the human)

Humans like to

- ✓ understand cause-effect relation in decision-making
- ✓ have a sense of control (critical for autonomous processes)

Based in Manuel A. Matos, Decision-making methods, PMAPS 2004 Tutorial

Decision-making: multi-criteria



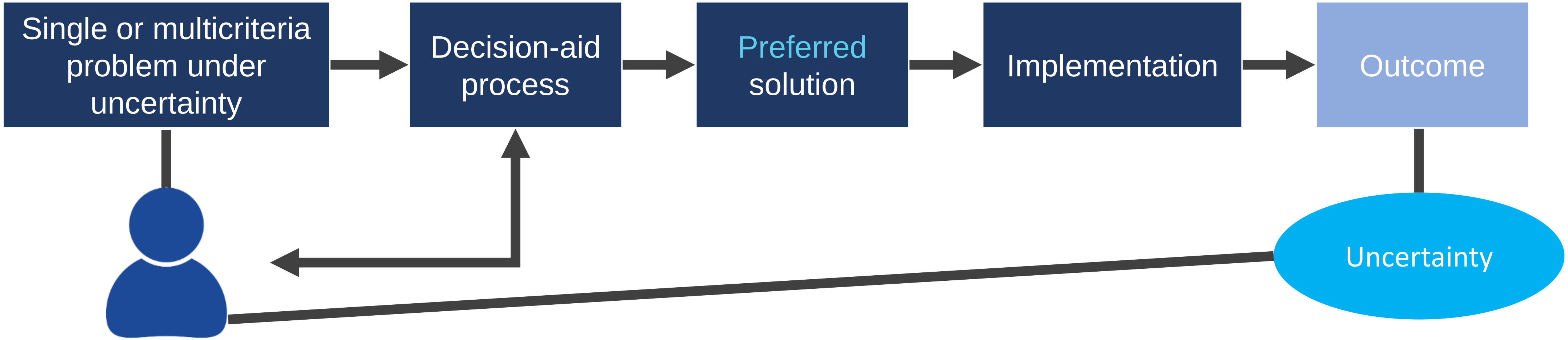
- ❑ Human participates in the problem formulation
- ❑ Human preferences must be integrated in the problem
- ❑ The process leads to a preferred solution

Iterative process (human-in-the-loop)

Interpretability is essential

Based in Manuel A. Matos, Decision-making methods, PMAPS 2004 Tutorial

Decision-making under uncertainty



- ❑ Human participates in the problem formulation & uncertainty analysis
- ❑ The preferred solution results from the human preferences and risk attitude

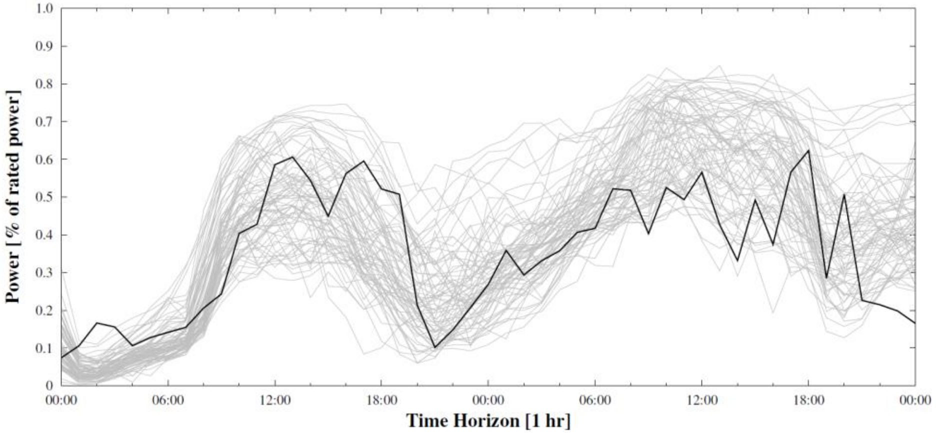
Yet…
* uncertainty forecasts brings **complexity** and **unperceived value** to humans
** **trust** is fundamental to avoid algorithm aversion

Based in Manuel A. Matos, Decision-making methods, PMAPS 2004 Tutorial

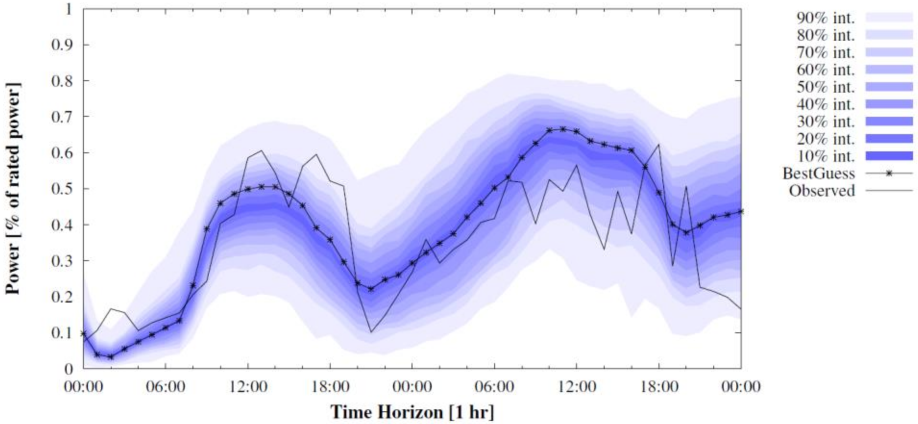
* Complexity

Forecast for a wind power plant (Sotavento, Spain)

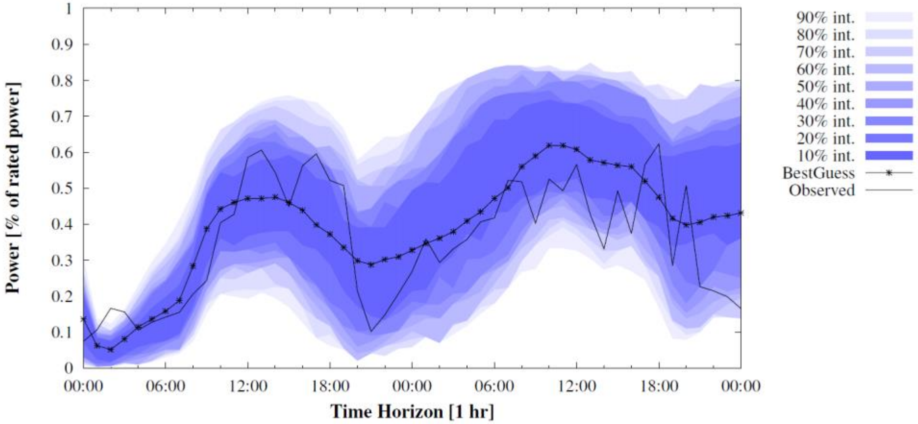
Physically-based temporal trajectories



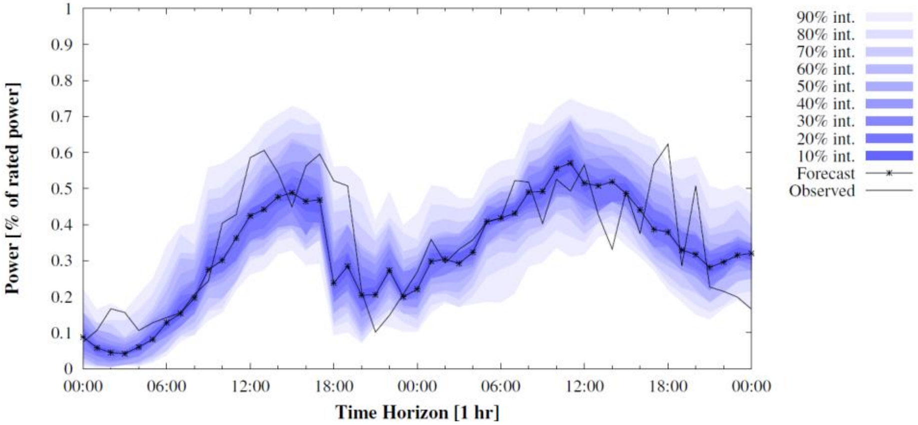
Physically-based (marginal) forecast intervals



Simultaneous forecast intervals



AI-based (marginal) forecast intervals



R.J. Bessa, C. Möhrlen, V. Fundel, M. Siefert, J. Browell, S. Haglund El Gaidi, Bri-Mathias Hodge, U. Cali, G. Kariniotakis, “Towards improved understanding of the applicability of uncertainty forecasts in the electric power industry,” Energies, vol. 10(9), pp. 1402, 2017

* Complexity

- Decision under risk

The decision maker has full information, in the sense that there is a subjective probability, i.e., $P(s_j|a_t)$ as the probability that s_j is the true state, if the alternative a_t is chosen

- Decision under uncertainty

The decision maker has no information (relevant to the decision) about the true state of nature

P. Gärdenfors, "Forecasts, decisions and uncertain probabilities," Erkenntnis, vol. 14(2), pp. 159-181, 1979

In real-world scenarios, the decision maker has partial information

State-of-the-art uncertainty forecasts **are calibrated** (nominal-empirical probabilities≈0)

Calibration is quantified in a frequentist manner

We might need to consider first and second order probabilities (*probability of a probability*) - **ambiguity**

P. Gärdenfors (1979)

* Unperceived value

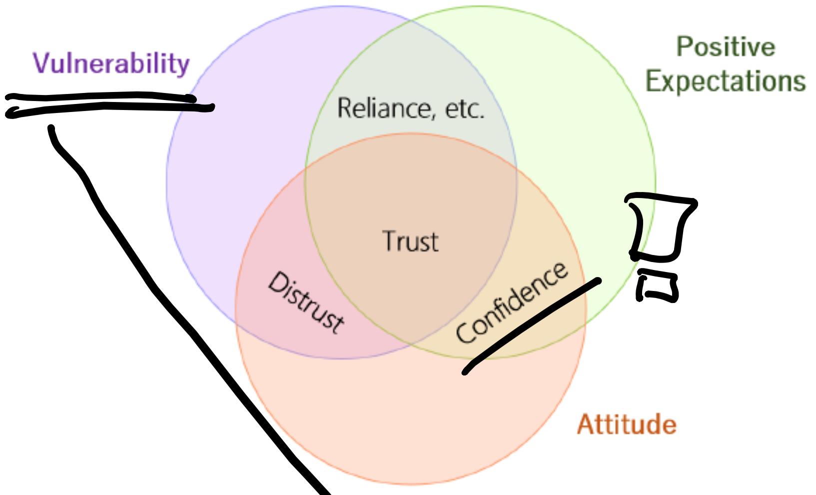
IEA Task 36 industry survey

Factors	Agree [%]	Not-Agree [%]
Weather is one out of many uncertainty sources	100	0
Insufficient knowledge about tools and approaches	53	47
Fear that speculative planning may result in a loss	64	36
Lack of staff to undertake the job	37	63
Lack of IT solutions	35	65
More information may lead to slower decision making and loss of important time	32	68
Flexibility in real-time staff resources would be desirable, but is not feasible	42	58
Company has access to confidential market information and is not allowed to speculate	33	67

inclusion of forecast uncertainty does not necessarily mean lower cost or higher profit if we just think in traditional performance metrics (total profit)

C. Mohrlen, R. J. Bessa, M. Barthod, G. Goretti, M. Siefert, “Use of forecast uncertainties in the power sector: state-of-the–art of business practices,” in Proc. of the 15th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants, Vienna, Austria, 15-17 Nov. 2016

