Improving Forecasting And Decision-Aid Tools To Accurately Predict And Manage High Volumes Of Renewable Energy Generation

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https://www.smart4res.eu

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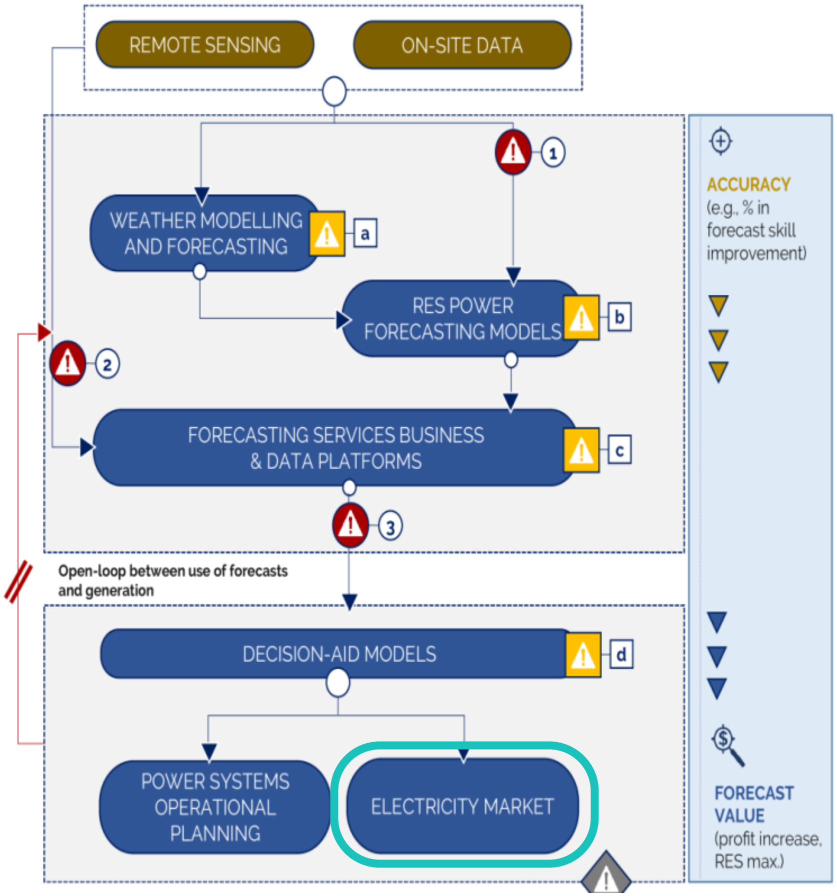
Summary

1. Identifying requirements for forecasting technologies to enable near 100% RES penetration
2. Streamlining the process of getting optimal value from data and forecasts
3. Utilising energy storage to mitigate uncertainties on renewable production
4. Lessons learnt and next steps

Smart4RES in a nutshell

Smart4RES

- RES forecasting is a mature technology with operational tools and commercial services used by different actors
- However, we want to make progress to improve the forecasting accuracy and to reduce costs of RES integration



Smart4RES vision

Science and industry closely co-operate to achieve outstanding improvements of RES forecasting by considering the whole model and value chain.

