Hybrid Approach for Wind Turbines Power Curve Modeling Founded on Multi-Agent System and Two Machine Learning Algorithms, K-Means Method and the K-Nearest Neighbors, in the Retrieve Phase of the Dynamic Case Based Reasoning

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Abstract—Wind turbine power curve (WTPC) plays an important role for energy assessment, power forecasting and condition monitoring. The WTPC captures the nonlinear relationship between wind speed and output power. Many modeling approaches have been proposed by researches to improve the WTPC model performance. In this paper, we present a hybrid approach of wind turbines power curve modeling based on Case Based Reasoning approach, multi agent system, the K-Means unsupervised machine learning method, and then the supervised machine learning algorithm, which is the K-Nearest Neighbors KNN method. The both of the Machine Learning algorithms, K-means and KNN, are used in the retrieve step of the Dynamic Case Based Reasoning (DCBR) cycle to facilitate the search of wind turbines with similar characteristics to our target case. These wind turbines are first grouped into homogeneous classes and then sorted on the basis of a feature similarity measure using the K-Nearest Neighbors supervised machine learning method. Finally, a set of WTPC with similar characteristics of the target case are proposed.

Keywords—Dynamic Case Based Reasoning (DCBR), Multi Agents System (MAS), Wind Turbines Power Curve (WTPC), machine learning algorithms: K-Means method and K-Nearest Neighbors algorithm (KNN)

1 Introduction

Wind energy plays a predominant role for power generation in a sustainable manner. It is very promising as the technology is commercially matured, economically viable and environmentally clean [1], and it can deliver an affordable energy. The global wind power capacity is on-track to reach 1,000 GW by the end of 2024, which is an increase of 54 per cent for total wind power installations compared to 2019 [2]. The generated wind power for a wind turbine mainly depends on the wind speed and direction. The relationship between the wind speed and generated power is depicted by the wind turbine power curve [3].

The wind turbine power curve (WTPC) shown in Figure 1 can be also used for power assessment and forecasting, wind turbine selection and capacity estimation [4]. The WTPC is essentially comprised of three regions [5, 6]. The first region when the wind speed is below a minimum speed threshold (Uc) known as the cut-in speed doesn't generate any wind power, so it has zero output. The second region, when the wind speed is situated between the cut-in speed (Uc) and the rated speed (Ur), the output power increases with the wind velocity. The third region gives a constant output power until the cutout speed (Us) is attained. The Fourth region is when the wind speed is larger than the cutout speed (Us), the wind turbine will be shut down for security concerns.

A wind turbine power curve, mainly indicate the performance of wind turbine. Modeled power curves can serve as a solid basis of comparison between the performances of the different available turbines, monitor their state of health and a tool for forecasting and power prediction too.

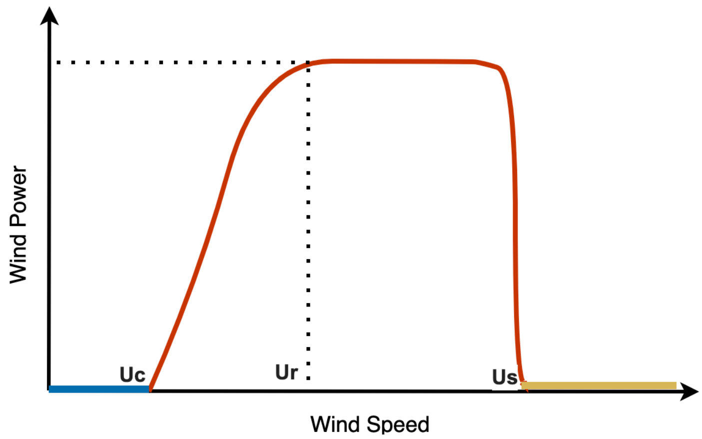

Fig. 1. Wind turbines power curve

For a smart monitoring of wind power prediction, we need to benefit from the past experiences of already installed wind turbines and reuse their wind turbine power curve to predict a new one.

In this paper, we present a hybrid approach of wind turbines power curve modeling based on the Dynamic Case Based Reasoning (DCBR) approach, Multi-Agents System (MAS), the K-Means Unsupervised Machine Learning method, and then the K-Nearest Neighbors Supervised Machine Learning algorithm. Both of the Machine Learning Algorithms K-Means and KNN are used in the retrieve step of the Dynamic Case Based Reasoning cycle to facilitate the search of wind turbines with similar characteristics.

