

Optimization Method for the Hydrodynamic Performance of Tidal Turbines Considering Blockage Effect

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Abstract

As crucial components in the advancement of tidal energy, tidal turbines are progressively transitioning from large standalone units to multi-unit arrays. In the context of tidal arrays, the blockage effect has become a key factor that necessitates careful consideration due to its substantial impact on turbine performance. This paper introduces an innovative optimization methodology aimed at improving the hydrodynamic performance of tidal turbines while specifically addressing the environmental blockage effect. The proposed approach integrates the blade element momentum–computational fluid dynamics hydrodynamic model, radial basis function neural networks, and the nondominated sorting genetic algorithm III optimization algorithm. A case study is used to demonstrate this methodology, focusing on the optimization of a tidal turbine under varying blockage intensity levels. Comparative analyses of optimal turbine configurations indicate that strategic modifications in design parameters can substantially improve hydrodynamic performance in response to varying blockage intensity. Specifically, increasing the root chord length and decreasing the tip chord length effectively reduce the turbine's load while maintaining operational efficiency as blockage intensity increases. Conversely, the blade pitch angle exhibits minimal sensitivity to the blockage effect. Moreover, the optimized turbines demonstrate lower velocity deficits in their near-field wake compared to the prototype. The case study not only validates the effectiveness of the proposed optimization method but also highlights the substantial impact of blockage effects on optimal turbine configurations. This research provides valuable theoretical insights for designing turbines intended for deployment in tidal arrays.

Keywords Tidal current turbine; Blade optimization; Blockage effect; BEM–CFD; RBF neural networks; NSGA-III

1 Introduction

In response to the depletion of traditional fossil fuels and the need to transform existing energy infrastructures, ocean energy has become a key area of focus for renewable energy sources (Edenhofer et al., 2011; Mofor et al., 2014). Among the various forms of ocean energy, tidal energy—driven by the gravitational interactions between the Earth and the

Moon—stands out for its predictability and high feasibility, offering a promising outlook for its application (Li and Zhu, 2023). However, the considerable development costs associated with tidal energy present substantial challenges to its commercialization. Consequently, numerous studies have concentrated on analyzing and optimizing the hydrodynamic performance of tidal turbines to enhance the efficiency and viability of tidal energy development.

Kim et al. (2015) optimized the airfoil shape of turbine blades, enhancing the performance of a 50 kW turbine. Laurens et al. (2016) focused on optimizing the pitch angle, chord length, and the number of blades, leading to the design of a highly efficient seven-blade turbine. Zhu et al. (2020) applied the multi-objective genetic algorithm, Non-dominated Sorting Genetic Algorithm II (NSGA-II), to optimize the chord length and pitch angle, allowing the optimized turbine to generate power efficiently across a wide range of operating speeds while enhancing its peak efficiency. Li et al. (2023) similarly optimized the blade chord length and pitch angle using genetic algorithms, which enhanced the peak efficiency and starting performance of the turbine. Wang et al. (2025) utilized CFD methods to investigate the effects of pitch motion on the hydrodynamic performance of turbines. Existing research primarily assumes

Article Highlights

- A novel turbine optimization method that incorporates environmental blockage effects is proposed.
- Turbine configurations can be strategically adjusted in response to varying blockage intensity to enhance performance.
- The blade pitch angles show minimal sensitivity to variations in environmental blockage intensity.
- The turbine configuration has a limited impact on the recovery rate of the far-field wake.

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unbounded flow conditions devoid of blockage effects, reflecting the trend toward the development of single large-scale turbines in recent years. However, due to constraints such as available marine space and structural safety, the efficient development of tidal energy through turbine arrays has gained increasing prominence. The blockage effects between units in an array can drastically influence the optimization design of turbines. Schluntz and Willden (2015) demonstrated that optimal turbine configurations change under varying blockage intensities. Wang et al. (2023) compared two turbines with varying solidities, finding that turbines with higher solidity exhibited improved startup performance and energy efficiency at low flow speeds, albeit at the cost of increased load. These studies indicate that turbines designed for unbounded flow conditions may not perform optimally in array applications, emphasizing the need to consider blockage effects from the outset of turbine design.

Current research on blockage effects predominantly analyzes the performance of individual turbines under different blockage intensities. Koh and Ng (2017) used the actual disk method to examine the impact of channels with varying aspect ratios on turbines, concluding that high-blockage ratios increase turbine thrust. They also recommend that, when examining blockage effects, the channel width should be varied while maintaining the depth to avoid confounding factors such as turbulence intensity. Badshah et al. (2019) applied computational fluid dynamics (CFD) methods to explore how blockage ratios affect turbine efficiency and thrust, discovering that the blockage effect becomes substantial only at high tip speed ratios (TSRs). Kolekar and Banerjee (2015) assessed the blockage effects of free surfaces and channel bottoms on turbines using CFD methods and flume experiments. They found that appropriate deformation of the free surface can enhance turbine efficiency, whereas excessive proximity to the free surface disrupts wake diffusion and recovery, subsequently degrading turbine performance. Despite extensive research on the impact of blockage effects on turbine hydrodynamic performance, a systematic design method for turbines operating under blockage conditions is still lacking.

The blade element momentum (BEM) and CFD methods are commonly used in turbine design. The BEM method provides a simple model with fast calculations but lacks the capability to model complex flow fields or account for blocking effects (Chen et al., 2020; Perez et al., 2022a; Perez et al., 2022b). Conversely, the CFD method can simulate conditions with complex flow domain boundaries and provides increased flexibility in modeling turbines and auxiliary equipment (Sun et al., 2022). However, the CFD method is computationally inefficient.

Aiming to reduce the computational costs associated with the CFD method, Malki et al. (2013) introduced the BEM–CFD method, which effectively combines the advantages of the BEM and CFD methods. The BEM–CFD method

employs blade element theory from the BEM method to replace detailed turbine modeling in CFD, while using the velocity field resolved by CFD for momentum theory in the BEM method. This approach allows for detailed flow field modeling similar to CFD, while substantially reducing computational requirements. Masters et al. (2013) applied the BEM–CFD method to study the effects of non-uniform flow conditions on turbine performance and wake. Vogel and Willden (2019) used the BEM–CFD method to assess how turbine operating conditions affect the overall performance of turbine arrays. Olczak et al. (2016) validated the effectiveness of the BEM–CFD method for calculating the performance of horizontal axis turbine arrays using experimental data. They observed that while the error increased with the addition of rows to the array, the performance calculations for single-row turbines closely matched with experimental results.

In turbine design involving complex multi-parameter optimization, the integration of optimization algorithms is crucial. These algorithms necessitate the performance evaluation of numerous parameter sets. While the BEM–CFD method considerably reduces computational load compared to the CFD method, it still fails to address the evaluation function requirements for optimization algorithms. Consequently, generating a dataset through numerical simulations and training a data-driven surrogate model to serve as the evaluation function within the optimization algorithm becomes imperative. Zhu et al. (2020) trained a radial basis function (RBF) as a surrogate model and integrated it with the multi-objective genetic algorithm NSGA-II for blade optimization. Li et al. (2023) used an artificial neural network as a surrogate model to improve turbine efficiency through a genetic algorithm. These studies relied on datasets generated by the CFD method to address the computational efficiency challenges for evaluation functions, albeit at the cost of substantial time required to establish the dataset. Thus, replacing the CFD method with the BEM–CFD method can lead to substantial time savings.

This research proposes an optimization method aimed at enhancing the hydrodynamic performance of turbines while considering the blockage effect. The method applies the BEM–CFD approach to generate a hydrodynamic performance dataset for the turbine. A radial basis function neural network (RBFNN) is established as the surrogate model, and multi-objective optimization is executed utilizing the NSGA-III algorithm. The optimization case study employs a turbine designed by Zhejiang University as the prototype, exploring optimization design under different levels of blockage intensity. The optimization focuses on the distribution of blade chord length and pitch angle, aiming to achieve the following objectives: ① maximizing peak efficiency, ② minimizing thrust at the optimal TSR, and ③ maximizing the average power output near the optimal TSR. The optimization results indicate that as blockage intensity increases, the

turbine can effectively reduce its load while maintaining efficiency through strategic adjustments in blade morphology. Additionally, the optimized turbines exhibit reduced velocity deficits in their near-field wake compared to the prototype. This optimization case not only confirms the feasibility of the proposed method but also provides a detailed analysis of the impact of environmental blockage intensity on turbine design. By comparing the morphological differences in optimized turbines across varying blockage conditions, the study offers valuable theoretical insights for the design of turbines intended for deployment in tidal arrays, contributing to the extensive goal of enhancing the efficiency and effectiveness of tidal energy systems.

2 Turbine model and methods

2.1 Overview of the optimization model

The optimization model proposed in this study comprises two main components: the surrogate model construction

module and the multi-objective optimization module. In the surrogate model construction module, the Latin hypercube sampling (LHS) approach is used to generate a sample set. The BEM–CFD method is then applied to swiftly compute the hydrodynamic performance of the sample set, generating a dataset that is used to train the RBFNN. The RBFNN is used as the surrogate model after validating its prediction accuracy. In the multi-objective optimization module, the types and ranges of optimization variables, as well as the optimization objectives, are defined. The NSGA-III algorithm iteratively refines the design, ultimately identifying a set of Pareto optimal solutions. A schematic of the optimization model is presented in Figure 1, with detailed descriptions of each component provided in Sections 2.2 to 2.6.