Smart4RES consortium

6 countries
12 partners

End-users

Research

Meteorologists

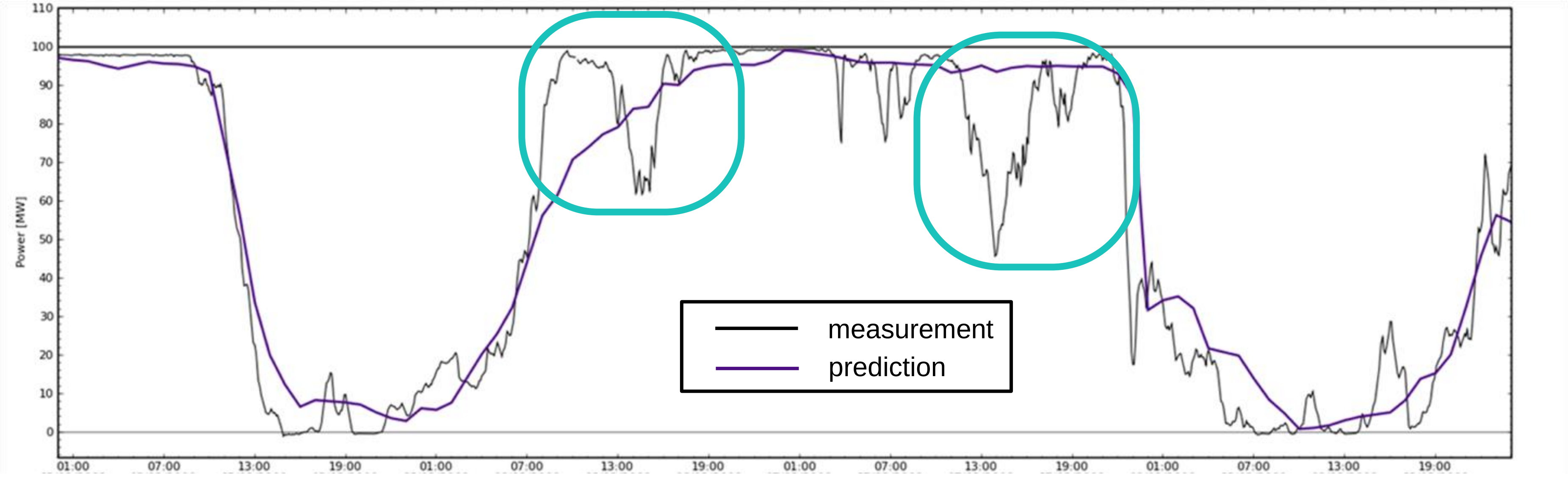
Funds: H2020 programme
Budget: 4 Mio€
Duration: 3.5 years

11/2019-4/2023

Renewable Forecasting is mature, but large prediction errors impact power systems and plant operators

Wind power forecasting based on state-of-the-art weather model at one hour resolution, misses fluctuations

- Large compensations from storage ie large cycling costs, cannot capture other market opportunities
- Need to quantify the uncertainty



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1. Identifying requirements for forecasting technologies to enable near 100% RES penetration

12 Use Cases developed, more than half directly concern storage

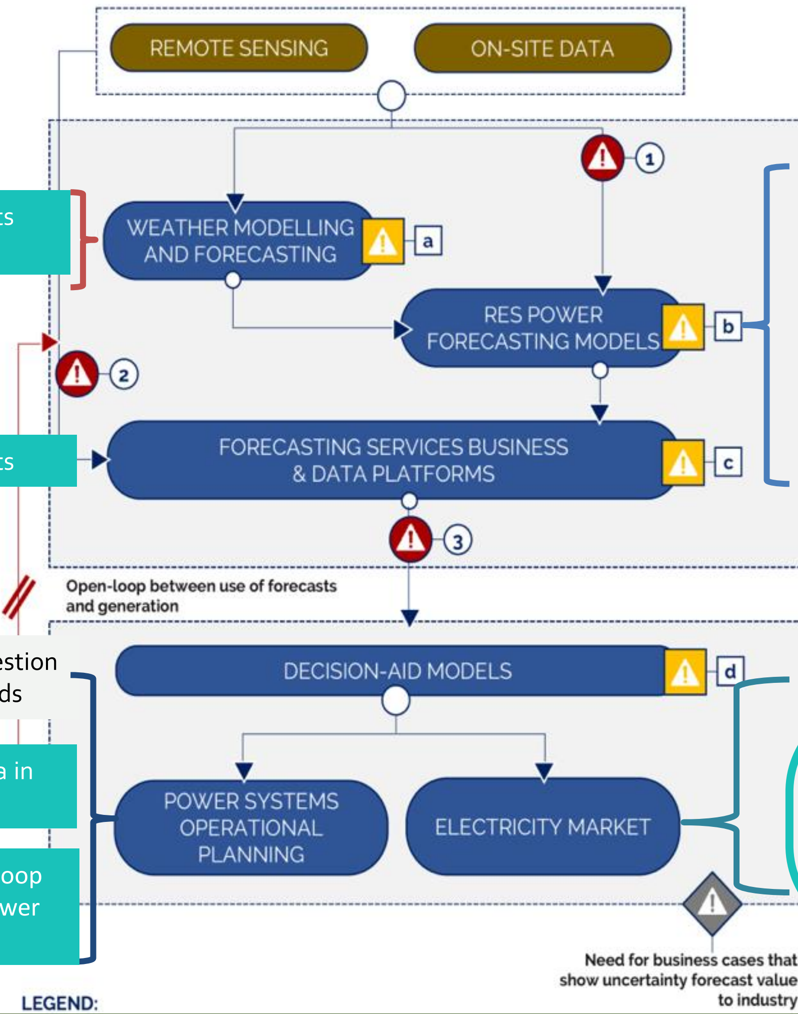
Highly resolved solar irradiance forecasts from Eye2Sky network

