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Kernel ridge regression with active learning for wind speed prediction

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HIGHLIGHTS

- ▶ This paper introduces the active learning approach for wind speed prediction.
- ▶ Three different active learning strategies are described.
- ▶ They are specifically developed for kernel ridge regression.
- ▶ Results show that a smart collection of training samples can be of great benefit.

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ABSTRACT

This paper introduces the active learning approach for wind speed prediction. The main objective of active learning is to opportunely collect training samples in such a way as to minimize the error of the prediction process while minimizing the number of training samples used, and thus to reduce the costs related to the training sample collection. In particular, we propose three different active learning strategies, developed for kernel ridge regression (KRR). The first strategy uses a pool of regressors in order to select the samples with the greater disagreements between the different regressors, while the second one relies on the idea to add samples that are distant from the available training samples, and the last strategy is based on the selection of samples which exhibit a high expected prediction error. A thorough experimental study is presented. It is based on ten different wind speed measurement stations distributed over the vast Algerian territory. Promising results are reported, showing that a smart collection of training samples can be of benefit for wind speed prediction problems.

1. Introduction

1.1. Wind speed estimation

As a consequence of increasing population and higher consumption of energy by developing countries, oil resources, natural gas and uranium will be depleted within a few decades. The unavoidable alternative becomes thus the development of renewable energy sources like solar energy, geothermal and wind power. In fact, the best use of renewable energies is an essential factor of development for all countries. Algeria is a country rich in renewable energy resources, thanks to its geographical location and its large area (2,381,741 km^2) which offer it great opportunities to find renewable energy sources (e.g., solar, wind, and geothermal) [1–3].

Focusing to the particular case of wind power, the estimation of wind speed in the short or the long-term represents an important target to evaluate the possibility to create new wind turbines or to predict the wind power production of existing ones [4]. In the literature, several wind speed prediction methods can be found. They can be divided into three categories: statistical methods [5–8], physical methods [9,10], and machine learning methods including neural networks and support vector machines since the estimation of the wind speed can be considered as a nonlinear regression problem [11–23].

In the literature, several sources of error and uncertainty in assessing wind power or speed have been identified. Among the most recently published works, we can find those presented in [24–29]. In greater detail, Lackner et al. [24] have proposed a deterministic method for combining uncertainties that arise in assessing the wind resource, and explicitly derived the sensitivity factors for wind speed measurement uncertainty and the Weibull parameters. In [25], it is shown that the maximum likelihood method is more efficient than the commonly used graphical method for the determination of the Weibull parameters. Akdag et al. [26] proposed an

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