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Short-term extreme wind speed forecast using Random Forest and LSTM: a classification approach

Paraskevi Modé [1], Cristoforo Demartino [2], Nikos Lagaros [3], Christos T. Georgakis [4]

[1] *National Technical University of Athens, Athens, Greece, pmode@mail.ntua.gr*
[2] *Zhejiang University, Haining, China, cristoforodemartino@intl.zju.edu.cn*
[3] *National Technical University of Athens, Athens, Greece, nlagaros@central.ntua.gr*
[4] *Aarhus University, Aarhus, Denmark, cg@cae.au.dk*

SUMMARY:
Wind forecasting is continuously gaining wide interest in the wind engineering community since it has many applications in several industrial domains. However, most of the research published to date focuses on mean wind speeds. In this context, this study presents a novel approach to forecast extreme wind speeds corresponding to specific return periods in a short-term window into the future (i.e., less than 3 hrs). Extreme wind events are classified by wind speeds above specified thresholds that are defined in terms of a defined exceedance of return period (frequency of exceedance). The Peaks Over Threshold (POT) method is used to calibrate the Extreme Value Analysis that defines the wind thresholds of the classes. The regression problem is tackled using two Machine Learning algorithms, the Random Forest (RF) and the Long Short-Term Memory (LSTM) neural networks and is finally formed as a time-series imbalanced binary classification. Both models have been post-optimized.

Keywords: extreme wind events, binary classification, short-term forecast

1. INTRODUCTION

Forecasting extreme wind events, that are typically at the tail of the wind distribution, are usually more critical for wind engineering applications than the forecast of the mean winds. However, extreme winds are scarcely represented in the wind dataset, which makes their forecast a challenging task. The purpose of this research is to forecast extreme wind events in a short-term horizon using computationally efficient methods.

First, an Extreme Value Analysis (EVA) based on the Peaks over Threshold (POT) method is conducted using historical weather data from O'hare International Airport (ORD) in Chicago. After obtaining the wind hazard curve of the site, the classification problem is formed. Extreme wind speeds are underrepresented in the dataset, a fact that leads to an extremely imbalanced classification. Random Forest (RF) and Long Short-Term Memory (LSTM) models are used for the imbalanced classification problem and a post-processing hyperparameter tuning defines the final results.

2. DATASET AND EXTREME WIND HAZARD ANALYSIS

Weather data, namely wind speed and direction, wind gust and direction, temperature, dew point and pressure, from O'hare International Airport (ORD) in Chicago, USA are used herewith. The data are obtained from Iowa State University's Environmental Mesonet system, (IEM, 2023). The data consists of the 2 min mean of 5 sec averages and it is stored every 1 min, (NOAA, 1998).

2.1. Pre-processing

Data are divided into a train and validation set (2005-2019) and a test set (2019-2022). Both sets are cleaned from global and local outliers using field knowledge and statistics. After the normalization of each variable of the sets, K-Nearest Neighbour (KNN), which is a non-parametric Machine Learning (ML) algorithm, is implemented for imputing the missing entries. KNN algorithm uses the 10 closest entries in the dataset for each missing entry.

2.2. Wind hazard estimation

In order to obtain the wind hazard curve, an EVA is conducted on 13.75 yrs of data (1/6/2005-1/3/2019) resampled at 10 min intervals. The wind extreme events are analysed using the commonly used method, POT, where the threshold of 13 m/s is adopted for the fixed parameter ξ of Eq. (1), after observing a change in the contributing Generalized Pareto Distribution (GPD) on the conditional mean exceedance graph. This graph is used since POT wind speeds asymptotically follow the GPD family. Assuming a 48 hrs interim of the extreme events and that the GPD fits them, 104 extreme wind events are obtained (see red dots in Fig. 1 left). Grey lines in Fig. 1 left represent the density of these events. Taking a null shape parameter of the GPD, the hazard curve can be expressed as:

$$U(T_r) = \xi + \alpha ln(\lambda T) \tag{1}$$

where U is the wind speed, T_r is the return period, ξ is the selected threshold and λ is the Poisson frequency rate. After the analysis, the parameters of Eq. (1) derive as follows: α = 1.12 m/s and λ = 104/13.75 = 7.56 yrs^{-1}. The illustration of Eq. (1) is the hazard curve that is shown Fig. 1 right along with a 95% confidence interval.

