## LITRATURE SURVEY ON PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITIONS

**TEAM ID**: PNT2022TMID33245

S.No	Title	Author	Advantages	Disadvantages
1.	Current methods and advances in forecasting of wind power generation.	Leahy ,A.Marvuglia, and E. J. McKeogh.	This paper presents an in-depth review of the current methods and advances in wind power forecasting and prediction. Firstly, numerical wind prediction methods from global to local scales, ensemble forecasting, upscaling and downscaling processes are discussed. Then the techniques used for benchmarking and uncertainty analysis of forecasts are overviewed, and the performance of various approaches over different forecast time horizons is examined. Finally, current research activities, challenges and potential future developments are appraised.	science related properties and terms are not
2.	Analysis of wind energy time series with kernel methods and neural networks.	O. Kramer and F. Gieseke.	This article shows how kernel methods and neural networks can serve as modeling, forecasting and monitoring techniques, and, how they contribute to a successful integration of wind into smart energy grids. First, we will employ kernel density estimation for modeling of wind data. Kernel density estimation allows a statistically sound modeling of time series data. The corresponding experiments are based on real data of wind energy time series from the NREL western wind resource dataset. Second, we will show how prediction of wind energy can be accomplished with the help of support vector regression. Last, we will use self-organizing feature maps to map highdimensional wind time series to colored sequences that can be used for error detection.	mostly on the wind power based on neural networks and kernel based methods rather than including any other methods of data science and machine learning like support vector

forecasting using Supportvector regression.  Gieseke.  based on the existing infrastructure of windmills in neighbored wind parks can be learned with a soft computing approach for wind energy paper based on prediction in the ten-minute to six-hour range.  For this sake we employ Support Vector Regression (SVR) for time series forecasting, and run experimental analyses on real-world wind data from the NREL western wind resource dataset. In the experimental part of the paper we concentrate on loss function parameterization of SVR. We try to answer how far ahead a reliable wind forecast is possible, and how much information from the past is necessary. We demonstrate the capabilities of SVR-based wind energy forecast on the micro-scale level of one wind grid point, and on the larger scale of a whole wind park.  4. Age-fitness Pareto optimization.  4. Age-fitness Pareto optimization.  4. Age-fitness Pareto optimization.  4. Description of the paper we concentrate on loss function parameterization of SVR-based wind energy forecast on the micro-scale level of one wind grid point, and on the larger scale of a whole wind park.  4. Age-fitness Pareto optimization.  4. Description of the paper we concentrate on loss function parameterization of SVR-based wind energy forecast on the micro-scale level of one wind grid point, and on the larger scale of a whole wind park.  4. Age-fitness Pareto optimization.  4. Description of the paper we concentrate on the two-dimensional Pareto front comprising (a) how long the genotype has been in the population (age); and (b) its performance (fitness). We compare this approach with previous approaches on the Symbolic Regression problem, sweeping the problem one of the objective and number of variables. Our results indicate that the multi-objective approach if failure or interruption one of the objective then the agelayered population and standard population methods. The multi-objective method also performs better on higher complexity problems and higher dimensional datasets - finding	3.	Cleart towns raind an area	O Vacanca and E	In this management if wind massessments	Chauld
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5.	Short-term prediction of wind farm power: A data mining approach.	A. Kusiak, H. Zheng, and Z. Song.	predicting the power of a wind farm at different time scales, i.e., 10-min and hour-long intervals. The time series models are built with data mining algorithms. Five different data mining algorithms have been tested on various wind farm datasets. Two of the five algorithms performed particularly well. The support vector machine regression algorithm provides accurate predictions of wind power and wind speed at 10-min intervals up to 1 h into the future, while the multilayer perceptron algorithm is accurate in predicting power over	Wind speed can be predicted fairly accurately based on its historical values; however, the power cannot be accuratel y determined given a power curve model
			future, while the multilayer perceptron	given a power