New forecast tools to enhance the value of VRE on the electricity markets

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Executive Summary

The present deliverable was developed as part of the research activities of the TradeRES project *Task 4.4 - Enhancing the value of VRE on the electricity markets with advanced forecasting and ramping tools*.

This report presents the first version of deliverable 4.9, which consists on the description and implementation of the forecasting techniques aiming to identify and explore the time synergies of meteorological effects and electricity market designs in order to maximize the value of variable renewable energy systems and minimize market imbalances.

An overview of key aspects that characterize a power forecast system is presented in this deliverable through a literature review. This overview addresses the: i) forecast time horizon; ii) type of approach (physical, statistical or hybrid); iii) data pre-processing procedures; iv) type of forecast output; and v) the most common metrics used to evaluate the performance of the forecast systems.

While in the TradeRES project work package 3 the conception of new market designs and products are presented from a theoretical point of view, in this deliverable, the power forecast capabilities to address the new designs and products are presented and discussed. The link between electricity markets time frames and the performance of the different power forecast approaches is analysed in this deliverable focusing on the day-ahead market. Thus, as an initial step, a non-disruptive change in the day-ahead market is proposed by simply postponing the gate closure hour according to the meteorological data availability from the global numerical prediction models while the 24 hours forecast periods are still used.

Some preliminary results regarding the potential certainty gain effect from changing the day-ahead market gate closure are presented and analysed in this deliverable. For the Iberian electricity market, high power forecast errors are still observed, especially for wind and solar power players. Even using a forecasting data from a forecast provider, limited improvements are attained with the updated data from numerical global models.

In order to improve the forecasting accuracy for wind and solar power players, a new forecast method developed within the scope of TradeRES is also presented. A key aspect embedded in this method is the use of meteorological features that traditionally are not used in power forecast systems and the definition of specific models according to the weather conditions. Preliminary results suggest that the use of meteorological parameters as wind gusts, wind power density, wind shear, and planetary boundary layer should be used to improve the wind power forecast.

Another aspect regarding the meteorological time synergy and electricity markets analysed in this deliverable is the identification of extreme events. A wind power ramping forecast approach implemented in the TradeRES forecast tools is described and aims to complement the existing deterministic/probabilistic time series. This approach can be used to increase the transmission system operators' awareness level and helping them to better scale the level of reserve required. Market players can also take advantage of this information to define strategic bidding.

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List of Abbreviations

AMIRIS	Agent-based Market model for the Investigation of Renewable and Integrated energy Systems
ANN	Artificial neural networks
AR	Autoregressive
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive Moving Average
Bias	Bias Score
BRPs	Balance responsible parties
CFD	Computational fluid dynamics
D	Deliverable
DAM	Day-Ahead Market
ECMWF	European Centre for Medium-Range Weather Forecasts
FN	False negative
FP	False positive
GFS	Global Forecast System
hPa	Hectopascal
IBC	Initial and Boundary Conditions
IDM	Intraday markets
KNN	K-nearest neighbour
KSS	Hanssen & Kuipers Skill Score
Lat	Latitude
Long	Longitude
MA	Moving Average
MAPE	Mean absolute percentage error
MATREM	Multi-Agent TRading in Electricity Markets
Meso	Mesoscale numerical model
Micro	Microscale numerical model
ML	Machine Learning
NB	Normalized bias
NRMSE	Normalized root mean square error
NWP	Numerical Weather Prediction
OF	Objective function
P	Mean sea level pressure
PCA	Principal component analysis
PCs	Principal components
PDF	Probability density functions
POD	Probability of detection
PV	Photovoltaic
r	Pearson correlation coefficient
RMSE	Root mean square error
SCADA	Supervisory control and data acquisition
SFF	Sequential forward feature
SIDC	Single Intraday Coupling
TCT	Target-circulation types
TN	True negative
TP	True positive
TSO	Transmission System Operator
UTC	Universal time coordinated
vRES	variable Renewable Energy Sources

WP	Work package
WR	Weather regime
WRF	Weather Research and Forecasting

1. Introduction

The present deliverable was developed as part of the research activities of the TradeRES project's *Task 4.4 - Enhancing the value of VRE on the electricity markets with advanced forecasting and ramping tools* (work package 4). This report presents the deliverable D4.9 which consists of the description of forecasting techniques implementation aiming to identify and explore the time synergies of meteorological effects and electricity market designs to maximize the value of variable renewable energy systems and minimize market imbalances.

One of the most important challenges in the energy sector is the large-scale integration of renewable energy sources (particularly, variable renewable energy sources - vRES such as wind and solar) into electrical power systems in an economic and environmentally sustainable way. Transmission system operators (TSOs) must always ensure the balance between electricity production and consumption. Currently, a safe and robust operation of a power system needs highly accurate forecasts of both vRES power production and consumption to minimize the need for balancing the energy in the reserve markets, typically at high costs [1]–[3]. With near to 100% renewable power systems, the role of the forecast system and its accuracy will be even more relevant.

Forecasts are also important to electricity markets. To participate in the different products from electricity markets, market players/actors need to rely on forecast systems to build their bids. With the existing market designs, when power producers do not follow the scheduled bid, they are penalized and its profits are strongly decreased [4]. Due to the intrinsic chaotic nature of atmosphere, the participation of vRES players in the existing markets is still a challenge, especially, when long time horizon forecasts are needed. In work package (WP) 3 of TradeRES project the shortcomings and alternative designs for a near 100% renewable electricity system were addressed. For day-ahead market (DAM), which is the most used and with higher liquidity market, the authors of deliverable 3.5 [5] suggested a reduction of the time gap between the DAM closure hour and the forecast's delivery time while keeping the current organization of wholesale electricity trade. Nevertheless, it is necessary to assess if the new gate closure's timing are enough to reduce expressively the vRES power forecast errors, or if it is necessary to replace the existing designs [5]. Therefore, to design electricity markets that are adequate to vRES trading it is crucial to understand the capabilities of power forecast systems as well as how they work in order to i) identify potential new time frames for this specific market, ii) identify the players that have more challenges to participate in the existing DAM, and iii) develop the forecast tools required for TradeRES project and the electricity markets for 2030 and beyond.

Another aspect regarding the synergy between meteorological timings and electricity markets refers to the identification of extreme events. Extreme events as wind power ramps usually have a significant impact on the DAM [6], [7]. In the case of wind power ramps, the early identification and forecasting of these events triggered by weather conditions can allow to raise the level of Transmission system operators' (TSOs) awareness helping them to better scale the level of risk that exists for the power system [7] as well as commit additional reserves, to minimize operational risks. It should be noted that this type of information can complement (and does not replace) traditional time-series forecast, allowing to dynamically allocate the level of reserves needed. Market players can also take advantage of this information to participate strategically in electricity markets since, under these conditions, large vRES forecast errors in DAM are expected [7].

Forecast of wind power ramps is a relatively novel research topic and the works already published highlight that the trigger mechanisms of such events are rarely similar across the control regions or wind parks [8]. Nevertheless, one of the most successful approaches to understand and forecast the dynamics of wind power ramps involve the use of holistic approaches capable of accounting the spatial and temporal development of atmospheric large-scale circulation [7], [9]. In [7], an automated cyclone detection algorithm was settled to identify challenging weather situations for the TSO. In [9], the authors also applied an automated cyclone detection algorithm and compared its performance with a windstorm algorithm. The highest performance to detect wind power ramps is observed with the windstorm detection algorithm. Nevertheless, all the previous algorithms have a common shortcoming: a wind power ramp is neither always a consequence nor it is always linked to the existence of extreme wind speed values, being essentially dependent from the previous (historical) state of the atmosphere. In this sense, a new algorithm that uses a time numerical differentiation to fit the particular case of wind power ramps events was developed and is presented in this deliverable.

This deliverable is organized as follows: an overview regarding the power forecast systems is provided in section 2. In section 3, the link between electricity market time frames and power forecasts capabilities are discussed. Section 4 provides some preliminary results. These results led to the development of the forecast approaches presented in this section and that will be applied and tested in regional market case studies (WP 5). Section 5 briefly presents some final remarks.

Finally, it should be highlighted that the work conducted so far in T4.4, which is summarised in this report, paves the way for addressing some of the market designs and products choices identified in TradeRES. This first version of deliverable will focus on DAM and a second version of this deliverable will be released at Month 41.

2. Power forecasts

The forecasting problem is transversal to several sectors of activity, such as financial, scientific, industrial, political, etc. In the energy sector, several systems have been developed in the recent years to predict the power output from wind or solar power plants as well as the electricity demand. In general, forecast is performed in an instant, *t*, for a future time horizon, *t+k.* Despite the developments observed in forecast tools/approaches, in the energy sector, most of the applications for European countries still refer to the average power, *Pt+k*, that is expected to be provided to the grid at time *t+k*. In the literature, several classifications for the power forecast systems are available [10]. These systems can be classified according to the forecast time horizon and type of approach. In the next subsections, these classifications are addressed as well as some of the additional steps to implement a forecast system.

It should be noted that this chapter provides a summary of approaches commonly applied in the energy sector aiming to highlight the different options available. This background is important to establish how to proceed to implement the forecast approaches most suitable to the different needs of the project. Detailed and up-to-date literature reviews forecast approaches can be found about wind power [1], [2], [10], solar power and electricity demand [11], [12].

2.1 The forecasting process and objectives

The forecasting process aims to transform one or more independent variables (inputs) into one or more dependent variables (outputs). This process is characterized by some key steps [13]:

- Problem definition
- Data collection
- Descriptive data analysis
- Forecast model selection
- Model validation
- Forecast
- Performance evaluation

Problem definition consists of evaluating the forecast period, forecast horizons and the time step of the outputs. The type of output needed and the establishment of admissible errors in the results are also established in this step. In the data collection phase, the variables under study (object of the forecast) and the independent variables necessary to build the forecast model need to be collected. For the descriptive analysis of the data, it is necessary, in the first place and when working with a time series, to take into account that successive observations are not independent events [14], and as such, the order of observations must be respected. According to [13], to obtain greater sensitivity of the data under analysis, they should be represented in the form of a temporal graph and a summary of some statistical parameters should be computed. This procedure makes possible to identify anomalies in the data, trends and seasonality that otherwise might not be evident.

After analysing the data, the forecasting method is applied. This task consists of choosing and adjusting one or more models to the specific case study, that is, reproducing the dependent variable, depending on the independent variable (or variables), within a certain margin of error. The model selection should take into consideration aspects as the time horizon and the type of information expected from these models (deterministic, probabilistic, or ramp event forecast). Once selected, the method must be validated. This validation is done by assessing the performance of the forecast. For this purpose, the method is normally adjusted to only a part of the available data, with the rest being used for its validation. Once validated, the method is implemented and its control is carried out continuously by measuring the forecast errors (e.g., bias) to verify the continued validity of the method, and, if necessary, make all necessary updates to reduce the errors.

2.2 Forecast time horizon

The time duration for which the power output is forecast is known as the forecast time horizon. The forecast horizon of interest depends on the different applications, and in energy sector it can be divided into four main time scales: very short-term, short-term, medium-term, and long-term [1], [15], [16] The time frames of this classification can slightly change among the different authors. The application for the different time frames is depicted in Table 1.

Table 1. Time horizon, temporal scale and common application of the forecast approaches [17].

Time horizon	Temporal scale	Applications
Very short-term	From seconds to 30 minutes	- Real-time dispatch and regulation operations on the network; - Forecasting the consumption of buildings in the context of micro-grids
Short-term	From 30 minutes to 6 hours	- Impacts on energy price determination in intraday markets; - Support decision on the status of network loads; - Support the decision to turn-on or off the generator set with quick response; - Security operations for the energy market.
Medium-term	Varies between 6 hours and 1 day	- Support the decision to turn generators on or off; - Safety time horizon for the day-ahead market. - Impacts on energy price determination - Allocation of power reserves
Long-term	More than a day	- Planning of maintenance operations; - Power system adequacy planning

2.3 Type of approach

In this section, the most common types of forecast approaches used in the energy sector are presented. Figure 1 depicts the recommended source of information/forecast approach according to the spatial and temporal horizon that will be further analysed in the next subsections.