Collaborative forecasting / Data Markets

Localized predictive management of congestion and voltage problems in distribution grids

Management of FCR and synthetic inertia in isolated power systems

Combined software and hardware in the loop tests for distribution grids and isolated power systems with high RES penetration



Seamless generic RES forecasting

Data-driven wind power forecast with multiple data sources

Forecasting RES production considering curtailment for increased RES penetration in isolated power systems

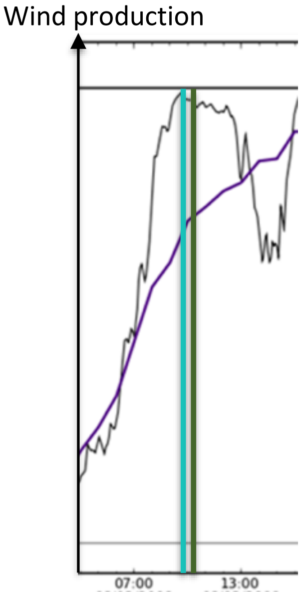
Flexibility Forecast at the TSO/DSO interface

Predictive maintenance of solar plants

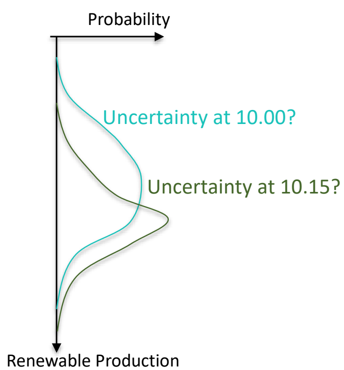
Optimized dispatch of RES with storage

Data-driven bidding strategy of RES + storage

Use Case: Optimize the value chain of trading including storage, under short-term uncertainty



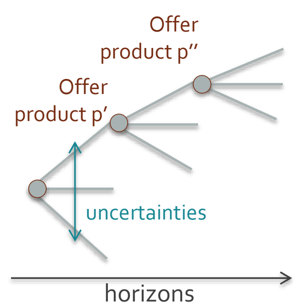
Renewable Forecast

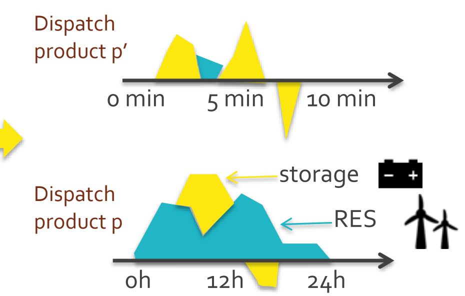


Market Forecast

Step 1: Optimize offer on available short-term markets (energy, ancillary services)

Step 2: Optimize storage dispatch





Feedback on dispatch performance

Utilities expectations:

Better battery performance

- Add a deadzone to the battery dispatch algorithm
- Reduce degradation without impacting performance (Temperature 25 °C +/-3 °C).
- Performance ratio above 90% (charge/discharge).
- Batteries warranty remains a challenge.

