An Evaluation on Diverse Machine Learning Algorithms for Hourly Univariate Wind Power Prediction in the Arctic

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An Evaluation on Diverse Machine Learning Algorithms for Hourly Univariate Wind Power Prediction in the Arctic

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Abstract. Wind power forecasting is crucial for wind power systems, grid load balance, maintenance, and grid operation optimization. The utilization of wind energy in the Arctic regions helps reduce greenhouse gas emissions in this environmentally vulnerable area. In the present study, eight various models, seven of which are representative machine learning algorithms, are used to make 1, 2, and 3 step hourly wind power predictions for five wind parks inside the Norwegian Arctic regions, and their performance is compared. Consequently, we recommend the persistence model, multilayer perceptron, and support vector regression for univariate time-series wind power forecasting within the time horizon of 3 hours.

1. Introduction

Wind energy is one of the fastest-growing renewable energy sources [1]. It is regarded as an attractive alternative to conventional energy sources generated from fossil fuels. Wind power, invested tremendously, has become an essential component in the state grid's operations in many nations [2].

Arctic regions are plentiful for wind resources. One reason is the Earth's atmospheric circulation, and the cold climate with less vegetation and trees makes wind energy easily accessible. Specifically, the Norwegian coastline is regarded as the area with one of the best wind energy resources in Europe wind energy [3]. However, this area's landscape is extremely complex due to the glacier erosion, which makes much wind local phenomenon and arduous to forecast.

Meanwhile, electricity-generating from wind power fluctuating from time to time because of the inherent characteristics undulations of wind. The knowledge of forecasting wind power can help whittle down the drawbacks of fluctuating wind power [4]. So, it is beneficial to investigate the wind power generation data and use proper methods to make predictions for the electricity generated by wind parks. In particular, hourly wind power forecasting is essential for maintaining the real-time grid and electricity market deals.

This paper does a systematic evaluation for the time-series forecasting of five wind farms with sufficient wind resources in the Norwegian Arctic region. The persistence model and seven most commonly used machine learning algorithms are researched in modeling, and their performance is compared. It is organized as follows: In section 2, we describe the sites and wind power data, section 3 includes a short introduction to each machine-learning model, while section 4 describes the statistical measured used for comparison. Results are presented in section 5, and we conclude our findings in section 6.

2. Wind parks and data description

In this paper, we concentrate on five wind parks in Northern Norway. The five wind farm power data, measured hourly, used in the research are taken from the Norwegian Water Resources and Energy Directorate (NVE). We choose the wind power data from 0:00 1st January 2017 to 23:00 31st December 2017. The number of the measured data is 8760 for each wind farm. The total size of wind power data is 43800 without any missing values. The annual mean powers, their standard deviations [5] of the five wind farms in 2017 are presented in Table 1.

Table 1. Five wind parks and statistics of the data.

Wind Park	Mean power (MW)	Standard deviation (MW)
Nygårdsfjellet	11.132	11.833
Fakken	15.239	15.858
Raggovidda	21.782	16.869
Kjøllefjord	12.349	12.786
Havøygavlen	10.311	11.037

Data scaling is a standard method to normalize the range of data. When using it in machine learning, the gradient descent converges much faster with feature scaling than without it [6]. The data are scaled with min-max normalization between 0.2 and 0.8 for practical reasons.

$$x' = a + \frac{(x - min(x))(b-a)}{max(x) - min(x)} \tag{1}$$

where a and b are the min and max values of the normalization scale.

3. Forecasting algorithms

For machine learning models in regression analysis, numerous changes are proposed by researchers, and it is impossible to conduct all of the existing differences in models. Therefore, our strategy is to consider each model's basic version for the comparative research on different hourly wind power forecasting algorithms.

The eight prediction models, one baseline model, and seven machine learning models are chosen since they are the most commonly used models. 1. Persistence Model, 2. Support Vector Regression (SVR), 3. K-Nearest Neighbor regression (KNN), 4. Multilayer Perceptron (MLP), 5. Radial Basis Functions (RBF), 6. Classification and Regression Trees (CART), 7. Random Forests (RF) and 8. Stochastic Gradient Boosting (SGB).