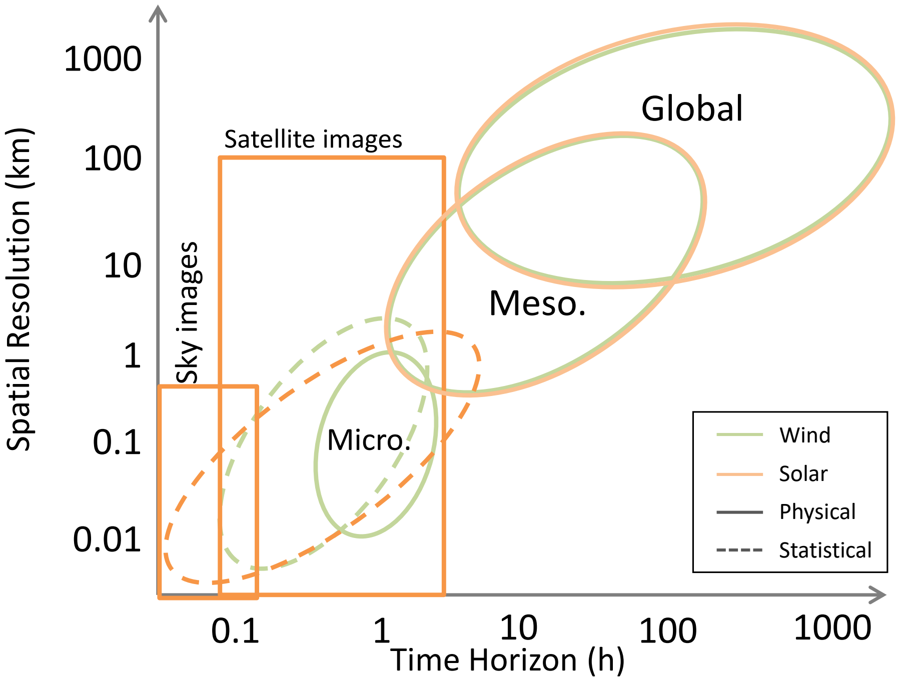

Figure 1. Recommended source of information/approach for solar and wind for the different time horizons and spatial resolution. Adapted from [18].

2.3.1. Physical approaches

The physical power forecast approaches are mainly based on the use of numerical meteorological models – Numerical Weather Prediction (NWP), which parameterize and simulate in detail the atmosphere and its circulation mechanisms. NWP models provide meteorological parameters as wind components, cloud coverage, air temperature, and pressure, that are used to generate forecasts.

This type of model is being developed since 1950 when NWP models were used to make weather forecasts with time horizons on the scale of days. They were, however, very primitive models based on quasi-geostrophic theories where it was impossible, either due to lack of knowledge or lack of computational resources, to include relevant physical processes (radiation processes and phase transition) to make reliable predictions[19]. Over the years and with substantial technological improvement, these models and the parameterizations that govern them were improved and the relevant physical processes missing were progressively added. Currently, these models are still the core of weather forecasting and have evolved substantially following the growing knowledge regarding the physical processes that govern the atmosphere dynamics and its circulation as well as the computational capabilities.

NWP models are, nowadays, less simplistic and with more detailed and precise physical parameterizations. Additionally, these models benefited from more efficient and representative data acquisition and assimilation systems around the globe, which includes meteorological stations, satellite data, radiosondes and measurements performed by airplanes and ships. All these improvements lead to a significant decrease in the forecast errors, as reported for the operational European Centre for Medium-Range Weather Forecasts (ECMWF) model, Figure 2. This figure also highlights that the errors are significantly higher for a time horizon of five-days compared to one-day time-horizon.

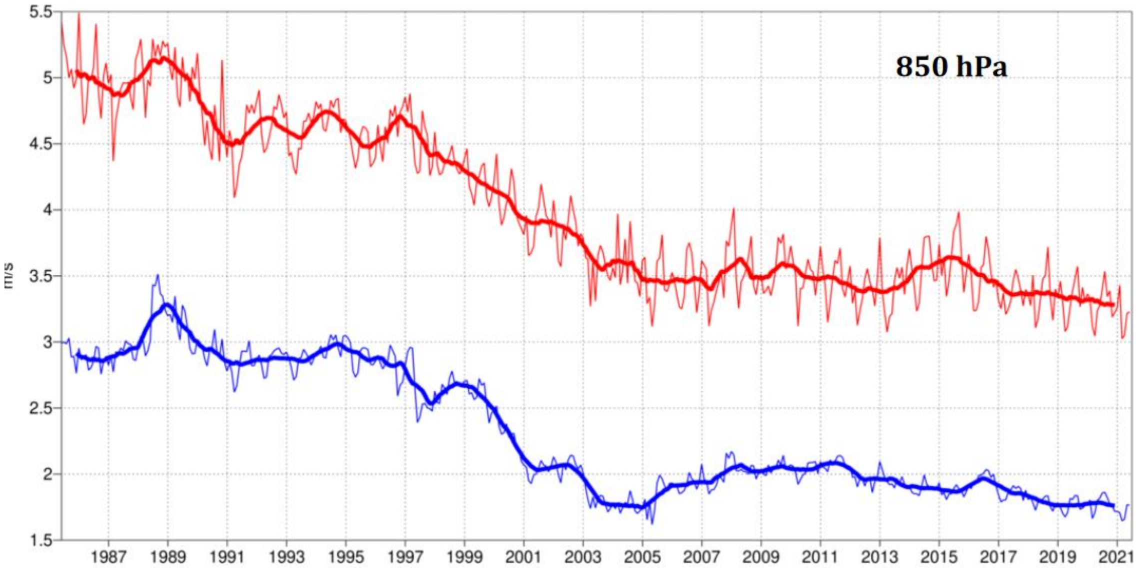

Figure 2. ECMWF forecast performance. Monthly wind speed root mean square error (RMSE) at 850 hPa for one-day (blue) and five-days (red) time horizon forecast. Bold lines represent a 12-month moving average of the results (figure extracted from [20]).

There are two major groups of NWP models: global models (grid covering all the Earth) and regional/mesoscale models (also known as limited area models) [21]. The main differences between these two groups are related to the spatial and temporal resolution of the model, the geographical area covered and the time horizon. Moreover, regional/mesoscale models are calibrated using physical parameterization for specific regions which can enable to reduce the forecast errors. These differences will have a significant impact on forecast accuracy and computational effort [21].

Table 2 characterizes the spatial and temporal resolution of some of the existing global and mesoscale/regional model.

Table 2. Example of global and regional models available. Adapted from [21].

Type of model	Provider	Model	Temporal resolution (hour)	Horizontal resolution (aprox. km)	Runs per day (UTC)
Global	European Centre for Medium-Range Weather Forecasts (ECMWF)	Integrated Fore-casting System	1	10	4 (00, 06, 12 and 18)
	Canadian Mete-orological Centre	Global Determinis-tic Prediction Sys-tem	3	25	2 (00, 12)
	National Centers for Environmental Prediction	Global Forecast System (GFS)	3	25	4 (00, 06, 12 and 18)
	Deutscher Wetter-dienst	Icosahedral Nonhy-drostatic	1	13	4 (00, 06, 12 and 18)
Regional	Deutscher Wetter-dienst	Consortium for Small-scale Model-ing	1	2.8	8 (00, 02, …, 18 and 21)
	Finnish Meteoro-logical Institute	High Resolution Limited Area Model	1	7.5	4 (00, 06, 12 and 18
		Weather Research and Forecasting (WRF)[1]	Defined by user (< 1 hour)	Defined by user (< 5 km)	User specif-ic (but lim-ited to the global mod-el availabil-ity)

Most of power forecast systems use a coupled approach by feeding the regional models with initial and boundary conditions (IBC) gathered from the global models. This approach aims to mitigate some of the drawbacks associated with global models that present low spatial and temporal resolutions by describing the behavior and evolution of the air masses, and explicitly treat the atmospheric phenomena that need high spatial and temporal resolution. On the other hand, numerical mesoscale/regional models always need to be forced with IBC at the limits of their domains (boundary, surface, and top of the domain), Figure 3. These IBC can be historical data from reanalysis projects (used to produce wind or irradiance atlases for example) or by operational global forecasts projects (as GFS).

[1] Example weather forecast providers using WRF model: Climetua (http://climetua.fis.ua.pt/weather) and MeteoGalicia (https://www.meteogalicia.gal).

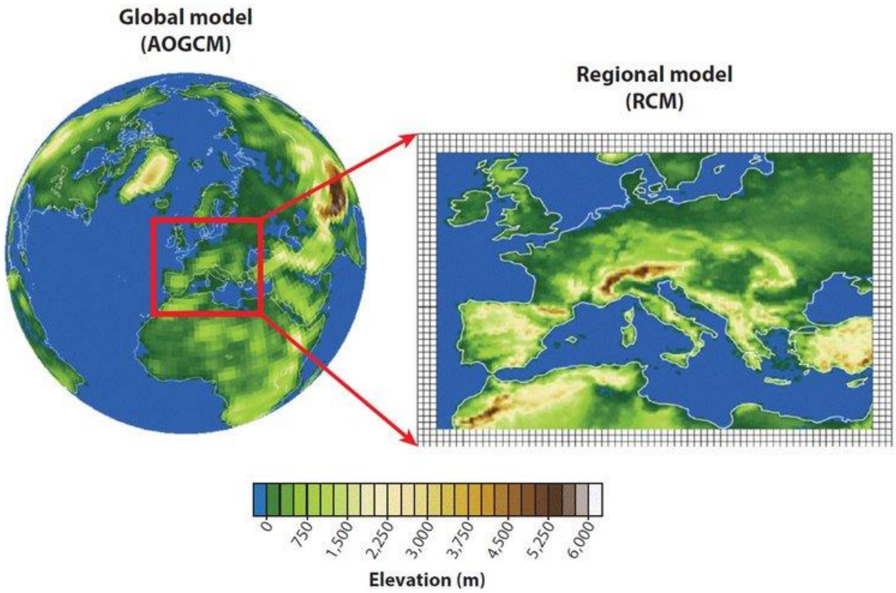

Figure 3. From global to mesoscale/regional numerical models (figure extracted from [22]).

Despite the improvement observed in NWP models, these models still present systematic errors partly explained by the: 1) inadequate model's physics parametrizations; 2) inability to handle sub-grid scale phenomena; 3) stochastic behaviour of the atmosphere and 4) uncertainty on IBC [21], [23]. Although, the precision of the results of these models increases proportionally to the number of data assimilated in these models, as well as the quality of these same data [21].

At the current stage of NWP, the model's parameterization and the spatial resolution from these models are unable to simulate some local effects as the exact location and extent of cloud fields in the case of solar power forecast. To properly account for these effects and correct the outputs from NWP, downscaling techniques can be applied to correct the data providing location-specific forecasts [24], [25]. Thus, downscaling consists of applying further methods to enhance the data extracted from the NWP with local/regional effects. This process can be performed through various statistical methods that establish relationships between local variables (such as wind speed) and variables with large-scale characteristics (such as pressure fields). Another possibility is the use of other physical approaches that varies according to the type of technology under consideration. Below, some examples of downscaling physical approaches for the wind and solar power cases are provided.

- Wind power

Microscale models: This type of model allows working with high spatial resolutions (up to 10 – 30 meters). With the growing need to estimate accurately the wind resource for different applications, new models for simulation of wind flow were developed. These models can be classified into linear and non-linear [26]. Linear models as the Wind Atlas Analysis and Application Program software have the advantage of low need for computing resources and it enables to evaluate, with reasonable accuracy, the wind resource for flat orography with small elevations, i.e., under non-complex terrain conditions [19]. However, these models tend to, e.g., miscalculate the wind speed behaviour in the lee side of the hills [26]. Therefore, these models are unsuitable for complex terrain. The advances in numerical modelling together with the increase in computational capabilities enabled the development of non-linear models in the flow simulation industry and in the assessment of wind potential. Among these non-linear models, in the wind sector, computational fluid dynamics (CFD) models stand out enabling to increase the accuracy of wind potential assessments, especially in complex terrain [27]. Results from several authors highlighted the benefits of this model against the linear models [28]. These benefits are derived from the inclusion of thermal effects in the vertical stratification of the CFD simulations. This type of approach was explored in [29] showing higher performance when compared to a traditional statistical approach, especially for periods with high or low energy levels and in the ascending wind power ramps.

Conversion to power: This type of approach is based on the power curves from the wind turbine manufacturers/or estimated based on historical wind speed and power data to determine the power from the wind turbine or park [30]. Typically, the historical power curves of wind turbines/parks are defined as a function of additional parameters, such as wind direction to account for physical features (e.g., wake effect of wind turbines, air density and terrain) in surrounding regions [30]–[32]. Based on the results of the NWP, namely, the wind speed and direction for the hub height of the wind turbine, the power curves are applied, and the forecast is obtained. This type of approach is the most common during the initial periods of wind park operation where there is no historical data.

Figure 4 presents the main steps commonly applied to obtain the physical-based wind power forecast.