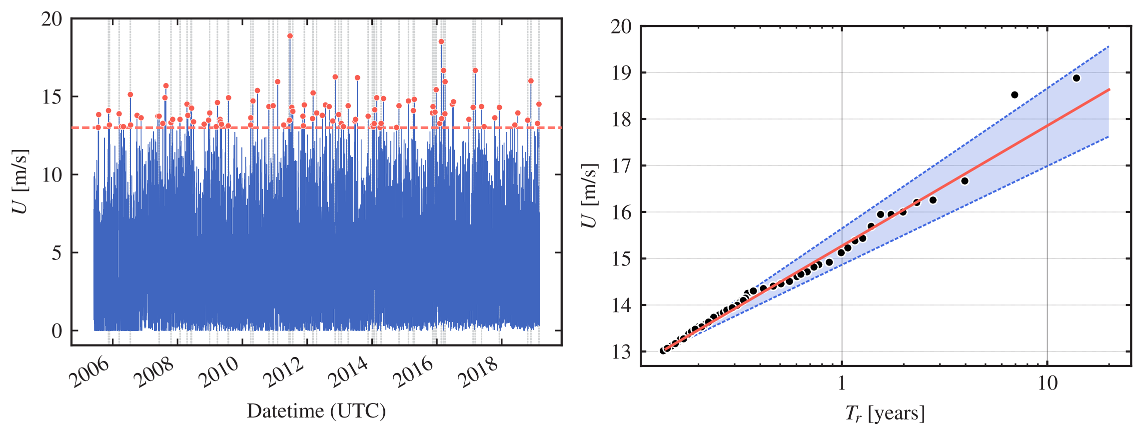

Figure 1. Extreme wind events using POT (left) and wind hazard curve with a 95% confidence interval (right).

3. CLASSIFICATION

The focus herewith is on the extreme wind speeds identification. Consequently, this study formulates the problem as a binary classification. The threshold of the two classes is a 10 min interval wind speed of $U = 13.3$ m/s, corresponding to a return period of $T_r = 2$ months as derived from Eq. (1). The positive class encompasses wind speeds of magnitudes $U \geq 13.3$ m/s, while the zero class $U < 13.3$ m/s. T_r is chosen as a trade-off between the need of having a high enough wind but still accounting a number of events that allows ML algorithms to learn from (see Fig. 2). The positive class in the train dataset (2005-2016) represents the 0.071% of the data of the class and in the validation (2016-2019) and test sets (2019-2022), the percentages are 0.089% and 0.085% respectively (see Fig. 2 for the representation of extreme wind values in each dataset). Since the classification is considered highly imbalanced, a cost-sensitive method is adopted in both models to deal with it (Brownlee, 2020).