** Trust

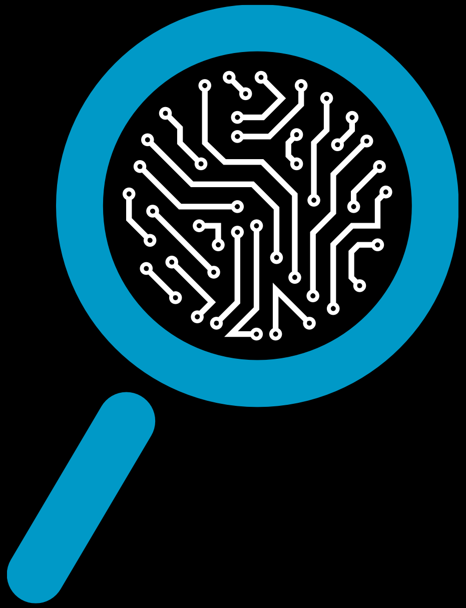


*key elements of **trust***

Source: O. Vereschak, G. Bailly, B. Caramiaux, "How to evaluate trust in AI-assisted decision making? A survey of empirical methodologies," CSCW, Oct. 2021

In the **outcome**: immerse decision makers in a state of vulnerability to feel that their decision matters, i.e., having something at **stake**

Classical paradigms and market bidding



A. Botterud, J. Wang, Z. Zhou, R.J. Bessa, H. Keko, J.S. Akilimali, V. Miranda, “Wind power trading under uncertainty in LMP markets,” IEEE Transactions on Power Systems, vol. 27(2), pp. 894-903, May 2012

Bidding in the Electricity Market

- Different rules (e.g., deviation penalties) and market sessions across countries

$$\overset{\text{Profit, hour } h}{\pi_h} = \overset{\text{DA price}}{\hat{p}_h^{DA}} \cdot \underset{\text{DA bid}}{q_h^{DA}} + \overset{\text{real-time price}}{\hat{p}_h^{RT}} \cdot (\overbrace{\underset{\text{real-time delivery}}{\hat{q}_h^{RT}} - q_h^{DA}}^{dev_h}) - \underset{\text{Deviation penalty}}{pen} \cdot \left| dev_h \right|$$

- Representation of uncertainty: marginal distributions (e.g., quantiles, pdf, pmf) for each lead-time → “uni-temporal” problem

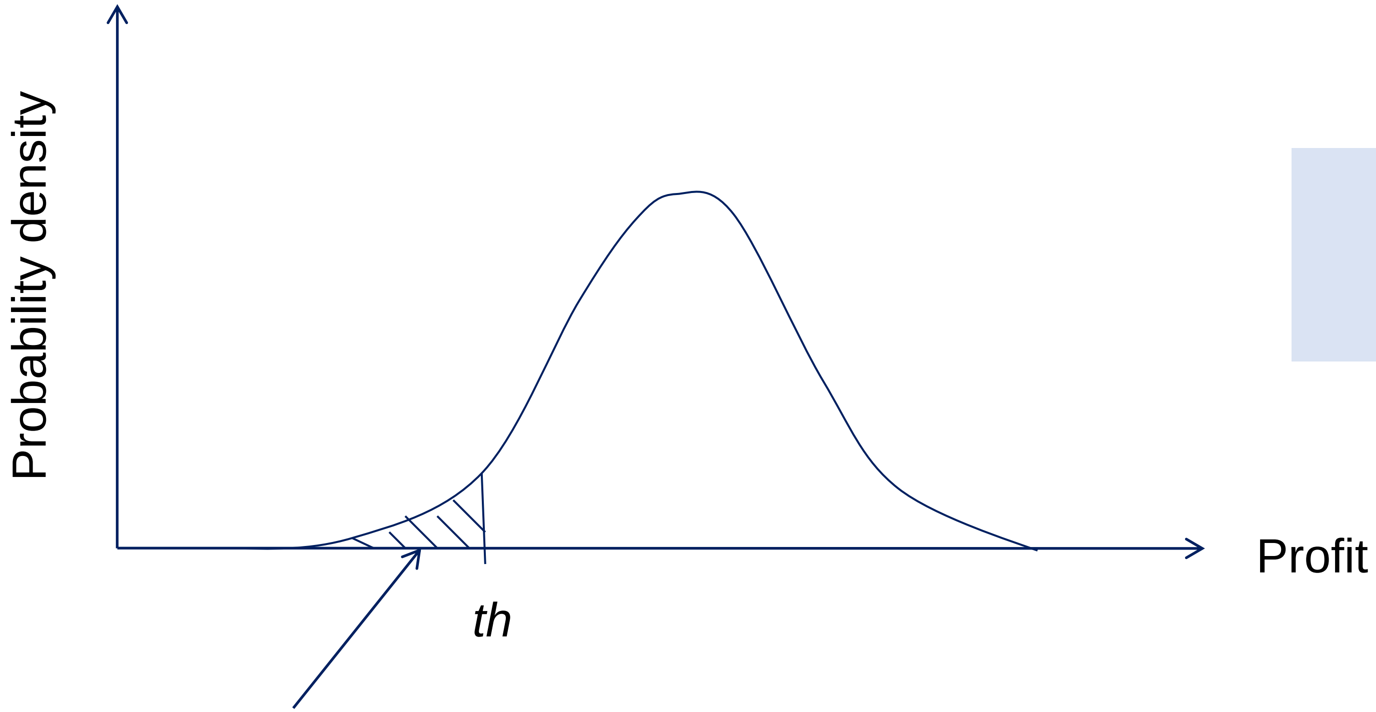
Classical Decision Paradigms

- We consider **three different decision paradigm**
- Expected profit – risk neutral decision-maker

$$max_{q_{DA,h}} \sum_{m=1}^{M} prob_m \cdot \pi_h^m(q_{DA,h})$$

Classical Decision Paradigms

Objective function: Max E(Profit) + *w**cVaR

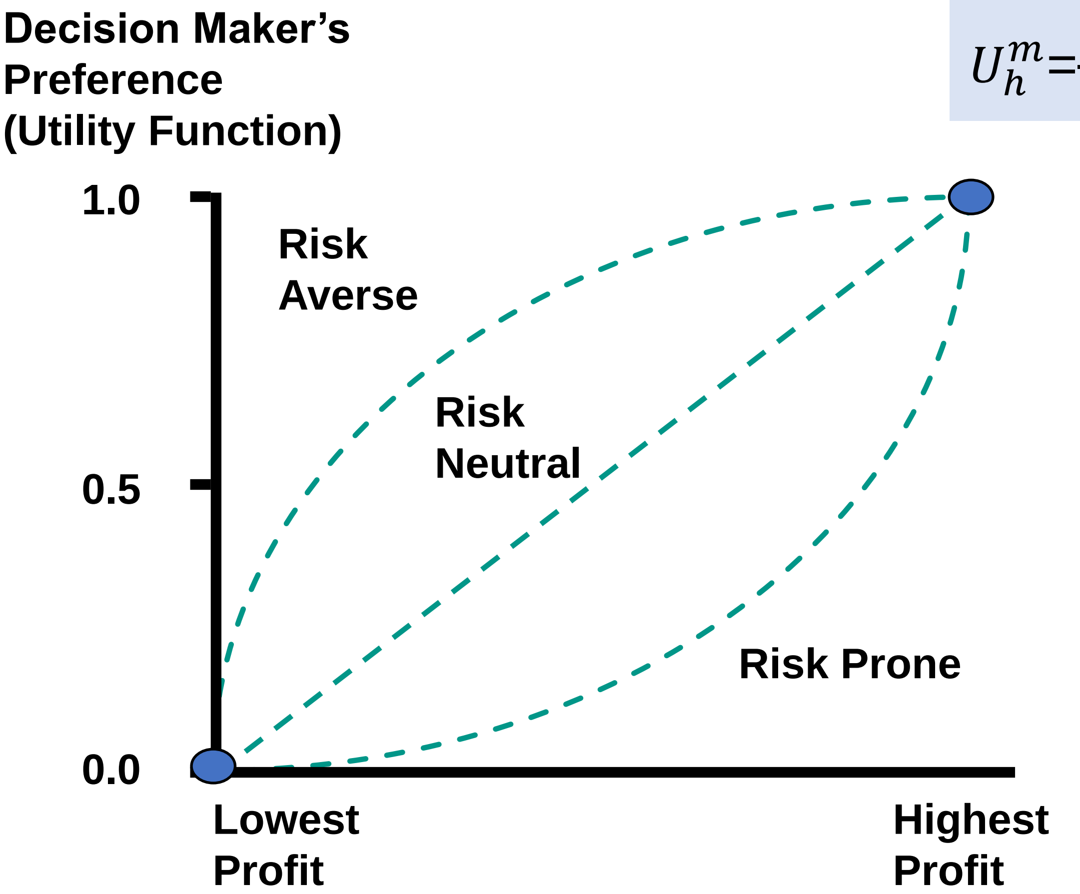


cVaR is the expected value of the profit below threshold, *th*

Trade-off Analysis – Deterministic & Multicriteria

Classical Decision Paradigms

Objective function: Max E(Utility)



$$U_h^m = \frac{1}{1-e^{\beta}}\left[1 - e^{\frac{\beta\left(\pi^m - \pi^{min}\right)}{\pi^{max} - \pi^{min}}}\right]$$

$\beta = 0$: neutral

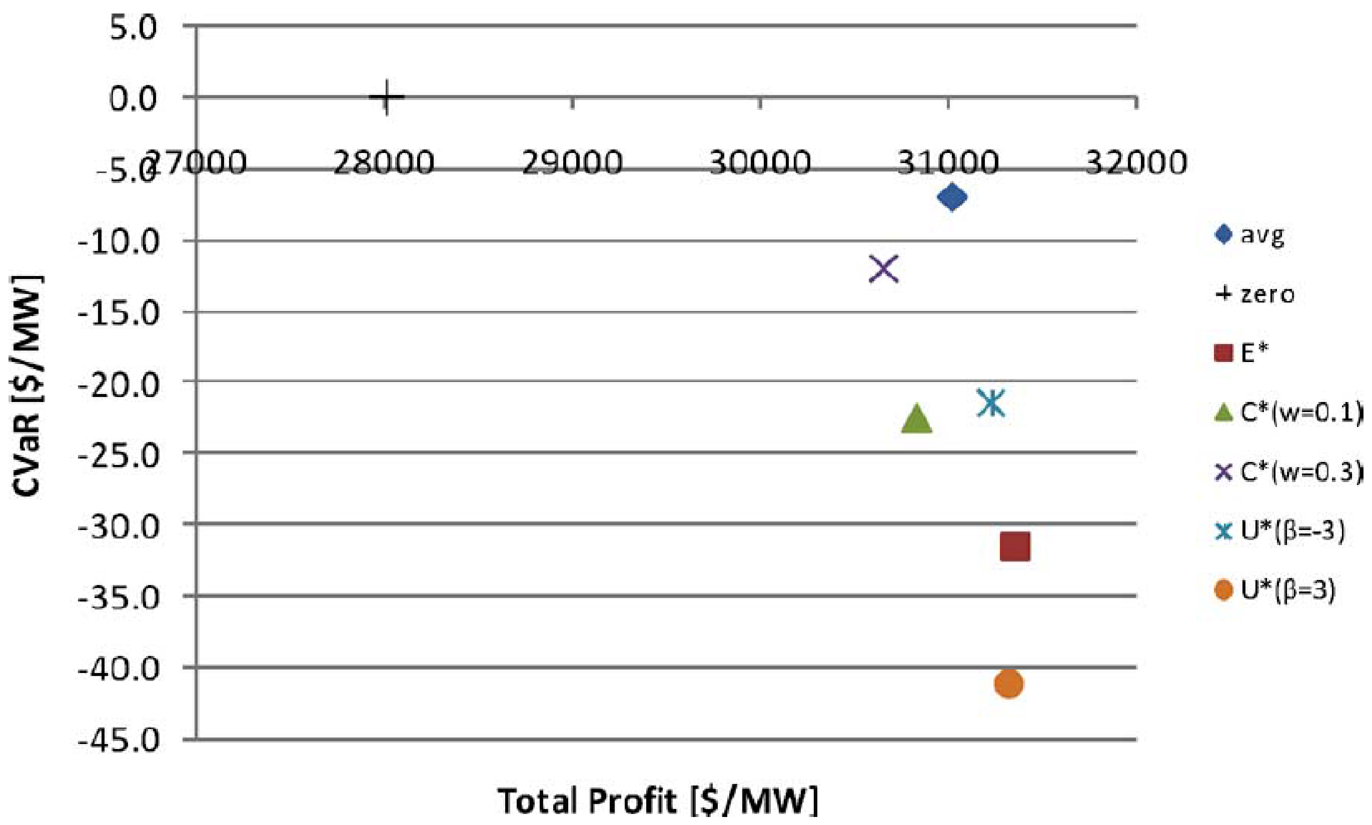
$\beta < 0$: risk averse

$\beta > 0$: risk prone

Utility Theory – Stochastic & Single and Multicriteria

Results for a Wind Power Plant in U.S.

