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Robust estimation of wind power ramp events with reservoir computing

M. Dorado-Moreno [a,*], L. Cornejo-Bueno [b], P.A. Gutiérrez [a], L. Prieto [c], C. Hervás-Martínez [a], S. Salcedo-Sanz [b]

[a] Department of Computer Science and Numerical Analysis, Universidad de Córdoba, Córdoba, Spain
[b] Department of Signal Processing and Communications, Universidad de Alcalá, Alcalá de Henares, Spain
[c] Department of Energy Resource, Iberdrola, Madrid, Spain

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ABSTRACT

Wind power ramp events are sudden increases or decreases of wind speed within a short period of time. Their prediction is nowadays one of the most important research trends in wind energy production because they can potentially damage wind turbines, causing an increase in wind farms management costs. In this paper, 6-h and 24-h binary (ramp/non-ramp) prediction based on reservoir computing methodology is proposed. This forecasting may be used to avoid damages in the turbines. Reservoir computing models are used because they are able to exploit the temporal structure of data. We focus on echo state networks, which are one of the most successfully applied reservoir computing models. The variables considered include past values of the ramp function and a set of meteorological variables, obtained from reanalysis data. Simulations of the system are performed in data from three wind farms located in Spain. The results show that our algorithm proposal is able to correctly predict about 60% of ramp events in both 6-h and 24-h prediction cases and 75% of the non-ramp events in the next 24-h case. These results are compared against state of the art models, obtaining in all cases significant improvements in favour of the proposed algorithm.

1. Introduction

The prediction of Wind Power Ramps Events (WPREs) in wind farms is one of the current hot topics in wind energy research. WPREs deeply affect local wind speed prediction, also increasing the management costs of wind farms, because of their potential damage effect in wind turbines [13,25]. WPREs consist of important fluctuations of wind power in a short period of time (within a few hours), leading to a significant increase or decrease of the power produced in the wind farm. The origin of WPREs are specific meteorological processes (usually crossing fronts, local fast changes in the wind, etc.). Currently, the most effective way of dealing with WPREs in wind farms is the correct prediction of these events, as has been recently reported [6,10].

Different previous works have dealt with the problem of WPREs prediction, many of them applying computational intelligence techniques. In Ref. [30], different time series prediction models have been evaluated in a problem of WPRE prediction, with a short-term prediction horizon between 10 min and 1 h. Experiments in a large wind farm with 100 wind turbines reports good performance of this data-mining approach. However, the short prediction time-horizon of this study makes difficult to apply it in real cases within wind farms. In Ref. [1], a hybrid Autoregressive Moving Average (ARMA) – Hidden Markov model approach has been proposed to predict wind ramp events. Experiments in two with farms in the USA show a good performance of the methodology proposed. In Ref. [27], a dynamic programming approach is proposed for detecting WPREs in time series of wind power. In Ref. [12], a neural network approach for switching between three different regimes of WPREs (ramp-up, ramp-down and no-ramp) is proposed, in which depending on the WPRE type, a different neural network is trained with specific structure and training algorithm. In Ref. [6], a neural network is used as a surrogate model of the wind power generation at a wind farm, then the neural network is used to simulate different possible future scenarios of wind power generation and WPREs. In Ref. [29], a Support Vector Machine (SVM) for classification is used to forecast WPREs, after grouping the ramp events in

* Corresponding author.
E-mail address: manuel.dorado@uco.es (M. Dorado-Moreno).

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Acronyms

WPRE	Wind power ramp event
ARMA	Autoregressive moving average model
USA	United States of America
SVM	Support vector machine
PCA	Principal components analysis
RC	Reservoir computing
ESN	Echo state network
RCX	Reservoir computing with exogenous inputs
CRC	Combined reservoir computing
IRC	Independent reservoir computing
LR	Logistic regression
ST	Sensitivity
SP	Specificity
GMS	geometric mean of the sensitivities
AUC	Area under the ROC curve
ROC	Receiver operating characteristics
hPa	Hectopascal

