Smart4RES

Use cases, requirements and KPIs for RES forecasting

D1.1 Use cases, requirements and KPIs for RES forecasting

WP1, T1.1

Version V2.0

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[1] PU = Public
PP = Restricted to other program participants (including the Commission Services)
RE = Restricted to a group specified by the consortium (including the Commission Services)
CO = Confidential, only for members of the consortium (including the Commission Services)

[2] R = Report, P = Prototype, D = Demonstrator, O = Other

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Executive summary

This document aims to "set the scene" for a logical forecasting model-chain that covers the requirements of current and future power systems and electricity markets with near-100% RES. It prepares input for the remaining WPs and covers as main objective to define the requirements for forecasts considering different use cases and end-users. Although there are a number of well-established use cases for which the requirements are well defined and forecasts are already used in business practices, there are several innovative use cases that will be tested in pilot conditions, where innovative RES forecasts are considered. The expected performance by end-users and corresponding metrics are also surveyed.

This deliverable defines the innovative use cases for the application of the improved forecasting and decision-aid methods developed in this project. All project partners have provided input by reaching out to potential stakeholders to gather their information, requirements and possible use cases. These stakeholders were selected from the extensive customer base of the project partners, international working groups (e.g., IEA, CIGRE, CIRED), and the reference group built in the proposal phase and included TSOs, DSOs, BRPs and traders. The aim is to make the synthesis of forecasting requirements for existing and new use cases, as well as the requirements in National grid codes and EU electricity network codes and guidelines. It also addresses the expected performance by end-users for each business process and the sensitivity of end-users to accuracy and will define performance metrics. Innovative forecasting products and methods for decision-making under RES uncertainty developed in this deliverable have been presented in a public webinar, held in June 2020 in collaboration with IEA-ISGAN.

Use cases addressing important challenges related to renewable energy have been collaboratively selected according to the main goals and resources of Work Packages 2 to 6. The selection process has followed the guidelines described in "8.2 Select Technologies", IEC PAS 62559:2008. Specific KPIs and a standard calculation procedure has also been developed for each use case, re-using a methodology considered in FP7 EU SafeWind project for forecasting skill evaluation and proposing new metrics for supporting the quantification of forecast value beyond traditional accuracy metrics.

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1 Introduction

1.1 Objectives of Smart4RES

The overarching objective of the Smart4RES project is to propose and test a number of forecasting and decision-aid tools to cover gaps and/or prepare the energy system of 2030 and beyond. It is supported by 6 specific objectives that span from the analysis of requirements and needs of stakeholders to the development of next-generation models, until the validation of these models in living labs:

1) Define requirements for forecasting technologies to enable near 100% RES penetration by 2030 and beyond
2) Develop a RES-dedicated view of weather forecasting, leading to improvements in forecasting of the relevant weather variables in the order of 10-15% using various sources of data (satellite, all-sky imagers, NWPs), and the development of very high-resolution forecasting approaches
3) Develop a new generation of RES forecasting tools that are able to improve RES power production forecasting by at least 15%
4) Streamline the process of getting optimal value from data and forecasts, through new forecasting products and data marketplaces, and novel business models
5) Develop new data-driven optimization and decision-aid tools for enabling the large-scale penetration of renewable energy, combined with storage, into the electricity market as well as to provide system services towards TSOs and DSOs
6) Validation of new models in living labs and assessment of forecasting value vs remedies

1.2 The role of Use Cases in the identification of solutions

The—to be developed—forecasting and decision-aid tools in Smart4RES all will have a specific task within a larger system that enables the power system to operate with near 100% RES penetration. This means that all the developments in this project need work together with each other and other parts and stakeholders in the power system.

Within the project a choice has been made to describe the projects development and tools in use cases. Use cases pose a good way to represent how these are supposed to work together and work with other elements in the power system in an abstracted manner. The use cases describe the purpose of a specific forecasting or decision-making tool in a larger context and also describe the interfaces and required communication with systems and stakeholders, the tool in question needs to cooperate with.

This focus on the specific role and interaction of the use case within a larger system makes the use case methodology a very useful tool to:

- Analyze the requirements the system puts on the use case, among others with respect to its purpose and results, and interaction;
- Analyze larger systems to identify possible new opportunities for improvements and reduce risks

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1.3 Applications of Use Cases in Smart4RES

The Use Cases presented in this document are primarily intended as conceptual solutions that are not necessarily assessed using real data within the project. However, a series of applications or test-cases containing operational data or laboratory tests will be considered within the project to evaluate the performance of a selection of the Use Cases in relation to the project objectives. The related applications are mapped below in the different domains of Smart4RES (cf. **Table 1**) and further detailed in **Appendix 1**. The datasets corresponding to the applications can be found in the Data Management Plan of Smart4RES [Smart4RES D1.3 2020].

Application (reference partner) / Domain	Weather Prediction	RES forecasting	Market-related solutions	Grid management solutions
NorthWest meteorological measurement network & PV plants (DLR)	x	x		
Network of PV plants at mid-west of France (HESPUL)		x	x	
RES plants in different areas of Europe (EDP-R)		x	x	
Load & PV in 3 non-interconnected islands aiming at installing RES-based hybrid systems (HEDNO)		x		x
The island of Crete as a reference case for forecasting (HEDNO)		x		
The island of Rhodes as a living lab (HEDNO)		x		x
Simulation and validation of (local) optimisation and control software interacting with a simulated environment using KERMIT (DNV GL)				x
Large Photovoltaic Power Plant (Solaïs)	x	x	x	
Wind Power Plant integrating storage (EDP-R)		x	x	
Floating Offshore Wind Power Plant (EDP-R)	x	x		
Offshore Wind Power Plant (Elia)		x		

Table 1: Mapping of applications in the domains addressed in Smart4RES

1.4 Objectives of the document

The objectives of the present Deliverable are driven by the first objective of the project, which aims at defining requirements for forecasting technologies in all applications that may be useful to reach a near 100% RES penetration by 2030 and beyond. More specifically, the objectives of this Deliverable are:

- Define the innovative use cases for the application of the improved forecasting methods developed in this project
- Make the synthesis of forecasting requirements for existing and new use cases, according to national grid codes and to EU electricity network codes and guidelines
- Address expected performance and sensitivity to accuracy by end-users for each business process

1.5 Structure of the document

The content of this Deliverable starts in **Section 2** with the methodology pursued to develop Use Cases, collect needs of end-users and identify Key Performance Indicators (KPIs). In this Section, particular attention has been placed in the identification of innovations in the solutions proposed on forecasting or decision-making related to RES uncertainties. To that end, Use Cases descriptions have been enriched compared to their standard structure: they incorporate specific sections which describe how uncertainties are handled and what are the claimed innovations.

Then, Use Cases are described in **Section 3** first by an overview and then in more details for each step in the project value chain (from weather/ production forecasts to applications).

An analysis of Use Cases in **Section 4** examines how Use Cases tackle the challenges of RES forecasting and related applications in their various dimensions: use of innovative solutions, associated priority levels and answers to bottlenecks in model and value chains.

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2 *Use Case Methodology*

2.1 Nomenclature

Following the IEC 62559-2 and Use Case descriptions of previous relevant projects [IEC 62559-2], [Integrid 2017], [Sensible 2015], [Nobel Grid], the subsequent terminology is used throughout this deliverable and all Use Cases:

Term	Definition	Reference
Use Case	Set of actions performed by a system, leading to a result that may be valuable to actors, end-users, stakeholders involved in this system	[IEC 62559-2]
Domain	Area of a system defined by concepts and terminology that are commonly accepted by practitioners of the area. Example: In the context of power systems, a domain can be power generation, transmission, distribution, distributed energy resources or customer premises.	[IEC 62559-2]
Actor	Entity that communicates and interacts with the system under discussion. Example: People, software, systems, databases, etc.	[IEC 62559-2]
Role	Role played by the actor in the system	[IEC 62559-2]
Functional requirements	Requirements necessary for the system to behave as expected by actors, end-users.	[Integrid 2017], [Sensible 2015]
Non-functional requirements	General constraints that are independent from specific functions, technology, business products. Example: – Reliability, Fault tolerance, – Security, – Reproductiblity / Flexibility / Scalability, – Priority, – Data Management, – etc.	[Integrid 2017], [Sensible 2015]

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2.1 Use Case Templates

To create a coherent and consistent overview of use cases, all partners contributing were asked to describe their use cases using the same templates. This facilitates a proper understanding of the to be developed applications of technology and ideas within the project to all project partners, including how these relate to relevant other technology application/use cases and stakeholders.

For this purpose, two different formats were used: a short 2 slide version to convey the general highlights and principle of a use case, and second more detailed template to describe the concept in more detail, including the necessary input and output, intermediary steps, related use cases and involved stakeholders.

Based on the use cases provided by the project partners, an analysis of requirements was made, resulting in the definition of additional KPI's which are presented in **Section 2.5**.

The Use Case templates are included in **Appendices 7 and 8**. The full use case descriptions are included in **Appendix 9**.

2.2 Identification of non-functional requirements

A section of the Use Case template foresees the possibility to include non-functional requirements. It is recalled that Use Cases are not meant to capture all non-functional requirements, because their description should remain short and their scenarios should be generic, independent from specific implementations in terms of technology or business conditions.

Non-functional requirements that are relevant in the context of Smart4RES include:

- Flexibility / scalability of a solution for different spatial and temporal scales,
- Security, in particular preservation of privacy,
- Data management: adaptability to realistic conditions experienced by end-users (e.g. massive amount of data streams available to energy traders, missing data for forecasting, etc.)
- Validation of the robustness of algorithms with real data

2.3 Identification of forecasting requirements

Functional requirements are defined in each step of the step-by-step description of the Use Cases. In Smart4RES, an original and important part of functional requirements consists in requirements on forecasting of weather conditions, RES production or other related uncertain quantities. This Section presents the methodology followed to define forecasting requirements: state-of-the-art applications are first analyzed to extract existing forecasting requirements (Section 2.3.1), and completed by needs of forecasting end-users (Section 2.3.2). Then, the methodology to identify innovative solutions is explained in Section 2.4, KPIs associated to forecasting and decision-making are listed in Section 2.5 and the template of Use Case Description in Section 2.6 ends the presentation of the methodology.

2.3.1 Review of forecasting requirements in the state of the art

2.3.1.1 Requirements for market-related applications

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RES forecasting errors have a direct impact on the revenue of RES producers who participate to electricity markets, as deviations between forecasts and observed production lead to imbalances on the energy market that translate into penalties which must be paid to the system operator in order to cover the cost of balancing the system [Morales 2011]. Furthermore RES forecasting errors are known to impact electricity prices in zones with significant RES penetration [Ziel 2017].

Several properties of RES production forecasts are important for a successful application in bidding on electricity markets:

- A classical result of portfolio theory tells that the optimal bid under uncertain production levels corresponds to a specific **optimal quantile** of the expected distribution of production [Morales 2011]. The **calibration** of quantile forecasts, i.e. the reliability of predicted levels compared to observed production, is essential in this context: this ensures that during bidding periods, the observed production level matches the optimal bid with minimal average deviation, hence minimal penalties on the market [Bessa 2017].
- **Sharpness,** i.e. the size of the interval defined by lowest and highest quantiles, is useful for risk-sensitive bidding strategies. For instance, a low sharpness (large size of prediction intervals) signals that the model anticipates a high level of uncertainty, therefore a risk-averse trader will be prone to lower his/her bids in these conditions [Bessa 2017].
- **Calibration of extreme quantiles** is required for offering specific services such as ancillary services from RES or Dynamic Line Rating (DLR). In this situation, probabilistic forecasts must be very reliable on extremal quantiles (e.g. DLR [Dupin 2020]).
- In applications where temporal correlations are important, for instance in the joint operation of RES and storage, **trajectories or ensembles of RES production** should represent as accurately as possible the original production signal. This accuracy can be evaluated by means of an analysis of autocorrelations, scores on global variability or specific events such as ramps.
- As many markets operate sequentially (e.g. day-ahead, intraday, real-time), a **seamless RES production forecast,** i.e. without discontinuities over the horizon range covering the successive markets, enables to take coherent positions through time [Carriere 2019].

In many cases, RES production sites are incorporated into aggregations in order to reach a minimum critical size on electricity markets. In this context of aggregated RES production, the following requirements appear for RES forecasting products:

- Forecasts at the top level of the aggregation should be **consistent** with forecast at lower levels of the aggregation (e.g. the total aggregated production forecast should match the sum of individual production forecasts at the level of individual production sites) [Lenzi 2017], [Ben Taieb 2017].

Prices on markets are usually unknown to RES producers when they bid, and volatility on electricity is generally high, with higher volatility when markets are closer to real-time. Forecasting products related to market quantities (prices, volumes, bidding curves, etc.) are therefore of primary importance for RES bidding and the following requirements exist in the state of the art:

- Deterministic price forecasts (minimized MAE, RMSE) should be **accurate**, i.e. their standard error metrics (absolute error, root mean squared error) should be minimized. Following the certainty equivalent theory, a deterministic information on prices/costs is sufficient if price/costs are independent from the uncertain supply/production variable [Morales 2011].

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- If RES production is correlated to some extent to electricity prices, due for instance to a large penetration of RES producers in the market, then a valuable forecasting product consists in the joint probabilistic distribution of RES production and of the price of interest [Shin 2017].
- If a RES producer can be considered as a potential price maker in a market, then the prediction of the bidding curve resulting from all suppliers [Mitridati 2018] is a useful information on the use of market power.
- In the context of ancillary services, the revenue of the balancing service provider depends on the activation of the corresponding assets. The prediction of the activation probability associated to the provision of ancillary service by the assets of a balancing service provider is an important factor for the optimization of ancillary service bidding [Bruninx 2016].

Forecasting of RES production has become an established service over the last years with many providers who offer professional wind and/or solar power forecasts on an international level. Indeed, the forecasting service where the user contracts one or more providers to send forecasts for a certain set of assets is by far the most popular business model. The advantages from the customer's side are obvious: convenient and quick assignment of vendors, with typically 12 months moderate duration of contracts, no on-premise infrastructure or know-how to generate forecasts need and, if several vendors are contracted, the best-performing providers can be kept and the others skipped easily. As RES forecasting is a mature field of business the basic forecasting products have converged in the sense that many forecasting vendors supply a standardized set of services. This comprises:

- a deterministic forecast of RES production for single plants or aggregates
- forecast horizon typically at least day-ahead but usually longer, e.g. four to ten days ahead
- forecasts are based on combination of different numerical weather models
- regular updates based on real-time data of RES production with update frequency according to the market requirements. The most important parameter is the time resolution of the trading intervals. In Europe updates are usually sent out at least every 15 min in other market systems, e.g. the United States, the market rules require update frequencies of 5 min or higher.
- probabilistic forecast information to assess the uncertainty of the specific forecast values. This can be provided in terms of classical confidence bands or based on ensemble approaches.
- Continuous calibration or re-training of the forecasts based on measurement data of production or further parameters

It turned out that many customers established internal quality control procedures to monitor and evaluate the forecasting performance of their contracted vendors on a regular basis, e.g. weekly or monthly. The error metrics that are mainly used for this purpose are very straightforward: RMSE, alternatively MAE and BIAS either in absolute numbers or normalized to the installed power. In addition, further standard metrics, such as correlation or ramp metrics, or in some cases specially created metrics are applied. The evaluation results are generally meant to provide an incentive to the forecast provider to improve the accuracy. Only in rare cases the payment of the provider is related to his performance ("pay-for-performance model"). Normally, the consequence of not providing a sufficient accuracy over the contract period is not getting a contract renewal.

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2.3.1.2 Requirements for grid management applications

System operators perform three main processes that constitute the day ahead and intraday generation management: the Day Ahead Scheduling (DAS), the Dispatch Scheduling (DS) and the Real Time Dispatch (RTD) in order to ensure constant power supply, to maximize RES energy penetration and to minimize operating cost of conventional units. Especially, system operators of isolated power systems apply curtailment strategies to RES units for security reasons, reducing the RES penetration. To minimize the energy curtailed and the operating costs while the system is kept flexible and stable, system operators need accurate **forecasts -deterministic and probabilistic- of the RES production and of the system load for both day-ahead and intraday periods**.

The main input of the system operator tools comes from RES forecasting models. These models require historical data to tune their parameters and real-time data to run operationally. The required data consists of the high resolution numerical weather predictions and RES unit production measurements, while additional data like RES unit maintenance etc. may improve the forecasting accuracy.

In the case of an isolated power system where curtailment rules are applied to RES units by the system operator, the recorded RES production by the meters corresponds to the penetrated power which may be curtailed [Hatziargyriou 2002, Stefanakis 1999]. System operators, however, need to know the total available RES production in order to perform their functionalities optimally. Consequently, the RES forecasting models should be tuned to provide the **RES production** that would be available before applying curtailment rules. In that case, RES forecast providers should compute the curtailed energy to adjust the historical power recording timeseries. To estimate the rejected RES production, firstly, the set-points applied by the system operators to the RES units should be available. The set-points are the maximum amount of RES production that permit to penetrate to the power grid and are sent to RES units in an hourly base. Additionally, wind speed and wind direction measurements recorded near to RES units are necessary to estimate the total RES production.

System operators of an isolated power system mostly use the hourly point RES forecasts for the day-ahead scheduling procedure and the forecasts with 15-min resolution for the real-time dispatch procedure [Hatziargyriou Pecas Lopes, Matos, 2002, Stefanakis 1999]. Due to the prioritization of solar production, solar power forecasting should be accurate as possible. The **accurate forecasting of ramp events** [Bossavy 2013] potentially represents a significant challenge for power system reliability with respect to the integration of variable generation. System operator main interest is the high forecasting accuracy to avoid security issues. Electrical (power, availability, curtailment) and meteorological data from wind and solar plants, delivered to the forecaster and system operator on a timely and reliable basis, are critical for forecast accuracy. Nowadays, they try to use operationally **probabilistic predictions** as input to more advanced operational tools like the stochastic unit commitment. Uncertainty values surrounding the forecast can be adjusted to best suit the needs of the system operator.

2.3.2 Needs expressed by end-users

2.3.2.1 Questionnaire to stakeholders

The opinion of stakeholders is essential in order to orient the developments of Smart4RES. These stakeholders are working in diverse sectors of research and power system industry. It is composed of 5 short sections combining open questions and multiple choices relative to the current use of forecasting tools, unresolved needs and main sources of interests towards the innovative solutions investigated in Smart4RES. The complete questionnaire is reported in Appendix 10. It has been

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created using the EUSurvey tool, and advertised via Linkedin, Smart4RES newsletter, a webinar and direct contacts.

A total of 12 persons replied to the questionnaire via its online form or bilateral interviews. The profile of respondents is reported in **Table 2.**

Domain	Research	Power system operators	Energy traders – service providers	RES producers
Number of respondents	7	3	1	1

Table 2: Profiles of respondents to Smart4RES WP1 Questionnaire

2.3.2.2 Current use of forecasting solutions

Respondents have indicated their current use of forecasting solutions. **Table 3** maps the different categories of forecasting solutions (in columns) in the applications indicated by respondents (in rows). It is noticed that probabilistic forecasts are the most used of all forecast types in this questionnaire which gathers diverse applications. This contrasts with a previous questionnaire of IEA Task 36 on Wind Forecasting, in which 20% of respondents indicated that they used probabilistic forecasts in their operations [Giebel 2016]. A partial explanation of this difference is that respondents in the present questionnaire are either involved in research or in close connection to R&D developments. Other forecasting solutions have similar levels of use, and deterministic forecasts (ie without quantification of uncertainty) are still commonly used.

	Deterministic forecasts	Probabilistic forecasts	Ensembles	Extreme events (peaks, high or low quantiles, etc.)	High-resolution forecasts (in space or time)	Simultaneous prediction intervals	Ramps of renewable production, load, etc.
Wind Power Forecasting		x	x				X

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Photovoltaic Power Forecasting	x	x			x		
Aggregated RES production Forecasting		x					
Load Forecasting	x						
Long-term Forecasting for distribution systems		x					
Planning Distribution System Operation				x			
V2G		x			x	x	
O&M Predictive maintenance			x				
Bidding in energy electricity markets	x	x		x	x		x
Thermal generator management in non-interconnected area	x						

Table 3: Mapping of current forecasting solutions in applications, Smart4RES WP1 Questionnaire

2.3.2.3 Limits with current forecasting solutions and associated needs

Respondents have mentioned the following limits relative to their use of current forecasting solutions:

- The difficulty to access data for researchers involved in forecasting is mentioned several times, e.g. production data of wind farms for wind power forecasting.
- State-of-the-art nonparametric statistical models appear to be limited in performance compared to machine learning / deep learning approaches
- Forecasting services have lower accuracy than expected
- Forecasting solutions are not adapted to applications requiring real-time response
- In the context of off-grid hybrid systems with thermal generators, errors of short-term PV forecast lead to the need of backup systems to avoid load shedding or blackout that are complex and generate carbon emissions

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- Wind production forecasts are based on numerical weather forecasts that do not use weather measurements on the location of wind farms.[1]
- Curtailment forecasting is difficult with the data publicly available
- Detection of sudden events such as localized storms are not well predicted

The following needs have been specified, most of which are specific to particular applications:

- Multi-time scale forecasting[2]
- Real-time forecasting model for Vehicle-To-Grid application
- Monthly spatio-temporal wind power generation integrating the correlation with hydroelectric production
- Need of more reliable load and RES forecast with smaller deviation for grid management
- Need of forecasting flexibility potential for grid management

Interestingly, some of the needs expressed above are addressed by Smart4RES developments and will be integrated in the Use Cases presented in **Section 3**. As a first example, a multi-time scale forecasting is proposed for weather predictions in Smart4RES Work Package 2 to cover multiple horizons up to 5 days ahead, and a seamless RES forecasting model is developed in a dedicated Use Case summarized in **Section 3.3**. A second example is the need of forecasting the flexibility potential of assets for grid management: this is proposed explicitly in a Use Case summarized in Section 3.5 which develops a grid-aware forecast of the aggregated flexibility potential of RES assets in a distribution grid.

2.3.2.4 Participation to relevant projects and use cases

Respondents have mentioned their participation to the following relevant projects and innovative Use Cases:

- Optimization of PV penetration in hybrid applications (PV/diesel). Backup solution for short term forecasting uncertainties based on sky imagers
- EEM20 Forecasting Competition (probabilistic regional wind power forecasting)

2.3.2.5 Suggestions relative to the standardization of forecasts

Respondents have made the following suggestions relative to the standardization of forecasts:

- Reuse pre-trained forecasting models
- Standardize forecasting error metrics and indices

2.3.2.6 Interest in innovative forecasting products and solutions

Respondents are interested to know about innovative forecasting products and solutions in various fields (Table 4). The 3 most voted fields are forecasting of market quantities, forecasting

[1] The state-of-the-art in wind production forecasting does not mention that the lack of weather measurement at the location of wind farm is a limiting factor in the use of numerical weather predictions in this context.

[2] This will be also called seamless forecasting in multiple time scales in the following sections of the document

renewable energy production and collaborative forecasting. The proposed properties of new forecasting products exposed in Table 5 are all deemed of interest, with a lower interest on privacy preserving but the number of respondents is too low to conclude.

Fields where you would be interested about new products or solutions	Number of respondents interested
Forecasting of renewable energy production	7
Forecasting of electricity market quantities	5
Collaborative forecasting	4
Management of isolated power systems	4
Data markets	4
Forecasting of flexibility capacities from aggregators, distributed resources, etc.	2
Numerical Weather Prediction	2
Joint optimization of renewables and storage	2
Human-in-the-loop approaches for trading or grid management	2
Data-driven approaches for trading or grid management	1

Table 4: Fields of interest for new forecasting products or solutions

Properties of new forecasting products	Number of respondents interested
Improve the explainability of forecasting	7
Ensure robustness of forecasting	7
Provide incentives to collaborate	5
Address high dimensionality (spatio-temporal or high resolution)	5
Preserve privacy	3

Table 5: Interest in properties of new forecasting products

2.4 Identification of innovations for forecasting / decision-making

This section presents the process established to identify innovations in forecasting or decision-making under RES uncertainty and integrate these innovations in Use Cases. We begin with the method followed to qualify the Use Case content as innovative, then we highlight how new forecasting products have emerged from the work on Use Cases.

2.4.1 Identification of innovative content

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In order to assess the degree of innovation in the various solutions proposed, the following procedure has been implemented:

1. **Handling of uncertainties**: Use Case contributors have been asked to describe how their solutions handle uncertainties relative to weather, RES production, or other uncertain variables related to the problem at hand. This enable to check that the role of uncertainties in predictive models or optimization approaches has not been overlooked.
2. **Innovative solutions**: Use Case contributors have been asked to write as bullet-points the original innovative contribution of their solutions, compared to the state of the art. As a complement to the Use Case description, 2-slide highlights have been produced to constitute a sort of 'graphical abstract' of the innovative solutions.
3. **Internal assessment**: The produced material constituted a base for internal discussions, at a dedicated WP1 virtual meeting and during the Consortium virtual meeting at M8. The outcomes of the discussions permitted to clarify propositions and proved to be complementary to the assessment of Task leader and WP leader.
4. **Dissemination:** Use Cases have been presented at the IEA Task 36 Meeting in June 2020. This presentation led to questions on the integration of probabilistic forecasting approaches in Use Cases and in the project in General. This confirms the interest of the community to how uncertainties are handled and modelled.

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2.4.2 Identification of new forecasting products

In parallel to the elaboration of Use Cases and KPIs in the present document, new forecasting products have been identified in Task 1.2 and are presented in Deliverable D1.2 [Smart4RES D1.2 2020]. Here, we provide some examples of the process which led to the definition of new forecasting products.

2.4.2.1 Seamless forecasting product

Practitioners in the field of renewable energy forecasting have observed a tendency to separate forecasting models between horizon intervals, because explanatory variables and endogenous properties of the production signal vary significantly with the horizon. This is also observed in the field of meteorology and is covered in Smart4RES WP2. Another reason of separating forecasting models by horizons or temporal scales originates from 'no free-lunch Theorems' [Wolpert, Macready 1997], showing that it may be vain to look for a general algorithm beating all other algorithms on a very large class of problems. However, separate forecasting products for different horizon intervals create discrepancies between different intervals. Furthermore, the existence of different forecasting products for each energy source (Wind, PV, run-of-river Hydro) complexifies the model chain of RES forecasting.

It can be argued that a generic seamless forecasting product, able to perform as good as baseline separate forecasts over a range of horizons and energy sources, could significantly improve RES forecasting in terms of coherence and simplicity of use (this solution is further described in Use Case RES Forecasting 1 in Appendix 9.2.1). The seamless product can be defended against 'No free-lunch' critics by observing that such a forecasting product answers to a limited problem compared to all possible problems in the field of RES forecasting. Additionally, the proven performance of models generating smooth transitions between separate production regimes [Pinson Kariniotakis 2010], processing multiple scales [Woo 2019], and dealing with various energy sources [Van der Meer 2018] support the assumption that such a multi-scale and source-generic product can be successfully delivered.

The process leading to this new forecasting product can be summarized as follows:

1. Identification of limits in existing solutions: discontinuities of prediction over the horizon, complex model chain
2. Structuring idea motivating the new product: generic seamless approach simplifying the model chain in the temporal scale and in the dimension of energy sources
3. Refine the definition of the new product: this new forecasting product needs to be precisely defined in order to be generated and subsequently used. This definition encompasses covered horizon intervals or time scales, energy sources and output format, i.e. density forecasts, ensembles, etc.

2.4.2.2 Forecasting product specific for isolated power systems

The previous forecasting product was created from an analysis of the limitations of existing forecasting products. In other cases, the forecasting product originates from a push in the technology that creates new conditions where forecasting can be applied. This is the case of the forecasting product of RES production during curtailment in isolated power systems. In such systems, security-level limits, either due to local network or system-wide security issues will force System Operators to reduce the power output of RES plants below the production securely penetrated into the power system , a practice known as "curtailment". Those restrictions are typically transmission congestion and local network constraints identified by the TSO.

The curtailment capacities, known as balancing capacities, are offered by a party contracted by the RES manager that is playing the role of balancing service provider (BSP) in front of the System Operator.

Specifically, in isolated power systems, when the production of Dispatchable RES Units with non-zero Dispatch Program exceeds the available RES margin[3] , the production of the Dispatchable RES Units (Wind farms) is reduced in a manner that achieves a fair and non-discriminatory allocation of the RES curtailment.

Wind power penetration in isolated power systems has increased over the last years, and concurrently improvements have been observed in the active power control of wind turbines [Mackensen 2017] and the estimation of available power during regulation [Göçmen 2016]. This new technological context enables to formulate a new forecasting product, namely available wind production under curtailment. To that end, the wind farm production is recorded after this curtailment and machine learning techniques need to be applied to estimate that power rejection in order to adjust the recorded wind power timeseries. Forecasting models are trained with the adjusted timeseries for providing forecasts of how a wind farm would operate without the curtailment. So, the more accurate wind power forecasts will contribute to shape more effective set-points and to optimal and fairer production dispatch. Estimating RES production more accurately, RES penetration to the isolated power system would be significantly increased (a more thorough description is done in the UC RES Forecasting 3, cf. Appendix 9.2.3). In summary, a new forecasting product is proposed based on a technological push in RES regulation capacity and associated prediction models.

[3] equals to the minimum of either: a)the load of the current Dispatch Hour minus the production of the Non-Dispatchable RES Units (mostly PVs, small Wind Turbines) minus the technical minima of the committed thermal Units or b) the load of the current Dispatch Hour minus the production of the Non-Dispatchable RES Units multiplied by the maximum RES penetration coefficient (which is defined for every non interconnected island individually and usually equals to 30%

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2.5 Identification of KPIs

2.5.1 General approach

The objectives of Smart4RES aim at general improvements in the performance of forecasting and decision-aid tools. This leads to the definition of Project KPIs which are recalled in the next Subsection. Baselines are explicitly defined in order to verify performance levels. These baselines are aligned on state-of-the art practice in the power system industry and in the communities of meteorology and RES production forecasting. In order to specify more precisely the innovative proposed solutions and their applications, Use Cases will be presented in Section 3. Several of these Use Cases contain specific KPIs, that derive from the project KPIs.

The general approach followed to define specific KPIs is based on the following criteria:

- **Coherent** with the project KPIs defined in the DoA
- **Adapted** to the configuration of Use Cases (in terms of dimensions, uncertainty levels, forecasting requirements, etc.)
- **Feasible** improvements compared to baselines defined in the DoA and described with more details in the KPI definition.
- **Verifiable** by means of a methodology calculation of the specific KPI and of a description of the associated experimentations and datasets.
- **Reproducible** in different experimentations, i.e. the KPI methodology must be robust with respect to different predictability levels, technical or economic conditions etc.

The definition of Smart4RES KPIs is inspired by previous projects and initiatives. The European Electricity Grid Initiative (EEGI) has established specific KPIs which enable to compare the performance of projects and measure the impact of groups of Research&Innovation activities [EEGI 2014]. In Smart4RES, some KPIs are adapted from the EEGI specific KPIs, for instance the *increased RES hosting capacity*. The Horizon2020 SENSIBLE project low-level KPIs are derived from high-level KPIs on MV grid investment deferral, increase in storage self-consumption etc. for all foreseen configurations [Sensible 2015]. The same approach is used here: high-level KPIs indexed as 1.1, 1.2, 2.1, etc. define the KPI scope, and low-level KPIs indexed as 1.1.a), 1.1.b) etc. precise the thresholds depending on specific evaluation conditions (e.g. horizon interval for forecasting solutions).