The remainder of this paper is arranged as follows: In section two, we present the literature review of which we introduce the main concepts related to our work. In the third section, we describe and detail our approach and its architecture. In section four, we present the result of our approach using the DCBR, the K-means method and the KNN algorithm. In the last section, we end-up with a conclusion and future direction.

2 Literature review

2.1 Dynamic Case Based Reasoning

The Dynamic Case based Reasoning is an artificial methodology and a problem-solving paradigm that solves a given problem based on similar past problems [7]. The problems that have been solved are called source cases and are stored in a data base cases and the problem to be solved is called target case. In Dynamic Case based Reasoning, new solutions for a current situation are generated by retrieving the most similar cases from the data base cases and adapting them to current contexts [8]. Solving a problem using the Dynamic Case Based Reasoning approach, can be done through a typical cycle with a set of five steps as shown in Figure 2: Elaboration, Retrieve, Reuse, Revise and Retain [9, 10, 11, 12]. The first step of the DCBR consists in identifying and building the specifications of the problem to be solved. In the second step, the elaborated target problem is then used to find the most similar cases to the current problem in the data base cases. In the Reuse step, the solutions of the source cases are modified and reused to obtain solutions to the target case. In the revision step, the proposed solutions will be evaluated, modified, refused or accepted by the user. Finally, in the Retain step, new experiences will be retained and added to the data base cases. The cycle of the Dynamic Case based Reasoning allows to control and stop the execution of certain steps and re-execute the others at each moment if there is a change in the description of the target case.

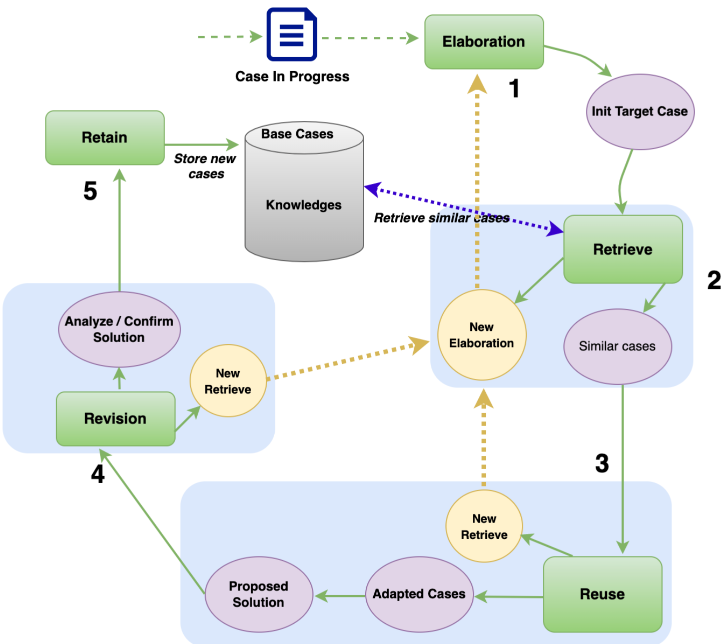

Fig. 2. Dynamic CBR cycle inspired from [9]

2.2 K-Means machine learning algorithm of clustering

Data clustering is the process of aggregation of items in a manner such that items in the same group are more identical to each other than in other groups [13]. In other words, the main objective is to find homogeneous subgroups with common characteristics [14] within the data such that data points in each cluster are as similar as possible according to a similarity measure such as Euclidean-based distance or correlation-based distance. Unlike supervised learning, clustering is considered an unsupervised learning method since we don't have the ground truth to compare the output of the clustering algorithm to the true labels to evaluate its performance. We only want to try to investigate the structure of the data by grouping the data points into distinct subgroups.

The **K-Means** Machine Learning algorithm is the most popular clustering algorithm. It is an iterative algorithm that tries to partition the dataset into *K* pre-defined distinct subgroups (clusters) where each data point belongs to only one group [14]. The main objective of the K-Means Machine Learning algorithm is to make the intra-cluster data points as similar as possible while also keeping the clusters as different as possible [15]. The less variation we have within clusters, the more similar the data points are within the same cluster. The K-Means has the ability to classify a large amount of data with relatively fast and efficient computation time [16].

The K-Means Unsupervised Machine Learning Algorithm works as follows:

- Specify number of clusters K.
- Initialize centroids by first shuffling the dataset and then randomly selecting K data points for the centroids without replacement.
- Keep iterating until there is no change to the centroids. i.e assignment of data points to clusters isn't changing.
- Compute the sum of the squared distance between data points and all centroids.
- Assign each data point to the closest cluster (centroid).
- Compute the centroids for the clusters by taking the average of the all data points that belong to each cluster.

