

Coordinated optimization on energy capture and torque fluctuation of wind turbines via variable weight NMPC with fuzzy regulator

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HIGHLIGHTS

- Fuzzy regulator considering average wind speed and turbulence intensity.
- Membership functions of fuzzy regulator are optimized by IMMPA.
- Fuzzy regulator dynamically updates the weight coefficient of cost function.
- Coordinated optimization of energy capture and generator torque by fuzzy regulator.

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ABSTRACT

The main challenge in improving energy harvest faced by modern large-scale wind turbines (WTs) comes from the fact that the blade rotor with the large inertia having a slow response impedes the optimal tip speed ratio tracking. On the premise that the future wind speed can be accurately predicted, nonlinear model predictive control (NMPC) can effectively improve the energy harvest efficiency of large WTs, but it is difficult to maximize the energy capture and minimize the torque fluctuation of the generator simultaneously. In this study, a fuzzy regulator is designed to update the weight coefficient of the cost function, and an improved multi-objective marine predator algorithm (IMMPPA) is proposed to optimize the fuzzy regulator, so it is realized the coordinated optimization on energy capture and generator torque fluctuation. Specifically, based on the analysis of the performance of NMPC with fixed weight coefficient under different wind conditions, a basic fuzzy regulator is designed to adjust the weight coefficient according to the characteristics of wind conditions, and four groups of candidate inputs are defined. In order to fully explore the potential of the fuzzy regulator, IMMPPA is used to optimize the membership function of the fuzzy regulator. Finally, the variable weight coefficient is used as the input of NMPC to update the objective function in real time. The simulation results show that compared with the one with the fixed weight coefficient, the NMPC controller using the variable weight improves the energy capture by 1.77% while reducing the generator torque fluctuation by 0.126%. Taking the concerned 1.5 MW WT as an example, the variable-weight NMPC could boost its annual energy production by 35842.5 kWh in comparison with the fixed-weight counterpart, showing its promising role in reducing the production cost for the WTs.

1. Introduction

The increase of energy demand and the deterioration of global environment promote the rapid development of renewable energy [1,2]. Wind energy is one of the most attractive renewable energies with

global, renewable and environment friendly characteristics [3–5]. Wind turbines (WTs) capture wind energy and turn it into electricity [6,7]. WTs operate in three zones depending on wind speed. When the wind speed is below the rated wind speed, WTs are operated with partial power output in the charge of torque control [8]. In the torque control working area, the objective is to operate the WTs at the maximum power

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Nomenclature			
Abbreviations			
WT	wind turbine	x	input/output variable
NMPC	nonlinear model predictive control	$f(x)$	degree of membership of x
MPC	model predictive control	A	constant
MMPA	multi-objective marine predator algorithm	B	constant
IMMPA	improved multi-objective marine predator algorithm	C	constant
STD	standard deviation	$\vec{Y}_i^*$	updated positions
Symbols		$\vec{Y}_i$	current positions
E	wind energy	$\vec{R}_1$	random of vector
T	control period	$\otimes$	dot product
R	rotor radius	$\vec{R}_m$	randomly generated number vector
V	average wind speed	$\vec{E}_i$	current location of the top predator
d	polynomial order	It	current iteration
h_i	aerodynamic fitting parameter	It_{max}	maximum number of iterations
ω_r	rotor speed	a	prediction step size
C_p	power coefficient	$\vec{R}_n$	random distribution number vector
C_p^{max}	maximum power coefficient	M	population size
Δt	short evaluation period	n	number of short periods
$\vec{Y}_U$	vectors related to upper limits of control variables	γ	gearbox ratio
V_k	average wind speed in short period	$\vec{Y}_L$	vectors related to lower limits of control variables
ω_{rk}	average rotor speed in short period	T_{gk}	generator torque at the k -th control cycle
λ_k	tip speed ratio for the n short periods	F_0	probability parameter that represents the effect of fish aggregation
C_{it}	adaptive parameter for monitoring step size	r	random number within the range of [0, 1]
WS_{min}	minimum average wind speed	μ	randomly generated values over the population size range
J_R	inertias of generator	WS_{max}	maximum average wind speed
T_m	torque fluctuation value	β	randomly generated values over the population size range
$\vec{U}$	vector of random binary numbers	m	number of samples
$F1$	energy capture loss rate of WT	n_d	dimension
$F2$	change rate of generator torque	s	random number within the range of [0, 1]
b	weight coefficient	$size$	IMMPA population size
T_g^{rated}	rated generator torque	Q	maximum number of iterations
ω_r^{rated}	rated rotor speed	nd	The number of variables to be optimized
T_g^{min}	minimum generator torque	ω_r^{cut-in}	cut rotor speed
P1	the optimal solution obtained by IMMPA optimizing fuzzy regulator	W_w	candidate input 1
P2	the optimal solution obtained by MMPA optimizing fuzzy regulator	P3	the fixed weight coefficient point with the same torque fluctuation as P1
W_a	candidate input 2	P4	the fixed weight coefficient point with the same energy capture as P1
T_w	candidate input 3	H_{au}	annual utilization hours
T_a	candidate input 4	C_{WT}	single capacity of WT
$W(k+i k)$	wind speed of step $k+i$ at time k	δ	power generation efficiency

point via maintaining the optimal tip speed ratio [9]. Tip speed ratio is a function of wind speed and rotor speed [10], but due to the large inertia of blade rotor, it is difficult to adjust the rotor speed to track the rapidly changing wind speed. Thus, the realization of maximum energy capture goal remains a challenge.

Recent progresses in remote measurements [11] and advanced prediction approaches [12,13], have shown promise in providing preview wind information in control utilization. On this basis, model predictive control (MPC), as a predictive control that simulates future responses, has been proposed to improve the performance of the WTs. Different from traditional control methods, MPC updates the optimization problem with the current measurement information at each sampling moment. This rolling optimization strategy makes MPC effective and efficient [14]. MPC based on linearization has low requirements on the computing resource [15], but the nature of WTs is a nonlinear and highly coupled system [16–18], of which the operating point is non-singular and changes in real time. Nonlinear model predictive control

(NMPC) is capable of solving the nonlinear problems caused by the variation of WTs operating points, such as the NMPC for pitch control used to avoid flutter aero-elastic instability [19]. In the torque control of WTs, NMPC could improve the energy capture efficiency to a certain extent. In order to further improve the control performance, researchers have conducted studies on the basis of traditional NMPC, such as discrete control model based on a large time step [20] and nonlinear predictive torque control based on novel Yin-Yang grey wolf optimization algorithm [21]. Although these strategies can effectively improve the energy capture efficiency, simply improving the energy capture efficiency might cause a sharp increase in the fatigue load of WTs, which will bring safety threats to the operation of WTs [20]. Therefore, researchers tend to study a control strategy of collaborative optimization. It was proposed a dynamic WT reference power algorithm based on distributed MPC, which significantly reduced the fatigue load of WTs, but failed to guarantee the energy capture efficiency [22]. A model predictive controller was designed based on blade-shaft loads

characteristic parameter of WT, which realized the collaborative optimization of energy capture and fatigue load [23]. However, this method was only applicable to pitch control. The torque control based on NMPC is still in its infancy in realizing the coordinated optimization of energy capture and torque fluctuation. In literature [25], a weight coefficient was introduced to directly connect the two control objectives, but the performance improvement of WTs was limited.