The derivation of specific KPIs relative to each Use Case enables to adapt the evaluation to each configuration. For example, the Use Case on seamless RES production forecasting covers multiple horizons and is generic in terms of energy source. Then it requires the derivation of a specific KPI that incorporates forecasting KPIs at intraday and day-ahead horizons. In other cases, specific KPIs may be complementary with the project KPIs (e.g. KPIs for validation in software/hardware-in-the-loop tests in Use Case Grid Management 4). Some Use Cases propose new application fields (e.g. the dense network of solar weather measurements in Use Case Weather 1) for which there exists no established reference in the state of the art, and therefore it is difficult to quantify targets relative to existing approaches. In this case, qualitative targets characterize the novelty of the Use Case.

The workflow for the definition of specific KPIs is the following:

1. Each Use Case contributor proposes a specific KPI related to a given Use Case, if the project KPIs are not adapted to the configuration associated to the Use Case.

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2. Proposed specific KPIs are reviewed by the Task Leader, Work Package Leader and partners with expertise on the subject of the KPI.
3. The coherence and completeness of specific KPIs are collaboratively analyzed by all UC contributors.

2.5.2 Project KPIs

The Project KPIs defined in the DoA are recalled below.

KPI 1.1 – Weather predictions: % of absolute improvement in root mean square error (RMSE) and in continuous ranked probability score (CRPS[4], when relevant) for time horizons from 15 minutes to 30 minutes and up to 96 hours-ahead:

1.1.a) 15 to 30 min-ahead with task 2.3: 10-15% RMSE for radiative variables; about 10% RMSE for wind speed [Baseline: current version of MeteoFrance's AROME model and LES model, GFS, ECMWF, DLR all sky imager, DLR satellite and EMSYS forecasts] [Verification D2.3]

1.1.b) few hours ahead with task 2.2.2 and 2.4: 10% RMSE for radiative variables; about 10% RMSE for wind speed [Baseline: Whiffle forecast driven with ECMWF boundary conditions and without data-assimilation] [Verification D2.2]

1.1.c) from few hours up to 96 hours-ahead with task 2.1, 2.2.1 and 2.4: 10% RMSE and 4-6% CRPS for radiative variables; 5-10% CRPS for wind variables [Baseline: 2018 operational models of MeteoFrance] [Verification D2.1, D2.2 and D2.4]

KPI 1.2 – RES production forecasting: % of improvement in root mean square error (RMSE) and continuous ranked probability score (CRPS) for time horizons up to 30-min and 96 hours-ahead for the range of errors.

These improvements are given below in ranges for RMSE and CRPS since they depend on the technology, site terrain complexity, climatic conditions and other factors:

1.2.a) 30 min-ahead: 9-12% (RMSE) and 3-5% (CRPS) for solar energy; 7-9% (RMSE) and 2-4% (CRPS) for wind energy

1.2.b) 96 hours-ahead: 16-20% (RMSE) and 4-6% (CRPS) for solar energy; 12-15% (RMSE) and 3-5% (CRPS) for wind energy [Baselines: EMSYS forecasting platform, results obtained in public datasets, forecast errors from EDP Renewables providers] [Verification: forecast error results in D6.1; CBA results in D6.4].

KPI 1.3:

[4] The Continuous Ranked Probability Score is a dedicated metric to evaluate probabilistic forecasts over the entire predicted distribution. Its formulation is presented in [Gneiting 2007]

1.3.a) % decrease of load shedding events in isolated power systems considering future scenarios with RES integration above 90%: > 80% (e.g., in Madeira island[5] load shedding occurs with rate-of-change-of-frequency < -1.5 Hz/s and absolute frequency value < 49 Hz) [Baseline: base case without Task 5.2 tool and storage system support functions from Task 5.1] [Verification: industrial laboratory results in D6.2]; **1.3.b) % of increased RES hosting capacity[6] in MV distribution grids: > 50%** [Baseline: base case without predictive management of flexibility from Task 5.3] [Verification: industrial laboratory results in D6.2]; **1.3.c) investment deferral in grid reinforcement (n° of years): > 2 years** [Baseline: traditional network reinforcement] [Verification: CBA results in D6.4]; **1.3.d) % of increase in electricity market revenue**: -10-15% decrease in costs stemming from balancing; - an increase of 10-15% of revenues from participation in energy plus ancillary services; - up to 20-25% from VPP (RES and storage) in energy and ancillary services [Baseline: market offers equal to a) point forecasts; b) optimal quantiles] [Verification: market bidding results in D6.3 and CBA in D6.4]
KPI 2.1: n° of recommendations for future grid codes in terms of systems services from RES and new forecasting requirements: > 4 [Verification: deliverable D6.4]. **KPI 2.2: n° of recommendations of new market schemes and rules to better integrate RES in the electricity market**: > 6 [Verification: deliverable D6.4].

[5] Beires, P. P., Moreira, C. L., Lopes, J. P., Figueira, A. G. The Need of synchronous inertia in autonomous power systems with increasing shares of renewables. Natural gas, 54, 14-6.

[6] The hosting capacity is the maximum penetration of RES (measured in terms of energy or power) at which the power system operates satisfactorily in terms of power security & quality, technical and economic constraints [Ismael et al 2019]

2.5.3 KPIs for weather forecasting

This Section describes KPIs on weather forecasting that complement the Project KPIs. The KPIs below refer to the application of a regional network of solar measurements (cf. Section 1.3) for the improvement of regional solar irradiance prediction or nowcasting. This will be formalized in the Use Case Weather Forecasting 1 in Section 3.

2.5.3.1 Eye2Sky network KPIs

The Eye2Sky network combines in its final stage all sky imager, radiometers, ceilometers, satellite and NWP forecasts. It will be capable to create improved solar irradiance nowcast/forecast for an area of roughly 10000 km² with an unseen spatial and temporal resolution. Two distinct specific KPIs are defined for the Eye2Sky network:

Specific KPI Name	**Increase of the spatial and temporal resolution of the regional forecast**
Specific KPI Index	**KPI 1.1.d**
Motivations for a Specific KPI	Strengths of satellite and all sky imager based nowcasting/forecasting approaches will be combined while overcoming limitations in coverage and resolution of the individual approaches.
KPI Assumptions	Sky camera forecasts have a very low spatial coverage (cloud scene) but very high spatial and temporal resolutions. From its part, the satellite forecasts have a very wide spatial coverage with lower spatial and temporal resolutions compared to sky cameras. The idea is to combine both forecasts techniques to increase the forecast quality. The satellite forecast can provide the cloud information outside of the skycam coverage (with is necessary for an accurate forecast of the movement of the clouds in and out the area of coverage) while the camera forecast will provide the higher resolved information that will enhance the the forecast result inside the area of coverage.
KPI Formula	n.a.
KPI Calculation Methodology and Target	The Eye2Sky network will increase spatial and temporal resolutions of the combined skycam + satellite regional nowcasts/forecasts <u>from km to m</u> and from <u>minutes to seconds</u>. This is achieved as the influence of the weaknesses of one system is reduced by the strengths of the other system.
Associated Use Cases	UC Weather Forecasting 1 'Highly resolved regional satellite + sky cameras nowcast/forecast for grid management and the energy market.'

Specific KPI Name	**Continous system validation based on moving error metrics.**

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Specific KPI Index	**KPI 1.1.e**
Motivations for a Specific KPI	The uncertainties of nowcasting and forecasting systems are strongly influenced by the prevailing conditions. Aggregated overall error metrics over a longer period such as an RMSE over multiple days, weeks, months or a full year obscure the influence between highly variable error prone conditions and less complex stable conditions (e.g. clear sky).
KPI Assumptions	As overall error metrics are unsuitable to describe nowcasting/forecasting system uncertainties at a specific point in time, a continuous moving validation of the Eye2Sky network irradiance information will be performed with up to 14 spatially distributed ground based reference radiometers.
KPI Formula	n.a.
KPI Calculation Methodology and Target	This validation will be performed over distinct time periods (from minutes to hours) and lead times calculating moving error metrics (e.g. RMSE, MAE, skill score,…). The distribution of historical validation results will be discretized in solar irradiance variability classifications, providing system uncertainties for distinct conditions, time periods and lead times. These distributions will be benchmarked with traditional approaches for nowcasting/forecasting which are based on satellite data and all sky imagers used independently without forming a network. A performance enhancement of the Eye2Sky network compared to the baseline approach with only 2 sky cameras (no network) is expected, namely with the following targets: • The network of several cameras will utilize redundancies when possible and <u>reduce uncertainties compared to the baseline solution</u>. Current preliminary results indicate a significant potential in reduction of uncertainties especially for the geolocation of clouds. • Satellite-based forecast for the Eye2Sky network site can benefit of the higher resolution in space and time of the all-sky cameras. For example, better resolved coverage information and automatic classification results can be utilized as input of a continuous correction of the determined radiative effect within specific pixels, <u>leading to lower errors of satellite-based forecasts compared to the baseline approach</u>.
Associated Use Cases	UC Weather Forecasting 1 'Highly resolved regional satellite + sky cameras nowcast/forecast for grid management and the energy market.'

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2.5.4 KPIs for RES forecasting

Here we discuss the evaluation of RES forecasting tools, and then propose specific KPIs adapted to Use Cases on RES forecasting.

2.5.4.1 Conditioned evaluation of RES forecasting on challenging situations

The values defined in project KPI 1.2 for improvement over the state-of-the-art performance refer to the distribution of RES forecast error values throughout a year. In contrast, the high-level Objective 3 of the project (cf. Section 1.1) is focused on the improvement of situations where the forecast error is larger than the average performance.

To find time periods or events where the forecasting error is higher than usual different criteria can be used. The approach taken here is to consider challenging situations as the situations where the forecasting error (deterministic or probabilistic) deviates from its average behaviour in a statistical sense.

Therefore, certain thresholds are defined in terms of the frequency distribution of errors to define "unusual" behaviour:

- one threshold is located close to *the median value of the* absolute *error (i.e. is greater 50% of times)*. The concept is illustrated in Figure 1. The median value of error can be retrieved by applying first a baseline forecasting model. The threshold is defined in order to capture a large enough number of errors and to be not too distant from the average error. Then the improvement claimed by Smart4RES models is evaluated on situations above the median error of baseline models.

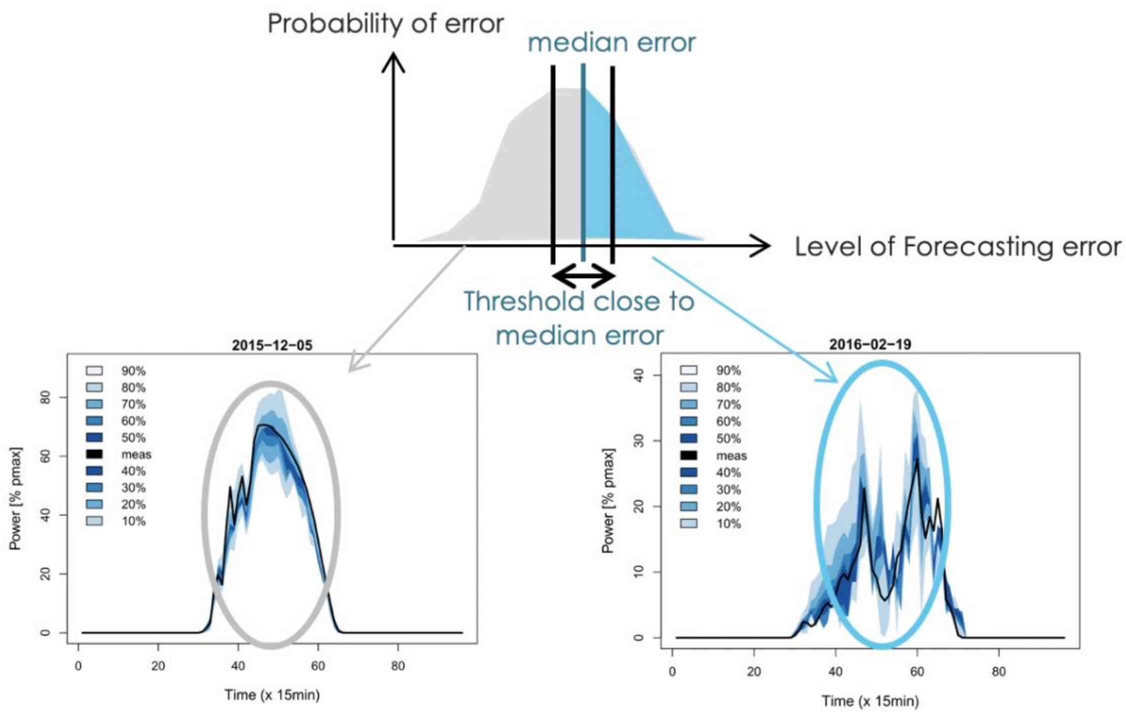

Figure 1: Conditioned evaluation of RES production forecasting. PV Probabilistic forecasts from [Agoua 2018]

- The second threshold is based on the distribution of the forecasting error as pointwise difference between forecast and measurement of power output as illustrated in **Error! Reference source not found.**. The suggestion is to consider unusual errors as those which are outside multiples of the sigma-interval, i.e. 2σ or 3σ. Knowing, of course, that the underlying error distribution is not Gaussian. But this is not relevant here as we do not seek for a specific share of the events.

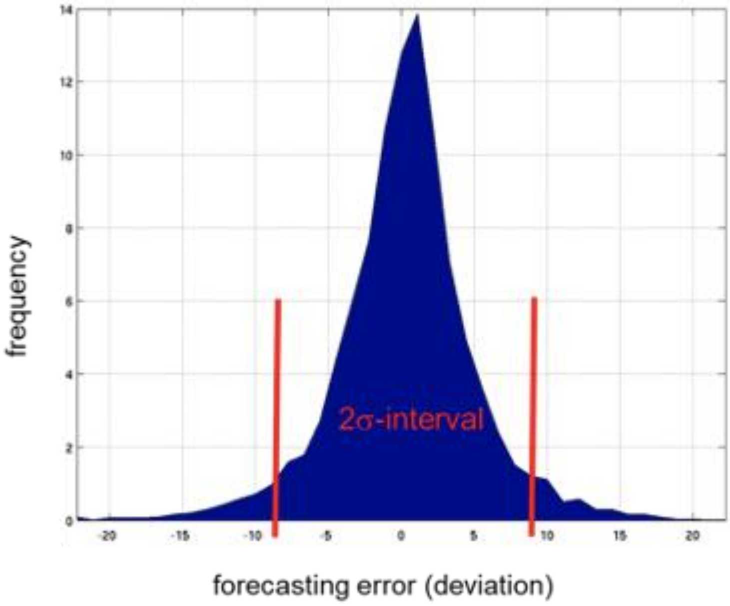

Figure 2: Error distribution of deviations (prediction – actual) per time step. The unusually large forecasting errors are outside the 2σ-interval (Source: EMSYS)

The KPI for these events would then be calculated on the subset of outliers to measure the increase of performance of the project's output compared to e.g. reference forecasts.

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2.5.4.2 Performance of ensemble forecasts

Specific KPI Name	**Variogram score of ensembles forecasts**
Specific KPI Index	**KPI 1.2.c**
Motivations for a Specific KPI	Several Use Cases make use of ensembles forecasts. Even if these are not related to project KPIs, it is important to evaluate their performance as an intermediate indicator of the performance of a Use Case The Variogram score evaluates the global skill of ensembles in their ability to reproduce the variability of the original signal
KPI Assumptions	The probability associated to each ensemble / scenario has been defined
KPI Formula	The KPI is derived as the normalized difference between Variogram-based Scores (VS) obtained with Smart4RES models and with baseline models. The score is applied on the horizon range H corresponding to horizons of the Use Case. $KPI_{Ensemble} = \frac{VS_{Smart4RES}(H) - VS_{baseline}(H)}{VS_{baseline}(H)}$ The Variogram-based Score is defined in [Scheuerer 2015] as the quadratic difference between the variogram of the observed signal (e.g. RES production level) and the average variogram of forecast ensembles. The variogram quantifies the variability of the signal over the horizon range.
KPI Calculation Methodology and Target	1. Ensembles are generated over the whole horizon range with Smart4RES models 2. Ensembles are generated over the whole horizon range with baseline models 3. Scores are compared to obtain the KPI The target of the KPI is to have at least a positive KPI value compared to state-of-the-art baseline models. The choice of this target is motivated by two reasons: (1) properties of ensembles are largely dependent on temporal correlations in the observed original signal (e.g. wind or PV production) and (2) ensembles are mostly intermediate outputs that will be integrated in decision-aid tools.
Associated Use Cases	UC Market 1 UC Grid Management 2

2.5.4.3 Seamless RES forecasting

The KPIs for seamless production forecasting are defined based on two widespread forecasting scores, namely RMSE and CRPS. The two scores hereby provide a simple yet informative assessment of forecasting accuracy in both deterministic and probabilistic frameworks.

Specific KPI Name	**Performance of generic seamless RES forecasting**

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Specific KPI Index	**KPI 1.2.d**
Motivations for a Specific KPI	Seamless forecasting intends to cover a large range of horizons, from 5 minutes to 96 hours ahead, for which different project KPIs have been defined, The seamless forecasting model is developed to be generic in terms of energy sources, and each energy source has a different predictability level
KPI Assumptions	Each horizon is considered equally important in applications on electricity markets and power system management
KPI Formula	The KPI for seamless forecasting is derived as a weighted combination of KPIs quantifying the improvement vs baselines where $w_{s,h}$ indicate weights for the various horizons $h \in [H_1, H_2, H_3]$ and energy sources $s \in [PV, OnshoreWind, OffshoreWind, RunofRiverHydro]$ comprised in the RES power plant or aggregation considered:

$$KPI_{Seamless} = \left\{ \begin{array}{c} KPI_{RMSE,Seamless} = \sum_{s,h} w_{s,h}\ \mathrm{KPI}_{\mathrm{RMSE,s,h}} \\ KPI_{CRPS,Seamless} = \sum_{s,h} w_{s,h}\ \mathrm{KPI}_{\mathrm{CRPS,s,h}} \end{array} \right\}$$

where:

$\mathrm{KPI}_{\mathrm{RMSE,s,h}}$	**PV**	**Onshore Wind**	**Offshore Wind**	**RunOfRiver Hydro**
$H_1 = [5\ \mathrm{min}\ , 30\ min]$	9-12 *(KPI 1.2.a)*	7-9 *(KPI 1.2.a)*	7-9	5-8
$H_2 = [30\ \mathrm{min}\ , 24\ h]$	16-20 *(KPI 1.2.b)*	12-15 *(KPI 1.2.b)*	12-15	11-14
$H_3 = [24\ \mathrm{h}\ , 96\ h]$	16-20 *(KPI 1.2.b)*	12-15 *(KPI 1.2.b)*	12-15	11-14

$\mathrm{KPI}_{\mathrm{CRPS,s,h}}$	**PV**	**Onshore Wind**	**Offshore Wind**	**RunOfRiver Hydro**
$H_1 = [5\ \mathrm{min}\ , 30\ min]$	3-5 *(KPI 1.2.a)*	2-4 *(KPI 1.2.a)*	2-4	2-4
$H_2 = [30\ \mathrm{min}\ , 24\ h]$	4-6 *(KPI 1.2.b)*	3-5 *(KPI 1.2.b)*	3-5	11-14
	4-6	3-5	3-5	11-14

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<table>
<tr><td></td><td><table><tr><td>$H_3 = [24\ \mathrm{h}\ , 96\ h]$</td><td>(KPI 1.2.b)</td><td>(KPI 1.2.b)</td><td></td><td></td></tr></table></td></tr>
<tr><td>KPI Calculation Methodology and Target</td><td>1. Seamless forecasting is done over the whole horizon range
2. Forecasting is performed with baseline models over each horizon interval
3. Results are compared for different energy sources
The KPI target corresponds to the combination of KPIs for the various energy sources and horizons as presented above.</td></tr>
<tr><td>Associated Use Cases</td><td>Use Case RES Forecasting 1</td></tr>
</table>

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2.5.5 KPIs for decision-making related to market applications

Here we discuss KPIs associated to market applications such as bidding on electricity markets and dispatch of RES production with storage. Specific KPIs are also proposed to evaluated results in line with the actual practice of energy traders.

Specific KPI Name	**Reduction in costs stemming from balancing**
Specific KPI Index	**KPI 1.3.d.1**
Motivations for a Specific KPI	The scope of this KPI is the calculation of the possible decrease of costs stemming from balancing when bidding on multiple markets, compared to standard benchmark bidding methods.
KPI Assumptions	Markets are organized in such a way that costs can be directly associated to balancing, due to forecasting errors, delivery deviating from bids for other reasons or penalties incurred because of the underfulfillment of an ancillary service.
KPI Formula	$KPI_{balancing\ costs}(\%) = \frac{Cost_{balancing}^{Smart4RES} - Cost_{balancing}^{baseline}}{Cost_{balancing}^{baseline}}$ Where: $Cost_{balancing}^{baseline}$: Balancing costs associated to benchmark bidding approaches, based on point forecasts / optimal quantiles $Cost_{balancing}^{Smart4RES}$: Balancing costs associated to advanced bidding approaches proposed in Smart4RES Use Cases
KPI Calculation Methodology and Target	Bids on multiple markets are obtained with both Smart4RES and baseline approaches, under the same realizations of RES production and market conditions. Bidding is operated on a testing dataset that is suitable for statistical analysis of the comparison and representative of expected average market conditions (this may include the choice of an adequate testing period, bootstrapping or other statistical methods to ensure enough diversity in testing conditions). Balancing costs are computed as a function of the deviation between bids and effectively supplied volumes corresponding to the observed RES production. The KPI is obtained by the comparison of balancing costs. The target for the KPI is the target mentioned in Section 2.5.2
Associated Use Cases	Use Case Market 1 'Data-driven method for RES bidding on electricity markets' Use Case Market 2 'Joint operation of RES and storage'

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Specific KPI Name	**Increase in average revenue**
Specific KPI Index	**KPI 1.3.d.2**
Motivations for a Specific KPI	The scope of this KPI is the calculation of the possible increase of revenue when bidding on multiple markets, compared to standard benchmark bidding methods.
KPI Assumptions	Assumptions on KPI 1.3.d.1 Market rules and main equilibria are stable during training and testing periods
KPI Formula	$KPI_{revenue}(\%) = \frac{Revenue^{Smart4RES} - Revenue^{Baseline}}{Revenue^{Baseline}}$ Where: $Revenue^{Smart4RES}$: Average revenue associated to baseline bidding approaches, based on point forecasts / optimal quantiles $Revenue^{Baseline}$: Average revenue associated to advanced bidding approaches proposed in Smart4RES Use Cases
KPI Calculation Methodology and Target	Bids on multiple markets are simulated with both Smart4RES and baseline approaches, under the same realizations of RES production and market conditions. Testing datasets are chosen to be representative of expected average market conditions (this may include the choice of an adequate testing period, bootstrapping or other statistical methods to ensure enough diversity in testing conditions). Average revenue is computed as a function of balancing costs and sales corresponding to bids and observed RES production The KPI is obtained by comparison of average revenues. The target for the KPI is the target mentioned in Section 2.5.2
Associated Use Cases	Use Case Market 1 'Data-driven method for bidding on electricity markets'

Specific KPI Name	**Increase in RES production**
Specific KPI Index	**KPI 1.4.a**
Motivations for a Specific KPI	Optimized maintenance can lead to higher RES production levels (under similar resource levels) which later create the opportunity of increased revenues.
KPI Assumptions	Production levels should be normalized by the available resource
KPI Formula	$KPI_{PROD} = \frac{P_A}{P_B}$, with: P = Energy Production of RES plant A = After Maintenance B = Before Maintenance $KPI_{PCU} = \frac{PCH_A}{PCH_b}$, with

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	PCU = Peak Capacity Utilization PCH = Number of hours producing at the Peak Capacity A = After Maintenance B = Before Maintenance
KPI Calculation Methodology and Target	The period for the calculation would be diary but the evaluation period of the KPI would be annual. Since there is little established reference in the state of the art, the target for both KPIs is to achieve at least KPI values superior to 1.
Associated Use Cases	Use Case Market 3 ‘Predictive maintenance of solar parks based on Artificial Intelligence.’

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Specific KPI Name	**Forecast evaluation by traders: analytic approach**
Specific KPI Index	**KPI 1.4.b**
Motivations for a Specific KPI	The scope of this KPI is to calculate the typical error metrics used by the performance analysis groups of trading companies.
KPI Assumptions	n.a.
KPI Formula	Mean absolute error (MAE) Root mean square error (RMSE) Mean error (BIAS)
KPI Calculation Methodology and Target	Calculate MAE, RMSE and BIAS of forecasts used for market applications over specific time interval (week, month, year), normalization to installed power of entity to be considered (single plant, aggregation) Target values correspond to usual error levels observed by energy traders in conditions similar to the chosen evaluation set
Associated Use Cases	Use Case Market 1 on data-driven method for bidding on electricity markets Use Case RES Forecasting 2 multi-source data input

Specific KPI Name	**Forecast evaluation by traders: “no big changes” approach (human input)**
Specific KPI Index	**KPI 1.4.c**
Motivations for a Specific KPI	The scope of this KPI is to find a metric that reflects the value of updates, i.e. changes in the forecast, versus the benefit of really trading the difference
KPI Assumptions	The assumption is to find a KPI that evaluates the benefit in decision making of human traders. The motivation for this KPI is that traders are human experts who base their decision making on experience (which is difficult to put into a KPI) and measurable factors like following forecasting updates to a certain degree.
KPI Formula	To be developed within WP5 in interaction with energy traders
KPI Calculation Methodology and Target	Possible approach: Calculate differences of forecasting updates for specific trading intervals, compare size and sign of new trading position with forecasting error and loss of profit that really occured. Include contribution of balancing and transaction costs into KPI.
Associated Use Cases	Use Case Market 1 on data-driven method for bidding on electricity markets

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2.5.6 KPIs for decision-making related to grid management

The KPIs below quantify the impact of proposed solutions for better penetration of RES production in isolated power systems and distribution grids. A set of KPIs is added to evaluate the performance of software-in-the-loop tests which aim at validating the robustness of grid management tools in realistic laboratory conditions.

Specific KPI Name	**Reduced energy curtailment of RES**
Specific KPI Index	**KPI 1.3.e**
Motivations for a Specific KPI	This indicator will measure the amount of available power which cannot be injected to the grid or stored. The main objective is to reduce as maximum as possible the RES curtailment due to the proper combination with storage technologies, guaranteeing a higher percentage of renewable power supply to the grid
KPI Assumptions	In order to calculate this KPI, historical power production and wind measurements data would be needed for comparing current energy losses without innovative forecasting product implementation and new energy losses considering the use of both innovative forecasting product.
KPI Formula	$KPI_{CURT}(\%) = \left(1 - \frac{E_{injected-grid} + E_{stored}}{E_{available}}\right)$ $E_{injected-grid}$: Energy injected to the grid directly from renewable resources (applied for a defined time period). (MWh) E_{stored}: Energy stored directly from renewable resources (applied for a defined time period). (MWh) $E_{available}$: Energy available from variable renewable sources. (MWh)
KPI Calculation Methodology and Target	Calculate energy curtailment with and without innovative forecasting product and storage usage. The target consists in minimizing the value of the KPI. As this KPI refers to an application integrating novel approaches such as the forecast of available active power and the combination of curtailment with storage in isolated power systems, there is no reference numerical target in the state-of-the art. However the curtailed energy can be compared with curtailment without these innovative solutions.
Associated Use Cases	Use Case RES Forecasting 3 'Increased RES penetration to isolated power system'

Specific KPI Name	**Revenue losses per production unit due to curtailment**
Specific KPI Index	**KPI 1.3.f**

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Motivations for a Specific KPI	This indicator will measure the losses per production unit due to curtailment. The main objective is to increase the revenues of the RES unit owners.
KPI Assumptions	In order to calculate this KPI, historical power production would be needed for comparing current revenues without innovative forecasting product implementation and new revenues considering the use of innovative forecasting product.
KPI Formula	$KPI_{Revenue\ losses} = \sum_{all\_RES\_units} Revenues_{forecasted\_cur} - Revenues_{real\_cur}$ $Revenues_{forecasted\_cur}$: Estimated production for curtailment periods $Revenues_{real\_cur}$: Real production during curtailment periods
KPI Calculation Methodology and Target	Calculate energy curtailment with and without innovative forecasting product. The target is to minimize this KPI, there is no established target in the state-of-the-art, the KPI will be compared with baseline approaches without advanced forecasting product of RES production under curtailment conditions.
Associated Use Cases	Use Case RES Forecasting 3 'Increased RES penetration to isolated power system'

Specific KPI Name	**Fulfilment of voltage limits**
Specific KPI Index	**KPI 1.3.g**
Motivations for a Specific KPI	Focused on the assessment of the voltage levels in accordance to standard EN 50160 stating that the voltage must remain in +/- 10% of its nominal value considering an integrating period of 10 minutes.
KPI Assumptions	n.a.
KPI Formula	$KPI_{VV\ events} = \frac{VV_{events,with\ UC} - VV_{events,without\ UC}}{VV_{events,without\ UC}}.100$ Where: VV_{events} = percentage of voltage violations reduction $VV_{events,with\ UC}$ = number of voltage violation events after grid optimization (flexibility activation) $VV_{events,without\ UC}$ = number of voltage violation events without optimizing the grid state
KPI Calculation Methodology and Target	1. Load flow calculation with actual grid topology and computation of the number of forecasted (hours, day-ahead) voltage violations 2. Run the Smart4RES methodology to define required flexibility and corresponding node for the next day/hours Apply "reserved" flexibility in real-time and compute voltage violations
Associated Use Cases	UC Grid Management 2 'Localized and predictive management of voltage and congestion problems in distribution grids' UC Grid Management 3 'Efficient identification of the flexibility at the interface between distribution and transmission systems'

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Specific KPI Name	**Fulfilment of branch current limits**
Specific KPI Index	**KPI 1.3.h**
Motivations for a Specific KPI	Focused on the assessment of the overcurrent in grid branches (overload above 100%) to avoid line disconnection and further cascading failures.
KPI Assumptions	n.a.
KPI Formula	$KPI_{Congestion\ events} = \frac{Congestion_{events,with\ UC} - Congestion_{events,without\ UC}}{Congestion_{events,without\ UC}} .100$ Where: $KPI_{Congestion\ events}$ = percentage of congestion problems reduction $Congestion_{events,with\ UC}$ = number of branch congestion events after grid optimization (flexibility activation) $Congestion_{events,without\ UC}$ = number of congestion events without optimizing the grid state
KPI Calculation Methodology and Target	Load flow calculation with actual grid topology and computation of the number of forecasted (hours, day-ahead) congested branches Run the Smart4RES methodology to define required flexibility and corresponding node for the next day/hours Apply "reserved" flexibility in real-time and compute current in branches (quantify congested branches)
Associated Use Cases	UC Grid Management 2 'Localized and predictive management of voltage and congestion problems in distribution grids' UC Grid Management 3 'Efficient identification of the flexibility at the interface between distribution and transmission systems'

Specific KPI Name	**Demonstration of a software in the loop run using an example from the project**
Specific KPI Index	**KPI 1.5.a**
Motivations for a Specific KPI	Emulate an environment for the software.
KPI Assumptions	Grid management software ready for software-in-the-loop testing
KPI Formula	n.a.
KPI Calculation Methodology and Target	Software-in-the-Loop run implementing a software developed in the project (both as code and as a black box on a separate device)

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Associated Use Cases	UC Grid Management 4 UC Grid Management 1 UC Grid Management 2 'Localized and predictive management of voltage and congestion problems in distribution grids'

Specific KPI Name	**Simulated environment including controls and interaction**
Specific KPI Index	**KPI 1.5.b**
Motivations for a Specific KPI	Emulate interaction of SIL with multiple algorithms in the loop.
KPI Assumptions	Grid management software ready for software-in-the-loop testing
KPI Formula	n.a.
KPI Calculation Methodology and Target	The environment includes controls and interaction with the simulated power system, e.g. via voltage management.
Associated Use Cases	UC Grid Management 4 UC Grid Management 1 UC Grid Management 2 'Localized and predictive management of voltage and congestion problems in distribution grids'

Specific KPI Name	**Test protocol to test for (at least) one potential risk.**
Specific KPI Index	**KPI 1.5.c**
Motivations for a Specific KPI	Protocols and scenarios to test specific situations and risks
KPI Assumptions	Grid management software ready for software-in-the-loop testing
KPI Formula	n.a.
KPI Calculation Methodology and Target	A test protocol is defined for at least one potential risk associated to the software solution under test.
Associated Use Cases	UC Grid Management 4 UC Grid Management 1 UC Grid Management 2 'Localized and predictive management of voltage and congestion problems in distribution grids'

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3 Overview of Use Cases

This Section presents the general concepts proposed by Use Cases. The application zones and domains of Use Cases are described and relationships between Use Cases are discussed in **Section 3.1**. The following sections provide an overview of all Use Cases, the complete descriptions are available in **Appendix 9**.