2.2 Turbine parameters

This study uses a 25 kW turbine designed by Zhejiang University as the optimization prototype. The turbine parameters are outlined in Tables 1 and 2 (Liu et al., 2016), and the turbine's appearance is depicted in Figure 2. The vari-

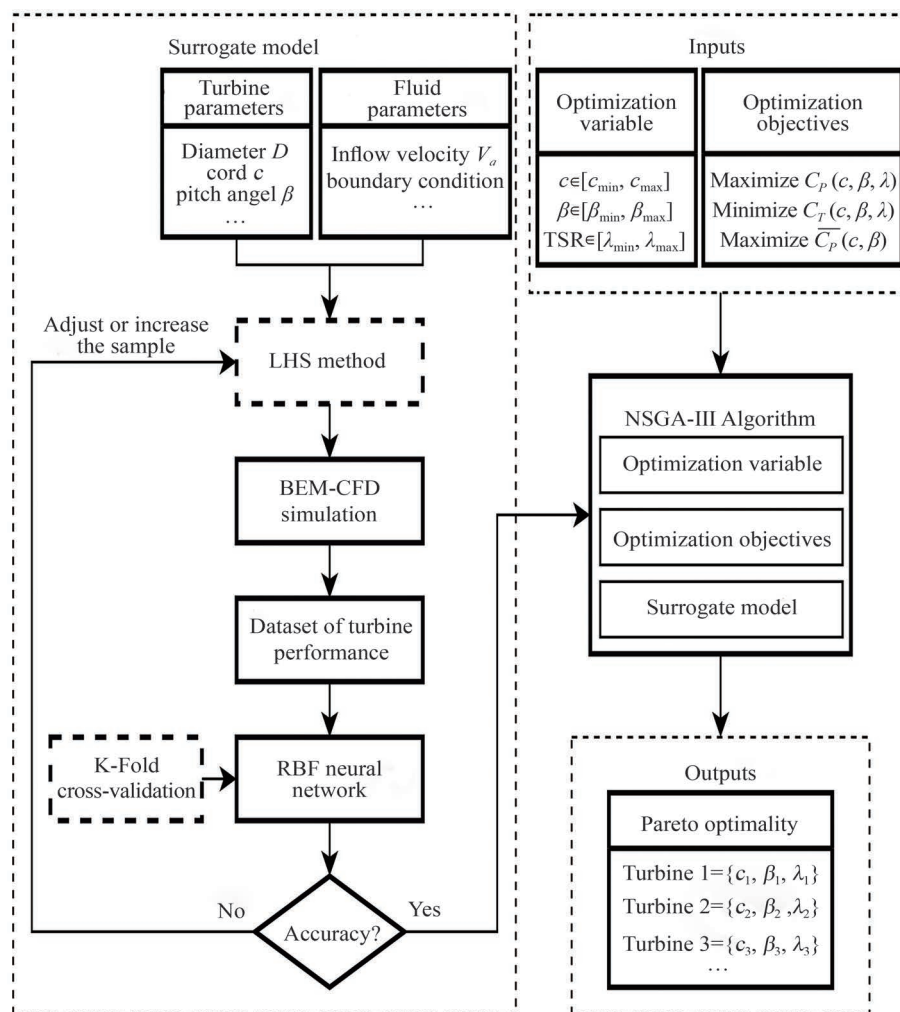


Figure 1 Overview of the optimization model

ables in Table 2 are defined as follows: r is the distance from the blade element section to the center of the turbine, R is the radius of the turbine, c is the chord length of the blade element, b indicates the blade pitch angle, and t indicates the maximum thickness of the airfoil.

Table 1 Main parameters of the turbine

Blade number N	Diameter D (m)	Hub diameter D_{hub} (m)	Airfoil	Rated flow speed V_A (m/s)
3	4.4	0.44	NACA63-4××	2.0

Table 2 Blade parameters of the turbine

r/R	r (m)	c (m)	β (°)	t/c (%)
0.25	0.55	0.397	21	30
0.30	0.66	0.358	17	22
0.35	0.77	0.324	13.50	20
0.40	0.88	0.293	10.52	20
0.45	0.99	0.268	8.94	20
0.50	1.10	0.245	7.65	20
0.55	1.21	0.226	6.55	20
0.60	1.32	0.210	5.60	20
0.65	1.43	0.195	4.79	20
0.70	1.54	0.182	4.07	20
0.75	1.65	0.171	3.43	20
0.80	1.76	0.160	2.82	20
0.85	1.87	0.150	2.23	20
0.90	1.98	0.140	1.61	20
0.95	2.09	0.130	0.80	20
1	2.20	0.120	0	18

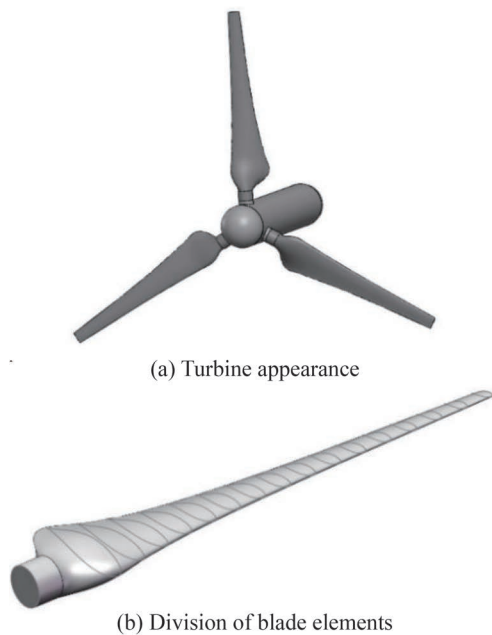


Figure 2 Turbine appearance and blade element division

Aiming to simplify the optimization variables, a second-order Bezier curve is used to fit the chord length and pitch angle distributions along the blade, as illustrated in Figure 3. Adjustments to the 16 blade element sections can be achieved by modifying the positions of the three Bezier control points. The variation ranges for these control points are detailed in Table 3.

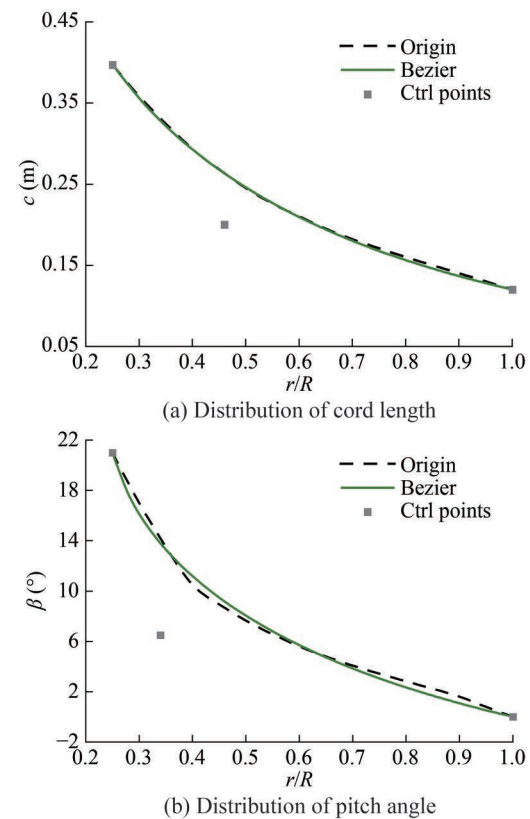


Figure 3 Bezier curves

Table 3 Range of Bezier control points variations

Position of the cord length control point	Control point value	Position of the pitch angle control point	Control point value
$r/R = 0.25$	[0.34, 0.52]	$r/R = 0.25$	[18.0, 24.0]
$r/R = 0.46$	[0.16, 0.28]	$r/R = 0.34$	[3.0, 9.0]
$r/R = 1.0$	[0.08, 0.20]	$r/R = 1.0$	[-3.0, 3.0]

Furthermore, the power coefficient C_p and the thrust coefficient C_T are key indicators for assessing the hydrodynamic performance of a tidal turbine. The former reflects the efficiency of energy conversion in the turbine, while the latter indicates the load on the turbine structure. The definitions of C_p and C_T are presented in Equations (1) and (2), respectively.

$$C_p = \frac{P}{0.5\rho V^3 A} \quad (1)$$

$$C_T = \frac{T}{0.5\rho V^2 A} \quad (2)$$

where P denotes the power output of the turbine, T denotes the thrust exerted by the turbine, ρ is the fluid density, V is the incoming flow velocity, and A is the projected area of the turbine facing the incoming flow.

