Dynamic Dimensioning of Balancing Reserves with Machine Learning Algorithms

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Agenda


elia

DYNAMIC DIMENSIONING OF THE FRR NEEDS

31/10/2017

How to balance power systems with increasing uncertainty driven by renewable generation?

How can machine learning provide solutions to predict and cope with this uncertainty?

Implementation of a dynamic dimensioning method for reserve capacity to balance the power system

Balancing increasing uncertainty in power systems

- **Imbalances result in frequency deviations, and large deviations result in protective disconnection of generation units and loads, and eventually system black-out.**
  - ➢ Interconnected system: each TSO is responsible for the balance in its control zone
  - ➢ Unbundled system: each market party is responsible for the balance in its portfolio

Uncertainty in Generation

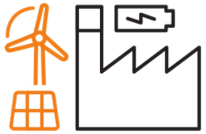
- Power plant outages
- Unforeseen variations of renewable and sustainable generation

CHALLENGE: Increasing shares of (offshore) wind and photovoltaic power

Uncertainty in Demand

- Unforeseen demand variations

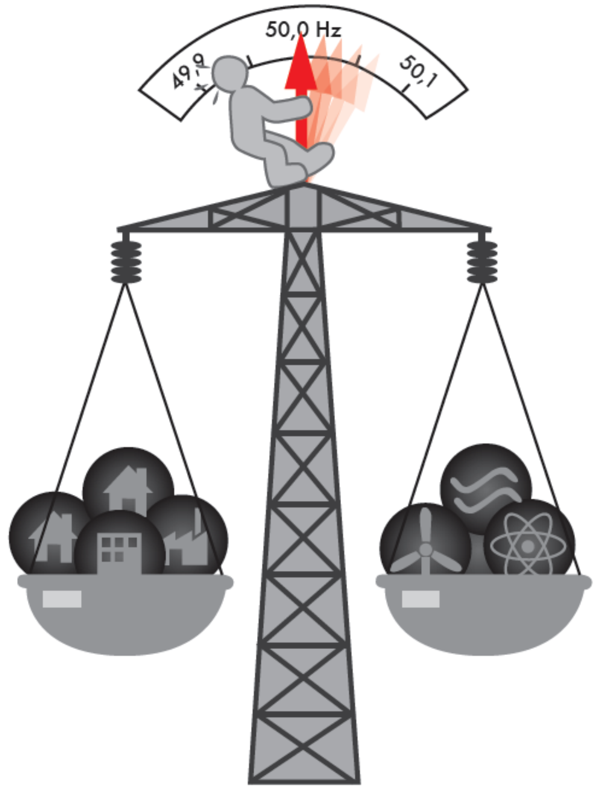
CHALLENGE: Electrification of heating and mobility



Uncertainty in the Network

- Transmission line outages

CHALLENGE: integration of HVDC-interconnectors



$$\sum P_{load} = \sum P_{generation}$$

Reserve capacity for balancing the power system

Elia, as transmission system operator, is responsible for covering the residual system imbalances between injection and off-take in its control zone by using reserve capacity

Elia incentivizes market players to balance their portfolio (imbalance tariffs)

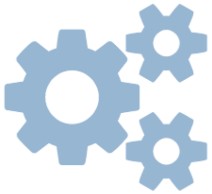
- Facilitated by using day-ahead and intra-day markets
- Facilitated by using balancing markets (allowing the participation of new technologies for flexibility)

Elia contracts reserve capacity (to ensure availability), which is activated in real-time to cover residual imbalances

- **aFRR (R2):** fast-response reserves to react on sudden imbalances and variations.
- **mFRR (R3):** slower-response reserve to cover larger imbalances, and for longer periods.

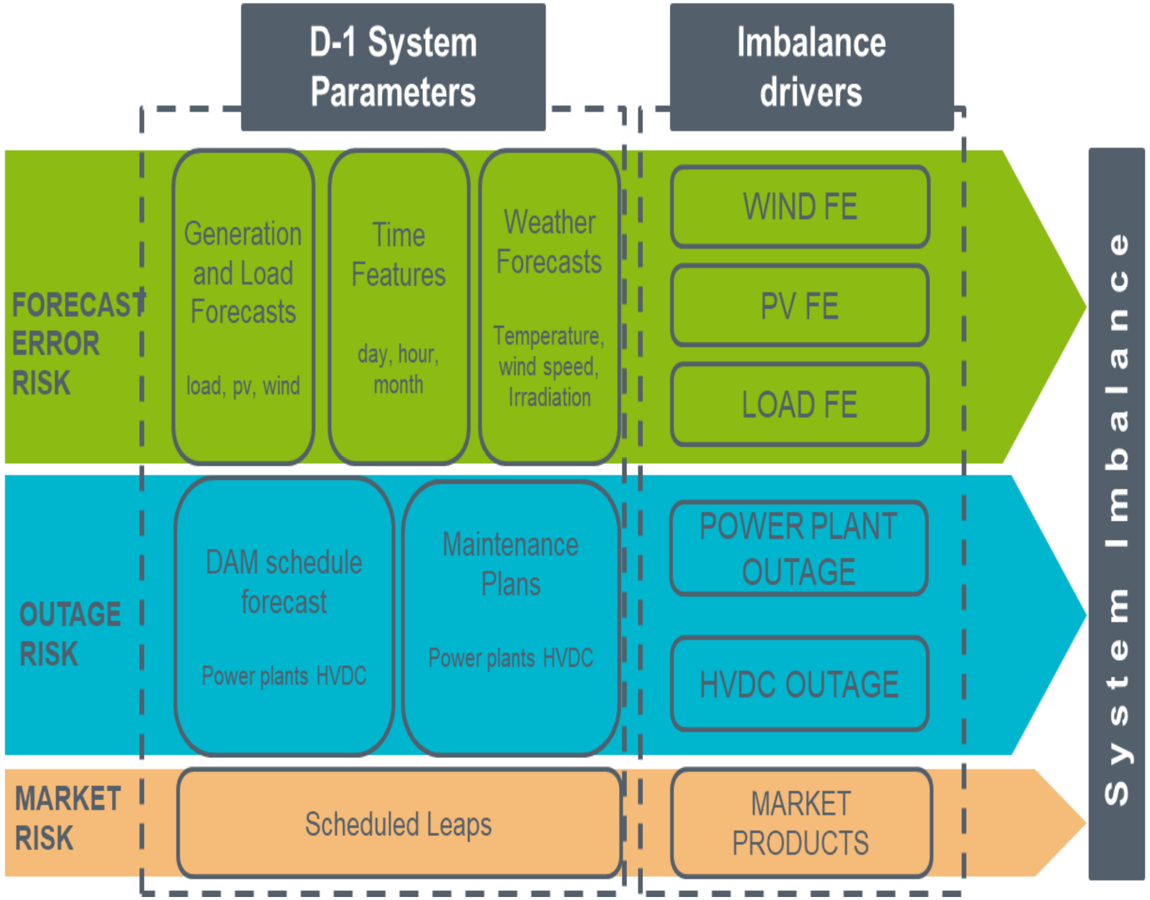
Elia calculates each year the required reserve capacity needs to cover the residual imbalances :

