Data-Driven PID Controller of Wind Turbine Systems Using Memory-based Smoothed Functional Algorithm

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***Abstract*— Stochastic nature of wind speed and turbulence generated between turbines are commone factors that cause stress in wind turbine. Hence, it is important to regulate the rotor speed of wind turbine based on the desired reference speed. Consequently, employing a PID-based controller is crucial for maintaining wind turbine system performance. Recently, there has been a growing interest in utilizing better optimization tools to tune the PID control parameters, providing an advantage in enhancing wind turbine system output response while maintaining the robustness and simplicity of PID controller. However, existing optimization tools for tuning PID controllers, particularly those based on multi-agent optimization, often involve a large number of function evaluations (NFE), resulting in high computational burdens. This study introduces a novel approach using a memory-based smoothed functional algorithm (MSFA) to tune the PID controller in wind turbine systems. The MSFA, which is in the class of single-agent based optimization techniques, requires fewer number of function evaluations per iteration, addressing the computational burden issue. Simulation analyses, encompassing the fitness function convergence curve, step response time specification analysis, Bode plot stability analysis, and computational effort analysis based on NFE, are performed to evaluate the effectiveness of the suggested PID controller for wind turbine systems based on MSFA. The results indicate that the proposed MSFA-based PID controller is highly effective in producing better integral absolute error (IAE) with less values of NFE in comparison with other existing based methods.**

Keywords*— *PID tuning, computational effort, single-agent optimizer, high control accuracy.

I. Introduction

The expanding global population and the subsequent rise in electricity demand pose an increased risk of depleting natural resources. However, there is a growing interest in renewable energy solutions to address this challenge [1]. Wind energy systems, emerging as significant contributors to electricity generation, employ diverse electrical machines, including induction machines with wound-rotor or cage-type rotor, and synchronous or double stator permanent magnet machines [2-3]. Modeling the dynamics of wind turbine energy generation systems often adopts a two-mass system approach due to its versatility in accommodating controllers suitable for various turbine sizes. This model incorporates the flexibility of wind turbines, accounting for modes present within it. Stresses in wind turbines originate from factors like wind fluctuations and excessive overshoot. The coupling of the wind turbine and generator through a gearbox, connecting them via two shafts, causes speed fluctuations to transfer to the generator. Consequently, effective speed control of two-mass wind turbines becomes crucial in mitigating rotor speed fluctuations and minimizing high overshoot [4].

So far, there are numerous control schemes that have been proposed to control wind turbines as well as the series of turbines in wind farm in handling the stochastic nature of the wind turbulence. For the case of series of turbines in wind farm, many researchers have been focusing on controlling the individual controller of wind turbine by tuning its axial induction factor such that the total power production of the wind farm is increased. In this context, a variety of optimization tools were employed to adjust the control parameters of each turbine, aiming to maximize power production, such as game theoretic approach [5], random search method [6-7], sine cosine algorithm [8], grey wolf optimizer [9], Bayesian ascent algorithm [10], reinforcement learning [11-12]. On the other hand, there are also research works focusing on improving the performance of standalone turbine with the aim of producing effective wind turbine rotation speed while mitigating the rotor speed fluctuations due to stochastic nature of wind speed. In [13], they have

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utilized the PID and fractional order PID (FOPID) controllers to track the desired wind turbine's speed based on the model of two-mass wind turbine. It is shown that the artificial bee colony (ABC)-based PID controller provides better control performance than the particle swarm optimization (PSO)-based PID controller and the flower pollination algorithm (FPA)-based PID controller. They also verified that the FOPID controller can produce better control performance than the optimized PID controller. Based on the same two-mass model, researchers in [14], have applied the genetic algorithm (GA), multi-objective GA (MOGA) and PSO to tune the FOPID controller. They have shown that the MOGA-based FOPID controller can provide better control performance than other existing based methods.

Based on the reported works above, many researchers consider population based optimization methods to find the optimal controllers either in wind farm or standalone wind turbine cases. While optimization-based methods can produce optimal controller parameters, the tuning process demands substantial computational resources. This is attributed to iteration computation times being proportional to the number of agents, resulting in escalated computational requirements for achieving the optimal controller. Consequently, relying on population-based optimization methods might not be a prudent choice, necessitating the exploration of alternative tuning strategies to alleviate computational burdens.