2.3 BEM–CFD model

The hydrodynamic performance of the turbine is computed using the BEM–CFD method, which calculates the loads through blade element theory while solving flow field evolution using the CFD method. The blade element theory calculations are expressed by Equations (3) and (4) as shown below.

$$dT = \frac{1}{2} \rho W^2 N c (C_L \cos \varphi + C_D \sin \varphi) dr \quad (3)$$

$$dM = \frac{1}{2} \rho W^2 N c (C_L \sin \varphi - C_D \cos \varphi) r dr \quad (4)$$

where W is the local resultant velocity at the blade element, N is the number of blades, c is the chord length of the blade element, C_L and C_D are the lift and drag coefficients, respectively, obtained via XFOIL software, and φ is the inflow angle at the blade element.

The local resultant velocity W and inflow angle φ at the blade element are determined using Equations (5) and (6), respectively.

$$W = \sqrt{V_a^2 + V_t^2} \quad (5)$$

$$\varphi = \arctan \frac{V_a}{V_t} \quad (6)$$

where V_a and V_t are the axial and tangential flow velocities at the blade element, respectively. Unlike the traditional BEM method, the BEM–CFD approach does not require the calculation of induced velocity factors. In the BEM–CFD method, the velocity distribution is obtained by solving the Navier–Stokes (N–S) equations. The local velocities across the turbine area are then transmitted to the blade element theory calculation program through the mesh of the virtual disk model, enabling the calculation of the turbine loads.

The N–S equations are used to incorporate the forces at each blade element position as additional source terms within the CFD flow field, as expressed in Equations (7) and (8).

$$\frac{\partial u_i}{\partial x_i} = 0 \quad (7)$$

$$\rho \frac{\partial u_i}{\partial t} + \rho u_j \frac{\partial u_i}{\partial x_j} = f_i - \frac{\partial p_i}{\partial x_i} + \mu \frac{\partial^2 u_i}{\partial x_j \partial x_j} \quad (8)$$

where u is the velocity of the fluid parcel, f includes any additional sources, and p is the surface pressure on the fluid parcel.

The SST k – ω turbulence model was integrated to close the system of N–S equations. Turbine forces and flow field distributions are obtained by solving Equations (3), (4), (7), and (8) iteratively. The calculation flowchart is depicted in Figure 4.

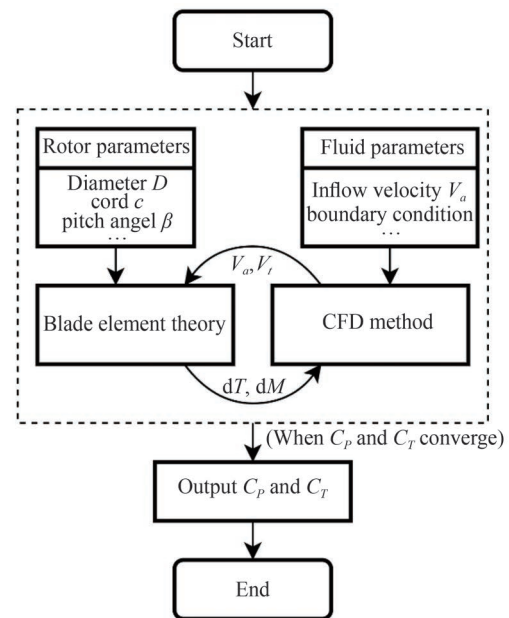


Figure 4 Calculation flowchart of the BEM–CFD method

In this study, the computational domain for the BEM–CFD method is illustrated in Figure 5. A virtual disk replaces the physical space of the rotor, and the grid covers the force source terms generated by the turbine. The model accommodates a nacelle with a diameter of 0.88 m. Aiming to minimize interference from the free surface and the tank bottom, the upper and lower boundaries of the computational domain are strategically positioned at a distance of $5D$ from the turbine. Additionally, a downstream distance of $30D$ is allocated to allow for sufficient wake development. The lateral distances from the turbine to the boundaries, denoted as A , are systematically varied to simulate different operating conditions with increasing blockage intensity. These distances are set to $5.0D$, $2.0D$, $1.0D$, and $0.2D$, enabling the study of the effects of varying blockage conditions on turbine performance.

Figure 6 illustrates the performance characteristics of the prototype turbine under four operating conditions. The data indicates that the prototype achieves maximum efficiency within the TSR range of 5 to 6. Based on this opti-

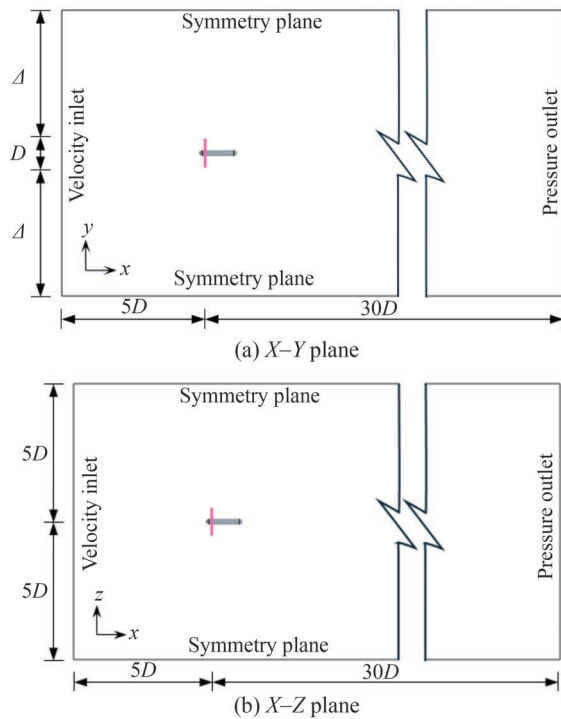


Figure 5 Computational domain

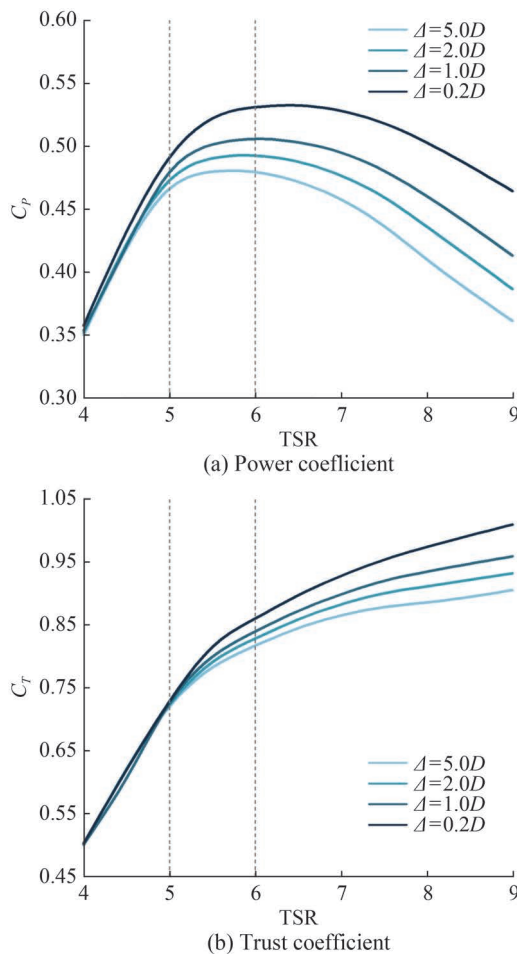


Figure 6 Hydrodynamic performance of the prototype turbine

mal performance range, subsequent optimization efforts will focus on this specific TSR interval.

2.4 Dataset sampling

The turbine optimization parameters comprise seven variables: three chord length control points $c = \{c_1, c_2, c_3\}$, three pitch angle control points $\beta = \{\beta_1, \beta_2, \beta_3\}$, and the operational TSR λ . The optimization objectives include the following:

- ① Maximize the peak power coefficient C_p ;
- ② Minimize the thrust coefficient C_T at the optimal TSR;
- ③ Maximize average power efficiency $\overline{C_p}$ within the TSR range of 5 to 6.

This optimization problem can be formally expressed as Equation (9).

$$\begin{cases} \text{maximize: } C_p(c, \beta, \lambda) \\ \text{minimize: } C_T(c, \beta, \lambda) \\ \text{maximize: } \overline{C_p}(c, \beta) \end{cases} \quad (9)$$

Considering the need to evaluate thousands of turbine configurations during optimization, the BEM–CFD method alone is insufficient due to its high computational demands. Therefore, developing a mathematical surrogate model to rapidly predict turbine performance is essential.

The dataset is generated using the LHS technique, which efficiently captures function characteristics with fewer samples (Helton and Davis, 2003). The sampling process involves uniformly dividing each variable dimension into intervals and randomly selecting values from those intervals to form sample points, as illustrated in Figure 7.

Aiming to address the issue of pathological sampling, as illustrated in Figure 7(b), this study adopts the improved sampling method proposed by Yi et al. (2017).

Initially, the sampling space is divided into predefined intervals, with one dimension designated as the reference dimension. For this reference dimension, intervals are selected sequentially during the sampling process. By contrast, for the other dimensions, the initial sampling retains a random selection of intervals. From the second sampling iteration onward, for any available sampling position within the multidimensional space, the Euclidean distances from that position to all existing sample points are calculated. The shortest distance among these points is recorded as the eigenvalue for that position. Subsequently, after determining the eigenvalues for all potential sampling positions, the position with the maximum eigenvalue is selected as the sample point for the current iteration. Once t sample points have been established, selecting the $t+1$ sample point becomes an optimization problem, as outlined in Equation (10).

