Power extraction efficiency optimization of horizontal-axis wind turbines through optimizing control parameters of yaw control systems using an intelligent method

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HIGHLIGHTS

- Two favorable yaw control systems are developed and optimized.
- Intelligent optimization method is proposed to optimize the potential performance.
- Power extraction efficiency is optimized by 0.32% and 0.8% for two control systems.
- Optimized efficiency under small wind variation is 1.5% more than the large variation one.
- Novel yaw control strategy employing optimized parameters is suggested.

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ABSTRACT

To optimize the power extraction from the wind, horizontal-axis wind turbines are normally manipulated by the yaw control system to track the wind direction. How is the potential power extraction efficiency of such wind turbines related to the parameter optimization of a yaw control system? We intend to answer this question in this study. First, we develop two control systems, a direct measurement-based conventional logic control (Control system 1), and a soft measurement-based advanced model predictive control (Control system 2). Then, a multi-objective Particle Swarm Optimization-based method is introduced to optimize control parameters and search for the Pareto Front, which represents different potential performance. On this basis, result investigation and analysis are carried out on an electrical yaw system of China Ming Yang 1.5 MW wind turbines based on three wind directions with different variations. Experimental results show that, under a large wind direction variation and with a 14% yaw actuator usage, 0.32% and 0.8% more power extraction efficiency are gained by Control system 1 and 2, respectively, after optimization. The achievable power extraction efficiency for the two yaw control systems goes down when the allowable yaw actuator usage is reduced. For instance, when the yaw actuator usage is 14%, 4.9% and 2%, the efficiency is 97.19%, 96.76% and 96.37% for Control system 1, and is 97.73%, 96.76% and 95.45% for Control system 2, respectively. Therefore, Control system 2 takes precedence over Control system 1 for having higher efficiency when the allowable yaw actuator usage is more than 4.9%. We also find that the potential power extraction efficiency of the two control systems is significantly influenced by the wind direction variation, that is, the optimized efficiency under small wind direction variation is 1.5% higher than that under large wind direction variation. In addition, the parameters of Control system 1 need to be re-optimized according to the wind condition, whereas the ones of Control system 2 may not. Finally, a novel yaw control strategy employing the optimized parameters as the query tables is suggested for the real applications.

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1. Introduction

To compete with other types of energy resources, the focus of research today in wind energy field lies in maximizing the power production of wind turbines (WTs) per unit investment. Accordingly, maximum power extraction efficiency (PEE) has been regarded as the primary objective of controlling WTs [1–3]. For a horizontal-axis WT, the maximum PEE is referred to as two aspects [4]: maximizing aerodynamic power coefficient, which is fulfilled through controlling the rotor speed and the pitch angle of WTs according to the wind speed, and minimizing the yaw error, which is achieved through adjusting the nacelle position of WTs to track the wind direction.

In the literature, great research interest has been drawn into the first aspect of maximum PEE, where effective wind speed estimation-based algorithms have been proven effective in providing high efficiency power production [5–7]. By comparison, quite limited efforts have been made towards minimizing the yaw error, which is in the charge of the yaw control system (YCS). The objective of the YCS is to minimize the yaw error with an acceptable yaw actuator usage. Nevertheless, the minimization of yaw error may induce the over usage of the yaw system, because it requires a continuous action of yaw actuator. For industrial WTs, the PEE performance achieved by the YCS is not fulfilled in a satisfactory manner. A study of operating WTs has revealed that the static yaw error is about 10 degree and 5 degree for wind speeds below and above 20 m/s, respectively [8]. In a typical case of Horns Reef wind farm, the potential power loss due to the yaw error is 2.7% [9]. Besides, the over usage of the yaw actuator has frequently occurred in the wind energy industry. The survey of wind power system failures reveals that the yaw failure rate is approximate 12.5% of the whole one [10]. From these results, it is concluded that the YCS should deserve more attention than it received.

Some control methods have been proposed for the YCS, and they directly rely on the measurement devices. Limited by the wind measurement technology, early WTs use the hill climbing control method to activate the yaw system [11,12]. As the development of wind direction sensors, modern WTs employ active yaw control strategies, which are comparably simple and use some predefined logic controls [13–16]. Although the control logic is simple, the difficulty consists in obtaining a precise and real-time control reference from the wind direction measurements which are noticeably disturbed by operation of the WTs [17]. To handle this issue, an averaging filter is widely utilized by the YCS of industrial WTs, but it results in a time delay for the control use. On the other hand, it is hard for the slowly moving nacelle position to track the quickly changing wind direction. Thus, the conventional yaw control methods based on the direct wind direction measurements could not provide sufficient performance. Recently, there has been a growing interest in how the YCS can be further improved using advanced measurement devices [18,19], but the measurement device is very expensive. The cost-effective alternative is the soft measurement-based method, which uses the short-term prediction of wind direction. Despite many efforts towards forecasting approaches relevant to the wind source [20–25], none of them tried to employ the predicted wind data into the control application of WTs. Motivated by above observations, we have proposed a novel yaw control solution using predicted wind directions for maximum PEE of WTs in [26], the structure of which consists of a wind predictive model and a novel model predictive control (MPC) strategy. By comparison to the industrial solution, the proposed one is capable of further reducing yaw error with a modest yaw actuator usage, but the ultimate potential of the PEE as a result of parameter optimization is not quantified and evaluated in the previous study. Indeed, establishing the performance limitations of different control methods through parameter optimization will provide insight to the control method that potentially will offer greater benefit to WTs. In addition, investigating the potential performance of different YCSs can help designers and customers of WTs to select the most suitable YCS according to their needs.