Total 4-month profit versus hourly cVaR, no deviation penalty



Human understanding of forecast uncertainty value

Corinna Möhrlen, R.J. Bessa, N. Fleischhut, “A decision-making experiment under wind power forecast uncertainty,” Meteorological Applications, vol. 29, no. 1, pp. e2077, May/June 2022

Key questions for the experiment

Do decision-makers make better decisions with information about forecast uncertainty, and in which situations?

Do they decide more risk averse or risk prone?

Do probabilistic forecasts allow better learning from feedback?

Decision-making experiment

Experiment 1 (2020)

Scenario: whether a high-speed shutdown (HSSD) takes place within the forecast horizon in 12 cases
Decision: whether to trade 50% or 100% of the generating power of an offshore wind power plant

Decision Tools:

- 3 deterministic forecasts for wind power and 1 for wind speed
- probabilistic forecast showing wind power and wind speed marginal forecast intervals

Experiment 2 (2021-2022) – on-going

Scenario:

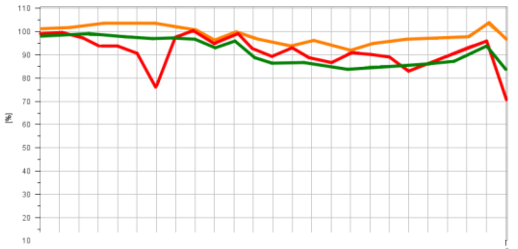
- 2 x times 20 cases (20 deterministic and 20 probabilistic cases)
- the participants make decisions based on either deterministic or probabilistic forecasts
- request on participant's confidence level regarding their decision
- real-time environment, e.g. participants may be surprised by forecasts that fail to warn or over-predict

Decision Tools:

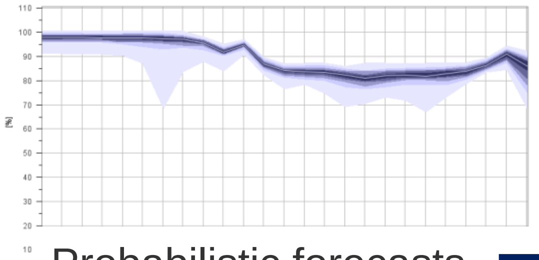
Same as experiment 1

Link for the 2nd experiment: https://arc-vlab.mpib-berlin.mpg.de/wind-power

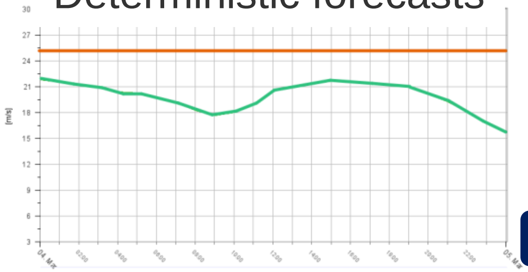
Experiment and cost function

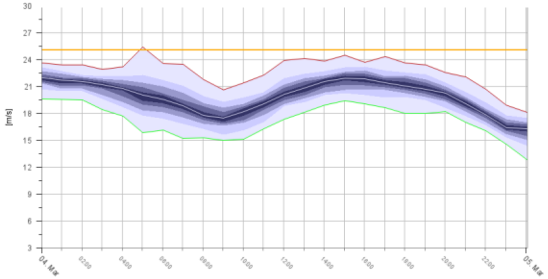


Power forecasts



Deterministic forecasts → 1st Decision → Probabilistic forecasts → 2nd Decision





Wind forecasts

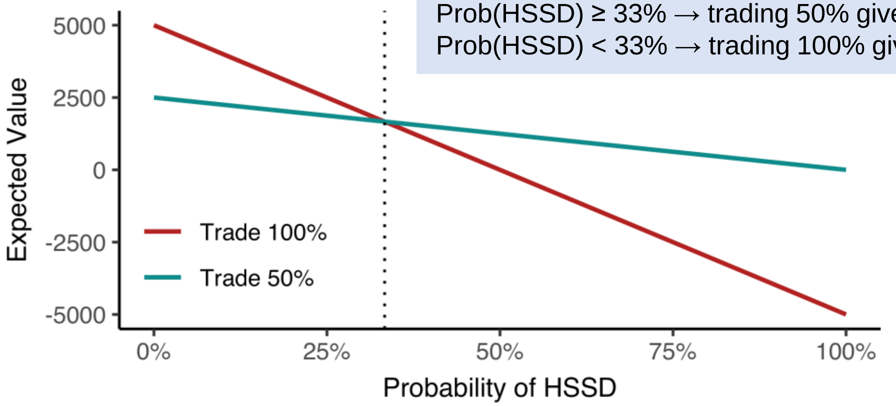
Trade 100% | Trade 50%

Trade 100% | Trade 50%

Cost Function

Trading	HSSD	No HSSD
100%	-5.000	5.000
50%	0	2.500

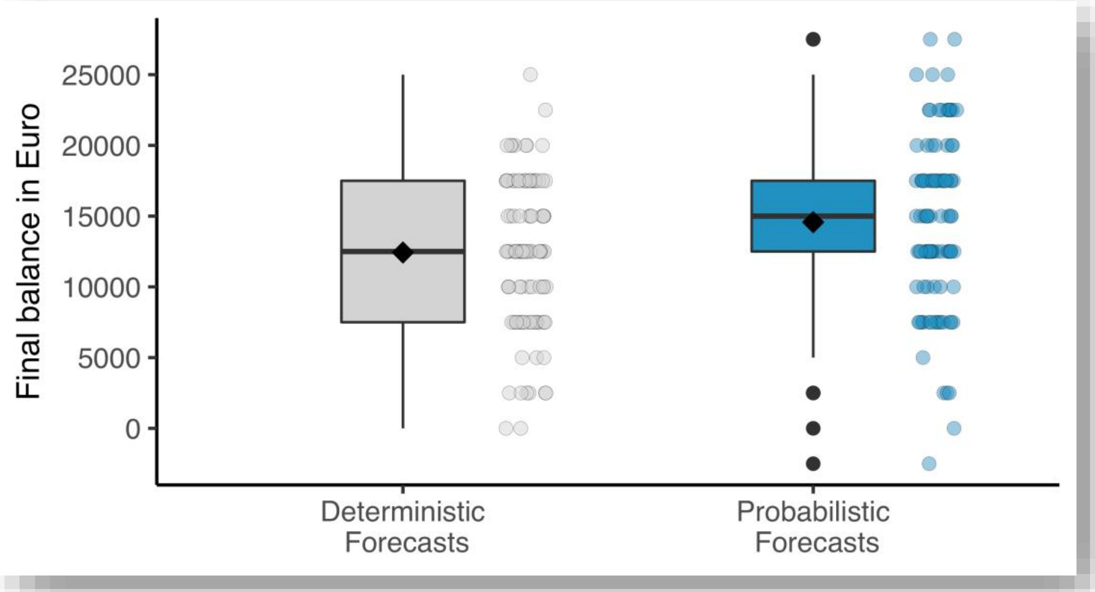
Prob(HSSD) ≥ 33% → trading 50% gives higher payoff
Prob(HSSD) < 33% → trading 100% gives higher payoff