Given that the sampling variables in this study are seven-

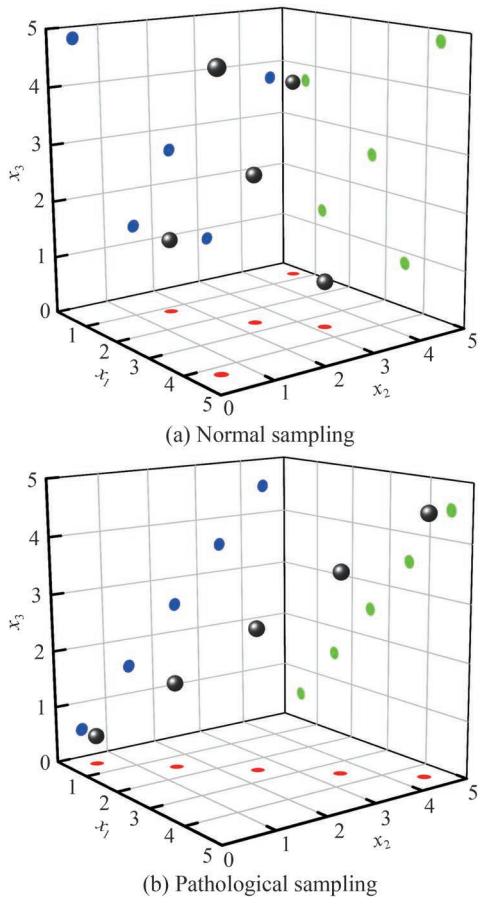


Figure 7 LHS method (The black balls represent the sample points, while the colored circles depict the projections of these sample points onto each respective plane)

dimensional, the particle swarm optimization (PSO) algorithm is used to effectively solve this optimization problem. The application of PSO not only aids in the selection of optimal sampling points but also reduces the computational burdens associated with high-dimensional sampling, thereby enhancing the overall efficiency of the optimization process.

$$\begin{cases} \text{maximize: } d_f(\mathbf{x}) = \min(d_1, d_2, \dots, d_s) \\ d_i = |\mathbf{s}_i - \mathbf{x}|, i \in [1, t] \end{cases} \quad (10)$$

where $\mathbf{x}$ is the coordinates of an available sample position, $\mathbf{s}_i$ is the coordinates of the i th sample point, d_i is the Euclidean distance between the two, and d_f is the eigenvalue corresponding to $\mathbf{x}$.

2.5 RBFNN model

The RBFNN model offers advantages, including robust nonlinear mapping capabilities, global approximation capability, and rapid training convergence. This model comprises

three layers: input, hidden, and output. The hidden layer contains multiple RBFs that serve as activation functions. The activation function is expressed by Equation (11).

$$R(\mathbf{x}_p - \mathbf{h}_i) = \exp\left(-\frac{1}{2\sigma^2} \|\mathbf{x}_p - \mathbf{h}_i\|^2\right) \quad (11)$$

where $\mathbf{x}_p$ represents the p th input parameter, $\mathbf{h}_i$ denotes the i th network center, and σ is the Gaussian function variance, which controls the influence range of the network center.

The input layer parameters include three chord length control points $\{c_1, c_2, c_3\}$, three pitch angle control points $\{\beta_1, \beta_2, \beta_3\}$, and the operating TSR. The model output parameters comprise the turbine power coefficient C_p and thrust coefficient C_T . The RBFNN structure is depicted in Figure 8.

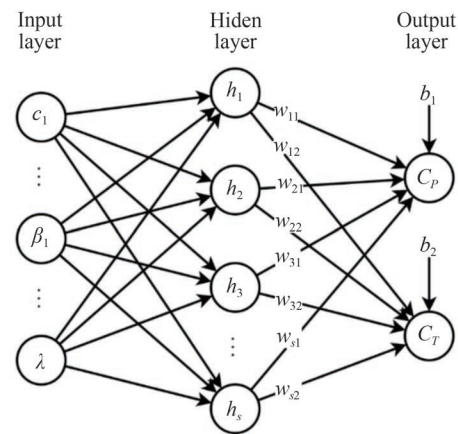


Figure 8 RBFNN structure diagram

RBFNN training involves the identification of network center positions, Gaussian variances σ , and output layer weights $\mathbf{w}$ and biases $\mathbf{b}$, all determined during the model training process via gradient descent.

In addition to the previously mentioned parameters, the number of network centers is a crucial hyperparameter that requires manual specification. The selection of the number of network centers has a considerable impact on the predictive capability and performance of the neural network. Specifically, an insufficient number of centers may lead to underfitting, where the model fails to capture the underlying patterns in the data. Conversely, an excessive number can cause overfitting, where the model becomes overly complex and begins to capture noise rather than the actual trends.

Aiming to determine the optimal number of network centers, this study uses the K-fold cross-validation method. The fundamental principle of K-fold cross-validation involves partitioning the dataset into k subsets, known as “folds”. In each iteration of the validation process, one fold is used as the validation set, while the remaining $k-1$ folds are used as the training set. This “train–validate” cycle is repeated k times, ensuring that each fold serves as the validation set once.

By averaging the errors from these iterations, K-fold cross-validation provides an objective assessment of the model's predictive accuracy and generalization capability. This methodology allows for a robust evaluation of the impact of varying the number of network centers on model performance.

2.6 NSGA-III genetic algorithm

Aiming to address the multi-objective optimization problem, the NSGA-III genetic algorithm is employed. The optimization process is illustrated in Figure 9, with the detailed steps outlined in Deb and Jain (2014). Each individual in the population represents a specific turbine configuration, characterized by seven optimization parameters. The fitness of each individual reflects its optimization level, which is calculated based on the turbine's hydrodynamic performance.

The NSGA-III method incorporates a unique reference point mechanism during offspring selection, which helps maintain diversity among individuals in the solution space when addressing optimization problems with three or more objectives. This method effectively mitigates the risk of converging to local optima, thereby improving the capability of the algorithm to explore a wide range of potential solutions.

During the initialization phase of the optimization algorithm, reference points are used to populate the solution space in a manner that ensures an even distribution of solutions.

Once the algorithm progresses to the selection of the offspring population, the process involves merging the parent population with the newly generated offspring, which has undergone crossover and mutation operations. Afterward, a fast non-dominated sorting procedure is applied to the combined population based on the optimization objectives described in Equation (9). This method classifies individuals into different layers based on their dominance relationships.

All individuals in layers 1 through $l-1$ are retained in the offspring population, where $l-1$ represents the maximum number of layers such that the cumulative total of individuals from layers 1 through $l-1$ does not exceed the predetermined size of the offspring population. If the offspring population remains deficient by m individuals after this selection process, then additional candidates are drawn from the n individuals in the l layer. The selection process prioritizes individuals based on the density of existing individuals relative to the reference points, with preference given to positions exhibiting lower density. This selection process is depicted in Figure 10.

In the initial stages of this work, the RBFNN model may produce unpredictable errors due to the dispersion of individuals. Aiming to address this issue, at the end of the evaluation phase, several key individuals, typically the best-performing and the worst-performing ones, will be selected. The accuracy of the RBFNN predictions for these individuals will then be validated using the BEM-CFD method. If the error exceeds a certain threshold, then the affected individual will be added to the training set for