The objective of the present study is to fill the aforementioned knowledge gap and to find the suitable YCS that provides the best achievable performance of the PEE with an acceptable yaw actuator usage. To do this, the conventional control method using the direct wind direction measurement and the advanced MPC method using the predicted wind directions are investigated. Specifically, this study evaluates the control strategy which is detailed in [13–15] and employed by the NREL CART3 (Controls Advanced Research Turbine 3-Bladed) turbine, and the control strategy proposed in [26], both of which use several predefined parameters. Therefore, it is important to carry out an investigation on the potential performance of the two control methods on the basis of parameter optimization. To do this, two YCSs based on these two yaw control methods are developed and optimized to simultaneously achieve two explicit objectives, namely, minimization of power reduction factor caused by the yaw error and minimization of yaw actuator usage during wind direction tracking. In order to address the two-objective issue and the constraints in the automated optimization process, multi-objective optimization method needs to be employed.

Currently, multi-objective optimizations based on Pareto optimal theories have been intensively studied, and some intelligent algorithms have been applied for the WT design. Using multi-objective optimization algorithms, the designers of WTs are able to identify a trade-off curve called Pareto Front that reveals the weakness, anomalies and rewards of certain targets [27]. For a stall regulated horizontal-axis WT design, a genetic diversity evaluation method is introduced to achieve the best trade-off performance between two objectives: maximization of annual energy production per square meter of wind farm, and minimization of cost of energy [28]. For a blade geometry optimization of WT rotors which considers aerodynamics, structures, noise, and cost, an existing computer program named PROPGA based on a genetic-algorithm (GA) is used in [29]. For a WT blade design with the objectives of power coefficient and noise levels under uncertainty, the GA optimization strategy is also used in [30]. For a WT blade design with the objectives of maximum of annual energy production and minimum of blade loads, and for a 5 MW WT blade design taking the maximum power coefficient and the minimum blade mass as the optimization objectives, the non-dominated sorting genetic (NSGA)-II algorithm is employed in [31] and [32], respectively. Recently, the same authors of [32] propose a gradient-based multi-objective evolution algorithm based on uniform decomposition and differential evolution for a 1.5 MW WT blade design [33].

Besides aforementioned intelligent optimization algorithms, Particle swarm optimization (PSO) is recognized as another simple concept algorithm, with easy coding implementation, robustness to control parameters and computational efficiency [34], and it has been proposed to minimize the blade mass of a 1.5 MW WT [35]. Since the PSO strategy was firstly extended for solving multi-objective problems in [36], multi-objective particle swarm optimization (MOPSO) has been widely used in solving multiple-objective optimization problems of renewable energy systems [37,38]. In this work, the MOPSO algorithm is proposed to solve the aforesaid two-objective issue through optimizing the control parameters of two YCSs. On this basis, the potential performance of the PEE provided by the two YCSs is optimized and evaluated, which corresponds to the yaw actuator usage and the control parameters.

The novel contributions of this study can be summarized as follows:

- This is the first study that addresses the achievable performance of the PEE for WTs through optimizing YCS. To our best of knowledge, only a few works have been carried out to propose new control solutions for the YCS of WTs, and none of them evaluates the potential performance of the PEE, which is surely affected by both the yaw actuator usage and the control parameters of the YCS.
- This study investigates the effects of wind direction condition on the potential performance of the YCS for the first time. Because the YCS...
aims to track the wind direction, the conditions of wind direction may have a significant impact on the YCS. However, this important issue is not investigated in the previous work. This study introduces the calculation of wind direction variation and investigates its impacts on the performance of the developed YCSs.

- The intelligent optimization algorithm-based data mining method is introduced to optimize control parameters of the YCS. Despite a great quantity of researches focusing on data-mining-based algorithms relevant to wind resource predictions in the recent years, but few of them draw attentions to the real application, which is actually the most important step of energy application research. It is our belief that the control optimization creates a very occasion where the data-mining methods could find their potential applications.

- A novel yaw control strategy is suggested, which employs the parameter optimization rule obtained from the result analysis. By analysing the obtained results, it is known that the achievable PEE is actually affected by the yaw actuator usage, wind direction condition, and the control parameters of YCSs. Accordingly, the novel yaw control strategy is suggested for the real application, which is able to adjust the control parameter based on the wind condition and the preferred performance.

The remaining sections are arranged as follows: basic information relevant to the YCSs of horizontal-axis turbines is introduced in Section 2. Section 3 proposes the MOPSO-based algorithm and discusses its application into the performance optimization of YCSs. It is followed by method validation and result analysis in Section 4. Finally, the conclusion is presented in Section 5.

2. Yaw control systems of horizontal-axis WTs

2.1. The benchmark turbine and its yaw system

The concerned WTs in this paper are 1.5 MW doubly fed machines with 82 m rotor diameter manufactured by China Ming Yang Wind Power (CMYWP). This type of WTs is horizontal-axis, and theoretically, the wind power $P_{ext}$ can be expressed by the following equations [4]:

$$P_{ext} = \rho A C_p V_e^3 \left( \cos^2(\vartheta_{np}) \right) / 2$$

(1a)

$$V_e = V_0 \cos(\vartheta_{np}) = V_0 \cos(\vartheta_{nd}-\vartheta_{np})$$

(1b)

where $\rho$ is air density; $A_r$ is rotor area; $C_p(\omega_r, V_0, \vartheta)$ is aerodynamic power coefficient relevant to rotor speed $\omega_r$, the free stream wind speed $V_0$, and pitch angle $\beta_v$; $V_e$ is the effective wind speed perpendicular to the rotor plane; and $\vartheta_{np}$ is the yaw error between the wind direction $\vartheta_{nd}$ and nacelle position $\vartheta_{np}$.