2.3 Classification with K-Nearest Neighbors machine learning algorithm

The K-Nearest Neighbors (KNN) algorithm is a non-parametric, supervised Machine Learning Algorithm. It can be used for both classification and regression problems. It is based on a simple and intuitive principle of grouping data according to their neighborhood. The goal of this algorithm is to classify new objects based on attribute and training data [17]. Each object is assigned to the class most represented among its k nearest neighbors. The K-Nearest Neighbors Machine Learning Algorithm has the following steps:

- Let (K) the number of nearest neighbors to use.
- Let $D(y_j)$ the training data set.
- Calculate the distance $d(x_i, y_j)$ between the new observation X_i and each data y_j of D [18].
- Select the K nearest data of the observation X_i.
  Classify the new observation X_i according to the class of its neighbors that gets the most votes.

Although the KNN Machine Learning Algorithm is simple and easy to implement, there are some limitations such as it gets significantly slower as the data set elements increase, the high cost computing of the calculation of the distance between the new observation Xi and each data yj of the data set D.

2.4 Multi agent system

The multi agent system (MAS) is a system composed of a collection of autonomous software agents that work together to accomplish a particular task irrespective of their capabilities and knowledge [19, 20, 21]. Multi agent system provides an environment with basic functionalities for the execution of agents for specific task. Agents have control over their actions and internal state. They are able to learn and act in their environment as presented in [22]. Agents may behave towards each other as collaborators, competitors or strangers [23, 24]. A System multi agent is composed of the environment, Agents and the relationships that link them with each other in their environment, Behaviors and Operations of each agent [25, 26].

3 Our proposed approach and its architecture

The aim of our approach is to provide a personalized power curve of the wind turbines. The proposed approach consists of a multi-Agents architecture which is developed in our DCBR cycle [27].

The agents of our proposed architecture carry out all the required tasks from constructing the specifications of the wind turbine to the simulation and the proposition of the WTPC for our target case.

The K-Means Unsupervised Machine Learning method and the K-Nearest Neighbors Machine Learning Algorithm are used in the retrieve step of the case based reasoning cycle to build our power curve model.

Schematically, we can represent our proposed approach as follows refer Figure 3 below:

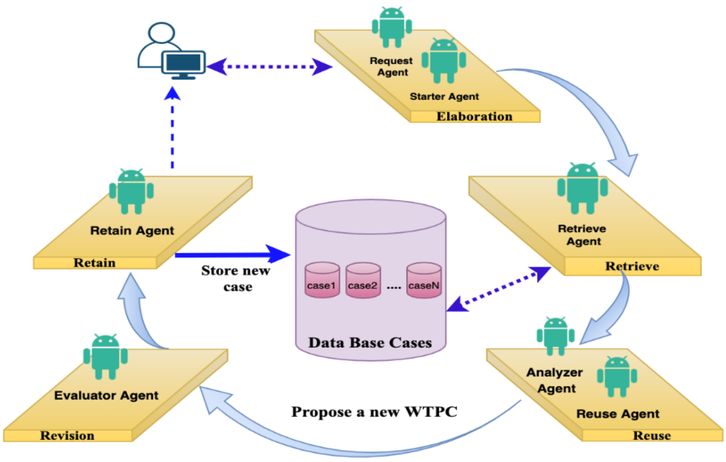

Fig. 3. Architecture of our approach

- Elaboration Layer: The goal of agents of this layer is to manage information collected from the environment and to construct the target case based on the specification of the wind turbine data. The Elaboration layer contains the following agents:
  - Request Agent: This agent establishes the link between the system and the environment. It feeds the system with necessary information and data.
  - Starter Agent: The role of this agent is to clean and process the collected data, construct and initialize the wind turbine target case. This serves to better guide the search for similar cases of our target case.
- Retrieve Layer: The goal of agents of this layer is to compare and retrieve the most similar cases of the target case. The Retrieve layer contains the following agents:
  - The Retrieve agent: The role of this agent is to evaluate and find a set of cases in the data base cases that are judged similar to our target case using similarity measure. To search for similar cases, we used the K-Means Unsupervised Machine Learning method and the K-Nearest Neighbors (KNN) Supervised Machine Learning algorithm.
- Reuse Layer: The agents of this layer aim to adapt and reuse all similar cases to our target case. This layer contains the following agents:
  - Reuse Agent: The reuse agent aims to adapt the solutions proposed by the retrieve agent and reuse them to obtain a new solution for the target case.
  - Analyzer agent: The analyzer agent checks continuously if there is any change in the target case, then this agent asks the starter agent to update the target case. This process will be triggered whenever an update is made to the target case.
- Revision Layer: The goal of the agent of this layer is to evaluate the proposed solution by the reuse agent and verify where is its similarity with our target case is sufficient or not.
- Retain Layer: In this layer, the retain agent retains the validated solution as a new learnt case and store it into the data base cases for future reuse.

