Smart4RES: Next generation solutions for renewable energy forecasting and its applications for power distribution grids

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Abstract

This paper presents the solutions on renewable energy forecasting proposed by the Horizon2020 Project Smart4RES. The ambition of the project is twofold: (1) increase substantially forecasting performance on weather and production of Renewable Energy Sources (RES), and (2) optimize decisions subject to RES uncertainty in power systems. Developments are based on latest advances in meteorology and original use of data science (combination of multiple data sources, data-driven approaches for trading and grid management). Finally, solutions such as flexibility forecast of distributed resources and data markets are oriented towards value for power system stakeholders.

1 Introduction

The uncertainty of variable Renewable Energy Sources (RES) impacts significantly power systems, despite the fact that prediction of RES production and optimization under RES uncertainty have become mature fields of research. The increasing penetration of RES in power systems led to new decision-making problems, such as the predictive management of flexibility in distribution grids or the bidding of RES production in electricity markets. In this context, renewable prediction models have evolved and seen significant improvements on the whole range of horizons from infra-hourly to day-ahead and further [1]. In particular, several research projects have structured the effort in RES forecasting innovations. ANEMOS constituted a seminal European collaboration on wind power forecasting and popularized probabilistic density forecasts [2]. It was continued by ANEMOS.plus, which developed advanced approaches such as prediction of extreme RES production levels [3]. In recent years, a wide range of approaches including statistical models, machine learning and hybrid statistical-physical models have been proposed to predict RES production [4].

In contrast with the continuous developments on RES forecasting, decision-makers in the power system industry have been relatively slow in adopting advanced prediction models and stochastic optimization tools [5]. In order to understand the challenges encountered by decision-makers, the value chain of RES forecasting from data to decision is presented in Figure 1. There are two main types of challenges that prevent RES forecasting from being optimally employed:

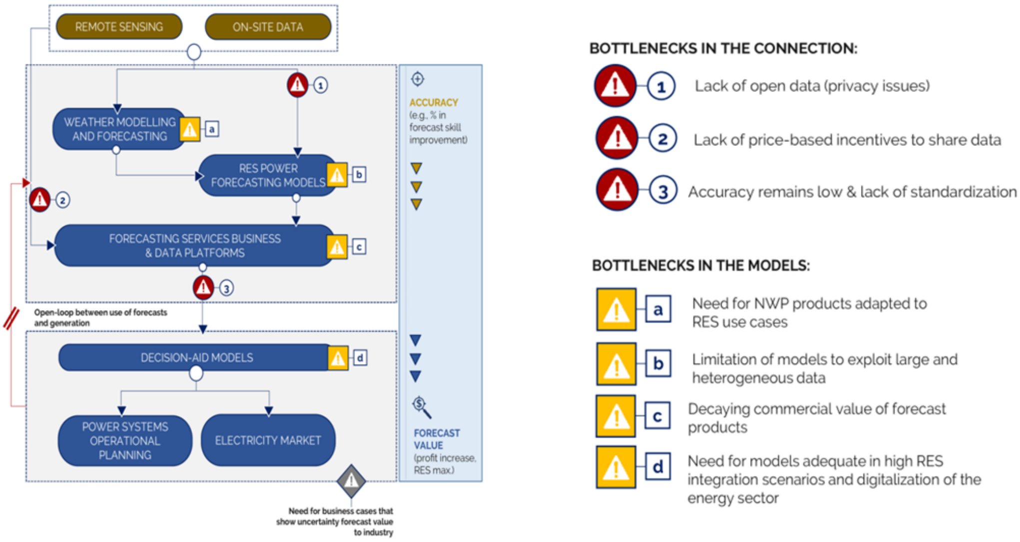

Fig. 1. Value chain of RES forecasting, including bottlenecks in connections and models

- there are *bottlenecks in connections* between individual steps in the forecasting chain, for instance the lack of incentives to share data that limits the volume of information available for efficient forecasting, and the lack of standardization that limits the confidence in prediction results and consequently the integration of forecasting tools in applications [6].
- there are *limitations in the various models* composing the RES forecasting value chain, for instance the decay of the commercial value of forecast product and the need for decision-aid models that are adequate in high RES integration scenarios.

Despite of the research effort in forecasting, the commercial value of weather and renewable production forecasting products is decaying. This is due in part to a lack of progress in terms of a lack of performance at high temporal resolution (e.g. below the minute) as well as high spatial resolution, where standard forecasting products do not integrate very local spatial effects that occur below hundreds of meters due to turbulences in wind [7] or heterogeneities in nebulosity.