When facing multiple control objectives, there have been some solutions such as utopia tracking, lexicographic and weighted multi-objective predictive controls. The main idea of utopia tracking multi-objective predictive control is to calculate the utopian point, where the control design is achieved by minimizing the distance of a set of cost functions to its steady-state utopia point [24]. When the preference of decision-maker cannot be clearly expressed, this method can automatically deal with the tradeoff between multi-objective functions [25]. Nevertheless, utopian tracking strategies may result in non-convergent behavior. Lexicographic multi-objective predictive control can obtain different optimal solutions by modifying the hierarchy of objective function [26]. It directly sets the priority of the goal to be optimized, so there is no need to adjust and select weights for the control goal [27]. However, the priority of optimization goals should be set according to the experience of designers. Weighted multi-objective predictive control uses weight to reflect the relative importance of each objective [28]. As shown in the research [29], weighted parameters were introduced to achieve process performance goals and minimize process costs. Although this strategy can reduce the amount of computation, how to choose the appropriate weight remains unsolved [30]. The weight coefficient distributes the importance of each control object, which is significant for the performance of the control system. However, weight coefficients are usually set empirically [31]. When the working point of the WT changes during operation, the predefined weight coefficients may not perform well, resulting in its performance difficult to meet the expected requirements.

When the operating state of WTs changes, the weight coefficient should also change with it. Neural network [32], analytic hierarchy process [33] and fuzzy logic control [34] can automatically update the weight coefficients. Considering that the influence of generator torque fluctuation on energy capture is difficult to be directly quantified, fuzzy logic control can introduce heuristic rules based on expert experience into updating weight coefficients. Therefore, fuzzy logic control is suitable for updating weight coefficients in NMPC of WTs. At present, fuzzy logic control has been applied in many fields [35–37], and widely used in the field of wind power generation. For example, a novel adaptive fuzzy logic control strategy was proposed for to improve performance of a grid-tied WT [38], and to improve rotor speed regulation and compensate estimation errors of sliding mode observation [34]. Based on this, a novel NMPC method using fuzzy regulator to adjust weight coefficients is proposed in this paper. The success of fuzzy reasoning depends on key factors such as linear and number of fuzzy membership functions, which are usually artificial [39]. In order to avoid the problem that the fuzzy regulator is difficult to achieve the expected performance due to the lack of experience of the designer, an improved multi-objective marine predator algorithm (IMMPA) is proposed to optimize the membership functions of the fuzzy regulator based on the design of the basic fuzzy regulator [40]. Multi-objective marine predator algorithm (MMPA) is a novel optimization algorithm, which is mainly inspired by the extensive foraging strategy of marine predators, i.e. the optimal encounter rate strategy of predator and prey interactions [41].

Compared with the existing literature, the main contributions of this paper are summarized as follows:

- 1) The effects of average wind speed and turbulence intensity on NMPC performance of WTs were analyzed. The results show that under different wind conditions, the corresponding weight coefficients of the WT to achieve the maximum energy capture and the minimum

generator torque fluctuation goal were significantly dependent on the typical characteristics of wind conditions, i.e. average wind speed and turbulence intensity.

- 2) A fuzzy regulator was introduced to adjust the weight coefficient. The fuzzy regulator was used to update the weight coefficient in real time, and the cost function was updated to adapt to the influence of wind speed change on WT. Considering that the power performance of WT was closely related to average wind speed and turbulence intensity, four candidate inputs were defined for the fuzzy regulator.
- 3) IMMPA was designed to optimize the membership function of fuzzy regulator. To improve MMPA, Latin Hypercube sampling was introduced to initialize the population, and random factors were added to select the population during the search and development of the algorithm. In this way, it avoids the influence of the total randomness of the population on the search performance of the algorithm. Considering the optimization requirements of input and output membership function of fuzzy regulator, the key parameters of input and output membership function were selected as the design variables of IMMPA.

The rest of this paper is as follows: In section 2, the cost function and constraint conditions of NMPC controller are designed, and the influences of average wind speed and turbulence intensity on control performance are analyzed. In section 3, the fuzzy regulator is designed and the optimization scheme is put forward. In section 4, method validation and results are discussed. Finally, a conclusion is made.

2. NMPC formulation and its influencing factors

In this section, the control objectives of maximize energy capture and minimize torque fluctuation for WTs nonlinear model prediction torque control are firstly introduced, and the two control objectives are converted into the final cost function of NMPC controller. Finally, the effects of wind speed and turbulence intensity on NMPC control performance of WTs are analyzed.

2.1. Design of NMPC cost function

The wind energy (E) extracted by the WT in a cycle is expressed as [21]:

$$E = \int_{t_0}^{t_0+T} \psi V^3 C_p dt = \int_{t_0}^{t_0+T} \psi V^3 \sum_{i=0}^d h_i \left(\frac{\omega_r R}{V} \right)^i dt \quad (1)$$

where T is the control period; $\psi = 0.5\rho\pi R^2$; R is the rotor radius; V is the average wind speed; d is a polynomial order; h_i is aerodynamic fitting parameter of blade; ω_r is the rotor speed; C_p is the power coefficient, which is a nonlinear function of tip speed ratio and pitch angle.

Since a WT is difficult to maintain the optimal operation all the time, it is reasonable to extract wind energy as much as possible in a long period. To this end, the long period T is divided into n short periods, and the maximize energy capture goal of WTs is expressed by:

$$\max E = \max \psi \Delta t \sum_{k=1}^n \left(V_k^3 \sum_{i=0}^d h_i \left(\frac{\omega_{rk} R}{V_k} \right)^i \right) \quad (2)$$

where Δt is the short evaluation period; $V_k (k = 1, 2, \dots, n)$, $\omega_{rk} (k = 1, 2, \dots, n)$ and $\lambda_k (k = 1, 2, \dots, n)$ are the average of wind speed, rotor speed and tip speed ratio for the n short periods, respectively.

Using the discrete model of the WT, the rotor speed is predicted by:

$$\omega_{rk} = \left(\psi V_k^3 \sum_{i=0}^d h_i \lambda_k^i / \omega_{rk-1} - \gamma T_{gk} \right) \Delta t / J_R + \omega_{rk-1} \quad (3)$$

where $\lambda_k \approx \omega_{rk-1} R / V_k$; γ is the gearbox ratio; J_R is the inertias of generator.

As a secondary control objective, minimizing the torque fluctuation

of the generator is expressed as:

$$\min T_m = \min \sqrt{\sum_{k=1}^n (T_{gk} - T_{gk-1})^2} \quad (4)$$

where T_m is the torque fluctuation value and T_{gk} is the generator torque of the k -th control cycle.

Considering the difference of order of magnitude between the two control objectives, each control objective is normalized as follows:

$$F1 = 1 - \frac{E}{E_{\max}} = 1 - \frac{\sum_{k=1}^n \left(V_k^3 \sum_{i=0}^d h_i \left(\frac{\omega_{gk} R}{V_k} \right)^i \right)}{\sum_{k=1}^n \left(V_k^3 C_p^{\max} \right)} \quad (5)$$

$$F2 = \frac{\sqrt{\sum_{k=1}^n \Delta T_{gk}^2}}{T_g^{\max}} \quad (6)$$

where $F1$ and $F2$ represent the loss ratio of energy capture and the variation degree of generator torque, respectively.