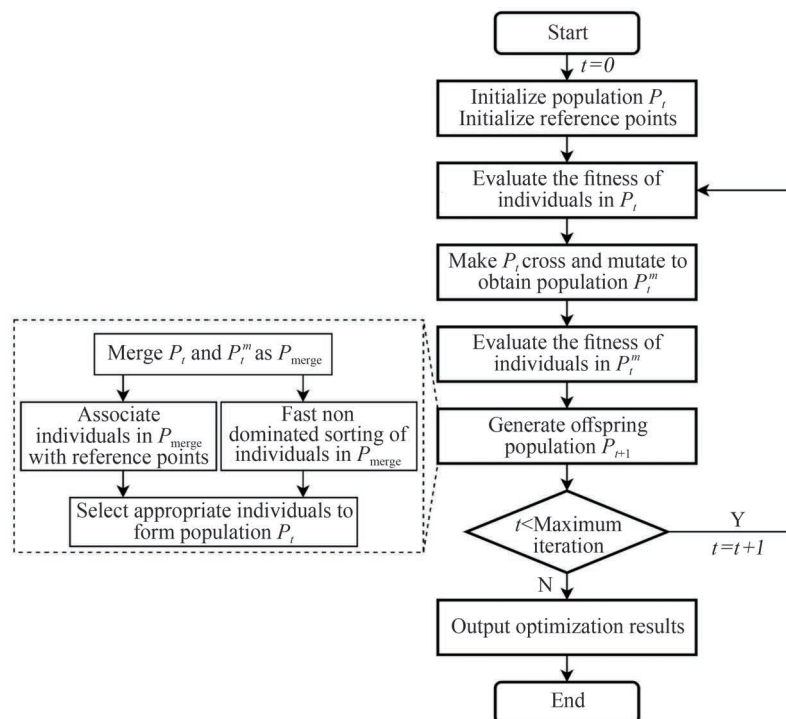


Figure 9 NSGA-III algorithm flowchart

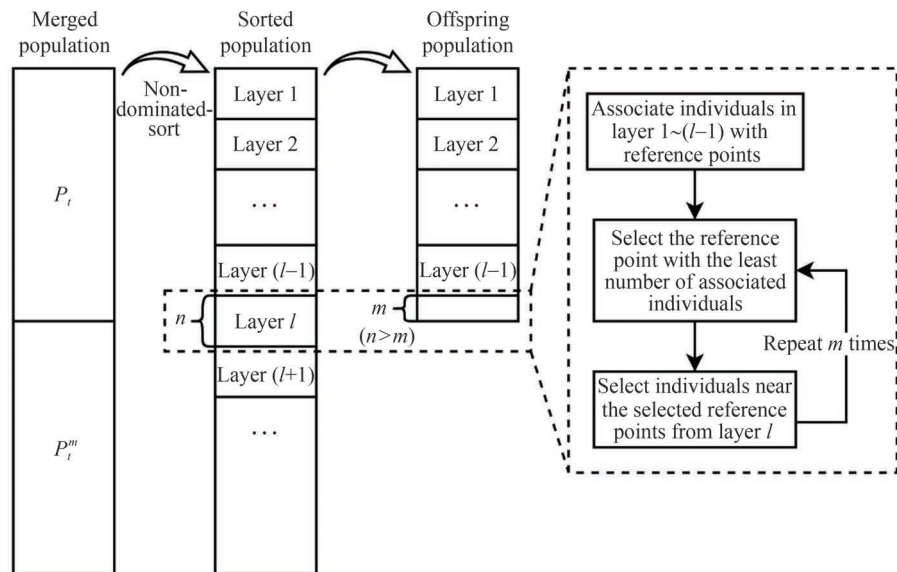


Figure 10 NSGA-III offspring selection diagram

retraining and updating the RBFNN model, after which the optimization will continue.

3 Validation of the methods and convergence study

3.1 Mesh convergence study

In the BEM–CFD method, the density of the computational mesh plays a crucial role in determining the accuracy of simulation results. This study adopts a refined mesh design, particularly in the turbine wake region and its surrounding area, as illustrated in Figure 11.

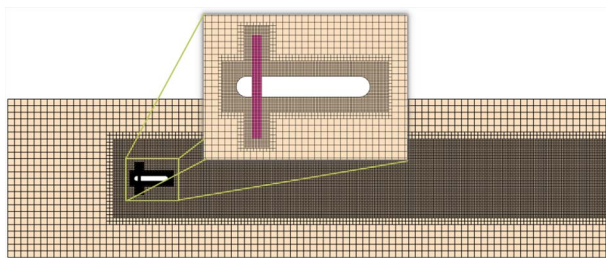


Figure 11 Flow field mesh division

Aiming to assess the impact of mesh density on the simulation outcomes, four distinct sets of meshes with varying densities were used. These mesh sets had the following total cell counts: 3.6×10^5 (mesh 1), 6.8×10^5 (mesh 2), 1.1×10^6 (mesh 3), and 2.6×10^6 (mesh 4). The results from these simulations are presented in Figure 12.

Based on the analysis in Figure 12(b), when the mesh density reaches 6.8×10^5 (mesh 2), the peak C_p exhibits minimal

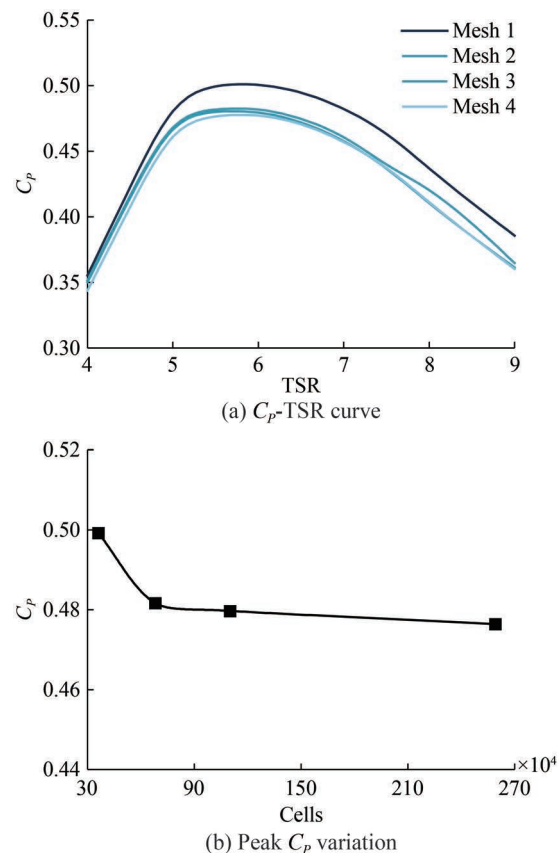


Figure 12 Mesh convergence

variation with further increases in mesh density. Conversely, Figure 12(a) reveals that within the TSR range of 7 to 9, the performance results from mesh 2 substantially differ from those obtained using meshes 3 and 4. Considering the accuracy of the results and the associated computational

costs, mesh 3, with a density of 1.1×10^6 , was ultimately selected for the simulations.

3.2 Validation of BEM–CFD method

The validation of the BEM–CFD method is conducted by comparing it with experimental data provided by Bahaj et al. (2007). These experiments were performed in a cavitation water tank at the University of Southampton, with key experimental parameters outlined in Table 4. Notably, the data presented by Bahaj has been adjusted to account for blockage effects.

Table 4 Main parameters of Bahaj’s experiment

Blade number N	Diameter D (m)	Hub diameter D_{hub} (m)	Airfoil	Rated flow speed V_A (m/s)
3	0.8	0.16	NACA63-8××	1.73

Aiming to simulate a blockage-free condition during the BEM–CFD modeling, a fluid domain with $A = 5D$ was employed. Figure 13 presents a comparative analysis between the experimental results and the corresponding BEM–CFD predictions.

From Figures 13(a) and 13(b), the results obtained from the BEM–CFD method closely align with the experimental data, with both datasets exhibiting similar trends across the range of tested conditions. Figure 13(c) presents a quantitative assessment of the relative error values for C_p and C_T . The analysis reveals that substantial errors are predominantly observed at notably high or low TSRs, with a maximum error of approximately 7.5%. Conversely, within the intermediate TSR range, the error for C_p remains consistently below 2%, while the error for C_T is generally below 4%.

Several factors may contribute to these observed errors. First, the absence of a standardized and precise dataset for the lift and drag coefficients of airfoils currently presents a challenge, potentially leading to inaccuracies in the calculation of blade loads. Second, the BEM–CFD method models the turbine as an actuator disk, simplifying the transient effects associated with rotating blades by reducing them to a steady-state problem. The most notable issue arising from this simplification lies in the inability to simulate three-dimensional rotational effects. When the blades rotate, surrounding fluid particles move from the blade root to the blade tip due to centrifugal forces. This flow delays flow separation on the blades, thereby affecting the lift-to-drag coefficients, particularly near the stall angle of attack. The virtual disk of the BEM–CFD cannot accurately simulate this effect; thus, errors in C_p and C_T are inevitably introduced. Additionally, while Bahaj’s experimental data have been corrected for blockage effects, the assumptions underlying the correction methodology may also contribute to discrepancies. Overall, the relative errors observed in this study are considerably acceptable, indicating that the BEM–CFD

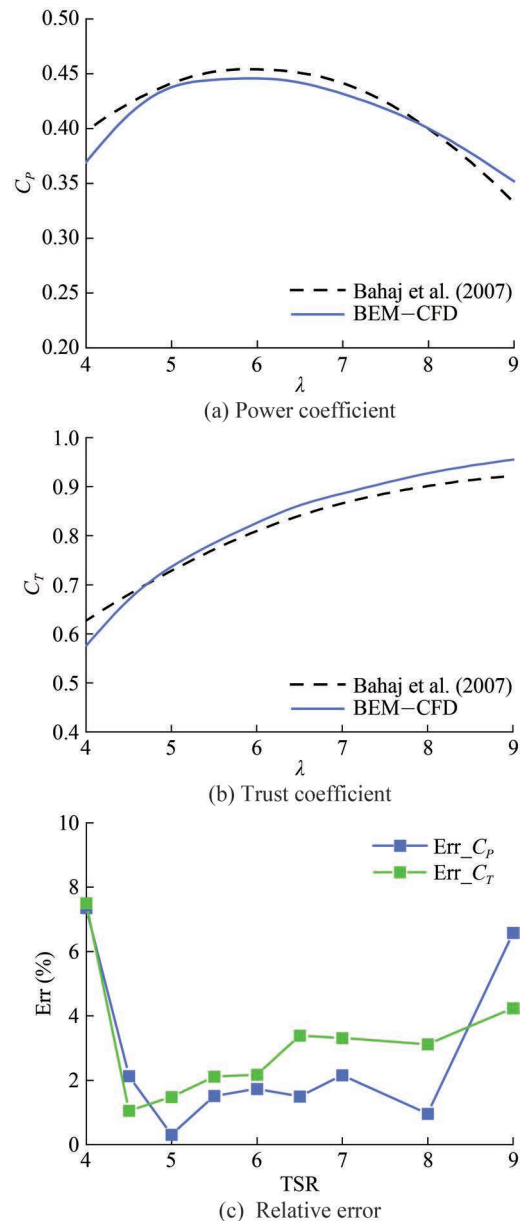


Figure 13 Comparison of experimental data and BEM–CFD results

method satisfactorily meets the computational requirements for this investigation.