3.1 Integration of Use Cases in the architecture of Smart4RES

The Use Cases developed in Smart4RES are mapped in the business layer of the Smart Grid Architecture Model (SGAM) [IEC 62552-9]. The result in **Figure 3** shows that Use Cases cover all zones and there is a significant number of possible interactions between Use Cases (indicated by arrows on the Figure, e.g. the UC on Software in the Loop is able to validate the control methods developed in the UC Frequency Management in isolated power systems). Use Cases dealing with grid management issues cover the Generation/Transmission scales. Most Use Cases are concentrated on the zone of DER, which is expected because most Use Cases are concerned with solutions at the scale of renewable power plants or renewable portfolios.

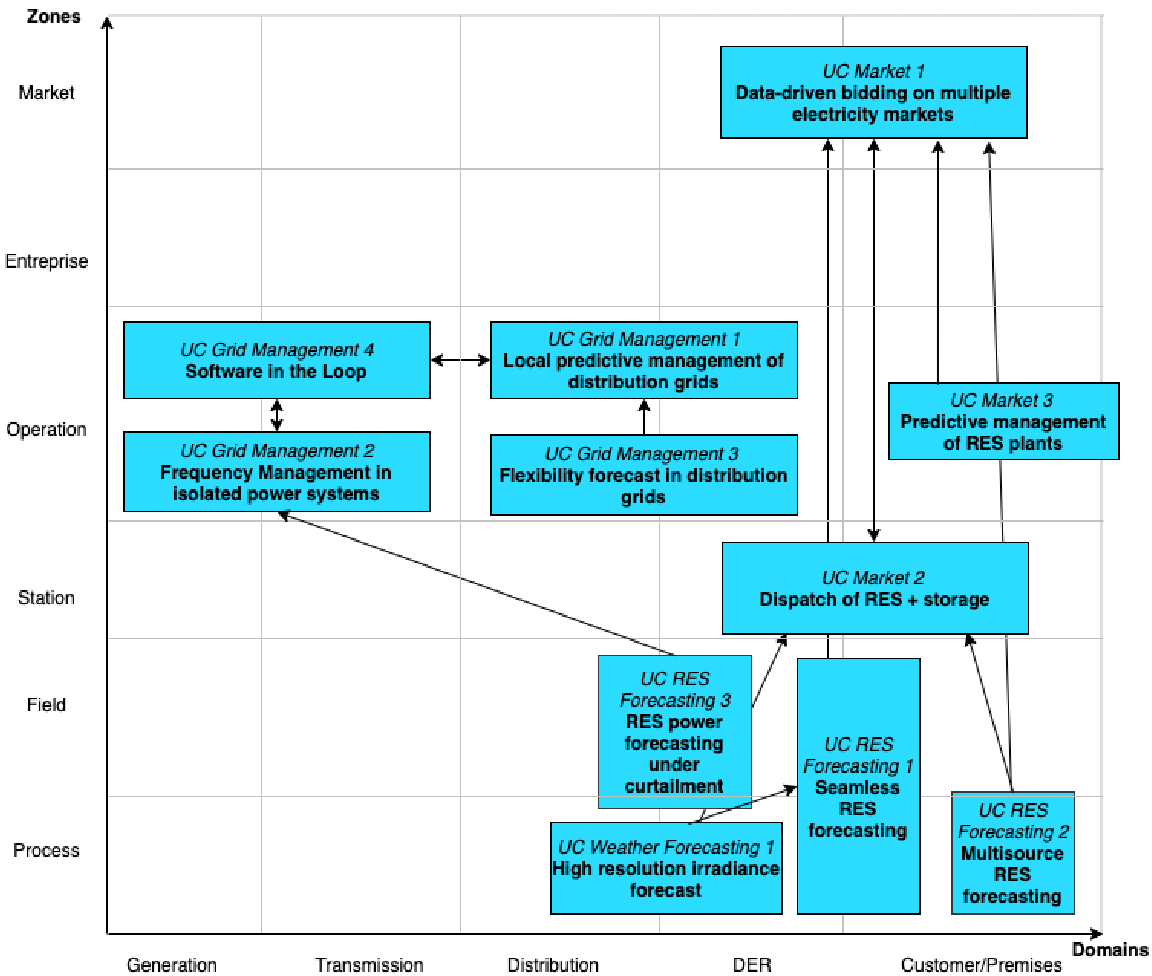

Figure 3: Mapping of Use Cases in SGAM business layer

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The 11 use cases are summarized briefly in Table 6 below. One notes that there are multiple solutions proposed in several domains such as RES forecasting, market applications and grid management, with 3 to 4 Use Cases for each domain. The Use Cases will be described in more details in the next paragraphs.

Use Case ID (Authors)	Summary	Link to complete Use Case description
UC Weather Forecasting 1 (DLR)	**Highly resolved regional satellite + sky cameras nowcast/forecast for grid management and the energy market.** The combination of high-resolution information leads to improvement in spatio-temporal resolution and forecasting error of regional solar irradiance.	Appendix 9.1
UC RES Forecasting 1 (ARMINES)	**Generic Seamless RES Production Forecasting for Multiple Time Scales.** The model is generic in the sense that it is designed to be efficiently adaptable to several renewable energy sources (e.g. Wind, Photovoltaics, Run-of-River Hydro)	Appendix 9.2.1
UC RES Forecasting 2 (EMSYS)	**RES Production Forecasting model able to exploit multiple sources of data,** This solution based on artificial intelligence and non-linear time series analysis is designed to handle diverse data formats and scales and update predictions close to real-time.	Appendix 9.2.2
UC RES Forecasting 3 (ICCS/HEDNO)	**Machine-learning based prediction of the available active power of wind farms subject to curtailment in isolated power systems.** A more accurate prediction of the available power can help optimize the curtailment and therefore potentially increase RES penetration in isolated power systems	Appendix 0
UC Market 1 (ARMINES)	**Data-driven approach for bidding RES production (potentially coupled with storage) on multiple electricity markets (e.g. day-ahead energy market, intraday energy market, ancillary services).** The approach is based on a value-oriented tool which shows similar levels of revenues and costs than a full model chain in which each uncertain variable (prices, RES production, etc.) is predicted and serves as input in a trading optimization model.	Appendix 9.3.1
UC Market 2 (EDP)	**Optimized dispatch of RES with storage to hedge against imbalance costs due to RES production**	Appendix 9.3.2

	deviating from the schedule and enhance revenue by offering flexibility. A machine learning algorithm optimizes the dispatch based on bids, observed prices and updated forecasts of RES production and prices.	
UC Market 3 (EDP)	**Predictive maintenance of solar parks based on Artificial Intelligence.** The maintenance tool exploits monitoring data, including images of the installation taken by drones.	Appendix 9.3.3
UC Grid Management 1 (INESC TEC)	**Management of frequency containment reserve and system inertia in isolated power systems** Dynamic security constrained unit commitment /economic dispatch of the generation fleet for the next day and on-line security monitoring/corrective control, in isolated power systems subject to large penetration of converter-interfaced renewable generation	Appendix 9.4.1
UC Grid Management 2 (INESC TEC)	**Localized and predictive management of voltage and congestion problems in distribution grids** Local predictive management of distribution grids, scheduling and activating flexibilities (active and reactive power modulation in the grid nodes) from distributed generation, demand response, storage (operated by a third-party), etc., aggregated or not by market players. The use case is structured by a data-driven controller which identifies flexibility needs in advance and provides fast decision-aid in real-time to human operators, and a decision-aid phase where the decision-maker balances flexibility risk and costs to make a final decision about flexibility activation.	Appendix 9.4.2
UC Grid Management 3 (ARMINES)	**Efficient identification of the flexibility at the interface between distribution and transmission systems** A set of controllable and stochastic resources in a distribution grid are aggregated by topology to provide regulation services at their connection point with the upper-level high-voltage grid. Coherent probabilistic forecasts are aggregated by a grid-aware algorithm to produce flexibility potential the HV/MV interface.	Appendix 9.4.3
UC Grid Management 4 (DNV GL)	**SIL (software in the loop) testing for the electricity system** Facility able to test claims about control and optimization software in the electricity system and	Appendix 9.4.4

	assess possible interference with other aspects of the system	

Table 6: Summary of Smart4RES Use Cases

3.2 Overview of Use Cases for weather forecasting

The regional network of meteorological measurements presented in **Section 1.4** enables to derive high resolution solar irradiance forecasts, with significant improvements compared to baselines quantified by the KPIs defined in **Section 2.5.3.1** . **Use Case Weather Forecasting 1** describes this regional solar irradiance forecast at high spatial-resolution, and proposes to combine the various available measurements (sky cameras, satellite, NWP) to provide high quality predictions of irradiance for different actors as indicated on the left of **Figure 4** below. UC Weather Forecasting 1 innovates with the following solutions:

- a **dense regional network of weather measurements** including overlapping sky imagers produces accurate irradiance forecasts at the scale of meters and seconds (instead of kms and minutes for the state-of-the-art)
- this high-resolution forecast can be provided as a **regional forecasting service consequently used by several actors**: providers of numerical weather predictions will use these forecasts to validate and calibrate their models, RES producers can optimize the predictive control of storage associated to PV plants, and grid operators can quantify better the impact of short-term PV variation on local distribution grids.

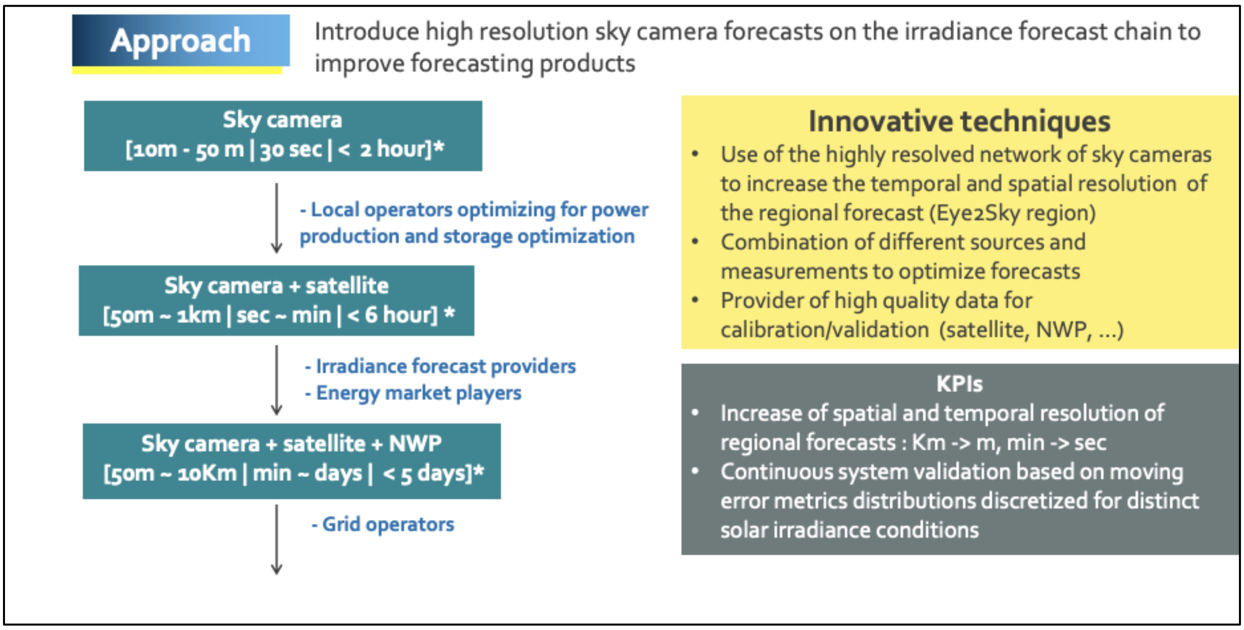

Figure 4: Proposed high resolution solar irradiance forecast (UC Weather Forecasting 1, DLR)

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3.3 Overview of Use Cases for RES production forecasting

The prediction of RES production over multiple time scales currently consists in applying separate forecasting tools for different horizon intervals (cf. **Figure 5**). This is due to the fact that different phenomena explain predicted production over the horizon range: for instance, production at a few minutes ahead is best predicted with last observed production levels and local weather observations (sky imagers, lidars, etc.) whereas NWP have a major contribution to predictions at several hours ahead. This results in a complex modelling chain and creates discontinuities at the junctions between intervals.

Use Case RES Forecasting 1 proposes a **seamless forecasting model** able to extract all the information available at different time scales (e.g. for PV forecasting recent measurements, satellite images, Numerical Weather Predictions, etc.). The different data sources are weighted according to a probabilistic metric. These weights lead to the identification of similar past observations, that integrate uncertainties in predictions. These predictions take the form of density forecasts and trajectories modelling temporal correlations over the horizon range. The Use Case is described in detail in **Appendix 9.2.1**. The **innovative solutions** of UC RES Forecasting 1 are the following:

- Generic multi-scale RES forecasting model, adaptive to numerous variable renewable energy sources
- Predictions are continuous over the horizon range, and consequently the associated performance (deterministic and probabilistic errors)
- The seamless approach reduces the number of required forecasting models, thereby streamlining the forecasting process.

This generic seamless forecasting model offers to end-users of RES production forecasts such as RES producers or aggregators the possibility to simplify their forecasting process: by implementing such a model or purchasing this type of product, they can optimize their decisions over a large horizon range and several energy sources without discontinuities. Encompassing multiple time scales is particularly useful when multiple decisions must be taken sequentially, e.g. bidding on a day-ahead market and adjust later the prior position at intraday market gates.

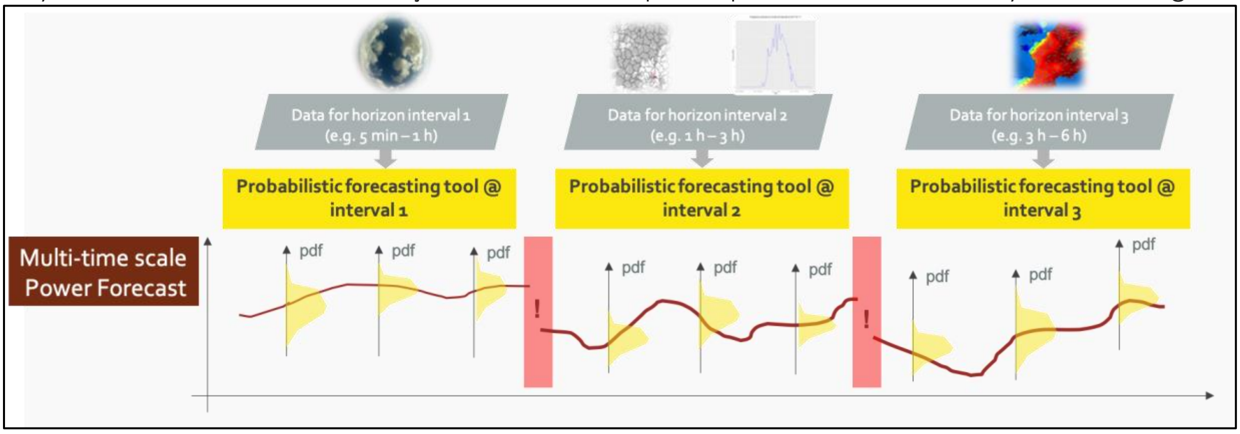

Figure 5: Challenge of RES forecasting over multiple time scales (UC RES Forecasting 1, ARMINES)

The wealth of multiple data sources is exploited by the tools developed in **Use Case RES Forecasting 2** to improve the performance of wind power forecasting in a context of very-short term prediction based on real operational data (**Figure 6**). When forecast is offered as a service,

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practical issues such as noise and gaps or constraining conditions (faults, lightning, etc.) have to be robustly addressed by the forecasting tool almost in real-time. In this Use Case, a **data-driven approach** handles the large volume and diversity of data sources. The data-driven forecasting tool incorporates the following original contributions:

- Efficient forecasting tool based on data science able to process large data volumes in real-time
- The tool is versatile in terms of data types, including spatio-temporal information, events, images, etc.)

End-users of forecasting service expect improved forecasting with lower errors, under the constraint of real-time operation for use in their applications, as confirmed by responses to the survey (cf. **Section 2.3.2**). The exploitation of multiple data sources reinforces the improvement capacity of the tool, which advocates for an effective use of this tool in the practice of forecast as a service.

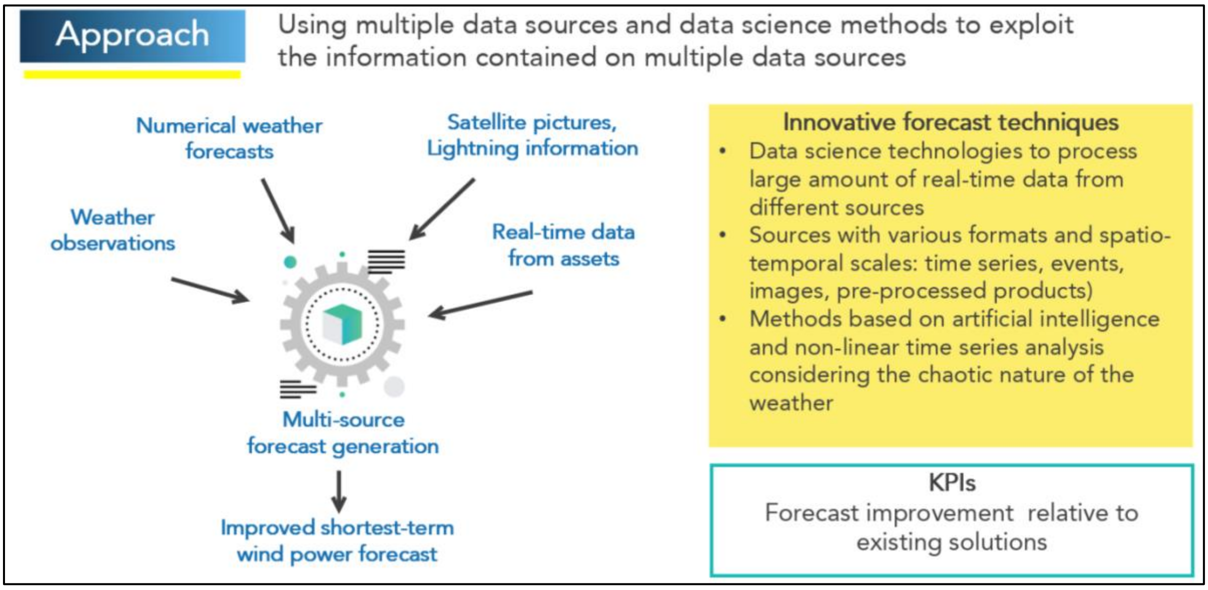

Figure 6: Proposed approach to improve very short term wind forecast thanks to multiple data sources (Use Case RES Forecasting 2, EMSYS)

In isolated power systems, high production levels of non-dispatchable RES (i.e. PV plants or small wind turbines that cannot follow setpoints or controls from grid operators) may be in conflict with grid stability, especially when day-ahead or intra-day schedules deviate significantly from the observed levels of load and generation. In these conditions the RES penetration may reach the maximum level defined by the grid operator and then a curtailment of RES production must be applied. The main lever of this curtailment consists today of large wind power plants. In order to achieve a fair curtailment, the available active power (AAP) production of such wind farms must be precisely predicted. This estimation enables also wind farms to potentially sell up-regulation after an initial curtailment, in order to provide balancing services to the grid [Göçmen 2016]. This is the amount of production that could be attained if curtailment would not have been enforced. Standard methods usually estimate the AAP based on weather measurements or predictions, and therefore lack of precision when AAP must be predicted ahead of delivery. **Use Case RES Forecasting 3** proposes to **forecast the AAP of wind farms** with the following innovations (cf. **Appendix 9.2.3**):

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- Prediction of the AAP of wind production using deep learning techniques to optimize forecasts
- The forecasting model exploits new datasets, namely the combination of curtailed RES production and associated weather conditions

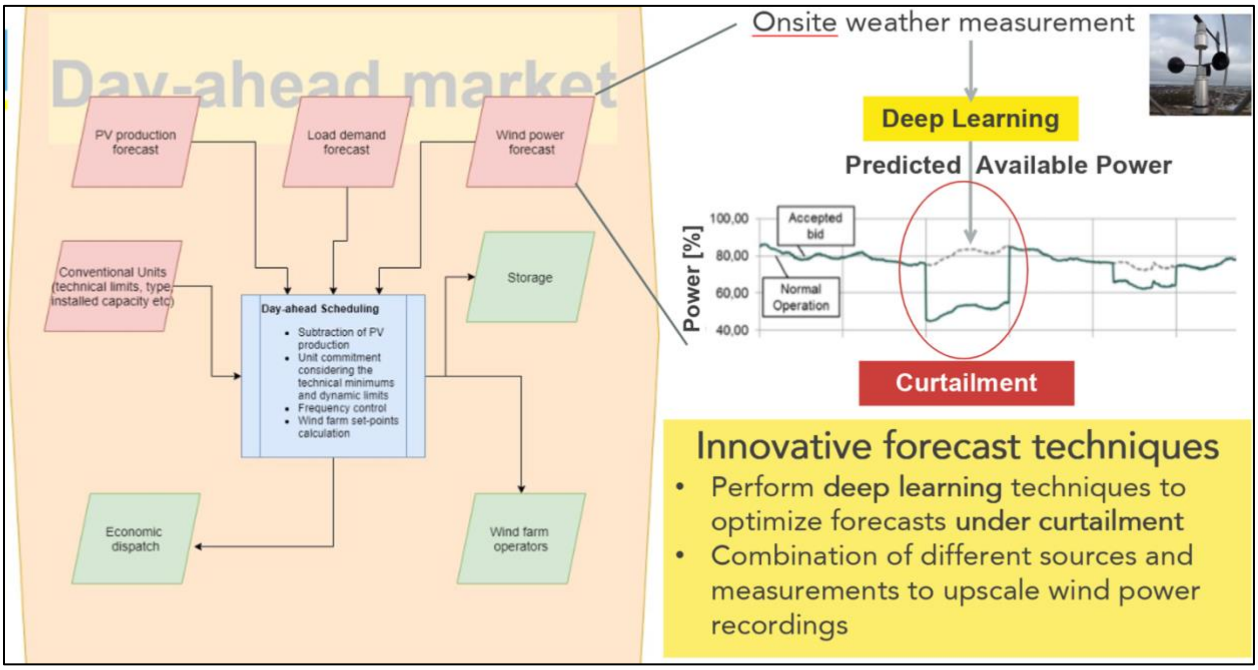

Figure 7: Proposed approach to optimize the forecast of available active power of RES during curtailment in isolated power systems (Use Case RES Forecasting 3, ICCS/HEDNO)

3.4 Overview of Use Cases for market applications

RES power plants are currently entering electricity markets, either directly or through transitional schemes such as feed-in premiums. In any case errors associated to RES production forecasting lead to imbalance penalties when the actual delivered production deviates from the bids. Such penalties can have a significant negative impact on the net revenue of RES producers. Optimization strategies have been proposed to minimize penalties in this context, for instance by operating jointly RES power plants and storage systems. However, the high investment associated to storage is usually not payed back by the avoided penalties. A timely challenge consists therefore in deriving optimal bidding strategies that integrate RES plants and storage systems, by considering all market opportunities. In this regard, **Use Case Market 1** formulates a **data-driven approach**, represented in **Figure 9**, that derives directly bids by **optimizing the value** of these bids on multiple electricity markets. The originality of this proposition is twofold:

- It removes the need to explicitly predict all uncertain variables (resulting for instance in 11 models + trading optimization if bidding RES on energy and reserve markets), therefore greatly simplifying the bidding model chain.
- The use of neural networks enables to simulate numerous interactions with markets. By doing so, complex interactions between RES, storage and markets may be captured and would have been difficult to consider explicitly in model-based formulations.

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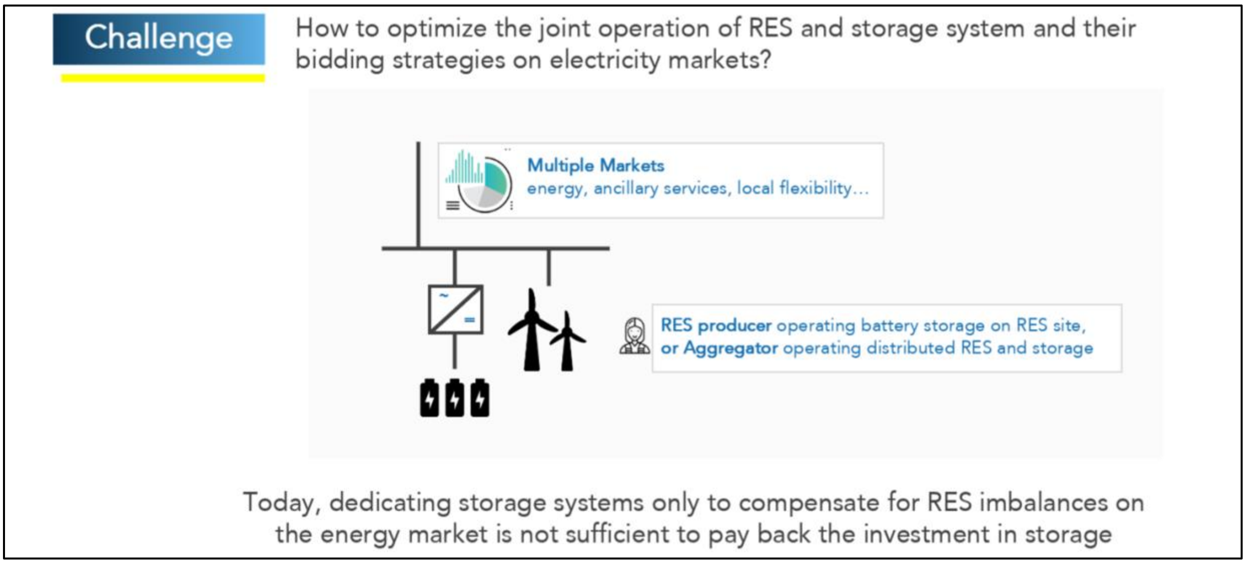

Figure 8: Challenge addressed by UC Market 1 (ARMINES)

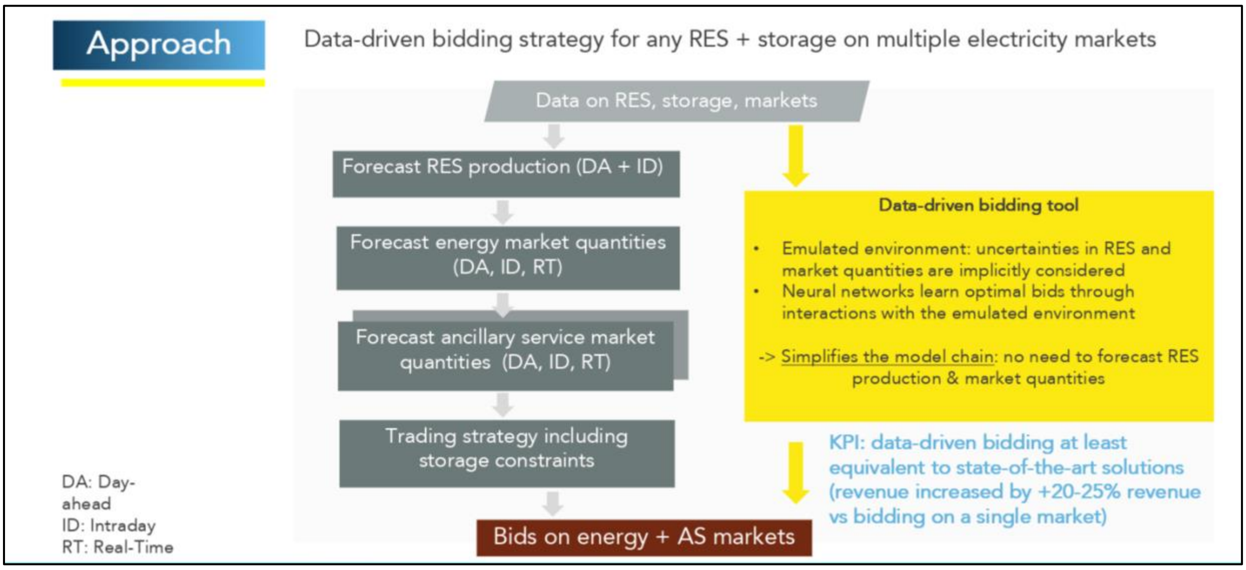

Figure 9: Proposed approach for bidding RES + storage on electricity markets (ARMINES)

The **Use Case Market 2** is linked to the previous Use Case. It proposes to optimize the dispatch of a RES power plant integrating a battery storage. The plant provides energy and flexibility. The innovation of the proposed approach lies in:

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- The development of a **machine learning algorithm for the dispatch**, resulting in lower costs on considered markets compared to standard dispatch solutions
- The solution will be **validated** on a Wind+storage site in operation in Romania (the application is described in **Appendix 9.3.2**).