To obtain a single-objective function, the weight coefficient (b) is used to connect the two control objectives, and the final cost function is obtained as follows:

$$\min CF = \min_{T_{gk}} ((1-b)*F1 + b*F2) \quad (7)$$

$$st. \begin{cases} T_g^{\min} \leq T_{gk} \leq T_g^{\text{rated}} \\ \omega_r^{\text{cut-in}} \leq \omega_r \leq \omega_r^{\text{rated}} \end{cases}$$

where T_g^{rated} and ω_r^{rated} are the rated generator torque and rotor speed, respectively; $T_g^{\min}$ is the minimum generator torque; $\omega_r^{\text{cut-in}}$ represent the cut rotor speed.

2.2. Analysis of influencing factors on NMPC performance

In literature [21], the factors affecting traditional maximum power point tracking of WTs have been analyzed from two aspects of wind condition characteristics and WT structure. Motivated by it, we investigated the effects of average wind speed and turbulence intensity on the control goals of maximize energy capture and minimize torque fluctuation of NMPC. Under different wind conditions with different average wind speed and turbulence intensity, the variation rules of energy capture and generator torque with different weight coefficients were simulated and analyzed, and the results are shown in Fig. 1.

In Fig. 1, one curve corresponding to the normalized values of energy capture and torque fluctuation was obtained when the weight coefficient traverses all values within the range of [0, 0.1] with the step size of 0.01.

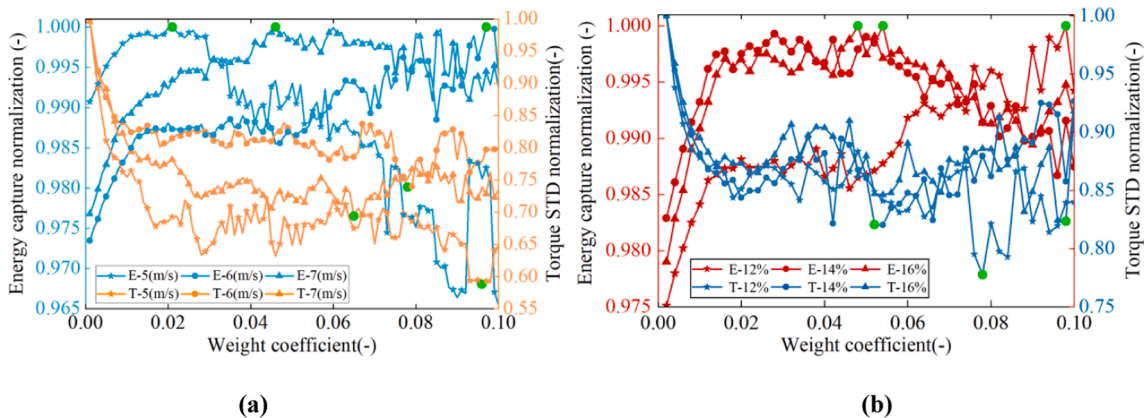


Fig. 1. Performance influence: (a) Different wind speeds; (b) Different turbulence intensity; (The green dots indicate the highest or lowest points of each curve). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Taking Fig. 1(a) as an example, the six curves represent the variation rules of captured energy and generator torque fluctuations when turbulence intensity is 12% and wind speed is 5, 6 and 7 m/s, respectively. Each point on curves corresponds to a weighting coefficient, representing the normalized value of energy capture and generator torque fluctuation, where the green point represents the highest or lowest point of each curve. It can be seen from Fig. 1(a) that when the average wind speed range is [5 m/s, 7 m/s], the weight coefficients corresponding to the highest point of the energy capture curve are 0.02, 0.098 and 0.046, respectively, while the weight coefficients corresponding to the lowest point of the generator torque standard deviation (STD) curve are 0.66, 0.78 and 0.96, respectively. As can be seen from Fig. 1(b), when the turbulence intensity range is [12%, 14%], the weight coefficients corresponding to the highest point of the energy capture curve are 0.98, 0.54 and 0.48, respectively, and the weight coefficients corresponding to the lowest point of the generator torque STD curve are 0.78, 0.52 and 0.98, respectively. Under the same weight coefficient, the difference of average wind speed and turbulence intensity results in the difference of energy capture and generator torque STD. Under the same mean wind speed and turbulence intensity, different weight coefficients bring about different energy capture and generator torque STD. Therefore, the average wind speed, turbulence intensity and weight coefficient together affect the control performance of WTs. How to adjust the weight coefficient of NMPC cost function to simultaneously maximize energy capture and minimize torque fluctuation is the focus of this paper.

3. Design and optimization of the fuzzy regulator for adjusting the weight coefficient

The control performance is affected by the average wind speed, turbulence intensity and other factors. The noticeable advantage of fuzzy control technology is that it does not need to establish accurate mathematical model and can be very convenient to solve the multi-variable nonlinear system problems. Therefore, this paper presents a fuzzy regulator to adjust the weight coefficient of the cost function. The framework of the proposed fuzzy regulator is shown in Fig. 2. Firstly, the obtained predicted wind speed is transformed into wind speed sequence $V_k (k = 1, 2, \dots, n)$. The predicted wind speed can be obtained by remote measurement devices, such as Lidar. Then, according to the influencing factors of wind turbine performance, four candidate input variables are defined, the basic fuzzy regulator is designed, and the linear of membership function is optimized by IMMPA. Finally, the weight coefficient of the optimized fuzzy regulator is used as the input of NMPC controller to realize the real-time updating of cost function.

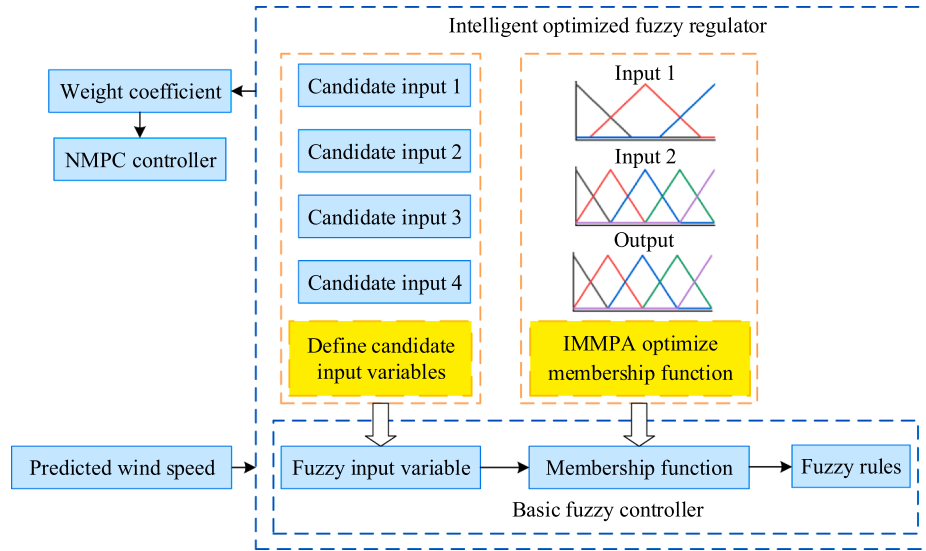


Fig. 2. The framework of the intelligent optimized fuzzy regulator.