Meanwhile, a memory-based smoothed functional algorithm (MSFA), categorized as a single agent-based optimization method, emerges as a promising optimization tool due to its capacity for minimizing computational efforts in fine-tuning the controller of the wind turbine system. The MSFA is an efficient local search algorithm that integrates the merits of gradient approximation method. In addition, the MSFA is able to get away from suboptimal solutions by incorporating the random operators and memory function. Moreover, it has been proven in [15] that the MSFA can obtain better fitness function accuracy than other population based methods including sine cosine algorithm (SCA), chaotic ant swarm (CAS), and particle swarm optimization (PSO) in tuning the fractional order PID control of AVR system. Hence, it is worth applying MSFA for tuning the PID controller of wind turbine system as well. This paper presents the application of MSFA in finding the optimal PID controller of wind turbine systems. In particular, the MSFA-based framework in tuning the control parameters (K_p, K_i and K_d) is explained. Here, the integral absolute error (IAE) is used as a fitness function such that the wind turbine can track the given desired speed while mitigating the rotor speed fluctuations. In addition, the number of function evaluation (NFE) analysis is also provided to indicate that the proposed MSFA-based method can produce faster and optimal PID controller tuning than other well-known optimization tools, such as PSO-PID [13], ABC-PID [13] and FPA-PID [13] controllers. In addition, the stability analysis of the closed-loop control using Bode plot is also provided.

The organization of the paper is as follows: Section 1 presents the evolution of data-driven optimization tools of control parameters for wind turbine systems. Section 2 describes the problem formulation of the PID controller for the wind turbine system. Section 3 explains the MSFA and its procedure to apply to tune the PID controller of the wind turbine system. Section 4 provides the simulation results and performance analysis, expressed in terms of Integral of Absolute Error (IAE) and Number of Function Evaluations (NFE). Section 5 summarizes the conclusions drawn from this study.

II. PID Controller of Wind Turbine System

The control system block diagram of wind turbine system with PID controller is shown in Fig. 1. The aim is to regulate the rotor speed of the wind turbine according to the desired input reference speed considering load uncertainty and any possible disturbances. The typical representation for the dynamics of a wind turbine involves a two-mass model, as described in [16]. This modeling approach is advantageous due to its general applicability, allowing controllers designed for this model to be suitable for wind turbines of various sizes. The transfer function of the wind turbine two-mass system is formulated as follow [16]:

$$G(s) = \frac{n_g^2 J_g s^2 + B_{ls} s + K_{ls}}{n_g^2 J_t J_g s^3 + B_{ls}\left(J_t + n_g^2 J_g\right) s^2 + K_{ls}\left(J_t + n_g^2 J_g\right) s}. \quad (1)$$

The coefficients of the above model are tabulated in Table I. The detailed derivation of the above transfer function is omitted in this paper due to limited space. Please refer [16] for the detail derivation of the mathematical model.

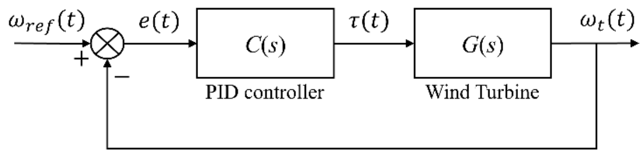

Fig. 1. Closed-lood PID control block diagram of wind turbine system.

TABLE I. THE COEFFICIENT OF WIND TURBINE SYSTEM.

Coefficients	Symbols and values
Air density	$\rho = 1.29$ kg/m^3
Turbine radius	$R = 21.65$ m
Gearbox ratio	$n_g = 43.165$
Turbine inertia	$J_t = 3.25 \times 10^5$ kgm^2
Generator inertia	$J_g = 34.4$ kgm^2
Turbine external damping	$K_t = 0$
Generator external damping	$K_g = 0$
Shaft stiffness	$K_{ls} = 2.691 \times 10^5$ Nm/rad
Shaft damping	$B_{ls} = 9500$ Nm/rad/s
Electromagnetic torque	$K_1 = 0.1082, K_2 = 0.2147$