Decision-aid problems require accurate forecasting models of RES uncertainty. Forecasting solutions must adapt to the complex dynamic behaviour of systems such as renewable sites integrating storage or aggregations of RES sites and process efficiently a large amount of information that is frequently updated (measurements, weather predictions, market data, etc.). In the context of grid management, optimizing the potential of distributed resources to solve local constraints leads to issues that are untackled by available spatio-temporal forecast products, for instance the integration of network constraints or the consistency of forecasts within the hierarchy of resources.

The model chain associated to classical decision-aid models is often complex (e.g. involving a dozen of forecasting products to propose a RES-based reserve bid [8]). This is why data-driven model-free approaches may streamline the model chain by looking directly for the optimal result without intermediate uncertainty models [9], [10].

To the best of the authors' knowledge, the existing research on RES forecasting has not addressed the entire value chain of RES applications from data to decision. The challenges identified above have not been tackled in a collaborative and interdisciplinary manner. Consequently, the original contributions of the present paper are the following:

- It provides hindsight on the contributions of the Smart4RES project to cutting-edge developments of weather and RES forecasting and their applications to distribution grids.
- The ensemble of proposed innovations form a collaborative response to the challenges encountered throughout the value chain of RES forecasting.

2 Methodology

Innovative forecasting products and decision-aid methods have been collaboratively developed by the Smart4RES consortium and formalized in Use Cases, detailing the applications for market strategies and grid operation. Use Cases have been selected following the guidelines described in "8.2 Select Technologies", IEC PAS 62559:2008. Within the 12 Use Cases, 7 solutions of high relevance for distribution grids are presented in this paper. These solutions cover the whole value chain from weather forecasting to grid management applications. They form the first results of the project and are presented in the sections below.

3 Results

3.1 Improved weather forecasts for application at a regional scale

Errors related to weather forecasts have a high impact on the operation of distribution grids which integrate weather-sensible consumers and weather-dependent renewable production sites.

One way to improve weather forecasts at the scale of a region is to extract information from distributed accurate measurement of weather conditions. A regional network of all-sky-imagers and meteorological stations enables to generate solar irradiance nowcasts reaching spatial resolution as high as 100 m (Fig. 2). These high-resolution forecasts can be used by RES producers to optimize the predictive control of storage associated to PV plants, and by Distribution System Operators (DSOs) to quantify better the impact of PV variability on their infrastructure.

3.2 Seamless generic RES production forecasting

A generic seamless probabilistic forecasting model is developed to streamline the model chain of renewable production forecasting. It is seamless because it is able to generate predictions over multiple horizons in a single run, avoiding the discontinuities in prediction that are observed in state-of-the-art approaches (cf. Figure 3). The model incorporates different data streams which are relevant for the various horizons from the next minute to the next day (recent measurements on site or on neighbouring sites, satellite images, numerical weather predictions). The baseline approach for the seamless model is based on Analog Ensembles retrieved following the principles presented first by [11]: a weighted metric is used to rank past situations based on the similarity of historical features with features describing the conditions to be predicted. Alternative regression models are developed, with the objective to reach similar performance than standard regression models trained separately for the different horizon intervals.

3.3 Data-driven wind power forecasting integrating multiple data sources

Many decisions taken under RES uncertainty need to be frequently updated at intraday horizons or close to real-time, when the uncertainty is lower than at day-ahead horizons. In that case, decision-aid models require that forecasting models of RES production should be able to process rapidly large volumes of heterogeneous data such as weather measurements

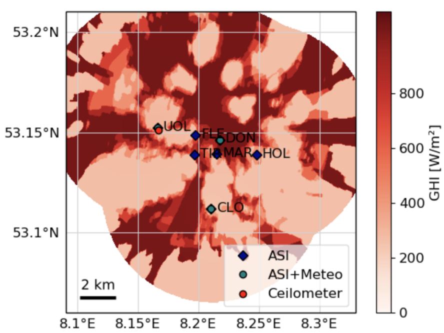

Fig. 2 Irradiance forecast based on 7 all-sky-imagers (Source: DLR)

and predictions, satellite images, lightning information and real-time data from the assets.