3.1. Basic fuzzy regulator

The fuzzy regulator mainly consists of three parts: input variable determination, membership function determination and fuzzy rule establishment, which are described below.

3.1.1. Input variable determination

One of the keys of the fuzzy regulator is to determine input variables. The average wind speed and turbulence intensity will cause the change of the relationship between the two control objectives, and the time dimension of the calculation of the average wind speed and turbulence intensity is minutes, which is much larger than the control cycle of NMPC. Therefore, according to the control cycle of NMPC, two inputs related to the average wind speed and turbulence intensity are set for the fuzzy regulator. Considering the influence of average wind speed, candidate inputs 1 and 2 are defined. Considering the influence of turbulence intensity, candidate inputs 3 and 4 are defined.

1) Candidate input 1 (W_w) defined as:

$$W_w = \sum_{i=1}^{\alpha} ((m+1-i) * W(k+i|k)) / \sum_{i=1}^{\alpha} i \quad (8)$$

2) Candidate input 2 (W_a) defined as:

$$W_a = \sum_{i=1}^{\alpha} (W(k+i|k)) / \alpha \quad (9)$$

3) Candidate input 3 (T_w) defined as:

$$T_w = \frac{\sqrt{\sum_{i=1}^{\alpha} (W(k+i|k) - W_w)^2 / \alpha}}{W_w} \quad (10)$$

4) Candidate input 4 (T_a) defined as:

$$T_a = \frac{\sqrt{\sum_{i=1}^{\alpha} (W(k+i|k) - W_a)^2 / \alpha}}{W_a} \quad (11)$$

where α represents the step size, and $W(k+i|k)$ represents the wind speed of step $k+i$ at time k .

According to their definition, the ranges of candidate inputs can be determined using the time series of historical wind speeds. There are four candidate inputs defined above, among which two candidates are selected as the fuzzy inputs of the fuzzy regulator. Therefore, four groups of candidate inputs (W_w and T_w , W_w and T_a , W_a and T_w , W_a and T_a) can be obtained, which are defined as G1, G2, G3 and G4, respectively.

3.1.2. Membership function determination

Using triangle as membership function, the input related to average wind speed is divided into three fuzzy sets, which are small (S), medium (M) and large (L), respectively, and the membership function is shown in Fig. 3(a). Similarly, the input and output related to turbulence intensity are divided into five fuzzy sets, which are very small (VS), small (S), medium (M), large (L) and very large (VL), respectively, and the membership function is shown in Fig. 3(b) and (c), respectively.

3.1.3. Fuzzy rule establishment

As can be seen from Fig. 3, the two input variables are mapped to three and five different language values, respectively, and the output variables are also mapped to five language values. A fuzzy rule table containing 15 different rules is established by using 15 language values, as shown in Table 1.

- 1) The larger average wind speed and smaller turbulence intensity will result in larger energy capture and smaller generator torque fluctuation;
- 2) The larger average wind speed and turbulence intensity will make the generator torque fluctuate more;
- 3) The smaller mean wind speeds and greater turbulence intensity result in smaller energy capture;
- 4) The smaller average wind speed and turbulence intensity make the energy capture smaller and the generator torque fluctuation smaller.

3.2. Intelligent optimization of fuzzy regulator

The mechanism of updating weight coefficient of fuzzy regulator is based on expert experience, but it also has its disadvantages, such as when the expert experience is inexperienced or there is error, the result of fuzzy regulator will not be reliable. Fuzzy relation under complex input is difficult to be directly given by expert experience, so the intelligent optimization of fuzzy regulator is put forward. In Section 2.1, two control objectives of NMPC for WTs are summarized: maximization of energy capture and minimization of generator torque fluctuations. The

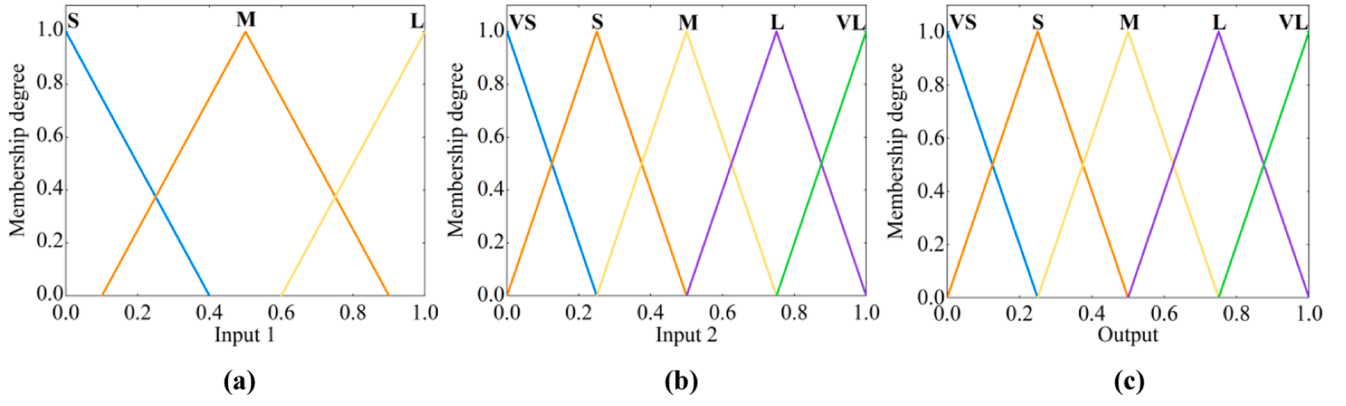


Fig. 3. Initial membership functions. (a) Input 1. (b) Input 2. (c) Output.

Table 1

Initial fuzzy rules.

S	VS	S	M	L	VL
M	VS	VS	S	M	L
L	S	M	L	VL	VL

fuzzy regulator is used to update the cost function of NMPC controller, so Eqs. (4)–(5) are taken as the optimization target of the fuzzy regulator.

3.2.1. Design variable selection for fuzzy regulator optimization

In addition to the input variables, the success of fuzzy regulator also depends on membership function and fuzzy rules. Fuzzy rules are based on language variables and directly affect the performance of the regulator, while membership function is an important value to calculate the fuzzy adjustment results. They are closely related, and the optimization of membership function is also the optimization of fuzzy rules, so membership function is selected.

Membership function shows the mapping relationship between fuzzy input and output. Different membership functions have different forms and characteristics. The triangle membership function is used and expressed as [42]:

$$f(x, A, B, C, D) = \begin{cases} 0 & , x \leq A \\ \frac{x-A}{B-A} & , A < x \leq B \\ \frac{x-A}{B-A} & , B < x < C \\ 0 & , x \geq C \end{cases} \quad (12)$$

where x is the input/output variable, $f(x)$ represents the degree of membership of x , parameters A and C determine the base of the triangle, and parameter B determines the vertex.

In order to improve the reliability of fuzzy regulator using membership function, parameters of input and output membership function are selected for optimization. Taking Fig. 3(c) as an example, there are 11 variables to be optimized, including the base point on the right side of the leftmost triangle membership function, the base point on the left side of the rightmost triangle membership function, and the vertex and base point of the middle three triangle membership functions. Similarly, the membership function of input 1 and input 2 contains 5 and 11 variables to be optimized, respectively. Therefore, the membership function contains 27 variables to be optimized.

