Wind power ramp characterisation and forecasting using Numerical Weather Prediction and Machine Learning models

Russell Sharp, Hisham Ihshaish and J. Ignacio Deza
Faculty of Environment and Technology,
University of the West of England, Bristol, BS16 1QY, United Kingdom

Abstract

The forecasting of large ramps in wind power output known as *ramp events* is crucial for the incorporation of large volumes of wind energy into national electricity grids. Large variations in wind power supply must be compensated by ancillary energy sources which can include the use of fossil fuels. Improved prediction of wind power will help to reduce dependency on supplemental energy sources along with their associated costs and emissions. In this paper, we discuss limitations of current predictive practices and explore the use of Machine Learning methods to enhance wind ramp event classification and prediction. We additionally outline a design for a novel approach to wind ramp prediction, in which high-resolution wind fields are incorporated to the modelling of wind power.

Keywords: Wind ramp prediction. Time Series Analysis. Deep Learning. Recurrent Neural Networks. Green energy. Autoregressive Moving Average.

1. Introduction

In recent decades, renewable energy sources have received significant attention due to global concerns over climate change and carbon emissions. As part of their commitments to the 2016 UN Paris Agreement, industrialised countries of the EU have committed to supplying certain proportions of their energy demand using renewable sources by the year 2030. The focus of this project is on wind energy data from two specific members of the EU: France and Spain. In order to meet its climate change objectives, the French government has pledged to increase its installed wind energy capacity from 16 GW in 2021 to a minimum of 38.4 GW in 2028 (Abassi et al., 2016). Meanwhile, the Spanish government has submitted plans to increase its capacity from 28 GW in 2020 to 50.3 GW in 2030 (European Commission, 2019). The dataset from La Haute Borne wind farm, north-eastern France, will be reported for initial analysis.

Despite the benefits of wind power, its potential as an energy source is hindered by its inherent intermittency, owing to its direct correlation to the natural variability of the wind. Generation is further beset by sudden large ramps in wind power output known as ramp events. Generally speaking, ramp events represent large and fast variations in power output from a wind farm or portfolio of wind farms. They are driven by naturally occurring, sudden large increases (positive ramp) or decreases (negative ramp) in wind strength referred to as wind ramps. Ramp events are manifest as local events in a wind power time series, generally over a short period of up to a few hours (Cutler et al., 2007; Gallego-Castillo et al., 2015) (Fig. 1).

Initial draft of this proposal has been submitted to *Tackling Climate Change with Machine Learning: workshop at NeurIPS 2021.*

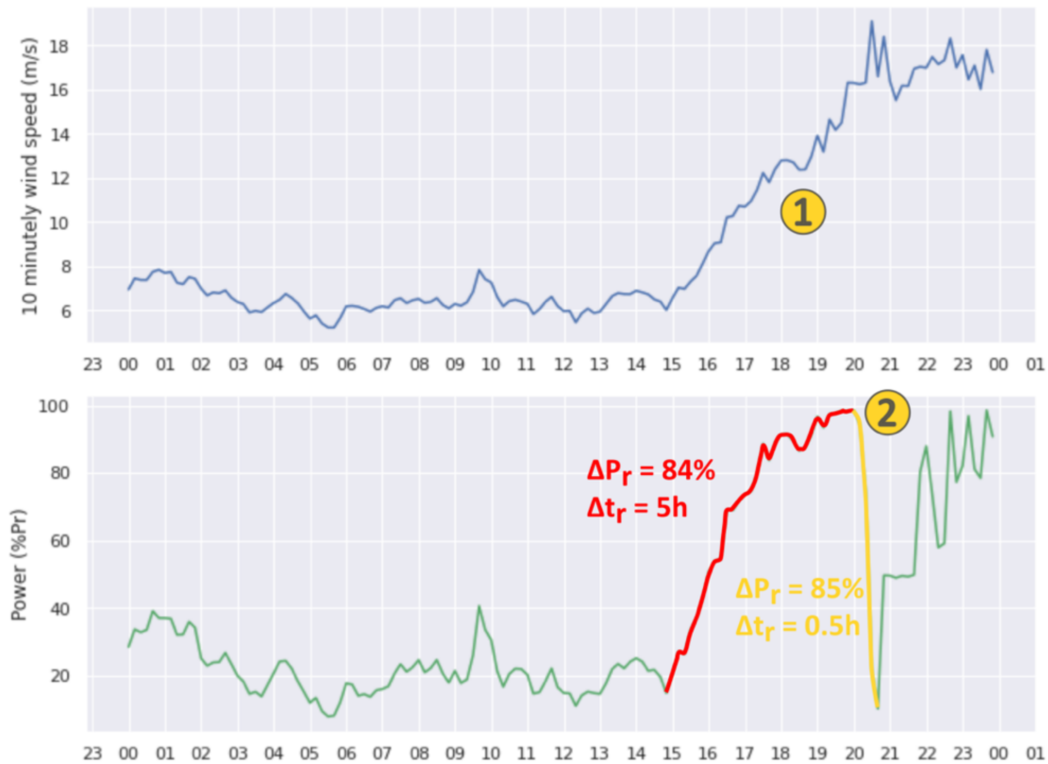

Figure 1. Example of two ramp events experienced on 13 January 2013 at the La Haute Borne wind farm, north-eastern France. Hour is plotted along the x-axis. Parameters employed to characterise ramps are P_r = Rated Power and t_r = time period over which the ramp takes place. Ramp direction is given by colour: red = ramp-up (positive), yellow = ramp-down (negative). The ramp-up event is driven by increasing wind speed (1). The ramp-down event in this instance is triggered as the farm's rated power is exceeded (2) and the turbines are shut-in to prevent damage. A detailed description of the dataset is presented in section 3.1.

The variability of wind power is a prominent obstacle for electricity Transmission System Operators (TSOs) towards incorporating commercial volumes into national power grids. TSOs must continually manage their power networks so that supply meets demand (Cutler et al., 2007). This is commonly done through the scheduling of *ancillary reserves* which consist of supplementary power sources that are flexible enough to adapt to variations in load and supply. This, however, carries additional costs and emissions. Most electricity markets operate around a set of short-term procedures known as Day-Ahead (DA) operations that enable them to prepare for Real-Time (RT) energy dispatch operations. Part of the DA operations is the allocation of ancillary reserves: by a given deadline, market participants submit bids of the volumes of reserves that they can provide for the following day to the TSO. As RT operations approach, the TSO will perform a re-commitment procedure to account for any forced outages and the forecasted load on the grid (Monteiro et al., 2009; Martínez-Arellano, 2015).