In order to comply with these operational constraints which are essential for power system stakeholders such as grid operators, data-driven forecasting models based on machine learning are developed and will be validated in the context of wind power forecasting delivered at horizons of 1 - 30 minutes by a professional forecasting provider.

3.4 Flexibility forecast at a TSO/DSO interface

RES forecasting is also needed at a larger scale, namely for the aggregated production of dispersed RES sites and its use by aggregators or grid operators. In distribution grids, a timely issue for DSOs consists in estimating the total flexibility potential of all RES sites connected under a specific primary substation (interface between TSO and DSO). Flexibility is defined as active and reactive power modulation of distributed RES sites or controllable consumers in the grid nodes. The estimation of this flexibility must take into account the grid topology and the dynamics of constraints resulting from load and RES production.

A state-of-the-art approach for estimating flexibility potential consists in deriving flexibility curves by means of a non-convex non-linear Optimal Power Flow, which does not consider RES uncertainty [12]. Furthermore, if the flexibility curve is estimated by a bottom-up approach summing forecasts of RES production issued at each site independently, ignoring spatio-temporal dependencies in the aggregation, then the estimated flexibility is likely to be biased and potentially infeasible.

Conversely, Smart4RES proposes to incorporate hierarchical probabilistic forecasting into a tractable approximate optimization of the power flow, resulting in an aggregated flexibility forecast illustrated in Figure 4. Consistent hierarchical forecasts enable to better model the aggregated impact of local RES variability on grid constraints.

3.5 Local predictive management of distribution grids

Besides the quantification of flexibility potential from RES, DSOs need to implement predictive strategies to manage local congestions and voltage constraints under the uncertainty of RES production and load (Figure 5). In contrast with robust or stochastic approaches, which have low interpretability and high computational time, Smart4RES proposes to combine a synthetic modelling of the grid sensitivity and a data-driven controller in order to provide fast decision-aid in real-time to human operators. Spatial ensembles modelling RES uncertainty are fed into the data-driven grid management tool, which simplifies the modelling chain by suppressing the need to run stochastic or robust optimization.

3.6 Combined software and hardware in the loop validation system

In order to validate a decision-aid tool such as the grid management tool presented above, a DSO may want to be assured

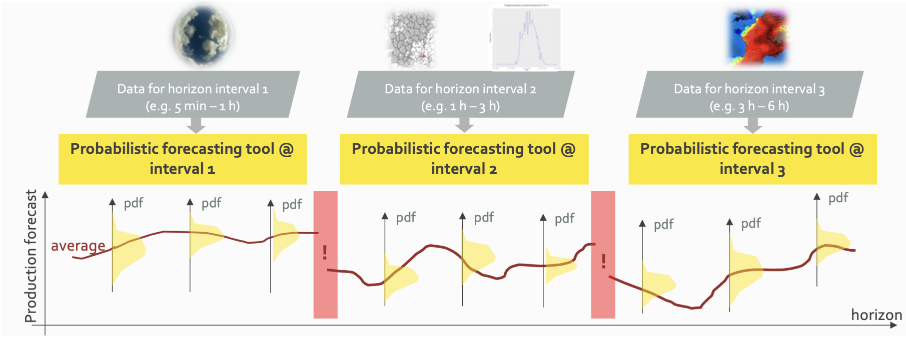

Fig. 3. Challenge of seamless renewable production over multiple time frames, illustrated for PV

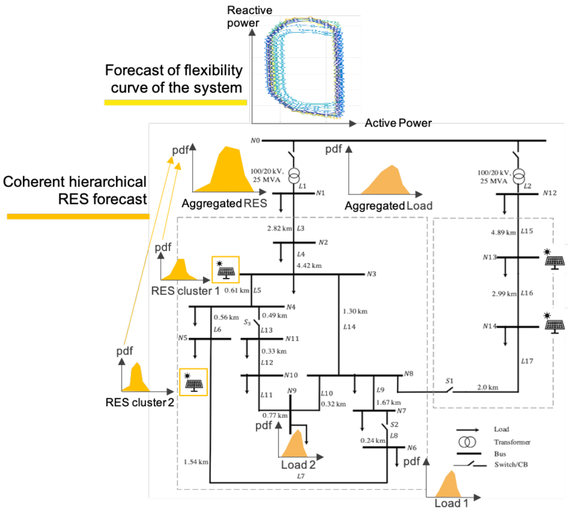

Fig. 4. Flexibility forecast at a TSO/DSO interface

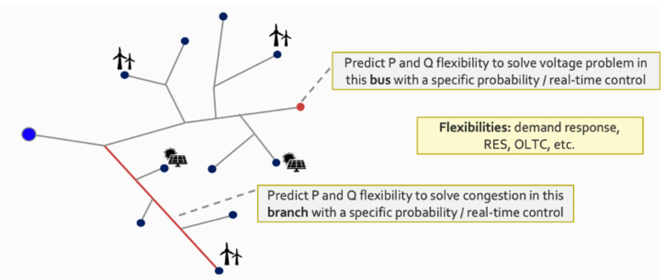

Fig. 5 Challenges of local predictive management of constraints in distribution grids