Method 1 is the comparison baseline in general, and methods 2 to 6 are representative machine learning algorithms with a single learner. The rest are two types of ensemble machine learning methods. Ensemble learning is an algorithm in which many base learning algorithms are organized to establish a new integrated learning model [7]. The followings are brief descriptions of each model.

Persistence: the persistence model considers that the wind power at $t + n$ is equal to wind power at t, where n is the following n steps in time series.

Support Vector Regression: SVR is the regression process conducted by the Support Vector Machine algorithm. SVR can make a non-linear regression because it provides kernel functions that map data from the input space to a high dimensional feature space where the linear regression is performed [8]. Standard kernel functions are linear, polynomial, and gaussian [9]. In this study, we set the coefficient C as 1.0 and the RBF kernel function.

K-Nearest Neighbor: KNN regression is a nonparametric machine learning algorithm based on the K-Nearest Neighbor classification, which focuses on feature similarity of different distance functions [10]. In the study, we conduct grid searches for K from 1 to 10 to find an appropriate K value and choose the KNN model with K equals 3, which performs the best in the investigations.

Multilayer Perceptron: MLP is a network of perceptrons. The perceptron computes a single output from multiple real-valued inputs by forming a linear combination according to its input weights and possibly

putting the output through some non-linear activation function [11]. In this study, the topology of MLP comprises three layers: one node input layer, ten nodes hidden layer, and one node output layer.
Radial Basis Functions: RBF network is a feed-forward network and similar in structure to the multilayer network. It utilizes radial basis functions as its activation functions [12]. In this paper, the topology of RBF is the same as the MLP.
Classification and Regression Trees: CART regression is a machine learning algorithm based on a tree-like recursive partition of the inputs [13]. The tree establishment processes are conducted from the root node to the leaves nodes to make mean square error reach an acceptable setting threshold and realize a final decision tree.
Random Forest: RF is an efficient bagging ensemble machine learning algorithm because it has good performance and relatively low computational cost. RF is based on the construction of a multitude of regression trees. Each tree is trained by using a bootstrap sample extracted from the whole training set [14].
Stochastic Gradient Boosting: SGB is a popular ensemble boosting tree learning algorithm, constructs additive regressions by sequentially fitting a simple parameterized function (base learner) to current "pseudo" residuals by least-squares at each iteration [15].

4. Experimental setup

4.1. Multi-steps Forecasting

The forecasting for short-term wind energy generation usually needs to provide multi-step (hourly ahead) predictions. There are two basic strategies for multi-step predictions in time-series forecasting: direct forecasting and iterative forecasting [16].
In the study, we focus on direct forecasting for wind power from t_1 to t_3. Namely, we conduct three modeling processes from one hour ahead to three hours ahead for each wind park. The direct forecasting formula is displayed in equation (2):

$$\hat{P}_{t+n} = f_{t+n}(P_t) + e_n, n = 1,2,3 \tag{2}$$

where $\hat{P}_{t+n}$ is the n steps wind power forecasting, f_{t+n} is the forecasting model, e_n is the model error.
Besides, the dataset is divided into training and testing sets. In the training process, the ten folds cross-validation is used to establish forecasting models, and these models are checked with two metrics in the testing set.
The procedure of forecasting is illustrated in Figure. 1.

