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A novel intelligent approach for yaw position forecasting in wind energy systems

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ABSTRACT

Yaw control systems orientate the rotor of a wind turbine into the wind direction, optimize the wind power generated by wind turbines and alleviate the mechanical stresses on a wind turbine. Regarding the advantages of yaw control systems, a k-nearest neighbor classifier (k-NN) has been developed in order to forecast the yaw position parameter at 10-min intervals in this study. Air temperature, atmosphere pressure, wind direction, wind speed, rotor speed and wind power parameters are used in 2, 3, 4, 5 and 6-dimensional input spaces. The forecasting model using Manhattan distance metric for $k = 3$ uncovered the most accurate performance for atmosphere pressure, wind direction, wind speed and rotor speed inputs. However, the forecasting model using Euclidean distance metric for $k = 1$ brought out the most inconsistent results for atmosphere pressure and wind speed inputs. As a result of multi-tupled analyses, many feasible inferences were achieved for yaw position control systems. In addition, the yaw position forecasting model developed was compared with the persistence model and it surpassed the persistence model significantly in terms of the improvement percent.

Introduction

A wind turbine includes many interconnected mechanical components such as blades, rotor, gearbox, bearings, yaw system, pitch system and tower [1,2]. Yaw and pitch control systems reduce the fatigue loads caused by the aerodynamic forces and increase the production of electrical energy from wind energy [3]. Particularly, yaw control systems track the wind direction and face the wind stream perpendicularly [4]. In addition, yaw control systems also drive the rotor mechanism out of the wind in order to decrease its rotational speed [5]. As a result, yaw position parameter has a critical role in wind energy systems. However, it is difficult to adjust yawing moment in time due to the inertia problem of wind turbine in automatic-oriented yaw control systems [6]. For this reason, yaw position forecasting contributes the efficient and the safe operation of wind turbines.

Farret et al. determined the maximum wind power corresponding to the optimum wind direction and a sensorless yaw control system was realized [7]. Chen et al. designed a fuzzy proportional-integral-derivative system for yaw position control and the wind direction was tracked in a high precision way [8]. Fadaeinedjad et al. simulated the aerodynamic, mechanical and electrical aspects of a fixed-speed wind turbine and yaw errors lead to the voltage and power oscillations [9]. Kusiak et al. optimized the blade yaw angle using an evolutionary computation algorithm and the power output of a wind turbine was upgraded [10]. Lee et al. implemented a maximum power point tracking algorithm and ensured the accurate yawing torque [11]. Rijanto et al. processed wind direction signals in an electronic yaw controller and dissipated the cyclic instabilities of a horizontal-axis wind turbine [12]. Chenghui et al. proposed an intelligent yaw controller based on artificial neuro-endocrine-immunity system and improved the stability and robustness of the yaw control system [13]. Owing to the lack of academic studies in the field of yaw position forecasting, the main objective of this paper is to forecast the yaw position parameter of a wind turbine using air temperature, atmosphere pressure, wind direction, wind speed, rotor speed and wind power parameters in multi-tupled inputs. The developed yaw position forecasting model considers the number of nearest

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Nomenclature

T_a	air temperature (°C)
P_a	atmosphere pressure (hPa)
W_d	wind direction (°)
W_s	wind speed (m/s)
R	rotor speed (rpm)
P_w	wind power (kW)
k-NN	k-nearest neighbor classifier
MAE	mean absolute error (°)
MAPE	mean absolute percentage error (%)
NRMSE	normalized root mean square error (%)

neighbors, the dimension of input parameters, the selected distance metric and minimized the yaw position error remarkably by reducing it to 1.100° of MAE, 0.405% of MAPE and 1.209% of NRMSE in this paper. However, maximum yaw error and standard deviation of 10° in the literature were distributed [14–16]. On the other hand, the k-NN classifier outperforms with 75.5% improvement in comparison for the persistence model. MAE, MAPE and NRMSE values of the persistence model were obtained as 3.966°, 1.652% and 6.634%, respectively.

This paper is organized as follows. Section 'Lazy learning model' focuses on the k-NN classifier as a lazy learning approach and introduces the activity diagram of the yaw position forecasting model developed. Section 'Yaw position forecasting' explains the dataset properties, and distance and error metrics used in this study. The yaw position forecasting results based on multi-tupled inputs were compared. Finally, in section 'Conclusions', the work was concluded and the future studies were given.