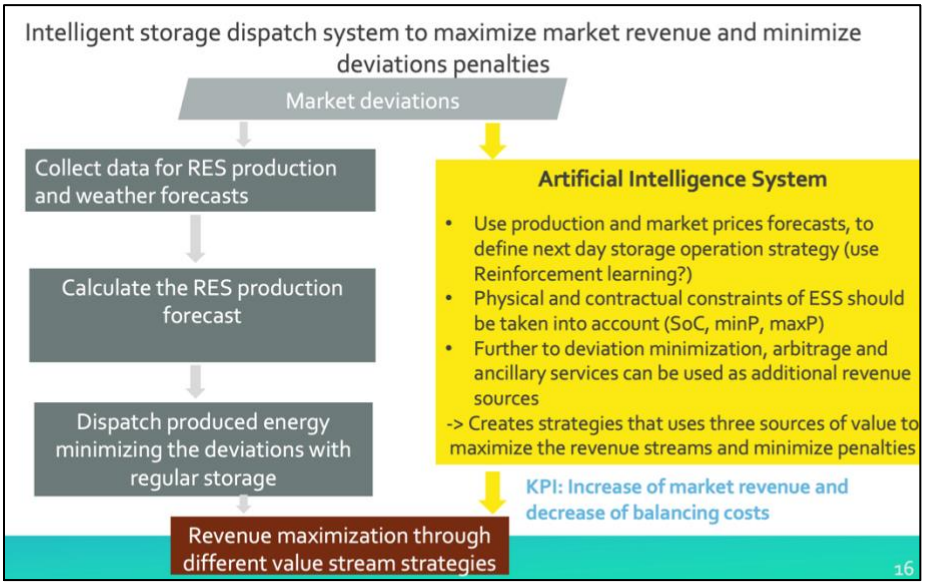

Figure 10: Proposed approach for the intelligent storage dispatch (UC Market 2, EDP)

In order to extract the full value of RES assets, their maintenance must be done at the best moments, for instance before necessary reparations are too costly, when expected revenues from the market are low. Operation & Maintenance amounts to a significant share of the Levelized Cost of Energy of solar parks, therefore **the predictive maintenance based on Artificial Intelligence** (AI) proposed by **Use Case Market 3** has potentially positive impacts on the revenue of RES producers (cf**. Figure 11**):

- AI is able to identify maintenance needs, therefore limits the need for physical inspection
- A better functioning plant increases the value on markets, but also leads to a higher quality of the operational data of the park, which helps AI perform better and the corresponding dataset can be monetized.

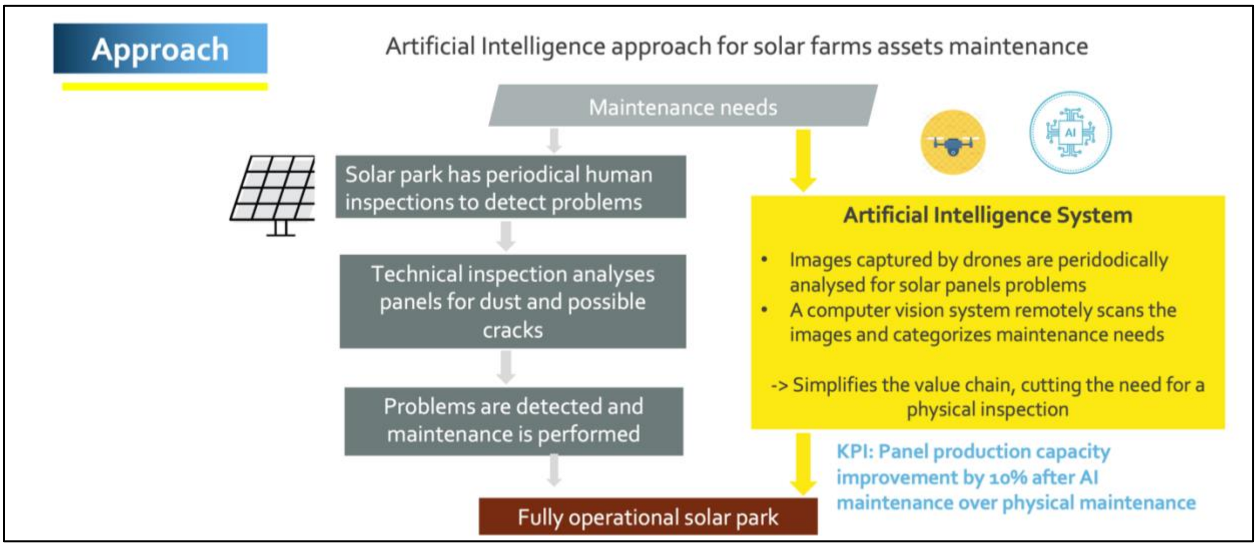

Figure 11: Proposed approach for the predictive maintenance of solar parks (UC Market 3, EDP)

3.5 Overview of Use Cases for grid management applications

In isolated power systems, a large penetration of renewable generation interfaced to the grid by converters will lead to a decrease of synchronous machines in operation, therefore lowering inertia and possibly also primary frequency reserves. In order to ensure the dynamic security of these networks, **Use Case Grid Management 1** develops a two-step approach composed of a **dynamic security constrained unit commitment and an online security monitoring/corrective control** (Figure 12). The Use Case contains the following innovations:

- The predictive dynamic security-constrained unit commitment is designed for severe faults occurring in isolated power systems, and prioritizes the dispatch of synchronous condensers or RES curtailment before the scheduling of conventional units.
- The online monitoring/corrective control signals the risk of insufficient power-frequency reserves and suggest corrective actions based on RES ramp forecasts, thus avoiding to impose static ramp rates to RES assets.

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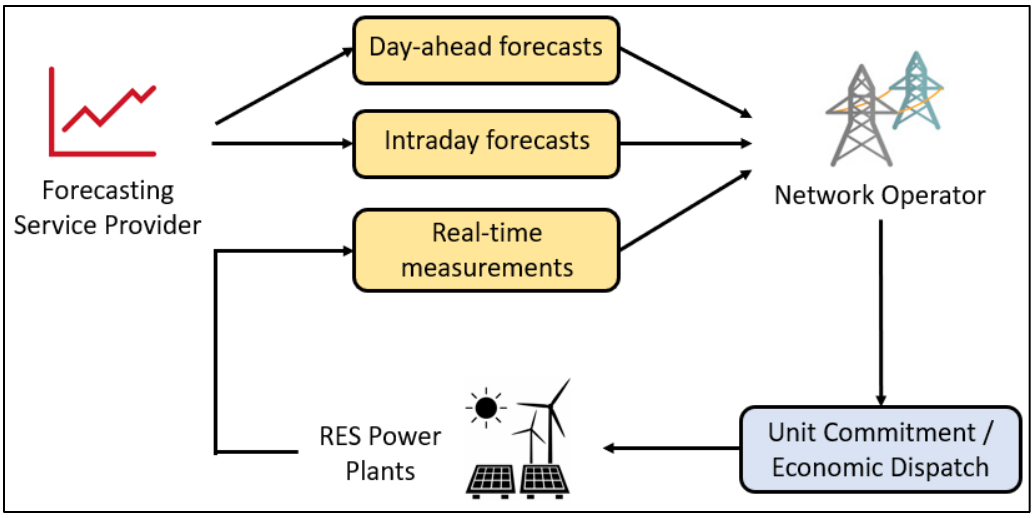

Figure 12: Proposed Unit Commitment for isolated power systems (UC Grid Management 1, INESC)

A similar two-step approach structures **Use Case Grid Management 2**, which addresses the challenge of optimizing the predictive management of distribution grids (**Figure 13**), with a planning phase (next day or hours) and a corrective control in quasi real-time. The state-of-the-art consists in applying stochastic or robust optimizations which have low predictability for power system operators. Instead, the present UC integrates forecast uncertainty in an original way summarized in **Figure 14** and incorporating these two important tools:

- **Data-driven estimation of flexibility needs** taking spatio-temporal ensembles of RES production as inputs,
- **Sensitivity indices** are derived on potentially constrained nodes, leading to interpretable flexibility curves parametrized by tolerated risk levels

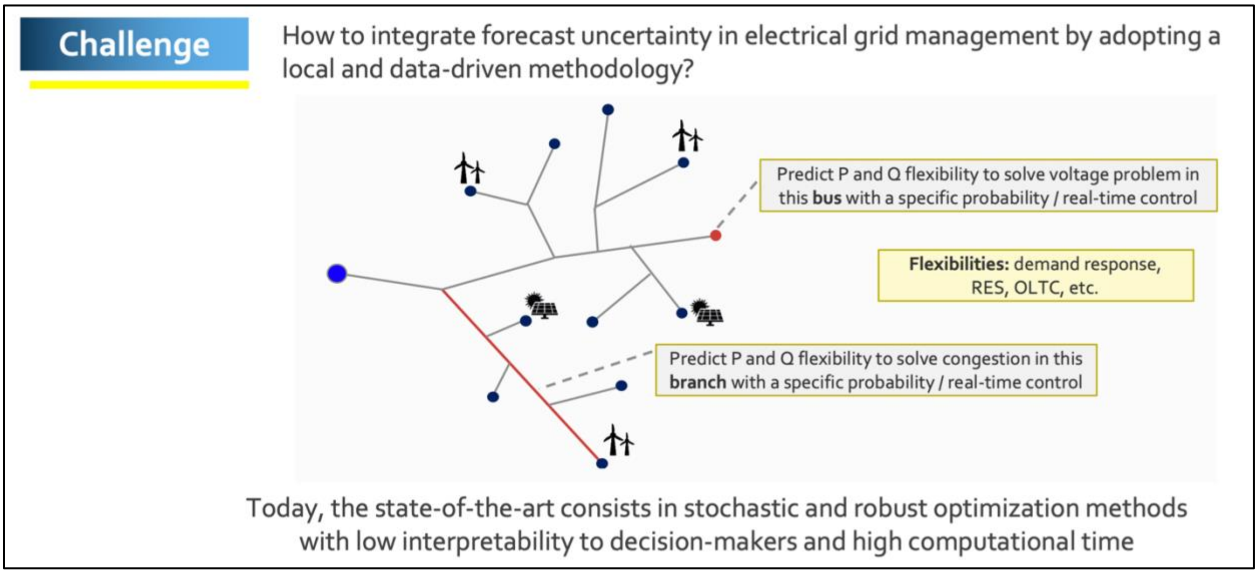

Figure 13: Challenges of local predictive management of distribution grid (UC Grid Management 2, INESC)

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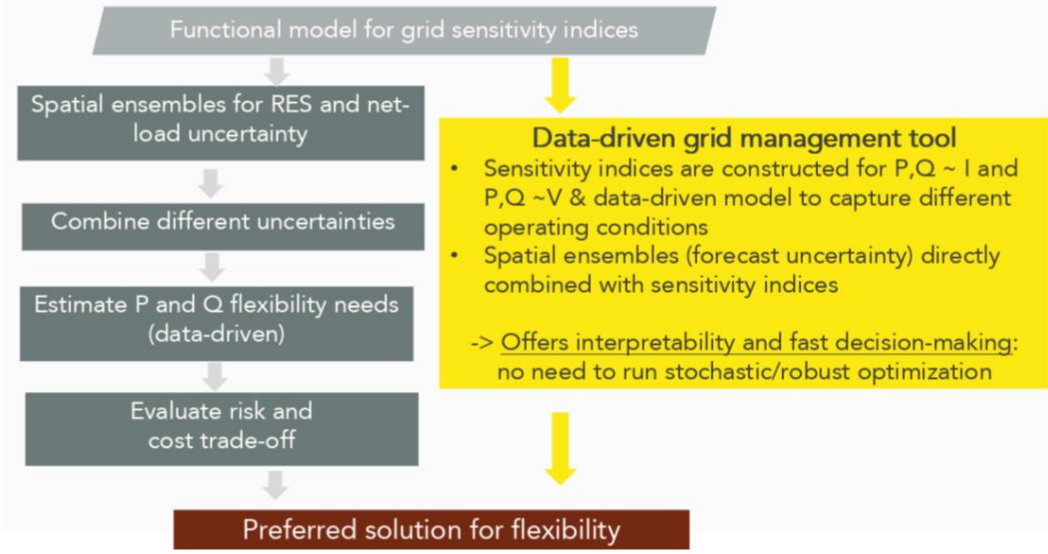

Figure 14: Summary of proposed approach for local predictive management of distribution grid (UC Grid Management 2, INESC)

In the same context, innovative forecasting product may contribute to the successful management of distribution grids. **Use Case Grid Management 3** describes a forecast of the flexibility potential of distributed resources aggregated under a common HV/MV interface. **Figure 15** illustrates the method, which is based on two main innovations:

- **Coherent forecasts of distributed resources** (e.g. PV plants) at the level of the plant and higher aggregation levels until the HV/MV interface
- **A grid-aware algorithm evaluates the flexibility curve** associated to these forecasts, taking into account grid losses and possible constraints.

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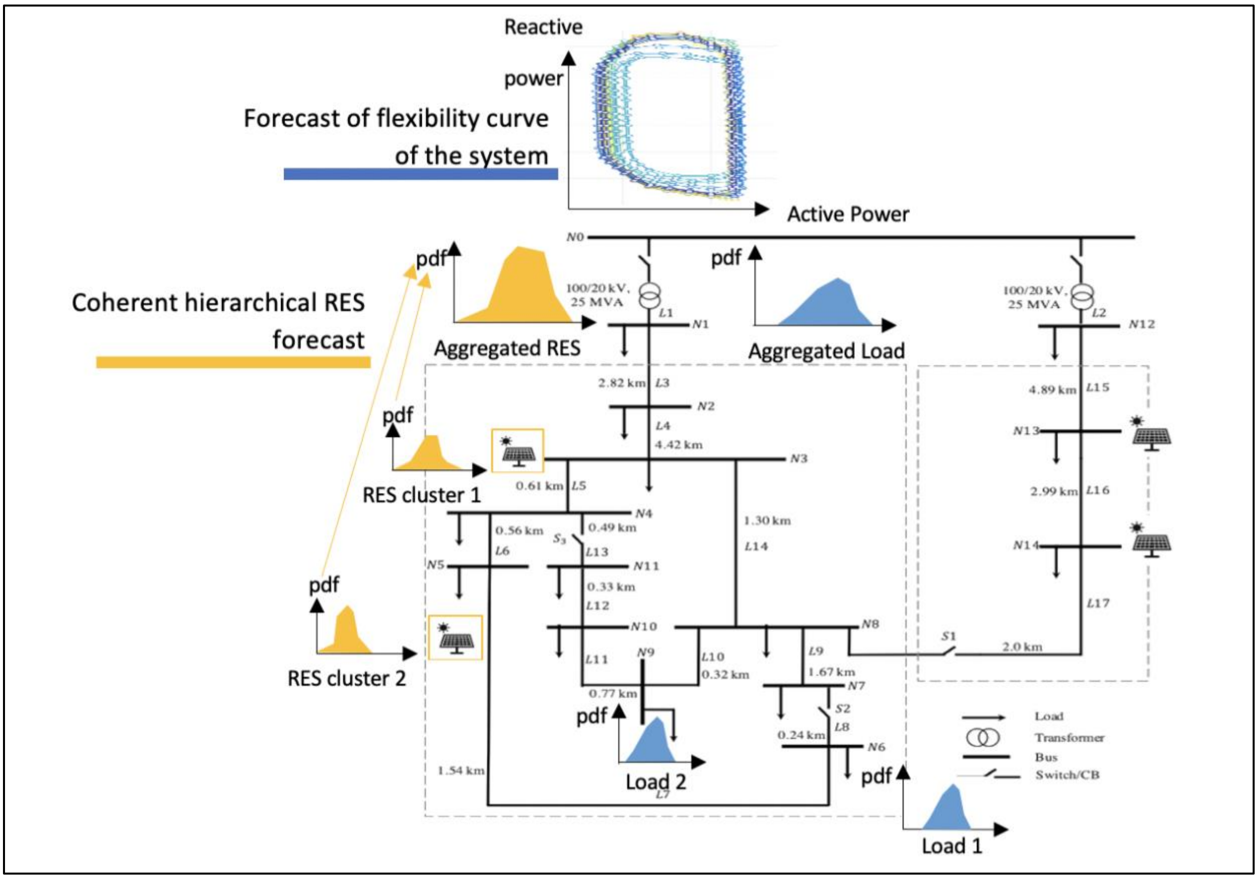

Figure 15: Grid-aware flexibility forecast proposed by UC Grid Management 3 (ARMINES)

Lastly, the Use Case Grid Management 4 proposes a Software-in-the-Loop facility to test algorithms for grid management (including other Uses Cas for grid management) and their possible undesired impacts on the quality and stability of grids (cf **Figure 16**).

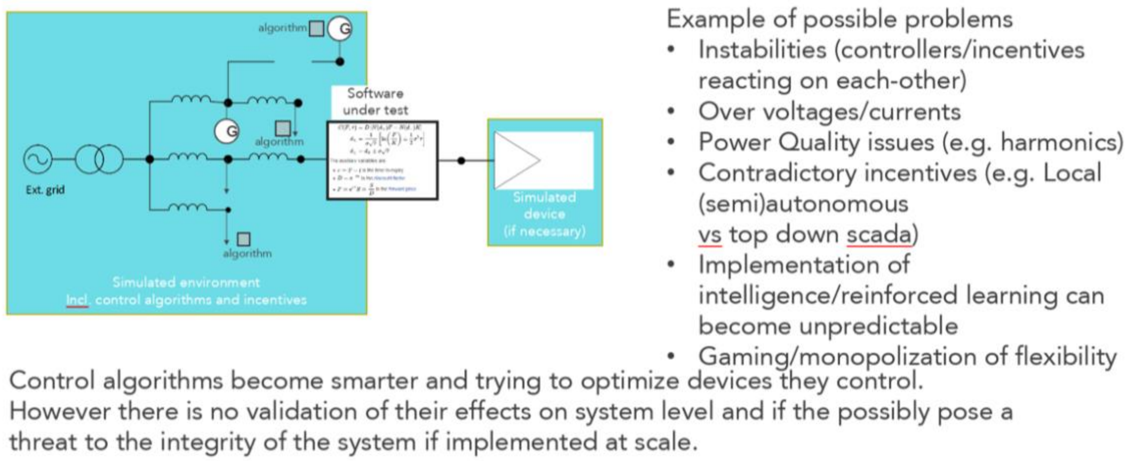

Figure 16: Challenges and approach of Use Case Grid Management 4 (DNV GL)

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4 Analysis and Conclusions

In this section, the content of Use Cases is analyzed in order to obtain an overview of their innovative content, map the distribution of solutions in different domains and finally understand the global contribution of the collection of Use Cases. This section starts with an analysis of Use Cases by levels of priority (Section 4.1) and operational requirements ensuring feasible implementation in practice (Section 4.2). Then Use Cases are analyzed collectively in Section 4.3 to individuate the role of forecasting products in Use Cases, differentiating state-of-the-art products needed for well-functioning UCs and innovative forecasting products proposed by UCs. Answers to bottlenecks in model and value chains are identified in Sections 4.4 and 4.5. General conclusions, including benefits of UCs to Smart4RES activities, are drawn in Section 4.6.

4.1 Analysis of Use Cases by priority levels

4.1.1 Definition of priority levels

There are multiple ways of defining priorities associated to Use Cases. A first common practice consists in defining priorities according to business goals, and priority can be quantified for instance depending on market readiness or expected added value. An alternative formulation of priority considers the replicability potential of solutions proposed in Use Cases [Integrid 2017].

In Smart4RES, Use Cases support the realization of significant improvements in a broad range of contexts (cf. The role of Use Cases in the identification of solutions). Priority consists therefore in the capacity of each solution to attain such improvements in the different areas of the forecasting value chain. As an important axis of Smart4RES is to develop seamless/continuous solutions, replicability is retained as an additional evaluation metric. Priority levels and replicability levels are defined in the following matrices. for forecasting and applications:

Replicability Level	Description
Low	Solution is specific to a technology, a market configuration, a grid typology, etc.
Medium	Solution has potential for other technologies, market configurations, grid typologies but additional research/development is needed to adapt the solution
High	Solution can be applied or transferred easily (ie without significant research/development effort) to other technologies, market configurations, grid typologies, etc.

Table 7: Replicability levels

Priority level	Weather Forecasting	RES Forecasting	Forecasting Services, Platforms
Low	Solution may contribute to the achievement of KPIs on weather forecasting, but gains are uncertain or maturity is low	Solution may contribute to the achievement of KPIs on RES forecasting, but gains are uncertain or maturity is low	Solution may help gain value of forecasting as a service, but gains are uncertain or maturity is low
Medium	Solution contributes to the achievement of KPIs on weather forecasting	Solution contributes to the achievement of KPIs on RES forecasting	Solution is assessed as helpful but not very important by experts for

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			improving the value of forecasting as a service
High	Solution is very important for achieving KPIs on weather forecasting	Solution is very important for achieving KPIs on RES forecasting	Solution is assessed as very important by experts for improving the value of forecasting as a service

Table 8: Priority levels for forecasting solutions in Use Cases

Priority level	Applications in electricity markets		Applications in grid management	
	Existing markets	**Future markets - high RES scenario**	**Interconnected power systems**	**Isolated power systems**
Low	Gains of solution for market participants or operators are unclear		Gains of solution for grid operators are unclear	
Medium	Solution contributes to a well-functioning market (added value cf. Smart4RES KPIs, market efficiency, fairness, etc.)		Solution contributes to improvements in a single control area or in multiple control areas	Solution contributes to improvements in a typical isolated power system
High	Solution is very important for a well-functioning market (added value cf. Smart4RES KPIs, market efficiency, fairness, etc.)	Solution is very important for a well-functioning market (proofs of concept for added value, market efficiency, fairness, etc.)	Solution is key for Smart4RES KPIs in a single control area or in multiple control areas	Solution is key for Smart4RES KPIs in isolated power systems

Table 9: Priority levels for applications in Use Cases

4.1.2 Evaluation of priority and replicability levels in Use Cases

Based on the scaling in the previous paragraph, all use cases have been scored, resulting in the table below, one for the forecasting use cases, and one for use cases that apply forecasting results.

	Use Case	Priority	Replicability

Forecasting	**Weather forecasting**	UC Weather Forecasting 1	High	Medium
	RES forecasting	UC RES Forecasting 1	High	High
		UC RES Forecasting 2	High	Medium
		UC RES Forecasting 3	High	Medium
Applications in electricity markets	**Existing markets**	UC Market 1	High	High
		UC Market 2	Low	Low
		UC Market 3	High	Medium
Applications in grid management	**Interconnected power systems**	UC Grid Management 1	High	High
		UC Grid Management 3	High	Medium
	Isolated power systems	UC Grid Management 2	High	Medium
		UC Grid Management 4	Medium	Medium

Table 10: Analysis of priority levels in Use Cases

Analyzing the results of the scoring shows that most use cases have a high priority, indicating that the project partners have a firm belief in the project. It also shows that the replicability has on average a relative lower score than the priority. Using the priority score as a norm, this means that the consortium partners think the use cases are relatively specialized. Looking at the absolute score, the replicability is considered still very high.

UC Market 2, Dispatch of RES in combination with storage scores relatively low. This does not necessarily mean that RES and storage is not a good combination. It shows that the relation between forecasting and battery storage is not straightforward and specific to market design, such as the allocation and settlement of imbalance. Storage, in combination with RES forecasting, can be used to optimize RES revenues on the market, but it can also be used to mitigate forecasting errors (and thus allows for a more aggressive bidding, which is subject to UC Market 1).

4.2 Requirements for operational deployment

Use Cases presented in this document can be operationally deployed only if data streams, available tools, architectures of markets and power systems are compatible with the requirements of Use Cases. This section does not aim to make a comprehensive list of such requirements, but rather aims at illustrating the final steps necessary to convert a Use Case into practice on the field. The necessary conditions for operational deployment are illustrated below with 3 Use Cases on market-related applications and 1 Use Case on RES forecasting.

In the UC Market 1 'Data-driven bidding strategy on multiple electricity markets', an operational deployment is possible only if:

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- RES power plants are allowed to participate to such markets (energy or ancillary services), at least within an aggregation;
- markets charge penalties in case of imbalances or under-fulfillments, otherwise it is difficult to derive an optimal bidding strategy;
- access to market data is continuous with reduced delays;
- delivery periods of ancillary services are small enough to enable RES participation (e.g. <= 4 hours)
- the data-driven optimization tools are able to update frequently in order to capture structural changes in market or production, and generate valid bids before gate closure time, even if the data quality is not optimal (e.g. presence of missing or incorrect values).

The necessary data streams involve many agents and data sources. These data streams can be ranked in terms of priority for a proper deployment of the Use Case. **Table 11** shows the main data streams needed in UC Market 2 'Joint dispatch of RES + Storage'. In this case, without information on the real RES production it is almost impossible to prepare an optimal dispatch. Instead, if the battery State Of Charge is badly measured or unavailable for a short duration, a robustly designed dispatch can cope with this situation without putting at risk the system or the volumes to be delivered. In UC Market 3 'Park predictive maintenance', drone images are a central source of information for the AI-based, so they have the highest priority, whereas forecasted production is important but the expected production will be secondary compared to the detection of a major technical problem revealed thanks to drone images (the same is true for other data streams such as detailed operational data from the power plant SCADA).

Priority	Type	Source	Description
1	Numerical	Production Site	Real RES Production
2	Numerical	Production Site	Forecasted RES Production
3	Numerical	Market Operator	Market Imbalances Prices
4	Numerical	Market Operator	Wholesale Market Prices
5	Numerical	Production Site	Battery Stored Energy
6	Numerical	Production Site	Battery State Of Charge

Table 11: Data streams for UC Market 2 'Joint Dispatch of RES+storage'

Also Use Cases that produce forecasts need to be supported by an operational infrastructure. An example is given here for UC RES Forecasting 3. The forecasting infrastructure receives wind power, wind speed and wind direction measurements together with the set-point signals sent by system

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operators to wind farm operators and produces forecasts using an infrastructure that manages the forecasting model operations. These operations are:

- Check the quality of received measurements.
- Computation of the rejected wind power, if curtailment is applied.
- Downloading the numerical weather prediction (NWP) files.
- Extracting the NWP files and organizing the NWP data required by each case study to segments that are sent to the corresponding forecasting model.
- Executing the forecasting models in parallel in order the produced forecasts to be delivered as soon as possible.
- Collecting the results and delivering them to the end-users.

That forecasting infrastructure uses micro-service architecture. The above operations are containerized using Docker and communicate with each other using asynchronous remote procedure calls (RPC) provided by the Rabbitmq message broker. Furthermore, the Mongodb database is used for storing the received observations and the produced predictions, while the overall processes are orchestrated with the KUBERNATES. The following **Figure 17** shows the infrastructure of the forecasting models. After the forecasting model executions, the predictions are gathered through the Rabbitmq manager and are sent to the end-users (DSO, independent producers etc.) to perform the depended functionalities related to the grid management.

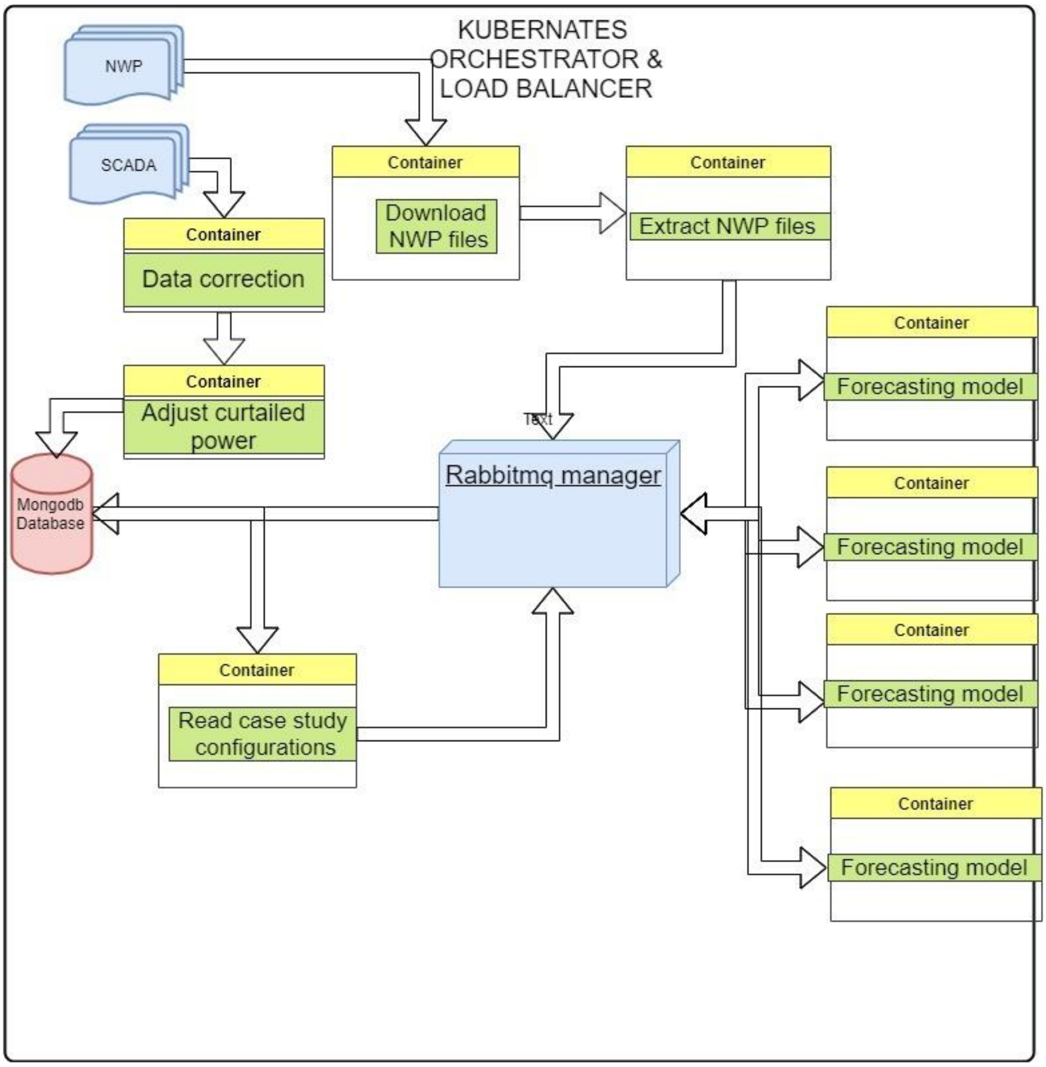

Figure 17: Operational infrastructure supporting UC RES Forecasting 3

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4.3 Forecasting products implemented by Use Cases

Smart4RES has the ambition to increase RES integration by improved forecasting and new forecasting products. This paragraph analyses how the different use cases contribute to this. First by analyzing the dependency of the use cases on existing state-of-the-art products in the market of weather and RES production. Second by highlighting the development and use of innovative forecasting products that reduce or mitigate the risks posed by high RES integration. Both aspects are discussed below, and exemplified in selected Use Cases.