The operation of wind turbine system is based on the basis of feedback error between actual output of wind turbine's rotor speed $\omega_t(t)$ signal and desired rotor speed $\omega_{ref}(t)$ signal. Particularly, the calculation of error rotor speed $e(t)$ is computed based on the disparity between $\omega_t(t)$ and $\omega_{ref}(t)$. The measured error voltage $e(t)$ is then fed through the PID controller to reduce the total error as well as achieves the desired tracking of the referenced rotor speed. The output from the PID controller is represented as torque $\tau(t)$ to regulate the rotor speed of the wind turbine. The PID controller expression is represented as follows

$$C(s) = \left(K_p + \frac{K_i}{s} + K_d \frac{s}{Ns+1}\right) \quad (2)$$

with three main parameters of K_p gain, K_i gain, and K_d gain, which are the main tuning parameter. Meanwhile, the filter coefficient N is fixed to 0.001. After achieving satisfactory PID controller results, ongoing debate surrounds its suitability for wind turbines due to significant computational effort for optimal parameters. Investigating refined, computationally efficient PID control is essential.

III. PID Control Tuning based on MSFA

This section presents the implementation of MSFA to tune the PID controller of wind turbine system in Fig.1. Firstly, a brief explanation of MSFA is presented. Then, a framework to apply MSFA to tune the PID controller of wind turbine system is demonstrated by incorporating the design parameter and fitness function in the MSFA with PID parameters and IAE, respectively, for wind turbine control problem.

Let the minimization problem is denoted as

$$\min_{x \in R^n} L(x) \tag{3}$$

where $L(x)$ is a fitness function and its corresponding design parameter is defined as a vector x. Then, the updated design parameter of the MSFA, which is taken from [9] is given by:

$$x(k+1) = x(k) - a(k) g(x(k), r(k)) \tag{4}$$

for $k = 1, 2, \dots, k_{max}$, where k_{max} is maximum iterations. In Eq. (4), $a(k)$ is a gain sequence such that $a(k+1) < a(k)$ as $k \to \infty$, $r(k)$ is random perturbation vector, and the function g is a gradient approximation function given by

$$g(x(k), r(k)) = \begin{bmatrix} \frac{r_1(k)}{2c(k)} (L(x_+) - L(x_-)) \\ \vdots \\ \frac{r_n(k)}{2c(k)} (L(x_+) - L(x_-)) \end{bmatrix} \tag{5}$$

where $x_+ = x(k) + c(k) r(k)$, $x_- = x(k) - c(k) r(k)$ and $c(k)$ is another gain sequence such that $c(k+1) < c(k)$ as $k \to \infty$. In [15], it's demonstrated that incorporating a memory function into the original Smoothed Functional Algorithm (SFA) resolves unstable convergence, and enhancing accuracy. For the sake of simplifying the explanation, let $\bar{x}$ and $\bar{L}$ be the current best design parameter and the current best fitness function, respectively. Particularly, the current best fitness function and its corresponding design parameter are obtained or restored as $\bar{L} = L(x(k+1))$ and $\bar{x} = x(k+1)$, when the condition $L(x(k+1)) < L(x(k))$ is achieved. The detail explanation on how the memory function can improve the original SFA is reported in [15]. The main pseudocode of the MSFA is given in **Algorithm 1** [15].

Algorithm 1: Memory-based SFA [15]

1: Initialize $a(k)$, $c(k)$ and $x(0)$.
2: Calculate $L(x(0))$ and let $\bar{x} = x(0)$ and $\bar{L} = L(\bar{x})$.
3: **for** $(k = 1\ to\ k_{max})$ **do**
4: Update $a(k)$ and $c(k)$
5: Execute updated equation in Eq. (4)
6: Calculate $L(x(k+1))$
7: **if** $L(x(k+1)) < \bar{L}$
8: Update $\bar{x} = x(k+1)$ and $\bar{L} = L(\bar{x})$
9: **end if**
10: $k = k + 1$
11: **end for**

In order to apply the MSFA for PID controller tuning of wind turbine system, an appropriate data-driven control framework is required. Particularly, the MSFA is applied as a data-driven tool to fine tune the PID control parameters based on the available input and output data such that a predetermined fitness function is minimized. Here, the fitness function is selected based on the integral absolute error (IAE), which is given as follows:

$$\text{IAE} = \int_0^{t_f} |e(t)| dt \tag{6}$$

where t_f is a final time and $e(t)$ is the error signal. Finally, the procedure to apply MSFA-based method is given as follows:

Step 1: Let $x_1 = \log K_p$, $x_2 = \log K_i$, $x_3 = \log K_d$ and select an appropriate initial values of PID parameters.