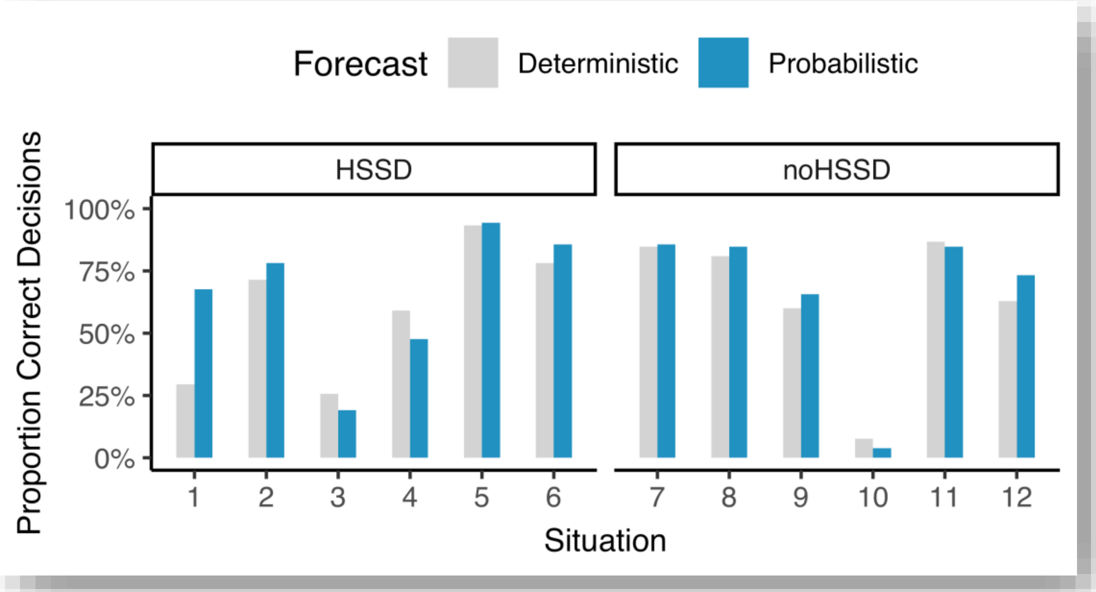
Experiment main results

Conducted with 105 participants from the energy industry

Slightly higher income with probabilistic forecasts



Proportion of correct decisions

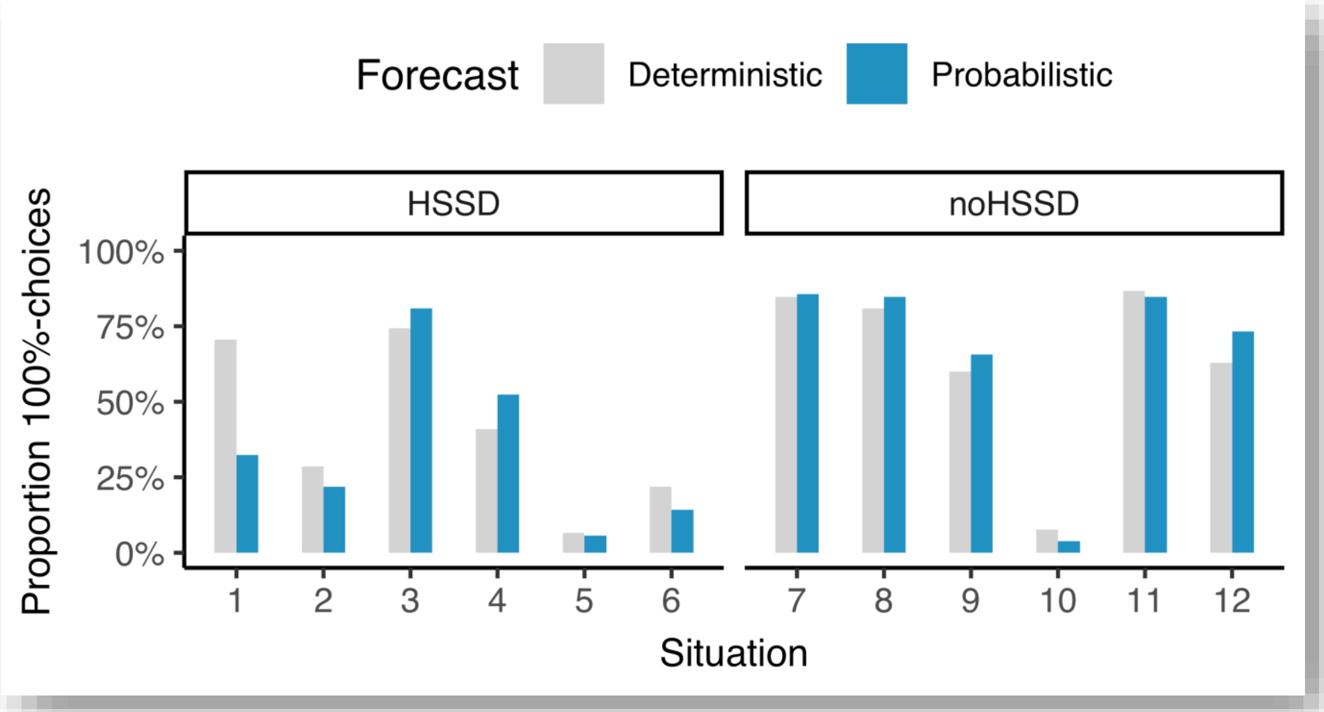


Other results

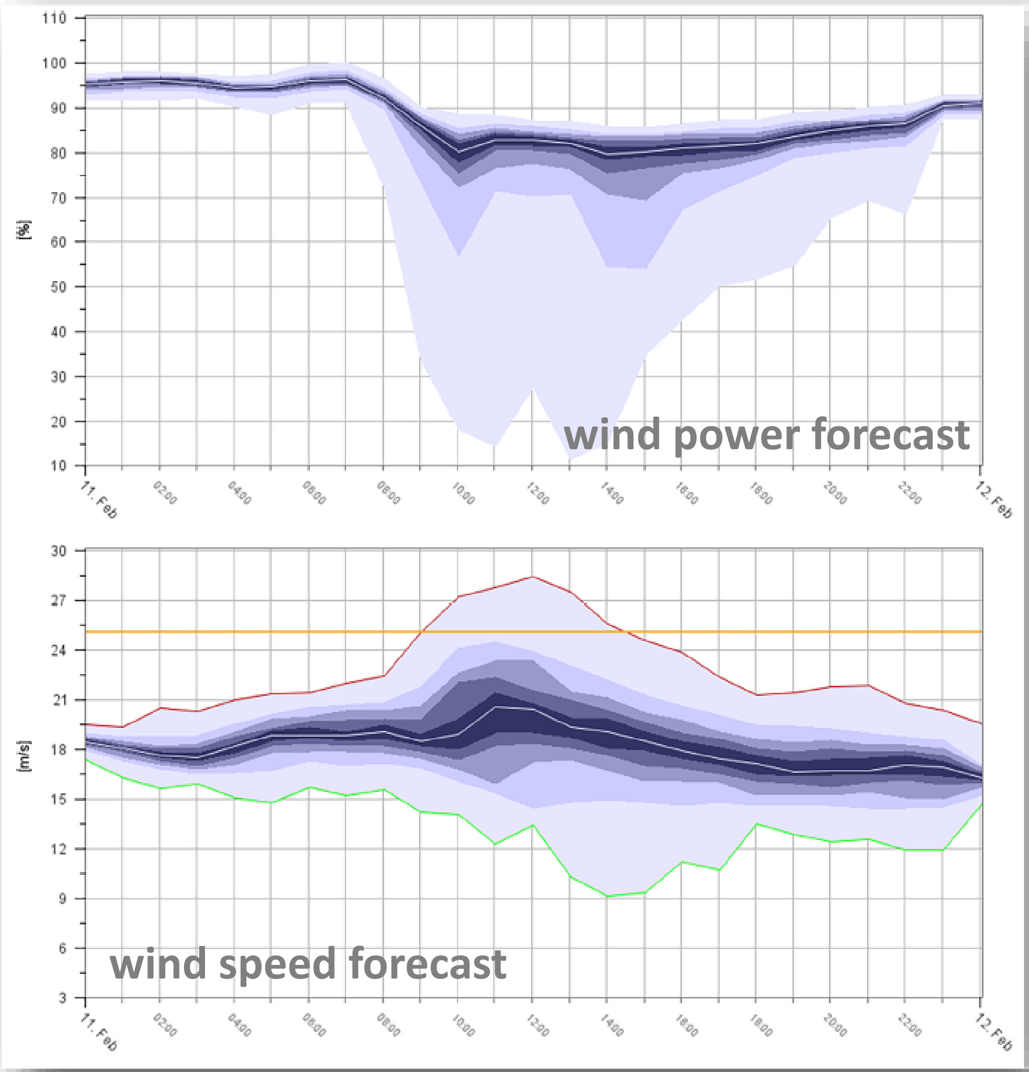
- In 9 out of 12 situations, more than 10% of the participants changed their mind
- In three cases 30%–23% changed their mind, and in one case (Situation 1) 48% did
- 93% preferred some type of probabilistic forecast

Experiment main results

Proportion of participants taking the risky option (trading 100%)



Situation 1



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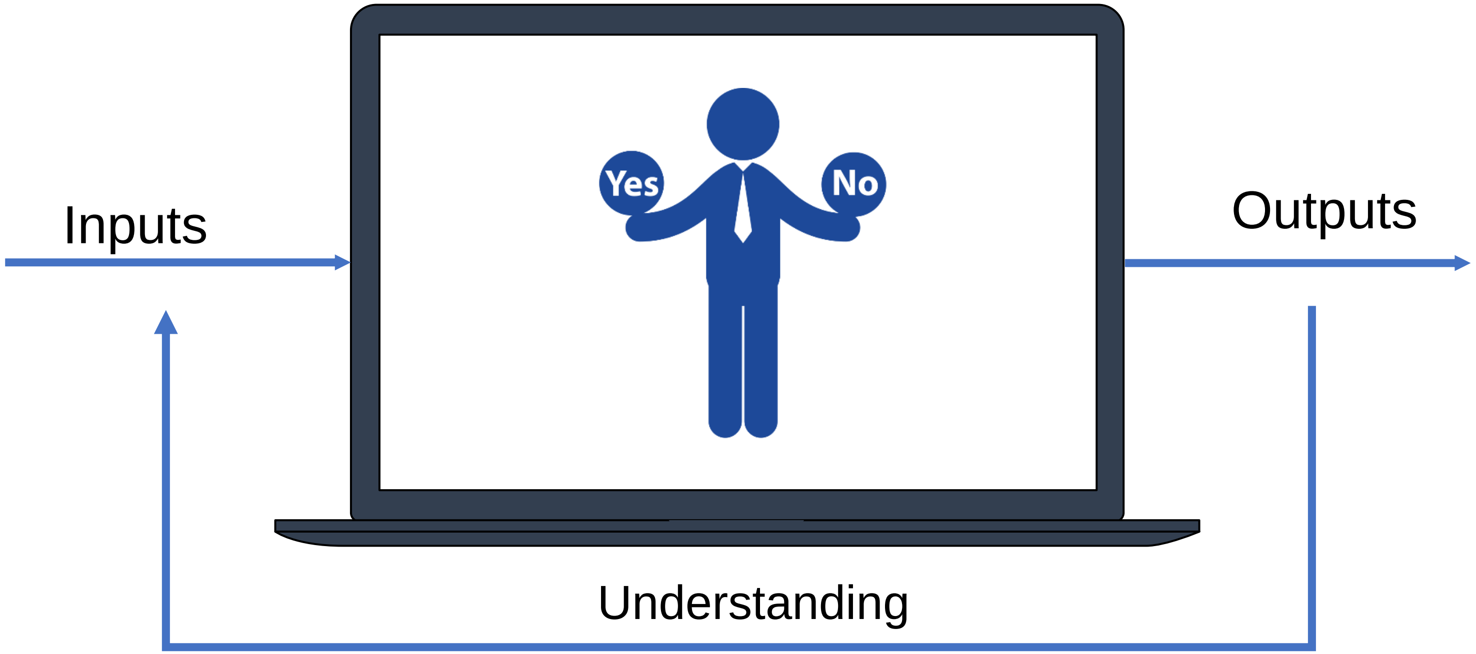
Human interpretability in energy trading

K. Parginos, R.J. Bessa, S. Camal, G. Kariniotakis, “Interpretable data-driven solar power plant trading strategies,” IEEE ISGT Europe 2022, Novi Sad, Serbia, 10-12 Oct. 2022.

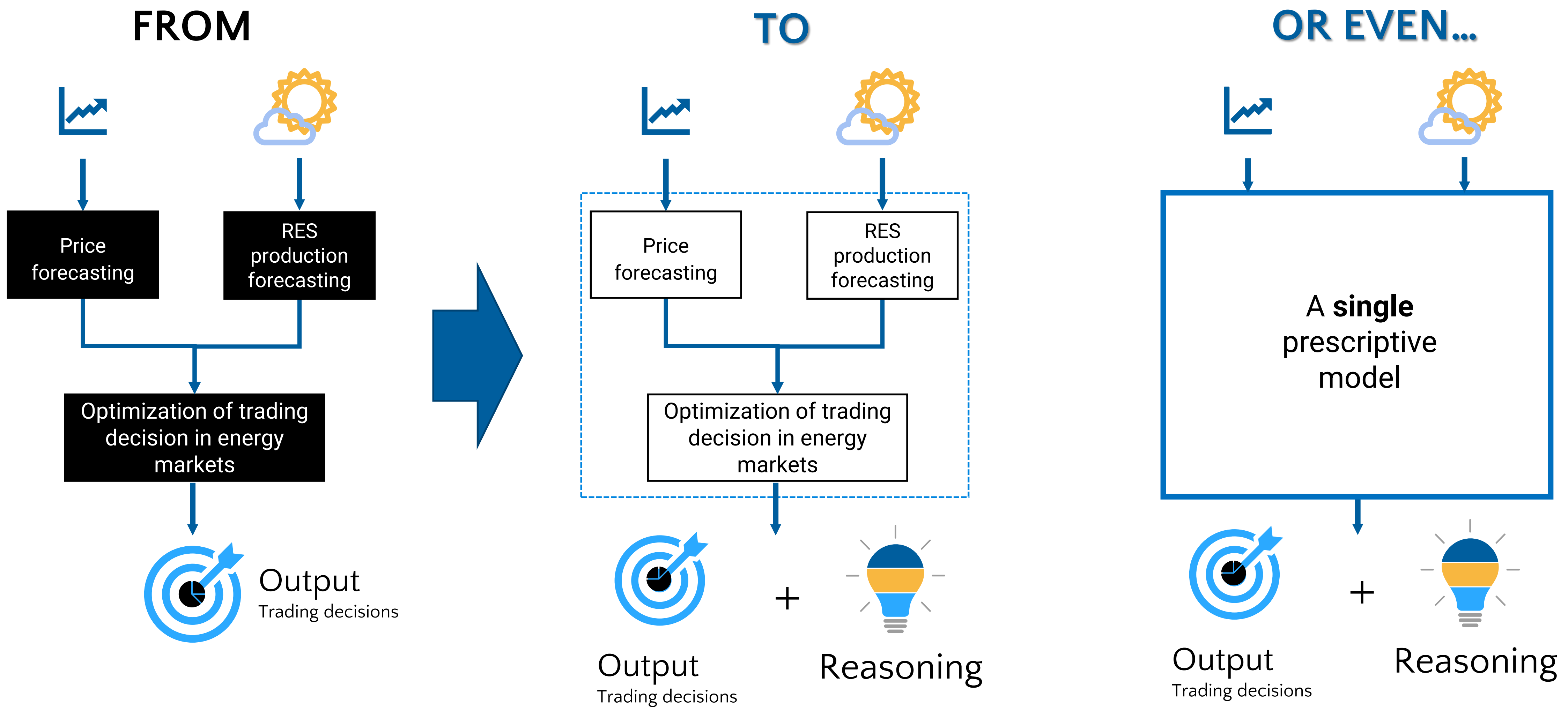
MINES PARIS | PSL | PERSEE

What is interpretability?