From Eq. (1), it is obvious that minimizing $\vartheta_{np}$ plays an important role of maximum PEE of the WT. Thus, the 1.5 MW turbines of CMYWP are equipped with the yaw system. The primary component of the yaw system is a large bearing that connects the main frame (nacelle) to the tower, and the yaw actuator refers to four electrical motors, each of which drives a pinion gear against a bull gear attached to the yaw bearing [39]. Owe to the special structure of the yaw system, the nacelle movement speed (measured by yaw speed) is 0.5 deg/s, which is very slow in comparison with the variation speed of the wind direction. Therefore, to enhance the wind direction tracking capability, the YCS should be properly selected and optimized.

2.2. Performance indexes for evaluating the YCS

Performance of the YCS is referred to as the PEE and the usage of the yaw actuator, which can be evaluated by checking the relevant data of yaw error and the yaw action time, respectively. Although the yaw error can be used to evaluate the wind direction tracking performance, its statistic values, such as mean absolute error and root mean squared error, may be more efficient to evaluate the overall performance within a certain period. Nevertheless, these values of yaw error cannot explicitly show the power extraction capability of YCS, because $P_{ext}$ is represented by a nonlinear relation with $\vartheta_{np}$ as follows:

$$P_{ext} = \rho A C_p V_e^3 \left( \cos^2(\vartheta_{np}) \right) / 2$$

(2)

Although the theoretical result tells $k = 3$, the experimental results have shown different results. This study uses $k = 1.5$, which is estimated by Schepers [40].

To better evaluate the influence of $\vartheta_{np}$ on the PEE of WTs under different YCS, the power reduction factor ($\xi$) is calculated by the following formula

$$\xi = 1 - \sum_{i=1}^{T_e} \left( \cos(\vartheta_{np}(t)) \right)^i / T_e$$

(3)

where $T_e$ is the time interval of evaluation.

The yaw action time ($t_{yaw}$) is expressed as

$$t_{yaw} = \sum_{i=0}^{T_e} (\vartheta_{np}(t) > 0)$$

(4)

where $\vartheta_{np}(t)$ is the yaw speed. In Eq. (4), the yaw action time is increased whenever there is a yaw action.

2.3. Two favorable YCSs

For a typical WT, the operation mechanism of the YCS can be described as follows:

Step 1: the wind wane and nacelle position transducers measure the yaw error and the nacelle position, respectively, and then send them as inputs to the yaw controller;
Step 2: the yaw controller processes the inputs and determines the output for the relays which are used to power on or off the yaw motors;
Step 3: the nacelle is moved by the gears which are driven by yaw motors.

From above steps, it can be known that the performance of the YCS is mainly determined by the control strategy employed. As discussed in the introduction part, there are two favorable types of control strategies recorded in the previous work. Accordingly, two control systems, denoted as Control system 1 and Control system 2, are developed for performance optimization, which are based on [13] and [26], respectively.

2.3.1. Control system 1

The structure of Control system 1 is illustrated in Fig. 1, including two parts: the yaw system (marked as 1) and the yaw controller (marked as 2). The yaw system fulfills the control command and sends measured information to the yaw controller, and accordingly the yaw controller receives the measured inputs and sends out the control command. The strategy employed by the yaw controller can be summarized as follows [13]: $\vartheta_{np}$ is filtered by two low-pass filters, producing a quickly changing measurement ($\vartheta_{flast}$) with a time constant $T_{flast} = 1$s and a slowly changing measurement ($\vartheta_{flow}$) with a time constant $T_{flow} = 60$s, and $\vartheta_{flast}$ is integrated and monitored; when the integrated error (AccErr) reaches the threshold ($Th = 6000$ deg), the yaw angle is moved to the set-point given by $\vartheta_{flow}$.

2.3.2. Control system 2

Similar to Control system 1, Control system 2 also comprises two parts: the yaw system (marked as 1) and the yaw controller (marked as 2). Its structure is illustrated in Fig. 2. This study revises the MPC-based method including predicted wind directions presented in [26] in the following two aspects:
\[ \delta_{\text{pv}}(k + 1|k) = f(\hat{\theta}_{\text{wp}}(k), \hat{\theta}_{\text{wp}}(k+1), \hat{\theta}_{\text{wp}}(k+2), \ldots, \hat{\theta}_{\text{wp}}(k+n)) \]  
(5)

where \( \delta_{\text{wp}}(k) = \hat{\theta}_{\text{wp}}(k) + \hat{\theta}_{\text{wp}}(k) \) is the averaged value of the sampling period.

- Predictive model: the yaw error is the predictive variable and can be formulated as:
\[ \hat{\delta}_{\text{wp}}(k + 1|k) = \delta_{\text{wp}}(k + 1|k) - \hat{\delta}_{\text{wp}}(k) - \hat{\delta}_{\text{wp}}(j)T_c \]  
(6)

where \( T_c \) is the control period; \( \hat{\delta}_{\text{wp}}(j) \) is the permissible action for the next control period and it can be categorized into a finite set as follows:
\[ \hat{\delta}_{\text{wp}}(j) = \begin{cases} -\text{Yawspeed}, & j = 0 \\ \text{Yawspeed}, & j = 1 \\ 0, & j = 2 \end{cases} \]  
(7)

- Quality function (QF): this study aims at minimization of yaw error and yaw actuator usage simultaneously, so QF is formulated as:
\[ QF(j) = w_1(\delta_{\text{wp}}(k + 1|k))^2 + w_2(\hat{\delta}_{\text{wp}}(j)| > 0)T_c \]  
(8)

where \( w_1 \) and \( w_2 \) are the two weighting factors.