Step 2: Execute **Algorithm 1** by relating fitness function of the problem in Eq. (6) with the fitness function of MSFA (i.e., L = IAE).

Step 3: After maximum iterations $k_{\max}$, record the optimum PID control parameters $[K_p\ \ K_i\ \ K_d] = [10^{\bar{x}_1}\ 10^{\bar{x}_2}\ 10^{\bar{x}_3}]$ and its corresponding IAE.

In Step 1, the logarithmic scale is used for each design parameter to accelerate the searching exploration.

IV. Simulation Results

The effectiveness of the proposed MSFA-based method in tuning the PID control parameters of wind turbine system is evaluated in this section. The analysis of time response specifications, the accuracy of IAE and the resultant NFE are conducted in this paper and those analyses are compared between the MSFA-based method with other existing based methods, which are PSO-PID [13], ABC-PID [13] and FPA-PID [13]. Note that the NFE for the multi-agent based optimization methods is calculated based on the multiplication of the population size and the maximum number of iterations.

The simulation was conducted utilizing MATLAB/Simulink version 8.3.0.532 (R2014a) on a personal computer equipped with an 8 GB RAM and a 2.8 GHz Intel® Core i7 processor. In the execution of the proposed MSFA-based method, the maximum iterations is set as $k_{\max} = 400$. Note that although the maximum iterations is quite higher than other existing based methods, it only provides 1200 NFE, where only three fitness functions are evaluated per iteration. Here, two fitness function evaluations are executed in Step 5 and one fitness function execution in Step 6 of **Algorithm 1**. Next, we set the gains $a(k) = 2.5/(k+25)^{0.602}$, $c(k) = 0.25/(k+1)^{0.1}$, the lower bound $l_b = -10$, the upper bound $u_b = 10$ and the initial values of PID control parameters $K_p = 10, K_i = 10, K_d = 10$. Note that the selection of the initial values of PID control parameters are within the l_b and u_b bounds, without any advance knowledge of optimum PID control parameters. Furthermore, $\omega_{ref}(t)$ is adopted based on a unit step function with $t_f = 5$ seconds and sampling time is set as 0.001 seconds.

TABLE II. OPTIMAL PID CONTROLLER PARAMATERS AND ITS CORRESPONDING TRANSIENT RESPONSE ANALYSIS.

Type of controllers	K_p	K_i	K_d	T_s (s)	T_r (s)	M_p	IAE	NFE
PSO-PID [13]	10E7	10E3	0	0.0131	7.2E-3	7.97E-7	4.4223	2500
ABC-PID [13]	9.389E7	9.262E6	136.753	0.014	7.6E-3	9.8E-3	5.7352	2500
FPA-PID [13]	10E7	10E3	0	0.0131	7.2E-3	7.97E-7	4.4223	2500
Proposed MSFA-PID	10E10	1.004E-10	1.002E-10	**1.27E-4**	**7.14E-5**	**0**	**1.0065**	**1200**

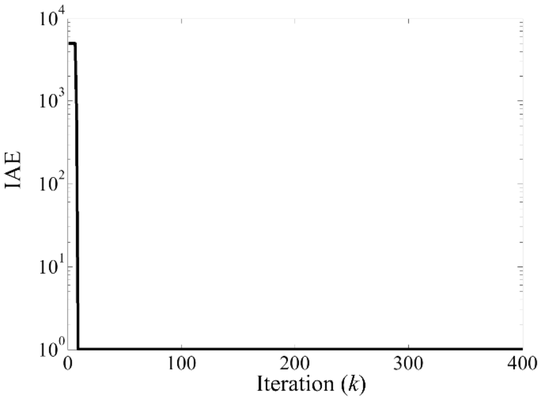

Fig. 2. Respose of convergence of the IAE using MSFA-based method.