4.2. K Folds Cross-validation and Two Evaluation Metrics

K-folds cross-validation is a vital and popular validation method for machine learning. It can ensure that every sample in the original data set can appear in the training and test sets. In this study, we take ten folds as common utilizations.
Two evaluation metrics are applied to the model evaluation. The first metric is the Mean Absolute Error (MAE); the second metric is the Root Mean Square Error (RMSE). The lower values of these two metrics are related to better performance. The definitions for MAE and RMSE are shown in equations (3) and (4):

$$MAE = \frac{\sum_{i=1}^{n} |prediction_i - observation_i|}{n} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (prediction_i - observation_i)^2}{n}} \tag{4}$$

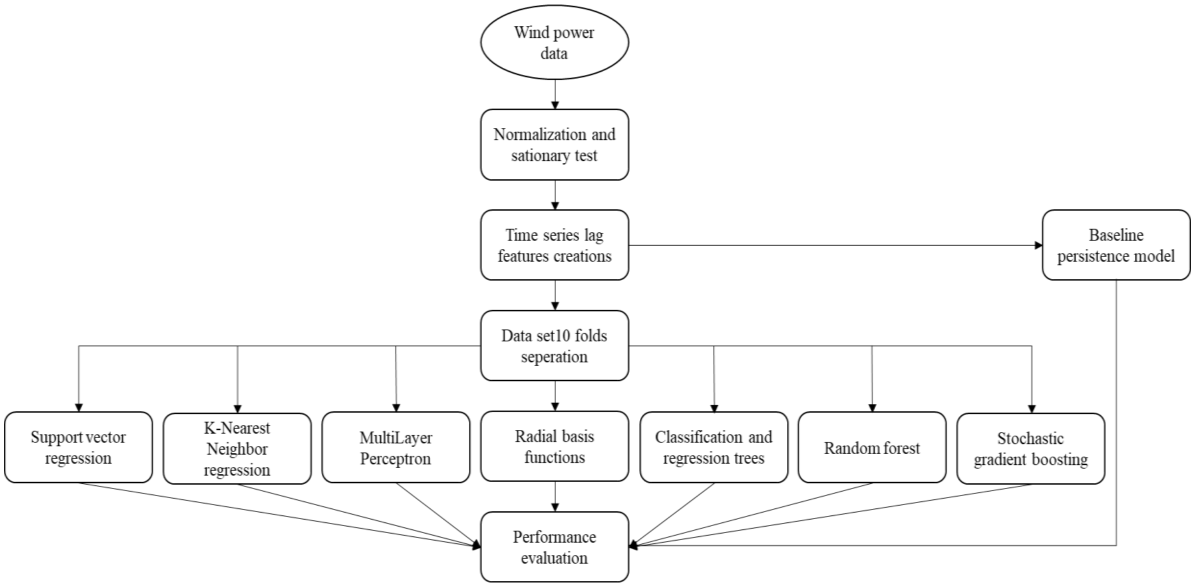
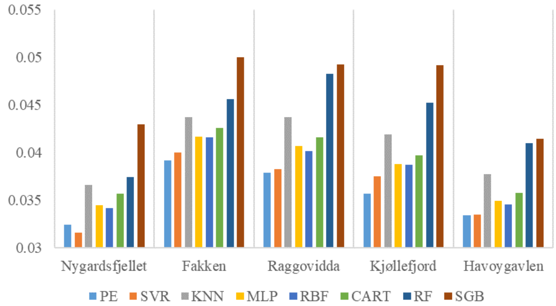


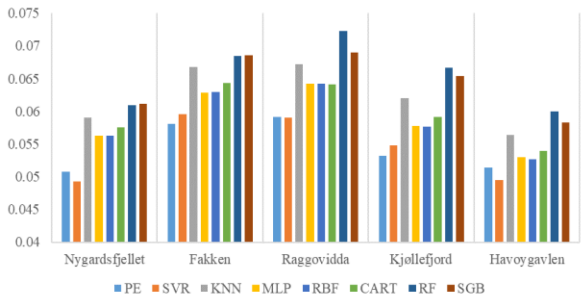
Figure 1. The procedure of algorithms for wind power forecasting.