- The current 'static' reserve capacity dimensioning fixes the reserve capacity only once a year.
- Does not recognize that risk for imbalances in the system may depend on system conditions.



Predicting the System Imbalance Risk

- System imbalances are mainly driven by:
  - **Prediction risks:** wind, photovoltaics, load forecast errors
  - **Outage risks:** power plant and transmission line outages
  - **Market risks:** ability of market players to balance their portfolio within 15’
- System imbalances are correlated with predicted system conditions (e.g. power plant and renewable generation schedules):
  - E.g. higher risk for shortages when predicting higher wind conditions
  - E.g. reduced outage risks when power plants are scheduled as unavailable
- Predicting the system imbalance risk allows Elia to dimension its reserve capacity needs to the risks of the system. This requires :
  - Mapping correlations between imbalances and predicted system conditions
  - Leverage these correlations to predict system imbalance based on day-ahead predicted system conditions



Agenda

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Implementation of a dynamic dimensioning method for reserve capacity to balance the power system

How to size the reserve dynamically?[1]

RISK linked to **FORCED OUTAGES**

- **Power plant outage** has effect on SI
- Considered separately as **rare event** for BE system
- Modelled via a "**Monte Carlo**" simulator

HOW TO MAKE IT **DYNAMIC**?
Considering a variable input in the Monte Carlo, e.g.:

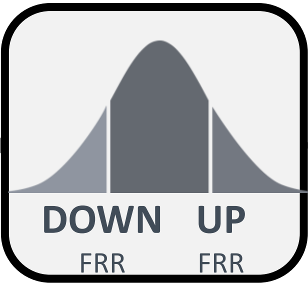
- DA power plant schedule
- HVDC interconnector schedule
- …

RISK linked to **Forecast Errors**

Risk is represented through past system imbalance data

HOW TO MAKE IT **DYNAMIC**?
Need to map system conditions (wind forecast, PV forecast…) to the imbalance risk…

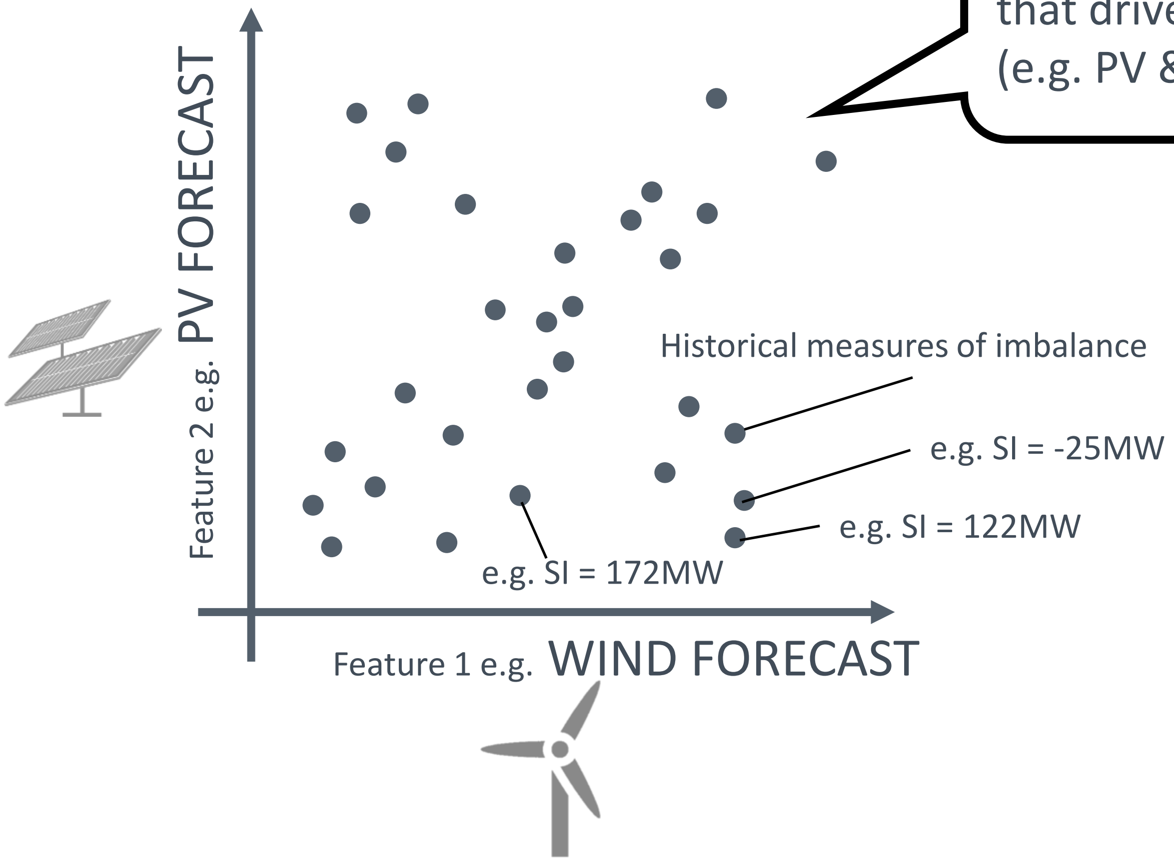
→ **How to map the system conditions to system imbalance?**