Reduction of forecast errors

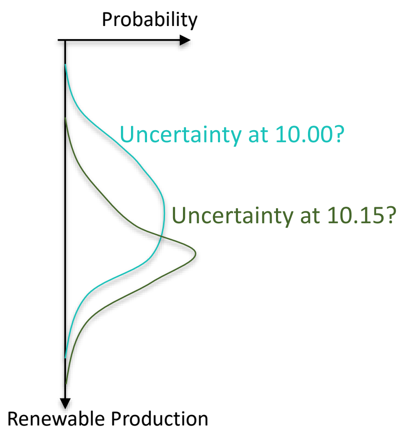
- Wind Forecast errors are partially predictable.
- A Neural Network adjustment can reduce deviation costs by between 40% and 65%.
- Neural Network adjustment allows to improve forecasts and reduce imbalance costs.

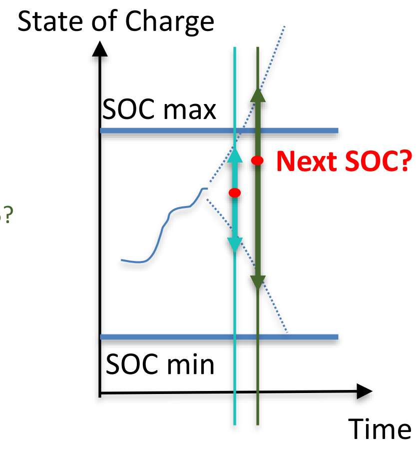
Optimize system operation

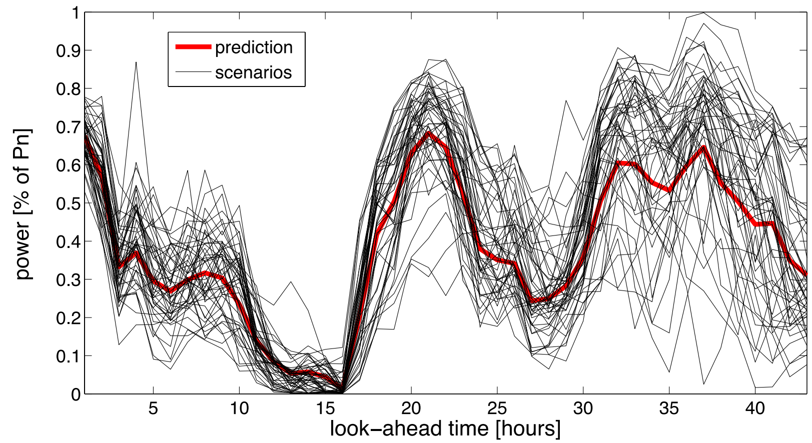
- For minimization of imbalances and battery stress.
- Integration of a degradation factor and compensation ratio into the optimization problem, for:
  - Optimal battery compensation power;
  - Optimal battery energy usage.

KPIS Defined in Smart4RES

In decision problems with storage, temporal correlation in renewable uncertainty is important