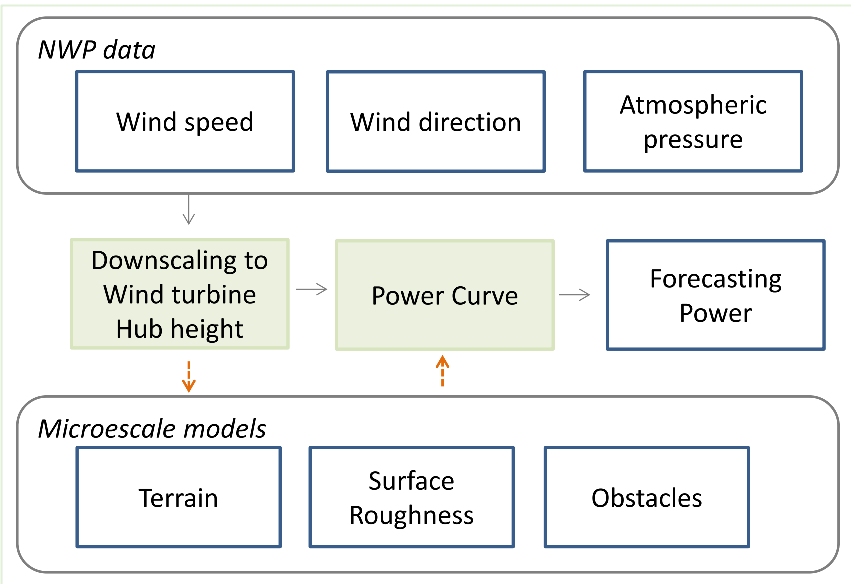

Figure 4. Main steps applied in the physical wind power forecast approaches. The interactions indicated with the orange arrow represent an alternative approach within the physical forecast approaches.

- Solar power

Cloud and all-sky imagery: In addition to the daily cycle, the other factor with the greatest impact on ground-level solar irradiation and, consequently, on solar production is the cloud cover [33]. This parameter presents a high variability that can be induced by local effects, which are not always correctly described by NWP. In recent years, models that forecast cloud cover from images from the sky taken from all-sky cameras or by artificial satellites have been developed. The all-sky cameras, installed at ground level, allow to obtain images of the sky, being very useful for very short and short-term forecast time horizons due to the reduced field of view of the camera [34], [35]. On the other hand, through satellites, it is possible to obtain images with a wide field of view, but with lower spatial and temporal resolution. In this sense, information obtained through satellites is more suitable for short and medium-term forecasts [36]. Regardless of the source of information (cameras or satellite), this type of approach uses algorithms that identify cloud coverage patterns between sequential images. The information from the images can be transformed, for instance, into cloud motion vectors, enabling to determine the movements (intensity and direction) of individual clouds [37]. This information regarding the cloud cover can then be used in different ways: i) correct the NWP outputs, or ii) apply semi-empirical models to obtain ground level solar irradiance.

The use of these models is crucial for weather-dependent generation technologies as wind and solar power forecast. Nevertheless, the outputs from these models are also used by several authors to improve the load forecast for short- and medium-term forecast horizons [12].

2.3.2. Statistical approaches

To overcome the inefficiencies of the physical methods described above and, at the same time, obtain operational forecasts with adequate precision to manage the variability of vRES, several statistical methodologies have been developed. These forecasting approaches are based on statistical approaches using historical time series (observed or forecasted) data. More precisely, this type of approach seeks to establish relationships between historical data series with what is currently observed, at the instant for which the forecast is to be made. Despite the constant emerging of new forecast techniques that require deep mathematical knowledge, compared to physical forecasting methods, this type of method presents reduced complexity and is less costly (whether in terms of time or resources) since the physical processes are not explicitly expressed. Within the statistical models, three distinct methods are usually considered: persistence, time series modelling, and automatic learning methods.

*Persistence methods***:** Persistence-based forecasting methodology is the most basic and simplest statistical forecasting methodology to be implemented. Despite belonging to the group of statistical forecasting methods, it is often addressed separately since it is considered as reference, or benchmark, against all other used methodologies. In this sense, to study the feasibility of implementing new forecasting methodologies, the results obtained through these must be matched with the results achieved by the persistence method. Only methodologies that present more favourable results than those generated by persistence are likely to be implemented. The persistence method assumes that the wind/solar power or electricity demand, remains equal, at a future instant, to the value observed at the instant for which a forecast is made. If the power, at time t, is given by p_t, then the power at the future time, $t+\Delta t$, will be given by:

$$p_{t+\Delta t} = p_t \tag{1}$$

where Δt corresponds to the time interval for which the forecast is to be performed. For very short forecast time horizons (Table 1), this model provides results, on average, with some accuracy. However, and as expected, due to the vRES variability as the forecast time horizon increases, the accuracy of this methodology decreases. For time series with high fluctuation in production (e.g., wind parks in areas with complex orography), the accuracy of this method is reduced. For solar power and electricity demand, the persistency can assume the value of the previous day and/or week.

Methods based on time series modelling: For very short and short forecast time horizons (Table 1), there is the possibility, with a certain degree of reliability, to use methods based exclusively on the statistical analysis of time series of real data. Specifically, this type of methodology tries to find out what is the relationship between a historical series of production or demand data, and its value at the instant for which the forecast is to be made, in order to obtain predictions for the following instants. Unlike physical models, in this type of forecasting methodology, only one step is needed to convert the input data into output data. Among the various statistical methods used in wind forecasting, the autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), the Box-Jenkins methodology, and the use of Kalman filters [1], [38].

Machine Learning Methods: A group of statistical data analysis methods that are applied to problems of this nature is machine learning methods. Machine learning (ML) or by "gray box" [39] are models essentially characterized by the capacity for self-learning through experience and training, i.e., ML offers the computational capacity to learn without explicit programming. As such, ML algorithms present the possibility of learning and making predictions on a set of data in an unexplicit way without following a set of static statistical learning instructions. The process of a self-learning model includes a few steps.

Firstly, it is necessary to obtain data referring to the past for a later training phase. Secondly, a relationship between the input and output data – the input and the output – desired through a target function is defined. The third step is to choose the self-learning model. Then, this model undergoes a training process, using the set of data and previously determined examples. In most cases, this type of methodology generally presents the best forecast results. However, the implementation of these methodologies has the disadvantage that it is not possible to describe the relationship between the elements of the model, i.e., it is not possible to describe or understand the relationships found by these models between the input variables and the output variables [40]. Among the methods of this group, the artificial neural networks (ANN) stand out for their simplicity and efficiency.

One of the disadvantages of statistical methods (e.g., multiple linear regression) lies in the inability to deal with the occurrence of events with distinct patterns within the time series itself, namely, the distinction between weekly, weekend and special days (e.g., holidays). ANN-based methods, on the other hand, are capable of accepting these characteristics as an independent variable and modelling implicit non-linear relationships between the forecast variable and the variables that affect it.

Figure 5 depicts an example of the main steps used to apply statistical forecast approaches. As can be seen in the figure for the case of wind power forecast typically only wind speed and power historical data are needed.

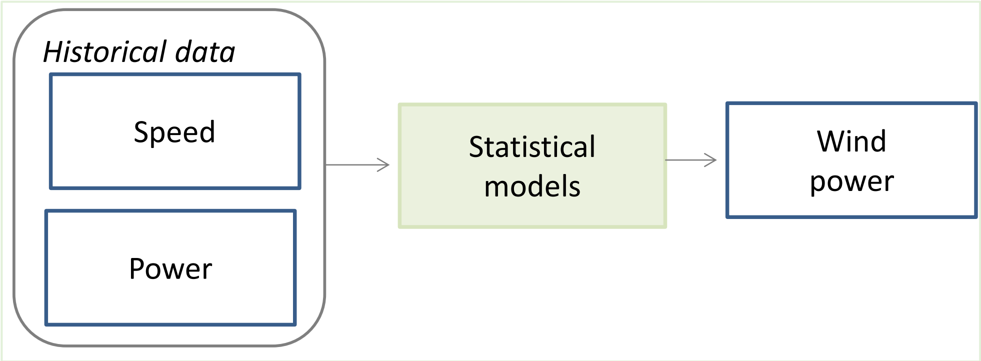

Figure 5. Example of the main steps applied in the statistical forecast approaches for wind power applications.

This type of approach is also common for load demand forecast [15]. In this case, socioeconomic variables economic growth rates are also frequently considered as well as historical values (delays) since the autocorrelation between successive events is high at different temporal scales, as can be observed in Figure 6. This figure depicts the energy demand autocorrelation in Portugal continental for different. The correlation with a 24 hour delays is 0.97.

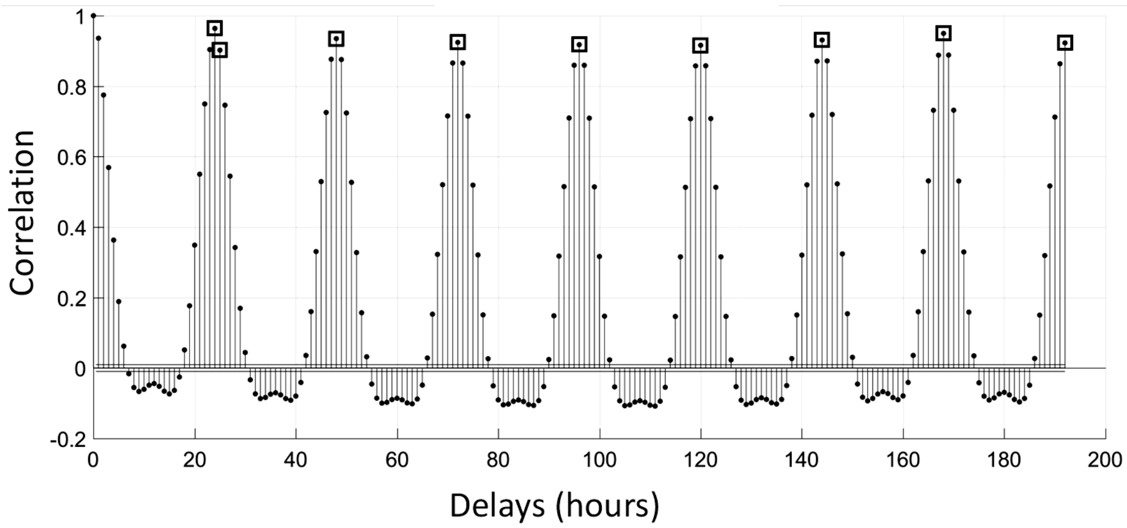

Figure 6. Autocorrelation values of electricity demand in Portugal for different hourly delays.

Table 3 presents a list of the most common statistical and learning approaches and their advantages/disadvantages.

Table 3. Characteristics of the most common forecasting methods [15], [41], [42].

Forecasting method	Advantages	Disadvantages
Linear Regression	Simplicity; You can use only one (Single) or several (Multiple) independent variables.	Only capture relationships between linearly correlated variables; Sensitive to extreme values (outliers); Variables used in forecasting must be linearly independent.
Time Series Analysis (Box-Jenkins)	Adaptable, there are many versions of the method and it has already been extensively studied; Able to deal with seasonality and non-stationarity.	Requires only historical data for the series; Unlikely to perform well in long-term forecasting; It is computationally demanding to estimate model parameters; Requires a solid knowledge of statistics inherent to the time series.
K-nearest neighbour (KNN)	It is relatively simple to understand and implement; It does not need a training phase, making its prediction based on observed historical values; Non-parametric approach, which does not imply any assumptions regarding the distribution of the variables to be predicted.	Requires an extensive period of historical data; Computationally demanding for large datasets.
Artificial Neural Networks	It is not necessary to know the relationship between dependent and independent variables; Capable to deal effectively with non-linear relationships; Capable to deal with the presence of noise in the dataset without significantly affecting the forecast result.	It is computationally demanding to train the neural network; Requires a large amount of historical data from independent variables; Do not result in a mathematical model with physical meaning.
Support Vector Machine	Adjustment of the adjustment parameter of the objective function helps to avoid over-fitting the training data (over-fitting); Convex optimization problem (there are no local minima); Use of the kernel trick, which maps the variable space to a non-linear vector space, allowing to capture non-linear relationships more efficiently.	It is difficult to define a “good” kernel function; Computationally demanding for large datasets.

2.3.3. Hybrid approaches

Hybrid power forecast models are models that combine two or more models of similar or different nature [40]. The genesis of such approach results from the combination of both statistical and physical models. The time scales applicable to forecasting methods can also be different because it is possible to join methods whose forecast horizon is different. In general, hybrid models are composed of a linear model and a non-linear model to be able to analyse the respective linear and non-linear components of the time series of data. Hybrid methods can be categorized into four different classes:

I. Weight-based methodologies: These methodologies are based on assigning weights to the various forecast models used according to their performance. It is a simple methodology, easy to implement and has the advantage of adapting to new datasets. It is a suitable methodology for a wide range of forecast time horizons. However, this does not guarantee the best forecasting efficiency for the entire forecasting time horizon and has the need for an additional model to assign the weights.

II. Methodologies based on the combination of different forecast approaches: the prediction is performed via the combination of different types of approaches (combine physical with statistical approaches). This type of methodology presents a robust behavior due to the sudden, nature of the vRES generation wind speed. Therefore, it is possible to obtain high forecasting efficiencies. However, this type of methodologies has the disadvantage of requiring the user to understand the complex mathematical model that performs the data decomposition and the absence of a dynamic behavior in the sense that the use of new data series, or the updating of the same, may result in a slow response of the methodology.

III. Methodologies based on optimization techniques and parameter selection: These methodologies are based on the optimization of the forecast model parameters – meteorological parameters such as temperature, wind speed and direction, precipitation, among others. Despite providing the user with a greater understanding of the impact of different parameters on forecasting effectiveness, this approach is difficult to implement.