3.2.2. Optimization of membership function based on IMMPA

(1) Multi-objective marine predator algorithm (MMPA)

MMPA is a nature-inspired optimization algorithm [40]. In MMPA, the iterative search process for predators to acquire prey is divided into three stages.

Firstly, the predators observe the surrounding area, and their positions are updated by [41]:

$$\vec{Y}_i^* = \vec{Y}_i + \frac{1}{2} \vec{R}_1 \otimes \vec{R}_m \otimes (\vec{E}_i - \vec{R}_m \otimes \vec{Y}_i), It \leq \frac{It_{max}}{3} \quad (13)$$

where $\vec{Y}_i^*$ and $\vec{Y}_i$ are the updated and current positions, respectively; $\vec{R}_1$ is the random vector; $\otimes$ stands for dot product; $\vec{R}_m$ is a randomly generated number vector; $\vec{E}_i$ indicates the current location of the top predator; It and It_{max} represent the current iteration and the maximum number of iterations, respectively.

In the middle third of the maximum iteration, the prey is responsible for development, the predators are responsible for exploration, and their positions are updated by:

$$\vec{Y}_i^* = \begin{cases} \vec{Y}_i + \frac{1}{2} \vec{R}_1 \otimes \vec{R}_n \otimes (\vec{E}_i - \vec{R}_n \otimes \vec{Y}_i), i \leq \frac{M}{2} \\ \vec{Y}_i + \frac{1}{2} C_{it} \otimes \vec{R}_m \otimes (\vec{R}_m \otimes \vec{E}_i - \vec{Y}_i), i > \frac{M}{2} \end{cases} \quad (14)$$

where $\vec{R}_n$ stands for random distribution number vector; M is population size; $C_{it} = (1 - It/It_{max})^{(2It/It_{max})}$ is an adaptive parameter for monitoring step size.

In the last third of the maximum iteration, when the location of the prey has been discovered, the predators are hunting the prey, and their positions are calculated by:

$$\vec{Y}_i^* = \vec{Y}_i + \frac{1}{2} C_{it} \otimes \vec{R}_n \otimes (\vec{R}_n \otimes \vec{E}_k - \vec{Y}_i), It \geq \frac{2It_{max}}{3} \quad (15)$$

When predators are influenced by vortices and fish gathering devices, the above renewal process may fall into local optimization. In order to avoid this situation, the following mathematical model is proposed:

$$\vec{Y}_i^* = \begin{cases} \vec{Y}_i + C_{it} (\vec{Y}_L + \vec{R}_1 \otimes (\vec{Y}_U - \vec{Y}_L)) \otimes \vec{U}, r \leq F_0 \\ \vec{Y}_i + (\vec{Y}_\mu - \vec{Y}_\beta) \cdot (F_0(1-r) + r), r > F_0 \end{cases} \quad (16)$$

where $\vec{Y}_U$ and $\vec{Y}_L$ are vectors related to upper and lower limits of control variables, respectively; $\vec{U}$ is a vector of random binary numbers; F_0 is the probability parameter that represents the effect of fish aggregation; r is a random number within the range of $[0, 1]$. μ and β are the two randomly generated values.

(2) Improved multi-objective marine predator algorithm (IMMPA)

The randomness of MMPA makes the optimization process easy to

fall into local optimization and requires a long iterative process. Therefore, IMMPA is proposed to improve the initialization stage and prey update position stage of MPPA. The random initialization of the MPPA population may seriously affect the convergence performance, so Latin Hypercube sampling is used to initialize population. Assuming m samples extracted in n_d -dimensional space, the specific steps of Latin Hypercube sampling include [43]:

- 1) Each dimension is divided into m non-overlapping intervals so that each interval has the same probability;
- 2) Pick one point randomly from each interval of each dimension;
- 3) Then the points selected in 2) are randomly extracted from each dimension and formed into vectors.

In the case of two-dimensional vectors and 100 samples, the distribution of the initial population through completely random and Latin Hypercube sampling is shown in Fig. 4. In Fig. 4(a), the population distribution at the lower left corner is relatively concentrated, while the population distribution at other places is sparse. In Fig. 4(b), when Latin hypercube sampling is used to initialize the population, the population is evenly distributed. Therefore, compared with the completely random method, Latin Hypercube sampling can make the distribution of the initial population more uniform.

In MPPA, the division of exploration and development in the transition stage of exploration and development is simply divided into two parts: one part moves as exploration operator, and the other part moves as development operator. As shown in Eq. (14), when $i \leq M/2$, the update of population position is in the exploration stage. When $i > M/2$, the update of population position is the development stage. When the population distribution is too concentrated, such partition will make the optimization fall into local optimum. In order to avoid the influence caused by population distribution, a random factor w is added for stage selection. The specific mathematical model is shown as follows:

$$\vec{Y}_i^* = \begin{cases} \vec{Y}_i + \frac{1}{2}\vec{R} \otimes \vec{R}_n \otimes (\vec{E}_i - \vec{R}_n \otimes \vec{Y}_i), & s \leq \frac{1}{2} \\ \vec{Y}_i + \frac{1}{2}\vec{C}_d \otimes \vec{R}_m \otimes (\vec{R}_m \otimes \vec{E}_i - \vec{Y}_i), & s > \frac{1}{2} \end{cases} \quad (17)$$

where s is a random number within the range of $[0, 1]$.

(3) Algorithm implementation

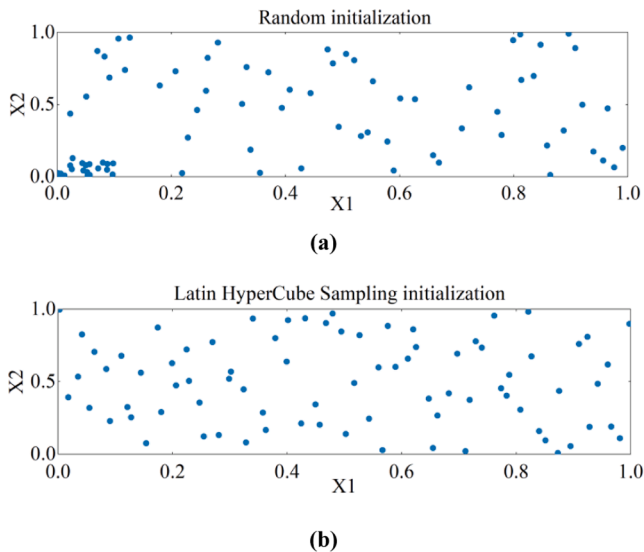


Fig. 4. Initialization of the particle distribution. (a) Completely random. (b) Latin Hypercube sampling.

The optimization process of the fuzzy regulator is shown in Fig. 5. Firstly, input wind speed data and initialize IMMPA parameters. Then the population was initialized with Latin Hypercube sampling. A pre-defined fuzzy regulator system was established, whose weight coefficients were used to update the cost function and evaluate the fitness of each prey to determine the top predator. Finally, if the maximum number of iterations is reached, the calculation will be stopped. Otherwise, the prey location and *Archive* are updated and the prey fitness is re-evaluated using Eqs. (12)–(16) until the stop condition is met.

4. Method validation

4.1. Preparation for the experiment

The validation is conducted on the 1.5 MW WT produced by MIN-GYANG Intelligent. Its specifications are shown in Table 2, where the polynomial order (d) is set to 4 [21]. In order to verify the proposed method, the membership function of the fuzzy regulator was optimized by IMMPA, and the optimized fuzzy regulator was used for carrying out simulations. Assume that the annual utilization hour of WT is 3000 h and the power generation efficiency is 0.45.