Wind power forecasts then, are essential for the incorporation of wind energy into power networks over the DA timeframe. This is especially true during ramp events. From a TSO point of view, a large negative ramp in wind power could require a fast response from ancillary sources to maintain the supply-demand balance, whilst a large positive ramp might require that power flow be kept below planned maxima in constrained parts of the network (Cutler et al., 2007). As the amount of wind energy in a country's energy mix increases, so too does the importance of accurate wind power predictions. These forecasts are mainly characterised by time horizon, that is, the future time period spanned by the prediction. Time horizons are generally separated into three categories, depending on the market (Table 1).

Table 1. Categories of wind power forecast time horizon (after Martinez-Arellano, 2015).

Category	Horizon
Very short-term	2 – 4/9 hours
Short-term	4/9 – 48/72 hours
Medium-term	72 hours - 7 days

Due to the increasing volume of wind power that is set to be incorporated into electricity markets by TSOs, and due to the DA operational timescales outlined above, short-term forecasts of wind power are currently an active area of research and form the horizon of interest in this research.

The aim of this study is to investigate potential ways to improve the characterisation and prediction of ramp events using Machine Learning methods. In order to achieve this, three main objectives are identified here and outlined further in the following sections: 1) Investigate wavelet signal transformation for the ramp event characterisation. It is anticipated that by using the WT, a *ramp function* is obtained which provides a continuous index related to ramp intensity at each time step of a given wind power time series. This in turn will enable the identification of ramp events often not captured by current binary ramp detection tools; 2) Study the feasibility of using Machine Learning models to learn the dynamics of the ramp function from wind power time-series; 3) Explore the use of prevailing wind direction to better account for misplacement errors in Numerical Weather Prediction (NWP) model outputs. Increasing the relative importance of upwind windspeed predictions is expected to reduce misplacement errors.

2. Related work

Machine Learning and time series forecasting techniques have been applied to the problem of wind power ramp event forecasting with some promising results (Ahmadi and Khashei, 2021; Gallego-Castillo et al., 2015; Sim and Yung, 2020; Wang et al., 2019; Yang et al., 2021 and references therein) but the field of study is still in its infancy.

There are two types of method for wind power forecasting: those based on time series analysis alone, and those based on a combination of time series analysis and Numerical Weather Prediction (NWP) model outputs. NWP models resolve a set of physical equations in order to estimate the dynamics of the atmosphere and output forecasted values of target variables to a 3D grid, but they do so at significant computational cost. A high-resolution NWP run of 0.5 km for example may take 48 hours to complete with limited resources, effectively rendering it useless for DA operations. Whilst TS+NWP prediction models typically out-perform TS approaches after a 3 to 6-hour time horizon (Giebel et al., 2011; Martinez-Arellano, 2015) the computational demands of NWPs exert challenging constraints on their deployment in any domain-specific application. *Downscaling* is a procedure that reduces computational cost by transforming NWP outputs from the low-resolution grids of NWP models to higher resolutions at specific physical locations of interest. It is commonly performed by statistical analysis of historic data to establish systematic relationships between NWP forecasts and measured observations (Cutler et al., 2007). Downscaling though, still depends on the interrogation and use of NWP datasets and carries with it associated computational and user expertise demands.

Most utilities require a short-term forecast of wind power, but one that is generated at relatively low computational cost and with relatively low user expertise requirements. Motivated by this, this study explores the possibility of a simplified wind power forecasting process based on Machine Learning methodologies.

2.1. Ramp event definition

Broadly, a ramp event is a large and rapid variation in wind power output (Cutler et al., 2007; Gallego-Castillo et al., 2015). However, the relative interpretation of 'large' and 'rapid' will differ according to the following factors:

- The end use of any ramp forecasting model. For example, a wind farm operator interested in projected market penalties will be interested in different time scales as compared to an energy trader interested in instantaneous market demand and spot prices (Cutler et al., 2007; Martínez-Arellano, 2015).
- The size of the wind farm/ portfolio. As an example, when defining ramps using an absolute power amplitude threshold value, a higher frequency of ramp events is likely to be observed as the installed capacity increases (Gallego-Castillo et al., 2015).
- The cost function considered. For instance, costs of ancillary reserves and electricity market penalties (Gallego et al., 2013).

Ramp events can generally be identified and characterised considering the following features:

Table 2. Ramp characterisation parameters used in the literature (after Gallego-Castillo et al., 2015).

Term	Parameter	Description
Magnitude	ΔP	Variation in power observed.
Duration	Δt	Time period over which a variation takes place.
Ramp rate	$\Delta P/\Delta t$	Variation divided by duration. Indicative of ramp intensity.
Timing	t_0	Time instance of ramp event. Can be start or central time.
Direction	+/-	Increase/ ramp-up (+) or decrease/ ramp-down (-) in power output.

Extracting ramp events from wind power time series, the parameters of table 2 can easily be analysed (e.g., Fig. 1). However, ramp forecasting usually entails the reverse; given certain characteristics or criteria, a forecaster must identify ramp events in order to determine underlying causes and create accurate predictive models. This establishes the need to set such criteria, or in other words: a ramp definition. Ramp event forecasting is a relatively immature research field. In the absence of a standard formal ramp event definition, the literature reports different characterisations depending on wind farm size and quantity (if aggregated), or the characteristics of the hosting power grid (Gallego-Castillo et al., 2015; Martínez-Arellano, 2015; Yang et al., 2021).

Most previous work has classified ramp events using a *binary* definition (Table 3). Binary definitions determine whether a ramp exists or not based on defined threshold values of magnitude and duration (ΔP_r and Δt_r respectively, Fig. 1). This approach, however, has two major disadvantages. The first is that classification can become highly sensitive to the (often arbitrary) threshold values used. For instance, with ΔP_r set to 50%, an impactful change in power output of 49% may not be detected. The second is that a binary approach characterises all ramps as similar to one another, despite the fact that ramps with different characteristics are often observed. Ultimately, a binary definition restricts the forecaster from exploiting potential relationships between different ramp levels and continuous explanatory variables such as NWP outputs, SCADA data or meteorological tower measurements (Gallego et al., 2013). Table 4 summarises some previously used binary ramp event definitions and their limitations.

It is worth noting that, despite the clear drawbacks of binary ramp event definitions, many recent works continue to use and refer to them (Table 3).