IV. Methodologies based on post-data processing techniques: These methodologies are based on a post-processing of forecast data. More specifically, this approach studies the impact of residual errors in the forecasts obtained, through the forecast models used, on the overall effectiveness. The effectiveness of forecasts considerably increased compared to other approaches. However, due to the need to calculate residual errors, computational and temporal resources required are much higher than those needed for the other approaches presented.

Figure 7 provides the main steps typically applied in hybrid power forecast approaches. Comparing with the previous approaches, it includes both NWP and historical data to feed the statistical models. As discussed in this section, for this type of approach different variations can be used.

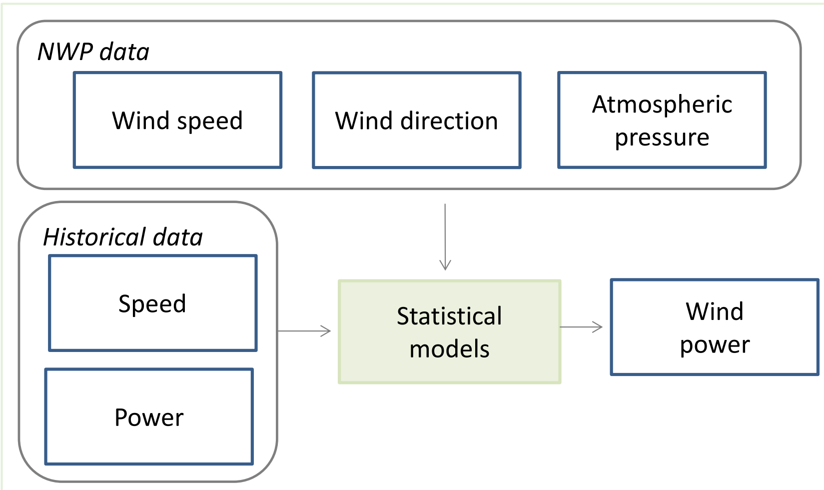

Figure 7. Main steps applied in the hybrid wind power forecast approaches based on a combination of different forecast approaches.

2.4 Data pre-processing

Before applying statistical forecasting methods, it is common to apply pre-processing procedures to the data under analysis [15], [43]–[45]. The most common types of pre-processing are data cleaning, integration, transformation and dimensional reduction. These treatments can be used in various combinations or alone. Data cleaning consists of removing or modifying values from incorrect values and entering missing values. Integration consists of combining data from different sources. The transformation consists, for example, in normalizing the data to scale them on a predefined range (e.g., [0, 1]) or in transforming a value recorded every 15 minutes into an hourly average.

Dimensional reduction consists of reducing the number of existing variables. This reduction can be done, for example, through principal component analysis (PCA), discriminant analysis, empirical mode decomposition or wavelet analysis [46]. In PCA, an orthogonal transformation is applied to convert the data into a set of values of linearly uncorrelated variables designated as principal components (PCs) [47]. With this procedure, the number of PCs generated in the process is always equal to or less than the number of original variables. The transformation applied with this technique allows the first PC to explain the largest possible variance, i.e., this PC characterizes the maximum possible variability observed in the data. With the restriction that it is orthogonal, the subsequent PC has the greatest possible variance that was not explained by the previous one. The process continues until the number of PCs became equal to the number of original variables. The resulting vectors enable to obtain an uncorrelated orthogonal basis set and they are used to feed the statistical forecasting techniques.

Another type of approach to reduce the data dimension is the application of feature selection algorithms [46]. The selection of the most relevant features aims to remove insignificant entries in the forecasting models allowing to reduce model complexity as well as computational costs [48]. These methods can be classified into three different types [45], [48]: filter, wrapper and embedded. The filter methods remove the less significant variables *a priori*, and then a model is created with the remaining features. Variables are eliminated with a criterion such as Pearson correlation. The wrapping methods involve the entire training algorithm in the variable selection process. The algorithm runs with several iterations (as many as there are variables) of the model by adding (or removing) variables and evaluating the performance of the model obtained. For the construction of the final model, the variables that enable to improve the result are kept and the rest discarded. Embedded methods introduce the variable selection process directly into the training process, in order to avoid the complete search that happens in wrapped methods, thus reducing computational complexity [49]. Additionally, combinations of these methods can be created, giving rise to the so-called hybrid methods. All these techniques aim to ensure the robustness of the data, also bringing benefits in improving computational efficiency.

Another type of pre-processing is the decomposition and classification of data by clustering [46]. Decomposition, in the context of the analysis of electricity demand forecast refers to the data separation according to the seasonal, weekly, and special days (holidays) effects. For the vRES case, this classification can refer to the so-called weather regimes (WR) types [50] or target-circulation types (TCT) [51]. The WRs allow to reduce the complexity of meteorological variability while enabling the identification of daily recurrent patterns in the climate system (top-down approach). On the contrary, TCT are derived from the power system's weather response (down-top approach), which can be the vRES generation [52].

2.5 Forecast output: deterministic, probabilistic, or ramp events

The initial focus of power forecast systems was to provide deterministic information, i.e., a value for each time step of the temporal horizon. Famous statistical methods are ARMA, ARIMA, Kalman filtering and Gaussian mixture models [39], [53], [54]. Other robust statistical approaches include ANN, KNN among others [55]–[57].

As presented in Figure 8, deterministic forecast approaches do not include information regarding its uncertainty, which can be very useful for utilities or for specific market players through the definition of strategic bidding [58]. The need to characterize and assess the uncertainty in the vRES power forecast to better integrate it in decision-making processes led to the development of various probabilistic forecasting techniques [59]–[63]. Probabilistic forecasts can allow: i) increase the revenues of market players within the electricity environments, e.g., [64], [65], and ii) suitable reserve allocation [66].

Broadly speaking, the probabilistic forecast allows to obtain probability density functions (PDF) for an specific time providing an interval of uncertainty of future events. The PDF can be achieved using physical approaches (e.g., NWP ensembles [67], [68]), statistical, or the combination of both. As described in [67], NWP ensembles forecasts are computationally demanding when compared with statistical methods. Power forecast uncertainty using statistical/hybrid models can be attained by calculating their distribution parameters based on: i) nonparametric regression assumptions as quantile regression [61] and kernel density estimators [69], [70], or ii) upon historical analogous [71]–[73] or iii) parametric distribution assumptions.

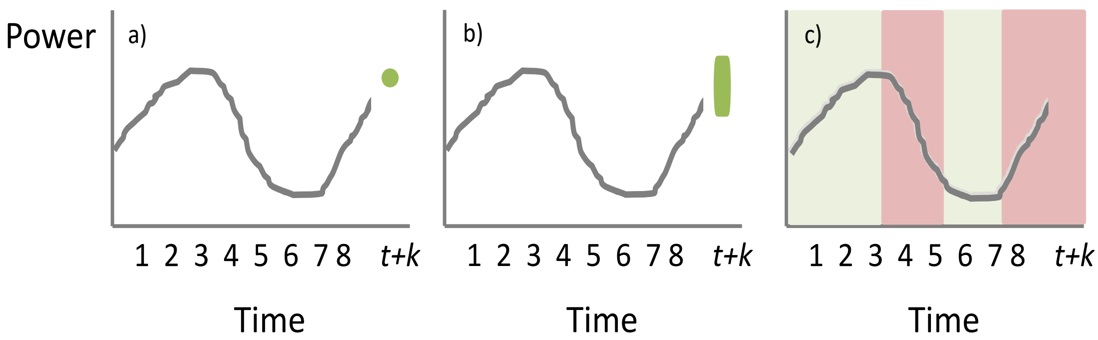

Figure 8. Different forecast outputs: a) deterministic, b) probabilistic, and c) ramp events (red background represents periods with severe power ramps and green background represents periods where power ramps are not expected).

Ramp events refer to the significant changes of power output in a short period. Thus, the importance of the detection of severe power ramps for TSOs lies on the necessity to control conventional power plants to balance those ramps in order to ensure the stable operation of the power system. Contrary to deterministic and probabilistic that provide time-series, this type of forecast provides binary information: existence or not of a power ramp [74]. This information should be integrated into the existing forecasting systems as an additional feature, but must not substitute the existing forecasting systems [7]. Thus, the main potential benefit of power ramps forecast is to alert the TSO regarding the existence (or not) of power (rapid) ramps events for which they should be prepared to commit additional reserves for safety and guarantee of robustness of the power system, in all meteorological conditions [7], [47].

2.6 Metrics to evaluate the performance of the forecast approaches

There is no single metric that can describe or measure the performance of a forecasting methodology. In existing literature, some new deterministic and probabilistic metrics have been proposed in the last years [75]. Nevertheless, most of them are not being adopted to energy sector being difficult to place the results among the values found in the literature. Taking into account this aspect, the following metrics will be used in TradeRES project to access the accuracy of time-series forecast - normalized bias (NB), RMSE or the normalized RMSE (NRMSE), the Pearson correlation coefficient (*r*) and the average value of the absolute forecast deviation ($\widehat{FD}$):

$$NB = \frac{\frac{1}{T}\sum_{t=1}^{T} Forecast\ \ (t) - Observed\ \ (t)}{NominalPower} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(Forcast\ \ (t) - Observed\ \ (t)\right)^2}{T}} \tag{3}$$

$$NRMSE = \frac{RMSE}{NominalPower} \tag{4}$$

$$r = \frac{\sum\ (Forecast\ \ (t)\ \ -\overline{Forecast\ \ (t)})(Observed(t)\ \ -\overline{Observed\ \ (t)})}{\sqrt{\sum\ (Forecast\ \ (t)\ \ -\overline{Forecast\ \ (t)})^2}\sqrt{\sum\ (Observed\ \ (t)\ \ -\overline{Forecast\ \ (t)})^2}} \tag{5}$$

$$\widehat{FD} = \frac{1}{T}\sum_{t=1}^{T}\frac{|Forecast\ \ (t) - Observed\ \ (t)|}{Observed\ \ (t)} \tag{6}$$

$NominalPower$ corresponds to the total nominal power of the control region or vRES power parks under analysis. The bias corresponds to systematic error present in the forecast. This metric denotes an average error value for the forecast time horizon allowing to assess whether the forecasting methodology tends to underestimate or overestimate comparing with the observed values. Ideally, a bias is sought, for the time horizon, as close as possible to zero. RMSE allows to identify the variation of amplitude errors, due to the squared nature of the differences. NRMSE, as aforementioned discussed, normalizes the RMSE for an easily comparison between different forecast approaches. The perfect score of the last two metric is also zero. The correlation coefficient measures the similarities between the obtained forecasts, for a forecast time horizon, and the observed value for the same time horizon. This coefficient varies between [-1 1]. A value close to zero means poor predictions, and the unit value represents perfect predictions. A value close to -1 means that the forecast is in phase opposition. The average value of the absolute forecast deviation allows to illustrate the mean forecast deviation in relation to the observed power.

To quantify the improvement of using the forecast methods proposed in TradeRES project, the approach followed in [73] is used for each metric:

$$\varepsilon(\%) = \left(1 - \frac{Forecast_{TradeRES}}{Forecast_{Benchmark}}\right) \times 100 \qquad (7)$$

where $Forecast_{TradeRES}$represents the results of a specific metric using the forecast method implemented in TradeRES project, and $Forecast_{Benchmark}$ represent the forecast results for the benchmarking approach (that will be defined according to each case study). A positive ε value indicates an improvement of the proposed forecast method. A negative value corresponds to an underperformance of the TradeRES forecast method. It needs to be mentioned that forecast tool proposed (section 4.3) provides probabilistic information. Thus, the previous metrics will be applied to the quantiles obtained. The quantile closer to the ideal score will be used.

Ramps power events refer to a dichotomous case, i.e., the existence or not of a power ramp. For this type of approach, a contingency table are usually built to derive the results. In Table 4, true positive (TP) corresponds to the ramps forecasted with the proposed methodology that occurred; false positive (FP) corresponds to the ramps forecasted but do not occur; false negative (FN) corresponds to power ramp events that occurred but were not forecasted; and true negative (TN) corresponds to power ramps forecasted and observed.

Table 4. Key Schematic 2X2 contingency table for power ramp detection. Adapted from: [47].

Event Foreseen	**Event Observation**		**Total**
	Yes	**No**	
Yes	TP	FP	Foreseen Yes
No	FN	TN	Foreseen No
Total	Observed Yes	Observed No	N=TP+FP+FN+TN

From the contingency table the following metrics can be computed: Bias Score (Bias), precision, the probability of detection (POD) and the Hanssen & Kuipers Skill Score (KSS):

$$Bias = \frac{TP + FP}{TP + FN} \qquad (8)$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$POD = \frac{TP}{TP + FN} \tag{10}$$

$$KSS = \frac{TP \times TN - FP \times FN}{(TP + FN) \times (FP + TN)} \tag{11}$$

The ideal score for the aforementioned metrics is 1. KSS ranges between 0 and 1 [76]. Bias, precision and POD metrics enables to understand if the power ramps algorithm has the tendency to over foreseen (precision, POD and Bias Score > 1) or under foreseen (precision, POD and Bias Score < 1) the number of power ramp events.