4.3.1 List of implemented state-of-the-art forecasting products

Many Use Cases rely on state-of-the art forecasting products either for baseline models or as part of a larger model chain. Beyond the example of spatio-temporal RES forecasts mentioned above, Table 12 lists all state-of-the-art forecasting and the Use Cases where those products are used. One notes that a large variety of forecast products is employed by Use Cases: this is due to the need of having tailored information for optimized decision and prediction processes.

An example of the essential role of state-of-the-art forecasting products in Use Cases is given by Use Case Grid Management 2 "Localized and predictive management of voltage and congestion problems in distribution grids". The main requirements in terms of forecasting products of this Use Case is the need to capture the spatial temporal dependency structure of forecast errors (or uncertainty). This product is already available and can be created either from statistical models (e.g., Gaussian copula) or physical models (NWP ensembles). This information is directly integrated in power flow equations and captures the influence of forecast errors in the predictive detection and management of technical constraints violation (under-/over-voltage, congestion, etc.). The main innovation consists in creating a simplified process to guide the human operator (decision-maker) in extracting meaningful information from the uncertainty forecast and enable its participation in the ultimate decision (i.e., flexibility reservation and activation).

State-of-the-art Forecasting products	Use Cases for which these products can be used
Deterministic NWP forecasts	UC Weather Forecasting 1, UC RES Forecasting 1, UC RES Forecasting 2
Probabilistic density NWP forecasts	UC Weather Forecasting 1
Ensembles of NWP forecasts	UC Grid Management 2
Deterministic RES production forecasts	UC RES Forecasting 2 (baseline), UC Market 1
Probabilistic density RES production forecasts	UC Market 1
Ensembles of RES production forecasts	UC Market 1
Spatio-temporal RES production forecasts	UC Grid Management 2
Ramp forecasts of RES production	UC Grid Management 1
Forecasts of RES production extremes	UC Market 1

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Table 12: List of state-of-the-art forecasting products

4.3.2 List of implemented innovative forecasting products

Several Use Cases go beyond standard forecasting products and lay out innovative forecasting products. In Table 13 below, all Use Cases developing innovative forecasting products are summarized. Nearly half of the Use Cases propose a new forecasting product, and covers a large range of domains (weather forecasting, RES forecasting, Grid management).

An example of innovative forecasting product is given by UC RES Forecasting 3. Renewable energy enjoys preferential treatment in the electricity system (e.g. privileged producer status, priority dispatch, etc.) as long as secure operation of the power system is not jeopardized. In some cases, however, security-level limits, either due to local network or system-wide security issues will force System Operators to reduce the power output of RES plants below the production obtained in the spot market, a practice known as “curtailment”. Those restrictions are typically transmission congestion and local network constraints identified by the TSO.

The curtailment capacities, known as balancing capacities, are offered by a party contracted by the RES manager that is playing the role of balancing service provider (BSP) in front of the System Operator. When the wind power production is curtailed, the power rejection should be estimated and adjusted to the recorded timeseries. Then, the forecasting models should be trained with the adjusted wind power timeseries providing to the system operator the future total production.

The resulting forecast of available active power under RES forecasting is an innovative forecasting product. Use Case ‘RES Forecasting 3’ provides the framework for a successful implementation of this product in the management of isolated power systems.

Use Cases proposing innovative forecasting products	Innovative Forecasting products
UC Weather Forecasting 1	High spatial resolution solar irradiance forecast
UC RES Forecasting 2	High temporal resolution RES production forecast
UC RES Forecasting 1	Generic seamless RES production forecast
UC Grid Management 3	Flexibility forecast at TSO/DSO interface
UC RES Forecasting 3	Forecast of available active power under RES curtailment

Table 13: List of innovative forecasting products

4.4 Answers to bottlenecks in model chains

Model chains in forecasting and decision-making under RES uncertainty face bottlenecks due for instance to a high level of complexity in the model chain (e.g. many models needed to encompass the entire uncertainty space), or lack of integration of human operators in the model chain which limits the applicability of solutions. Answers to these bottlenecks in Smart4RES Use Cases are described below.

Weather forecasting

The Use Case Weather Forecasting 1 “Next Generation of Weather Forecasting Models for RES Purpose” proposes to combine within an area of 10000 km² inputs of multiple ground base sensors (all sky imager, radiometers and ceilometers) as well as satellite data. The combined forecasts will utilize redundancies and will reduce the influence of weaknesses of individual systems on the forecast quality. Ultimately this represents a simplification compared to the individual treatment of each data source using distinct approaches.

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RES production forecasting

The Use Case RES Forecasting 1 "Generic Seamless RES forecasting" contains a simplification of the modelling chain associated with RES production forecasting. This simplification is twofold: (1) it covers a large range of horizons instead of separate models for each horizon interval and (2) it is valid for different renewable energy sources.

Applications on electricity markets

The Use Case Market 1 "Data-driven bidding on multiple electricity markets" proposes a direct approach to optimal bids by bypassing the need of forecasting all the uncertain variables associated with the bidding, namely RES production and market quantities. The value-oriented approach aims at minimizing costs or alternatively maximizing profit directly by learning on the entire available data. This has been proven to be effective in simple cases such as bidding on the wholesale short-term electricity market, a challenge for the application of such data-driven approach is to demonstrate their capacities in more complex situations such as bidding on multiple markets (e.g. energy + ancillary services) or bidding of a joint operation of RES plant + storage, which introduces complex temporal constraints.

Applications on grid management

The use case Grid Management 2 "Localized and predictive management of voltage and congestion problems in distribution grids" proposes a simplification of the model chain for technical management of grid constraints. The basic idea is the following:

- Explore the concept of sensitivity indices between active/reactive power flexibility and bus's voltage and branch current. This information can be combined with uncertainty forecasts to provide a clear notion to the human operator of its impact and simplifies the analysis of the network constraints (i.e., linearization of the relations between electrical variables).
- Place the focus only in congested branches or buses with voltage problems and identify the most interesting flexible resources. Guide the human operator in the choice of a final solution (i.e., reserve flexibility) by presenting him with a sequence of risk-cost curves.

In this case, the model chain consists in forecasting and decision-aid with high interpretability and interaction with the decision-maker.

4.5 Answers to bottlenecks in value chains

The adaptation of RES forecasting and related decision-making tools is limited by bottlenecks in value chains, e.g. due to the lack of connection between forecasting and applications in markets or grid management and consequently the decaying commercial value of forecasting products, or the inaccuracies in data or RES forecasting leading to high costs in applications. Answers of Smart4RES Use Cases to bottlenecks in value chains are described below.

Use Case Market 1: Data-driven bidding methods on multiple electricity markets

Currently most forecasting models are tuned upon their prediction accuracy of RES production, electricity prices, etc. Once forecasting models have been optimized, they are subsequently used by a decision-making model, which in turns optimizes the decision (i.e. a market bid) based on these forecasts. However, it is not always the case that forecasts optimized independently lead automatically to improved value of decisions. In contrast, **value-oriented approaches** look for optimal strategies without optimizing explicitly every source of uncertainty. Such a value-oriented strategy is implemented in the Use Case: all models (forecasting of production and price, decision-making) are optimized together via a heuristic tool, answering to the bottleneck of an 'open loop' between forecasting models and applications.

Use Case Market 2: Joint dispatch of RES + storage

Imbalances in the electrical market correspond to the difference between the actual production and the volume associated to the market bid. In fact, transposing this definition for our operating scenario would mean that our computational system predicts that a certain amount of energy would be produced by the wind farm on a certain day, but the delivered generation would be a percentual amount above or below the predicted value. This way, to create a negative nudge on this type of behaviour, the electricity market attributes economical penalties to the players who cause imbalances in the electrical system.

In order to reduce the abovementioned imbalances, two possible approaches can be followed: a quantitative and a qualitative one. Qualitatively, we can act on the system by enhancing the engineering system in a way that the excess or recess of energy is automatically balanced by the system and doesn't affect the transmission side. Specifically on this Use Case, the battery system compensates automatically the imbalances resulting from the deviation between forecast and observed wind production. Quantitatively, the approach aims at minimizing the error of that prediction. The quantitative approach is chosen in the Use Case, it consists in using advanced machine learning algorithms to minimize the imbalance volume in a joint RES+storage application.

Although the battery system is a significant improvement to solve the imbalances problem, it isn't automatically an optimal solution. From one side, the cost of the storage system is still too high to be paid back by the reduction of penalties associated to imbalances. Furthermore, storage systems present several technical constraints that must be taken in consideration (such as storage capacity, maximal charging and discharging power, etc.). The system will thus need to be subject to an optimization approach so that it can deliver the maximum value considering the storage size and constraints. In particular, the **bottleneck of the high investment of storage system** is tackled by a **multi-objective optimization which seeks to capture value on multiple electricity markets**, e.g. energy and ancillary services.

As we've explained, the energy imbalances aren't automatically solved with a storage system. It will be manually calibrated and deliver the needed energy when excess imbalances occur, but the delivered energy can fail to accomplish the task if the system is not well dimensioned or if there is not enough stored energy when the demand is necessary.

Previously we have concluded that the storage system is needed but may suffer from optimization problems, so, once again, we look at machine learning as a solution. Recurring to prediction algorithms, such as neural networks or random forests, the energy storage will be dispatched in an optimal manner which will minimize imbalances and its costs, optimizing the use of the available storage capacity.

Use Case Market 3: Park predictive maintenance

Scheduling maintenance in solar parks or windfarms is a cumbersome process. It consists of having a human operator, part of an asset management team, monitor the production capacity of the assets through analytics or physical components auditing. Sometimes, during these procedures, anomalies are detected which trigger a field intervention and the corresponding maintenance. When no anomaly is detected a routine maintenance is defined. These are costly operations and their impact are not always easily quantifiable, thus it's difficult for the park operator to decide when to optimally intervene without more advanced and data-driven systems.

If we use machine learning as a tool to inform us when and under which conditions will the system components need maintenance, there could be a personalized contract per client with very accurate maintenance periods, instead of routine ones. This machine learning can be fed with detailed data from the SCADA system, but also images of components of the plant taken by drones, which could even realize simple repetitive maintenance tasks such as cleaning. This predictive maintenance approach would only leave us with spontaneous anomalies to be resolved, outside the model predictions.

In terms of efficiency gains there would be an improvement in the business operations, since the maintenance teams would have specific dates for action and the client would have tailored dates to its system enhancing the relationship. An automatized maintenance will lead to **higher volumes of renewable production**, therefore potentially higher revenue for RES producers and a contribution to lower carbon emissions. Lastly, this predictive maintenance reduces the occurrence of recurring faults which can lead to erroneous data records (plant functioning partially, in degraded mode or with drifts in data measurements). Datasets obtained over a long period under such an optimized predictive maintenance would have an **increased data quality** for internal or external use than standard datasets where missing or wrong values are frequent and not currently labelled.

Use Case Grid Management 3: Efficient forecast of interaction between distribution and transmission power systems

Distributed energy resources have the capacity to provide flexibility to power systems via aggregations and virtual power plant control systems. Forecasting only active power or simple flexibility curves that are unaware of the grid state has a limited value for power systems operators. In Use Case Grid Management 3, the grid-aware hierarchical flexibility forecasting tool enables to assess the flexibility potential of distributed resources such as PV plants aggregated under a MV/HV interface, with integration of grid typology and constraints. This new forecasting product **answers to the decaying commercial value of standard RES forecasting products**: here aggregators or system operators dispose of structured predictions of distributed flexibility potential, which can be used efficiently in robust decision-making such as solving local constraints or formulating flexibility offers.

Towards data markets for RES forecasting

In many applications related to RES forecasting, the continuous exchange of data between agents is a key element in the performance of proposed solutions. In the case of geographically distributed resources (e.g. RES production plants), the absence of collaboration in the exchange of data limits the potential of this data, because it is known that data from nearby sites can successfully reduce the uncertainty of prediction using for instance spatio-temporal approaches [Agoua 2018]. This bottleneck in the value chain of RES forecasting is addressed in Smart4RES via the proposition of the new concept of **data markets for RES forecasting**. It is based on a privacy-preserving collaborative forecasting approach, exploiting the data shared by geographically distributed RES sites. A market mechanism is developed in order to settle the price of the data shared by data owners. Such a mechanism is presented in Figure 18 **:** a Wind farm WF1 buys data from neighbouring wind farms WF2 and WF3 via the marketplace where it formulates a bid as a function of the improvement in forecasting error which can be expected with the shared data. The design of the associated marketplace and auction mechanism are presented and evaluated on a realistic case study in [Gonçalves 2020]. This concept will be further developed in the frame

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of Smart4RES Work Package 4 'Collaborative Framework to RES Forecasting and Resulting Business Models'.

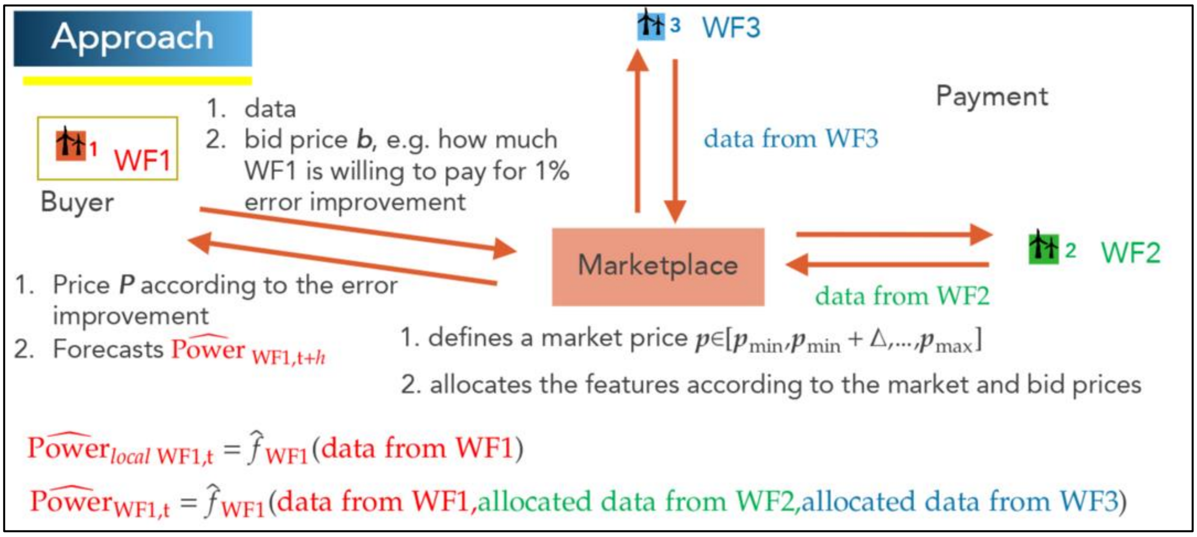

Figure 18: Proposed approach for data markets of RES forecasting (DTU / INESC)

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4.6 Conclusion

We want to close this report with a description of how Use Cases integrate into the general project concept and its different objectives and Work Packages. The Smart4RES DoA defines the project concept as 'based on a holistic approach that aims to address the entire model and value chain of the RES forecasting technology.' We will see first the implementation of the holistic approach in Use Cases, and then how Use Cases contribute to Smart4RES Work Packages.

The project objectives are mainly focused on enhancing the RES forecast quantitative performances, through the enhancement of predictive models and reduction of induced costs on power systems. Several Use Cases aim at improving parts of the model chain of the RES forecasting technology, thereby contributing directly to the project objectives. The holistic approach leads to Use Cases that integrate improved forecasting in order to generate more value: for instance, Use Case Market 2 (Joint dispatch of RES + storage) brings to the table direct improvements on the RES production forecasts as well as market imbalances optimization. The Use Case Market 3 (Predictive Park Maintenance) leverages enhancements on the predictive maintenance models used in the industry so that technical faults on the parks are not propagated to problems in the power system. The holistic approach translates also into connections between the proposed solutions in Use Cases: for instance, the high-resolution solar irradiance developed in Use Case Weather 1 is a valuable input for the multi-source RES production forecast in Use Case RES Forecasting 2.

Finally, the holistic approach means that Use Cases promote a diversity of approaches in forecasting and optimization: while data-driven, AI-based methods constitute a pillar of innovative solutions of several Use Cases, interestingly these have the potential to combine with less computation intensive approaches, e.g. reopening expert analysis, as in Use Case Grid Management 2 where a data-driven controller is interfaced with sensitivity indices simplifying the analysis of distribution grids.

As shown in this report, the outputs of the Use Cases are mainly be predictive and optimization models. The potential contributions of the outputs of the Use Cases in Smart4RES Work Packages are represented below in **Table 14**, and ranked by degree of importance in the respective Work Packages.

Work Package 2 (Next Generation of Weather Forecasting Models for RES Purpose) will benefit from the Use Case on solar irradiance forecasting. Work Package 3 (Data Science and the Future of RES Forecasting) will benefit from the forecasting strategies developed on the Use Cases enriching the whole data science strategy of the project, both from RES production forecasting and weather forecasting.

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WP / Tasks	WP2	WP3			WP4	WP5				WP6		
Use Cases (UC)	**T2.3**	**T3.1**	**T3.2**	**T3.3**	**T4.1**	**T5.1**	**T5.2**	**T5.3**	**T5.4**	**T6.1**	**T6.2**	**T6.3**
UC Weather Forecasting 1												
UC RES Forecasting 1												
UC RES Forecasting 2												
UC RES Forecasting 3												
UC Grid Management 1												
UC Grid Management 2												
UC Grid Management 3												
UC Grid Management 4												
UC Market 1												
UC Market 2												
UC Market 3												

Task 2.3 'Short-term solar resource forecasting by merging various inputs'
Task 3.1 'Multi-source data approach to short-term RES forecasting'
Task 3.2 'Towards a generic seamless forecasting approach for multiple time scales'
Task 3.3 'Evaluation and post-processing of NWP data from WP2 for power forecasting of RES'
Task 4.1: 'Distributed and collaborative forecasting'
Task 5.1: 'Joint optimization and dispatch of RES power plants and storage'
Task 5.2: 'Forecasting and management of Frequency Containment Reserve and system inertia in isolated power systems'
Task 5.3: 'Localized and predictive management of voltage and congestion problems in electrical grids'
Task 5.4: 'Market trading of RES and storage'
Task 6.1: 'RES power forecasting live demonstration'
Task 6.2: 'Laboratory test-bed for power systems with near-100% RES'
Task 6.3: 'Market trading test bed'

	UC outputs are a central part of Task
	UC outputs are not central, but implemented in Task
	UC outputs are valuable inputs for Task
	UC outputs could be used in Task, value to be assessed

Table 14: Contributions of Use Cases to Smart4RES Work Packages

Finally, Work Package 5 (Modelling Tools for Integrating RES Forecasting in the Electrical Grids, Electricity Markets and Storage Operation) will be getting inputs from the market optimization strategies developed in Use Case Market 1, as well as from the storage optimization strategies developed in Use Cases Market 2. Grid management tasks in WP5 will be based on Use Cases for Grid management 1 to 3, but will also make use of Use Cases at both ends of the model chain,

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i.e. addressing RES production forecasting and Software-in-the-Loop validation tests in Use Case Grid Management 4.

A common challenge emerges in this collection of Use Cases: the proposed solutions require large and frequently updated data streams, and generate themselves new data and products which have potentially high value. In order to organize the exchanges of these streams of raw data and forecasting products, data markets are needed to foster collaboration between power system agents operating at different locations and with distinct objectives and to settle prices optimizing welfare. These data markets are developed in Work Package 4 (Collaborative Framework to RES Forecasting and Resulting Business Models).

In conclusion, it appears that the 11 Use Cases form an important skeleton for Smart4RES activities because they span all Work Packages and have significant interactions, even multi-disciplinary e.g. between energy meteorology and grid integration. As Use Cases are a conceptual exercise with the aim of being replicable in different contexts, they may be useful for dissemination and insightful to other research and industrial activities in the field of power systems.

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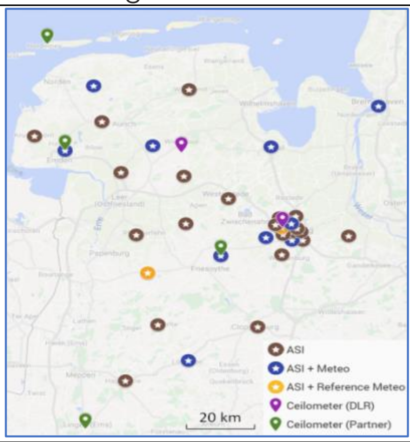
6 Appendix: Resources and Applications used in Smart4RES use cases

Application name	**1/ Eye2Sky - NorthWest meteorological measurement network & PV plant (DLR)**
Data providers	DLR (Consortium Partner, DE), EMSYS (Consortium Partner, DE)
Localization	Oldenburg, DE
Illustration	 Measurement stations in urban area of Oldenburg, DE (source: DLR)
Application description	Network of meteorological measurement and PV production in area of Oldenburg, Germany (110 km by 100 km). High spatial and temporal resolution (100 m, 30 seconds) of the data provided by 34 all-sky imagers, 6 ceilometers, 7 rotating shadowband irradiometers. Measurements from 1 Rooftop PV plant.
Use in Smart4RES	WP2: High-resolution weather forecasting (100 m, 30 seconds) WP3: Multi-source RES power forecasting WP6: Cost-benefit assessment of improved weather and RES forecasting

Application name	**2/ Network of PV plants at mid-west of France (HESPUL - SERGIES)**
Data providers	HESPUL (Reference Group, FR) – SERGIES (External, FR)
Localization	Mid-west hexagonal France
Illustration	(source ARMINES)

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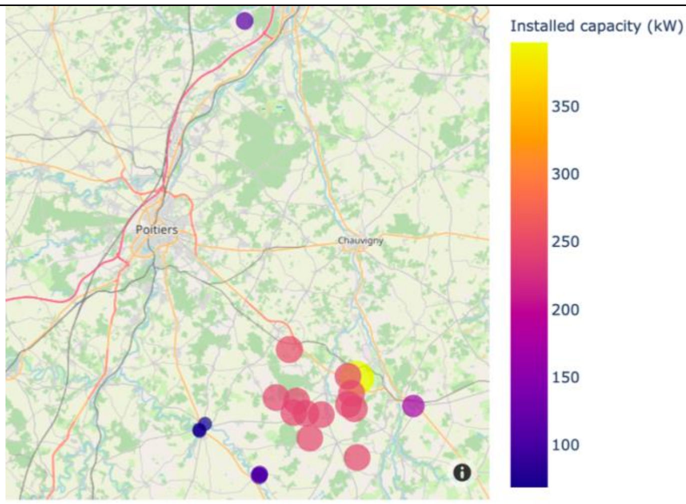
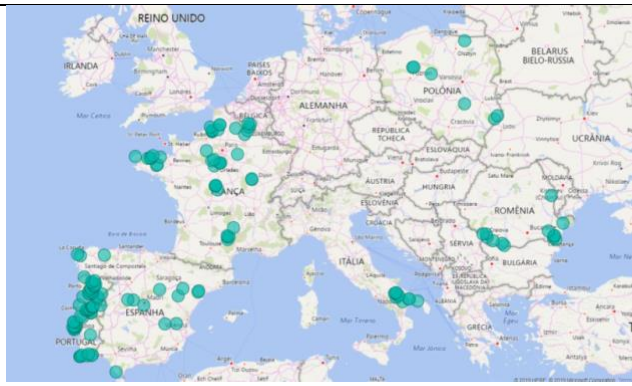
	
Application description	20 PV power plants located in mid-west France, with a peak power ranging from 69 kWp to 397 kWp. The distance between plants varies from 1 km to 60 km. The available data start from October 2018 with a 5-min temporal resolution. An API enables to retrieve the data online.
Use in Smart4RES	WP2: data assimilation and validation of weather models WP3: multi-source RES forecasting WP4: collaborative RES forecasting and data markets WP6: cost-benefit assessment of improved RES forecasting and data markets

Application reference	**3/ Onshore Wind plants in Portugal (EDP-R)**
Data provider	EDP-R (Reference Group, PT)
Localization	Portugal
Illustration	 Localization of RES plants from EDP-R in Europe (source EDP)
Application description	EDP Renewables provides production and weather data from 11 onshore wind farms of its portfolio in Portugal
Use in Smart4RES	WP2: data assimilation and validation of weather models WP3: seamless RES forecasting at multiple time scales WP5: Market trading of RES

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	WP6: Cost-benefit assessment of improved RES forecasting

Application reference	**4/ Historical time series of load & PV in 3 non-interconnected islands aiming at installing RES-based hybrid systems (HEDNO)**
Data provider	HEDNO (Consortium Partner, GR)
Localization	Astypalea, Symi, Megisti, GR
Illustration	 Non-interconnected island Power Systems operated by HEDNO
Application description	Historical time series on load and PV (installed capacities between 1 MWp and 8.5 MWp) in 3 non-interconnected Greek islands.
Use in Smart4RES	Hybrid systems comprising PV, Wind and storage are foreseen by HEDNO in 3 non-interconnected islands to achieve an annual RES penetration of 60% and provide ancillary services. WP5: Forecasting and management of ancillary services in isolated power systems WP6: Validation in test-bed laboratories

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Application reference	**5/ The island of Crete as a reference case for forecasting (HEDNO)**
Data provider	HEDNO (Consortium Partner, GR)
Localization	Crete, GR
Illustration	 Wind farms located in Crete (source HEDNO)
Application description	Crete is a challenging test case for forecasting due to its complex terrain and impacts of sea/earth interactions on weather conditions. Historical Wind and PV production data of the island (total installed capacity Wind 230 MW, PV 98 MW) is available to validate the performance of forecasting models.
Use in Smart4RES	WP3: Multi-source RES forecasting, seamless RES forecasting at multiple time scales WP6: Cost-benefit analysis of advanced RES forecasting

Application reference	**6/ The island of Rhodes as a living lab (HEDNO)**
Data providers	HEDNO (Consortium Partner, GR)
Localization	Rhodes, GR
Illustration	 Rhodes in island Power Systems operated by HEDNO
Application description	Rhodes Island is supplied by 2 power stations with total 358 MW capacity, plus 19 MW PV and 48 MW Wind. Historical data is available for wind, load and aggregated PV at 10 substations on the island at a 1-minute resolution
Use in Smart4RES	WP3, WP6: The most promising RES prediction models developed in Smart4RES will be tested operationally on-line for one year. WP5, WP6: A stochastic scheduling will incorporate advanced RES forecasts and be adapted to the context of non-interconnected islands. Validation offline (WP5) then online (WP6) with realistic operational conditions.

Application reference	**7/ Wind + Storage System in Romania (EDP-R)**
Data providers	EDP-R (Reference Group, PT)
Localization	Cobadin, Romania
Illustration	 Stocare battery energy storage system coupled to Wind farm in Cobadin, Romania (source EDP-R)
Application description	EDP-R operates the 26 MW Wind Farm in Cobadin, Romania, coupled with a storage system (1.26 MW/1.37 MWh) to flatten forecasting errors. Historical data of Wind production and battery energy storage system are available from September 2018 and from January 2020 respectively.
Use in Smart4RES	WP3: Seamless forecasting at multiple time scales WP5: Joint optimization and dispatch of RES power plants and storage, Market trading of RES and storage: data-driven and human-in-the-loop approaches WP6: Cost-benefit analysis of advanced RES forecasting and market trading tools, Market trading test bed

Table 15: Dataset 7: Wind + Storage System in Romania (EDP-R)

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Application reference	8/ Wind-Float Atlantic (EDP-R)
Data providers	EDP-R (Reference Group, PT)
Localization	Offshore Portugal (Aguçadora, Viana do Castelo)
Illustration	 Wind Float Atlantic 1 (source EDP)
Application description	Offshore 2MW Wind turbine with floating foundations ("water entrapment plates" below pillars + static and dynamic ballast). 5 years of historical data is available between its grid connection in 2011 and its decommissioning in 2016.
Use in Smart4RES	WP3: Seamless forecasting at multiple time scales, Multi-source RES forecasting WP6: Cost-benefit analysis of advanced RES forecasting

Table 16: Dataset 8: Wind-Float Atlantic (EDP-R)

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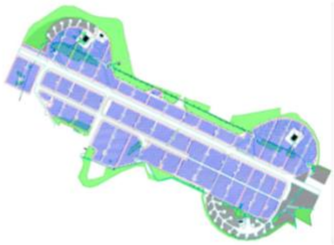
Application reference	**9/ Large power plant (Solaïs/Thirdstep)**
Data providers	Solaïs/Third Step(Reference Group, FR)
Localization	North-East France
Illustration	  Layout of the 150 MW (75 MW owned by Solaïs/Thirdstep) on ancient Airport
Application description	Solaïs / Third step has commissioned in first trimester 2021 the third largest PV plant in Europe (150 MWp, 265 ha) in Northern France. 5-minute data streams (power production, pyranometers, temperature) available from June 2021 onwards.
Use in Smart4RES	WP2: Validation of advanced weather prediction models WP3: Seamless forecasting at multiple time scales, Multi-source RES forecasting WP4: Collaborative forecasting and data markets WP5: Market trading of RES and storage: data-driven and human-in-the-loop approaches

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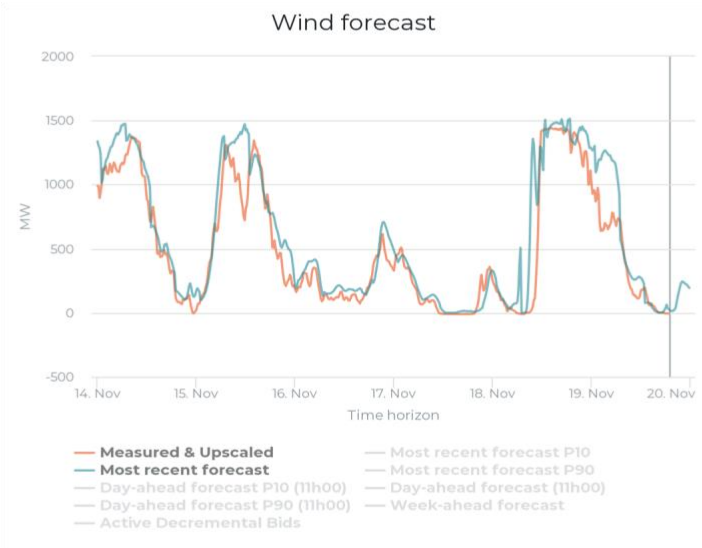
Application reference	**10/ Offshore wind production in Belgium (ELIA)**
Data providers	ELIA(External provider, BE) RVO (External provider, NL)
Localization	Offshore Belgium
Illustration	 Offshore production in Belgium from the Elia website
Application description	All Belgian wind farms are located in a 25 km radius and can therefore be considered as a single large wind farm. Data on power generation, availability and forecasts are published by the TSO Elia, and LiDAR measurements from the near offshore farm zone of Borssele in Netherlands are also available for the period 2015-2017.
Use in Smart4RES	WP3: Seamless forecasting at multiple time scales, Evaluation and post-processing of NWP data from WP2 for power forecasting of RES WP6: Cost-benefit analysis of advanced RES forecasting and market trading tools