In order to overcome the drawbacks of the binary definition approach, Gallego et al. (2013) introduced the idea of using *wavelet transform* (WT) to characterise ramp events. The method requires the manual manipulation of only one input parameter (related to maximum ramp duration) which leaves model tuning in the hands of the end user. Using the WT methodology, a *ramp function* is obtained which provides a continuous index related to ramp intensity at each time step of a given wind power time series. Wavelet transform is adopted in this study (reported later in Section 3.2) to identify ramp events, thus adding the desired outcomes or 'labels' to the dataset that is introduced to the ML algorithms.

A comprehensive review of wind power ramp forecasting was undertaken by Gallego-Castillo et al. in 2015. This section provides a summary of the relevant work in the field that has been carried out since its publication (Table 3).

Recent statistical analyses of ramp events include Aguilar (2019), Dalton et al. (2019, 2021), DeMarco and Basu (2018), Kelly et al. (2021), Pereyra-Castro et al. (2019), Pereyra-Castro et al. (2020), Pichault et al. (2021). Literature reviews of wind forecasting include Ahmadi and Khashei (2021), Sim and Yung (2020), Wang et al. (2019) and Yang et al. (2021).

Table 3. Main ramp forecasting literature reviewed[1].

Author	Year	Model type	Definition	Algorithms/ methodology	Evaluation metrics	Horizons	Outputs	Location
Fernández et al.	2013	TS	Binary	Local Mahalanobis K-NN, Anisotropic Diffusion	CM	3 h	Ramp occ.	ESP
Sevilan and Rajagopal	2013	TS	Binary	Dynamic Programming	CM	Varied	Power output	USA
Martínez-Arellano et al.	2014	NWP + TS	Non-binary	GP	CM, FIS score	100 h	Power output	ESP
Martínez-Arellano	2015	NWP + TS	Non-binary	GP, Spatial fields	FIS score	12-36 h	Power output	ESP
Ji et al.	2015	TS	Non-binary	WT, neuro-fuzzy network	n/a	n/a	Power output	n/a
Heckenbergerova et al.	2016	TS	Binary	PCA	Box plots	4 h	Ramp occ. (prob)	USA
Gallego-Castillo et al.	2016	NWP + TS	Non-binary	Reproducing Kernel Hilbert Space	CRPS	12 h	Power output (prob)	USA
Zha et al.	2016	TS	Binary	SVR, Swinging door algorithm	MAE, MAPE, RMSE, CC	3.5-5.5 h	Power output	USA
Li et al	2017	NWP + TS	Binary	Gabor Filtering, BPNN	FA, RC, RMSE	24 h	Power output	CAN
Dorado-Moreno et al.	2017	NWP + TS	Binary	Reservoir computing, Echo state networks	CM, Sensitivity, Specificity, GMS	6-24 h	Ramp occ.	ESP
Taylor	2017	TS	Binary	AR logit models	Brier score	1-2 h	Power output (prob)	GRC
Zhang et al.	2017	NWP + TS	Binary	Swinging Door Algorithm	POD, CSI, FBIAS	1-6 h	Ramp occ. (prob)	USA
Liu et al.	2017	NWP + TS	Binary	Orthogonal Test, SVM	RC, FA, CSI	0.5 to 24 h	Ramp occ.	CHN
Dorado-Moreno et al.	2018	NWP + TS	Binary	RNN, Echo State, Delay line reservoir	Geometric mean, CCR, AMAE	6 h	Power output	ESP
Dhiman et al.	2019	TS	Binary	SVR, WT	AE, RMSE, MAE, CPU time	0.5-3 h	Power output	ESP, USA, AUS, IND
Zhang et al.	2019	TS	Binary	NN, ARMA, WSR, PSO, KDE	MAE, MAPE, MSE, RMSE	16 h	Wind speed	CHN, ESP
Liu et al.	2019	TS	Binary	KDE, Back Propagation Neural Network (BPNN)	RMSE	4 h	Power output	CHN
Ouyang et al.	2019	NWP + TS	Binary	MLP	BIAS, MAE, RMSE, CM	72 h	Power output	CHN
Fujimoto et al.	2019	NWP + TS	Binary	RF, RUS, ROS, SMOTE, Laplacian kernel function	RMSE, Precision, Recall, CSI	0.5-48 h	Ramp occ., power output	JPN
Zhao et al.	2020	TS	Non-binary	Bayesian Network	CM	30 min	Ramp occ. (prob)	CHN
Lyners et al.	2020	TS	Binary	Multi-parameter segmentation algorithm	PDFs	25 h	Ramp occ.	ZAF
Ye et al.	2020	NWP + TS	Non-binary	Wave Division, Grey Wolf Optimizer, Fuzzy C-means clustering, LSTM	NMAE, NRMSE, ACR	24-72 h	Power output	CHN
Cornejo-Bueno et al.	2020	NWP + TS	Binary	Extreme Learning Machine, SVR, SMOTE	ROC, CM	6 h	Ramp occ.	ESP
Dorado-Moreno et al.	2020	NWP + TS	Binary	Multi-task Learning, Deep Neural Networks	Accuracy, Sensitivity, GMS,	6 h	Ramp occ.	ESP
Lyners et al.	2021	TS	Binary	Multi-parameter segmentation algorithm	POD, CSI, FBIAS, SR	n/a	Power output	ZAF
Hirata et al.	2021	TS	Non-binary	K-NN	MAE, Ignorance score	1-12 h	Power output	Japan
Pichault et al.	2021	TS	Non-binary	Haar WT, Ramp Function	Statistical analysis	1 h	Ramp characterisation	AUS
Couto et al.	2021	NWP	Binary	ANN	Statistical analysis	24 h	Power output	PRT
Dhiman and Deb	2021	TS	Non-binary	TSVR, RFR, CNN, WT	RMSE	10 min	Power output	UK, NLD, AUS
Zhou et al.	2021	TS	Binary	Generative Adversarial Network	MAE, MAPE, RMSE, FA, RC	42 h	Power output	BEL, CHN

[1] **Model abbreviations:** Time series, TS; Numerical Weather Prediction Model, NWP; Genetic Programming, GP; K-Nearest Neighbour, K-NN; Wavelet Transform, WT; Principal Component Analysis, PCA; Support Vector Machines, SVM; Auto-Regressive, AR; Artificial/Convolutional/ Recurrent Neural Network, A/C/RNN; Kernel Density Estimation, KDE; Random Forest, RF; Long Short-Term Memory, LSTM.