3. Electricity markets time frames and power forecasts

The existing designs of most European electricity markets were defined during a conventional energy technology dominated period. These technologies can respond to the demand variability, they are easily adjustable and, if requested in due time, they can respond efficiently to operational set-points. However, in addition to the negative environmental impacts of using fossil technologies, the marginal cost to operate these technologies is high. In contrast, vRES are weather dependent and still present significant forecast errors, especially for long time horizons.

DAMs require the forecast of electricity production 12-36 hours before physical delivery in central Europe due to coupled DAM auction at noon, or 13-37 hours in Great Britain[2], Ireland and Portugal. This time gap between bidding and the first deliverable can jeopardize the profitability of vRES [77]. The DAM shortcomings and alternative designs for a near 100% renewable electricity system were addressed in Deliverable 3.5 from TradeRES project [5]. The authors suggested a reduction of the time gap between the DAM closure and the delivery time. This reduction could facilitate vRES, since it allows reducing the uncertainty associated to power forecasts, and many flexibility options. The authors concluded that the "*choice for European market design is whether to maintain the current organization of wholesale electricity trade, in which the 24 hours of each day are traded together at noon the day before, or to replace it with a different wholesale market design*."

As shown in Figure 9 and Figure 10, for a time horizon above six hours, NWP-based forecast is the recommended approach for vRES technologies. Nevertheless, the forecast performance is worse than the one expected for very short and short time horizons. In [78], the authors quantify the annual value of using solar power forecast in the Iberian electricity market. The forecast models that use NWP data showed the highest revenue. The benefits from using a NWP-based forecast approach, with respect to the persistence prediction, ranges from 1 to 6 kEUR *per* MW of PV capacity *per* year.

From a forecasting point of view, the motivation for the DAM closure change is related to the availability of the IBC conditions used to feed the NWP models. As mentioned in section 2, the quality of the forecast strongly relies on these data. For the European countries, IBC availability from global models is limited to updates every 6 hours (at 00, 06, 12 and 18 UTC). For participate in DAM, currently, the NWP-based power forecast systems use the IBC from 00 or 06 UTC to obtain the expected vRES production or electricity demand. In order to benefit from updated IBC data, postponing in some hours the DAM closure gate (Figure 11) could allow to keep its overall structure, while it is expected to reduce the forecast uncertainties. The new gate closure hour is associated with the IBC delivery hour plus an additional period of two hours to perform all required steps (down-

[2] For Great Britain, the Day-ahead auction for 60 min products has been moved to 9.20 due to the Brexit, even enlarging the lead times. In addition, there is a 30 min auction held at 15.30.

load the IBC data, run the numerical mesoscale/regional model and apply the different forecast approach) to obtain the forecast.

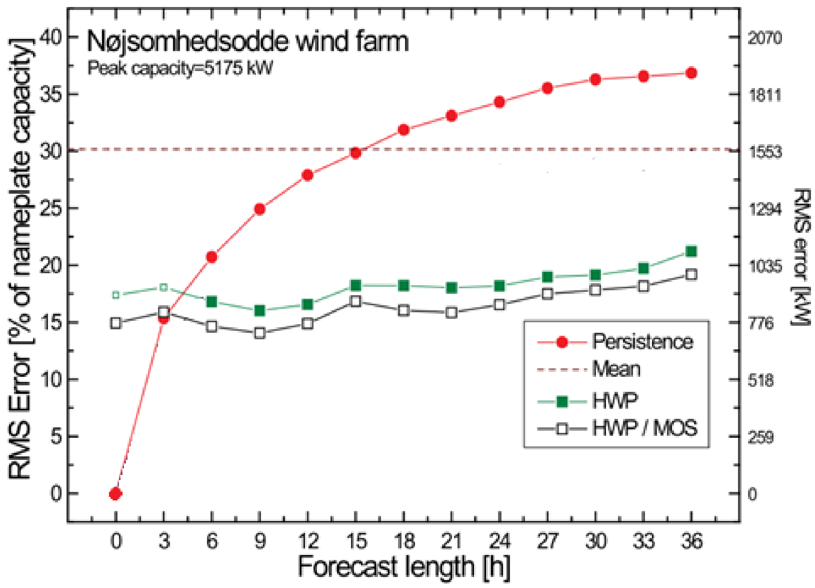

Figure 9. Forecast errors according to time horizon for different wind power forecast approaches. HWP approach refers to a physical approach and "HWP/MOS" refers to a hybrid forecast approach. Figure adapted from [33].

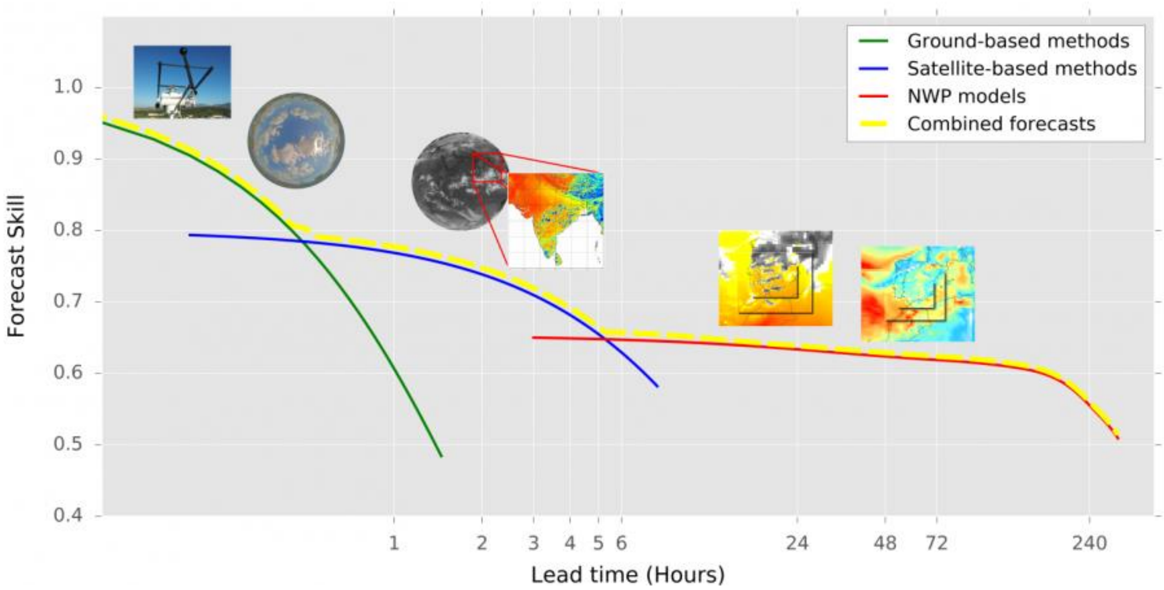

Figure 10. Solar power forecast skills according to time horizon and type of forecast approach. Figure extracted [79].

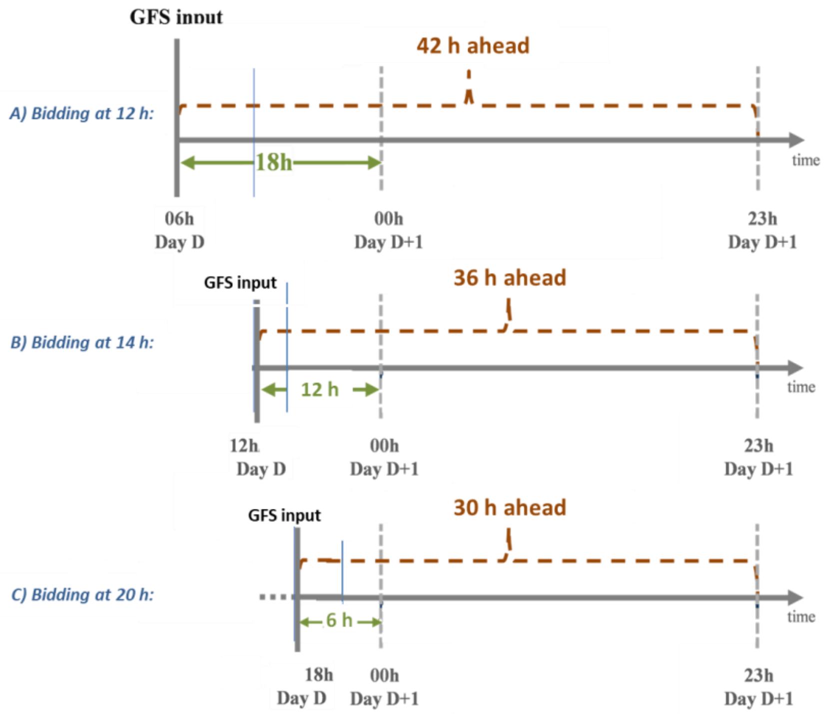

Figure 11. Identifying the time synergy between the meteorological data availability and DAM possible designs. D represents the day on which the simulation is carried out (Figure extracted from [80]).

In this energy transition phase toward a near 100% renewable power system, this postponing does not require any disruptive change in the market designs and, as described in Deliverable 3.5 [5], it can allow a "*compromise between the need to accommodate facilities with ramping constraints, which need longer lead times, and variable renewable energy sources, for which a short time between market clearing and delivery reduces weather uncertainty*".

In the current market design, market participants can already make use of short-term forecasts with high accuracy on intraday markets (IDM). Compared to the DAM design, intraday market designs show a larger variability across European countries. There are some (opening) auctions held on the day before delivery for some countries, such as the IDM auction for Austria, Belgium, Denmark and Netherlands at 15:00 in which 15 min products are traded. For the continuous trading, a greater degree of harmonization has been established from the Single Intraday Coupling (SIDC) (see [81] and also TradeRES D3.5). Continuous intraday markets allow a trading up until real-time for Finland. For other markets, lead times are rather short and range from 5 mins for Austria, Belgium, Denmark and Netherlands to 30 mins for France and Switzerland [81].

Improved forecasting accuracy can lead to smaller asymmetry for balance responsible parties (BRPs), ultimately reducing their imbalance payments. Thus, there is already a benefit of increasing generation forecast quality which will be further increased with trading even closer to lead time, potentially also in DAM markets, as well as rising shares of vRES.

3.1 Impact on market modelling

Following the approach presented in Deliverable 4.1 [80], the Agent-based Market model for the Investigation of Renewable and Integrated energy Systems (AMIRIS) was enhanced to consider power forecast errors for agents marketing renewable energy. Since error distribution functions for different technologies and varying gate closure lead times are not yet fully integrated, a Gaussian distribution was chosen to represent the forecast error. The distribution parameters are exemplary and were selected to illustrate the impact of forecast errors on the market simulations and to demonstrate the basic functionality developed within TradeRES. The data used does, however, not yet represent realistic data regarding power forecast errors. Such realistic data – potentially also considering error dependency on a given weather situation – will be developed in the project and integrated into AMIRIS in the near future.

In this demonstration of the approach, the renewable energy trading agent was configured to consider power forecast errors with a constant distribution function over time. Thus, each hour of the day was assumed to follow the same error distribution. It is assumed that the power forecast error follows a normal distribution formulation. Generated values represent levels with different relative error. To obtain power supply bids that include these errors, the error level is multiplied with the perfect foresight power infeed (see also Section 3.3.1.2 in Deliverable 4.1) which can be extracted from historical time series data. Figure 12 shows the incidence of actual power forecast error levels obtained within AMIRIS. The normal distribution of the error levels is clearly visible. The positive mean of the distribution (12) corresponds to an average overestimation of renewable power. Due to the variance of the distribution (13), however, also negative error values occur, reflecting a lower-than-actual feed-in estimate.

$$\mu = 0.05 \tag{12}$$

$$\sigma^2 = 0.1 \tag{13}$$

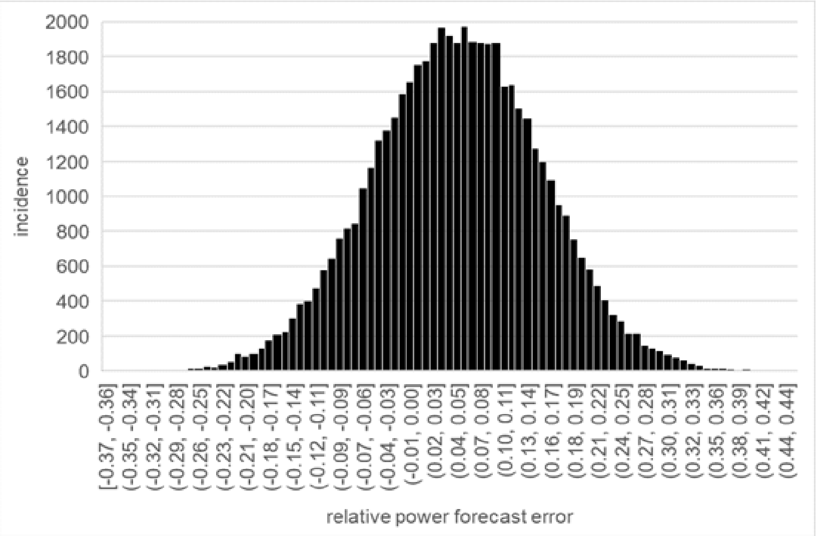

Figure 12. Histogram of power forecast error levels created in AMIRIS following a normal distribution with a mean of 0.05 and a standard deviation of 0.1; 8760 hourly data points representing one year.