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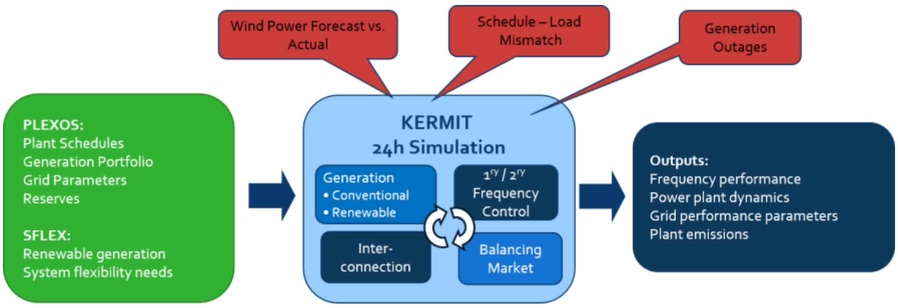
Application reference	**11/ Simulation and validation of (local) optimisation and control software interacting with a simulated environment using KERMIT**
Involved partners	DNV GL(Consortium partner, NL) INESC (Consortium partner, PT)
Localization	Arnhem, Netherlands
Illustration	Illustration of Kermit:  Output from control actions optimized by the software-under-test (SUT) is fed into Kermit and then fed back to the SUT (possibly with other information, like changing weather patterns), etc. The test is about under which circumstances this loop will lead to undesired outcomes, like instabilities.
Application description	The predictive grid management tool developed by INESC will be implemented and validated in a specialized model modelling inertia and balancing up to 15 minutes scale, called 'Kermit'. Kermit will be one of the simulated 'environments' needed for software in the loop testing that will be developed in WP6 (task 2)
Use in Smart4RES	WP5: Management of frequency containment reserve and system inertia in isolated power systems WP6: Laboratory test bed and living lab for power systems with near 100% RES

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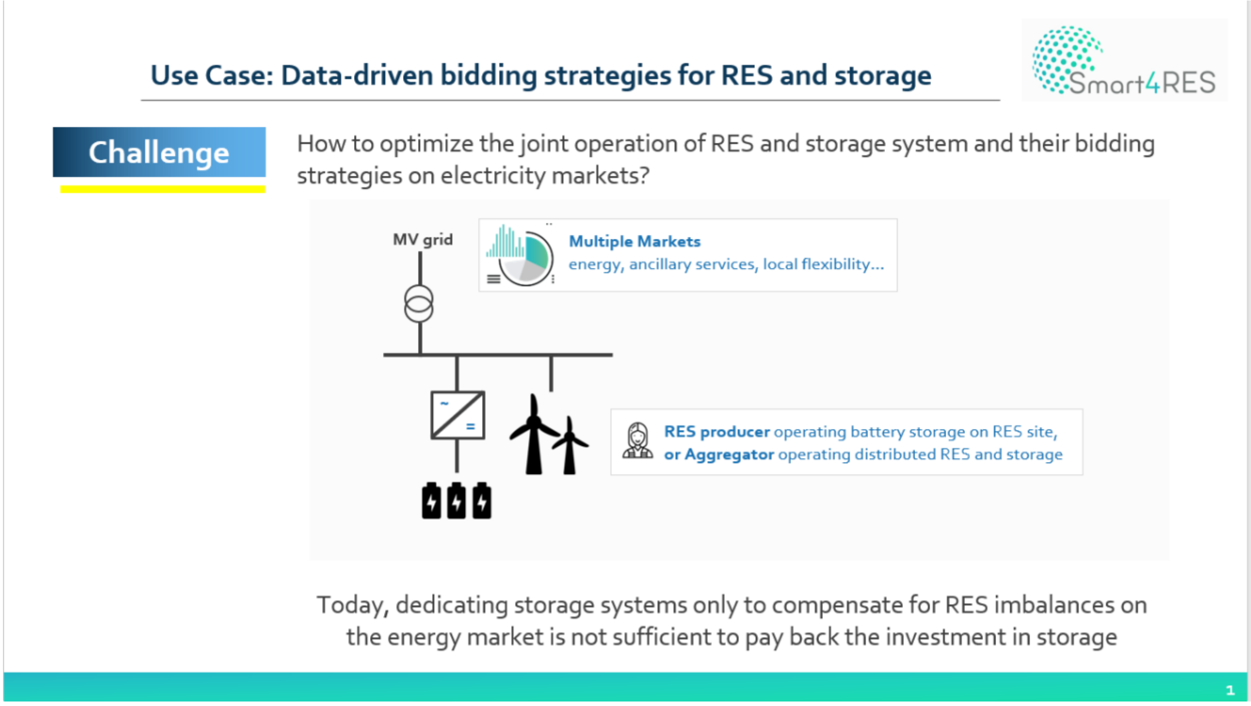
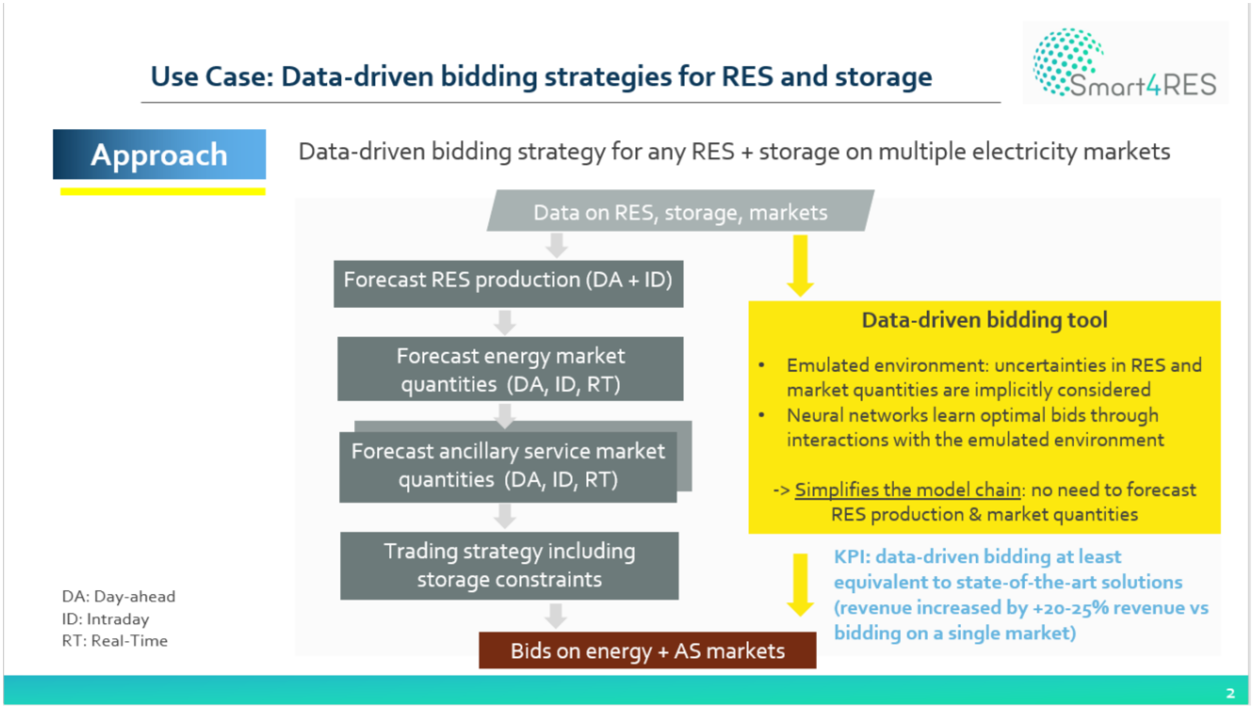
7 Appendix: Highlight Use Case Template example





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Revision	Date	Description	Author (Organisation)
V0.1			
V0.2			

8 Appendix: Detailed Use Case template

Authors (organisation):
<Person1 (Organisation 1)> <Person2 (Organisation 2)>

Abstract:
<Short summary of use case of about 150 words>

Keywords:
<Keywords describing the use case, e.g. RES forecasting, Ancillary Services, …>

Revision History

Use Case ID	<Title of Use Case >
Cluster / Work package	<Work package(s) in which UC is being developed>
Classification	<Primary, secondary or … Use Case>
Description	<Short description of UC (3 to 4 lines)>
Actors involved	<Actors involved in the Use Case>
Triggering Event	<Event triggering the Use Case>
Pre-condition	<Prerequisites >
Other Smart4RES Use Cases and systems involved	<Use Cases and systems in the project that are connected to the Use Case>
Post-condition	<Result of the Use Case>
KPIs	<Specific KPIs evaluating the results of the Use Case. These KPIs should be coherent with Smart4RES KPIs.>

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Innovative forecasting solutions in Use Case	
Forecasting requirements	< Characteristics of forecasting needs (horizons, dimensions, resolution, architecture, etc.), what is missing from the state of the art>
Handling of uncertainties	<How should uncertainties be considered/modelled by forecasting solutions in the Use Case>
Innovative content of forecasting solutions	<Expected original contributions of forecasting solutions implemented in Smart4RES compared to state-of-the-art forecasting solutions>

Innovative solutions beyond forecasting dealing with uncertainties on renewables and related processes in Use Case	
Consideration of uncertainties	<How should uncertainties be considered/modelled by solutions in the Use Case>
Innovative content of solutions	<Expected original contributions of solutions implemented in Smart4RES compared to state-of-the-art forecasting solutions>

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1					
2					
3					

Use Case Diagrams

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<put possible diagrams, pictures and graphs here>	
Realization of the Use Case	
Main responsible partners (Author)	<Project partner responsible for developing the use case>
Contributing partners	<Project partners contributing to the Use Case>
Priority	<to be determined>

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9 Appendix: Complete Use Case descriptions

9.1 Use Cases for advanced weather forecasting

Authors (organization):
Bijan Nouri (DLR SF) Jorge Lezaca (DLR VE)

Abstract:
Decarbonization of the human society requires a significant integration of renewable sources like solar and wind power into the electrical grids. The intermittent nature of these sources causes new technical challenges that need to be tackled. Accurate high-resolution weather and renewable energy forecasts could help to optimize operations of storage facilities and support power systems in order to balance fluctuations induced into the electrical grids. The new innovative Eye2Sky network located in North-West Germany combines various remote sensing technics including radiometers, sky images and satellites. This worldwide unique setup covers an area >10000 km² and permits both in time and space highly resolved solar irradiance forecast. Regional grid, storage and plant operators can benefit from these unseen highly resolved forecasts. Other regions could also benefit from the Eye2Sky network as the network offers the possibility to validate other less resolved forecasting approaches (satellites and NWPs).

Keywords:
Solar resource nowcasting, camera based, satellite based, NWP, combined forecast/nowcast, ground measurement network

Revision History

Revision	Date	Description	Author (Organization)
V0.1	07/05/2020	Initial version	Bijan Nouri DLR SF, Jorge Lezaca (DLR VE)
V1.0	01/07/2020	Revised version after WP1 Call	Bijan Nouri DLR SF, Jorge Lezaca (DLR VE)

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Use Case ID	**UC Weather Forecasting 1: Highly resolved regional satellite + sky cameras nowcast/forecast for grid management and the energy market**
Cluster / Work package	WP2 – Next Generation of Weather Forecasting Models for RES Purpose
Classification	Primary
Description	The combination of a spatially distributed network of all sky imager, radiometers and ceilometers over an area of roughly 10.000 km² with satellite data will provide a regional highly resolved nowcast/forecast of solar irradiance. This so called Eye2Sky network is already partially in operation and will be finalized within the next months. It will provide regional grid, storage and plant operators a possibility to optimize their operations. In addition, other forecast providers could use the highly resolved data to validate their approaches.
Actors involved	DLR VE, DLR SF + Smart4RES participants to WP2 / WP3
Triggering Event	Continuous
Pre-condition	Finalization Eye2Sky network construction Development of a new and innovative evaluation strategy combining data from radiometers, ceilometer, all sky imager and satellites
Other Smart4RES Use Cases and systems involved	Use cases making use of high resolution solar forecast: – UC RES Forecasting 1 – UC RES Forecasting 2
Post-condition	Both in time and space highly resolved solar irradiance nowcast/forecast data will be available, by combining the one of a kind Eye2Sky network with satellite data. For the region covered by the Eye2Sky network increased nowcast/forecast accuracies compared to traditional approaches are expected. The Eye2Sky Network permits to validate satellite and NWP approaches over a large area with an unseen spatial and temporal resolution.
KPIs	• KPI 1.1.d: Increase of spatial and temporal resolution of regional forecasts from km -> m, min -> sec • KPI 1.1.e: Benchmark: Continuous system validation based on moving error metrics distributions (e.g. RMSE, MAE, skill score,…) discretized for distinct conditions (solar irradiance variability classification). Performance enhancements compared to traditional none network based all sky imager and satellite based nowcasts/forecasts are expected.

Innovative forecasting solutions in Use Case

Forecasting requirements	State of the art satellite based forecast approaches cover large areas but are limited both in spatial and temporal resolution. On the other hand state of the art all sky imager nowcasting approaches can deliver highly resolved nowcast but are limited in there spatial coverage. The innovative Eye2Sky network will overcome the limitations of traditional Satellite and all sky imager based nowcasting/forecasting systems and deliver a highly resolved nowcast/forecast for a large area (≈10.000 km²) with lower uncertainties.
Handling of uncertainties	The Eye2Sky network will provide spatial irradiance information with a high resolution. Within the covered area the Eye2Sky network includes in his final setup 14 meteorological stations equipped with radiometers. The corresponding pixels of the derived spatial irradiance information are continuously validated with the corresponding irradiance measurements. Moving error metrics (e.g. RMSE, MAE, skill score,…) will be calculated over distinct time periods (e.g. 5:5:120 min) for distinct lead times. Furthermore, analogue auto validations comparing distinct lead times will be performed with spatial averages. Therefore, each nowcast from the Eye2sky network will include corresponding performance indicators of the recent past. Furthermore, distributions of observed error metrics from historical data, discretized over irradiance variability conditions, will be available. Making uncertainty assessments is conceivable for potential users of the Eye2Sky network.
Innovative content of forecasting solutions	The Eye2Sky network will provide for a large area in north west Germany solar irradiance nowcasts/forecast with until now unseen spatial and temporal resolutions and potentially lower uncertainties. Furthermore, the Eye2Sky network provides a highly resolved validation data set for satellite and NWP based forecasting systems. Supporting the further development of these forecasting approaches.

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. Exchanged**	**Actor producing the information**	**Actor receiving the information**
1	Irradiance nowcast ASI network	Create solar irradiance nowcast from all sky imager (ASI) network	High resolution spatial irradiance information + meta data	Network operator	RES producer
2	Irradiance nowcast from satellite images	Create solar irradiance forecast from satellite images	Irradiance information for a large area and horizons of several hours + meta data	Network operator	RES producer
3	Combined nowcast / forecast	Combine ASI, satellite and NWP nowcasts/fo	Improved Irradiance nowcast/forecasts + meta data	Network operator	RES producer

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		recast to a single forecast with variable resolution			
4	Validation satellite and NWP forecast	Validation of satellite and NWP forecast with high resolution ASI data	System uncertainties	Forecast provider	Forecast provider

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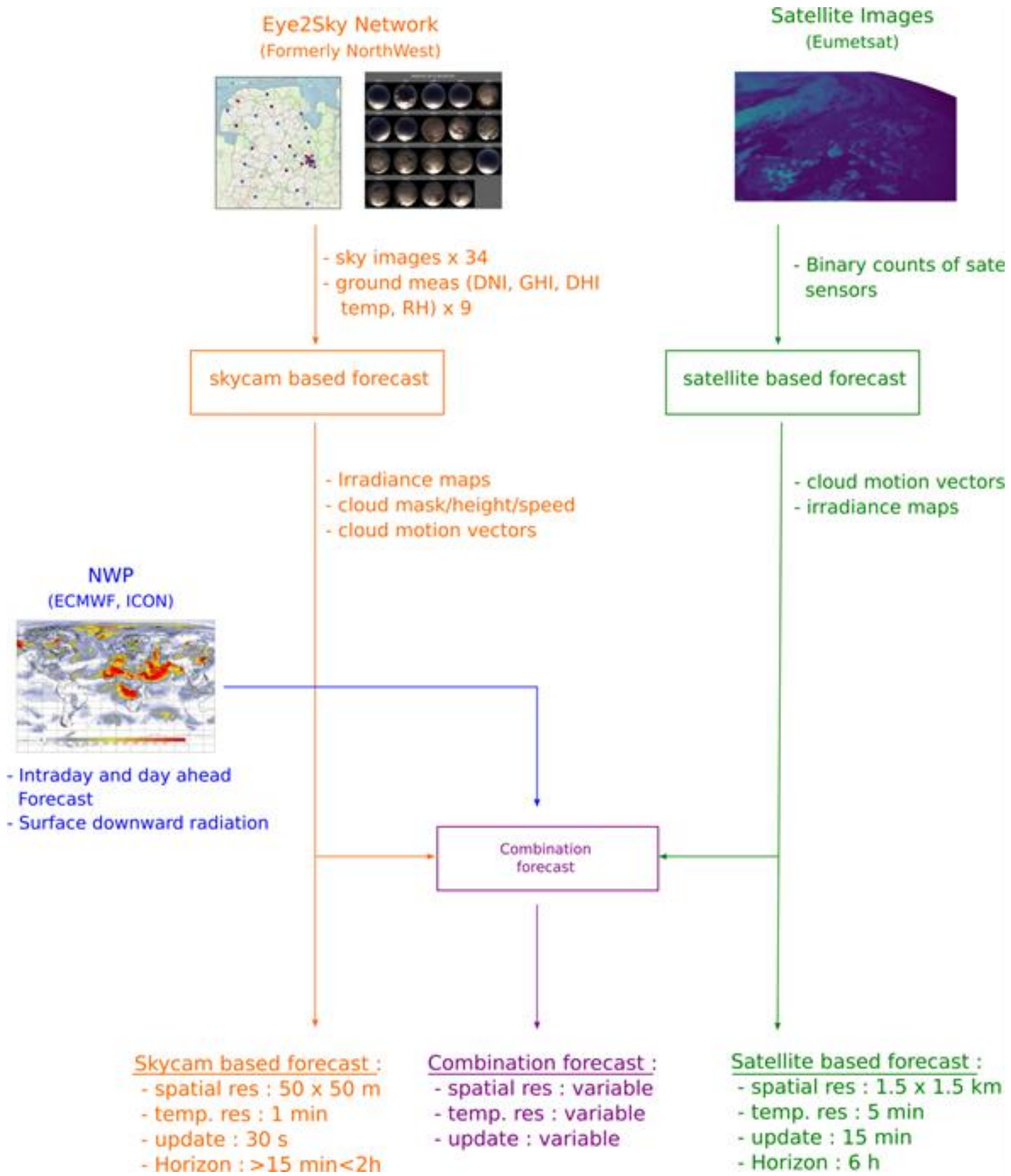
Use Case Diagrams	



Realization of the Use Case	
Main responsible partners (Author)	DLR
Contributing partners	n.a.
Priority	High

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9.2 Use Cases for advanced RES forecasting

9.2.1 Generic Seamless RES Production Forecasting

Authors (organization):
Simon CAMAL, ARMINES George Kariniotakis, ARMINES

Abstract:
A generic seamless forecasting model enables to derive RES production forecasts for various weather-dependent energy sources (Wind, PV, run-of-river Hydro) at multiple time scales (e.g. from 1 min to 2 days, from 1 day to 1 month), without the need to re-train or re-configure the model at each horizon. Forecasts incorporate a probabilistic model of production uncertainty. An incremental approach is proposed to generate forecasts either at the plant level or at the level of an aggregation of plants, with coherent forecasts throughout the hierarchy of the aggregation.

Keywords:
RES forecasting, seamless, generic, probabilistic, multi-scale

Revision History

Revision	Date	Description	Author (Organization)
V0.1	04/03/2020	Initial Version	Simon Camal (ARMINES)
V1.0	23/06/2020	Corrected Version after Revision by Task Leader (DNV GL)	Simon Camal (ARMINES)

Use Case ID	UC RES Forecasting 1: Generic Seamless RES Production Forecasting for Multiple Time Scales
Cluster / Work package	WP3
Classification	Primary Use Case
Description	The production of a single RES plant or of an aggregation of RES plants is forecasted by a generic model, adaptive to several energy sources and able to predict multiple time scales at once (e.g. from 1 min to 2 days).

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Actors involved	RES producers, Aggregators
Triggering Event	Frequently required update of RES forecasting for market applications or grid management
Pre-condition	Good quality of data on all considered RES plants, diversity in available data sources (including power production at neighbouring sites, weather observations by satellite, imagers...)
Other Smart4RES Use Cases and systems involved	Possible links: – Distributed collaborative forecasting in case of forecasting an aggregation with plants that are located in the same region. – Seamless forecasting provides updated information on production levels and therefore enables to correct bids in Use Cases implementing bidding strategies
Post-condition	The Use Case provides a continuous performance over the range of horizon intervals considered, with a unique forecasting model instead of at least two (e.g. one for intraday and one for day-ahead). Considering the use of multiple data sources, the model is competitive in terms of forecasting scores compared to an advanced benchmark (auto-regressive models below 1 hour horizon, decision-tree models for day-ahead horizons). The forecasting model is also evaluated in terms of value in practical applications which require forecasts at multiple horizons: bidding on multiple markets and bidding with storage.
KPIs	KPI 1.2.c: Evaluation of RMSE and CRPS in the context of generic seamless RES forecasting

Innovative forecasting solutions in Use Case	
Forecasting requirements	Forecasting needs: - Fast training (inferior to shortest horizon) or limited need to frequently retrain - Good performance with limited adjustment when considering different energy sources, possibly mixed in the aggregation - Continuous outputs across horizon intervals Limits in state of the art: - the consideration of multiple time scales in coherent forecasts for aggregations has not been intensively studied - no generic model proposed for a multi-scale approach

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Handling of uncertainties	Past conditions are optimally weighted by their degree of similarity with the expected situation, informed by multiple data sources (weather prediction, satellite images, production on site and at close locations, etc.). Observations are further grouped to obtain nearest neighbours or clusters from which a probabilistic density forecast is produced. An output in the form of trajectories modelling temporal correlations is also generated.
Innovative content of forecasting solutions	The original contributions of this solution are: - continuous forecasting performance over the total horizon range - streamlined forecasting process with a reduction of at least 50% in the number of required forecasting models - a generic model, adaptive to numerous variable renewable energy sources

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. Exchanged**	**Actor producing the information**	**Actor receiving the information**
1	Data retrieval for forecasting the production of RES plants	The forecast provider receives data from RES plants and from weather data providers	Production data, status of plants, Weather data (predictions, observations)	RES aggregator Weather data providers (for predictions and observations)	Forecasting Provider
2	Re-training of model if necessary	Periodically, the model is re-trained to optimize its forecasting performance.	Notification of update in forecasting model sent to forecast users + Interpretation of learning characteristics of the model	Forecasting Provider	Users of forecasts are informed of the update of the forecasting model
3	If aggregation is considered, ensure coherency of forecasts	Forecasts are first issued at each level of the aggregation, then a reconciliation step	If plants are near and a collaborative approach is implemented,	If plants are near and a collaborative approach is	If plants are near and a collaborative approach is

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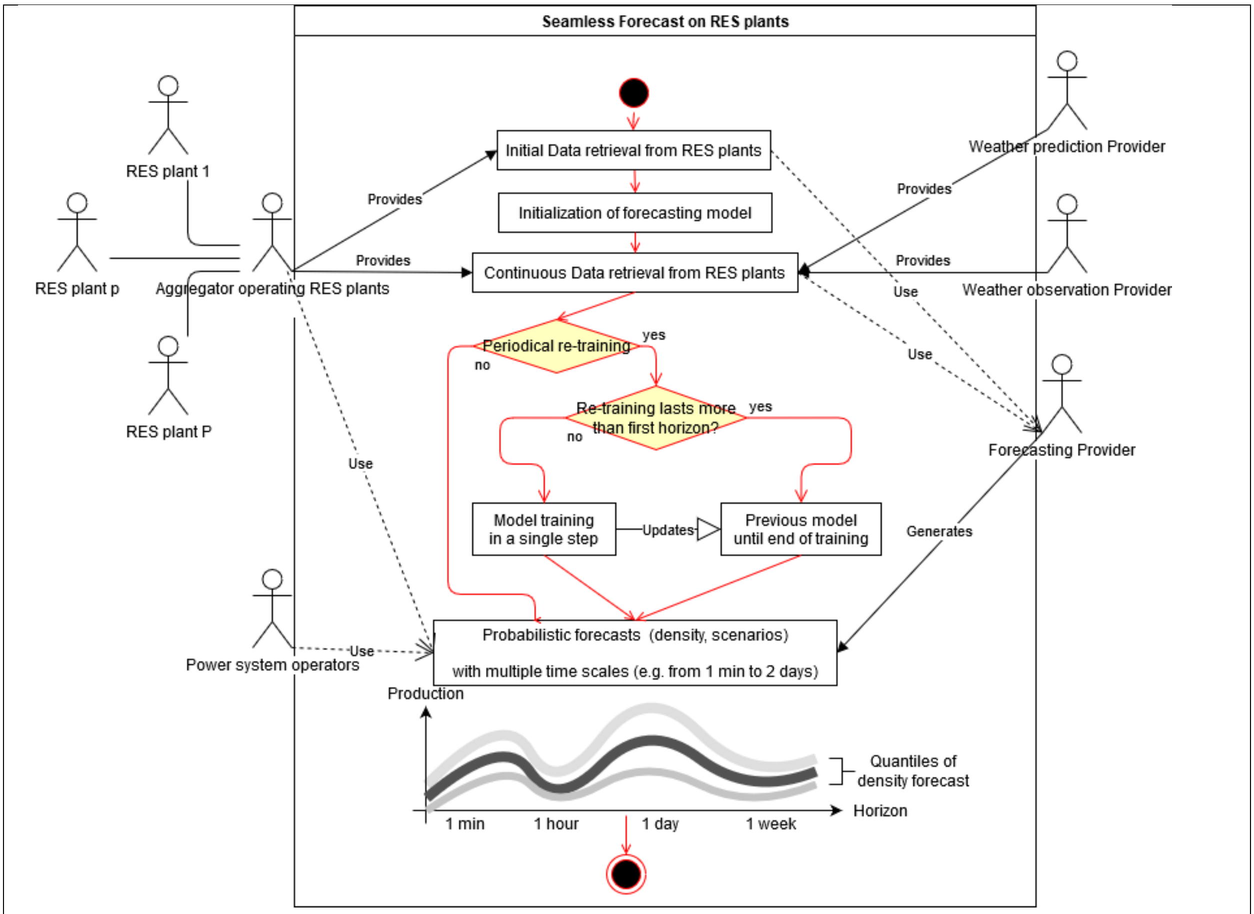
	throughout the aggregation	modifies base forecasts to ensure coherence (e.g. all means sum correctly to the predicted aggregated mean)	then base forecasts are sent from the plants to the aggregation, and the reconciliation can also be distributed.	implemented, RES plants	implemented, RES plants and RES aggregator
4	Probabilistic forecasts are generated at multiple time scales	Forecasts are generated at frequent runtimes (e.g. each hour) in the form of densities or scenarios	Numerical representation of forecasts + Graphical illustration + Situational awareness	Forecasting Provider	RES aggregator, Power system operators

Use Case Diagrams



Realization of the Use Case	
Main responsible partners (Author)	ARMINES
Contributing partners	ARMINES
Priority	High

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

9.2.2 Multi-source data for smart wind power forecasting

Authors (organisation):
Matthias Lange (EMSYS) Anna Mehrens (EMSYS)

Abstract:
Combination of different data sources and data science technologies to improve wind power forecasts of individual sites and portfolios in the time range 1-30 min ahead. The idea is to make the method choose the appropriate reaction under the current production level, machine state and weather conditions (i.e. multiple data sources) based on pure data analysis with modern deep learning techniques to locally optimize the forecast performance by extrapolating the power production into the near future. The innovation lies in choosing a data science methodology that involves data from many different sources in parallel and that the methodology for the shortest-term forecasts considers the non-linear behaviour of the underlying equations of motion under the real-world conditions of noise and gaps in the data and the fact that only a limited number of data points is available.

Keywords:
RES forecasting, machine learning, multiple data sources

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	2020-05-20	First Draft	Matthias Lange (EMSYS)
V0.2	2020-07-10	Amendment on innovation	Matthias Lange (EMSYS)
V1.0	2020-08-27	Review by author after WP1 Call	Matthias Lange (EMSYS)

Use Case ID	UC RES Forecasting 2: Multi-source data-driven wind power forecast
Cluster / Work package	WP3
Classification	Primary Use Case
Description	Improve wind power forecasts of individual sites and portfolios in the time range 1-30 min ahead by using multiple data sources (such as satellite images, measurement data, radar images, lightning detection) and methods using data science methodology that considers the non-linear behaviour of the underlying equations of motion under the real-world conditions of noise and gaps in the data and the fact that only a limited number of data points is available.
Actors involved	RES operators, Aggregators

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Triggering Event	The short-term forecast is very important to the actors in the energy system. While large amounts of real-time data from different sources are available, it is still very challenging to exploit this information for better forecasting results.
Pre-condition	Data from Test Cases (RES plants) available, NWP data and image data available.
Other Smart4RES Use Cases and systems involved	Mainly linked to short-term solar irradiance forecast in WP2 and solar power forecast in WP3
Post-condition	Improved wind power forecasts for the shortest-term time frame contribute to better integration of wind energy into energy markets and grid operation. Better use of real-time data from wind farms, weather observations and rapidly updated NWP models.
KPIs	Improvement w.r.t. to reference forecast of existing methodology analogous to project's KPIs, namely KPIs 1.1 and 1.2

Innovative forecasting solutions in Use Case	
Forecasting requirements	State- of the art forecast, real-time data from assets, NWP data
Handling of uncertainties	Uncertainties are managed with probabilistic approaches by seamlessly combining the empirical uncertainties under specific conditions with inherent uncertainties of the spread among weather models.
Innovative content of forecasting solutions	The innovations in this use case are: new methods in short-term forecasting of wind power, explicit consideration of multiple data sources from assets, weather observations and NWP forecasting.