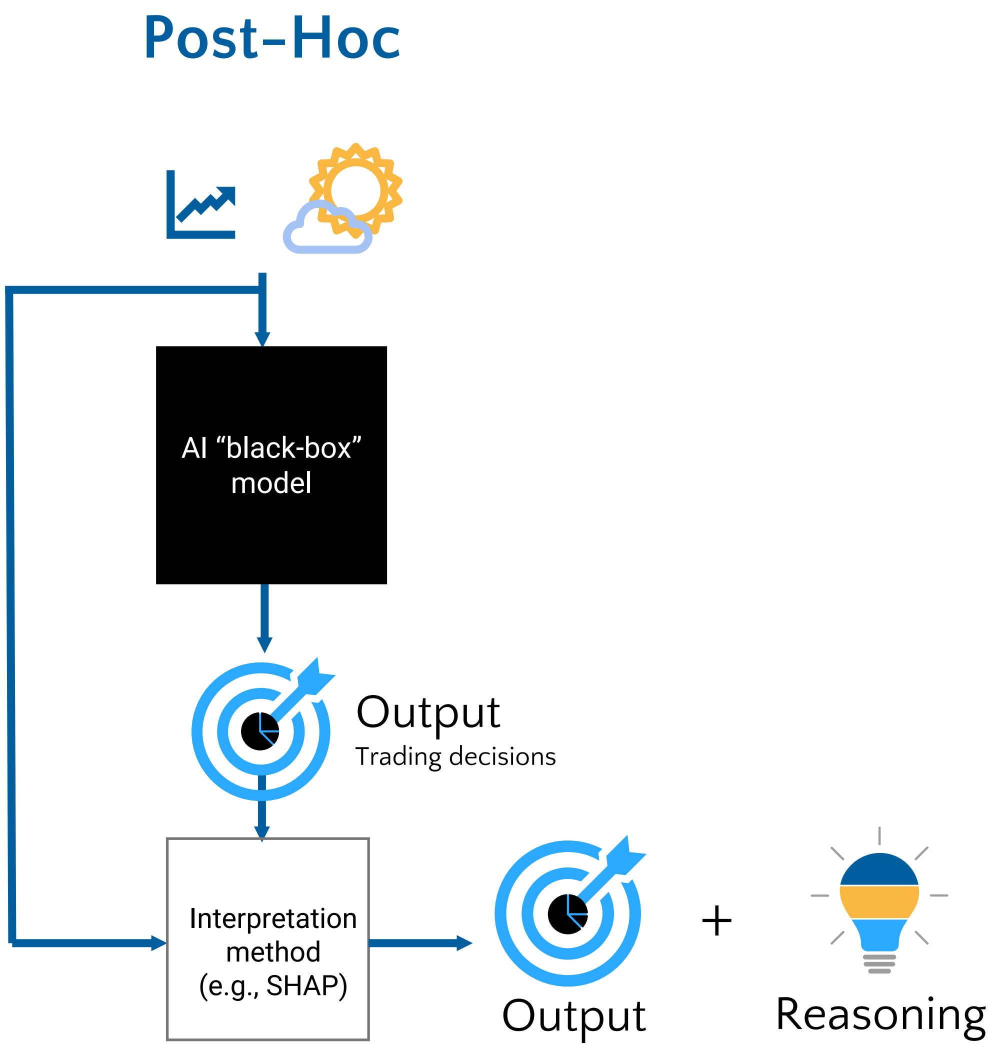


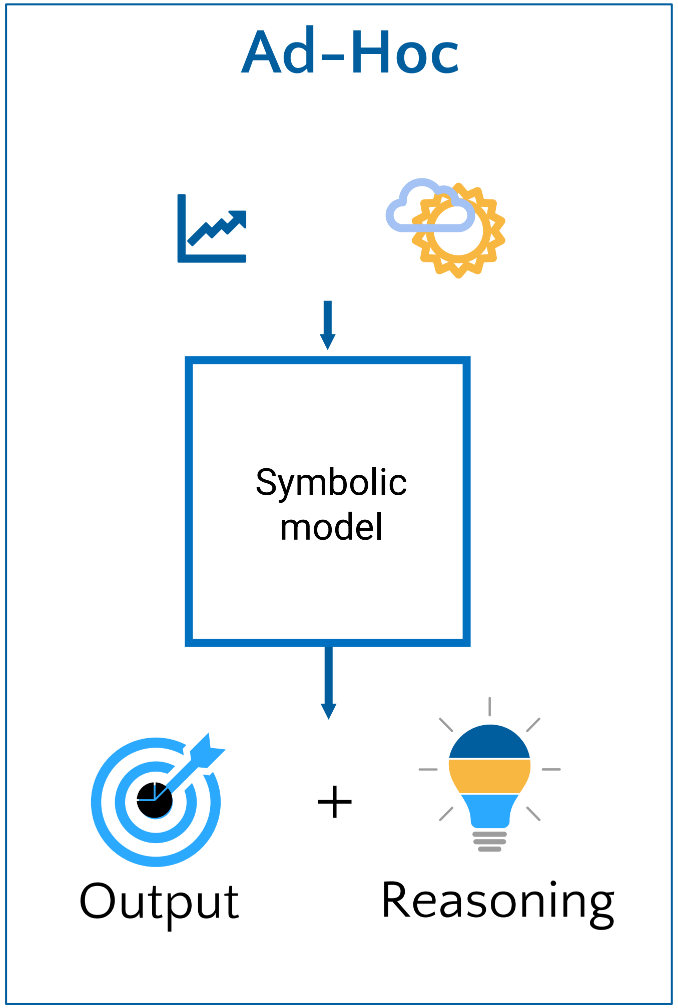
" The ability to explain or to present a model output in understandable terms to a human", Doshi-Velez & Been Kim, 2017

AI/ML frameworks for RES trading



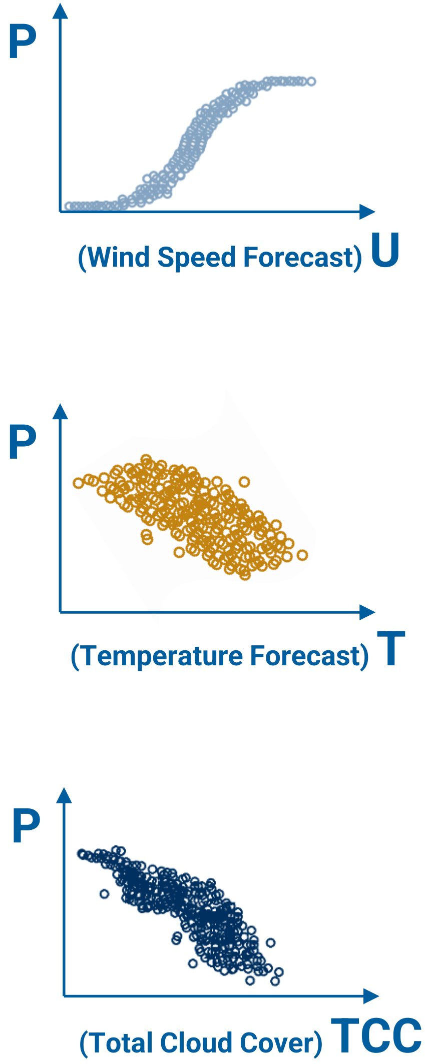
Main interpretable approaches



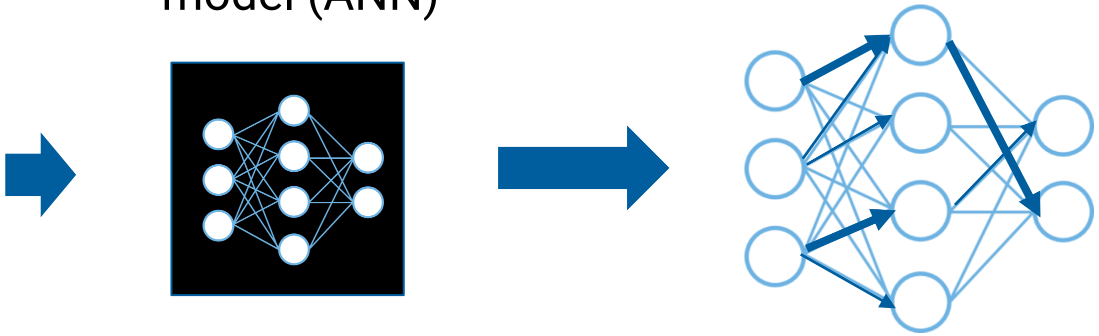


Interpretability & prescriptive model in trading

Input Data



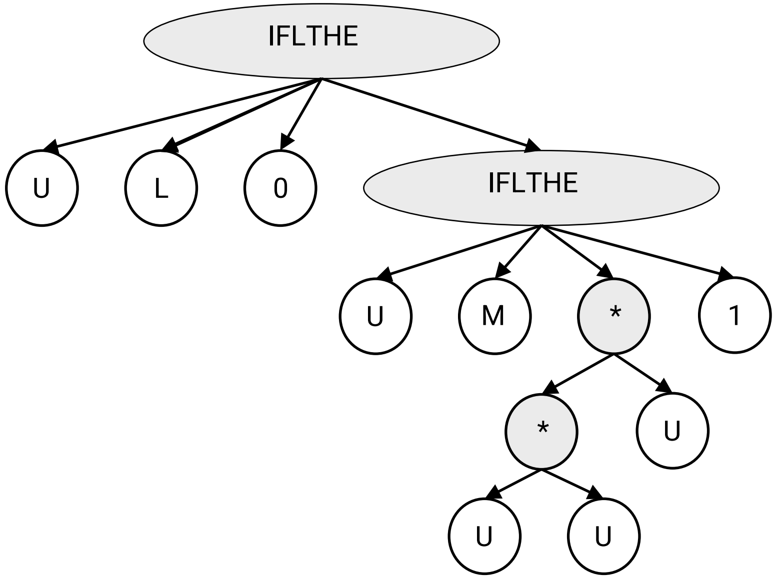
model (ANN)



Trading decisions

R. Bessa, et al., “Good or bad wind power forecasts: a relative concept,” Wind Energy, vol. 14(5), pp. 625-636, July 2011