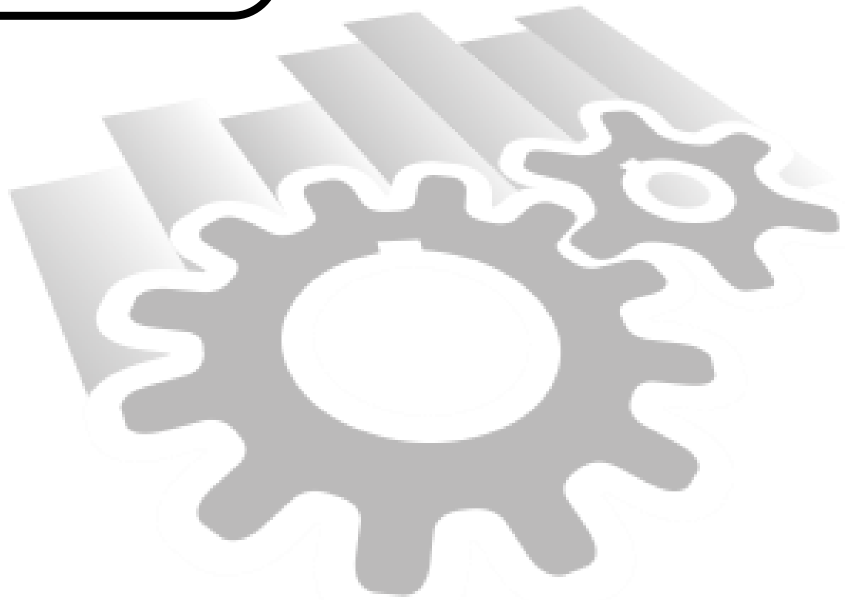


1 Approach proposed in the DRS study and proof of concept performed by ELIA with N-SIDE support

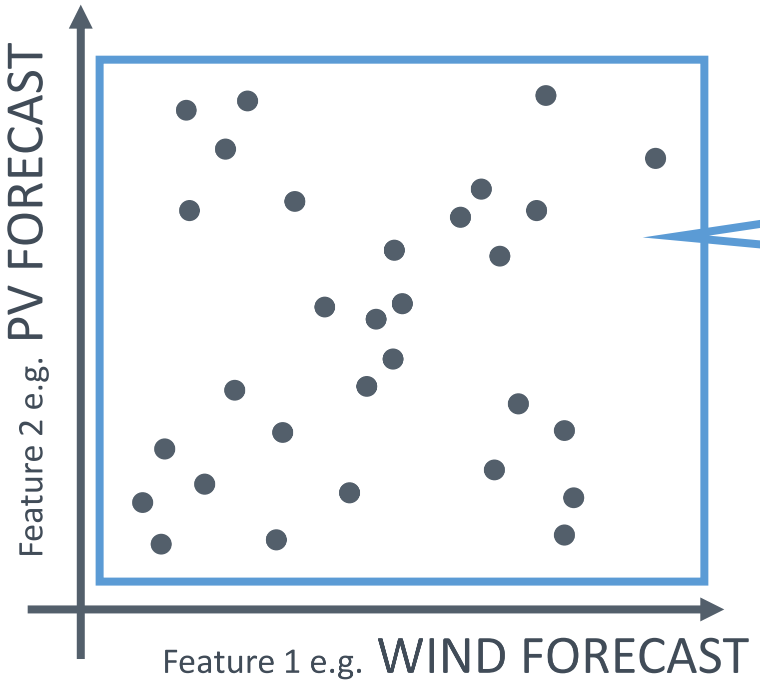
How to map the system conditions to system imbalance?

Step 1: Determine features that drive the imbalance (e.g. PV & WIND)