The power forecast errors are created during the bid preparation stage of AMIRIS and propagate through the simulation. Therefore, these errors can impact the day-ahead market clearing price, traders' profits and system costs as well as other subsequent markets (e.g., intra-day, ancillary services) which, however, are not explicitly modelled in AMIRIS. Figure 13 demonstrates the possible impact of power forecast errors on the day-ahead electricity market clearing price using the same error distribution as before. For most situations, prices found with erroneous forecasts are below the "perfect foresight" prices that do not contain any forecast errors. This matches the expectation since an on-average higher renewable feed-in should lead to lower prices due to the merit-order effect [82].

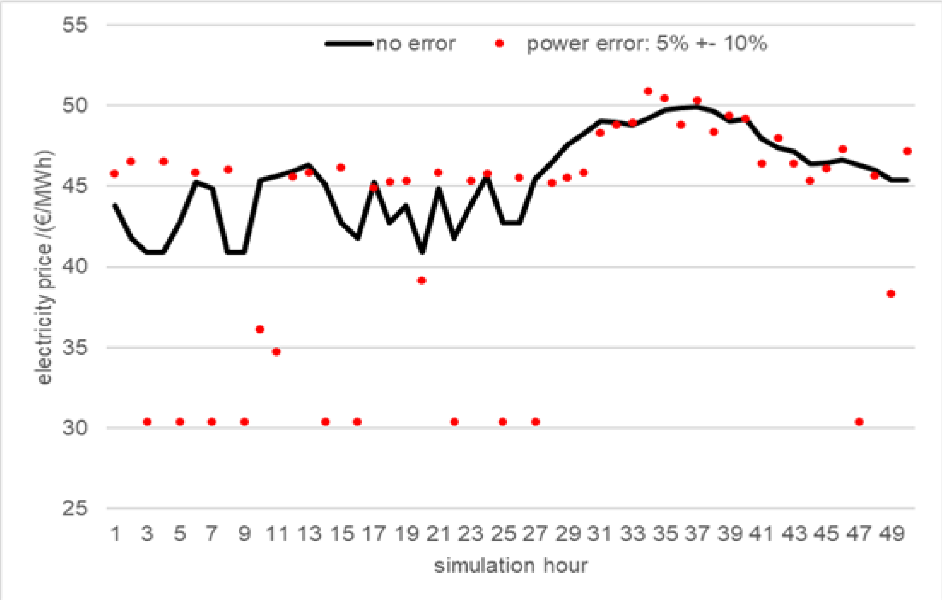

Figure 13. Sample impact of power forecast errors on (non-realistic) DAM clearing prices; black curve represents prices without power forecast errors, red dots resemble prices that include modified renewable feed-in estimates based on the same error distribution function as shown in Figure 12.

This simple example highlights the possible impact of power forecast errors on the market prices. However, it must be noted that several aspects are not yet satisfyingly reflected. For instance, real-world forecast errors might depend on the specific type of technology and the hour of the day. In addition, the errors shown here have no autocorrelation, while real-world error series often have autocorrelative features. Thus, to obtain a more realistic time series of errors, correlations should also be considered.

4. Forecast approaches developed in TradeRES project

In this section, some preliminary results are presented as a drive for the first version of TradeRES vRES power forecast tools. Specifications of the market players/agents that will benefit from these forecasts are also presented. Detailed results will be presented in the deliverables from WP 5.

4.1 Preliminary results

4.1.1. Wind, solar, small hydro and electricity demand forecast

The potential benefit of changing the day-ahead market closure gate to an hour near the time real operation was analysed for different technologies (wind, solar PV, small hydro) and for electricity demand. This benefit is usually referred as the "certainty gain effect" and it represents the potential economic surplus that the market players can obtain by building their offers in the day-ahead market with a highest level of certainty on power forecast and, consequently, with low-risk exposure [83].

From a forecasting point of view, the motivation for the DAM change is related to the availability of the IBC conditions used to feed the NWP models that are crucial for forecasting systems for the considered time horizon. The work conducted so far intends to understand which market players can benefit most from this change in the market design. On the other hand, and since the forecasts are obtained from a partner who is a forecast provider (including for some players in the Iberian electricity market), it allows to identify which technologies/players have more challenges to participate in electricity market and, therefore, require further developments regarding the forecast approaches during the TradeRES project.

- *Method and data*

The approach followed is based on the work presented in [4]. Although, in this case, the approach is extended to other technologies and to electricity demand players. The first step was the identification of representative days. Representative days are a widely used statistical approach to detect the most typical daily patterns of a dataset under analysis. This approach, based on a statistical clustering technique, allows, at the same time, to group days that exhibit identical patterns. With this procedure, it is possible to feed the agent-based electricity models (in this case the Multi-Agent TRading in Electricity Markets - MATREM) and identify the profiles that can jeopardize the income of different players / market agents enabling the adoption of measures to mitigate their exposure to risk. By applying the K-medois clustering [4] to the Portuguese aggregated wind, solar PV, and small-hydro power production, nine typical profiles were identified, Figure 14.

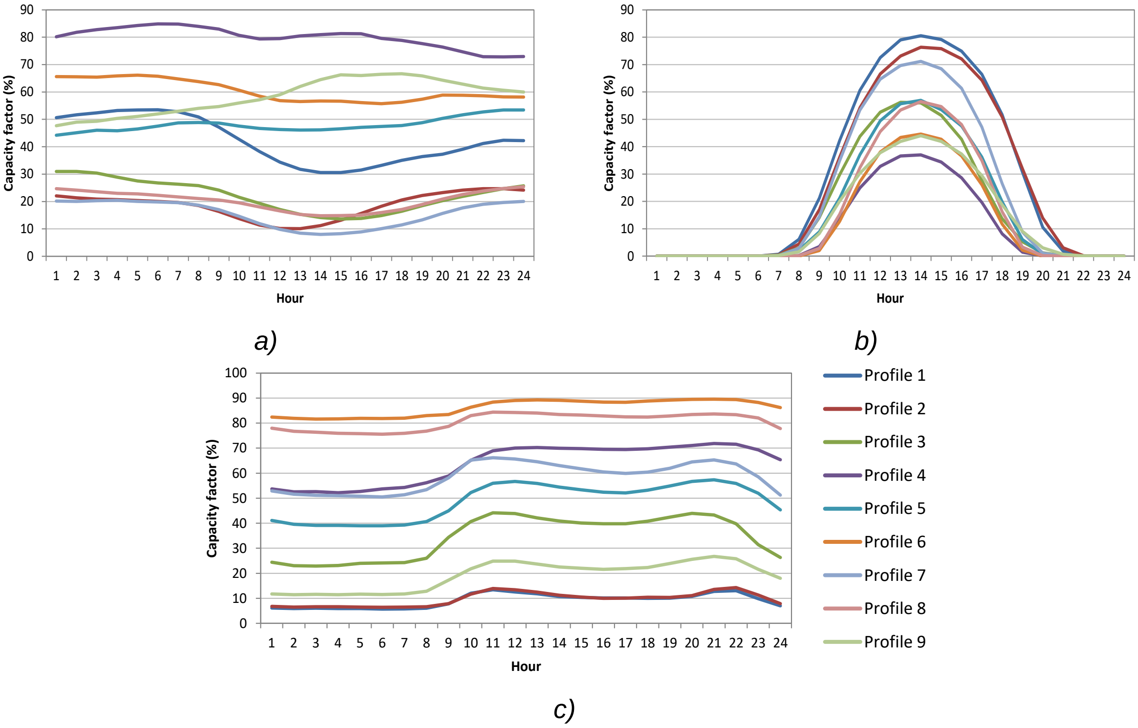

Figure 14. Daily average profiles for a) wind, b) solar PV and c) small hydro for the nine clusters (profiles) for Portugal.

For the days that correspond to the medoids of each cluster, the forecast using different IBC was attained. The forecast is based on a combination of machine learning approaches (ANN and KNN) that uses an input a combination of weather sources from the ECMWF and GFS global models. Different models use different weather variables depend on technology. Usually, the models are trained using the last 2 historical years, and when data is available, we create a model by site. At the end of the process, an aggregated model is used to combine all sites for each technology. Models run every 6 hours using the best weather data available. Some of these models consider the last real values collected from the SCADA to improve the very short-term forecast.

- *Metrics of market performance*

The following metrics are used to compare the results between the base and the upgraded forecast scenarios. Considering each i scenario, the total remuneration of each player, R_i, from the markets is computed as follows:

$$R_i = \sum_{t=0}^{T} Forecast\ \ (t) C^{DAM}(t) + \begin{cases} [Observed\ \ (t) - Forecast\ \ (t)] C^{UP}(t) & for\ Forecast\ \ (t) < Observed\ \ (t) \\ [Forecast\ \ (t) - Observed\ \ (t)] C^{DOWN}(t) & for\ Forecast\ \ (t) > Observed\ \ (t) \end{cases} \quad (14)$$

where t is the period number, $C^{DAM}(t)$ is the DAM price, $C^{UP}(t)$, is the up deviation cost, $C^{DOWN}(t)$ is the down deviation cost. $Forecast\ \ (t) C^{DAM}(t)$ is the parcel that consists in the remuneration obtained from the DAM. The other parcel of the equation represents the remuneration obtained from the deviations. Therefore, considering that scenario 0 is the current scenario, the remuneration gain effect, R_{ge}, of rolling the gate closure is computed as follows:

$$R_{ge} = \frac{R_i - R_0}{R_0} \times 100\ [\%] \tag{15}$$

The cost, C_i, paid in each scenario due to the penalties (difference between the forecast and observed values) is computed as follows:

$$C_i = \begin{cases} [Observed\ \ (t) - Forecast\ \ (t)]\left[C^{UP}(t) - C^{DAM}(t)\right] & for\ Forecast\ \ (t) < Observed\ \ (t) \\ [Observed\ \ (t) - Forecast\ \ (t)]\left[C^{DAM}(t) - C^{DOWN}(t)\right] & for\ Forecast\ \ (t) > Observed\ \ (t) \end{cases} \tag{16}$$

- *Scenarios and synthesis of the main results*

To quantify the certainty gain effect for different players with the existing electricity market design and products, the MATREM simulator was feed step-by-step using the scenarios presented in Table 5.

Table 5. Scenarios analysed to quantify the certainty gain effect for different electricity market players.

Scenario	Description
1	Wind forecast and observed values for other generation technologies + load
2	Solar forecast and observed values for other generation technologies + load
3	Small hydro forecast and observed values for other generation technologies + load
4	Load forecast + observed for generation technologies

The lowest forecast errors were observed for small hydro and load players. Preliminary results show that the certainty gain effect of using updated IBCs is relatively small. Table 6 showns the results for the scenario 1 using the forecast data at 6 UTC as a benchmark. In the case of a wind power producer, the reduction in the RMSE reaches nearly 1%. The total energy deviation for the representative days analysed reduces 1.47% and 2.17% comparing with the use of IBC from global models provided at 06:00 UTC. Regarding the remuneration, an increase of 5.76% is expected when the IBC from 12:00 UTC is used. For the IBC from the 18:00, the increase in the remuneration only increases 1.68%. Results will be further analysed in WP 5, in specific, *D5.3- Performance assessment of current and new market designs and trading mechanisms for National and Regional Markets*.

Table 6. Results for scenario 1 (wind power forecast) in relation to the DAM forecast at 06:00 (UTC).

Metrics	IBC forecast data	
Forecast at (UTC)	**12:00**	**18:00**
RMSE (%)	-0.77	-1.06
Energy deviation (%)	-1.47	-2.17
Penalties to DAM schedule (%)	-2.53	-5.52
Total remuneration (%)	+5.67	+1.68

4.1.2. Power forecast with feature selection

As discussed in the previous sections, and supported by several authors (e.g., [84]), the vRES power forecast accuracy for short and medium time horizons strongly relies on the outcomes of NWP models. The main error in the final forecast comes from the meteorological input rather than the existing statistical techniques applied in power forecast systems [84]. For instance, using one source of meteorology for wind speed forecast the mean absolute percentage error (MAPE) is approximately 15%. Using this wind speed as input, MAPE for wind power forecast is approximately 23%. However, using the same algorithm with another source of meteorology, with wind speed MAPE of 24%, the MAPE error for power forecast has a substantial increase, around 45%. A generic graphical representation of a generation modern wind turbine power curve, which presents typically a cubic dependency of wind speed for the range between 4-11 m/s. For these wind speed ranges, we can intuitively understand that an absolute error of 1 m/s in wind speed can represent a high error value in power forecast. However, the full potential of the output of these models was not fully explored. For instance, most of vRES power system uses a single point information from the NWP grid and a limited number of meteorological parameters.