Evaluation Metric abbreviations: Confusion Matrices, CM; Fuzzy Inference Score, FIS; Mean Absolute (Percentage) Error, MA(P)E; Root Mean Squared Error, RMSE; Ramp Capture, RC; Probability Density Function, PDF; Receiver Operating Characteristic; Forecast Accuracy, FA.

Table 4. Binary ramp definitions used in the literature.
* Ramp-up is signified by $P_t < (Pt + \Delta t)$, ramp-down by $P_t > (Pt + \Delta t)$.
** Wind power can exhibit high variability over timescales shorter than typical ramp lengths. Therefore, ramp characterisation may become sensitive to noise. To overcome this issue, Bossavy et al. (2010) introduced the idea of a filtered signal.

Reference	Definition	Description	Limitations
Kamath (2010)*	$P_t + \Delta t - P_t > P_{val}$	A ramp event occurs if the magnitude of the change in the power signal between two time series observations exceeds a pre-set threshold.	Based on start and end values of Δt so doesn't account for ramps that may occur during the interval.
Kamath (2010)	$max\left([P_t, t + \Delta t]\right) - min\left([P_t, P_t + \Delta t]\right) > P_{val}$	A ramp event occurs if the difference between the maximum and minimum power output measured during Δt exceeds a pre-set threshold.	Does not characterise rate of change (ramp rate).
Zheng and Kusiak (2009)*	$\frac{P_t + \Delta t - P_t}{\Delta t} > P_{rr}$	A ramp event occurs if absolute difference between start and end values of Δt and the size of Δt itself are greater than pre-set power ramp rate value, P_{rr}	Sensitive to threshold value.
Bossavy et al. (2010)**	$\left\|P_t^f\right\| > P_{val}$ And: $P_t^f = mean(P_{t+h} - P_{t+h-n}; h = 1, \ldots, n_{nam})$	Where: P_t^f= filtered version of power signal (transformed using k-order differences in power amplitude) and n_{nam}= number of average power measures to consider (replaces Δt). Ramp events are identified using the filtered version of the power signal obtained according to the equations. The n_{nam} parameter allows model sensitivity to be tuned to a characteristic ramp event time length that is considered of interest.	Sensitive to threshold value.

3. Proposed methods

There are three main steps for short-term wind power prediction using NWP models: 1) downscaling, 2) conversion to power and 3) upscaling. Several downscaling approaches have been explored in published literature with varying degrees of success (Cutler et al, 2009; Gallegos-Castillo 2015; Martínez-Arellano, 2015). This study explores a novel downscaling approach to meteorological fields, and Machine Learning methods to provide feasible and comparably accurate wind ramp event prediction. The technical design for this proposal is shown in figure 2, and discussed throughout the remainder of this section.

The learning methods on wind power time-series, as a univariate system, will include the Autoregressive Moving Average (ARMA) and its integrated and seasonal variants (ARIMA and SARIMA) to solve for seasonality and non-stationarity of the system. This is besides Recurrent Neural Networks, namely the LSTMs as well as Prophet time-series model of Facebook. The performance of the above models will be examined with respect to the accuracy of their ramp event identification and prediction. Additionally, a multivariate analysis of the system will include NWP high-resolution outputs so that wind power system can be analysed and subsequently predicted through wind field observations/assimilated values or predictions, instead of wind power historic data.

3.1. Dataset

The dataset used in this project is a Supervisory Control and Data Acquisition (SCADA) dataset collected from the La Haute Borne wind farm between December 2012 and January 2018. La Haute Borne is an 8,200-kW capacity onshore wind farm located in north-eastern France, centred at 48.45°N, 5.59°W. The farm is owned by the French energy and utilities company, Engie, and comprises four Senvion MM82 wind turbines. SCADA data generated from an array of sensors within each turbine is recorded in two large csv files (1.105 GB in total). The files contain readings of each turbine's components such as rotor speed and gearbox bearing temperatures, grid information such as frequency and voltage, and, of most relevance to this study, physical information including wind speed, wind direction and active power. Table 5 provides a description of the variables used in this study.

Table 5. LHB dataset feature description.

Term	Name	Units	Description
Ws_avg	Wind speed	m/s	10-min avg from two anemometers on the nacelle of each turbine
Wa_avg	Wind direction	degrees (°)	10-min avg from the wind vane of each turbine
P_avg	Active power	kW	10-min avg from each turbine
Ot_avg	Outside temperature	°C	10-min avg from the wind vane of each turbine
Calculated features			
P_tot	Total active power	kW	Sum of P_avg from all turbines
%P_rated	Percentage of rated power	%	P_tot divided by 8200 kW*, multiplied by 100

The data are recorded at ten-minute intervals between 7 January 2013 (00:20) and 14 December 2017 (04:50). The dataset therefore equates to 1,057,968 observations over a four-year period.

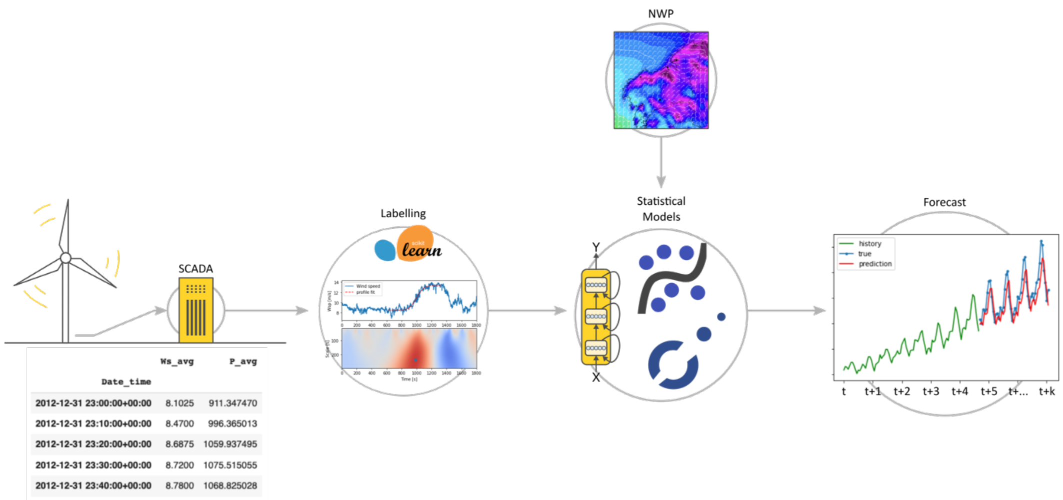

Figure 2. Flow chart of the methodology employed in this research. Ramps are identified ('labelled') in the raw data using *wavelet transform*. The family of ML algorithms is trained on the raw data, then used to forecast power output and associated ramp events. Using this methodology, NWP outputs may be used as an alternative data source (see text for explanation). Ramp function plot from Hannesdóttir and Kelly (2019a). NWP output from Xunta de Galicia (2021).