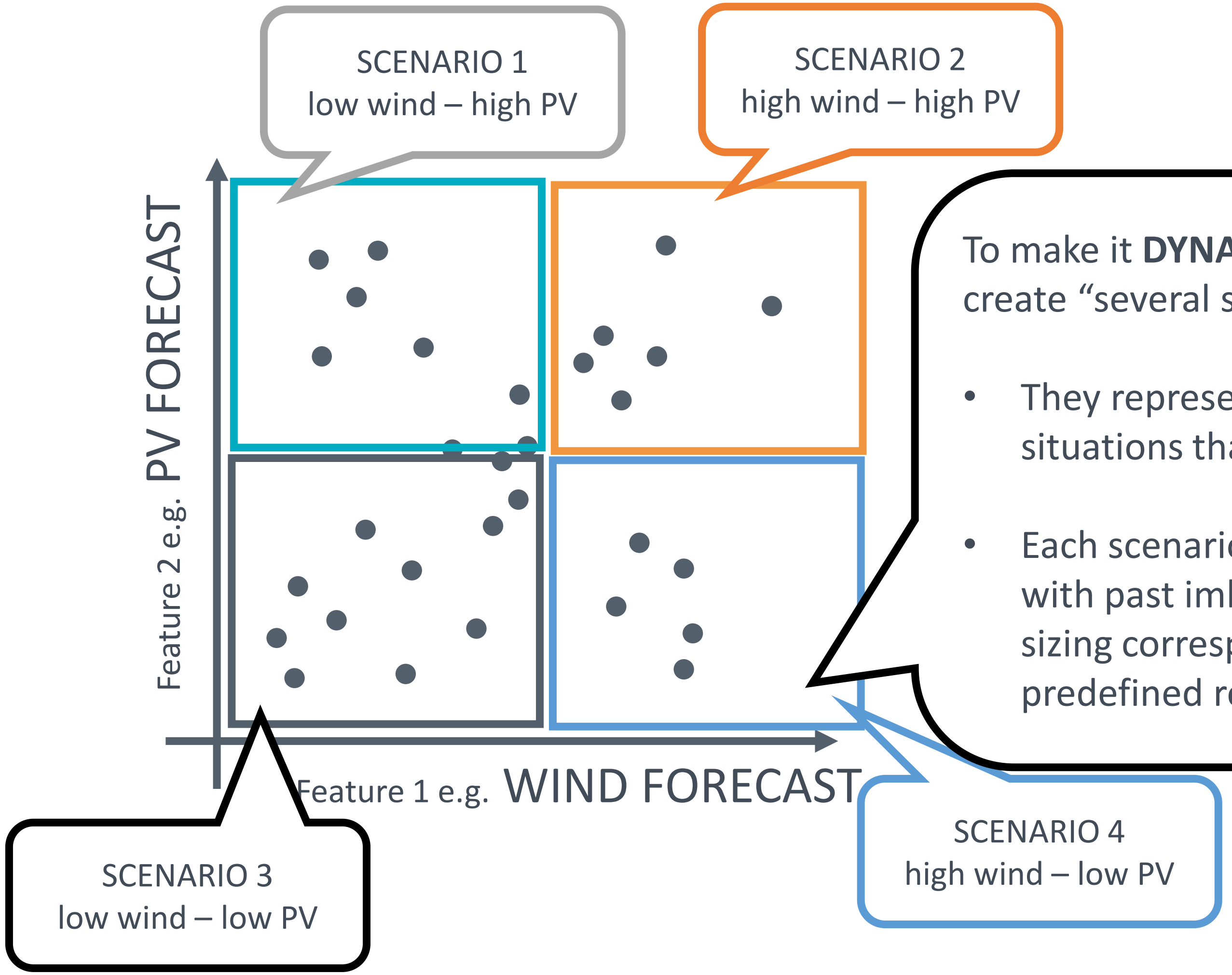


How to map the system conditions to system imbalance?



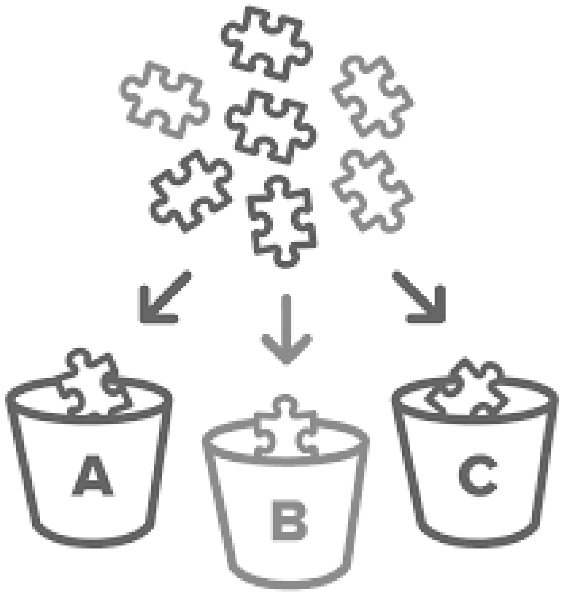
STATIC sizing would just use all the data without considering the features

How to map the system conditions to system imbalance?



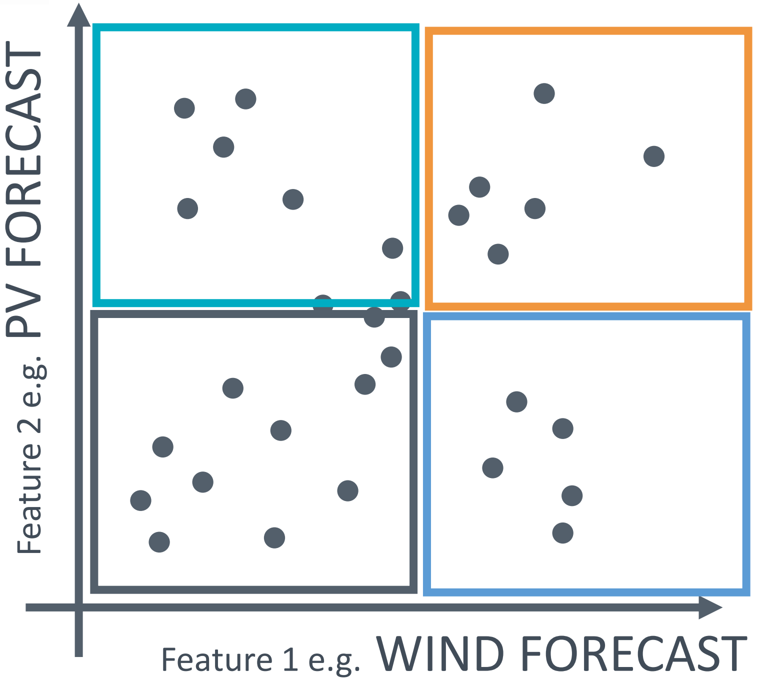
To make it **DYNAMIC**, you need to create "several scenarios"

- They represent several situations that could occur
- Each scenario is associated with past imbalance data and sizing corresponding to predefined reliability



How to map the system conditions to system imbalance?

What are the issues & open questions with such an approach?



This approach seems to work **qualitatively**… The problem is how to **quantitatively** compute these scenarios.

- Each feature is split into 2? 3? 4?... buckets
- How to compute each interval?

How to design a **methodology to compute these parameters** carefully?