Interpretable symbolic model



Library of Analytical Functions

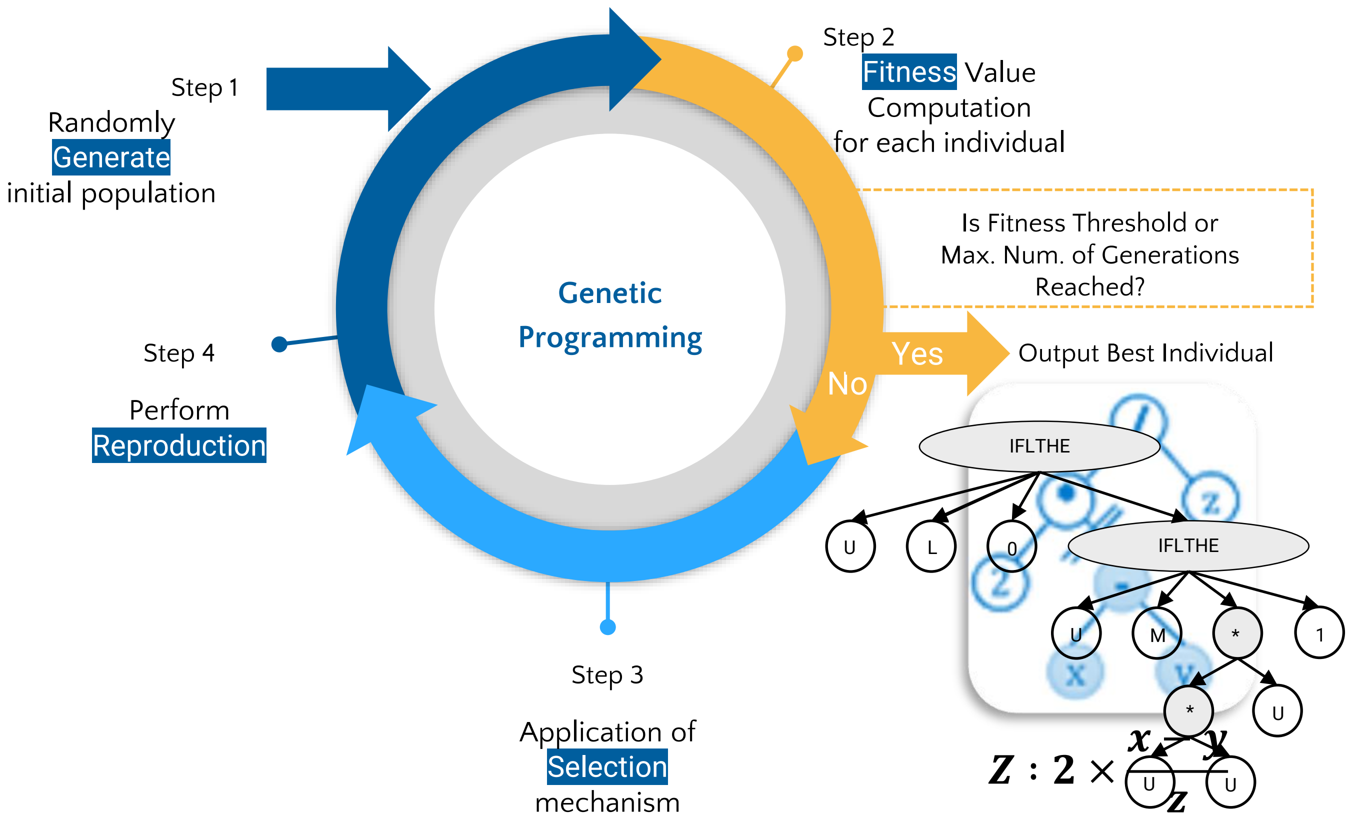
$TD = U^3$

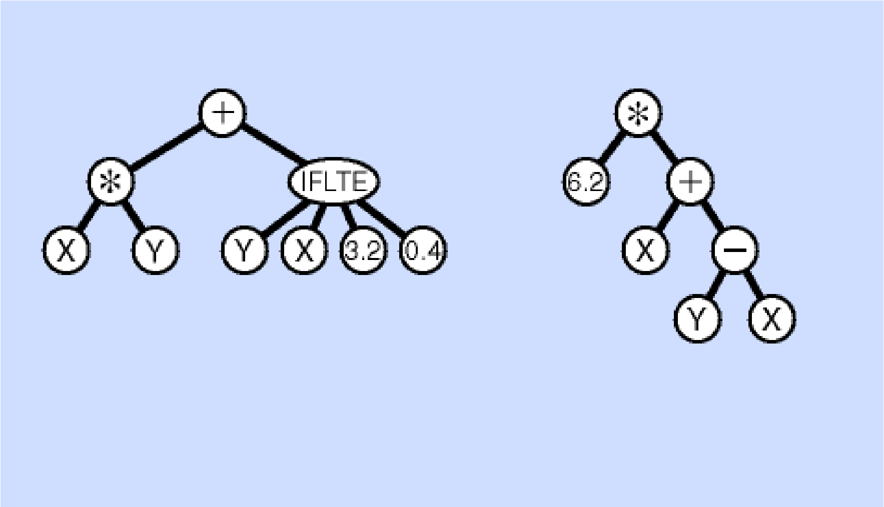
$TD = 4T$

$TD = U^2/3$

$TD = U^3 + TCC$

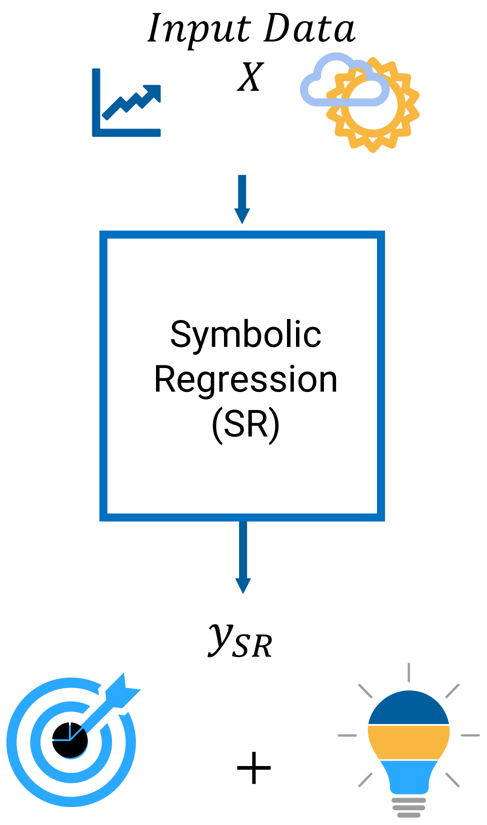
Symbolic Regression





Trading problem formulation

Ad-Hoc



Definitions

$$y_{SR} = G(Z_{E,\theta}, X)$$

$$Z_{opt} = \underset{\{Z_{E,\theta} \in \Phi\}}{\operatorname{argmin}} L(G(Z_{E,\theta}, X), y)$$

Formulation of fitness function L to optimize trading value

$y = p^E$: Actual energy produced

$\lambda^{\uparrow}, \lambda^{\downarrow}$: Imbalance prices

$$L = \underbrace{\left[-\lambda^{\uparrow}(p^E - y_{SR})^{-} + \lambda^{\downarrow}(p^E - y_{SR})^{+}\right]}_{imbalance\ cost}$$

Two Approaches

Non-Clustered Data

SR_{Global}

Clustered Data

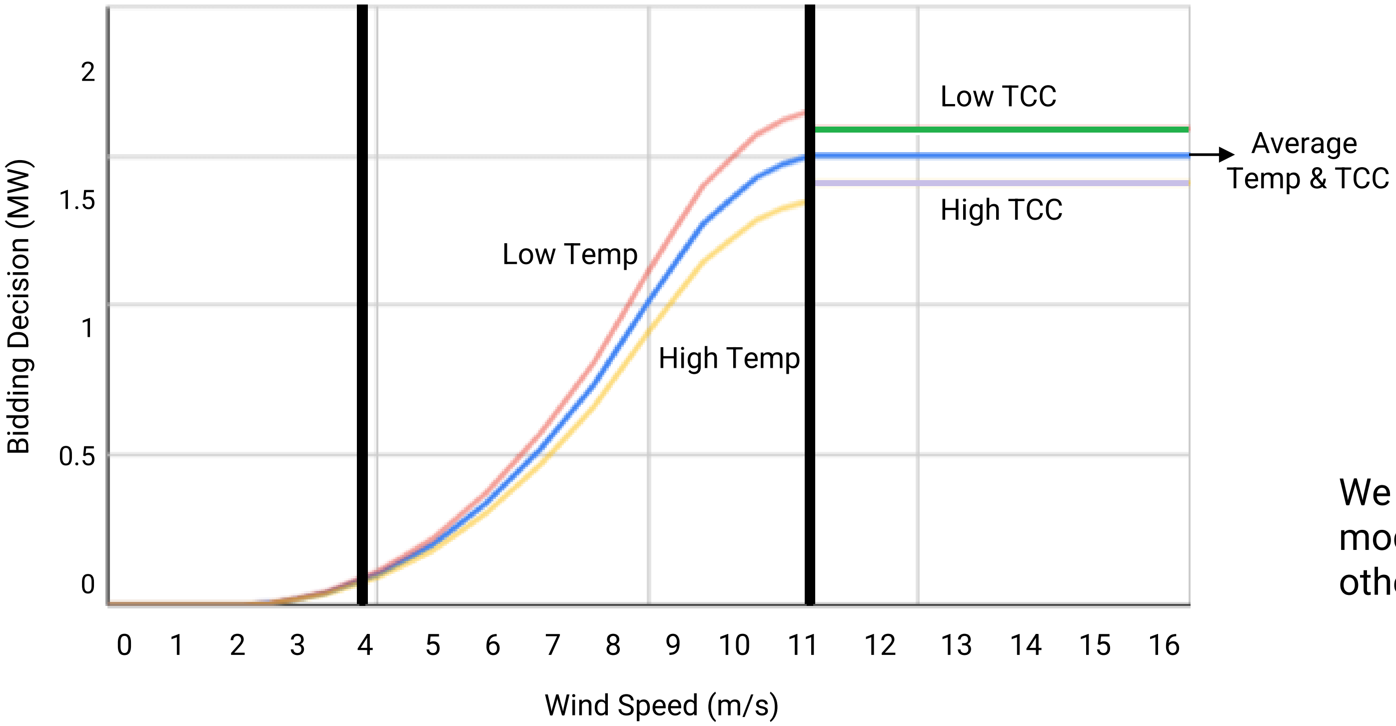
$SR_{(Low,Medium,High)}$

Case-study: wind energy day-ahead bidding

	Low wind speed	Medium wind speed	High wind speed
SR expression	$0.04 \cdot w_{speed}^2$	$-0.027 + \frac{0.87 \cdot w_{speed}^3}{Temp}$	$\frac{1.77 \cdot w_{speed}}{2TCC + w_{speed}}$

Global SR

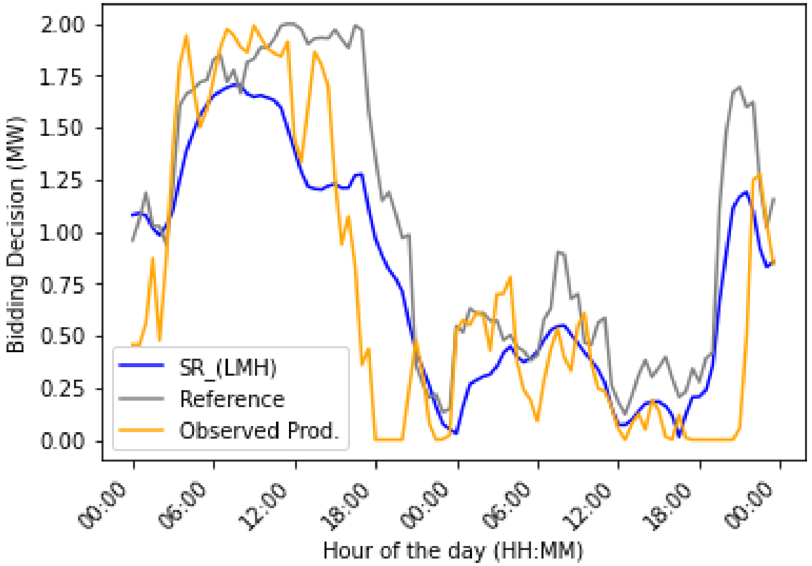
$0.11 \cdot w_{speed}$



We can identify the key features that drive our model, as well as how they interact with each other in different wind speed conditions

Case-study: wind energy day-ahead bidding

4 x 2MW wind turbines, located in France (period of March 2019-May 2020)