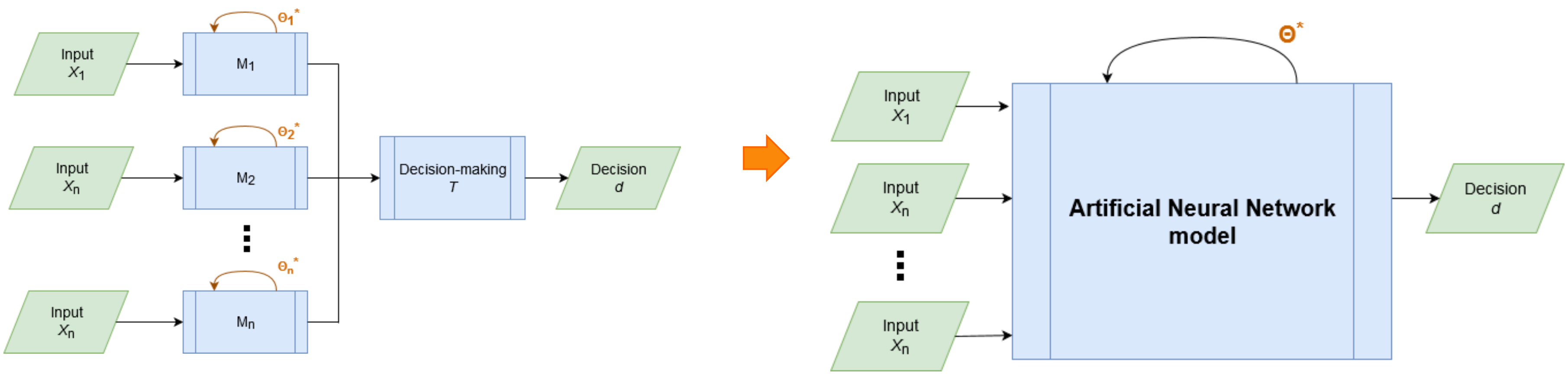




- Independent probability distributions at each time steps don’t inform on the sequence of possible events
- This is why scenarios and now uncertainty regions were proposed

2. Streamlining the process of getting optimal value from data and forecasts

- How to simplify the model chain



Forecasting

Artificial Intelligence able to integrate:

- temporal constraints
- Uncertainties

3. Utilising energy storage to mitigate uncertainties on renewable production

BESS (Battery Energy Storage System) embedded in Cobadin Wind Power Plant

edp renewables

WPP Cobadin

26MW

13 WTGs Vestas V90 (2 MW)

LG Chem

Modular Electrical Energy Storage System (BESS)

Installed Power/Energy (@BoL):

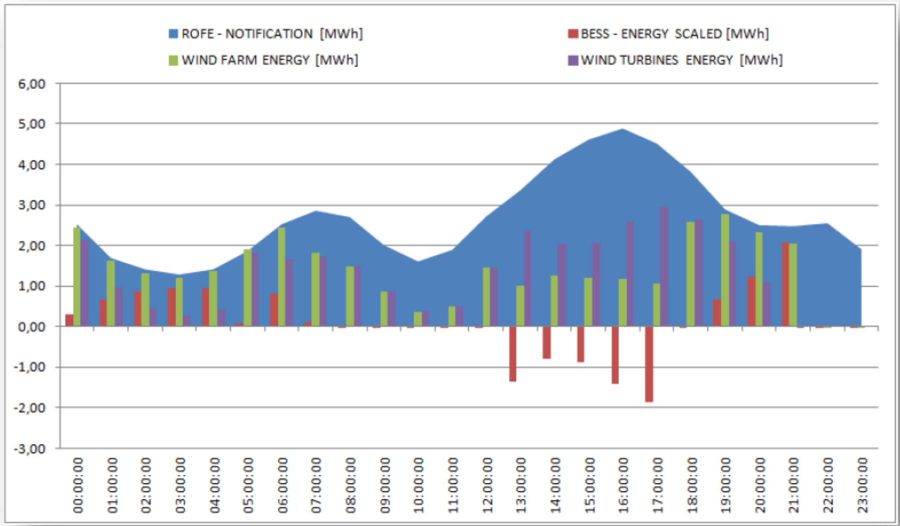
1,26 MW • 1,368 MWh

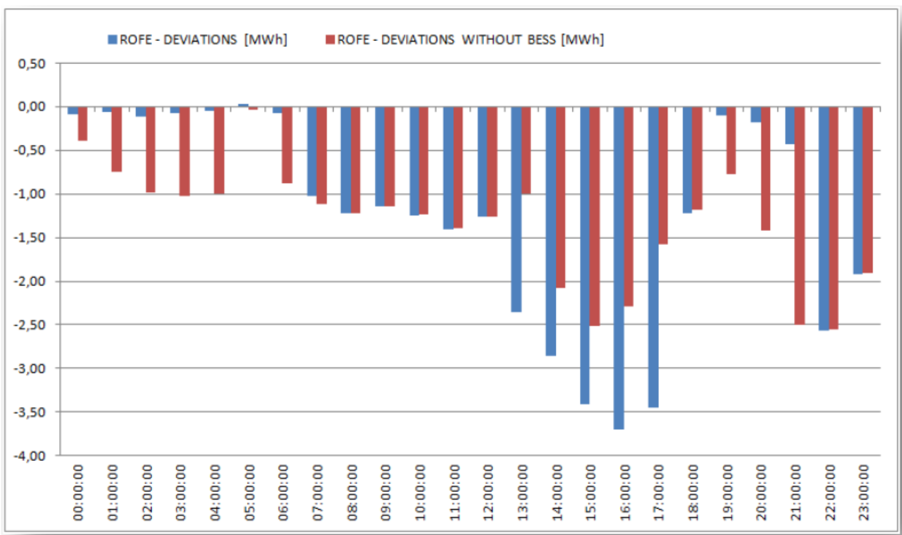
(1MW during 1 hour at BESS POI)