3.2. Ramp characterisation

The ramp characterisation method used in this paper focusses on the DA TSO end-use case introduced in Section 1. During a ramp-down event a TSO must compensate for the loss of generation through the scheduling of ancillary reserves. During a ramp-up event the TSO may need to limit excessive wind power input to ensure grid safety (Martínez-Arellano, 2015).

The strategies of the TSO will also depend on how far in advance the ramp is forecast and the availability and the response times of ancillary energy sources. Current network flows and energy demand are also factors that must be considered (Cutler et al., 2007; Martínez-Arellano, 2015) however, these are beyond the scope of this paper. For recent studies modelling the power grid impacts of ramp events, the reader is directed to Veron et al. (2018) and Wang et al. (2016).
Using the WT methodology, a ramp function is obtained which provides a non-binary/ continuous index related to ramp intensity at each time step of a given wind power time series (Figure 3).

The wavelets are shifted and dilated versions of a so-called *mother wavelet*, ψ^{τ}, and are derived as:

$$\psi^{\tau,\lambda}(t) = \frac{1}{\sqrt{\lambda}}\psi\left(\frac{t-\tau}{\lambda}\right) \quad (1)$$

where:

τ relates to the shift (expressed on a continuous scale between min and max)
λ relates to the dilation

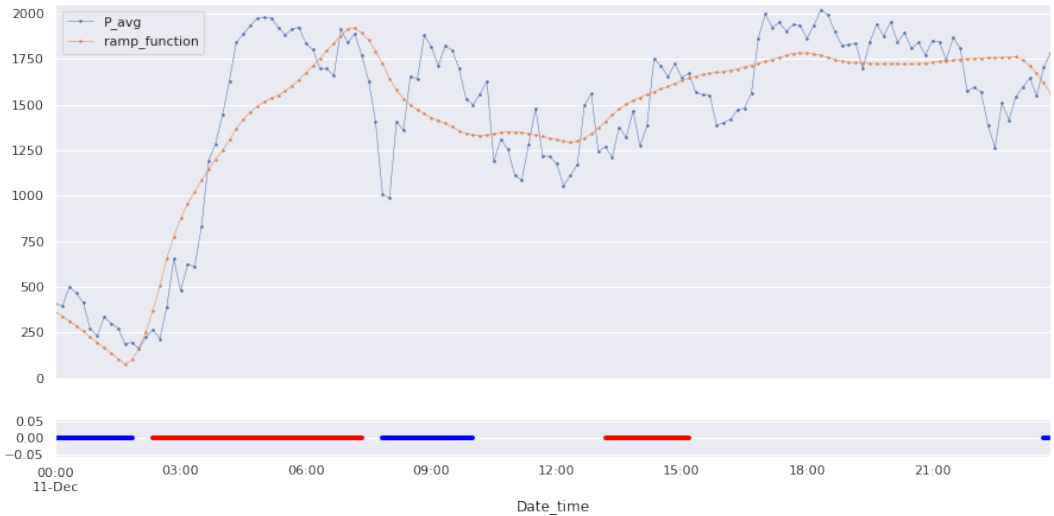

Figure 3. Ramp function plot against wind power. The continuous/ non-binary ramp function is plotted in orange. For comparison, the subplot displays a binary ramp function (red = positive ramp, blue = negative ramp, empty space = non-ramp). The difference in granularity between the two ramp definition approaches can be readily observed. For example, depending on the threshold values set, the increase in power output at approx. 17:00 is not captured using a binary ramp definition.

The WT of a time series, $\{y_t\}$, consists of a set of coefficients obtained:

$$W^{\tau,\lambda} = \sum_{-\infty}^{\infty} \psi_t^{\tau,\lambda} \cdot y_t \qquad (2)$$

where:

$\tau \in Z$

$\lambda \in Z^+$

and $\psi_t^{\tau,\lambda}$ relates to the wavelet function employed[2].

Several wavelets exists and the choice of wavelet depends on purpose of the study. Gallego et al. chose the Haar wavelet in order to obtain information about the gradient experienced at different timescales, λ, since the Haar wavelet reveals local events where a large gradient is observed within a range of time scales. More recently, in a study aiming to characterise extreme wind speed ramps, Hannesdóttir and Kelly (2019) selected the first derivative of a Gaussian wavelet (DOG1) as their choice of analysing wavelet. Unfortunately, however, the authors do not discuss the reasons behind this choice.

The fundamental concept of a ramp event is that a certain large gradient is maintained during consecutive time steps of the time series. Therefore, a ramp can be said to show self-similarity. This means that the whole ramp event is similar to a smaller part of it, or in other words, the shape of the event is preserved at different scales. During the period of the ramp event, the wavelet transform, $W^{\tau,\lambda}$, provides increasing coefficients for a broad range of times scales, λ, since each $W^{\tau,\lambda}$ is related to the gradient at time $t = \tau$, evaluated in a time scale $\Delta t = \lambda$. The increase of $W^{\tau,\lambda}$ with respect to λ occurs because the scale is contributed as $\lambda^{-\frac{1}{2}}$ in (1). Hence the gradient is high for both short and long-time scales, where 'long' means close to the length of the overall event. If a period is considered where $\{y_t\}$ exhibits many high-frequency fluctuations, similar coefficients are observed for short scales but not for long scales, in other words, the gradient is no

[2] The wavelets are defined such that the sign of the coefficient obtained is opposite to that of the ramp event gradient.

longer self-similar at longer time scales. Finally, if a period is considered where $\{y_t\}$ does not exhibit high gradients, the coefficients $W^{\tau,\lambda}$ would be close to zero for every scale, λ, considered. This is utilised in the ramp characterisation process by defining the ramp function, $\{R_t\}$, as the sum of the wavelet coefficients $W^{\tau,\lambda}$ at time $t = \tau$ for the interval of scales, λ, given by $[\lambda_1, \lambda_N]$:

$$R_t(\lambda_1, \lambda_N) = \sum_{\lambda=\lambda_1}^{\lambda_N} W^{\tau,\lambda} \qquad (3)$$

In this way, $\{R_t\}$ becomes related to the sharpness of the ramp event because it gathers at each time step the contribution of the gradient evaluated under different timescales. Time scale λ_1 is the smallest that can be considered, and the minimum possible value is $\lambda_1 = 2$ because at least two values are required to define a gradient. The maximum time window (in terms of time steps) to be evaluated, λ_N, requires end-user input. According to Gallego et al. (2013), appropriate values of λ for hourly wind power time series data are between 5 and 10. Irrespective of this however, the ramp function is not expected to be highly sensitive to small changes in λ, primarily because the addition of the wavelet transform coefficients across the range of scales from λ_1 to λ_N (2) reduces the impact of any additional scale λ_{N+1}.