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**

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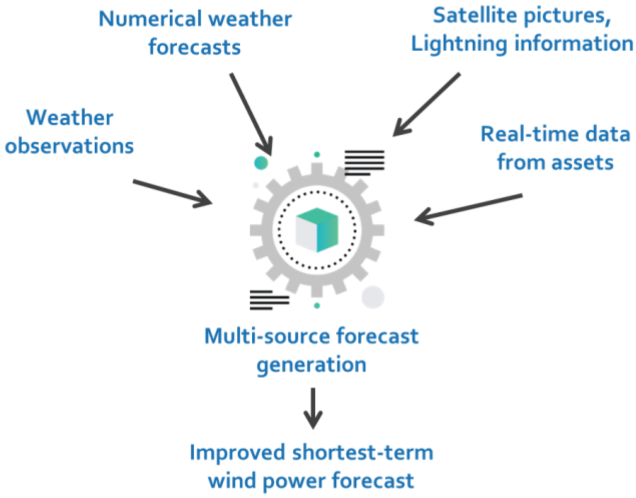
1	Data retrieval	Forecast provider receives data from RES plants and from weather data providers	Production data, status of plants, outage information, weather data (predictions, observations)	RES operators / aggregators, Weather data providers (for NWP and observations)	Forecasting Provider
2	Data processing (internally)	Data is stored or streamed, quality checked and processed to be made available in internal formats	Standardised data format, quality flags	Forecasting provider	Forecasting provider
3	Generation and delivery of forecasts	Forecasts are generated with high frequency (e.g. every minute)	Updated wind power forecasts in electronic formats	Forecasting provider	Customer (grid operator, trader, aggregator)

Use Case Diagrams	
	
Realization of the Use Case	
Main responsible partners (Author)	EMSYS
Contributing partners	DLR, MF
Priority	High

9.2.3 Increased RES penetration to isolated power system

Authors (organisation):

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

Aris Dimeas, ICCS
George Sideratos, ICCS
Christos Vitellas, HEDNO

Abstract:

System operators of isolated power systems apply curtailment strategies to RES units, for security reasons, reducing the RES penetration. To minimize the energy curtailed and the operating costs while the system is kept flexible and stable, system operators needs accurate forecasts of the RES production and of the system load for both day-ahead and intraday periods. However, the recorded RES production by the meters corresponds to the penetrated power which may be curtailed and machine learning techniques need to be applied to adjust the wind power timeseries with the power rejection. Forecasting models should be trained with the adjusted timeseries in order to provide forecasts of how a wind farm would operate without the curtailment. Then, more accurate wind power forecasts will contribute to more effective set-points and to optimal production dispatch. As a result, RES penetration to the isolated power system will be significantly increased.

Keywords:

RES penetration, RES forecasting, RES curtailment, Isolate power systems

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	09/04/2020	Initial Version	George Sideratos (ICCS)
V1.0	29/05/2020	Improved version after WP1 call	George Sideratos (ICCS)

Use Case ID	**UC RES Forecasting 3: Increase RES penetration to isolated power system**
Cluster / Work package	Work Package 5: Modelling Tools for Integrating RES Forecasting in Electrical Grids, Electricity Markets and Storage Operation
Classification	Primary
Description	Estimation of RES curtailment using weather observations to adjust wind power timeseries in the case of isolated power systems which will result to increased RES penetration and to optimal energy management
Actors involved	RES producers, Aggregators, Forecast providers
Triggering Event	At the forecasting model training and every time the RES production is recorded

Pre-condition	Good quality of data on all considered RES plants, diversity in available data sources (weather observations, satellite images)
KPIs	KPI 1.3.b Increased RES hosting capacity KPI 1.3.d Reduced RES curtailment KPI 1.3.e Amount of curtailed energy KPI 1.3.f Revenue losses per production unit due to curtailment

Innovative forecasting solutions in Use Case	
Forecasting requirements	15min time step for 8 hour ahead forecasts 1 hour time step for day-ahead forecasts availability of wind speed and direction measurements availability of set-points
Innovative content of forecasting solutions	Curtailed power estimation using machine learning

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1	Data retrieval for the production of RES plants and weather observations	The forecast provider receives data from RES plants, from Power system operators and from weather data providers	Production data, Set-points, Weather data (observations)	RES producer Weather data providers (for observations) Power system operators	Forecasting Provider
2	Adjust the RES production if set-point is not equal to 1	Estimation of RES curtailment.	Adjusted RES production	Forecasting Provider	Forecasting Provider Power system operators
3	RES forecast	Calculate the RES forecast based on weather forecast and the adjusted production	RES production forecast for the next hours in order to participate in electricity markets	Forecast providers	RES producers Power system operators

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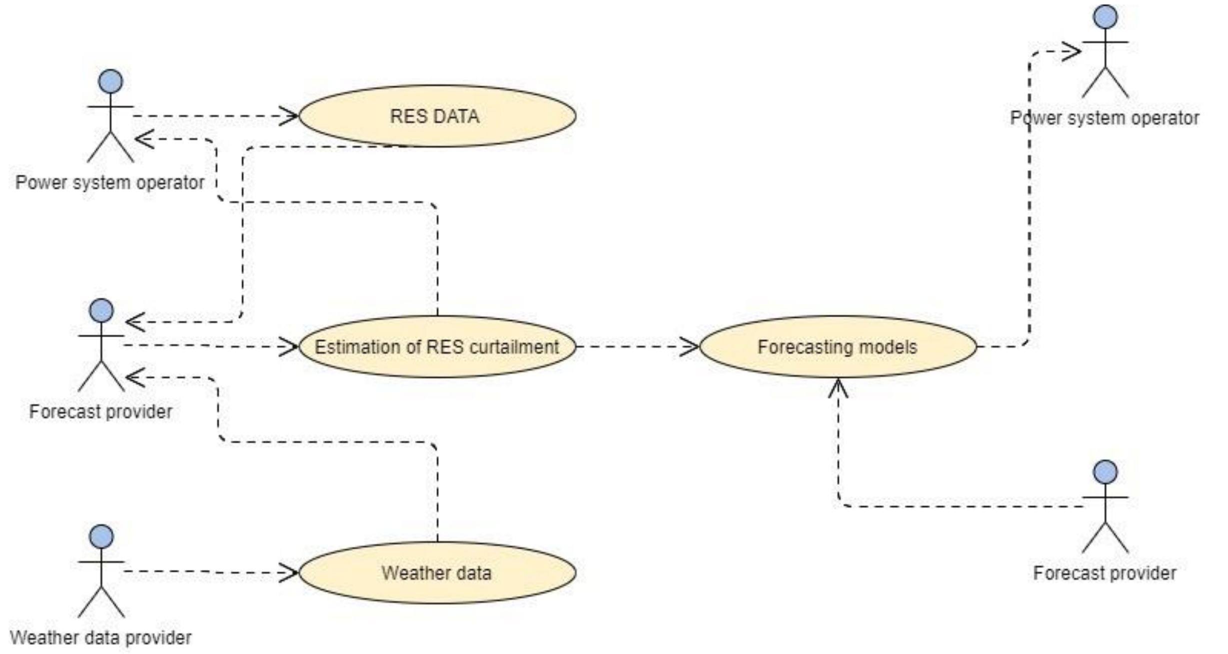
		data from RES plants.			

Use Case Diagrams	
	
Realization of the Use Case	
Main responsible partners (Author)	ICCS-HEDNO
Contributing partners	DTU Wind
Priority	High

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9.3 Use Cases for decision-making related to market applications

This section contains descriptions of Use Cases related to market applications such as bidding on electricity markets or operation of storage in a context of RES production facing imbalance prices.

9.3.1 Data-driven bidding of RES production + storage

Authors (organisation):
Simon CAMAL, ARMINES George KARINIOTAKIS, ARMINES

Abstract:
A data-driven bidding strategy is proposed to simplify bidding on electricity markets for operators of RES plants and storage facilities. It simplifies the modelling chain compared to a classic approach where numerous forecasts are needed before decision can be made (RES production and market conditions). Here the bidding strategy is learnt directly on an objective function computed from the observed production levels and market quantities. A model-free approach is developed with a progressive incorporation of complexity, in terms of learning approaches (recurrent neural networks, Alternate Direction of Multipliers Method (ADMM), reinforcement learning) and bidding applications (futures+ day-ahead + intraday, energy + ancillary services markets). The data-driven approach is compared with benchmark model-based approaches based on Adjustable Robust Optimization (ARO) and stochastic optimization on two configurations: (1) hybrid (RES+storage at a common point of connection or virtually connected by a VPP) and (2) standalone (RES and storage operate independently at distinct points of connections). In the case of large plants, a game-theoretical analysis investigates possible market power.

Keywords:
data-driven, model-free, reinforcement learning, ADMM, ARO, game-theory

Revision History

Revision	**Date**	**Description**	**Author (Organisation)**
V0.1	15/03/2020	Initial Draft	Simon CAMAL (ARMINES)
V0.2	15/05/2020	Review by Task Leader	Marcel Eljgelaar (DNV GL)
V1.0	23/06/2020	Revised Version	Simon CAMAL (ARMINES)

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Use Case ID	UC Market 1: Data-driven bidding of RES production and storage capacity on short-term electricity markets
Cluster / Work package	Work Package 5: Modelling Tools for Integrating RES Forecasting in Electrical Grids, Electricity Markets and Storage Operation
Classification	Primary Use Case
Description	The optimization of bidding strategies for operators of RES plants and storage facilities requires traditionally multiple predictions (RES production, market quantities, possibly grid state at points of connection). Although such predictions provide an information environment to the decision-maker, having so many predictions represents a cost for operators (predictions are often purchased from third parties) and can be source of inefficiency by cumulating forecasting errors. The proposed data-driven approach enables a direct derivation of bids on electricity markets by RES power plants, possibly operated jointly with storage facilities. The approach is thought to be generic, ie adaptable to various energy sources (Wind, PV, run-of-the-river Hydro), and capable of integrating storage and its corresponding constraints. The approach is model-free in the sense that it is optimizing value without imposing specific underlying models on production nor markets. It is developed based on 3 increasing levels of complexity: – recurrent neural network architecture trained directly on the objective function, based on the work of [Carriere 2019] – extension to multi-dimensional case with multiple RES plants and storage facilities using distributed optimization – Reinforcement Learning (RL), with optimized policy learning outperforming direct RL such as in [Mazzi 2016]
Actors involved	RES producers, Aggregators
Triggering Event	Decision of bidding on mutiple electricity markets with a defined portfolio, possibly including storage
Pre-condition	Good quality of data on all considered RES plants Valid assumptions on technical characteristics of storage / good quality of storage monitoring data, Liquid intraday markets, large size of RES plants and storage facilities for game-theory analysis on ancillary service markets.
Other Smart4RES Use Cases and systems involved	Possibly linked with the Use Case of storage optimization by EDP, experimented on Stocare.

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Post-condition	Data-driven model-free strategies are evaluated to be competitive in terms of bidding value with model-based benchmarks. The data-driven strategies based on Reinforcement Learning exhibit better anticipation capacities than a simple data-driven method based on optimized neural networks. The interest of hybrid configurations of RES+ storage is evaluated over the whole range of possible markets.
KPIs	KPI 1.3.d.1 Reduction of costs from balancing KPI 1.3.d.2 Increase of average revenue KPI 1.4.b Evaluation by traders – analytic approach KPI 1.4.c Evaluation by traders – 'no big change approach'

Innovative forecasting solutions in Use Case	
Forecasting requirements	Forecasting needs: Good forecasting performance on RES production and prices at intraday horizons (10 minutes to 1 day) for benchmark model-based approaches) Data-driven approaches: Guarantee of convergence in training and testing and stability of bidding behaviour (compatibility with market rules) Limits in state of the art: Published approaches in direct data-driven bidding approaches are not generic in terms of RES and do not integrate storage Reinforcement Learning approaches for bidding RES production are based on direct RL approaches, therefore lacking capacity of learning complex behaviours with neural networks for instance.
Handling of uncertainties	Forecasting baselines: Trajectories needed for stochastic optimization are generated by a multivariate copula fitted on density forecasts of RES production, and forecasts of extreme quantiles needed for robust optimization are generated by clusterized exponential distributions. Data-driven approaches: networks are trained with uncertainty-handling capacities (e.g. variational inference, dropout, etc.) to model uncertainties associated with production and market quantities. In RL methods, a stochastic policy enables to explore a variety of environment states and control actions, therefore reproducing an uncertain environment for decision-making.

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Innovative content of forecasting solutions	The original contributions of this Use Case are: – bypass of forecasting models for RES production and market quantities (1 data-driven bidding method instead of 10 or more forecasting models) – Integration of storage with realistic modelling of associated constraints in a data-driven bidding method – Reinforcement Learning has benefits in terms of revenue and avoided large losses due to situations that are hard to predict (including combinations of uncertain events on RES production, markets and grids)

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1		The operator of RES and storage facilities receives data streams prior to gate closure time on the various markets	Production data, status of plants, Weather data (predictions, observations), Market data, Grid state data, data on previous taken positions on the markets	Operator of RES and storage facilities Weather data providers (for predictions and observations) Market operators (energy and ancillary services) TSO/DSO	Operator of RES and storage facilities
2		The data-driven method and model-based baselines are trained / updated before gate closure time.		-	-
3	Bidding decision before Gate	The operator bids on the available markets at	Bids of energy and ancillary services	Operator of RES plants and	Market operators (energy and

	Closure Times of market	each gate closure.	(quantity, price, duration)	storage facilities	ancillary services)
4	Market operators transmit results of bids, TSO/DSO activate flexibilities offered	Data-driven method send control setpoints to RES plants and storages facilities in order to supply bid quantities / follow activation signals	Results of market tenders / pools / bilateral exchanges	Market operators (energy and ancillary services)	Operator of RES plants and storage facilities
5	Penalties for deviations, underfulfilments and payments for flexibility activations are communicated by Market operators	Penalties for deviations + payments for activations are integrated to update the data-driven method and the model-based baselines. Revenues between all approaches are compared.	Penalties for deviations + payments for activations on all markets	Market operators (energy and ancillary services)	Operator of RES plants and storage facilities

Use Case Diagrams

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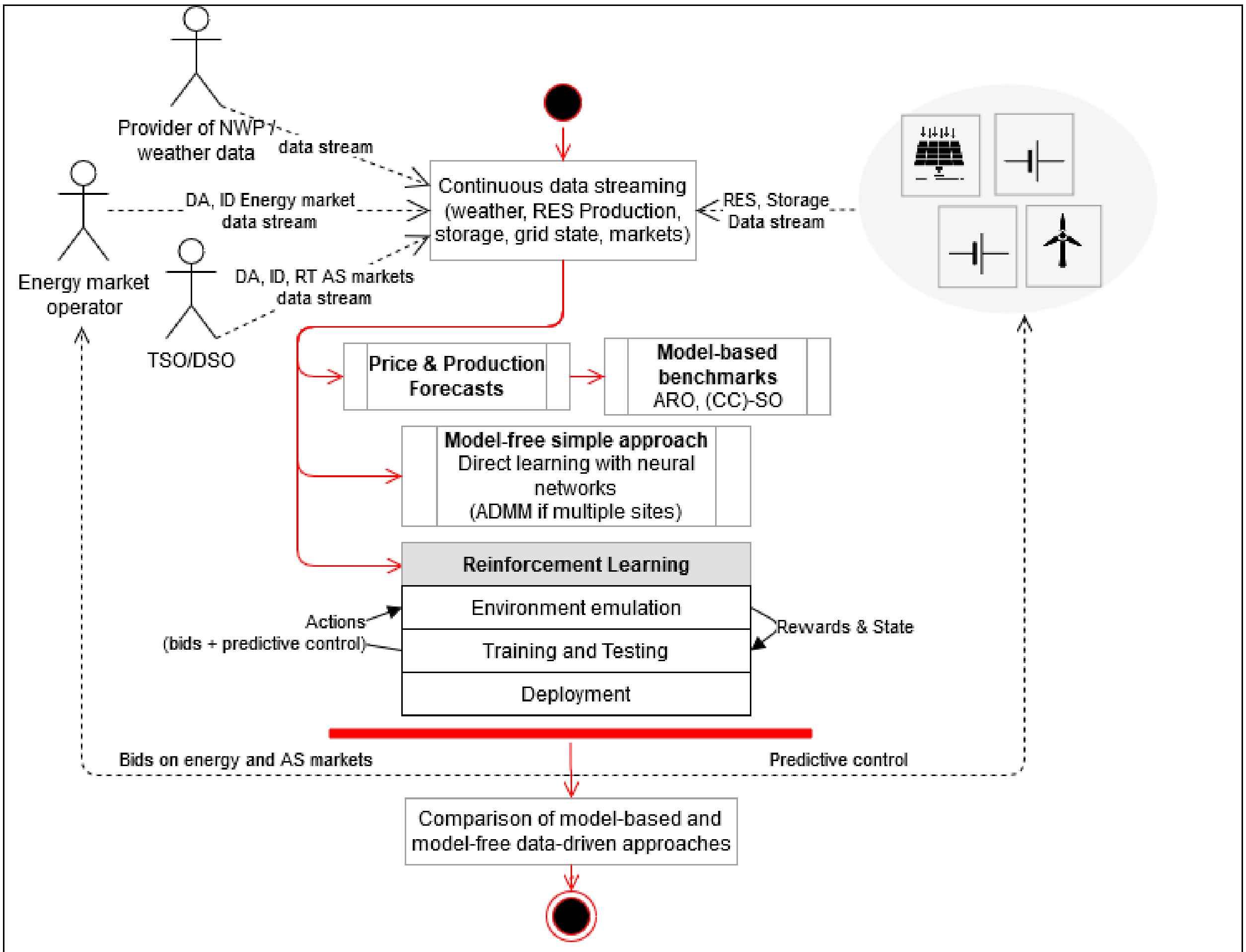

Realization of the Use Case	
Main responsible partners (Author)	ARMINES
Contributing partners	n.a.
Priority	high

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9.3.2 Joint dispatch of RES + storage

Authors (organisation):
Gisela Mendes (EDP) Ricardo Santos (EDP)

Abstract:
Some RES plants are no longer receiving feed-in tariffs, so they have to participate in electricity markets with the same rules as the regular plants. However, forecasts are not accurate enough and the inherent intermittent nature of RES generation pose several challenges for their participation in electricity markets because producers are financially penalised if they not comply with the plan. Optimized dispatch of RES with storage is a promising study field since energy storage can provide the flexibility to plan their output according to a desired production schedule. In addition, the dispatch can also occur when electricity prices are more favourable to RES producers. Thus, storage enables short term rapid response to sudden loss of generation, is able to secure mid-term schedule and offers the opportunity of revenue enhancement to producers as an asset to offer flexibility.

Keywords:
RES dispatch, RES forecasting, storage, market participation,

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	11/03/2020	First version of UC	Gisela Mendes and Ricardo Santos (EDP)
V1.0	02/07/2020	Innovative solution and KPI updates after WP1 leader review	Gisela Mendes and Ricardo Santos (EDP)

Use Case ID	UC Market 2: Optimized dispatch of RES with storage
Cluster / Work Package	Work Package 5: Modelling Tools for Integrating RES Forecasting in Electrical Grids, Electricity Markets and Storage Operation
Classification	Primary Use Case
Description	This Use Case is aimed at maximizing the revenues of dispatching RES with storage in electricity markets by flattening forecasting errors and absorb the intermittence of production. In addition, storage can be used to dispatch RES when the price is more attractive for producers. However, constraints related to the operation of the batteries should be taken in consideration, namely the specification from the manufacturer to ensure that the warranty is not affected.

	(This use case can be validated in the Stocare Project – Cobadin Wind Farm – Romania (EDP, EDP Renewables)) Finally, we'll also recur to energy arbitrage for revenue maximization, since buying energy for storage in low demand times will be cheaper than high demand. Besides this, we'll also tap into the ancillary services market participation for an extra source of revenue.
Actors involved	RES power Plants, storage systems, energy markets, forecast providers
Triggering Event	Every day, when the bids (amount of energy and its price per hour) for electricity market participation are ready, the storage operation plan can be calculated. Also, in real-time, according to the actual renewable generation, the storage operation will be regularly recalculated.
Pre-condition	Weather forecasts, RES participating in electricity markets, data from RES plants, data from storage systems
Other Smart4RES Use Cases and systems involved	Data-driven bidding of RES production + storage. This Use Case shall receive information about the storage status and provide the bids for the market participation.
Post-condition	Optimal participation of RES combined with storage in electricity markets
KPIs	KPI 1.3.d.1 Reduction of balancing costs KPI 1.3.d.2 Increase in average revenue

Innovative solutions beyond forecasting dealing with uncertainties on renewables and related processes in Use Case	
Consideration of uncertainties	Uncertainties should be modelled as a risk parameter. It is the quantity that will define the accuracy of the final prediction, so it is a risk metric that should be mitigated through proper modelling.
Innovative content of solutions	Not only the forecast model will go beyond the state of the art, but the holistic approach between the production prediction and deviation minimization through storage will be innovative. If we add the modelling of uncertainties as a risk parameter it only enhances the novelty of the approach.

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**

1	RES forecast	Calculate the RES forecast based on weather forecast and historical data from RES plants.	RES production forecast for the next hours in order to participate in electricity markets	Forecast providers	RES producers
2	Electricity prices forecast	Compute the forecast for electricity price in the electricity markets (day ahead)	Electricity price forecast for the next day in the electricity market	Forecast providers	RES producers
3	SoC forecasts	Calculate the State of Charge (SoC) forecast of the batteries for the considered timeframe	SoC forecast	Forecast providers	RES producers
4	Optimal plan	Calculate the optimal plan for dispatching RES taking into account the previous forecasts and ensuring the operation of batteries is according to manufacturer's specifications. Machine learning techniques may be needed to know (1) how much of the storage capacity should be used for RES optimal dispatch according to price (thus compute the optimal plan for the day ahead) and (2) the remaining capacity of the battery that should be left for flattening forecast errors and the intermittence of RES production during the execution of the plan	RES bids	RES producers	Energy market operator
5	RES dispatch	Produce electricity according to the plan	Real RES production		

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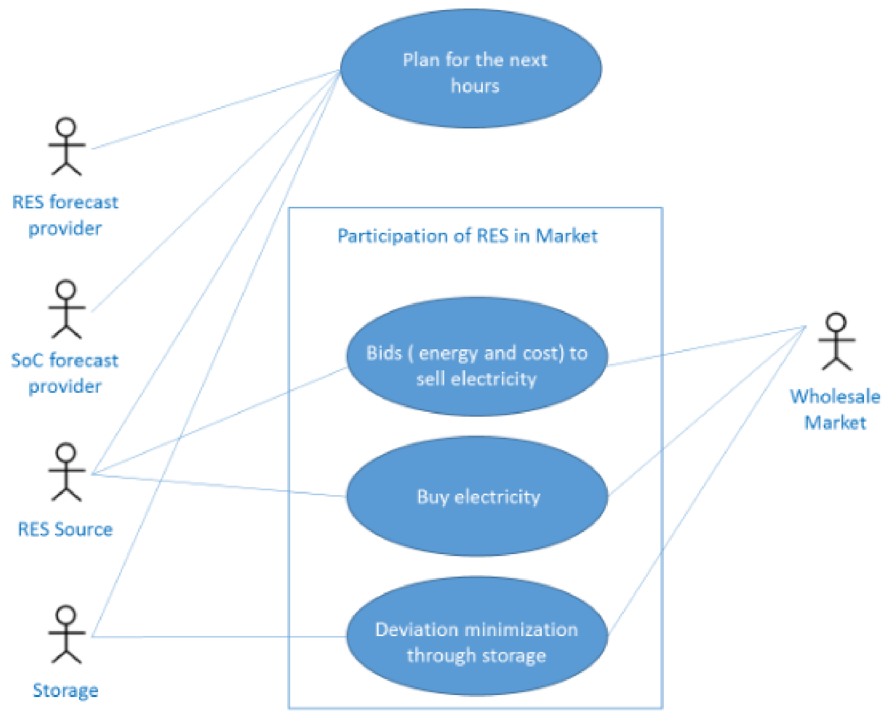
6	Correction of deviations	If deviations occur, use the energy storage system to minimise them, ensuring once again, the batteries' operation modes according to the manufacture.	Deviation from the storage plan	RES Producers	RES producers

Use Case Diagrams


Realization of the Use Case	
Main responsible partners (Author)	EDP
Contributing partners	ARMINES for the bidding formulation
Priority	High

9.3.3 Park predictive maintenance

Authors (organisation):
Ricardo Santos (EDP CNET) Gisela Mendes (EDP CNET)

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

Abstract:
Operation and Maintenance (O&M) of solar farms represent around 23% of the LCOE cost and as the scale of the solar parks is growing, the complexity of the O&M activities is also increasing, as its costs. Furthermore, fault detection in a solar park is difficult since different causes may result in similar effects such as overall performance reduction, leading to an increase in the time needed to have the fault cause detected, higher energy losses and O&M costs. Artificial intelligence will revolutionize the way predictive maintenance is done in solar parks, wind turbines and every other energy system which can be monitored by a set of sensors and drones. This will allow for the use of artificial intelligence algorithms, based on the gathered data, that predict the best maintenance strategy of a solar park.

Keywords:
RES Forecast, Artificial Intelligence, Solar Plant, Predictive maintenance

Revision History

Revision	**Date**	**Description**	**Author (Organisation)**
V0.1	04/03/2020	Template filling	Ricardo Santos e Gisela Mendes (EDP CNET)
V0.2	11/03/2020	Finishing document	Ricardo Santos e Gisela Mendes (EDP CNET)
V1.0	22/07/2020	KPI and data requirements enhancement after WP1 Call	Ricardo Santos e Gisela Mendes (EDP CNET)

Use Case ID	**UC Electricity Markets 3: Solar Plant: Predictive Maintenance**
Cluster / Work package	Work Package 5: Modelling Tools for Integrating RES Forecasting in Electrical Grids, Electricity Markets and Storage Operation
Classification	Primary Use Case
Description	Solar plants are highly populated with solar panels that produce energy all day long. To have production at its maximum, panels should have a clean surface (with no dirt or other kind of residue). This way, investing in predictive maintenance is a smart move for the long-term health of the panels and the solar plant total production. The three main phases of this process: 1. Fly over the panels, with drones, taking pictures of them; 2. Automatically analyze the pictures, so that problems can be identified; 3. Use this historical data to predict future problems 4. Use weather forecasts to calculate the best maintenance plan
Actors involved	Plant Manager, DSO

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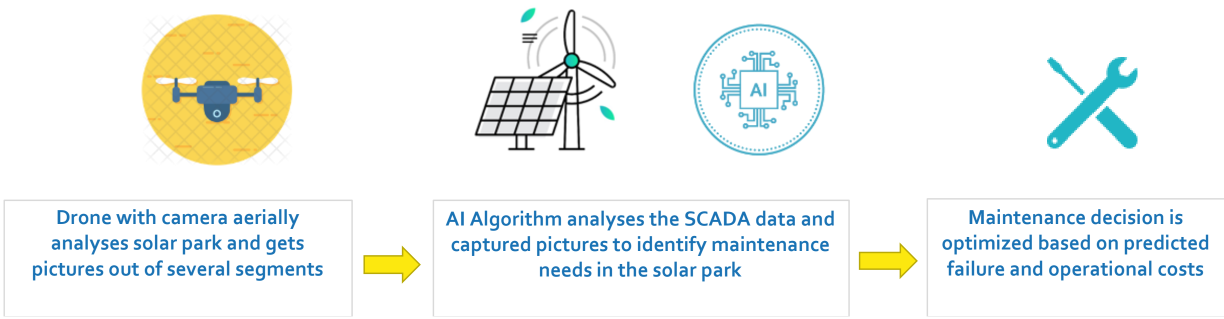
Triggering Event	Periodic examinations of the solar plant
Pre-condition	Authorization to fly the solar plant with drones
Other Smart4RES Use Cases and systems involved	None
Post-condition	Prediction of dates for maintenance intervention
KPIs	KPI 1.4.a Increase in RES production

Innovative solutions beyond forecasting dealing with uncertainties on renewables and related processes in Use Case	
Consideration of uncertainties	The Artificial Intelligence tool is able to handle missing data, doubtful interpretation of segments in park images in order to generate robust maintenance recommendations
Innovative content of solutions	Current available solutions propose to automate the identification of failures from pictures (visible and infrared, cf. https://industryeurope.com/tso-develops-solar-plant-maintenance-software-using-drones/). Here the proposed solution incorporates a learning algorithm to identify the best O&M possible dates given expected conditions (weather and possibly market)

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1		Drone technology application	Drone flight authorization	Plant Manager	DSO
2		Image analysis	Drone captured images	DSO	Plant Manager
3		Data on the grid stability to choose the optimal time for the maintenance operation	Grid stability data	DSO	Plant Manager
4		Maintenance prediction	Dates for maintenance	DSO	Plant Manager

Use Case Diagrams

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



Realization of the Use Case	
Main responsible partners (Author)	EDP CNET
Contributing partners	n.a.
Priority	Low

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

9.4 Use Cases for decision-making related to grid management

9.4.1 Management of frequency containment reserve and system inertia in isolated power systems

Authors (organisation):
Carlos Moreira (INESC TEC) José Gouveia (INESC TEC)

Abstract:
The scope of this use-case lies within the large-scale integration of converter-interfaced renewable energy sources (CI-RES) in isolated power systems, which has a direct impact on the reduction of synchronous machines (SM) in operation. Consequently, the volume of synchronous inertia can be drastically reduced, alongside with the primary power-frequency control reserves. The installation of synchronous condensers as a mechanism to mitigate the reduction of synchronous inertia is a technical option being considered. In this context, the main goal can be defined as the ability to assure the dynamic security of the isolated systems in face of certain grid disturbances (generation trip and network faults) taking into account admissible RoCoF and frequency deviations (directly linked to the available primary frequency reserve volume). This objective is to be tacked in two-time horizons: 1) dynamic security constrained unit commitment (UC)/ economic dispatch (ED) of the generation fleet for the next day and 2) on-line security monitoring/corrective control.