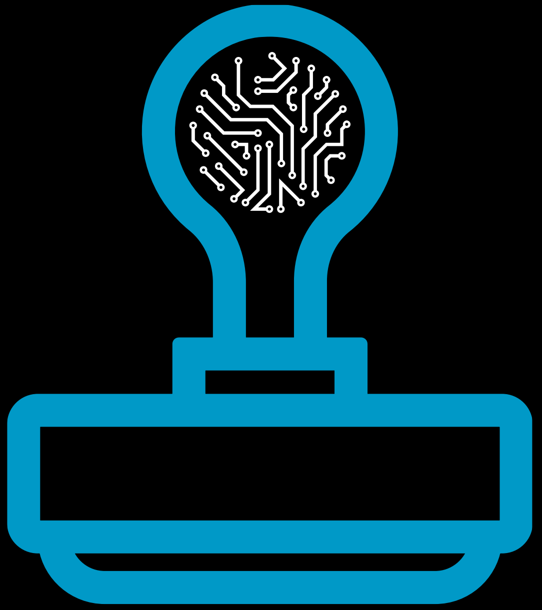
Selected Strategy	Total Revenue (€) WT_1	WT_2	WT_3	WT_4	Comparison w./ Ref. Bidding
Perfect hindsight	*272.209*	*264.449*	*254.960*	*253.068*	*7.15%*
Reference bidding (opt. quantile)	*257.158*	*241.241*	*238.468*	*238.145*	*0.00%*
SR_{Global}	*238.632*	*228.124*	*219.630*	*219.744*	*-7.06%*
$SR_{(Low,Medium,High)}$	*250.051*	*241.338*	*232.002*	*231.072*	*-2.11%*

Reference model (opt. quantile)

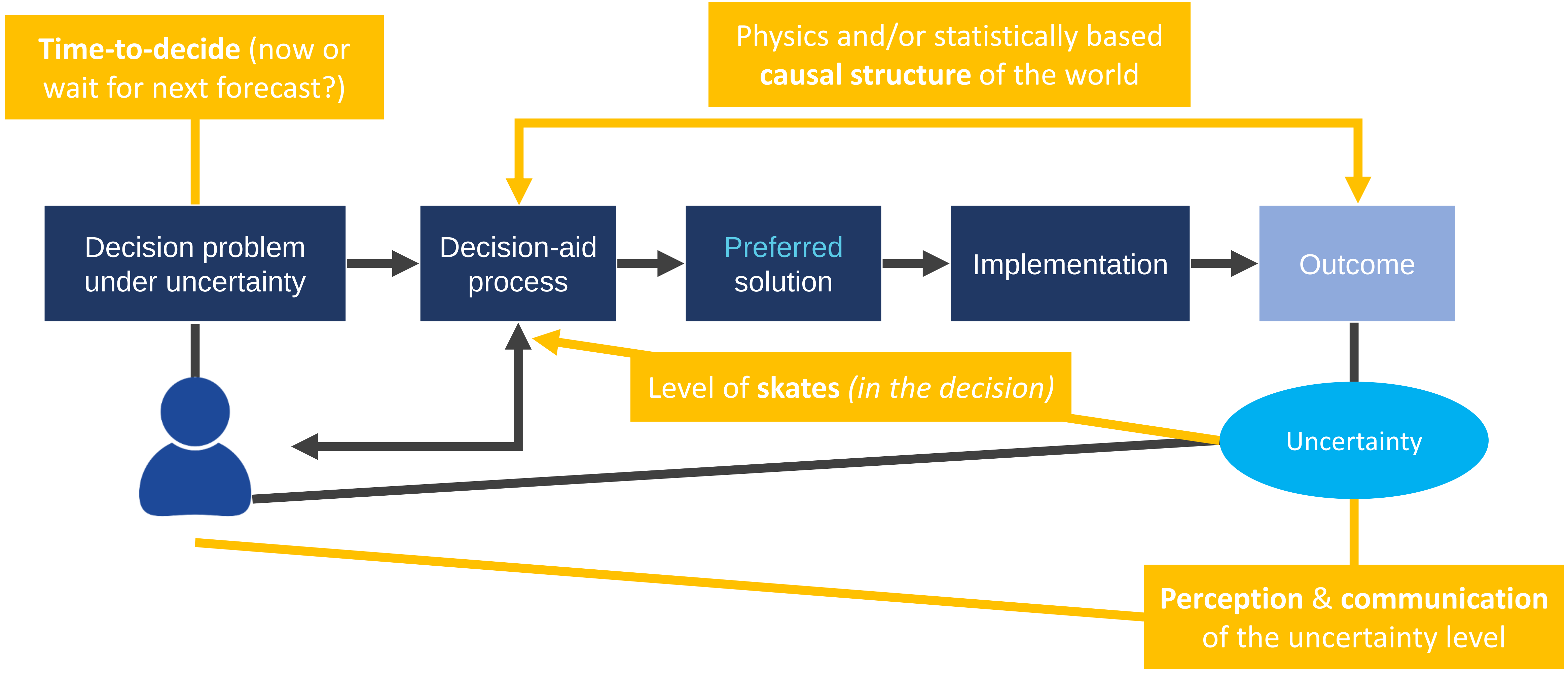
$$\alpha_t^* = \frac{\lambda^{\downarrow}}{\lambda^{\uparrow} + \lambda^{\downarrow}}$$

optimal bid (min expected imbalance cost) is given by $F^{-1}(\alpha_t^*)$

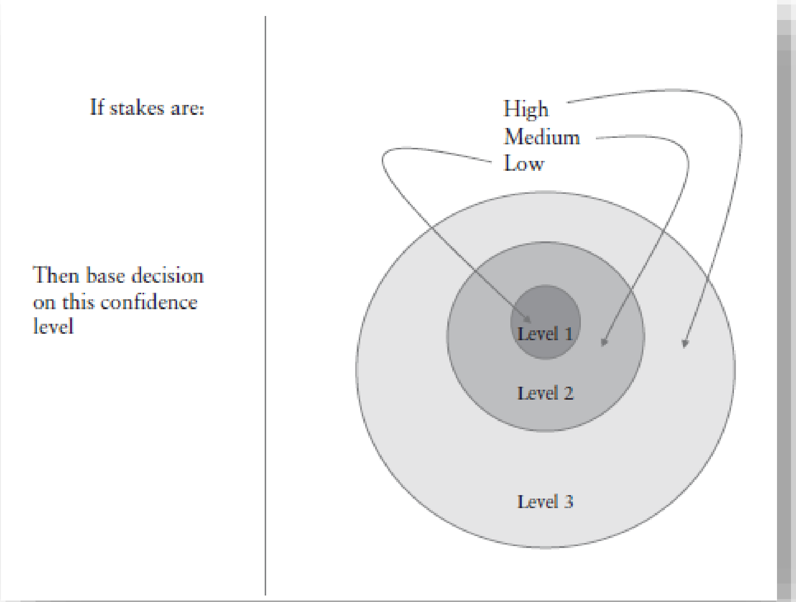
Towards new decision paradigms



Revised decision framework



Confidence-based decisions



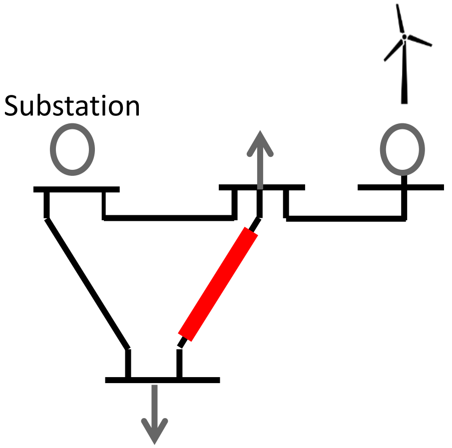
Hill (2013). Confidence and decision. Games and Economic Behavior, 82, 675-692

Uncertainty forecasts with a larger spread can be helpful in catching low-probability-high-impact events, but can lead to expensive decisions due to high uncertainty

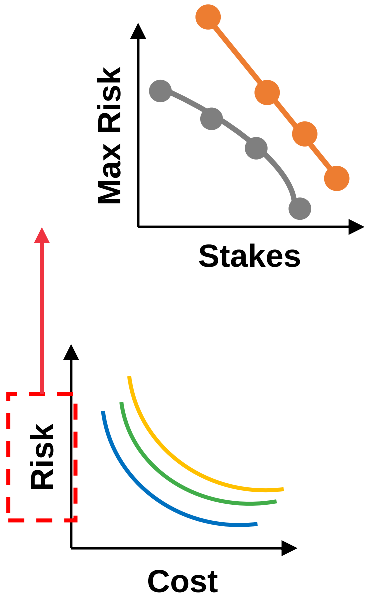
Narrow forecast intervals can on the other hand lead a decision-maker to over-confidence in a decision

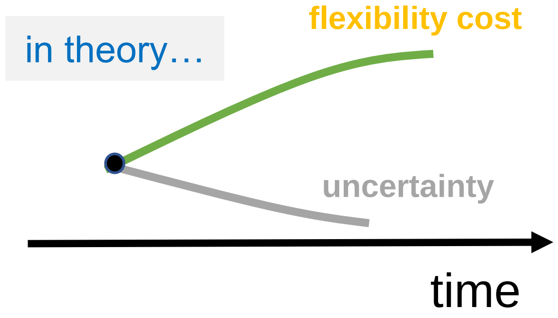
Framework applied to electrical grid management

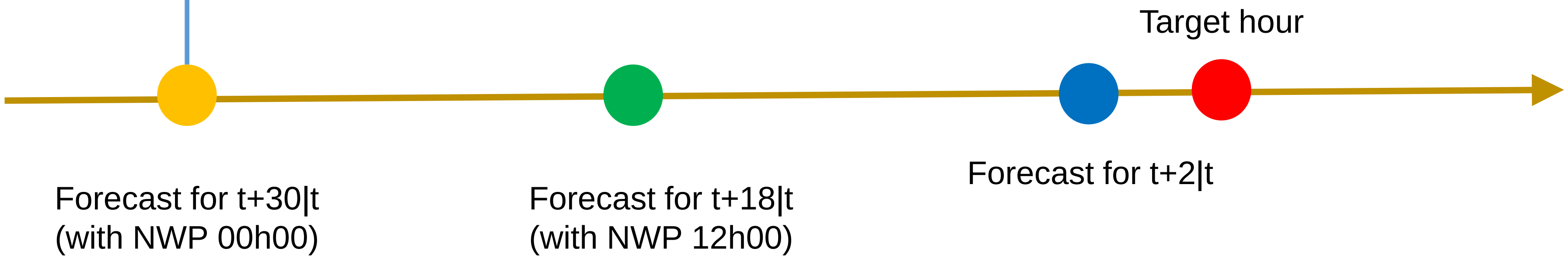
Probability of a congestion for day D+1 (lead time: t+30|t)
> Decide now (i.e., "reserve" DER flexibility) or wait?



meta-forecast: forecast the uncertainty of the "future" forecasts for t+18|t & t+2|t



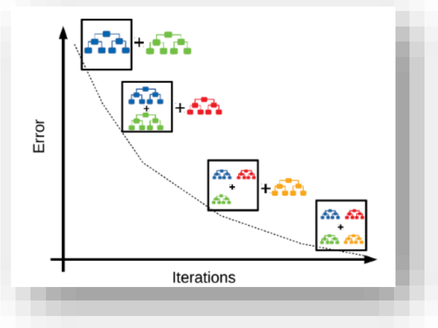




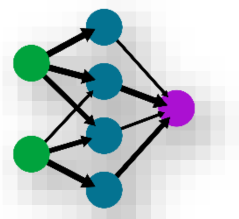
Meta-forecasting

Forecasted generated with 0h00 NWP
+
Features characterizing uncertainty level (IQR, forecasted quantiles, stdev.)