3.3 Validation of RBFNN

Prior to the formal modeling of the RBFNN, K-fold cross-validation is used to assess the effect of the number of network centers N_c on model accuracy. The results of this analysis are summarized in Table 5, which presents the average relative error for C_p and C_T , along with the probability of the relative error exceeding 2% for each model configuration. The number of folds was set to $k = 20$.

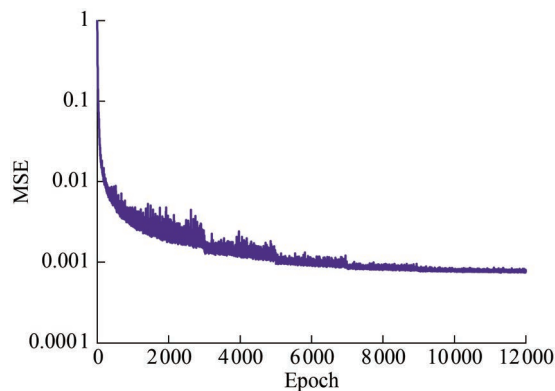
The performance metrics indicate that when the number of network centers is set to $N_c = 21$, the model exhibits optimal values across most error indicators. Consequently,

Table 5 Results of K-fold cross-validation (The minimum value of each item is marked with “*”)

N_c	Err (C_p)	Err (C_T)	$P(\text{Err} (C_p) > 2\%)$	$P(\text{Err} (C_T) > 2\%)$
7	0.88%	0.86%	9.29%	8.81%
14	0.59%	0.43%	* 5.25%	2.28%
21	* 0.57%	* 0.38%	5.31%	* 1.96%
28	0.63%	0.39%	7.48%	2.44%
35	0.64%	0.41%	7.32%	2.92%
42	0.69%	0.44%	8.92%	4.09%

the RBFNN with 21 network centers is selected for further analysis.

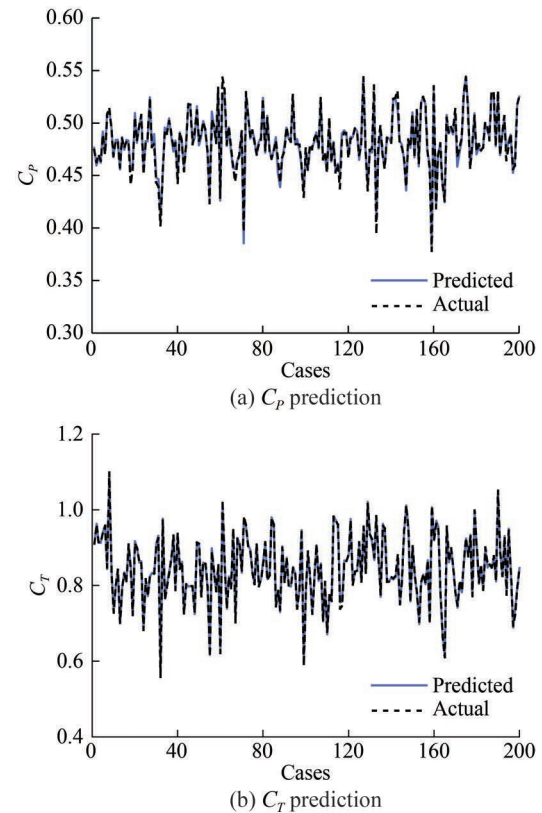
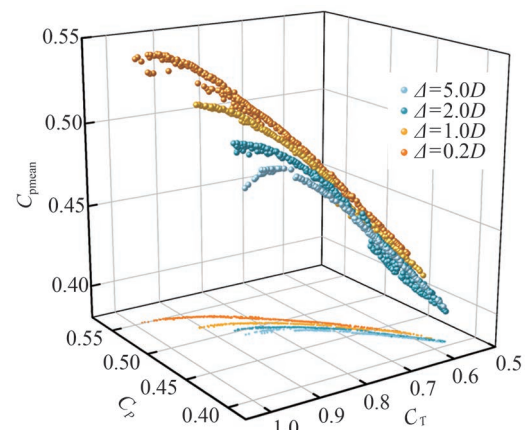
The dataset used for establishing the neural network model comprises 400 samples, with 80% allocated for the training and the remaining 20% for validation. The maximum number of training epochs is set to 12 000. As illustrated in Figure 14, the training process demonstrates convergence around the 9 000th epoch, where the mean square error is approximately 7×10^{-4} . Furthermore, Figure 15 presents the validation results of the RBFNN model. The predicted values generated by the RBFNN closely align with the actual values, indicating that the model meets the computational requirements necessary for the optimization algorithm. With this validation, the model is well-equipped to support further analyses and optimizations in turbine design and performance evaluation.

**Figure 14** Training error convergence

4 Results and discussions

4.1 Analysis of pareto front (PF)

Aiming to investigate the influence of blockage effects on the optimal configuration of tidal turbines, NSGA-III was applied to perform multi-objective optimization under the following four distinct working conditions: $\Delta = 5.0D$, $2.0D$, $1.0D$, and $0.2D$. The optimization objectives are defined in Equation (9), and the corresponding results are illustrated in Figure 16.

**Figure 15** Performance of RBFNN on the validation set**Figure 16** Pareto front for NSGA-III optimization

In Figure 16, each sphere represents an individual turbine, characterized by a set of seven optimized design parameters. Considering the three-objective nature of the optimization, the optimal solutions form a three-dimensional surface known as PF. For any two turbines, namely A and B, on the PF, at least one of the three optimization indicators of turbine A will be better than that of turbine B, and vice versa. Additionally, for any turbine located within the inner area of the PF, there exists at least one turbine on the PF that performs better in all optimization indicators. Therefore, solutions located on the PF can be considered irre-

placeable optimal solutions. In practical applications, the selection of specific individuals from the PF should be based on the particular requirements of the design objectives.

The analysis of Figure 16 demonstrates that as the intensity of the blockage effect increases, the position of the PF shifts toward areas characterized by an increase in C_p , an increase in $\overline{C_p}$, and a decrease in C_T . However, this trend does not mean that a turbine can simultaneously achieve high efficiency and low load under conditions of increased blockage. The PF does not provide direct insight into the performance variations of individual turbines. For instance, in the C_p – C_T plane illustrated in Figure 16, maintaining a constant C_p while observing changes in C_T reveals that, as blockage intensity increases, C_T tends to decrease. This observation indicates that, in high-blockage environments, identifying turbine configurations that achieve lower thrust while sustaining the same efficiency level as the original turbine design is possible. Similarly, this observation also indicates that as the blockage effect intensifies, turbine configurations that deliver the same thrust but with improved efficiency can be identified. These findings affirm that environmental blockage effects play a crucial role in influencing turbine design strategies, emphasizing the importance for designers to consider blockage conditions when developing turbine configurations.

4.2 Optimization results of hydrodynamic performance

As previously discussed, the selection of individuals from the PF is inherently subjective. In this study, Turbines 1 to 4 were chosen for analysis under each working condition: $\lambda = 5.0D$, $2.0D$, $1.0D$, and $0.2D$. The selection was based on specific criteria: the peak C_p of each turbine should closely match that of the prototype, while maximizing the average power coefficient $\overline{C_p}$ within the TSR range of 5 to 6. The hydrodynamic performance of these selected turbines under the corresponding working conditions is depicted in Figure 17.

The analysis of Figure 17 reveals notable trends in the hydrodynamic performance of the selected turbines. Figures 17(a), (c), (e), and (g) demonstrate that the optimized turbines achieve high C_p values at low TSRs, which can be attributed to optimization objective ③, aimed at improving the mean performance of the turbine across the operational range. Moreover, Figures 17(b), (d), (f), and (h) indicate that the C_T for the optimized turbines is lower than that of the prototype at higher TSRs, while the C_p remains comparable to that of the prototype. At low TSRs, the C_T of the optimized turbines exhibits an increase, which reflects a necessary tradeoff between optimization objectives ② and ③. Additionally, the maximum increase in C_p for the optimized turbine occurs at $\text{TSR} = 4.5$, while the maximum reduction in C_T is observed at $\text{TSR} = 6.5$. Table 6 presents a quantita-

tive summary of the performance variations of the optimized turbines at these specific TSRs.

From a practical engineering standpoint, the optimized turbines provide the advantage of reducing the maximum load without compromising energy efficiency. This improvement is critical for enhancing structural safety and potentially lowering construction costs. Although thrust increases at low TSRs, this effect is generally considered negligible, because the maximum load remains the primary concern in structural design.

4.3 Influence of blockage effect on turbine design

Aiming to analyze the influence of the blockage effect on turbine blade design, Figure 18 presents a comparison of the chord length and pitch angle distributions for Turbines 1 to 4.