The range spanned by R_t depends on the range spanned by the original wind power time series, which is related to the size of the wind farm. Therefore, it is necessary to re-scale the ramp function between -1 and 1 by defining the relative ramp function, r_t, as:

$$r_t = \frac{R_t}{max\{\,|R_t|\,\}} \qquad (4)$$

To isolate ramp performance during ramp up, r_t^u, ramp down, r_t^d, and non-ramp, r_t^0, events, the ramp function can be decomposed into three time series as follows:

$$r_t^u = \{\ r_t,\ \ if\ \ r_t\ \geq 0\ 0,\ if\ \ r_t\ < 0$$
$$r_t^d = \{\ -r_t,\ \ if\ \ r_t\ \leq 0\ 0,\ if\ \ r_t\ > 0$$
$$r_t^0 = 1 - \ r_t^u - r_t^d \qquad (5)$$

Finally, the ramp frequency, f_r, of a time series is the percentage of times in which a ramp is observed, and can be derived (Gallego et al., 2013):

$$f_r(\%) = 100.\frac{\sum_{t=1}^{N} |r_t|}{N} \qquad (6)$$

where:

r_t = relative ramp function

t = time

N = number of samples

Gallego et al. showed that the use of a continuous index-based ramp definition led to more reliable ramp characterisations than the four binary ramp classifications of Cutler (2007), Potter (2009), Greaves (2009) and Bradford (2010) because it is less sensitive to input parameters. It is noted however that these works were based on different datasets. Comparative relative ramps frequencies observed using the same dataset were as follows:

Table 6. Relative frequency of ramp events (%) observed by different ramp definitions using the same dataset. It should be noted that the models were not designed using the same datasets/ site locations. * = Binary, ** = Non-binary. *** = range given by varying λ_N from 5 to 8 (see text for details).

Reference/ methodology	Relative ramp frequency (%)
Cutler (2007)*	1.4
Potter (2009)*	27.9
Greaves (2009)*	13.5
Bradford (2010)*	8.8
Gallego et al. (2013)**	10-11.4%***

Though it is not strictly possible to compare models like for like, the differences between the range of values given by the various binary definitions and the range given by varying the non-binary definition give some indication of the relative model 'stabilities' of the binary versus the non-binary approaches.

4. Perspective and pathway to climate impact

Wind power is a clean, cheap and abundant source of energy with an unquestionable ability to reduce dependence on fossil fuels. Even among the currently available renewable energy sources, it is believed to be the least harmful to the environment (Abassi et al., 2016). Furthermore, increased levels of wind penetration (the amount of wind power in a market's energy mix) have been shown to reduce overall energy costs. However, it has also been shown that the variability of wind power and associated errors of forecasting its output can cause short term price rises and price volatilities (Ortega-Vazquez and Kirschen, 2010). Wind farm costs arising from imbalances between contracted and produced energy are directly proportional to forecast errors (Girard et al, 2013). This relationship was quantified in the case of a Dutch wind farm where improved forecasting was shown to reduce annual (regulatory) costs by 39% (Pinson et al., 2007). Currently, state-of-the-art wind power forecasting systems can achieve a RMSE of 10-15% of total installed capacity over a 36-hour horizon (Giebel et al., 2011; Martínez-Arellano, 2015), thus representing a target for continued development. Any improvements, however, must be made with parsimony, computational demands and user expertise requirements in mind.

It is evident then, that improvements in capacity factors such as those outlined in this work have and will continue to drive down the costs of wind power. To further illustrate the importance of this, the European Commission estimates that investments equating to installed capacity of between 240 and 450 GW of offshore wind power will be needed by 2050 to keep global temperature rises below 1.5°C (European Commission, 2021). Since investment is favoured by low costs and high revenues, cost-effective predictive modelling of wind power output could play an important role in combatting climate change.

Acknowledgments

RS and HI would like to thank Alexis Tantet from Laboratoire de Météorologie Dynamique, École Polytechnique (Paris, France) for the initial discussions leading to this study.

References

Abbasi, S.A., Tabassum-Abbasi and Abbasi, T. (2016) Impact of wind-energy generation on climate: A rising spectre. *Renewable and Sustainable Energy Reviews*. [online]. 59, pp.1591–1598.

Addison, P.S. (2017) *The illustrated wavelet transform handbook: introductory theory and applications in science, engineering, medicine and finance.* CRC press.

Aguilar, T.A. (2019) *Detecting the long-term frequency of large-scale wind power ramp events observed in ERCOT's aggregated wind power time-series data.* Thesis [online]. Available from: https://ttu-ir.tdl.org/handle/2346/85506 [Accessed 12 October 2021].

Ahmadi, M. and Khashei, M. (2021) Current status of hybrid structures in wind forecasting. *Engineering Applications of Artificial Intelligence* [online]. 99, Pergamon, p.104-133.

Bianco, L. et al. (2016) A Wind Energy Ramp Tool and Metric for Measuring the Skill of Numerical Weather Prediction Models. *Weather and Forecasting*. [online]. 31 (4), American Meteorological Society, pp.1137–1156.

Bossavy, A., Girard, R. and Kariniotakis, G. (2013) Forecasting ramps of wind power production with numerical weather prediction ensembles. *Wind Energy*. [online]. 16 (1), pp.51–63.

Cornejo Bueno, Laura & Camacho-Gómez, C. & Aybar Ruiz, Adrián & Prieto, Luis & Barea-Ropero, A. & Salcedo-Sanz, Sancho. (2020). Correction to: Wind power ramp event detection with a hybrid neuro-evolutionary approach. Neural Computing and Applications. 32. 1-1.