5. Results

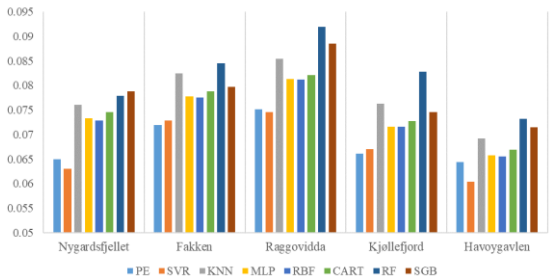
The MAE of multi-step forecasts for five wind parks is displayed in Figure. 2. It is shown that as the forecasting step adds, the MAEs of all models increase. Persistence models perform as well as SVR models in all wind parks, the KNN, MLP, RBF, and CART have similar MAEs, and nearly all of them have more unsatisfactory results than the persistence and SVR do. The ensemble learning methods show the largest MAEs. The averages (shorten as ML Average) of MAEs of machine learning algorithms for a forecasting process are calculated and compared with the persistence and SVR models in the growth rate with the forecasting step's increase. MAE's growth rate is shown in Table 2. The persistence model's MAEs generally increase faster than the average level of machine learning models and SVR, which means the persistence model's performance drops more quickly than machine learning models in terms of MAE for all the wind parks.



(a) One hour ahead forecasting.



(b) Two hours ahead forecasting



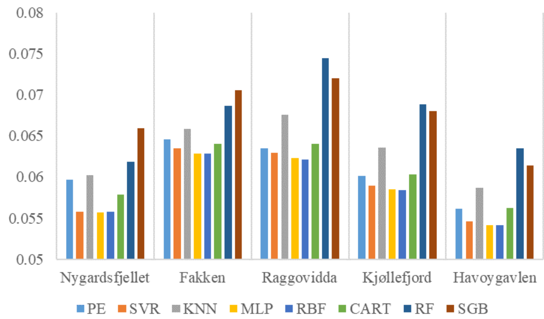
(c) Three hours ahead forecasting

Figure 2. The MAE of eight forecasting models.

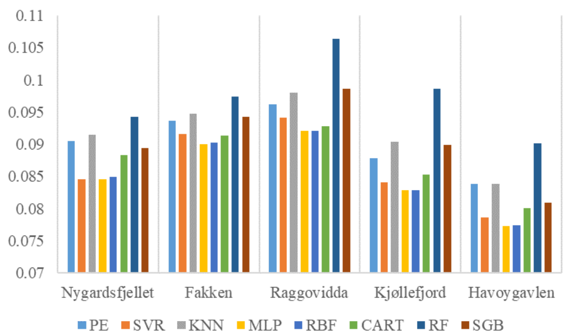
Table 2. The growth rate of MAE.

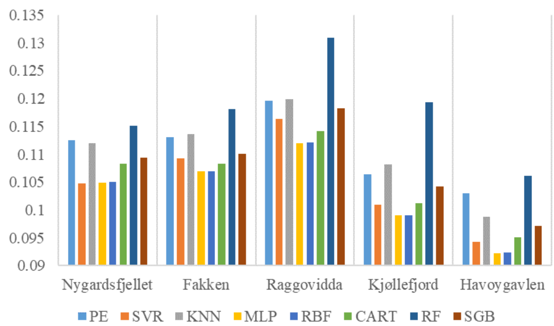
1 to 2 step	***Persistence***	***ML Average***	***SVR***
Nygårdsfjellet	56.31%	58.22%	55.91%
Fakken	48.30%	48.54%	48.98%
Raggovidda	55.78%	52.28%	54.19%
Kjøllefjord	49.13%	45.41%	45.99%
Havøygavlen	53.48%	48.10%	47.97%
2 to 3 step	***Persistence***	***ML Average***	***SVR***
Nygårdsfjellet	27.88%	28.95%	27.77%
Fakken	23.82%	22.10%	22.25%
Raggovidda	27.22%	27.19%	26.38%
Kjøllefjord	24.08%	22.04%	22.29%
Havøygavlen	25.44%	23.13%	22.01%