Lazy learning model

Lazy learners store the training instances and do not construct any classification model until receiving a test instance [17]. However, lazy learners enable to model complex decision spaces having hyperpolygonal shapes compared to other learning algorithms [18]. Therefore, lazy learners have a wide range of application in pattern recognition. The k-NN classifier is also based on lazy learning and it initially considers each instance in training and test datasets as a point in an n-dimensional input space. Afterwards, it makes a classification for a test instance by comparing it to the most similar ones in the training dataset [19,20]. In here, each instance represents an n-dimensional attribute tuple. The detailed flow chart of the yaw position forecasting model developed in this study is given in Fig. 1.

After browsing the training and test datasets, selecting the distance and error metrics, assigning the value of k, the file reading method is called and the data points in training and test datasets are assigned to the separate arrays. The selected distance calculation method determines the close distance values among each data point in test and training datasets. So, the distance table array is created in a matrix form of $m \times n$. m and n identify the number of data points in test and training datasets, respectively. The nearest neighbor method searches the k smallest distance in each row of the distance table arrays and their row numbers in training dataset are assigned to an array having a matrix form of $m \times k$. In here, k identifies the number of nearest neighbors. In case of using the neighbors averaging method, the observed classes of the related row numbers in training dataset are averaged for each test data to achieve the forecasted classes. As a result, the observed values, the observed classes and the forecasted classes are first written to an Excel file and the observed classes and the forecasted classes are then visualized in a graphical form. Besides, the error table array is created by means of the selected error calculation method and the error results of the forecasting process are also represented in a graphical form as aforementioned. Finally, MAE, MAPE and NRMSE values are presented in graphical forms to the user.

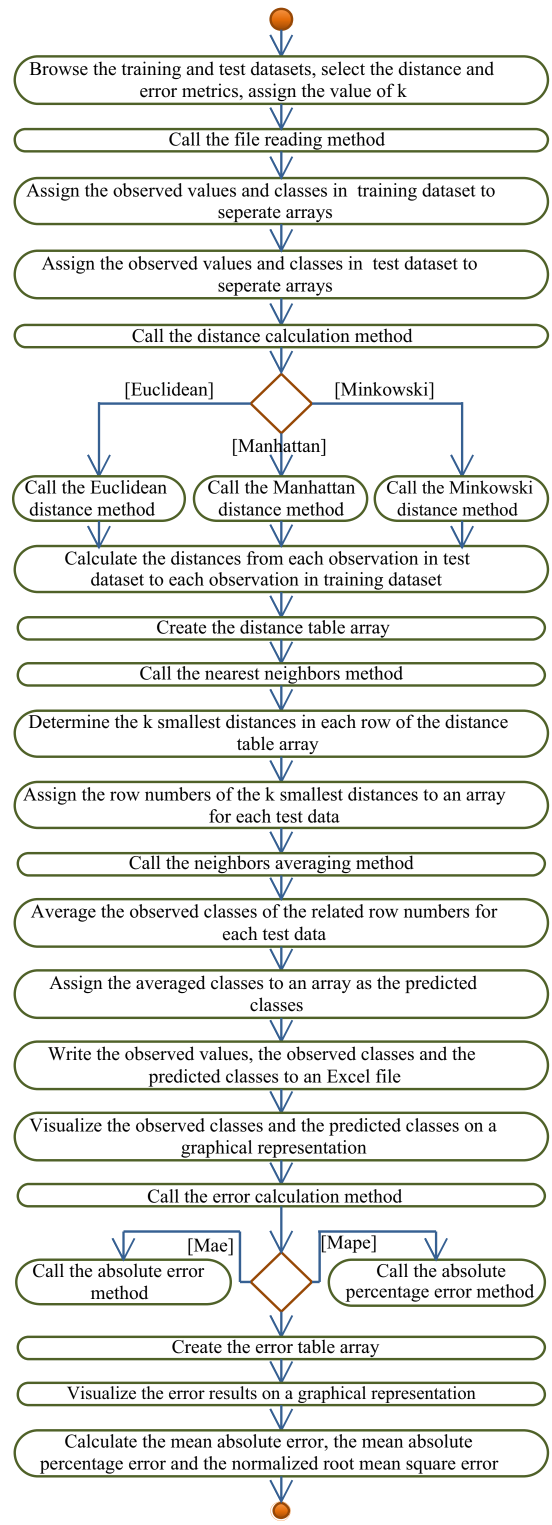

Fig. 1. A detailed flow chart of the model for the yaw position forecasting.