Correia, J.M. et al. (2017) The influence of the main large-scale circulation patterns on wind power production in Portugal. *Renewable Energy*. [online]. 102, pp.214–223.

Cutler, N. et al. (2007) Detecting, categorizing and forecasting large ramps in wind farm power output using meteorological observations and WPPT. *Wind Energy* [online]. 10 (5), pp.453–470.

Cutler, N.J. et al. (2009) Characterizing future large, rapid changes in aggregated wind power using numerical weather prediction spatial fields. *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology*. 12 (6), Wiley Online Library, pp.542–555.

Dhiman, H.S. and Deb, D. (2021) Machine intelligent and deep learning techniques for large training data in short-term wind speed and ramp event forecasting. *International Transactions on Electrical Energy Systems,* 31 (9), e12818.

Dhiman, H.S., Deb, D. and Guerrero, J.M. (2019) Hybrid machine intelligent SVR variants for wind forecasting and ramp events. *Renewable and Sustainable Energy Reviews* [online]. 108, pp.369–379.

Dorado-Moreno, M. et al. (2018) Prediccion ordinal de rampas de viento usando Echo State Networks de complejidad reducida. *Conferencia de la Asociacion Espanola para la Inteligencia Artificial*. XVIII, p.7.

European Commission (2019) *National energy and climate plans (NECPs) Energy* [online]. Available from: https://ec.europa.eu/energy/topics/energy-strategy/national-energy-climate-plans_en [Accessed 12 September 2021].

European Commission (2021) *Renewable energy directive Energy* [online]. Available from: https://ec.europa.eu/energy/topics/renewable-energy/directive-targets-and-rules/renewable-energy-directive_en [Accessed 13 September 2021].

Fernández, Á. et al. (2013) Diffusion Methods for Wind Power Ramp Detection. In: Rojas, I., Joya, G. and Gabestany, J. (eds.) *Advances in Computational Intelligence*. *Lecture Notes in Computer Science* [online]. Berlin, Heidelberg, Springer, 106–113.

Fujimoto, Y., Takahashi, Y. and Hayashi, Y. (2019) Alerting to Rare Large-Scale Ramp Events in Wind Power Generation. IEEE Transactions on Sustainable Energy. [online]. *IEEE Transactions on Sustainable Energy* 10 (1), pp.55–65.

Gallego Castillo, C.J. (2013) *Statistical models for short-term wind power ramp forecasting*phd [online]. E.T.S.I. Aeronáuticos (UPM). Available from: https://oa.upm.es/21912/ [Accessed 23 September 2021].

Gallego-Castillo, C. et al. (2013) A wavelet-based approach for large wind power ramp characterisation. *Wind Energy*. 16 (2), pp.257–278.

Gallego-Castillo, C. et al. (2016) *Wind power probabilistic forecast in the Reproducing Kernel Hilbert Space*In: *2016 Power Systems Computation Conference (PSCC)*. [online]. 2016 Power Systems Computation Conference (PSCC) 1–7.

Gallego-Castillo, C., Cuerva-Tejero, A. and Lopez-Garcia, O. (2015) A review on the recent history of wind power ramp forecasting. *Renewable and Sustainable Energy Reviews*. [online]. 52, pp.1148–1157.

Giebel, G. et al. (2011) The state-of-the-art in short-term prediction of wind power. A literature overview.

Girard, R., Laquaine, K. and Kariniotakis, G. (2013) Assessment of wind power predictability as a decision factor in the investment phase of wind farms. *Applied Energy*. [online]. 101, p.609.

Greaves, B. et al. (2009) Temporal Forecast Uncertainty for Ramp Events. *Wind Engineering*. [online]. 33 (4), SAGE Publications, pp.309–319.

Hannesdóttir, Á. and Kelly, M. (2019a) Detection and characterization of extreme wind speed ramps. *Wind Energy Science*. [online]. 4 (3), Copernicus GmbH, pp.385–396.

Hannesdóttir, Á., Kelly, M. and Dimitrov, N. (2019) Extreme wind fluctuations: joint statistics, extreme turbulence, and impact on wind turbine loads. *Wind Energy Science*. [online]. 4 (2), Copernicus GmbH, pp.325–342.

Ji, F., Cai, X. and Zhang, J. (2015) Wind power prediction interval estimation method using wavelet-transform neuro-fuzzy network. *Journal of Intelligent & Fuzzy Systems*. 29 (6), IOS Press, pp.2439–2445.

Liu, H. et al. (2019a) Smart wind speed deep learning based multi-step forecasting model using singular spectrum analysis, convolutional Gated Recurrent Unit network and Support Vector Regression. *Renewable energy*. 143, Elsevier, pp.842–854.

Liu, Y. et al. (2019b) Quantitative method for evaluating detailed volatility of wind power at multiple temporal-spatial scales. *Global Energy Interconnection*. 2 (4), pp.318–327.

Liu, Z. et al. (2018) Novel forecasting model based on improved wavelet transform, informative feature selection, and hybrid support vector machine on wind power forecasting. *Journal of Ambient Intelligence and Humanized Computing*. 9 (6), pp.1919–1931.

López, E. et al. (2020) *Comparison of Recurrent Neural Networks for Wind Power Forecasting*In: Figueroa Mora, K.M. et al. (eds.) *Pattern Recognition*. Cham, Springer International Publishing, 25–34.

Lyners, D., Vermeulen, H. and Groch, M. (2021) Wind power ramp event detection using a multi-parameter segmentation algorithm. *Energy Reports*. 7, pp.5536–5548.

Martín Martínez, S. (2013) Análisis y regulación de fluctuaciones de potencia en parques eólicos. [online]. Sergio Martín Martínez. Available from: https://repositorio.upct.es/handle/10317/3451 [Accessed 11 June 2021].

Martínez-Arellano, G. et al. (2014) Characterisation of large changes in wind power for the day-ahead market using a fuzzy logic approach. *KI-Künstliche Intelligenz*. 28 (4), Springer, pp.239–253.

Martínez-Arellano, G. (2015) *Forecasting wind power for the day-ahead market using numerical weather prediction models and computational intelligence techniques*doctoral [online]. Nottingham Trent University. Available from: http://irep.ntu.ac.uk/id/eprint/322/ [Accessed 24 June 2021].