In the simulation experiment, random turbulent wind with average wind speed of 6 m/s is adopted. The wind speed distribution is shown in Fig. 6. The sampling period is set to 0.02, same as the execution time of the normal controller. The first 400 s of 600 s wind speed is used to select the best input combination and membership function training of fuzzy regulator, and the last 200 s is used for application and verification. Parameters of IMMPA are shown in Table 3. Where *size* is the IMMPA population size, Q is the maximum number of iterations of IMMPA, and nd is the optimized dimension.

4.2. Input selection for the fuzzy regulator

The fuzzy controller calculates the candidate inputs according to the average wind speed in the control cycle; then the candidate inputs go through fuzzification, fuzzy reasoning and defuzzification; finally, the weight coefficient is obtained, where the range of the weight coefficient is $[0, 0.1]$, the range of W_w and W_a is $[3, 10.05]$, the range of T_w and T_a is $[0, 1.06]$. To select the most suitable input set, four controllers with different inputs were run, and their results were shown in Fig. 7. Fig. 7(a) shows that the energy capture gap of the four input combinations is not obvious, but Fig. 7(b) shows that the fluctuation difference of the four curves is significant, among which G1 curve has the smallest fluctuation and G2 curve has the largest fluctuation. Their standard deviation is calculated as 1664.32, 1796.45, 1764.66 and 1770.60, respectively.

In order to eliminate the accidental influence of average wind speed distribution on fuzzy regulator input and further determine a group of optimal candidate inputs, G1, G2, G3 and G4 were used as fuzzy regulators input for simulation under different wind speeds. There is little difference in energy capture in the simulation results, while the normalization results of torque STD values are shown in Fig. 8. When G2, G3 and G4 are used as the input of the fuzzy regulator, the generator torque STD at the three wind speeds is very high. Especially when G2 is used as the input, the generator torque STD is always at the highest point, while G1 is the smallest. Therefore, when G1 (combination of W_w and T_w) is used as the input of fuzzy regulator, the control performance of WT can reach the best.

4.3. Results of the optimized fuzzy regulator

In order to verify the optimization effect of fuzzy regulator, the controller with fixed weight, the controller optimized by MPPA and the controller optimized by IMMPA were compared. Where the fixed weight means that the weight coefficient ranges from 0.001 to 0.1 in step size

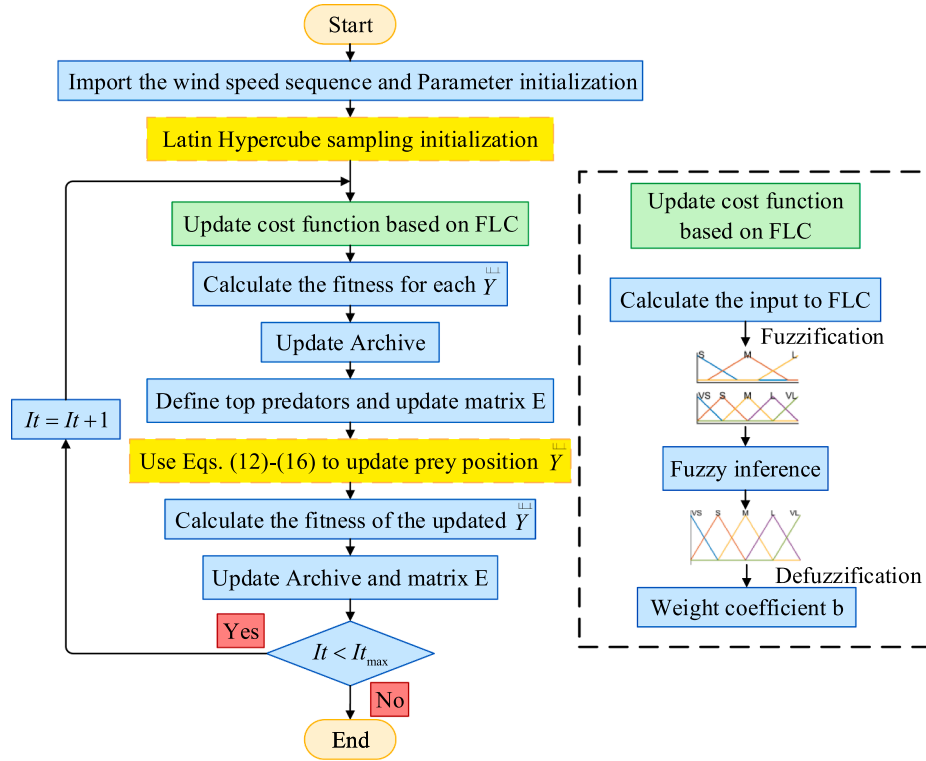


Fig. 5. Optimization process of membership function.

Table 2
Related parameters of WT.

Parameters	Value
Rated power	1.5(MW)
Rated rotor speed	183.26(rad/s)
Rated generator torque	8185(Nm)
Rotor radius	41.2(m)
Gear box ratio	100.48
Integration inertial	5.78×10^6 (kg/ m ²)
Maximum power coefficient	0.4827
Optimum blade tip ratio	9.5
Annual utilization hours	3000(h)
Power generation efficiency	0.45
d	4
h_0	-1.621
h_1	0.6582
h_2	-0.07541
h_3	$3.813e-3$
h_4	$-7.539e-5$

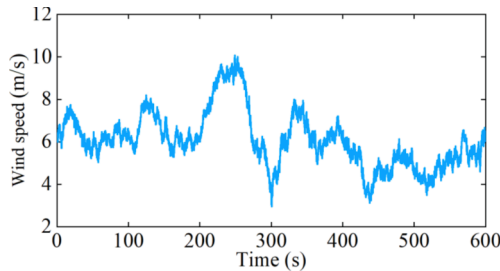


Fig. 6. Time series of the wind speed.

0.001. The training optimization results are shown in Fig. 9. The optimized IMMPA particle finally converges to the Pareto front represented by the red dot, and the Pareto front of IMMPA is located below the

Table 3
Algorithm parameters.

Parameter	IMMPA	size	Q	nd
F_0	0.2	1000	100	27

Pareto front of MMPA and the fixed weight controller. Therefore, the controller using IMMPA optimized fuzzy regulator can obtain the best performance, increase energy capture, and reduce the generator torque fluctuation effectively.

After the completion of iterative calculation, the Pareto front composed of two sets of optimal solutions can be obtained. These solutions are not sorted, so the optimal solution cannot be determined. Therefore, the Euclidean distance between all solutions on the Pareto front and point [0.005, 0.05] is calculated, and the solution with the smallest distance is the optimal one. In Fig. 9, the optimal solution of IMMPA and MMPA is P1 and P2, respectively. In order to compare with the optimal result, two straight lines perpendicular to the X axis and Y axis were drawn based on the coordinates of point P1, respectively. Their intersection points are marked by green five-pointed stars, which are named by P3 and P4, corresponding to the weight coefficients owning the same torque volatility and energy capture efficiency as P1, respectively.