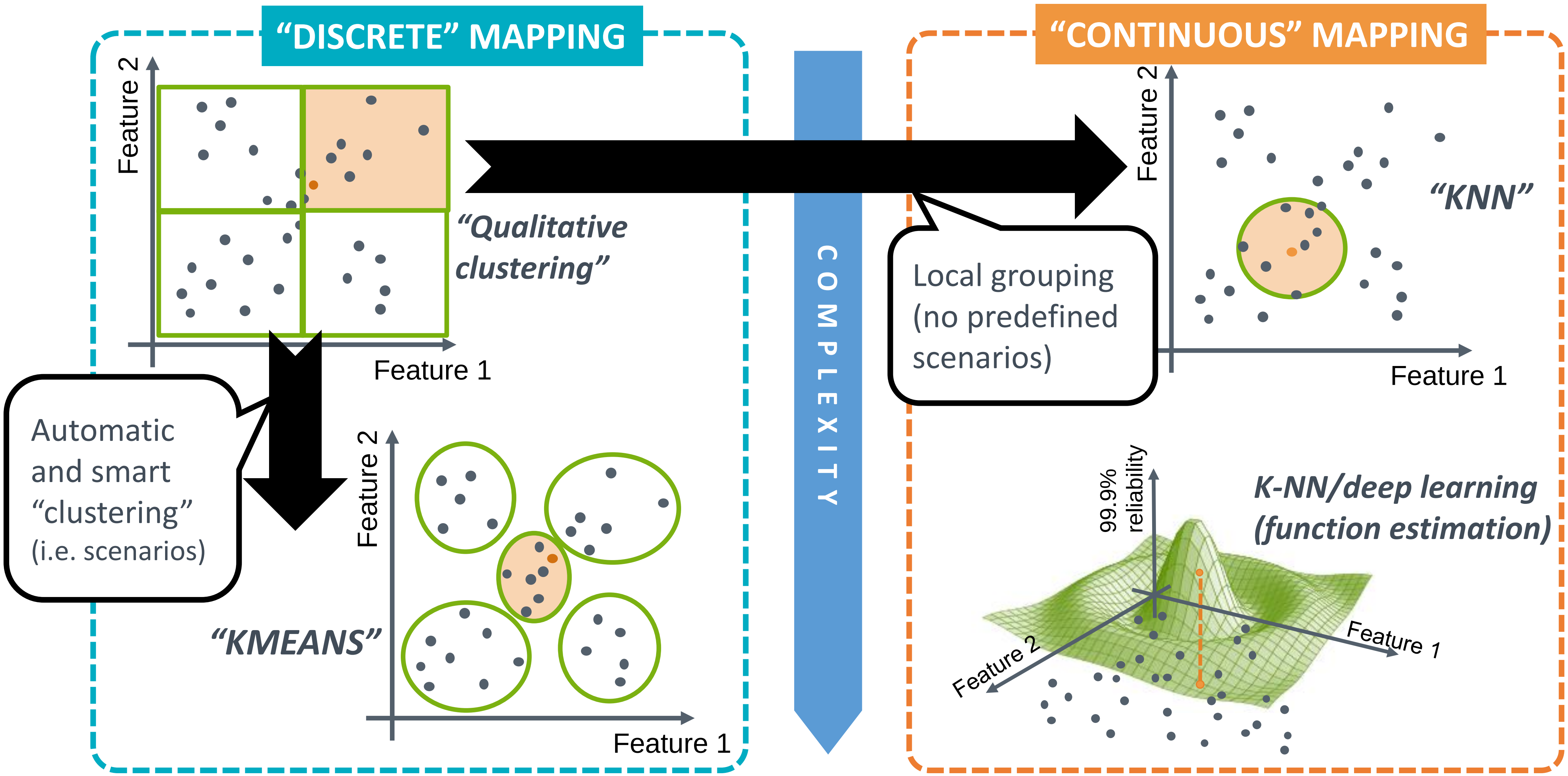
Even if an agreement is found on these parameters, how to **automatically update them with new data** (large amounts of data)?

More features are needed to properly make the mapping → with this basic method, **the number of scenarios will grow exponentially**, e.g. if each feature is discretized into 2 values:

- 2 features → 4 scenarios
- 10 features (which is reasonable) → 1024 scenarios

These are key concerns that can be addressed with MACHINE LEARNING

Machine learning offers powerful tools to carefully map the system conditions to imbalance



Machine learning offers powerful tools to smartly map the system conditions to imbalance

"DISCRETE" MAPPING

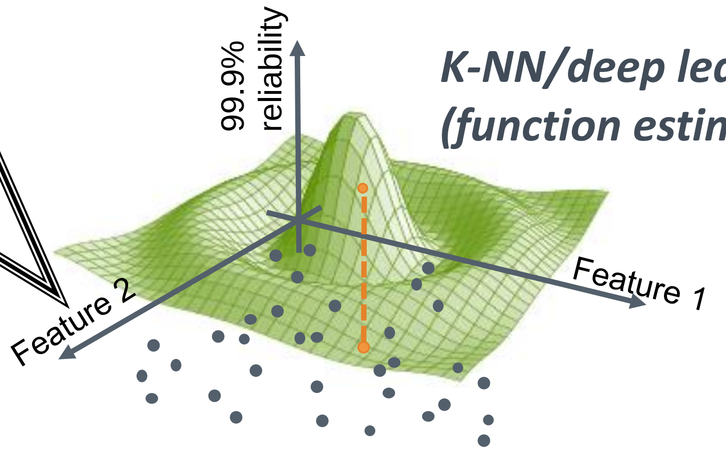
"CONTINUOUS" MAPPING

DEEP LEARNING & MORE ADVANCED APPROACHES?

- **Neural networks and deep learning** are powerful machine learning approaches, also considered for dynamic dimensioning of reserve
- However, they are not the most suited for this application for technical reasons linked to the methodology (i.e. the need to convolve an FE distribution with FO distribution…)
- Though they could be applicable considering some adaptations
- More **advanced techniques** relying on **hybrids** of several ML algorithms are also leveraged towards industrialization

Automatic and smart "clustering" (i.e. scenarios)

Local grouping (no predefined scenarios)



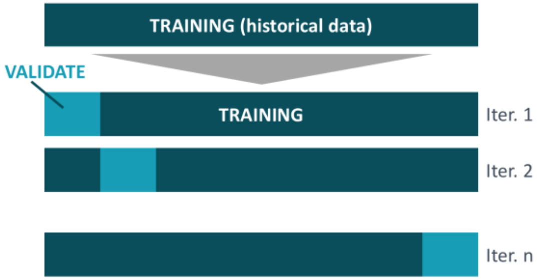
K-NN/deep learning (function estimation)

Machine learning Methodology: from Model Design to Prediction

- 1 -
MODEL DESIGN

OUTPUT theoretical ML model:
- # clusters?
- Features?
- Parameters of the algo…

- Define a list of possible models
- **TRAIN & VALIDATE** on historical data
  (get the most out of the data)



MODEL 1
MODEL 2
MODEL 3
…
MODEL N

KPI 1 … KPI k

The models are assessed and compared against several KPIs

MODEL x

Machine learning Methodology: from Model Design to Prediction

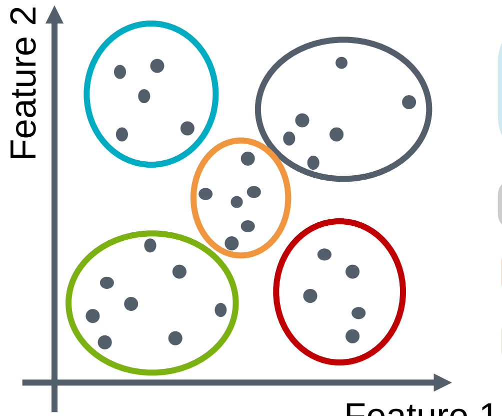
DATA INPUT
Historical data (>1 year) of SI and system features (DA forecast of wind, PV…)