An analysis of Turbine 4's blade profile in Figure 18, along with its corresponding hydrodynamic performance illustrated in Figures 17(g) and (f), highlights the critical role of the blade tip in influencing overall hydrodynamic performance. Notably, the chord length and pitch angle at the blade tip of Turbine 4 are nearly identical to those of the prototype. This similarity in design contributes to the comparable hydrodynamic performance observed between the two turbines.

Moreover, as depicted in Figure 18(a), an increase in the flow field blockage effect leads to a trend where the blade profiles become thicker at the root and thinner at the tip. Modifications to the blade chord length directly influence the turbine's solidity, which is a key factor in determining the intensity of the blockage effect on the external flow field. A large blade chord length enhances the interaction between the blades and the incoming flow, thereby improving the turbine's energy capture capability. However, a high solidity can also impede the incoming flow, reducing the flow rate through the turbine, which may ultimately decrease its energy capture efficiency.

Consequently, optimizing the chord length distribution of the blades involves adjusting the turbine's solidity to align with the environmental blockage intensity under varying operating conditions. As the environmental blockage intensity increases for Turbines 1 to 4, the chord lengths at the blade roots increase correspondingly, while the chord lengths at the blade tips decrease. This design choice is influenced by the requirement that the peak C_p of the optimized turbines must match that of the prototype, thereby preventing any further increases in peak C_p while simultaneously reducing the thrust experienced by the optimized design.

Considering the pitch angle, as shown in Figure 18(b), the optimized turbines generally exhibit larger pitch angles compared to the prototype. The pitch angle is mainly determined by the hydrodynamic characteristics of the airfoil and the local flow conditions around the blades. Adjusting the pitch angle enables the blades at various positions to achieve an optimal angle of attack. In this study, the variation

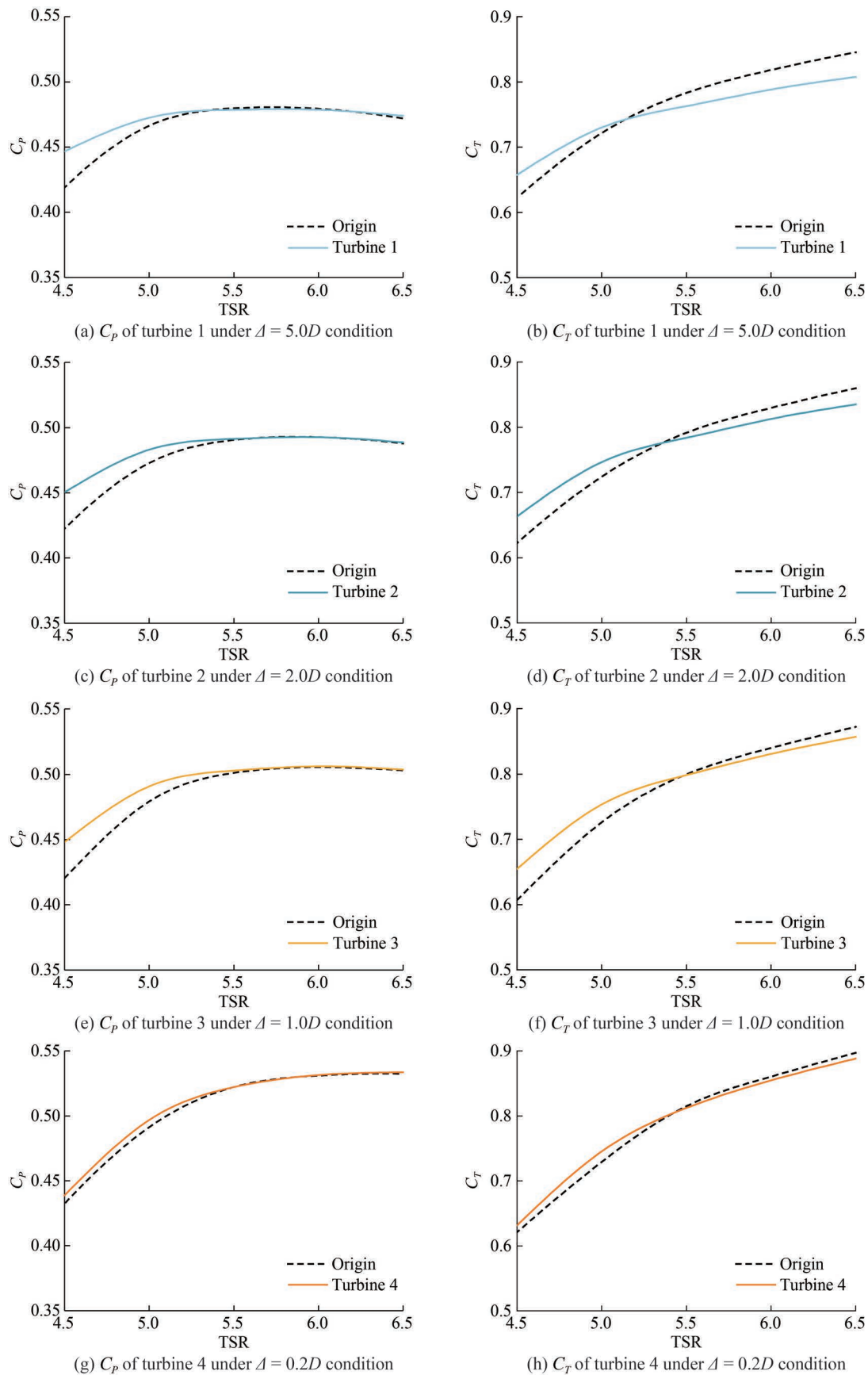


Figure 17 Turbine performance under different operating conditions

in pitch angle for Turbines 1 to 4 is minimal, with the maximum difference at the blade tips being approximately 1° . This observation indicates that while the environmental blockage effect has a substantial influence on the distribution of chord lengths, its impact on the pitch angle is relatively minor.

Table 6 Performance variations of optimized turbines

Turbine	C_p growth rate (%) TSR = 4.5	C_T reduction rate (%) TSR = 6.5
1	6.45	4.47
2	6.49	2.86
3	6.57	1.78
4	2.07	0.77

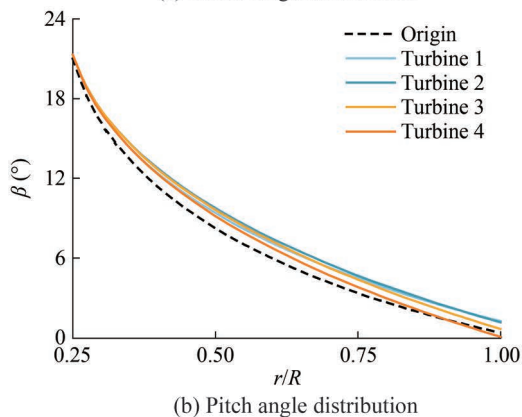
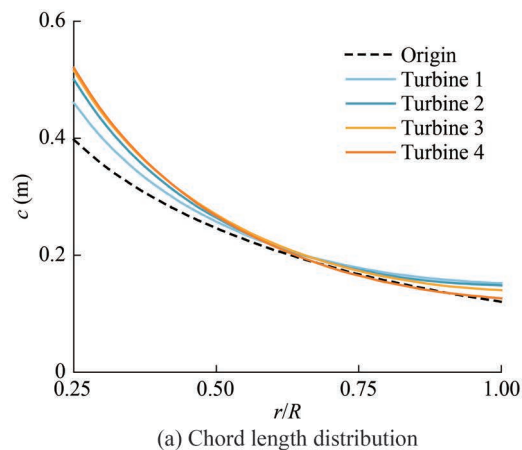


Figure 18 Blade profile parameters

4.4 Wake of the optimized turbine

Figures 19 and 20 illustrate the velocity profiles at the $5D$ position on the rear side of the turbine operating at the optimal TSR under different conditions. A comparative analysis reveals that the four optimized turbines exhibit varying levels of improvement in the velocity valley values compared to the prototype turbine. Turbine 4 shows an enhancement of 7.30%, while Turbines 1–3 demonstrate improvements of over 10%, as summarized in Table 7. This improvement in minimum velocity can be primarily attributed to the reduction in the C_T , as discussed in Section 4.2.

Table 7 Velocity variations of optimized turbines

Turbine	Velocity growth ratio at valley (%)	Velocity reduction ratio at peak (%)
1	16.30	4.03
2	18.72	6.38
3	12.36	6.33
4	7.30	7.36

However, at the turbine axis position, the optimized turbines display lower velocities, with all four turbines showing a comparable reduction in peak velocity, ranging from approximately 4% to 7%. This phenomenon can be attributed to the increased thickness of the blade roots in the optimized designs, which intensifies the local blockage effect near the turbine axis and consequently reduces the flow velocity at this position.

Figure 21 illustrates the maximum velocity deficit values at various cross-sections of the flow field in the flow direction, with the slope of the curve representing the wake recovery rate. The analysis shows that, within a flow field extending up to approximately $15D$ downstream of the turbine, the optimized turbines exhibit a smaller velocity deficit compared to the prototype. However, the wake recovery rate for the optimized turbines is slower than that of the prototype. This discrepancy can be attributed to the higher wake velocity along the axis of the prototype, which generates greater turbulent kinetic energy and thus promotes a faster wake recovery.