Martínez-Arellano, G. and Nolle, L. (2013) *Genetic Programming for Wind Power Forecasting and Ramp Detection.* In: Bramer, M. and Petridis, M. (eds.) *Research and Development in Intelligent Systems XXX*. Cham, Springer International Publishing, 403–417.

Monteiro, C. et al. (2009) *Wind power forecasting: State-of-the-art 2009.* [online]. Argonne National Lab. (ANL), Argonne, IL (United States). Available from: https://publications.anl.gov/anlpubs/2009/11/65614.pdf.

Noceda, M.Á. (2020) *El Gobierno lanza el nuevo Plan de Energía como palanca para la recuperación EL PAÍS*.1 April 2020 [online]. Available from: https://elpais.com/economia/2020-04-01/el-gobierno-lanza-el-nuevo-plan-de-energia-como-palanca-para-la-recuperacion.html [Accessed 5 June 2021].

Olauson, J. (2018) ERA5: The new champion of wind power modelling? *Renewable Energy*. 126, pp.322–331.

Ortega-Vazquez, M.A. and Kirschen, D.S. (2010) Assessing the impact of wind power generation on operating costs. *IEEE Transactions on Smart Grid*. 1 (3), IEEE, pp.295–301.

Pereyra-Castro, K. et al. (2020) Wind and Wind Power Ramp Variability over Northern Mexico. *Atmosphere*. [online]. 11 (12), Multidisciplinary Digital Publishing Institute, p.1281.

Pereyra-Castro, K., Caetano Neto, E.D.S. and Martinez-Alvarado, O. (2019) Wind Power Ramp Characteristics over Northern Mexico.AGU Fall Meeting Abstracts 2019, pp.GC53F-1177.

Pichault, M. et al. (2021) Characterisation of intra-hourly wind power ramps at the wind farm scale and associated processes. *Wind Energy Science*. 6 (1), Copernicus GmbH, pp.131–147.

Pinson, P., Chevallier, C. and Kariniotakis, G.N. (2007) Trading wind generation from short-term probabilistic forecasts of wind power. *IEEE Transactions on Power Systems*. 22 (3), IEEE, pp.1148–1156.

Potter, C.W., Grimit, E. and Nijssen, B. (2009) *Potential benefits of a dedicated probabilistic rapid ramp event forecast tool*In: *2009 IEEE/PES Power Systems Conference and Exposition*. 2009 IEEE/PES Power Systems Conference and Exposition 1–5.

Shi, Z., Liang, H. and Dinavahi, V. (2018) Direct Interval Forecast of Uncertain Wind Power Based on Recurrent Neural Networks. *IEEE Transactions on Sustainable Energy*. IEEE Transactions on Sustainable Energy 9 (3), pp.1177–1187.

Sim, M.K. and Jung, J.-Y. (2020) *A Short Review on Predictions for Wind Power Generation – Its Limitation and Future Directions* [online]. ICIC International 学会. Available from: https://doi.org/10.24507/icicelb.11.10.995.

Taylor, S.J. and Letham, B. (2017) *Forecasting at scale* [online]. PeerJ Preprints. Available from: https://peerj.com/preprints/3190 [Accessed 11 November 2021].

Veron, D.E. et al. (2018) Modeling the electrical grid impact of wind ramp-up forecasting error offshore in the Mid-Atlantic region. *Journal of Renewable and Sustainable Energy*. [online]. 10 (1), American Institute of Physics, p.013308.

Wang, L. et al. (2021) Effective wind power prediction using novel deep learning network: Stacked independently recurrent autoencoder. *Renewable Energy*. 164, pp.642–655.

Wang, Q. et al. (2016) The value of improved wind power forecasting: Grid flexibility quantification, ramp capability analysis, and impacts of electricity market operation timescales. *Applied Energy*. 184, pp.696–713.

Xunta de Galicia (2021) *Xunta de Galicia | Consellería de medio ambiente, territorio e vivenda, MeteoGalicia*2021 [online]. Available from: https://www.meteogalicia.gal/web/inicio.action?request_locale=es [Accessed 18 September 2021].

Yang, B. et al. (2021) State-of-the-art one-stop handbook on wind forecasting technologies: An overview of classifications, methodologies, and analysis. *Journal of Cleaner Production*. 283, p.124628.

Ye, L. et al. (2020) *Combined Approach for Short-Term Wind Power Forecasting Considering Meteorological Fluctuation and Feature Extraction*In: *2020 IEEE/IAS Industrial and Commercial Power System Asia (I CPS Asia)*. 2020 IEEE/IAS Industrial and Commercial Power System Asia (I CPS Asia) 1334–1343.

Yu, C. et al. (2018) A novel framework for wind speed prediction based on recurrent neural networks and support vector machine. *Energy Conversion and Management*. 178, Elsevier, pp.137–145.

Zack, J.W. (2007) *Optimization of wind power production forecast performance during critical periods for grid management*Proceedings of the European Wind Energy Conference EWEC, Milano (IT) 8.

Zhang, Y. et al. (2020a) A new prediction method based on VMD-PRBF-ARMA-E model considering wind speed characteristic. *Energy Conversion and Management*. 203, p.112254.

Zhang, Y. et al. (2020b) Wind Speed Interval Prediction Based on Lorenz Disturbance Distribution. *IEEE Transactions on Sustainable Energy*. [online]. IEEE Transactions on Sustainable Energy 11 (2), pp.807–816.

Zhang, Y. et al. (2018) Wind Speed Prediction of IPSO-BP Neural Network Based on Lorenz Disturbance. *IEEE Access*. IEEE Access 6, pp.53168–53179.

Zhang, Y. et al. (2019) Wind Speed Prediction Research Considering Wind Speed Ramp and Residual Distribution. *IEEE Access*. IEEE Access 7, pp.131873–131887.

Zhao, Y. et al. (2020) Bayesian Network Based Imprecise Probability Estimation Method for Wind Power Ramp Events. *Journal of Modern Power Systems and Clean Energy*. [online]. Journal of Modern Power Systems and Clean Energy pp.1–10.

Zheng, H. and Kusiak, A. (2009) Prediction of Wind Farm Power Ramp Rates: A Data-Mining Approach. *Journal of Solar Energy Engineering*. [online]. 131 (3). Available from: https://doi.org/10.1115/1.3142727 [Accessed 18 June 2021].

Zhou, B. et al. (2021) Short-term prediction of wind power and its ramp events based on semi-supervised generative adversarial network. *International Journal of Electrical Power & Energy Systems*. 125, p.106411.