of its behaviour when put under testing protocols for accuracy, robustness, expected interactions with systems of different configurations (e.g. weak or strong grid, rural or urban environment). In Smart4RES, selected decision-aid tools for distribution grids and isolated systems will be tested in a combined software and hardware in-the-loop validation system (Figure **??**). The decision-aid tool is run as a black box interacting with a simulated environment representing the grid and

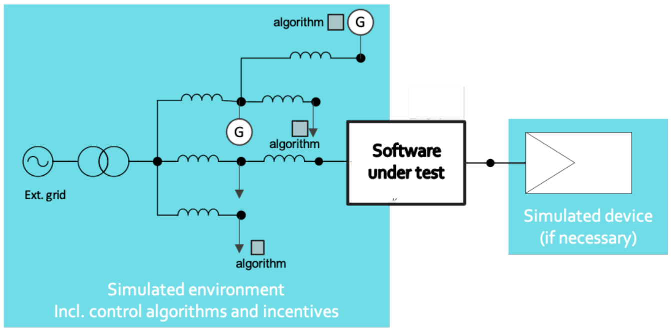

Fig. 6 Validation system for decision-aid tools by combined software and hardware in-the-loop

its rules, complemented when necessary by a hardware-in-the-loop simulation of particular devices such as converters of RES plants.

3.7 Data markets increase the value of RES forecasting in distribution grids

It is known that disposing of recent measurements of production or weather at neighbouring sites increases the performance of spatio-temporal forecasting models [13]. However monetization of RES forecasting data (forecasts, observations, a.o.) is a pre-requesite for collaborative data sharing between different stakeholders. The principles of this monetization are established in the concept of data markets [14], which can secure value for RES operators and providers of forecasting-related services (cf. Fig. **??**): decentralized data exchanges are priced based on their contribution to the reduction of forecasting error, leading to bilateral payments while preserving the privacy of all participants.

4 Conclusion

The prediction of RES production and the optimization of RES-related decision-making, albeit being mature research fields, face major challenges to improve their accuracy and value for end-users. The Smart4RES project proposes to address the whole model chain of RES forecasting from data to decisions. This paper shows an overview of the solutions

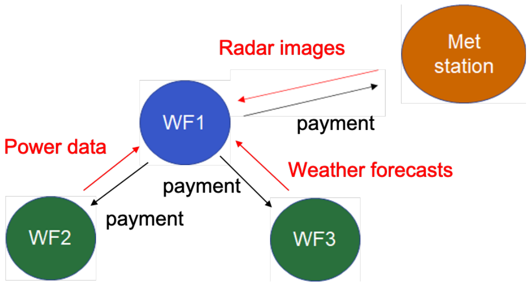

Fig. 7 Data streams and payments in a data market involving Wind Farms (WF) and local meteorological station

proposed by Smart4RES to improve dramatically the performances of RES forecasting, with a focus on the potential of these solutions for use cases related to distribution grids. Three major contributions are stemming from data science, meteorology and power system analysis: (1) enhanced predictions of weather and RES production, (2) streamlined value-oriented decision-making, (3) a proposed concept for data markets.

Forecasting solutions will propose a step forward in terms of prediction errors and spatio-temporal resolution, by integrating novel data sources such as networks of sky imagers. The proposed developments are oriented towards value, meaning that forecasting products will be created to answer specific needs of the power system industry, such as the forecast of the flexibility potential of dispersed RES sites in distribution grids. Finally, the value of data is placed at the core of the Smart4RES project. Data-driven approaches will investigate how existing approaches can be simplified by deep exploitation of large datasets, and subsequently the economic potential of sharing such datasets will be addressed by solutions for collaborative forecasting and data markets. Use cases and forecasting solutions are further detailed on the project website [15].

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