EDPR aims to study and test following **applications/use cases** for energy storage in combination with wind power generation, in order of priority:

- **Energy Management:**
  - Reduce forecast errors from the power schedule submitted day-ahead to reduce balancing costs.
  - Reduce the energy losses resulting from TSO curtailments.
- **Ancillary Services:**
  - Frequency stability and providing primary reserve.
  - Voltage stability related to reactive power.
  - Reactive power compensation at no-load (meaning no active power generation).

3. Utilising energy storage to mitigate uncertainties on renewable production





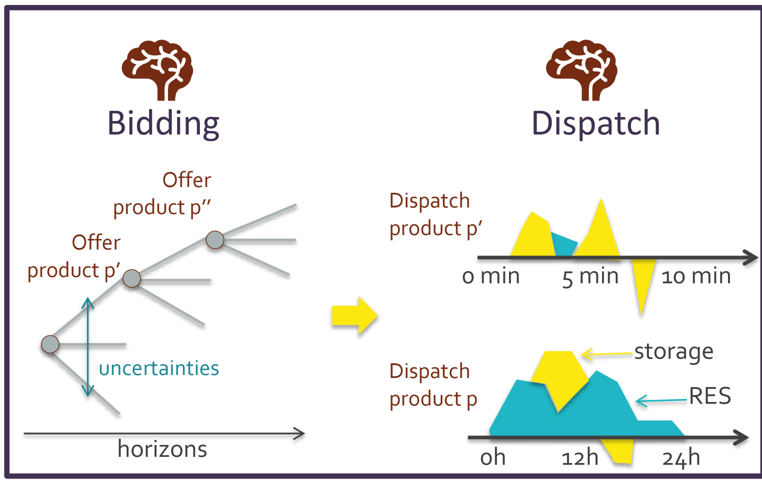
- **RoFe algorithm worked correctly, discharging in order to reach the Physical Notification**
- **WPP production increased above 2 MW at 19:00**, thus **correctly allowing the RoFE compensation to re-start.**
- **In between, the system tried to charge (despite the RoFE) in order to avoid going below acceptable SOC**

Rofe -> System Dispatch Control

3. Utilising energy storage to mitigate uncertainties on renewable production

Experimentation site
Cobadin, Romania (EDP-R)

Multi-objective optimization by Data-driven / AI-based method



- Maximize revenue on multiple markets (e.g. energy + ancillary services)
- Minimize imbalances / penalties on these markets
- Minimize operational costs e.g. wear&tear
- …

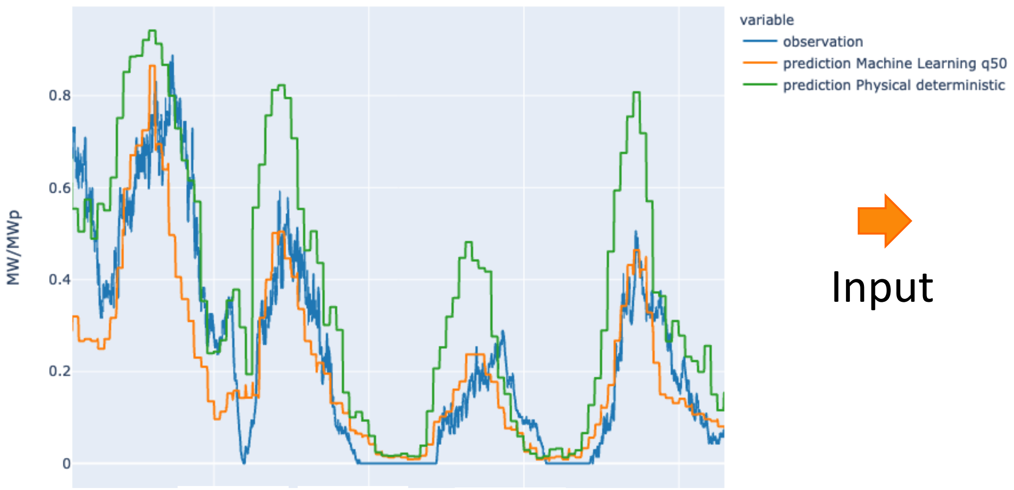
KPI: revenues at least equivalent to state-of-the-art solutions (revenue increased by +20-25% vs bidding on a single market)