- 1 -
MODEL DESIGN

OUTPUT
theoretical ML model:
- # clusters?
- Features?
- Parameters of the algo…

- 2 -
TRAINING

OUTPUT
The ML model trained on past observed data



Scenario 1

Up reserve = xxx
Down reserve = xxx

Scenario 2 •••

Scenario 3 •••

Scenario 4 •••

Scenario 5 •••

Machine learning Methodology: from Model Design to Prediction

- 1 -
MODEL DESIGN

OUTPUT
theoretical ML model:
- # clusters?
- Features?
- Parameters of the algo…

DATA INPUT
Historical data (>1 year) of SI and system features (DA forecast of wind, PV…)

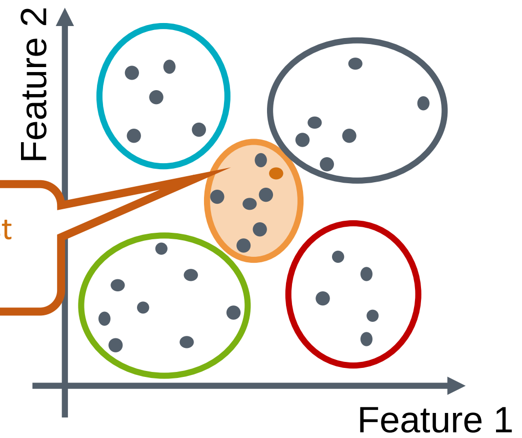
- 2 -
TRAINING

OUTPUT
ML model trained on past data

DATA INPUT
Day-ahead system conditions for the next day

- 3 -
PREDICTION

Imbalance risk for the next day



Orange point = forecast features for next day

Scenario 1
Scenario 2

For each hour of tomorrow,
check in which cluster we are.
E.g. Tomorrow at 10am is cluster 3!

Scenario 3

Up reserve = xxx
Down reserve = xxx

Scenario 4
Scenario 5

Agenda

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The timeline of the Dynamic Sizing Method

STATIC

Sizing for the full year

- **Constant capacity** for the entire year
- **Basic** computations based on observed system imbalance

Year ahead | Month ahead | Day ahead | DA market | D Day

DYNAMIC

Advanced methodology based on **MACHINE LEARNING**

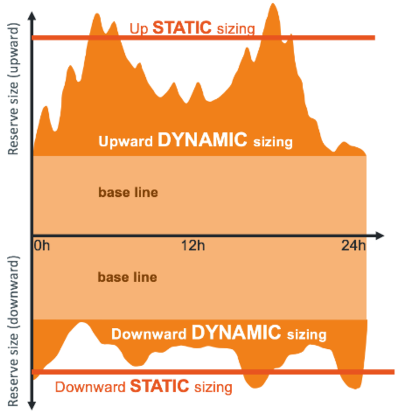
Training Machine Learning tool

Historical data of system conditions and imbalance used to train algorithms for **detecting patterns**

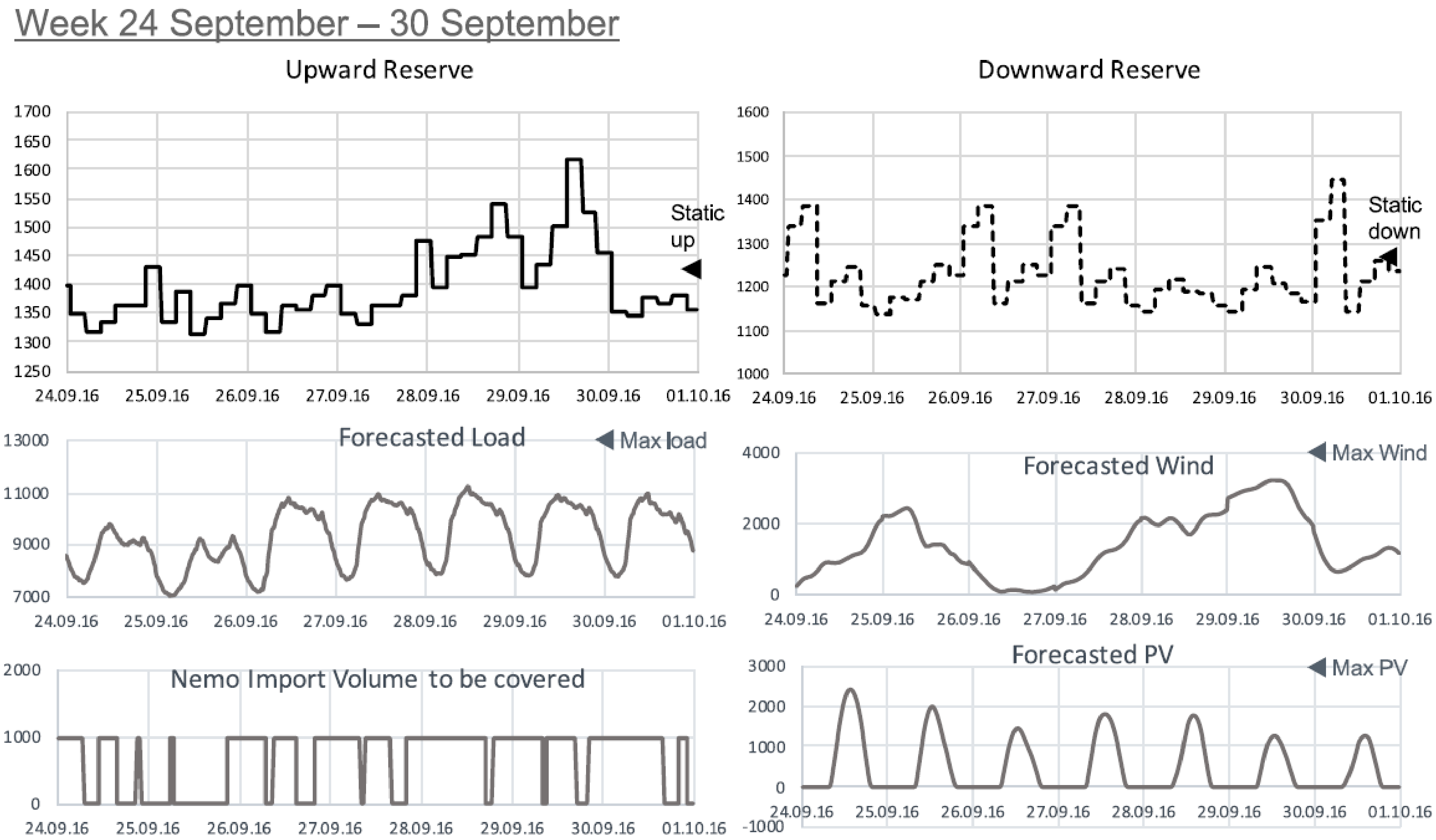
Sizing

Forecasts of
- Demand
- Renewable generation
- Power plant schedules
- Schedule of HVDC-cable