- Minimization of QF: the minimization of QF is implemented as a “for” cycle, which predicts the yaw errors in Eq. (6) for the three permissible control actions in Eq. (7), evaluates \( QF(j) \) in Eq. (8), and
stores the minimum value \(QF(\text{min})\). The algorithm can be described in the pseudo code as follows:

\[
\text{Set } QF(\text{min}) \text{ To inf and Set min To inf}
\]

For \(j = 0: 2\)

Calculate \(QF(j)\) Using Eqs. (7–9)

If \(QF(j) < QF(\text{min})\) Set \(QF(\text{min})\) And \(\text{Set min To } j\)

End

Apply \(\hat{\delta}_{\text{opt}}(\text{min})\)

2.4. Summarization of the proposed optimization for the YCS

Performance of the yaw control system is determined both by the structure component, and the control algorithm. Therefore, a comprehensive optimization for the yaw control system requires involving the update of the hardware and software. Nevertheless, the hardware update requires the extra design cost, and thus the control parameters are used for the optimization in this study. In this study, regarding the fact that a wind farm may have certain wind conditions, we collect the historical data of wind direction from the wind farm and use it as the model input of MOPSO algorithm to obtain the optimal performance of YCS. The proposed optimization for the yaw control systems can be summarized in Table 1. In the following section, the detailed optimization method will be elaborated.

3. Performance optimization of YCSs using MOPSO-based method

In this study, the performance index includes two explicit objectives, namely, minimization of power reduction factor and minimization of actuator usage. Therefore, the performance optimization is actually a multi-objective optimization problem (MOP), which is usually formulated as follows

\[
\min \quad F(X) = (f_1(X),...,f_n(X))
\]

s. t. \(X \in S\) \hspace{1cm} (9)

where \(X = (x_1,x_2,...,x_m)^T\) is the decision vector belonging to the non-empty feasible region \(S \subseteq R^n\), and \(F(X)\) is the objective function vector including \(n\) objective functions (denoted as \(f_1(X),...,f_n(X)\)). In MOP, \(F(X)\) is optimal if the components cannot be further improved without deterioration to at least one of the other components. In mathematical terms, \(X^*\) is called non-dominated solution set or Pareto optimal if there is no other vector \(X \in S\) such that \(f_j(X) \leq f_j(X^*)\) for all \(i = 1,2,...,m\) and \(f_j(X) \leq f_j(X^*)\) for at least one \(j\) where \(j = 1,2,...,m\). Accordingly, \(F(X^*)\) is regarded as Pareto Front (PF). Because MOP solutions are vectors which cannot be ordered completely, all the Pareto optimal solutions are equally desirable and the most preferred one needs to be chosen based on the ones’ preference.

Currently, some intelligent evolutionary algorithms have been applied for the WT design [27–35,43–45]. The present work employs the MOPSO method to handle the search for the group of optimal solutions following the principle of Pareto concept. Based on the MOPSO-based method, the potential performance of the two YCSs can be optimized and investigated.

3.1. Performance optimization using data-mining approach based on MOPSO

Fig. 3 illustrates the flowchart of the performance optimization method, which actually is to search the optimal parameters out through iteration simulations using historical data of wind direction as the model input. The procedures can be summarized as follows:

- First, an initial model is created, which includes the historical data of wind direction collected, YCS developed, MOPSO parameters selected, and objective functions defined.
- Subsequently, initial control parameters provided by MOPSO algorithm are used to run simulation test, which is kept running until that the historical data of wind direction is completely run out of.
- After that, each individual in the population is evaluated based on the defined objective functions and constraints.
- The final step is to judge the optimization results based on the stopping principle, namely, reaching the maximum of the iteration time. If the stopping principle is satisfied, the un-dominated solutions are stored as the ultimate optimal solutions; otherwise, the iteration goes on, and the evaluation results are used by MOPSO algorithm, which generates the next generation of control parameters.

3.2. Employed MOPSO algorithm

The PSO algorithm was firstly proposed in [46,47]. In PSO, the algorithm initializes a set of solutions and searches for optimal solutions by updating them throughout population evolution. The set of potential solutions is a set of particle called as a swarm, which moves in the search space with a cooperative operation. The velocity operator performs these movements guided by a local component and a social component based on following equations:

\[
u_{id}(t + 1) = w_{id}(t) + c_1 r_1(p_{id}(t) - x_{id}(t)) + c_2 r_2(p_{gd}(t) - x_{id}(t)) \tag{10a}
\]

\[
x_{id}(t + 1) = x_{id}(t) + v_{id}(t) \tag{10b}
\]

where \(t = 1,2,...,T_{\text{max}}\) is running index of the generation, and \(T_{\text{max}}\) is the maximum number of population; \(t\) is the current generation; \(i = 1,2,...,N_s\) is the running index of particles, and \(N_s\) denotes the population size; \(d = 1,2,...,D\) is the particle dimension and \(D\) denotes the dimension size; \(v_{id}(t)\) represents the velocity of particle \(i\) in the generation of \(t\). Similarly, \(x_{id}(t)\) denotes the particle position. \(p_{id}(t)\) is the individual best position found by particle \(i\) while \(p_{gd}(t)\) is the global best position found so far in the whole swarm; the constants \(c_1, c_2\) are the acceleration coefficients; \(r_1, r_2\) are random values uniformly distributed in \([0,1]\); and \(w\) is the inertia weight given by

\[
w = w_{\text{max}} - (w_{\text{max}} - w_{\text{min}}) * t/T_{\text{max}} \tag{10c}
\]

where \(w_{\text{min}}\) and \(w_{\text{max}}\) are the maximum and minimum inertia weight, respectively.

The main idea of MOPSO algorithm is that the output of PSO is a set of solutions which are named non-dominated solutions or PF. In this study, the Non-dominated Sorting PSO (NSPSO) algorithm, which was proposed in [48], is employed to simultaneously minimize power reduction factor and yaw actuator usage. The main feature of this method is to update each particle by comparing all particles’ personal bests and their offspring in the entire population, and thus, it is effective in

Table 1
Summary of the proposed optimization for the YCS.