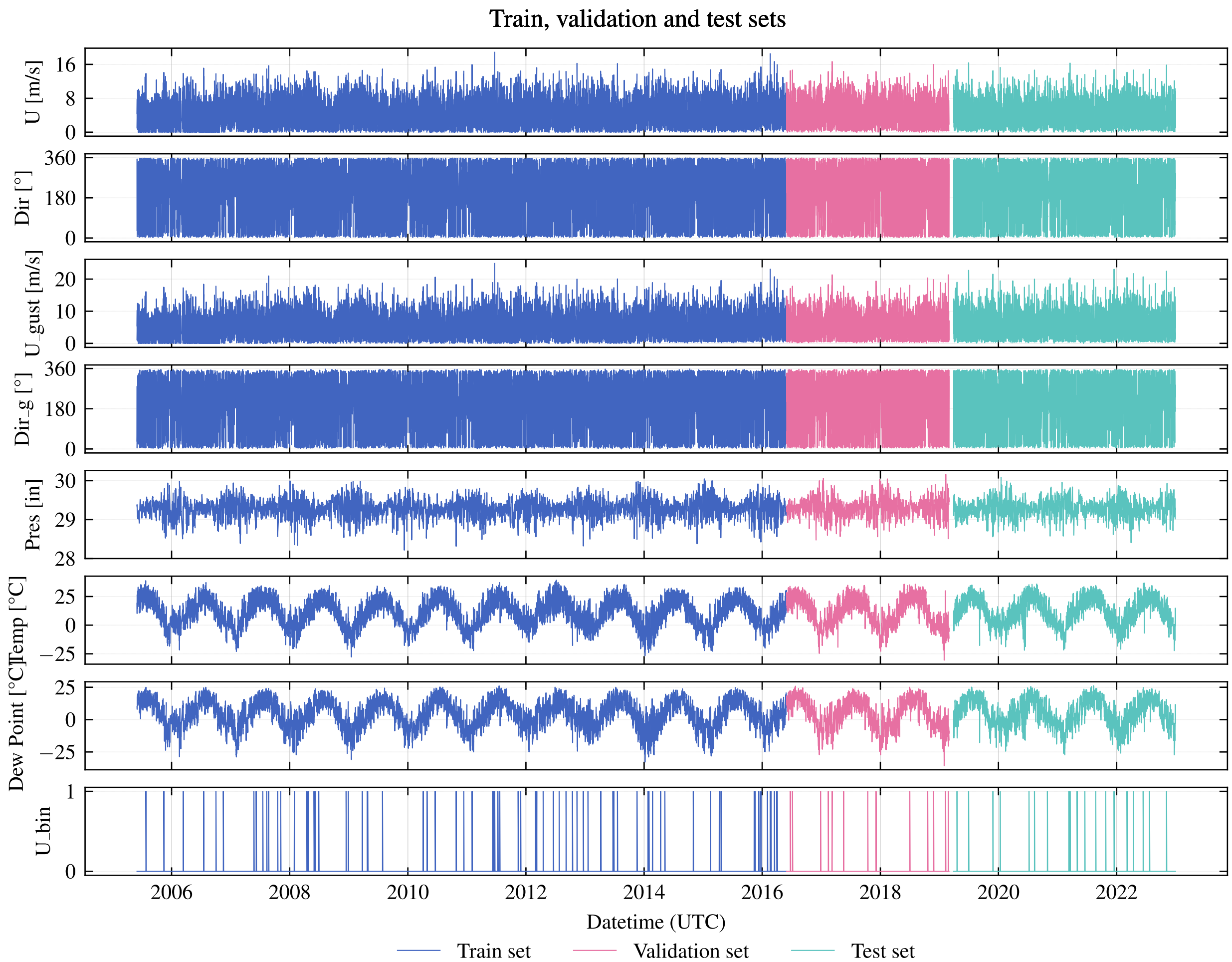

Figure 2. 10min interval datasets including extreme wind speeds.

3.1. Methods

Random Forest (RF) and LSTM network are the two methods that are used. RF is an ensemble method that is chosen due to its low demand on computational power and its high accuracy in classification tasks in other domains such as the trade-market's. Grid search is conducted in order to estimate its parameters, such as estimators and depth of the trees. The LSTM that is used as a baseline model, is a single-layer LSTM network fed with 6 hrs sequences of historical weather data. Data are pre-processed in the same way for both models and the forecast window is 30 min ahead. The output of the models is a probability distribution over the positive class which is optimized for F1-measure, which is the harmonic mean of precision and recall, (Sokolova et al., 2006).

4. RESULTS

The F1-measure is 1 for a perfect model. In this study, the performance achieved on the train set is approximately 91% and 47% for the RF and the LSTM, respectively. On the test set, it is around 53% using the RF and 51% using the LSTM. The final performance of the two models is similar (see Fig. 3) however, LSTM is more computationally demanding.

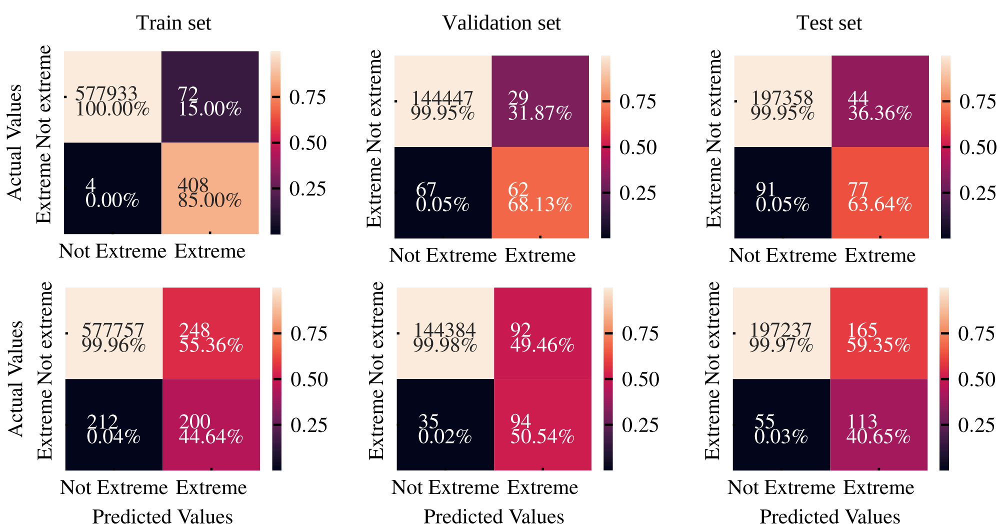

Figure 3. Confusion matrices for train, validation and test sets, of RF (above) and LSTM (below).

5. CONCLUSIONS

This study proposes a classification approach of forecasting extreme wind events using ML algorithms. It compares two algorithms, a RF and a simple LSTM architecture. The parameters of both models are optimised for F1-measure due to the extreme imbalance of the positive class. The findings of this study suggest that the performance of the RF and the LSTM network is similar.

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