Nomenclature

t	Time instant
P_t	Power produced at time t
S_t	Ramp function at time t
$\mathbb{R}$	The set of real numbers
Δ	Variation of a measure
max	Maximum
min	Minimum
cos	Cosine
sin	Sine
arccos	Arccosine
tanh	Hyperbolic tangent
y_t	Indicator function to be used as a label for binary classification
S_0	Threshold for discretizing WPREs
$\mathbf{z}_t$	Reanalysis data input at time t
d	Distance
p_i	Latitude and longitude of geographical point i
w_i	Weight applied to the reanalysis node i to compute the weighted average
N	Number of neurons in the reservoir
$\mathbf{W}$	Matrix of weights of the reservoir
$\mathbf{W}^{\text{in}}$	Vector of weights from the input layer to the reservoir
$\mathbf{x}(t)$	Vector containing the reservoir activations at time t
$p()$	Probability
$\hat{y}_t$	Estimated class label at time t
$\hat{S}_t$	Estimated wind ramp function at time t
$\mathbf{x}_t^{\text{S}}$	States of neurons at time t (RC and RCX architectures)
$\mathbf{x}_{t+1}^{\text{S}}$	Updated states of neurons at time $t+1$ (RC and RCX architectures)
$\mathbf{x}_t^{\text{R}}$	States of neurons at time t (IRC architecture)
$\mathbf{x}_{t+1}^{\text{R}}$	Updated states of neurons at time $t+1$ (IRC architecture)
$\mathbf{x}_t^{\text{C}}$	States of neurons at time t (CRC architecture)
$\mathbf{x}_{t+1}^{\text{C}}$	Updated states of neurons at time $t+1$ (CRC architecture)
$\mathbf{W}^{\text{out}}$	Vector of weights from the reservoir to the output layer
$\mathbf{v}_t$	Vector of inputs for the output layer
N_{R}	Number of ramp events in the dataset
N_{P}	Total number of events in the dataset
T_{P}	True Positive (correct WPRE prediction)
F_{P}	False Positive (incorrect WPRE prediction)
T_{N}	True Negative (correct non-WPRE prediction)
F_{N}	False Negative (incorrect non-WPRE prediction)
C	Regularization coefficient of LR
α	Significance level of statistical tests
n_{A}	Number of architectures compared

different classes. The reported results show a good performance in WPRE prediction with this methodology. In Ref. [3], different signal processing techniques (filters) are proposed to the practical prediction of WPREs. Finally, anisotropic diffusion maps have been used to detect WPREs [9], based on a k-nearest neighbours approach. The prediction is tackled using hourly and daily resolutions, and the results are improved by including numerical weather prediction outputs. Recently, a work dealing with WPRE prediction from reanalysis data has been presented in Ref. [14]. Specifically, data from Global Circulation Models (reanalysis data) are used to identify possible meteorological causes of WPREs, and a methodology based on wavelets and PCA has been applied to estimate the best set of features (predictive variables) to estimate WPREs.

In this paper, we consider the prediction of WPRE in wind farms, using a classification model to solve the problem. Specifically, we propose a novel WPRE prediction methodology based on Reservoir Computing (RC), adapted to binary classification. Moreover, the RC methodology proposed combines real ramp function measures within wind farms with numerical meteorological data (from the ERA-Interim Reanalysis) in order to perform WPRE prediction. The inclusion of reanalysis data has been successful in several previous studies on wind speed prediction, including WPRE estimation cases [4,14]. Reanalysis is a reliable source of meteorological data, which covers almost 40 years (from 1979 onwards in the case of ERA-Interim), with a high resolution at global level, making it a valuable tool in wind energy applications. In this paper, several variables from the ERA-Interim reanalysis are considered, mainly wind and temperature variables at different heights, from the complete record of variables. The resolution of this reanalysis is 0.75×0.75 Km, giving us the possibility of covering any location with good quality predictive variables. This work introduces another significant contribution, related to the exploration of different RC architectures to exploit the temporal structure of the ramp function values and the reanalysis data. In this respect, a specific kind of models based on recurrent neural networks has been recently proposed for time series prediction problems, including *Echo State Networks* [20] and *Liquid State Machines* [24]. These proposals are grouped into the *Reservoir Computing* paradigm [23] used in this paper. The structure and hidden weights of this kind of models are randomly created and kept unaltered during the training process. This dynamical memory (made of non-linear transformations of the inputs) is known as the *reservoir* [23]. The network output is then calculated as a linear combination of the outputs of the reservoir (e.g., using linear regression for regression problems). Because of this easy way of creating and training this network's structure and its good performance in many different problems, the RC approach is currently a state of the art algorithm for prediction problems where a temporal structure is found in the data. RC has also been successfully applied to a number of renewable energy-related problems in wind and solar applications [2,5,11,21,22], but not specifically to WPRE prediction, to our knowledge, up until now. With the previous concepts in mind, the