In the region between $15D$ and $20D$, both turbines demonstrate a substantial increase in the slopes of their velocity

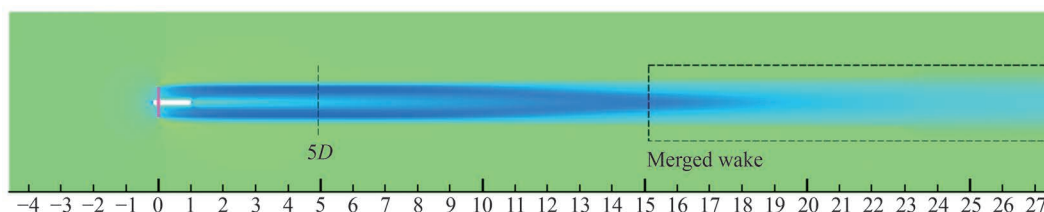


Figure 19 Annotation of the current meter location and the wake fusion region

deficit curves. This behavior aligns with the wake merging area depicted in Figure 19, where the higher-velocity wake along the axis merges with the surrounding annular low-

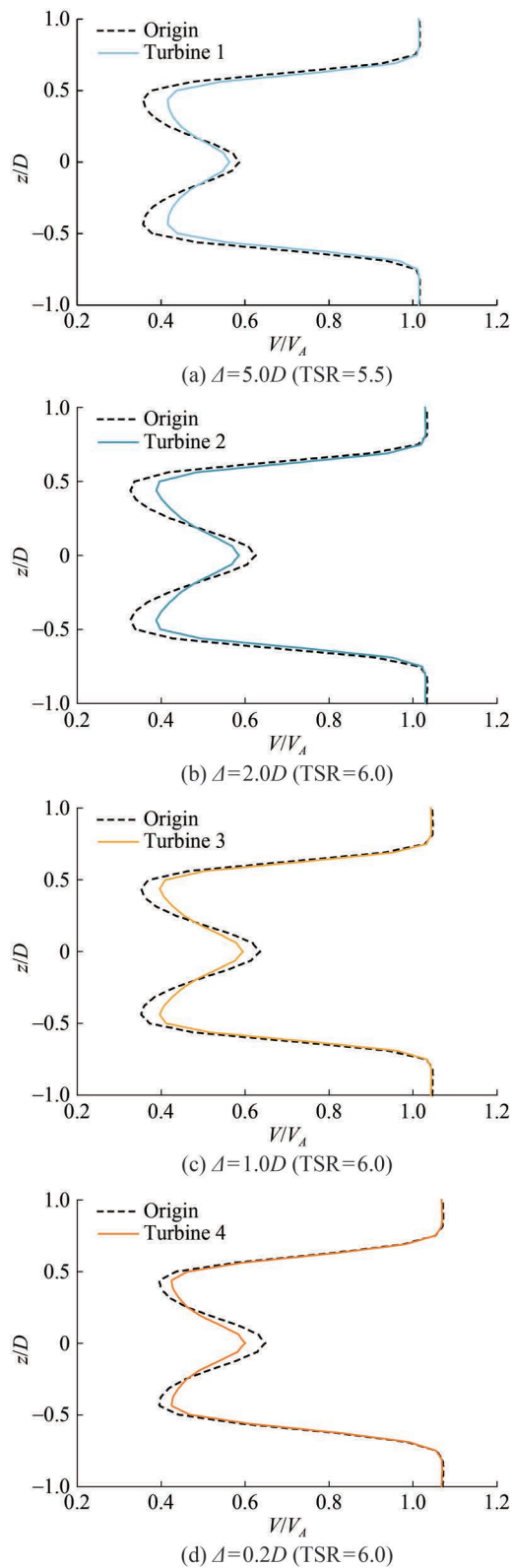


Figure 20 Velocity profile at $5D$ behind the turbine

velocity wake. During this phase, the slopes of the velocity deficit curves for the optimized turbines approach those of

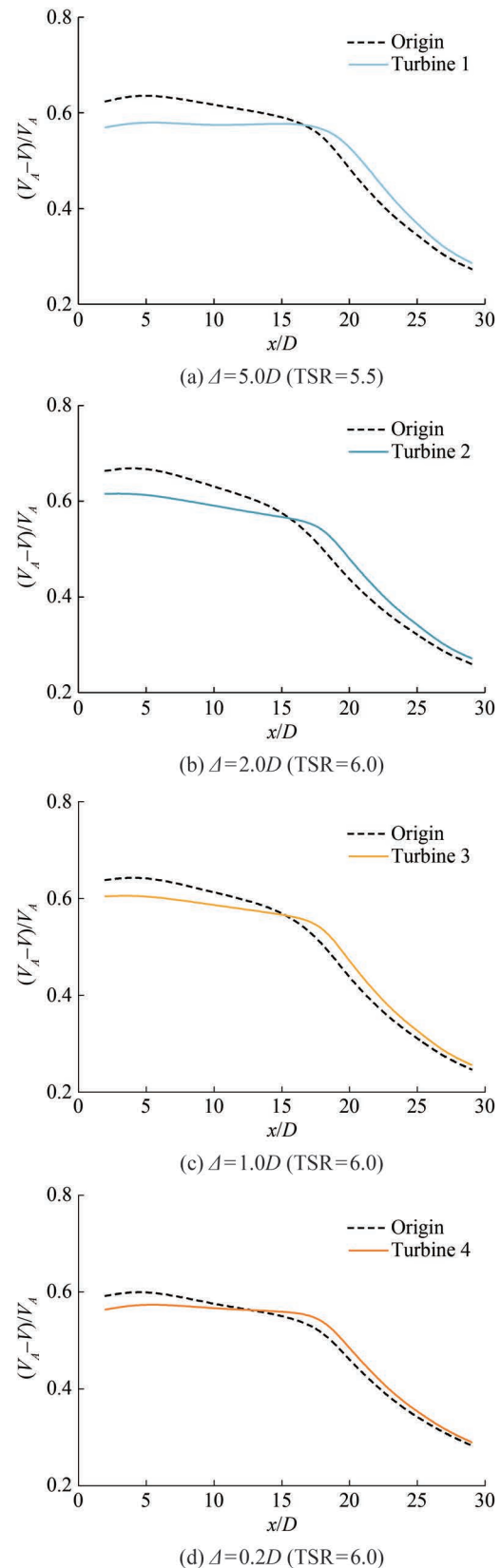


Figure 21 Velocity deficit along flow direction

the prototype, indicating that their wake recovery rates become nearly identical. This finding indicates that the turbine configuration has minimal impact on the recovery rate of the far-field wake beyond the merging region.

Furthermore, the wake of the optimized turbines enters the merging phase later than that of the prototype. This delay can be attributed to the lower turbulent kinetic energy carried by the wake along the axis of the optimized turbines.

Overall, the analysis indicates that the optimized turbines demonstrate a smaller velocity deficit within approximately $15D$ downstream. However, they exhibit a slower wake recovery rate and enter the wake merging phase later than the prototype. Notably, during the wake merging phase, the recovery rates of the optimized turbines and the prototype become nearly identical. This finding indicates that while the optimized turbine design enhances initial flow dynamics, its influence diminishes in the far-field wake recovery process, highlighting the complex interactions between turbine design and flow characteristics in tidal energy applications.

5 Conclusion

This paper introduces a novel turbine optimization method that incorporates environmental blockage effects, combining BEM theory, the CFD method, an RBFNN model, and the NSGA-III optimization algorithm. The feasibility of this method is validated through an optimization case study based on a turbine designed by Zhejiang University.

The multi-objective optimization results demonstrate that optimal turbine configurations substantially vary with changes in blockage intensity. As blockage intensity increases, turbine configurations can either be adjusted to reduce turbine load without compromising efficiency or to enhance efficiency without increasing load. A comparative analysis of the hydrodynamic performance between the optimized turbines and the prototype, maintaining the same peak C_p , indicates that increasing blockage intensity enables turbine blades to reduce load while preserving efficiency. This condition is achieved by increasing the blade root thickness and reducing the blade tip thickness. Furthermore, the pitch angles of the blades exhibit minimal sensitivity to changes in environmental blockage intensity.

The optimized turbine demonstrates a smaller velocity deficit within approximately $15D$ downstream. However, its wake recovery rate is slower compared to that of the prototype. While the optimized turbine enters the wake merging phase slightly later than the prototype, once within the merging region, the wake recovery rates of both turbines become nearly identical. This finding indicates that the turbine configuration has a minimal effect on the recovery rate of the far-field wake.

The proposed optimization method, which uses the efficient and flexible BEM–CFD approach, not only effectively

accounts for blockage effects but also optimizes turbine designs under various other complex operating conditions. Additionally, the insights gained from the optimization case are expected to guide future turbine design efforts, particularly in high-blockage environments such as turbine arrays or narrow channels.

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Competing interest The authors have no competing interests to declare that are relevant to the content of this article.

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