A group of 27-dimensional data represented by optimal P1 were the parameters of the optimized membership function, as shown in Fig. 10. In Fig. 10(a), there is no crossover between the right side of the left-most triangle membership function and the left side of the right-most triangle membership function in the initial state, and the distance between the two is 0.2. After optimization, there is crossover between the two membership functions with a distance of 0.3059. The changes in Fig. 10 (b) and Fig. 10(c) are more significant. In the initial state, the membership function is equilateral triangle and the interval between each vertex is 0.2. After optimization, the triangle corresponding to vertex M in Fig. 10(b) moves to the triangle corresponding to vertex L and VL. In

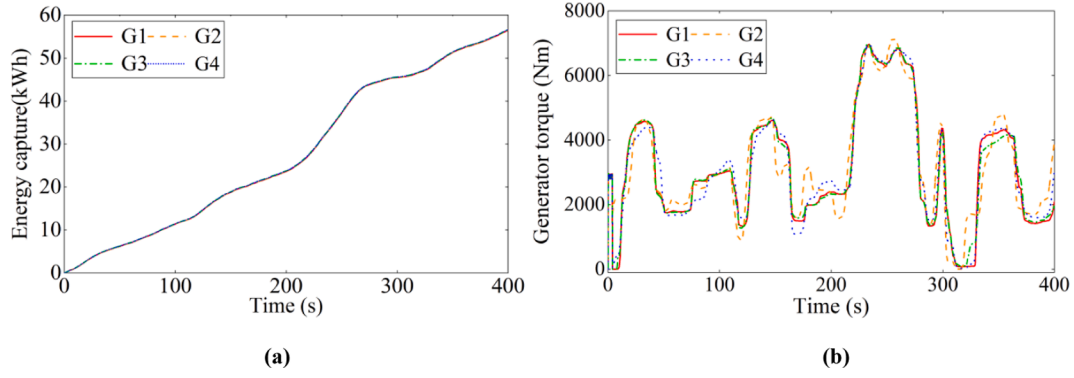


Fig. 7. Results of different inputs. (a) Energy capture. (b) Generator torque.

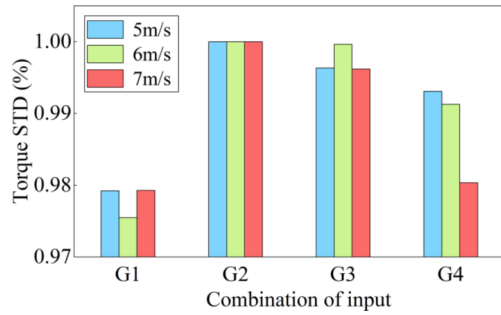


Fig. 8. Results of different fuzzy regulator inputs at different wind speeds.

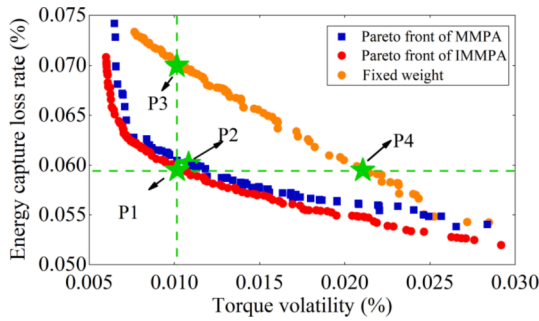


Fig. 9. Result comparison among three fuzzy regulators (P1 and P2 denote the optimal solutions obtained by the fuzzy regulator with IMMPA optimizer and MMPA optimizer, respectively; P3 and P4 represent the fixed solution with the same torque fluctuation and with the same energy capture as P1, respectively).

Fig. 10(c), the triangle corresponding to vertex S is also moved back between the triangles corresponding to vertices L and VL. After optimization, the order of membership functions of input 2 and output is switched, which indicates that IMMPA optimizes fuzzy rules to a certain extent while optimizing membership correspondence lines.

4.4. Verification of optimization results

The results of application and verification based on the wind speed sequence for the last 200 s are shown in Fig. 11 and Fig. 12. Curves in different colors represent the simulation results of the four controllers with different weights discussed in the last section.

Fig. 11 shows the change curves of weight coefficients during the operation of P2 and P1 controllers. The weight coefficients of the two controllers change dramatically with the wind speed and most of the values fall on [0.05, 0.08], showing the activation of the two weight regulators.

Fig. 12 shows other simulation results for four different controllers.

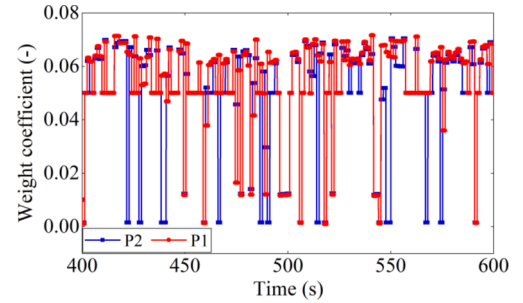


Fig. 11. Results of weight coefficients for P2 and P1.

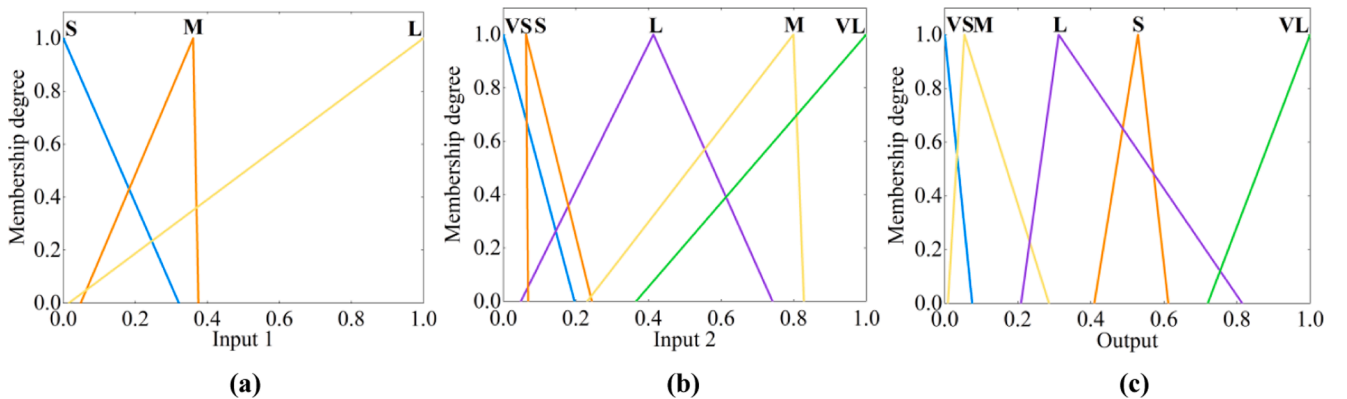


Fig. 10. Optimized membership functions. (a) Input 1. (b) Input 2. (c) Output.