Keywords:
Economic Dispatch, Frequency Containment Reserve, RoCoF, Synchronous Inertia, Unit Commitment

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	16/03/2020	First draft	Carlos Moreira (INESC TEC)
V1.0	29/05/2020	Revised Version after WP1 Call	Carlos Moreira, Ricardo Bessa (INESC TEC)

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

Use Case ID	**UC Grid Management 1: Management of FCR / synthetic inertia in isolated power systems**
Cluster / Work package	Task 5.2
Classification	Primary
Description	The dynamic security assessment is a key issue in the isolated power systems operation and management. Within the context of the MORE CARE project, aiming to increase RES integration, it was developed a dynamic security control approach [Hatziargiryou 2001]. However, the project was conducted during the early 2000s, and so, the correspondent isolated systems were characterized by a significant synchronous generation component. Therefore, the system dynamic security was ensured by the rescheduling of the UC or by re-dispatching of the generating units. More recently, the Australian energy market operator predicted that the expected net load for 2030 will be significantly light, and consequently, fewer SM will be required operate the network, causing a shortage of synchronous inertia, and so, jeopardizing the frequency stability. Therefore, in [Gu 2018] the authors proposed a synchronous inertia constrained economic dispatch, where synchronous condensers dispatch and wind reserve were proposed to keep the network synchronous inertia adequacy. The proposed solution is validated considering only the largest generation unit disconnection in a simplified single-bus network model. Nevertheless, in isolated systems network faults tend to become the most severe frequency stability contingency in contrast to sudden outages of generation units. This is a direct consequence of the low residual voltages observed in the moments subsequent to a network fault that leads to significant active power dips in CI-RES, which may affect frequency stability [O'Sullivan 2014]. This use case is intended to support the UC/ED activity in isolated power systems and consists of: • A predictive dynamic security constrained approach to the day-ahead UC/ED problem to ensure the system dynamic stability in face of different disturbances (sudden generation disconnection and critical bus/line network faults), where the dynamic security is a constraint of the UC/ED optimization problem. The dynamic stability is target in terms of the admissible RoCoF and effective frequency deviations, aiming to avoid the activation of under-frequency load shedding. Assuring system security is expected to require the dispatching of synchronous condensers and/or RES curtailment versus conventional units dispatching;

	• An on-line monitoring approach to provide support for system operators in the control centre. Two situations can be considered: - From the online measurements, dispatch centre operator is informed about system security with respect to a set of pre-defined disturbances - Corrective measures can be activated/suggested if necessary; The mitigation of the RES intermittency (particularly solar photovoltaic generation – PV) is a critical issue in the isolated power systems operation with high shares of renewable-based generation. One common solution consists of imposing static PV ramp rates [Madeira 2019]. However, in such cases, the renewable resource is not exploited in an efficient way. Therefore, the proposed approach intends to preventively characterize such events, through the adoption of short-term fast RES ramps forecasts. Thus,online signalling of risk on insufficient power-frequency reserves for the next hour can be triggered, followed by suggestions of re-dispatching.
Actors involved	RES power plants, network operator, forecasting service provider
Triggering Event	Identification of unsecure operation states during the day-ahead unit commitment/economic dispatch problem as well as during real-time operation
Pre-condition	The availability of adequate load and RES forecasts for day-ahead and for very short-term (i.e., from minutes to hour-ahead) horizons
Other Smart4RES Use Cases and systems involved	(not clear at his stage)
Post-condition	Isolated system operator relies on the developed algorithm for the dispatching of the generating units during the network operation and to monitor system security in real time
KPIs	KPI 1.3.a: "Decrease of load shedding events in isolated power systems considering future scenarios with RES integration above 90%" (section 2.5.2) KPI 1.3.e: "Reduced energy curtailment of RES" (section 2.5.6)

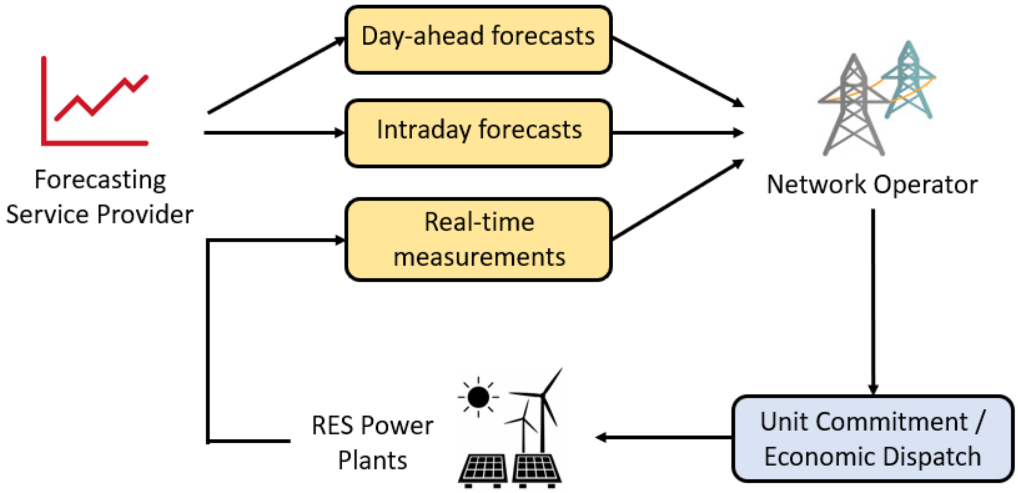
Innovative forecasting solutions in Use Case

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

Forecasting requirements	Set of temporal ensembles for day-ahead aggregated load forecasts – time resolution of 15min, time horizon up to day-ahead. Set of ensembles with temporal and spatial dependency for day-ahead RES power forecasts – time resolution of 15min, dimension 1 day (96 timestamps), additional statistics (in addition to the mean): min, max and standard deviation. Set of ensembles with temporal dependency for aggregated RES forecasts – time resolution of 15min, time horizon up to day-ahead, additional statistics (in addition to the mean): min, max and standard deviation. Forecast of very short-term RES ramps (1 hour ahead, 5 minutes temporal resolution), additional statistics (in addition to the mean): min, max and standard deviation.
Handling of uncertainties	As provided by the ensembles
Innovative content of forecasting solutions	Instead of using averages values in the temporal resolution interval, we are also planning to consider other statistics calculated for each temporal interval, namely: min, max and standard deviation (ideally we would like to have confidence intervals for these statistics as well).

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1		Reception of day-ahead forecasts	Forecasts	Forecasts provider entity	Network operator
2		Determine UC/ED solution including synchronous condensers dispatch and RES curtailment actions	Operational dispatch	Network operator	Generation promotors, ancillary services providers
3		Reception of fast ramps forecasts	Forecasts	Forecasts provider entity	Network operator
4		Operational dispatch correction (in case system lacks power-frequency control reserves)	Operational dispatch updates	Network operator	Generation promotors, ancillary services promotors

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

Use Case Diagrams	
	
Realization of the Use Case	
Main responsible partners (Author)	INESC TEC
Contributing partners	n.a.
Priority	High (promised in WP5)

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9.4.2 Localized and predictive management of voltage and congestion problems in distribution grids

Authors (organisation):
Ricardo Bessa, INESC TEC Luis Teixeira, INESC TEC

Abstract:
The context of this use case is the operation of electrical grids under forecast uncertainty from renewable energy and load. The main goal is to manage the technical constraints of the electrical grid (mainly congestion management and voltage control) in two different time horizons: operational planning (next day and hours); corrective control (*quasi* real-time). The use case is divided in three main phases: (1) modelling of electrical grid sensitivities and uncertainties; (2) data-driven controller where the forecast uncertainty is implicitly included and used to identify flexibility needs in advance and provide fast decision-aid in real-time to human operators, (3) decision-aid phase with the decision-maker balances flexibility risk and costs to make a final decision about flexibility activation. Flexibility is here defined as active and reactive power modulation in the grid nodes (available via a specific market mechanism), which can be from distributed generation, demand response, storage (operated by a third-party), etc., aggregated or not by market players.

Keywords:
Grid Management, Flexibility, Forecast Uncertainty, Sensitivity Analysis

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	11/03/2020	First draft	Ricardo Bessa
V1.0	18/05/2020	Revised version (after WP1 webcall)	Ricardo Bessa

Use Case ID	**UC Grid Management 2: Localised and predictive management of voltage and congestion problems in distribution grids**
Cluster / Work package	WP5
Classification	Primary
Description	This use case corresponds to a data-driven decision-aid method divided in three main blocks: • Probabilistic analysis (with spatial dependency structure of forecast uncertainty) of the network technical constraints

	to identify potential congested branches and over-/under-voltage problems. • Construct a sensitivity matrix and tree to identify branches/buses more "exposed" to forecast uncertainty and establish a control relation between state and control variables. • Data-driven controller that defines control actions to solve technical problems in two time horizons: predictive (hours/day-ahead) and real-time. This controller should be capable of exploiting knowledge from past experiences, empirical rules for grid operation and sensitivity indices. A key requirement is to offer high interpretability to human operators and support fast decision-aid. The final decision in terms of flexibility activation corresponds to an evaluation the cost (of purchasing flexibility) and risk (of constraint violation) associated to flexibility management.
Actors involved	Forecasting Services Provider, Distribution System Operator, Flexibility Operator, Distributed Energy Resource (DER)
Triggering Event	Potential technical problem (voltage outside min and max limits, overcurrent), e.g. detected by a power flow applies to multiple spatial trajectories of forecast errors
Pre-condition	Network topology available. Renewable energy and load uncertainty forecasts available.
Other Smart4RES Use Cases and systems involved	• Flexibility Forecast at the TSO/DSO interface • Seamless RES forecasting
Post-condition	Active/reactive power flexibility (power and node) that is required to solve a grid technical problem.
KPIs	KPI 1.3.g Fulfilment of voltage limits KPI 1.3.h Fulfilment of branch congestion limits

Innovative forecasting solutions in Use Case	
Forecasting requirements	• 48 hours ahead with 15-min resolution • 6 hours ahead with 15-min resolution • Ensembles with spatial dependency structure for power (generation and load) • Forecast for each network node: load, generation and net-load

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Handling of uncertainties	Uncertainty will be included with two potential representations: ensembles or simultaneous forecast intervals. Note: we are assuming that storage is operated by a third-party and therefore its multi-period constraints are ignored and temporal dependency structure is not considered.
Innovative content of forecasting solutions	The main innovation is the approach adopted to integrate forecast uncertainty in active/reactive flexibility management in electrical grids. The typical representation of uncertainty by ensembles is explored, but instead of integrating the ensembles in stochastic optimization, a Monte Carlo approach is used to combine different uncertainties (i.e., sensitivity indices estimation, forecast uncertainty) and construct a distribution of required flexibility to solve technical problems. Another potential result is a methodology that forecasts the amount of flexibility requirements per node to handle technical constraints originated by forecast errors and high RES integration.

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1		Run a deterministic power flow applied to multiple spatial trajectories of forecast uncertainty (ensembles). → probabilistic characterization of the electrical variables	Identification of potential congested branches and over-/under-voltage problems & probability of occurrence (**a**)	DSO	DSO
2		For each congested branch and bus with voltage problem (**a > threshold**), identify the branches/buses that are more "exposed" to forecast uncertainty (i.e., sensitivity weighted by size of the simultaneous forecast intervals extracted from the spatial ensemble, β) and active/reactive power flexibility with influence (related to β magnitude) in the technical problem(s)	List of branches and buses with potential technical problems and candidate nodes for flexibility provision	DSO	DSO

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3		For each flexible resource (e.g., distributed generation, flexible load) or flexibility operator with influence in the congestion and voltage problem (identified in step 2) a data-driven approach is applied to predict the flexibility requirements. The outcome is a curve relating the required flexibility and risk of congestion/voltage problem.	Curve: flexibility vs risk for the predicted technical problems	DSO	DSO
4		"Reserve" or contract active and reactive power flexibility from the network nodes (e.g., from distributed generation, demand response, storage operated by a third-party, etc., aggregated or not by market players).	Active/reactive power flexibility request (node, power, direction)	DSO	Flexibility Operator (via a market mechanism or a bilateral contract)
5	Technical problem identified	Implementation of control set-point	Active/reactive power change (node, power, direction)	Flexibility Operator	DER

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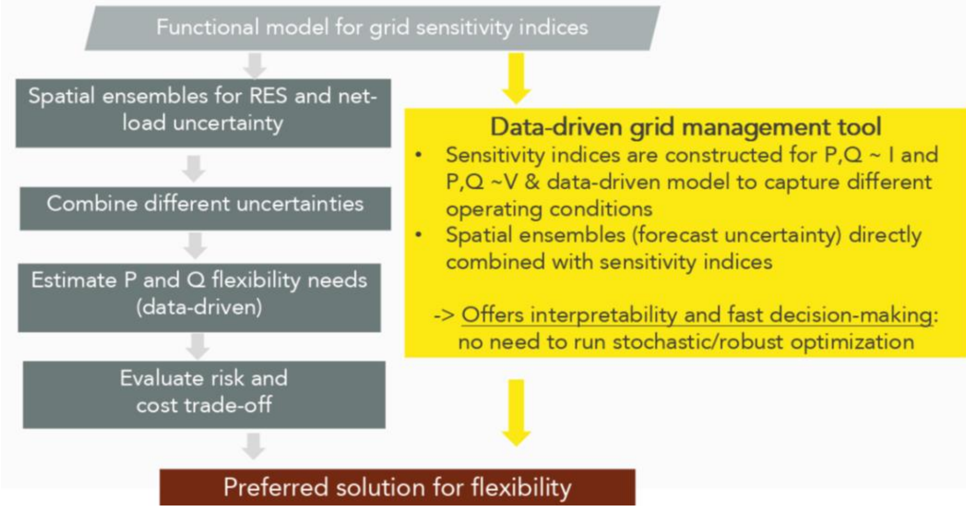
Use Case Diagrams	
	
Realization of the Use Case	
Main responsible partners (Author)	INESC TEC
Contributing partners	n.a.
Priority	High

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9.4.3 Efficient identification of the flexibility at the interface between distribution and transmission systems

Authors (organisation):
Fabrizio Sossan, ARMINES Simon Camal, ARMINES George Kariniotakis, ARMINES

Abstract:
Electrical distribution grids will play a key role in providing ancillary services to transmission system operators (TSO). This use case refers to a set of controllable and stochastic resources in a distribution grid that are aggregated by topology to provide regulation services at their connection point with the upper-level high-voltage grid. The main requirements for this application are: aggregation and activation of the flexibility of downstream controllable resources should respect the operational constraints of the local grid and account for power losses, stochastic resources (most notably PV in distribution systems) should be modelled accounting for their spatial correlation and time correlation (for multi-period aggregation).

Keywords:
Grid-aware aggregation, integration of forecasts, ancillary services, identification of flexibility

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	30/04/2020	Initial structure	Fabrizio Sossan (ARMINES)
V1.0	20/05/2020	Revised version after WP1 Call	Fabrizio Sossan (ARMINES)

Use Case ID	**UC Grid Management 3: Efficient identification of the flexibility at the interface between distribution and transmission systems**
Cluster / Work package	WP5
Classification	Primary use case
Description	The flexibility of distributed energy resources is aggregated at the interface with the upper-level high-voltage grid to provide *regulation* services to the transmission system operator.
Actors involved	Distribution system operators, aggregators, providers of forecasting solutions
Triggering Event	Efficient methods to model the flexibility of clusters of distributed energy resources that can be used by distribution system operator to assess the capacity of their grids to provide ancillary services to the upper-level grid.

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Pre-condition	Model of the distribution grid, knowledge of the controllable resources, measurements of the aggregated power flow (possibly disaggregated for each kind of resource), forecasts of stochastic resources.
Other Smart4RES Use Cases and systems involved	To identify
Post-condition	A set of active and reactive power set-points at the MV/HV interface that identifies the feasible operating points of the distribution network. This can be used as an abstract model of the flexibility of the network.
KPIs	KPI 1.3.g KPI 1.3.h

Innovative forecasting solutions in Use Case	
Forecasting requirements	Prediction intervals of the demand and distributed generation (PV) at a low level of aggregation (e.g., small cluster of resources to model local power flows and grid constraints), and higher-level hierarchical forecasting to characterize the power flow at the medium voltage (MV)/high voltage (HV) connection point. Forecasting horizons of both 1- and 24-hour-ahead to assess the need for short- and long-term regulation needs of TSOs.
Handling of uncertainties	Prediction intervals modelling the spatio-temporal correlation of the distributed resources.
Innovative content of forecasting solutions	The aggregation scheme will account for grid constraints and line losses. With respect to the existing technical literature on the identification of the flexibility of the TSO/DSO interfaces, we will have the possibilities of benefiting from real forecasts delivered by NWPs provider. In this context, a key challenge will be to design efficient aggregation strategies that can comprehensively capture the forecasting uncertainty of many distributed enegy resources given that existing methods can typically handle up to a certain number of forecast scenarios (see e.g. [Kalantar], [Silva]).

Typical steps					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1	NWPs retrieval	Collect relevant numerical weather predictions (NWPs)	E.g., global horizontal irradiance, air temperature	NWPs providers	Aggregator at the MV/HV interface

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2	Forecast of the disaggregated generation and demand	Compute forecasts of the distributed PV generation and demand at the various nodes of the grid	Time series of the demand and distributed generation (eg. PV generation)	Single plants, local aggregator	Aggregator at the MV/HV interface
3	Forecast of the aggregated generation and demand	Apply hierarchical forecasting to evaluate the power flow at the HV/MV interface	Forecasts of the distributed PV generation	Aggregator at the MV/HV interface	Aggregator at the MV/HV interface
4	Computation of the flexibility at the MV/HV interface	Collect all the forecasts (disaggregated and aggregated) in a suitable algorithm to calculate how the power at the MV/HV interface can be "reshaped" by suitably implementing control set-points in the downstream distribution network. This "reshaping action" will finally result in grid-feasible operating region that will model the flexibility of the network.	Disaggregated and aggregated forecasts.	Aggregator at the MV/HV interface	Transmission system operator.

Use Case Diagrams

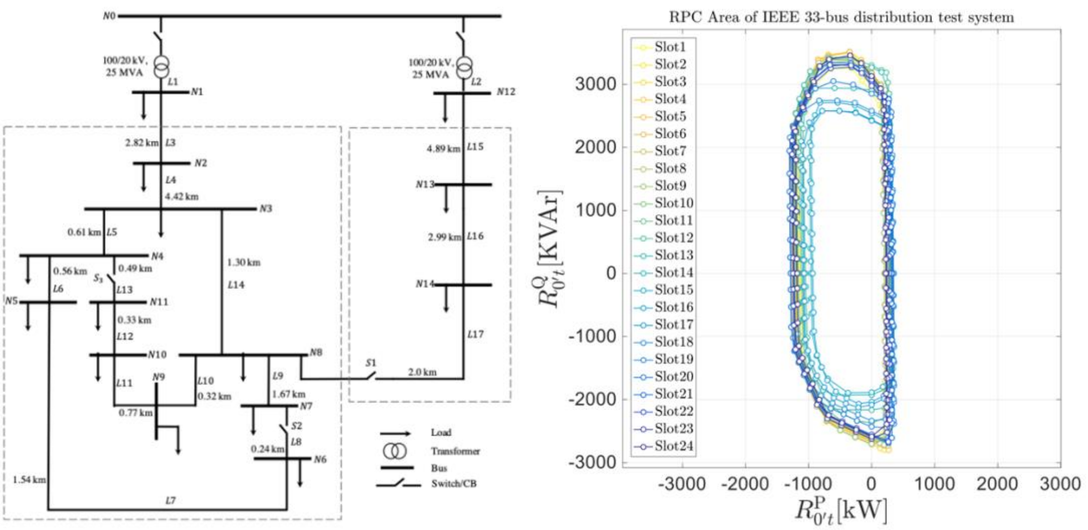

Figure: The topology of the CIGRE benchmark grid for medium voltage systems (left) and an example of the boundaries of the active (P) and reactive power flow (Q) at the grid

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connection point of the grid along the day (right) [CIGRE], [Kalantar]. The property of the region inside the boundaries of the plot on the right is that any of its points can be implemented by changing one or more set-points of the controllable resources while still respecting the grid constraints.	
Realization of the Use Case	
Main responsible partners (Author)	ARMINES
Contributing partners	To identify. (At least a NWP provider)
Priority	high

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

Authors (organisation):
Ganesh Sauba, DNV GL Theo Bosma, DNV GL Marcel Eijgelaar, DNV GL

Abstract:

Assurance of control and decision support software in the electricity system, by testing it in a simulated environment. (Software in the Loop).

The risks of using advanced (control and decision support) software and algorithms that (autonomous) lead to an action in the electricity system, including interactions with this system, and validate claims on the software under different circumstances (for example a weak grid, strong grid, large, small, urban rural).

Aim to assess the risks of applying the software in the actual power system with regard to its robustness, accuracy and precision, potential risks necessary margins.

Actions:

- Environment development: Model parts of power systems (all aspects, and different systems)
- Define testing protocols and (robustness, accuracy, interactions, etc.)
- Put in algorithm under test (If run as a 'black box', this might require the simulation to run real time)
- Actual testing for robustness, reliability, cyber security, etc., claim of accuracy, precision, etc…., potential risks.

Note: in the project this will be demonstrated with 1 or 2 of the developed tools.

Keywords:
Control software, decision support software, testing, validation, risk assessment, software in the loop.

Revision History

Revision	Date	Description	Author (Organisation)
V0.1	03/04/2020	Initial draft	Marcel Eijgelaar (DNV GL)
V1.0	03/06/2020	Added KPIs and use case diagram after WP1 call	Marcel Eijgelaar (DNV GL)

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

Use Case ID	Combined software and hardware in the loop tests for distribution grids and isolated power systems with high RES penetration
Cluster / Work package	WP6 Task 2
Classification	Primary
Description	Testing
Actors involved	Provider of the Control/decision Software under test (SUT), System operator opting to apply the SUT
Triggering Event	Request for validation and risk assessment
Pre-condition	
Other Smart4RES Use Cases and systems involved	Use Cases Grid Management 1 and 2 (INESC)
Post-condition	Test report consisting of verified claims and risk assessment of the application of SUT.
KPIs	Objective: emulate an environment for the software **Associated KPI**: Demonstration of a software in the loop run using an example from the project (both as code and as a black box on a separate device) Objective: Emulate interaction of SIL with multiple algorithms in the loop. **Associated KPI**: Simulated environment with including controls and interaction (such as voltage management) Objective: Protocols and scenarios to test specific situations and risks **Associated KPI**: Having a test protocol to test for (at least) one potential risk.

Typical steps

Step No.	Event	Description of process/ Activity	Info. exchanged	Actor producing the information	Actor receiving the information
1		Request for assessment	Request	Client	DNV GL
2		Defining the application of the algorithm (SUT)	Circumstances for application of SUT	Client	DNV GL
3		Specifying the circumstances, possible risks and validation topics.	Proposed test program for application of SUT	DNV GL	Client

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4		Building/choosing the simulation environment(s) and test program (incl. risk assessment)	Detailed power system model for RT modelling	DNV GL	DNV GL
5		Receiving (black boxed) application	(Black boxed) SUT	Client	DNV GL
6		Perform tests and assessments	Test results	DNV GL	Client
7		Analysis and validation report	Test and validation report	DNV GL	Client
Exception path					
Step No.	**Event**	**Description of process/ Activity**	**Info. exchanged**	**Actor producing the information**	**Actor receiving the information**
1	Additional questions	Perform additional testing and validation	Additional questions and requirements for testing/validation	Client	DNV GL
2	Additional found risks	Request for additional testing and validation (and sequential testing/validation)	Request	DNV GL	Client
3					

Systems and Functions		
System Name	**System type**	**System description**
RTDS	Real time digital simulator (brand OPAL RT or RTDS)	A digital simulator able to do real time calculations of (possibly combined, One RTDS to run the control systems that are part of the environment, and one to run the grid.)

Use Case Diagrams

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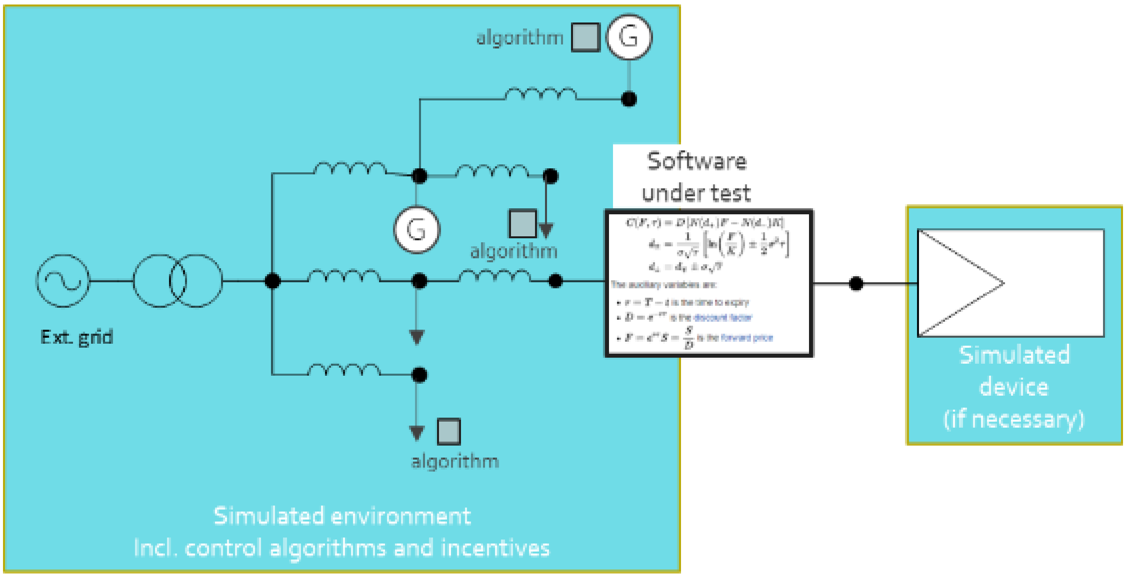

A piece of software is tested as black box in a simulated environment, including controls of other software and devices. In this simulated environment situations can be simulated to check the total systems, including the software under test.

Examples of problems to test for:

- Instabilities (controllers/incentives reacting on each-other)
- Over voltages/currents
- Power Quality issues (e.g. harmonics)
- Contradictory incentives (e.g. Local (semi)autonomous vs top down SCADA)
- Implementation of intelligence/reinforced learning can become unpredictable
- Gaming/monopolization of flexibility

Realization of the Use Case

Main responsible partners (Author)	DNV GL
Contributing partners	DNV GL EDP (link to T6.3 market trading test bed) INESC (providing software under test from WP5), HEDNO and ICCS proving living labs on Greek islands
Priority	High (deliverable 6.2)

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10 Appendix: Questionnaire to stakeholders

This Section present the questionnaire to stakeholders, published via the EUSurvey Tool. The questionnaire can be accessed at the following link: https://ec.europa.eu/eusurvey/runner/02027011-b975-7860-1c35-4037eb359764

The first section of the Questionnaire asks stakeholders about their current use of forecasting solutions (cf. Figure 19). The second part of the questionnaire consists in open questions regarding limits, unresolved needs, and standardization of forecasting solutions (cf.Figure 20). The last part asks respondents about their interest in new forecasting products (cf. Figure 21and Figure 22).

* Which type of forecasting solutions do you use currently in your applications to predict RES production or other related uncertain quantities (eg. weather, electricity prices, demand, flexibilities, activation probabilities, etc.)?

Forecasting solutions are illustrated in the .pdf file in Appendix

- ☐ Deterministic forecasts
- ☐ Probabilistic forecasts
- ☐ Simultaneous prediction intervals
- ☐ Ensembles
- ☐ Extreme events (peaks, high or low quantiles...)
- ☐ Ramps of renewable production, load, etc.
- ☐ High-resolution forecasts (in space or in time)

In which applications do you use the aforementioned forecasting solutions?

Enter any application in your discipline, related e.g. to trading on electricity markets, operating renewable energy plants, power systems, etc.
You can also refer to the list of applications contained in the .pdf file in Appendix.

	Applications
Deterministic forecasts	
Probabilistic forecasts	
Simultaneous prediction intervals	
Ensembles	
Extreme events (peaks, high or low quantiles...)	
Ramps or renewable production, load, etc.	
High-resolution forecasts (in space or in time)	

Figure 19: Questionnaire: Section on use of forecasting solutions

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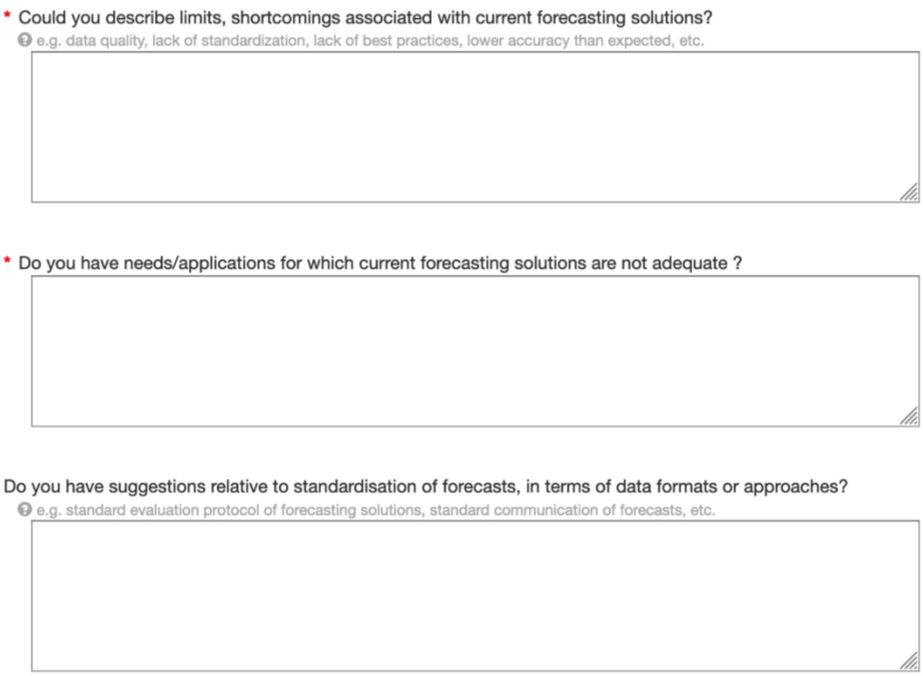

* Could you describe limits, shortcomings associated with current forecasting solutions?
e.g. data quality, lack of standardization, lack of best practices, lower accuracy than expected, etc.

* Do you have needs/applications for which current forecasting solutions are not adequate ?

Do you have suggestions relative to standardisation of forecasts, in terms of data formats or approaches?
e.g. standard evaluation protocol of forecasting solutions, standard communication of forecasts, etc.

Figure 20: Questionnaire: Limits and needs not satisfied with current forecasting solutions

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In which of the following fields would you be interested to know more about new solutions?

- [ ] Collaborative forecasting
- [ ] Data markets
- [ ] Data-driven approaches for trading or grid management
- [ ] Forecasting of electricity market quantities
- [ ] Forecasting of flexibility capacities from aggregators, distributed resources, etc.
- [ ] Forecasting of renewable energy production
- [ ] Human-in-the-loop approaches for trading or grid management
- [ ] Joint optimization of renewables and storage
- [ ] Management of isolated power systems
- [ ] Numerical Weather Prediction

Are you interested in new forecast products that improve the **explainability** of forecasting?

Explainability can be achieved by developing interpretable models or physics-inspired models, adding situational awareness to forecasts, etc.

- [ ] No
- [ ] Neutral
- [ ] Yes

If yes, do you have expectations or recommendations on new forecast products that improve the **explainability** of forecasting?

Are you interested in new forecast products that ensure the **robustness** of forecasting?

Robustness means conservative assessment of uncertainties associated to RES production or other related variables, and implies also the ability to generate a forecast even if the quality of data is limited

- [ ] No
- [ ] Neutral
- [ ] Yes

If yes, do you have expectations or recommendations on new forecast products that ensure the **robustness** of forecasting?

Figure 21: Questionnaire Part 4: Interest in new forecasting solutions

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Are you interested in new forecast products that preserve **privacy**, e.g. in the context of distributed forecasting?

In distributed forecasting, a central server collects the contributions of multiple contractual agents.

- [ ] No
- [ ] Neutral
- [ ] Yes

If yes, do you have expectations or recommendations on new forecast products that preserve **privacy** in forecasting?

Are you interested in new forecast products that provide **incentives to collaborate**, e.g. in the context of decentralized forecasting?

In decentralized forecasting, agents collaborate without a central server.

- [ ] No
- [ ] Neutral
- [ ] Yes

If yes, do you have expectations or recommendations on new forecast products that provide **incentives to collaborate** in forecasting?

Are you interested in new forecast products that address **high dimensionality**, in terms of spatio-temporal models or high resolution?

For instance high temporal resolution of RES forecast at the second scale, high spatial resolution of NWP at the meter scale, large and sparse spatio-temporal models, etc.

- [ ] No
- [ ] Neutral
- [ ] Yes

If yes, do you have expectations or recommendations on new forecast products that address **high dimensionality** in forecasting?

Finally, what is your opinion about the **applicability of new forecasts**, especially uncertainty forecasts, in energy systems at present and in the future?

You can refer to this open-access publication for an overview of the applicability of uncertainty forecasts in the electric power industry: https://www.mdpi.com/1996-1073/10/9/1402

Figure 22: Questionnaire Part 5 : Interests in new forecasting solutions (continued)

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