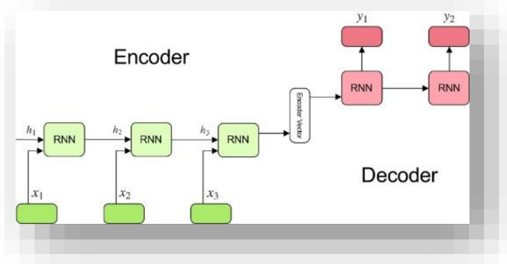
Gradient Boosting Trees

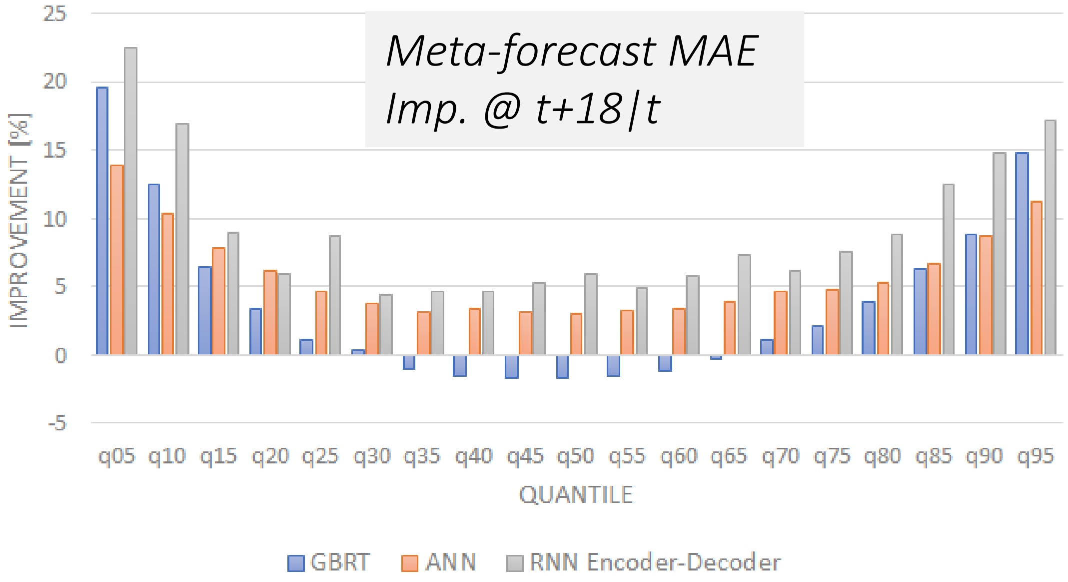


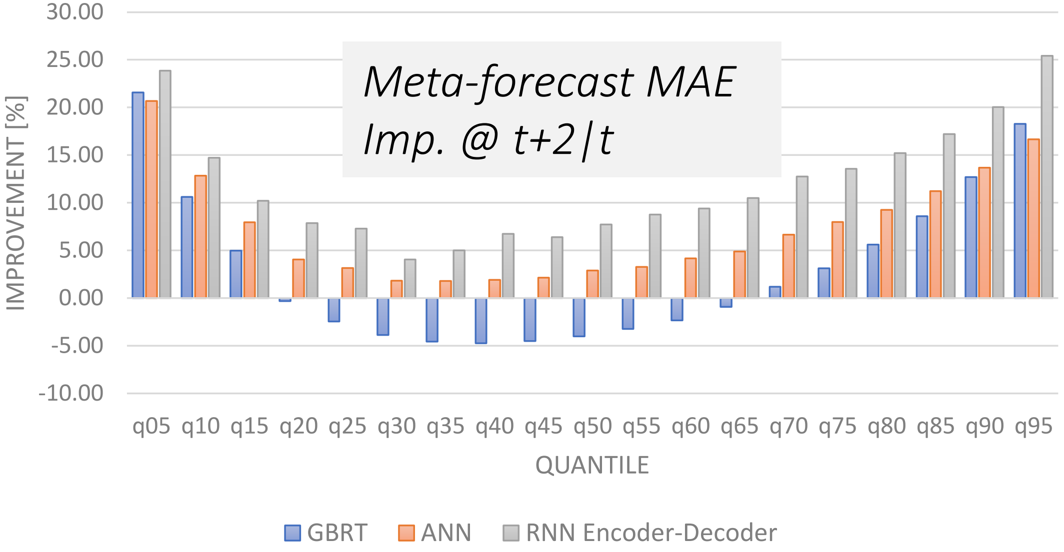
ANN



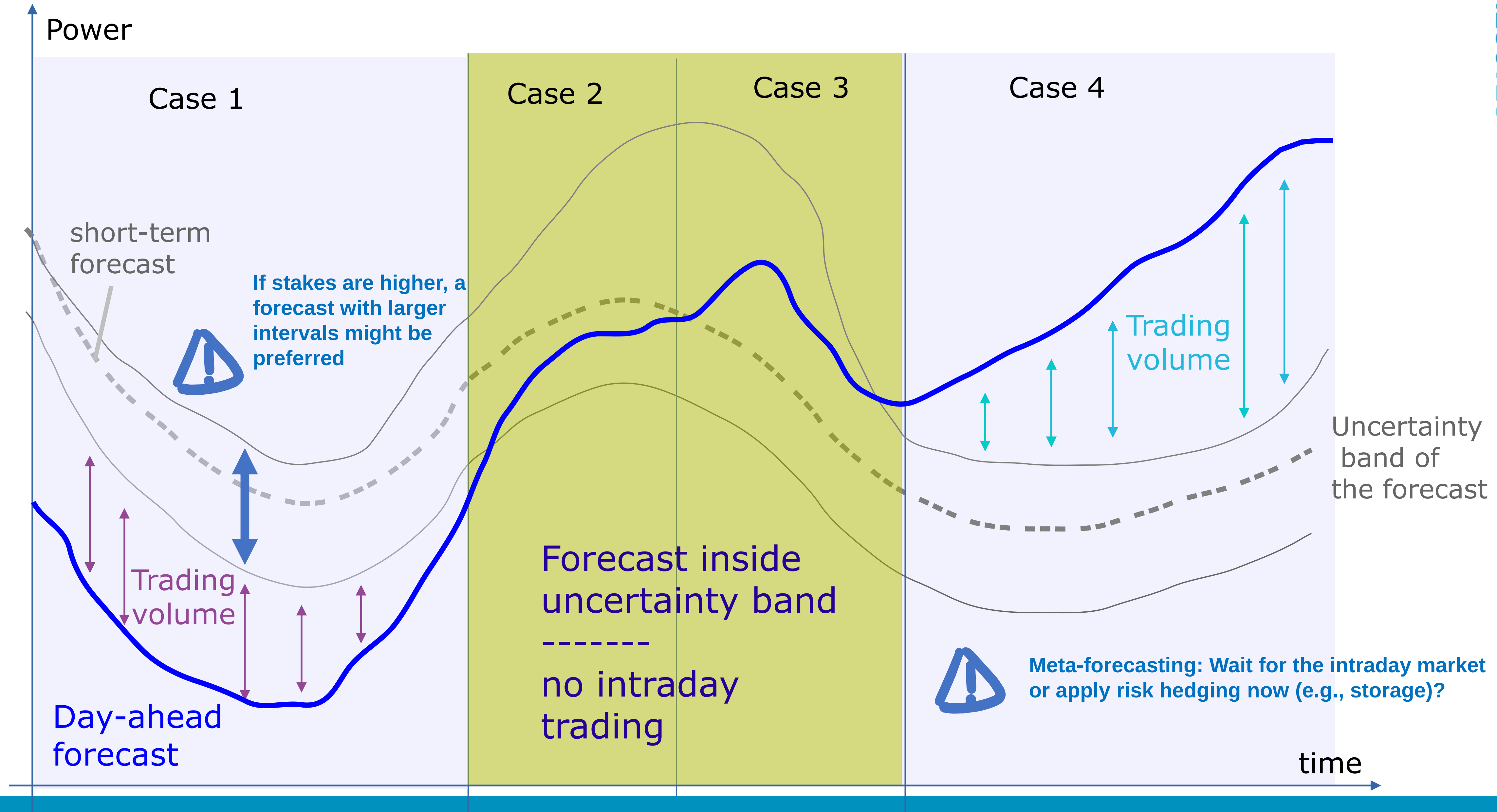
RNN







Application in energy markets



Concluding remarks

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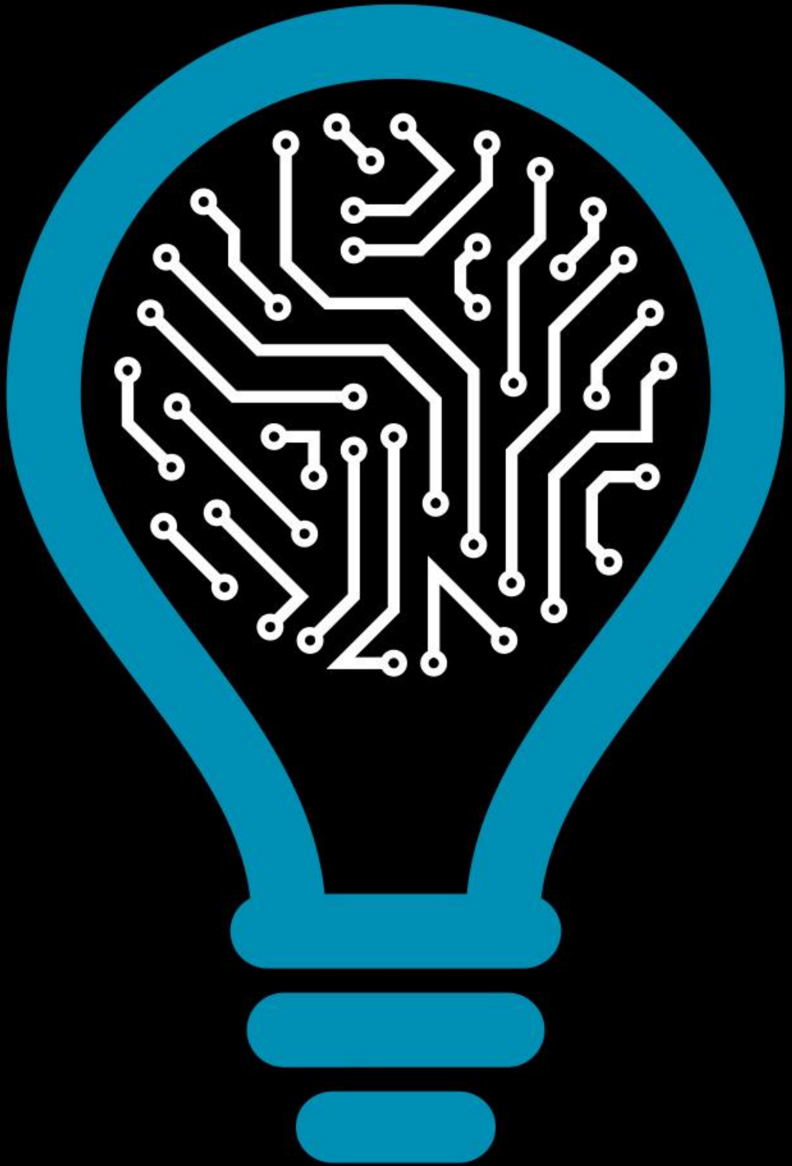
- Different levels of information abstraction might be needed for trading under forecast uncertainty
- Revise traditional decision-making process in the context of **Trust**
- Improve risk perception via transparent representations of information and **stakes** *(vulnerabilities)*
- Integrate model confidence and reaction to failure
- Temporal dimension of decisions is frequently forgotten
- Hybridization of traditional decision-making theory, operations research and ML

from knowledge
production to
science-based
innovation



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