<table>
<thead>
<tr>
<th>Control algorithm</th>
<th>Wind measurement</th>
<th>Optimization method</th>
<th>Assumption</th>
<th>Limitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control system 1</td>
<td>Logical control</td>
<td>Normal measurement</td>
<td>MOPSO</td>
<td>A wind farm has certain wind</td>
</tr>
<tr>
<td>Control system 2</td>
<td>Model predictive</td>
<td>Soft measurement</td>
<td></td>
<td>conditions</td>
</tr>
</tbody>
</table>

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providing an appropriate selection pressure to propel the swarm population towards PF. Besides, to maintain a diverse non-dominated solution set, this study employs the crowding distance niching method to select $p_{g(t)}$.

3.3. Objective functions

Since the performance optimization of the YCS aims at minimization of power reduction factor and minimization of actuator usage, the performance index can be used here. Therefore, the first objective function selects the power reduction factor, which is expressed as

\[ f_1(X) = \xi = 1 - \sum_{i=1}^{N} (\cos(\theta_s(s)))^{1.5} / N \]  

(11)

where $N$ is the sampling number of historical data, and $\cos(\theta_s(s))$ is the yaw error at the s th sampling.

The second objective function selects the yaw actuator usage, which can be calculated using yaw action time and expressed as

\[ f_2(X) = t_{yaw}/T_s = \sum_{i=1}^{N} (|\theta_{yaw}(s)| > 0) / N \]  

(12)

From Eq. (12), it is clear that the yaw actuator usage is the ratio of the yaw actuator action time to the evaluation time. For example, the yaw actuator usage is evaluated for each day, the evaluation time will be $T_s = 86400$ s, and the yaw actuator action time can be calculated by second through summing up the yaw actuator is activated (denoted as $|\theta_{yaw}(s)| > 0$).

3.4. Designed variables

Design variables of the YCSs can be categorized as hardware-relevant variables and software-relevant variables. Since hardware-relevant variables, such as the yaw speed, require the hardware update, which may bring about extra cost. Thus in this study, design variables of the YCSs use the software-relevant variables, namely, the control parameters.

For Control system 1, $T_{slow}$ and $Th$ are selected as the designed control parameters from the three control parameters ($T_{fast}$, $T_{slow}$, and $Th$), because $T_{fast}$ and $Th$ are logically relevant. Considering their physical meanings, these two parameters are selected in the following ranges

\[ T_{slow} \in [10s, 600s] \]  
\[ Th \in [10deg, 60,000deg] \]  

(13)

Besides the individual range given by Eq. (13), $T_{slow}$ and $Th$ are constrained as a set by the achievable objective functions

\[ \left\{ \begin{array}{l} f_1(T_{slow}, Th) < 0.1 \\ f_2(T_{slow}, Th) < 0.15 \end{array} \right. \]  

(14)

Based on Eq. (14), the control parameter set $(T_{slow}, Th)$ will be regarded as a dominated solution set and discarded when the power reduction percentage is not less than 10%, or the yaw actuator usage percentage is not less than 15%.

For Control system 2, the MPC-based control strategy uses two control parameters, $w_1$ and $w_2$. Thus, these two parameters are selected as the designed control parameters and their ranges are respectively preselected as

\[ \left\{ \begin{array}{l} w_1 \in [1,100] \\ w_2 \in [1,100] \end{array} \right. \]  

(15)

Similarly, the control parameter set $(w_1, w_2)$ is constrained by

\[ \left\{ \begin{array}{l} f_1(w_1, w_2) < 0.1 \\ f_2(w_1, w_2) < 0.15 \end{array} \right. \]  

(16)

4. Model application and results discussion

The main objective of this section is to demonstrate the capabilities of the proposed method and to investigate the performance results of the two YCSs with different optimization parameters sets. Therefore, the real wind direction data collected by the wind wanes mounted on the nacelle of operating WTs are used, and then the optimization method is implemented based on the procedure illustrated in Fig. 3.

4.1. Model inputs preparation

As illustrated in Fig. 3, the first step of the parameter optimization is to prepare the model inputs, which includes the historical data of wind direction, MOPSO parameters, YCS, and objective functions.

4.1.1. Wind direction data collection

Wind direction data is obtained from a wind farm located in Inner Mongolia of China, which was saved in the supervisory control and data acquisition system per second. Regarding that the wind direction condition may influence the yaw control performance, we select and use the wind direction data of three typical days, which presents different variation degree. Fig. 4(a–c) show the time series of wind direction for these three days.

As shown in Fig. 4, the original time series of wind direction data are mixed with high-frequency noises and some disturbances. Although
these noises and disturbances can be removed by some data processing algorithms, the difference between the original data and the processed data may affect the performance evaluation. Thus, these original data are directly used as the model input.

Table 2 gives the results of wind direction variation ($\delta(\theta_{wd})$) calculated by the following equation:

$$\delta(\theta_{wd}) = \sqrt{\sum_{s=2}^{N} (\theta_{wd}(s) - \theta_{wd}(s-1))^2} / (N-1), N = 86400$$

(17)

4.1.2. MOPSO algorithm parameters
There is no additional parameter required by the employed NSPSO algorithm, and the relative parameters are chosen as follows:

- Population size: $N_p = 100$;
- Maximum number of generation: $T_{max} = 100$;

<table>
<thead>
<tr>
<th>Day</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta(\theta_{wd})$</td>
<td>5.17</td>
<td>4.16</td>
<td>6.54</td>
</tr>
</tbody>
</table>

Fig. 4. Wind direction time series of: (a) Day 1; (b) Day 2; (c) Day 3.
• Acceleration coefficients: $c_1 = 0.8$, and $c_2 = 2.0$;
• Inertia weights: $w_{\text{max}} = 0.9$, and $w_{\text{min}} = 0.4$;

4.2. Results analysis and discussion

As shown in Table 2, the variations of wind direction are 5.17, 4.16, and 6.54 for Day 1, Day 2 and Day 3, respectively. For convenience of investigation, the results based on wind direction data of Day 3 are used for a detailed analysis, which is carried out through investigating performance results of the two YCS using different optimal parameter sets. In addition, the results of the other two days are used for the sensitivity analysis considering the influence of different wind direction conditions.