For the specific case of the single point outputs, the variability in generation observed in a given wind or solar power plant depends not only on the local dynamics, but it is also influenced by large-scale atmospheric patterns [73]. Although these patterns may be well simulated, in a specific location, the time series may present deviations [85]. Thus, another feature of the NWP that is not usually explored in forecasting systems is the use of the results of a spatial grid in contrast to the use of only data from a single spatial point or the midpoints of the NWP domain surrounding a wind power plant/ solar PV [86]. In [73], a methodology that combines a gradient boosting trees algorithm with feature engineering techniques, aiming to extract the maximum spatial and temporal information from the NWP grid to improve wind and solar power, was implemented. The authors identified that the use of PCA enables to improve the wind power forecast accuracy. Thus, the achieved results indicate that an adequate extraction of features from the raw data of the NWP can improve the forecast systems. The authors recommend more investment in the data mining phase as well as the application of statistical downscaling techniques capable of incorporating all data.

Regarding the meteorological parameters extracted from NWP, recent works have shown that a careful selection of input variables for statistical methods can improve the accuracy of the wind and solar power forecasts [46], [49]. In the case of wind power, the most common meteorological parameters used as input to feed the downscaling approaches are the wind speed and direction. The influence of parameters related to the conversion efficiency as air temperature and pressure are included in some works. In [85] the authors included parameters from the upper levels of the atmosphere (e.g., the 850 and 500 hPa pressure levels) as input to improve the performance of the statistical models. Using a PCA, in the work conducted by [87], the following parameters were identified as the most relevant to forecast the wind power variability: mean sea level pressure, geopotential height, and the meridional wind component and humidity relative. A physics-oriented pre-processing with a NWP feature selection approach had a positive impact on the model performance from the team that won the European Energy Market Conference competition [88]. In [46], the author identified that a possible development trend to improve the power forecast systems is to include exogenous meteorological input variables.

For solar power, [45] identified that parameters as precipitation intensity and wind speed penalized the performance of the forecast. On the other hand, parameters as ultraviolet index, wind bearing, and dew point could allow to improve the solar power forecast.

Against this background, in TradeRES, a method was implemented to identify if the inclusion of meteorological parameters derived directly from a NWP and others with impact in wind and solar power generation behaviour. These meteorological parameters include both, surface (e.g., latent flux) and vertical levels information.

- *Method and data*

The method implemented uses a greedy sequential forward feature (SFF) selection algorithm [49] to select iteratively the meteorological features (based on the principal components scores), which minimizes an objective function, in this case, the root mean square error. The SFF starts with an empty set of features. Then, at each iteration, it extends the previous set with the feature that allows to minimize a pre-determined objective function (OF). The RMSE was used as an objective function in this case study.

The ANN approach implemented in Matlab toolbox [89] was used to provide the power forecast due to the features described in section 2.2.2. Estimating with the ANN involves two main steps: training and learning. One of the most effective learning algorithms in ANN is the backpropagation algorithm [90]–[92]. The backpropagation algorithm uses supervised learning to adjust the weights and biases in each unit [90]. The process of training the network is the adjustment of the network weights to produce the desired response to the given inputs. Consequently, the training begins with random weights that iteratively are adjusted so that the error (the difference between estimated and expected results) based on inputs and outputs data will always be minimized to an acceptable value. The goal of the backpropagation algorithm is to reduce this error until the ANN learns the training data [90]. The following parameters were imposed during the ANN setup:

a) the number of hidden layers - In this case, it was considered only one hidden layer;

b) different numbers of units in each layer. There is no predefined rule and therefore a rule-of-thumb for determining the correct number was followed. In this case, the number of hidden units is always 2/3 the size of the input layer, plus the size of the output layer [93];

c) different types of transfer functions. In this case, a sigmoid function was considered for each unit in the hidden layer;

d) learning algorithm. In this case, the Levenberg-Marquardt algorithm was adopted [91], [93].

As a baseline to assess the benefit of the SFF selection algorithm, an ANN approach was feed with the meteorological parameters similar to the ones used in [73] azimuthal wind speed, meridional wind speed and wind speed module. For each wind park analysed, the data is obtained for the nearest grid point of NWP. Data from the WRF model provided by MeteoGalicia[3] are used. These data are available, free of charge, and contain several meteorological historical forecast parameters such as wind speed components and gust, convective available potential energy, cloud cover at high levels, surface downwelling shortwave flux and visibility.

The two following case studies were also analysed: i) use the PCA approach without applying the feature selection algorithm, and ii) single point data with the feature selection algorithm.

The method was applied to seven wind parks in Portugal located in regions with different climatic conditions (coastal and mountains regions) to understand the consistency of the meteorological features along the different regions.

- *Synthesis of the main results*

The average impact for the seven locations analysed different configurations of the wind forecast power approach is depicted in Figure 15.

By applying the PCA and the feature selection algorithm the RMSE can reduce nearly 25% comparing to the benchmarking approach (single-point forecast with limited number of meteorological parameters), Figure 15. If only PCA is applied, the results show a reduction in the RMSE values of nearly 8%. Although, the use of PCA improves the forecast, an insightful selection of the meteorological features is paramount to reduce the uncertainty in the wind power forecasts. Parameters as wind gust, wind power density, wind shear, and planetary boundary layer should be used to improve the wind power forecast.

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[3] Data available at: http://mandeo.meteogalicia.es/thredds/catalogos/DATOS/ARCHIVE/WRF/WRF_hist.html (accessed on 02 November 2020).

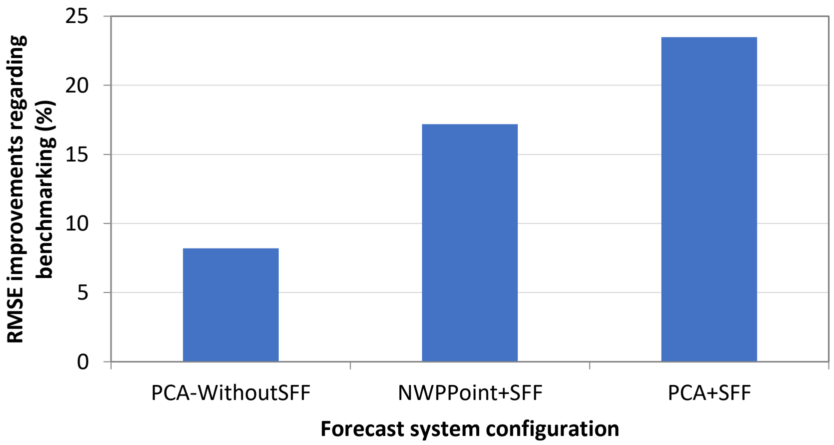

Figure 15. Average RMSE improvements for the seven wind parks analysed compared with the benchmarking approach. “PCA-WithoutSFF” – PCA approach without applying SFF algorithm; “NWPPoint+SFF” – data from NWP was extracted to the nearest point of each wind park and the SFF was applied; “PCA+SFF” – PCA approach and application of the SFF algorithm.

Despite the improvements observed, it is noted a tendency to underestimate the days with a high level of wind power production. On contrary, an overestimation of the observed wind power production is observed for days with low level of wind power production.

4.1.3. TradeRES - vRES power forecast approach

Based on the preliminary results, the main steps of the vRES power forecast method applied in TradeRES are presented in Figure 16.

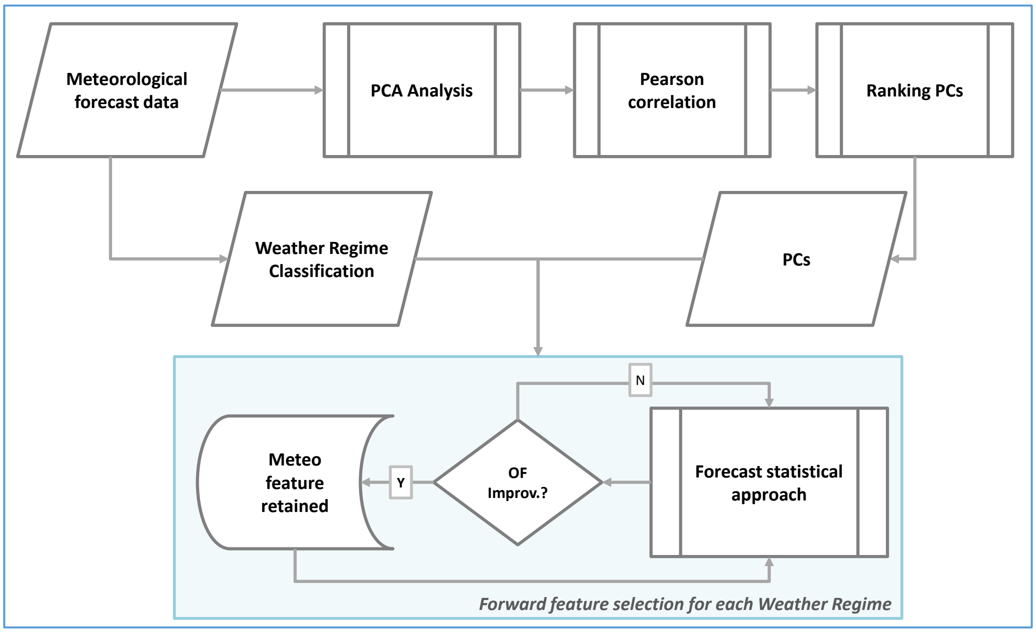

Figure 16. Power forecast approach implemented in TradeRES project.

The forecasting approach is also based on a SFF algorithm but, in this case, a calibration procedure according to the different weather regimes is performed. The classification of atmospheric circulation states into distinct types is a common approach used for understanding and scrutinizing weather patterns and their impact on a predetermined parameter. For instance, in [94] the weather regimes were used to estimate Europe-wide wind power generation. Thus, the goal is to improve the drawbacks identified in the previous subsection by obtaining a forecast configuration for similar weather conditions. As related by several authors [84], the weather conditions have a strong impact on the wind power variability as well as in the uncertainty in its forecast. This can be partly explained by the weather conditions that unleash different responses, *e.g.*, heating and cooling between land/sea surfaces, and thermal stratification [47], [95], [96]. The performance of solar power forecast systems depends on the cloud coverage, which can be distinguished using weather regimes.

To accomplish the specification requested by some market players, probabilistic outputs will be provided with this approach. One of the objectives of this approach is to enable bidding strategically of market players by identifying the most adequate quantile (e.g., the quantile that maximizes the revenue in the day-ahead market) [97].

Below, further details of each step in the methodology implemented are provided:

- *Meteorological data*: The NWP data will be provided from the two weather sources the ECMWF and GFS global models.
- Several meteorological parameters from the NWP will be tested to identify meteorological features that enable to improve the wind or solar power forecast accuracy. New variables such as mean seal level gradient or atmospheric instability [47] to account for the energy conversion processes will be computed.
- *PCA analysis:* After obtaining the data, a PCA analysis is implemented for each meteorological parameter. Only the PCs that explain 90% of the total variability are retained since the remaining PCs only describe local effects.
- *Pearson coefficient correlation:* is then applied to identify the correlation among the PCs and the wind/solar PV power (or the combination of both) and the PCs are ranking in a descending way. In parallel with this process, a weather regime classification is computed.
- *Weather regime classification*: each forecast day will be classified into a specific WR using a Lamb-type approach [50]. This approach uses the mean sea level pressure from 16 grid points to identify twenty-six dissimilar weather patterns. Two of the weather patterns are classified as pure low-pressure system or anticyclonic, eight are defined as directional – according to the wind rose (N, NE, E, SE, S, SW, W and NW), and the remaining sixteen are defined as hybrid.
- *FSS for each weather regime*: It is a greedy algorithm that chooses the “most attractive” solution in each iteration. In this case, the SFS attempts to find the “optimal” feature subset by selecting, iteratively, the meteorological PC that improves reduces the RMSE value. Sensitivity tests will be implemented for each case study and technology to identify the most adequate OF. The OF will depend on the perspective: i) for market players as wind and solar power producers (or vRES aggregator), the RMSE and electricity market revenue (including day-ahead and imbalances) will be

tested and compared, and ii) for the TSOs, the RMSE will be used. The ANN will be the statistical approach implemented. A quantile spline regression technique will be applied to obtain the probabilistic forecasts [98].

The power forecast approach will be tested in the regional cases studies defined in WP 5, and the benefit from this approach will be discussed as an outcome of WP 5.

Output: Wind or solar power probabilistic forecast with 15- and 60-minutes time resolution, according to the needs of the different players. When deterministic forecast is required, the quantile that minimizes the RMSE or maximizes the producers' revenues will be applied.

Agent-based models that will benefit from these data: Wind and solar power producers, aggregators/virtual power plants, and TSO.