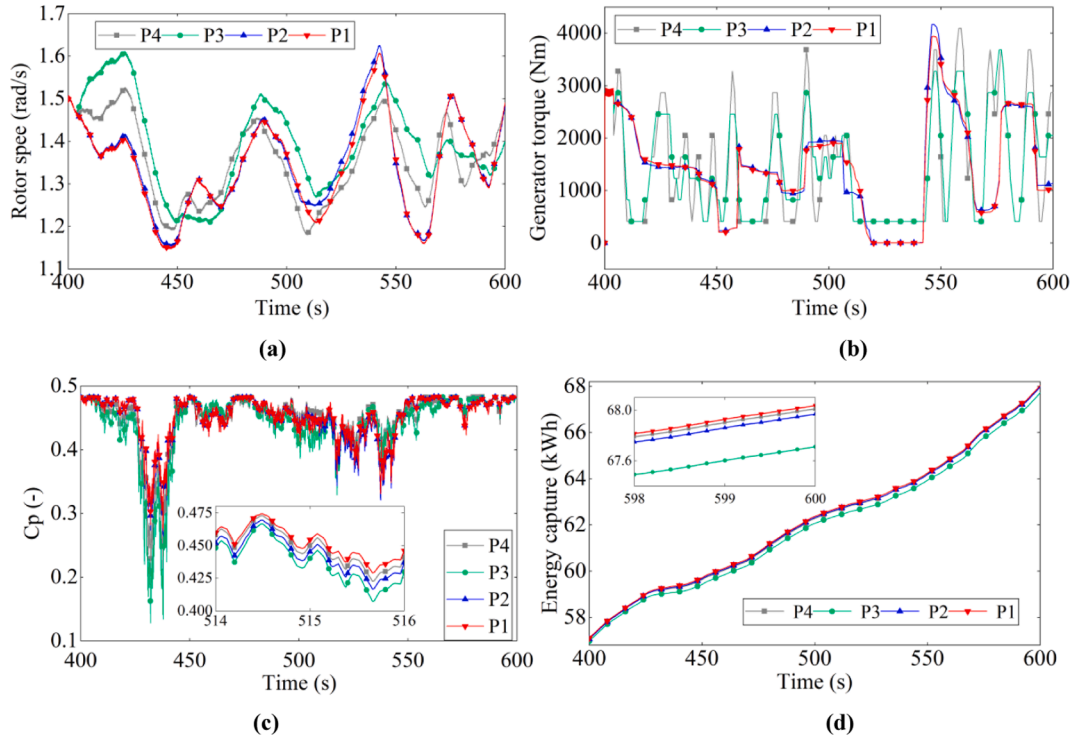


Fig. 12. Result comparison among four controllers. (a) Rotor speed. (b) Generator torque. (c) Power coefficient. (d) Energy capture (The four curves of P1-P4 correspond to the four points of P1-P4 in Fig. 9, respectively, and each point represents a specific controller).

The controllers represented by P2 and by P1 show similar performance in rotor speed, generator torque. However, in terms of power coefficient and energy capture as shown in Fig. 12(c) and (d), P1 curve is obviously above P2 curve through the enlarged detail diagram. By comparing the results of P1 and P3, it can be seen from Fig. 12(b) that there are few differences between the generator torque fluctuations of the two curves. However, it can be seen from Fig. 12(c) that the value obtained by P1 controller is closer to the maximum value (0.4827) of the concerned WT. Similar results also appear in the energy capture of Fig. 12(d). It can be seen from the randomly intercepted fragments that, compared with the results of P3 controller, the energy capture of P1 controller is higher, in line with the results in Fig. 9. By comparing the results of P1 and P4 controllers, although there is no obvious difference in energy capture between the two controllers, the generator torque fluctuation of P1 controller in Fig. 12(b) is obviously smaller.

To further compare the performance of different controllers, the numerical results of generator torque, power coefficient and energy capture in Fig. 12 are summarized in Table 4. Compared with P2, average C_p of P1 is increased by 0.36%, energy capture is increased by 0.2%, and generator torque STD also is decreased by 0.984%. Compared with P3, average C_p of P1 is increased by 2.8%. Compared with P4, the average C_p of P1 is increased by 0.4%. In terms of generator torque STD, P1 is decreased by 0.126% compared with P3 and 12.01% compared with P4. In terms of total energy capture, P1 is 1.77% and 0.08% more than P3 and P4, respectively. Taking the concerned 1.5 MW WT as an example, the annual energy production (AEP) can be obtained as follows

[44]:

$$AEP = C_{WT} * H_{an} * \delta \quad (18)$$

where, C_{WT} is the single capacity of WT; H_{an} is the annual utilization hours; δ is the power generation efficiency. The variable-weight NMPC optimized by MMPA and IMMPA could boost its annual energy production by 35842.5 kWh and 31,590 kWh, respectively, in comparison with the WT using the fixed-weight NMPC. Thus, the developed variable-weight NMPC is promising in reducing the production cost for the WTs.

5. Conclusions

Aiming at the contradiction between the rapid of wind speed and the large inertia of WTs, a fuzzy regulator was proposed to adjust the weight coefficient of model predictive torque control. In order to improve the precision of fuzzy regulator, IMMPA was introduced to optimize the fuzzy regulator. The main conclusions of this study are summarized as follows:

- 1) Different fuzzy regulators with different inputs have different results. In other words, different inputs will affect the results of fuzzy regulators, and the optimal input can reduce the generator torque fluctuation of WTs by more than 6%.
- 2) Under different mean wind speed, turbulence intensity and weight coefficient, the performance of energy capture and generator torque

Table 4
The numerical statistical results.

Performance	P4	P3	P2	P1	P1/P2	P1/P3	P1/P4
mean T_g (Nm)	1412.6	1423.9	1451.5	1455.4	100.27%	102.21%	103.03%
STD T_g (-)	1067.9	940.83	948.98	939.64	99.016%	99.874%	87.990%
mean C_p (-)	0.4503	0.4398	0.4505	0.4521	100.36%	102.80%	100.40%
STD C_p (-)	0.0422	0.0540	0.0369	0.0345	93.496%	63.889%	81.754%
E (kWh)	10.928	10.747	10.915	10.937	100.20%	101.77%	100.08%

fluctuation presents different, which means that these three factors together affect the model predictive torque control performance of WT.

- 3) The optimized fuzzy regulator fulfills the coordinated optimization on energy capture and generator torque. Compared with controllers with different fixed coefficients, the proposed method improves energy capture by 1.77%, while reducing torque fluctuation by 12.01%.
- 4) Compared with MMPA, IMMPA is more effective in searching the optimal weight coefficients. More in detail, the model predictive torque control optimized by the IMMPA further improves energy capture by 0.2% and reduces generator torque fluctuation by 0.984%, in comparison with the one by the MMPA.

Based on the proposed fuzzy regulator, the performance of the model predictive torque control has been considerably enhanced. To apply the variable-weight model predictive torque control into real WTs, detailed tests should be conducted within the full range of torque control working area. When the predictive model deviates from the real one, special attentions should be given towards robust NMPC and stochastic NMPC, of which the dynamic weight coefficient can be derived using the proposed methodology.

CRedit authorship contribution statement

Dongran Song: Conceptualization, Methodology, Funding acquisition, Writing – review & editing. **Yanping Tu:** Writing – original draft, Visualization, Software. **Lei Wang:** Supervision, Funding acquisition, Writing – review & editing, Visualization. **Fangjun Jin:** Visualization, Software. **Ziqun Li:** Methodology, Software. **Chaoneng Huang:** Resources, Formal analysis. **E Xia:** Investigation, Data curation. **Rizk M. Rizk-Allah:** Writing – review & editing, Visualization. **Jian Yang:** Visualization, Investigation. **Mei Su:** Software, Investigation. **Young Hoon Joo:** Data curation, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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