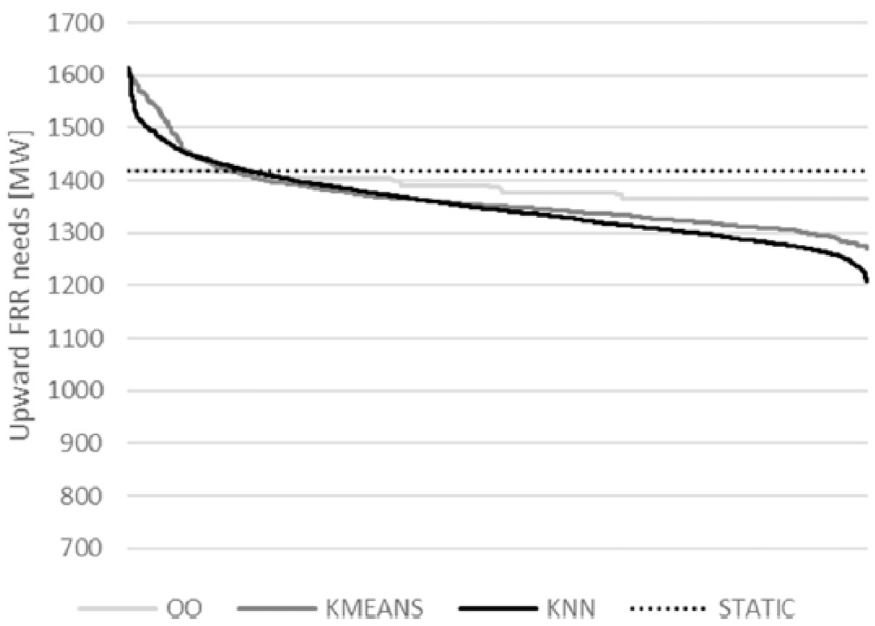
Procurement

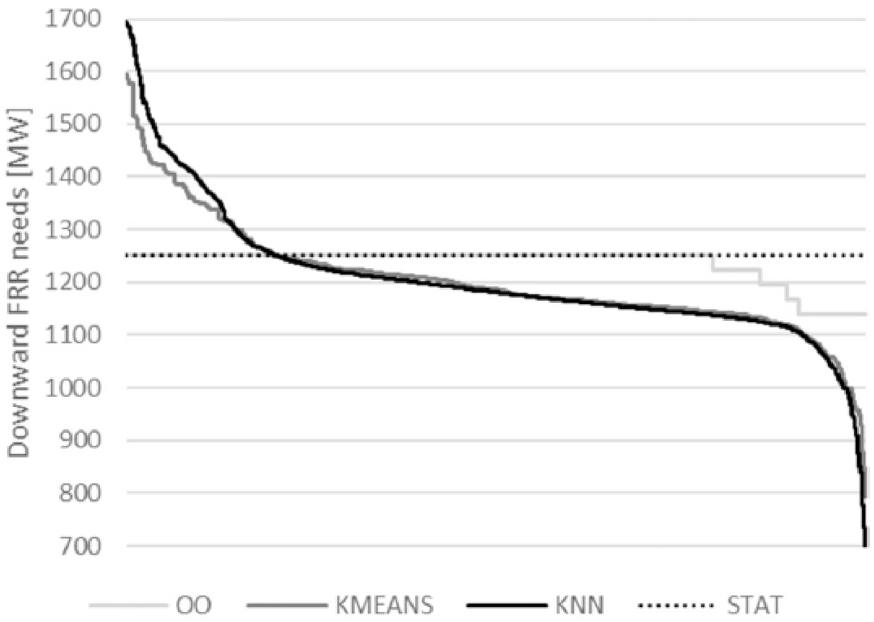


Example week



Cumulative density function of upward and downward reserves





- 80-85% of the time, ML methods below the static requirement
- Downward reserve requirements below 1 GW only 2.5% of the time
- k-means and KNN quite close, but still occasional differences in peak requirements

Smooth spread of risk in dynamic sizing methods

Comparison of the KMEANS, KNN and static methods on their reliability level and corresponding FRR needs for the high and low risk periods.

		KMEANS		KNN	
		Static (Reliability, FRRneed)	KMEANS (Reliability, FRRneed)	Static (Reliability FRRneed)	KNN (Reliability, FRRneed)
UPWARD FRR NEEDS	High Risk	99.86%; 1417 MW	99.89%; 1457 MW	99.84%; 1417 MW	99.84%; 1463 MW
	Low Risk	99.96%; 1417 MW	99.91%; 1304 MW	99.96%; 1417 MW	99.91%; 1271 MW
DOWNWARD FRR NEEDS	High Risk	99.87%; 1251 MW	99.90%; 1362 MW	99.96%; 1251 MW	99.98%; 1384 MW
	Low Risk	99.97%; 1251 MW	99.89%; 1053 MW	99.97%; 1251 MW	99.92%; 1025 MW

- All methods are seeking to achieve a reliability of **99.9% reliability** *on average*
- Definition of low/high-risk periods: periods with lowest/highest 20% reserve capacity
- Static sizing tends to ***over-insure* in low-risk periods**, ***under-insure* in high-risk periods**

Sizing results for 2020

Average, minimum, maximum reserve requirements, dynamic potential (Δ) and dynamic spread (expressed in MW).