4.2 Wind power ramping forecast

As the share of wind and solar PV increases in most of the power systems, ramping alert tools are being implemented by some TSOs [7], [99]. The goal of such tool is to complement the existing deterministic or probabilistic forecast systems enabling to increase the level of situational awareness available to the TSO by helping them to better scale the level of risk that exists in the system. This risk can then be managed by taking into consideration additional factors, such as potential changes in energy consumption, additional reserves that can be deployed, and additional generators that may be available for unit commitment. Furthermore, players capable to provide temporal and sectoral flexibility can also take advantage of this information to strategically participate into electricity markets.

The characterization and definition of wind power ramps are linked to the notion of an "*event that is critical enough to deserve special attention*" [50]. In specific, ramp events consist of a rapid and substantial change in the wind power during a time interval Δt. Since no clear definition is available in the literature to classify power ramps, the definition (17) and principles used in [9] will be followed in TradeRES project as a "first-guess".

$$\frac{\|Power(t+\Delta t)-Power(t)\|}{\Delta t} \geq \mathrm{PRRval} \tag{17}$$

where, t denotes the time and $PRRval$ is the reference value. For these parameters, the values identified in [9] will be used.

Understanding power ramps events is not an easy task as the weather conditions are rarely the same for different wind parks. In fact, even when two wind parks are placed in similar latitudes, these triggering mechanisms can be very different due to local effects as the terrain characteristics, roughness and topography or phenomena like sea/land breezes [74]. Recent works, e.g., [9] state that, in order to understand and forecast the dynamics of wind power ramps, holistic methodologies should be used to account for the spatial and temporal evolution of atmospheric large-scale circulation. In this sense, in their work, the authors implemented a windstorm detection algorithm and compared the performance with a common cyclone detection algorithm [100], [101]. Windstorm algorithm presented a highest performance. Nevertheless, some issues were identified in the current windstorm detection methodologies. The most critical one is that a wind power ramp is not always a consequence or is always linked to the existence of extreme wind speed values, being essentially dependent from the previous (historical) state of the flow. Moreover, these algorithms are unable to distinguish upward from downward power ramps. For that reason, information from the previous time step ("memory effect") needs to be included in this type of fast ramping tool. In the next section, an algorithm that uses a time numerical differentiation in order to fit the particular case of wind power ramps events is described.

4.2.1. Ramp detection algorithm

This algorithm is based on the forecast mean sea level pressure from the NWP. In order to be able to identify areas where there is the highest variation in the meteorological field, the pressure gradient was calculated as follows:

$$\nabla P = \frac{\partial P}{\partial Long}\hat{\imath} + \frac{\partial P}{\partial Lat}\hat{\jmath} \approx \frac{P_{i+1,j} - P_{i-1,j}}{2\Delta Long} + \frac{P_{i,j+1} - P_{i,j-1}}{2\Delta Lat} \tag{18}$$

where *p* is the average pressure at sea level, *Long* the longitude and *Lat* the latitude. Next, and in order to introduce a “memory effect”, the derivative in time of the pressure gradient is calculated according to the following expression:

$$\frac{\partial \,\|\nabla P\|}{\partial t} \approx \frac{\|\nabla P\|_t - \|\nabla P\|_{t-1}}{\Delta t} \tag{19}$$

The remaining detection algorithm is equal to the windstorm algorithm presented in [9]. Therefore, the major differences between the two methodologies are the following aspects: *i)* use of pressure data, ensuring better identification of the synoptic centres [9]; *ii)* identification of extreme events associated with positive/negative power changes in time, enabling a better relationship with the wind power ramp events. In this sense, it is considered that the events with negative variations are those with a change in the pressure gradient of less than the 2nd percentile. On the other hand, the positive events are identified as regions with a variation above the 98th percentile in the pressure gradient.

In the case of upward ramps, the algorithm starts to determine the grid points where the pressure gradient is above a certain percentile. The spatial percentile calculation is based on the following formula [9]:

$$\mathrm{Perc_x} = \mathrm{F}_*^{-1}(\mathrm{p}) = \min\{\nabla\mathrm{P} : \mathrm{p} \leq \mathrm{F}_*(\nabla\mathrm{P})\} \tag{20}$$

where, *p* represents the percentile considered and F_* stands for the cumulative distribution function weighted by the cosine of the latitude of {W (Long, Lat, t):(Long, Lat)∈δ} being δ the spatial domain [102]. For downward power ramps, the 2nd percentile is considered, and the search is for grid points where the pressure gradient is below this value.

Then, contiguous grid points for which the percentile condition occurs are enclosed into the same candidate [9]. A convex hull approximation is employed in this step to identify the convex polygon comprising all the spatial grid points that can belong to the same meteorological event (see black line in Figure 17). After, the average geometric center of each event is computed (magenta "*" symbols in Figure 17). As outcome, this spatial search algorithm provides a list of the possible location of events associated with synoptic systems. Only events with a minimum area of 150 000 km^2 [103] are considered. This step is performed for each temporal time-step.

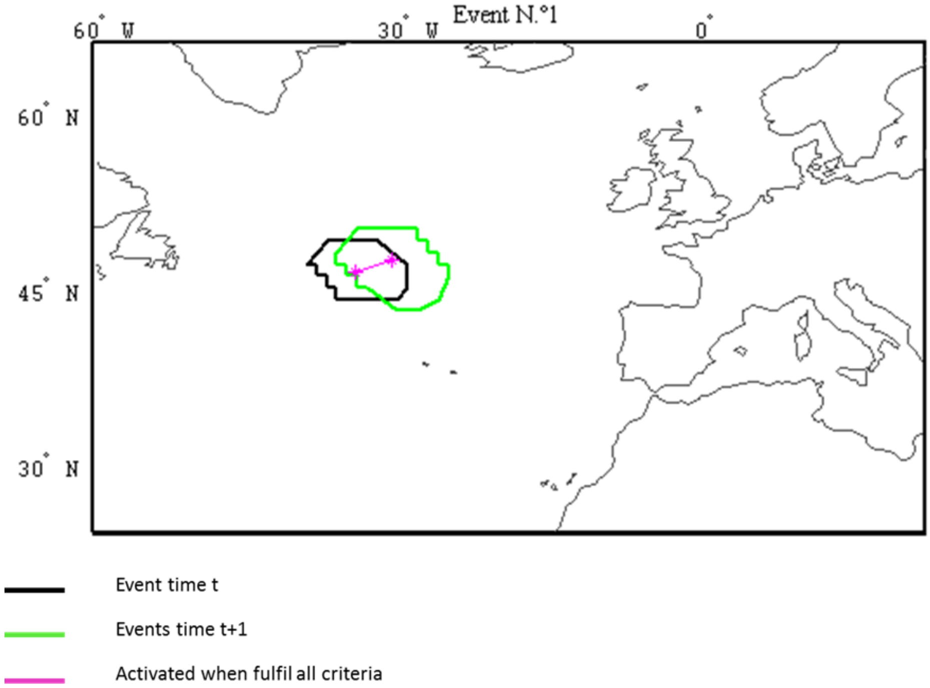

Figure 17. Example of one event in time *t* (black line) and one event in time *t+1* (green line). The magenta "*" symbols represent the average geometric center of each candidate, while the magenta line indicates the trajectory of the meteorological event.

Once the synoptic events are identified in the time step *t*, it becomes necessary to stitch to the nearest candidate at the time *t+1* to build the trajectory. The following assumptions are imposed in this step [9]:

1. The maximum Euclidean distance between the centers of two consecutive time-steps is 720 km [103];
2. Only events with a lifetime above 2h or with a maximum speed of 120 km/h are retained.

All events with no continuity are eliminated, and when two or more candidates are found, a cost function is applied in order to determine the most appropriate trajectory. The cost function applied is similar to the one shown by [104], which is expressed by:

$$\mathrm{Tracking} = \operatorname{argmin}\left(\sum_{j=1}^{j=N}(\mathrm{C_t} - \mathrm{C_{t+1,j}}) \times \left(\left\|\frac{(\mathrm{Int_t} - \mathrm{Int_{t+1,j}}}{\mathrm{Int_t}}\right\|\right)\right) \tag{21}$$

where, $\mathrm{C_t}$ are the coordinates of the center for a determined synoptic event at time step *t*, $\mathrm{C_{t+1,j}}$ are the coordinates of the center for the *j*th synoptic event at time step t+1, $\mathrm{Int_t}$ is the intensity observed at the geometric center of the event at time-step *t* and $Int_{t+1,j}$ is the intensity observed of the geometric center for the *j*th synoptic event at time-step *t+1*.

At the end, the algorithm retains a tracking table with the different trajectories of the extreme events detected and some basic characteristics, *e.g.*, their lifetime, occurrence dates, speed, area of influence. In real-time operation, an alert will be issued when these events are nearby the region under analysis.

The power ramp power forecast accuracy will be assessed and analysed in the regional cases from WP 5.

4.2.2. A nested forecast approach

Based on the probabilistic and power ramp detection algorithm, a nested forecast approach will be established aiming to reduce the system cost associated with less committed reserves. Thus, the power reserves' allocation can be dynamically established and dependent on the probability of existence (or not) of wind ramps. Other market players as flexibility providers or wind power producers can also benefit from this nested approach since it can allow for strategic participation in electricity markets. An example of the outcomes of this tool is shown in Figure 18.

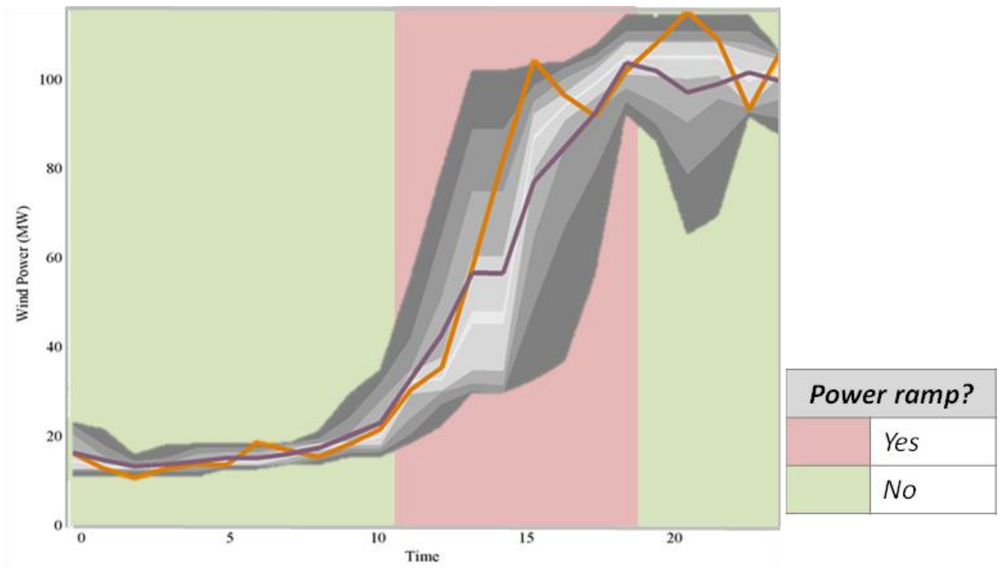

Figure 18. Example of the outcomes from the nested forecast approach.

Output: Hourly binary information regarding the occurrence (or not) of wind power ramps.

Agent-based models that will benefit from these data: All TradeRES agent-based models may benefit from these data by incorporating it in TSO agent capabilities or in flexibility provider and wind power producers' agent behaviour, using this information to strategically participate in the electricity markets.

5. Final remarks

In this report, a non-extensive review of the different forecasting methods was presented focusing on the technologies under analysis in the TradeRES project. This review served as the basis for framing the advantages and disadvantages of the different forecast approaches commonly applied in the energy sector. Moreover, it allowed to identify the synergies among the different approaches and existing electricity market time-frames. Based on this background and preliminary results from TradeRES, a nested forecasting approach was presented to feed specific market players.

Preliminary results were presented highlighting that current power forecast approaches already allow to have a significant level of accuracy in forecasting electricity demand and in small hydro power plants. However, for the time-frame on which this report is focused (day-ahead market) wind and solar PV technologies (or vRES aggregator) continue to show significant errors, even assuming a postponing of their bids to an hour closer to real-time. To improve the existing forecast systems, a new approach is proposed in TradeRES. Results showed that the use of numerical weather prediction (NWP) grid data coupled with a feature selection algorithm could enable to improve the forecast performance, when compared with a forecast based only a NWP single-point data. Preliminary results also show that meteorological parameters as wind gust (traditionally not considered in the wind power forecast systems) enable to reduce the wind power forecast errors.

In this deliverable, some values and principles were defined as “first-guess” based on a literature review. Due to the iterative nature of the project, it is expected that some values can be further improved in the second version of this deliverable at Month 41 based on the outcomes of the remaining work packages. It should be noted that the focus of this deliverable was the day-ahead market, which is one of the most important in the current electricity markets designs and detailed results will be presented in work package 5. In the second version of deliverable 4.9, the work is expected to focus on the very-short and short time horizons - in line with the new market electricity designs/products that are being proposed in work package 3 of the project.

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