**Wind power forecasting based on daily wind speed data using machine learning algorithms**

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| **Indicator** | **Details** |
| Objective | * To forecast the generated wind power with respect to daily wind speed data * To test eligibility of the generated wind power forecasting model for one location to be used in other locations |
| Y | year-ahead wind power generation  (note: wind power generation for the training set is calculated based on a equation) |
| x | * Daily wind speed (converted from hourly wind speed) * Daily standard deviation of hourly wind speed |
| Data span | 5 years: 4 years for training, 1 year for testing |
| Algorithms used | * LASSO * kNN * XGBoost * RF * SVR |
| Training | The machine learning algorithms were trained on 4 years of daily mean wind speed, standard deviation, and the daily total wind power and final one year were forecasted  Split: 80% (4 years), 20% (1 year) |
| Validation / CV | No |
| Metric | R-squared, MAE, RMSE |
| Results |  |
| Contributions | To better demonstrate the efficiency of our proposed machine learning based wind power forecasting models, authors tested the models against the wind speed values of four different locations |

**A Machine Learning-Based Gradient Boosting Regression Approach for Wind Power Production Forecasting: A Step towards Smart Grid Environments**

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| **Indicator** | **Details** |
| Objective | * Test various machine learning methods to forecast wind power based on wind speed and wind direction data |
| Y | Produced power (10min granularity for both training and test samples collected 1 wind farm in Turkey) |
| x | * Wind speed * Wind direction * Theoretical wind power |
| Data span |  |
| Algorithms used | * RF * kNN * GBM * Decision tree * Extra tree |
| Training | the dataset, i.e., 47,033 data points, were considered for implementing the machine learning models  Split: training (70%), test (30%) |
| Validation / CV | No |
| Metric | R-squared, MAE, MPE, RMSE, MSE |
| Results |  |
| Contributions | Short-term wind power forecasting on the basis of the historical values of wind speed, wind direction, and wind power by using  ML algorithms |

**Efficient Wind Power Prediction Using Machine Learning Methods: A Comparative Study**

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| **Indicator** | **Details** |
| Objective | Demonstrate greater efficiency of ML algorithms other static algorithms |
| Y | Wind power production |
| x | * Wind direction * Wind speed |
| Data span | For France data, the investigated models are trained using data recorded from 1 February 2017 to 30 June 2017.  For the Turkey data, the train data are collected from 1 February 2018 to 30 June 2018.  Kaggle data contain some significant periods with missing values, which are discarded. We considered only periods with a few missing values. Specifically, we selected data for training from 1 January 2020 to 30 March 2020. |
| Algorithms used | Listed in Results |
| Training | We took the next three days of each training dataset for testing (i.e., 432 data points). |
| Validation / CV | 5-fold cross-validation procedure is adopted in training to avoid overfitting |
| Metric | R-squared, MAE, RMSE |
| Results |  |
| Contributions | This study first applied and compared several machine learning approaches to model the nonlinear wind power dynamics and forecast the future trends of wind power. |