4 Results and discussions

4.1 Data processing and presentation

In this section, we test the effectiveness of our approach for the resolution of the power curve modeling problem using the combination of the Machine Learning Algorithms: K-Means method and the KNN algorithm in the retrieve step of the DCBR cycle. Firstable, we apply the K-Means method to partition the dataset into clusters, then we use the KNN algorithm to find the nearest source cases of our wind turbine target case. We define the following elements:

- The number of wind turbine source cases is 67 after the clean of abnormal data.
- To determine an optimal value K of the number of clusters and neighbors, we used the Elbow method which is one of the most popular methods to find this value of k [28].

- Each wind turbine is represented by a vector Casei of characteristics (nominal power, rotor diameter, hub height, power density, power curve wind speed, power curve values).

$$Casei = \begin{pmatrix} n\_power \\ r\_diameter \\ h\_height \\ p\_density \\ pcw\_speed \\ pc\_pow\_value \end{pmatrix} \tag{1}$$

We have grouped our wind turbines in Table 1. Each row of the table presents a source Casei of our data base cases. The Table 2 contains a set of vector values that captures the relationship between wind speed and wind power of power curve for each source case.

Table 1. Parameters of the vector Casei

	Nominal Power	Rotor diameter	Hub height	Power density
1	4200	141	129	269
2	4200	127	135	331
3	3500	101	99	436.8
4	3200	116	122	304.4
5	3050	101	124	380.7
...	…	…	…	…
65	8000	168	104	302
66	7500	127	125	1.69
67	7580	127	127	345

Table 2. Vector values that captures the relationship between wind speed and wind power

	Power Curve Wind Speeds	Power Curve Values
1	[1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, ...]	[0.0, 22.0, 104.0, 260.0, 523.0, 920.0, 1471.0...]
2	[1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, ...]	[0.0, 0.0, 58.0, 185.0, 400.0, 745.0, 1200.0, ...]
3	[1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, ...]	[0.0, 3.0, 37.0, 116.0, 253.0, 469.0, 775.0, 1...]
4	[1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, ...]	[0.0, 3.0, 49.0, 155.0, 339.0, 628.0, 1036.0, ...]
5	[0.0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, …]	[0.0, 0.0, 0.0, 0.0, 3.0, 22.0, 49.0, 92.0, 15...]
...	…	…
65	[1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, ...]	[0.0, 0.0, 0.0, 100.0, 500.0, 1000.0, 2000.0, ...]
66	[0.0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, …]	[0.0, 0.0, 0.0, 0.0, 0.0, 25.0, 55.0, 110.0, 1...]
67	[0.0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, …]	[0.0, 0.0, 0.0, 0.0, 0.0, 25.0, 55.0, 110.0, 1...]

4.2 Combination of the K-Means and the KNN machine learning algorithms

In order to achieve the maximum accuracy of the model, we need to determine the optimal value of k which represents the number of clusters of our data source cases.

The Elbow method [29, 30, 31] is very popular to determine this value of k. After training our model with different values of k using both the training and testing data set, the optimal k value for our model is 3 as shown in the Figure 4.

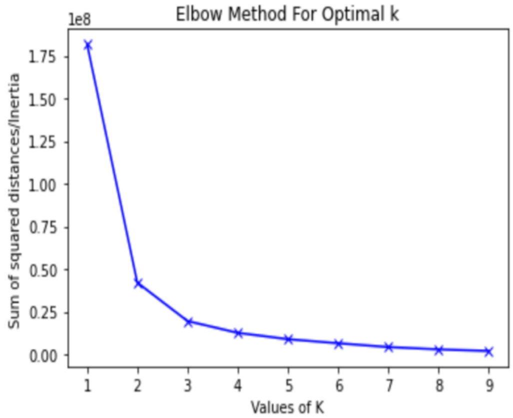

Fig. 4. Error rate vs. K value

We apply the K means algorithm using the optimal value k = 3 of number of clusters. We obtain the result shown in Figure 5 which grouping our cases in three clusters (yellow, purple, green) according to the four parameters presented in Table 1. This figure is generated using matplotlib library [32] and python programming language [33].