4.2.1. Potential performance and parameter optimization of the two YCSs

(1) Results of Control system 1

PF shown in Fig. 5 is obtained by carrying out the optimization method with the two objectives discussed in the Section 3.3. Meanwhile, the dominated optimal solutions during searching process are collected together. Besides, the results of the original control design by NREL (denoted as Reference) and four optimal solutions by PF (denoted as Solutions 1, 2, 3, and 4) are drawn for comparison, the details of which are summarized in Table 3.

From Fig. 5, it is observed that PF is essentially the interface between feasible and infeasible zones in the objective space, and the PEE is lifted up at the cost of the yaw actuator usage.

When checking the numerical results in Table 3, Solution 1 has the highest PEE being 97.2% at the highest cost of the yaw actuator usage being 14.68%, while Solution 4 has the lowest efficiency being 96.11% at the lowest expense of the yaw actuator usage being 1.53%. By comparison to Reference with the PEE being 96.88% and the yaw actuator usage being 8.9%, the four optimal solutions show better performance:

• Solution 1, increasing 0.34% of the PEE at the expense of the actuator usage increased by 5.9%;
• Solution 2, increasing 0.15% of the PEE while maintaining the same actuator usage;
• Solution 3, decreasing 2.03% of the actuator usage while maintaining the same PEE;
• Solution 4, decreasing 7.37% of the actuator usage at the cost of the PEE reduced by 0.77%.

Table 3

<table>
<thead>
<tr>
<th></th>
<th>Reference</th>
<th>Solution 1</th>
<th>Solution 2</th>
<th>Solution 3</th>
<th>Solution 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>0.0312</td>
<td>0.0280</td>
<td>0.0297</td>
<td>0.0312</td>
<td>0.0389</td>
</tr>
<tr>
<td>$f_2$</td>
<td>0.0890</td>
<td>0.1468</td>
<td>0.0900</td>
<td>0.0687</td>
<td>0.0153</td>
</tr>
<tr>
<td>$T_{\text{slow}}$</td>
<td>60</td>
<td>19.68</td>
<td>37.16</td>
<td>42.54</td>
<td>311.25</td>
</tr>
<tr>
<td>$T_h$</td>
<td>6000</td>
<td>3546.28</td>
<td>6913.29</td>
<td>11453.19</td>
<td>60,000</td>
</tr>
</tbody>
</table>

Fig. 5. The solutions searched for Control system 1.

Fig. 6. The designed parameter sets searched for Control system 1.

Obviously, the PEE of Control system 1 is enhanced while maintaining the same usage of the yaw actuator. In addition, PF gives a performance reference list from which the investors can select the one according to their own needs.

Fig. 6 presents the distributions of the designed control parameters set ($T_{\text{slow}}, T_h$) and their Pareto optimal which are consistent with the optimal solutions and PF shown in Fig. 5. It is obvious that during the searching process, the sets of the designed control parameters distribute in a wide range which is only constrained by the design space. After iteration, these sets gradually converge to the Pareto optimal, which presents a roughly linear relation between $T_h$ and $T_{\text{slow}}$, that is, $T_h \propto T_{\text{slow}}$. In Fig. 6, the reference set ($T_h = 60,000, T_{\text{slow}} = 60$) is closing to the four sets (denoted as Sets 1, 2, 3, and 4), but it is not Pareto optimal.

To further investigate the rule of parameter optimization, the individual distributions of PF at each designed control parameter of Pareto optimal are presented in Fig. 7. It is noticeable that both of the increments of $T_h$ and $T_{\text{slow}}$ bring down the actuator usage and lift up the power reduction factor. Accordingly, a proper range for $T_h$ and $T_{\text{slow}}$ can be defined. For instance, when $f_1 < 0.36$ and $f_2 < 0.1$ are required, $T_{\text{slow}}$ should be selected in a range of $[33.33, 156.7]$, while $T_h$ in a range of $[6299, 39810]$. More specifically, the Pareto optimal can be selected from the ones corresponding to the selectable solutions contained by the rectangles in Fig. 7(a) and (b).

(2) Results of Control system 2

PF and the optimal solutions during the searching process are collected and shown in Fig. 8. Meanwhile, the results from the original control design (denoted as Reference) and two optimal solutions of PF (denoted as Solutions 1 and 2) are drawn for comparison, the details of which are summarized in Table 4. When investigating the PF points, the same phenomenon in Fig. 5 is found in Fig. 8, that is, the PEE is gained at the cost of the yaw actuator usage. As shown in Table 4, the PEE provided by Solution 1 is 97.73% with the yaw actuator usage being 14.04%, while the one provided by Solution 2 is 95.01% with the yaw actuator usage being 1.58%. By comparison to the results of Control system 1, the PEE of Control system 2 decreases more fast when the yaw actuator usage is brought down.

In Fig. 8, it is interesting to find out a fact that PF and the optimal solutions are superposed at each other, which well justifies that the developed MPC-based strategy is an effective algorithm achieving the multi-objectives by explicitly including them into the quality functions [49]. In this study, the designed control parameters $w_1$ and $w_2$ actually embody the compromise of the two objectives. In this regard, the original design already provides an optimal performance with the results of $f_1 = 0.0307$ and $f_2 = 0.0508$. Nevertheless, other optimal solutions obtained by the optimization method give an insight into the potential performance of Control system 2. In Table 4, comparing to Reference, Solutions 1 lifts up the PEE by 0.8% with the actuator usage increased by 8.96%, whereas Solution 2 brings down the actuator usage by 3.5% with a 1.92% reduced PEE. Based on these data, the investors can easily
select the solutions with regard to their preference.