Subject to Constraints:

- Contracts in place
- Continuous update on weather and market forecasts
- Storage constraints
- Grid constraints / setpoints (e.g. curtailment or Automatic Generation Control)

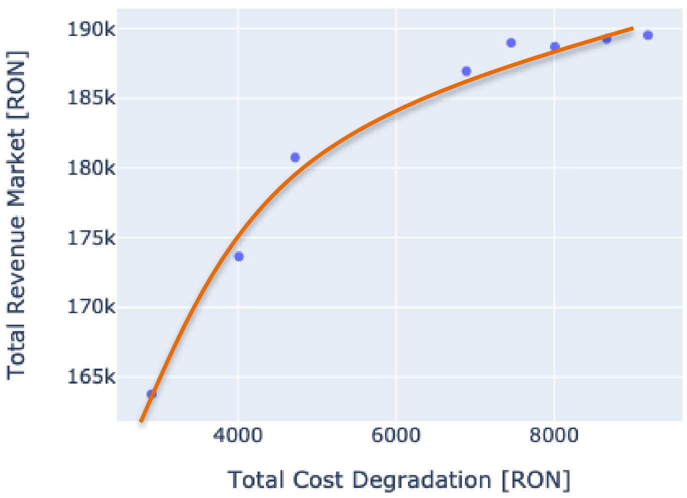
Initial Results (Offering on energy market + degradation)

Machine Learning reduces forecasting error (improvement of -6% RMSE vs physics-based model)



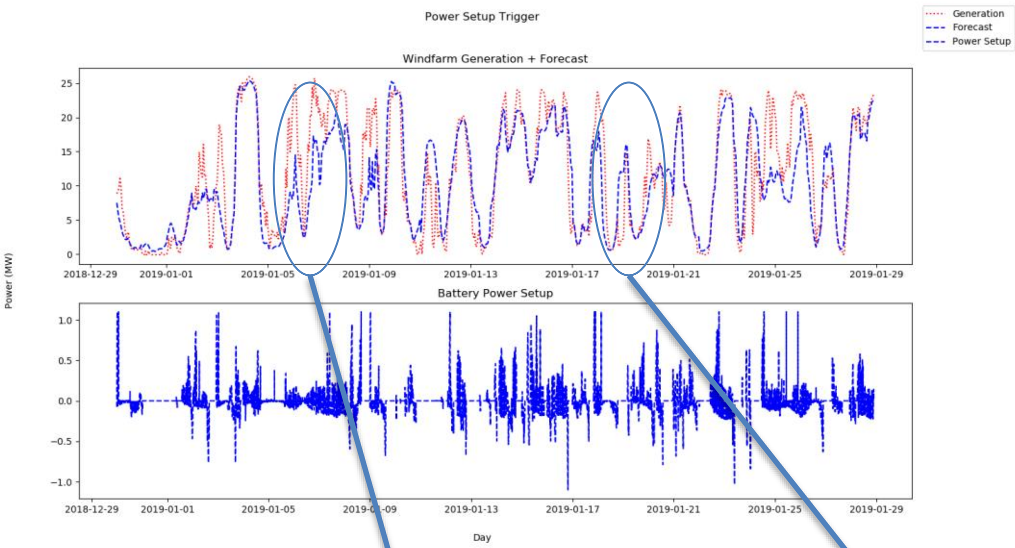
Input

Multi-optimization enables to derive an optimal front of decisions, balance between revenue and battery degradation