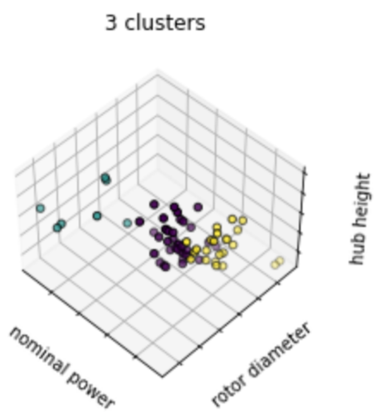

Fig. 5. Partition of cases into three clusters

The optimal value k in this case, represents the number of nearest neighbors in a cluster where our target case belongs to. After applying the Elbow method, the optimal k value for our model is 3 as shown in the Figure 6.

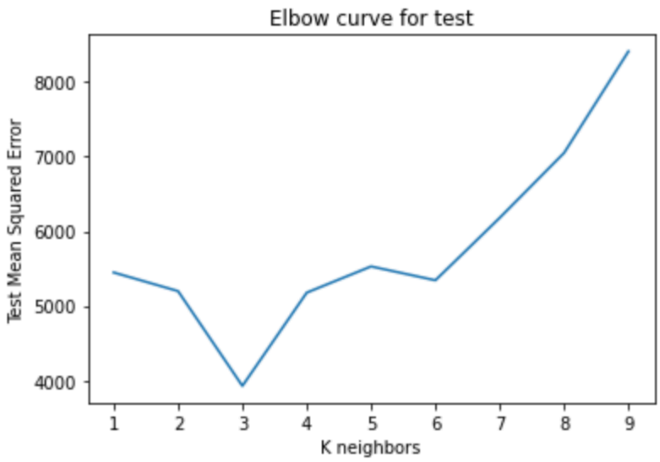

Fig. 6. Error rate vs. K value

We retrain our model using the KNN [34] algorithm for the optimal value k = 3 and on the cluster where our target case belongs to, we get the following result for the three nearest neighbors as shown in Figure 7. Each curve is a function that captures the relationship between the wind speed and the power wind value for all of the obtained nearest neighbors and which represent the most similar source cases for our target case.

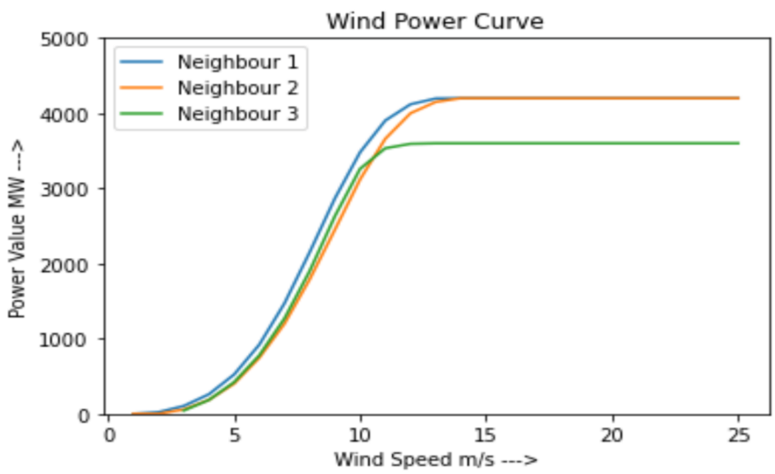

Fig. 7. Wind power curve for the three nearest neighbors

5 Conclusion and perspectives

A hybrid approach of wind turbines power curve modeling has been developed using Multi-Agents System, Dynamic Case Based Reasoning approach and Machine Learning Algorithms (K-Means and KNN) to obtain an accurate model for wind turbine power curve based on the WTPC of similar ones. To enhance the search process, we opted to use the K-means and the KNN Machine Learning Algorithms that have been used in the retrieve step of our DCBR cycle to search for source cases with similar characteristics of our target case. These source cases are first grouped into homogeneous clusters and then sorted on the basis of a feature similarity measure using the K-Nearest Neighbors supervised machine learning algorithm. Finally, a set of WTPC with similar characteristics of the target case are proposed. In this step, a new case has been retained and stored into the data base cases for a future use to solve power curve modeling problem.

Our future work is to test our model on a large dataset of wind turbines that will enrich our database cases, also to increase the number of features in order to get a better accuracy of our model. Finally, we will try to implement our approach on a web based tool using Multi-Agents System.

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