The RMSE of multiple steps predictions for five wind parks is shown in Figure. 3. RMSEs of all models increases with the forecasting step increases from 1 to 3. The MLP, RBF, and SVR have the best performance in RMSE, in which MLP has the lowest overall RMSE. The persistence, KNN, CART, and SGB have similar RMSEs, and nearly all of them have worse results than MLP, RBF, and SVR. The RF model has the highest RMSE. The averages of NMSEs of machine learning algorithms for a forecasting process are also calculated and compared with the persistence and MLP models in the growth rate with the increasing prediction step. The growth rate of NMSE is shown in Table 3 which shows that all models' RMSE growth rates decrease as the forecasting step increases. The RMSEs of the persistence model generally grow faster than the average level of machine learning models and MLP, which demonstrates the performance of the persistence has a more unsatisfactory performance of RMSE than machine learning models, which is similar to the results of MAE.



(a) One hour ahead forecasting.





(b) Two hours ahead forecasting (c) Three hours ahead forecasting

Figure 3. The RMSE of eight forecasting models.

Table 3. The growth rate of RMSE.

1 to 2 step	***Persistence***	***ML Average***	***MLP***
Nygårdsfjellet	51.70%	49.48%	51.80%
Fakken	44.90%	41.74%	43.10%
Raggovidda	51.36%	44.82%	47.81%
Kjøllefjord	46.09%	40.66%	41.82%
Havøygavlen	49.39%	41.16%	42.77%
2 to 3 step	***Persistence***	***ML Average***	***MLP***
Nygårdsfjellet	24.28%	22.99%	24.12%
Fakken	20.75%	19.01%	18.86%
Raggovidda	24.43%	22.14%	21.58%
Kjøllefjord	21.17%	19.17%	19.46%
Havøygavlen	22.81%	18.91%	19.32%

Moreover, based on the above results, it can be seen that the persistence, SVR, and MLP models have similar advantageous performance. However, the apparent differences between them are not intuitively apparent from Figure. 2 and Figure. 3. To understand more about the models themselves and their effectiveness in wind power forecasting for different wind farms. We take the one-way analysis of variance (ANOVA) for five wind farms with the average MAE and RMSE of these three algorithms for three-time steps.

H_0: The three algorithms do not have significant differences in temporal average performance.

H_a: They have significant differences.

From the ANOVA, its F distribution is with 2 and 12 degrees of freedom. The F values of MAE and RMSE equal 1.509 and 1.116, respectively, related to p-values of 0.26 and 0.359. The two p-values are both larger than 0.05. So, the H_0 cannot be rejected. It is concluded that there exists statistical evidence that these three algorithms, on average, do not perform differently in wind power forecasting in our cases.

6. Conclusion

We conduct the univariate time-series forecasting with eight algorithms introduced above to make 1, 2, and 3 hours ahead of wind power predictions for five wind parks inside the Norwegian Arctic regions. As a result of the study, the following conclusions can be demonstrated.

There are only slight differences in performance between the persistence method and machine learning methods for the univariate time-series wind power forecasting in our cases. The typical machine learning algorithms SVR and MLP perform as well as the persistence model. However, the ensemble learning methods like RF and SGB have relatively disappointed prediction results.

MAE's best machine learning performance is SVR, whose average MAE is almost the same (0.18% lower) with the persistence model, which shows the all weighted equally individual differences between wind power predictions by the persistence and SVR are smaller than other machine learning algorithms in this study. Meanwhile, MLP has the best performance in RMSE, which is 5.4% lower than the persistence model. RBF and SVR also have lower RMSE than the persistence model does. These mean the wind power forecasted by Persistence model has more large error than these machine learning algorithms.

In terms of predicted time steps, the persistence model's performance decreases faster than the average performance of machine learning models, especially in the measurement of RMSE, which means the persistence model is relatively unstable in the horizon of and more sensitive with the forecasting time.

Given that computing time and model complexity, we recommend the persistence model and SVR for univariate time-series wind power forecasting for the five wind parks within the time horizon of 3 hours.

For more accurate predictions within 3 hours or longer time ahead forecasting, the improved machine learning models and methods considering methodological or topographic factors should be utilized.

7. References

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