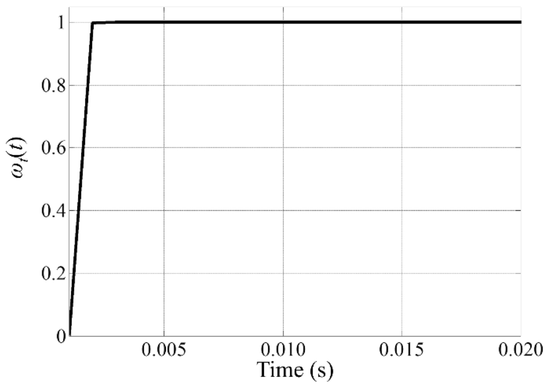

Fig. 3. Responses of the rotor speed of wind turbine.

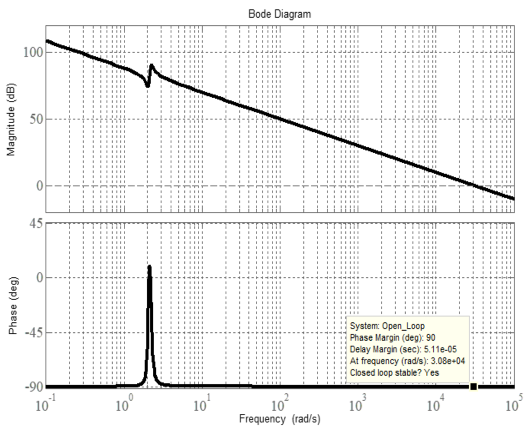

Fig. 4. Responses of the bode plot.

Fig. 2 shows the response of the fitness function convergence after 400 iterations for the MSFA-based method to produce the optimum PID controller parameters, as presented in Table 2. The convergence curve in Fig. 2 shows that despite being a single-agent-based method, the MSFA-based approach exhibits an accelerated convergence rate, reaching a fitness function value of 1.0065 by the 9th iteration..

The rotor speed of wind turbine response producedy by the MSFA-based PID controller is shown in Fig. 3. It can be observed that the proposed MSFA-based PID controller is able to exhibits fast reponse with minmum overshoot. These observations are supported with the tabulated transient response data in Table II, where the proposed MSFA-based PID controller produces settling time $T_s = 1.27$E-4 s and maximum overshoot $M_p = 1.000$, which are the lowest amongst compared algorithms. In addition, the lowest settling time and maximum overshoot thus help the MSFA-based PID controller to produce the lowest resultant IAE in comparison to PSO-PID, ABC-PID and FPA-PID controllers. From Table II, the total NFE performance between the MSFA-based PID controller and all the compared algorithms are also tabulated. In this context, the justification is provided that the MSFA-based PID controller can yield an optimal PID controller with nearly half the NFE compared to other algorithms, thereby confirming its capability to reduce computational effort significantly. In the meantime, to justify the stability of the closed-loop system of the MSFA-based PID controller of wind turbine system, the Bode plot of the open-loop system is provided in Fig. 4. Here, it is shown that the phase margin obtained by the MSFA-based PID controller are 90 degree at 3.08E4 rad/s, respectively, thus verify that the closed-loop MSFA-based PID controller of wind turbine system is stable.

V. CONCLUSION

In this paper, a novel search algorithm based on memory-based smoothed functional algorithm has been utilized for PID control tuning of wind turbine system. The main findings of this study is to justify that the MSFA-based method is effective in providing optimal PID control parameters with less number of function evaluations, thus reducing the computational burdens produced by many of multi-agent optimization based methods. The significant outcomes of the proposed method have been shown through the less IAE and NFE, while retain a stable closed-loop system in comparison with other well-known based methods in tuning the PID controller of wind turbine system. In the future, further analysis of MSFA-based method for tuning the PID controller will be explored in terms of the statistical analysis of the IAE and other error based control performance (i.e., integral square error, integral time multiply absolute error etc.), trajectory tracking analysis, root-locus analysis, disturbance and noise analyses, and uncertainty analysis. Further comparison with other variants of PID controller such as BELBIC PID sigmoid PID, and PIDD controllers will be conducted to justify its effectiveness in providing better IAE with less values of NFE.

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