Fig. 9 presents the distributions of the designed control parameters \( w_1 \) and \( w_2 \) and their Pareto optimal which give results of the optimal solutions and PF shown in Fig. 8. When the feasible parameter sets are limited by the design space of \( \in [1,100] \) and \( \in [1,100] \), they are also affected by the constraint imposed by Eq. (16). During searching process, the invalid parameter sets are discarded. As a result, the valid parameter sets distribute in a special feasible zone, and they gradually converge to the Pareto optimal, which concentrates in a small zone of \( \in [1,2.8] \) and \( \in [7,67] \). Obviously, the original parameter set \((w_1 = 1, w_2 = 14)\) locates inside the optimal range.

To further check the distribution of the optimal parameters, the individual distributions of PF at \( w_1 \) and \( w_2 \) of Pareto optimal are presented in Fig. 10. It is noticed that \( w_1 \) has an intensively dense distribution within \([1,2.2]\), whereas \( w_2 \) has a loose distribution. The increment of \( w_2 \) within \([8,40]\) decreases the actuator usage from 14% to 0.8% and increases the power reduction factor from 2% to 10%. Comparing to the parameter selection for control system 1, the selection principle of \( w_1 \) and \( w_2 \) becomes explicit, that is, by fixing \( w_1 \) at 1, increase \( w_2 \) from 8 by step, and select the one that provides favorable performance. This principle is well consistent with the guidelines for weighting factors design in MPC-based method introduced by [50].

4.2.2. Performance comparison between the two YCSs

Performance of the two YCSs is compared based on PF obtained by the optimization method. Fig. 11 presents PF of the two YCSs, from which it is clear that the potential performance is different for the two YCSs. To clarify this issue, three optimal solutions are drawn in Fig. 11 and their numeric results are summarized in Table 5. In Fig. 11, Control systems 1 and 2 are abbreviated as Con1 and Con2, respectively.

From Fig. 11 and Table 5, it is noticeable that Solution 2 \((f_1 = 0.0324, f_2 = 0.049)\) is the division determining the better control
When more than 4.9% of the yaw actuator usage is allowable, Control system 2 has a high PEE ranging in [96.76%, 97.73%], while Control system 1 has a low one in a range of [96.76%, 97.19%].

Otherwise, Control system 1 has a high PEE between [96.37%, 96.76%], while Control system 2 has a low one of [95.45%, 96.76%].

Therefore, considering the primary objective of the YCS, Control system 2 is a good choice for its high PEE of within an acceptable yaw actuator usage [4.9%, 14%]. When a 14% yaw actuator usage is permitted, Control system 2 can extract more wind power by 0.54% than its counterpart.

4.2.3. Sensitivity analysis

In this section, a sensitivity analysis is performed to investigate the effects of wind direction condition on the potential performance of the two YCSs. For this purpose, the results of PF using the wind direction data of Day 1 and Day 2 are presented in Fig. 12, together with the ones of Day 3.

In Fig. 12, there is an obvious phenomenon that when the wind direction variation decreases, all PF curves are moving from right side to left side:

- When the wind direction variation $\delta(\theta_{wd})$ decreases from 6.54 of Day 3 to 5.17 of Day 1, approximate 1% of the PEE is increased for both YCSs, while maintaining the same yaw actuator usage;
- When the wind direction variation $\delta(\theta_{wd})$ is further decreased to 4.16 of Day 2, another 0.5% of the PEE is gained for both YCSs, while maintaining the same yaw actuator usage.

The fact that the small wind direction variation improves the overall

<table>
<thead>
<tr>
<th>Solution 1</th>
<th>Solution 2</th>
<th>Solution 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control system 1</td>
<td>($f_1 = 0.0281, f_2 = 0.14$)</td>
<td>($f_1 = 0.0324, f_2 = 0.049$)</td>
</tr>
<tr>
<td>Control system 2</td>
<td>($f_1 = 0.0227, f_2 = 0.14$)</td>
<td>($f_1 = 0.0363, f_2 = 0.02$)</td>
</tr>
</tbody>
</table>

 performance is reasonable, because it is easier for the YCS to track the wind direction with less variation. When the wind direction variation presents a significant effect on the PEE of the two YCSs, it is worth mentioning that this type of effect does not change the result of performance comparison discussed in the last section. That is, the PEE of Control system 2 is higher than the one of Control system 1, when the yaw actuator usage is higher than the division, the value of which is slightly decreased from 4.9% to 4.3% caused by the lowered wind direction variation. Therefore, it can be concluded that under different wind conditions, Control system 2 is always a good choice for having high PEE when the yaw actuator usage is allowed more than 5%.

Another aspect of sensitivity analysis is to investigate the effectiveness of the optimized parameters under different wind direction conditions. To do this, the optimized control parameters of Day 1 are used to obtain their performance results for Day 1 and Day 2, which are drawn in Fig. 12 and summarized in Table 6. It has been clear that the performance under these parameters is improved, which is induced by the smaller variation of wind direction. Nevertheless, the performance results of Control system 1 using the designed control parameters optimized in Day 3 deviate from the PF curves of Days 2 and 3, whereas the ones of Control system 2 are not. It means that when the wind direction condition changes, the optimization parameters of Control system 1 need to be re-optimized, whereas the optimization parameters of control system 2 are re-useable. This advantage of Control system 2 again justifies that the developed MPC-based strategy is an effective algorithm which achieves the two objectives in an optimal way.

5. Novel yaw control strategy including optimized parameters

In the above section, we have obtained the optimized parameters sets which correspond to three wind direction conditions and different operational performance. To implement the optimized parameters in the control system, we suggest a novel yaw control strategy, which is illustrated in Fig. 13.