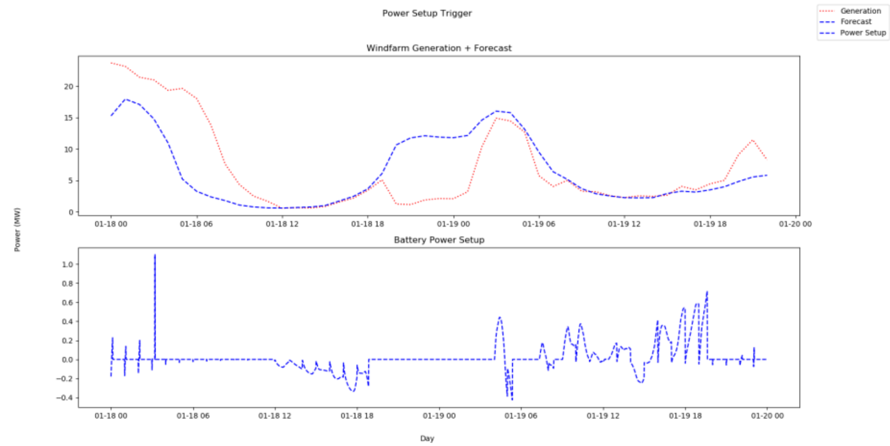


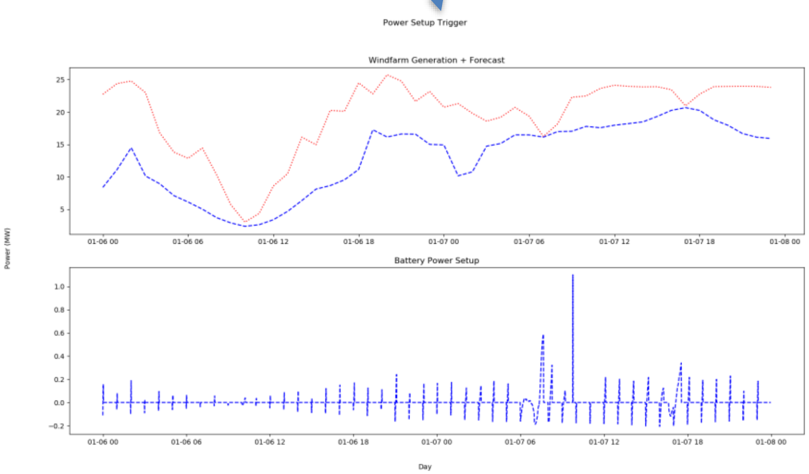
Simplified linear degradation model with constant price (30 Eur/cycle)
Training on 2018/2020, Testing on 145 days of 2020
Results given per MWp of wind capacity
Battery capacity in MWh is assumed 20% of installed wind capacity

3. Utilising energy storage to mitigate uncertainties on renewable production



- The battery is able to compensate minor deviations
- On higher deviations there is no ability to compensate





- On constant deviations the battery compensates small portions
- The battery charges when there are no deviations

3. Utilising energy storage to mitigate uncertainties on renewable production

Compensation Ratio

$$C = \frac{D_C}{D.B}$$

, where C is the compensation ratio, Dc the Deviation compensation, D the total deviations and B the battery capacity

$$C = 12.5\ \%$$

Measurements	Compensated Deviation (MW)	Total Deviation (MW)
Mean	0.93	1.06
Std	4.50	4.70
Min	-17.13	-17.13
25%	**-0.82**	**-1.39**
50%	0.35	0.61
75%	**2.47**	**3.31**
max	14.53	14.53

- Utility of requirements & Use Cases
  - Focus specific situations where we need improvements of forecasting and decisions ('large errors')
  - For utilities, able to 'choose' appropriate model given the diversity of available solutions
- Challenges
  - Validation from industrial operation is particularly important for storage (dispatch, degradation)
  - Bridging the gap between academia and industry
- Next steps
  - Predictive models adaptive to the uncertainty levels & utility needs
  - Machine-Learning / Artificial Intelligence alternatives to optimization models