	Upward					Downward				
	Avg	Max	Min	Δ	Spread	Avg	Max	Min	Δ	Spread
STAT	1417			–	–	1251			–	–
KMEANS	1365	1616	1270	52	346	1204	1593	794	47	799
KNN	1353	1616	1208	64	407	1205	1693	698	46	995
OO	1387	1418	1364	30	53	1237	1252	1140	14	112

- Potential of dynamic sizing to reduce requirements is robust to ability of market players to forecast
- Lower ability of market player to control imbalances => greater benefits of dynamic sizing

Average, minimum, maximum reserve needs, dynamic potential (Δ) and dynamic spread (expressed in MW) for the *high* and *low* 2020 scenarios.

		Upward					Downward				
		Avg	Max	Min	Δ	Spread	Avg	Max	Min	Δ	Spread
High scenario	STAT	1364			–	–	1180			–	–
	KMEANS	1325	1473	1243	39	230	1141	1390	715	38	675
	KNN	1318	1491	1190	46	301	1145	1527	628	35	899
	OO	1339	1364	1320	25	45	1160	1181	1027	20	154
Low scenario	STAT	1564			–	–	1426			–	–
	KMEANS	1471	1971	1325	93	647	1356	1710	960	70	750
	KNN	1436	1977	1245	128	731	1362	2031	844	64	1187
	OO	1546	1565	1532	18	33	1420	1427	1377	6	50

Sizing results for 2027

Average, minimum, maximum reserve needs, dynamic potential (Δ) and dynamic spread (expressed in MW) for the *post-nuclear 2027*scenario.

[MW]	Upward					Downward				
	Avg	Max	Min	Δ	Spread	Avg	Max	Min	Δ	Spread
STAT	1284			–	–	1340			–	–
KMEANS	1186	1534	905	98	629	1286	1700	866	54	834
KNN	1160	1532	793	124	739	1286	1778	841	54	937
OO	1253	1284	1205	31	78	1327	1340	1272	13	67

- Post-nuclear system requires fewer reserves
- Benetis of dynamic sizing persist

Proof of Concept on 2020 and 2027 shows

- Better management of reliability with higher FRR requirements during higher-risk periods
- Financial gains following reductions in average FRR requirements (outweighing the implementation costs)
- A robust methodology towards the middle and long-term system with more uncertainty driven by renewables
    - **With increasing advantages under higher share of renewable generation in 2027**

The method is adaptive

Trends in the system (better or worse performance of BRPs in terms of balancing) will immediately impact the future reserve needs.

The method is transparent

Methods and interfaces allow system operators (real-time) and stakeholders (ex post) to accept the results by understanding how the results are obtained.

The method is robust

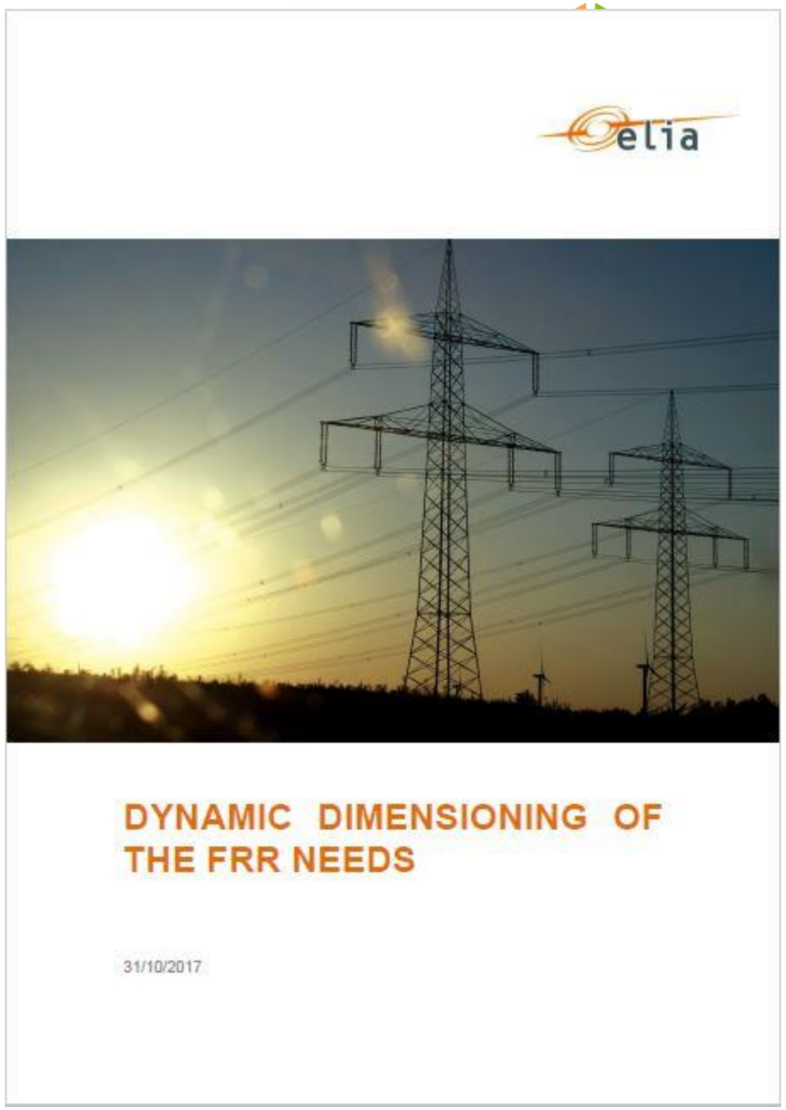
Advantages of the method increase in power systems with larger renewable generation penetration and in a context without nuclear generation.

Conclusions

- Power system operations face increasing uncertainty with large-scale integration of new technologies

- Machine learning can help in capturing this system behavior, and allowing system operators to better cope with these evolutions
  - **Efficiency:** reducing average reserve capacity
  - **Reliability**: ensuring adequate reserve capacity during high needs
  - **Sustainability**: facilitating the integration of renewable energy

- Elia is pursuing implementation of this method towards 2020, while further investigating the potential applications of machine learning in system operations.


DYNAMIC DIMENSIONING OF THE FRR NEEDS

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Proof of Concept : www.elia.be > users' group > working group balancing > projects and publications