In Fig. 13, the novel yaw control strategy comprises the parameter optimization module (denoted as 1), and the normal yaw control algorithm module (denoted as 2). For the parameter optimization module, there are three inputs: the sampled wind direction used by the wind class clarification block to output its variation class n, the preferred yaw actuator usage and the preferred power reduction factor determining the optimal parameters which are obtained from the query table n (1 ≤ n ≤ N). Accordingly, there are N query tables to be predefined which correspond to the N types of wind direction variation class. For instance, we can define 3 query tables using the obtained optimal results based on the three typical wind direction data. However, it is worth mentioning that the parameter optimization obtained from 3 query tables may only provide a preliminary optimization, because the 3 types of wind class may not fully represent the whole characteristics of wind conditions in the wind farm. To achieve a satisfactory performance for WTns in a specific wind farm, a detailed procedure of the parameter optimization implementation is given as follows:

- First, collect the historical wind direction data as much as possible, and sort it out according to its variation class.
- Subsequently, run the MOPSO algorithm and search out the optimal results for each different class of wind direction variations.
- After that, create N query tables using the obtained optimal results.
- Finally, implement the parameter optimization module in the novel yaw control strategy.

6. Conclusions and future work

This paper has presented the novel study investigating the achievable performance of power extraction efficiency for wind turbines under two yaw control systems with different yaw actuator usages, which has been achieved with the help of historical data of wind direction as model inputs and multi-objective Particle Swarm Optimization as the intelligent optimization algorithm. The investigated yaw control systems have employed two favorable types of yaw control strategies, one with normal measurements and the other with soft measurements. The proposed intelligent algorithm has provided the Pareto Front of the two conflicting objectives, minimization of power reduction factor and minimization of yaw actuator usage, from which the results using real wind direction data has been evaluated and can be summarized as follows:

- The two yaw control systems result in different achievable power extraction efficiency of wind turbines. Under the large wind direction variation being 6.54 and with a 14% usage of the yaw actuator, the achievable power extraction efficiency of Control system 2 is 97.73%, which is 0.54% over the one with Control system 1. Therefore, Control system 2 is the good candidate for its favorable power extraction efficiency performance when considering the primary control objective of wind turbines.
- The achievable power extraction efficiency of wind turbines under the two yaw control systems becomes worse when the yaw actuator usage is brought down. In the case of the large wind direction variation, when the yaw actuator usage is decreased from 14% to 2%, achievable power extraction efficiency with Control system 1 is reduced by 0.82%, whereas the one with Control system 2 is lowered by 2.28%.
- Wind direction condition has a significant influence on the

Table 6

<table>
<thead>
<tr>
<th>Parameter set</th>
<th>Performance on Day 1</th>
<th>Performance on Day 2</th>
<th>Performance on Day 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control system 1</td>
<td>(19.68, 3546.28) (0.0199, 0.1012)</td>
<td>(0.0144, 0.0739) (0.0280, 0.1468)</td>
<td>(0.0280, 0.1468)</td>
</tr>
<tr>
<td></td>
<td>(37.16, 6913.29) (0.0203, 0.0514)</td>
<td>(0.0144, 0.0374) (0.0297, 0.0900)</td>
<td>(0.0297, 0.0900)</td>
</tr>
<tr>
<td></td>
<td>(42.54, 11453.19) (0.0209, 0.0358)</td>
<td>(0.0155, 0.0270) (0.0312, 0.0687)</td>
<td>(0.0312, 0.0687)</td>
</tr>
<tr>
<td></td>
<td>(311.25, 60,000) (0.0255, 0.0094)</td>
<td>(0.0179, 0.0060) (0.0389, 0.0153)</td>
<td>(0.0389, 0.0153)</td>
</tr>
<tr>
<td></td>
<td>(42.54, 11453.19) (0.0209, 0.0358)</td>
<td>(0.0179, 0.0060) (0.0389, 0.0153)</td>
<td>(0.0389, 0.0153)</td>
</tr>
<tr>
<td>Control system 2</td>
<td>(1, 14) (0.0238, 0.0263)</td>
<td>(0.0188, 0.0148) (0.0307, 0.0508)</td>
<td>(0.0307, 0.0508)</td>
</tr>
<tr>
<td></td>
<td>(1.82, 12.26) (0.0165, 0.1209)</td>
<td>(0.0119, 0.0773) (0.0227, 0.1404)</td>
<td>(0.0227, 0.1404)</td>
</tr>
<tr>
<td></td>
<td>(1.15, 26.69) (0.0424, 0.0059)</td>
<td>(0.0429, 0.0060) (0.0499, 0.0158)</td>
<td>(0.0499, 0.0158)</td>
</tr>
</tbody>
</table>
achievable power extraction efficiency for WTs under the two yaw control systems. Compared to the one under the wind direction variation being 6.5%, achievable power extraction efficiency under smaller wind direction variation being 5.17 and 4.16, is lifted up by approximately 1.0% and 1.5%, respectively, while maintaining the same actuator usage.

- The achievable performance of wind turbines can be predefined through selecting suitable optimized parameters with the proposed optimized method, but the optimal parameters of Control system 1 need to be re-optimized according to the wind direction condition. Thus, the developed model predictive control strategy employed by Control system 2 outperforms the conventional yaw control strategy employed by Control system 1 in the aspect of parameter tuning complexity.

Based on the above investigation results, we convince that the designers and customers of wind turbines can choose the proper yaw control system.

Finally, we have suggested a novel yaw control strategy which is able to adjust the parameter according to the wind direction condition and the preferred performance. In our future work, the novel yaw control strategy will be implemented in the industrial turbines to test its effectiveness and to improve its performance.

Acknowledgments

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