Prediction and multi-objective optimization of tidal current turbines considering cavitation based on GA-ANN methods

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Abstract
As a new type of energy, tidal current energy is increasingly gaining attention worldwide. However, the tidal current energy development field faces a key technical problem of how to improve the generation efficiency and service life of tidal current generators. In this study, an innovative optimized design method of the horizontal axis tidal turbine was applied to the rotor blade design. To be specific, blade cavitation was considered as a factor for optimization and then was improved using a modern optimization method that combined artificial neural networks and genetic algorithms, solving for a numerical solution. In the optimization program, the annual energy output and the superficial area of the rotor blade served as the optimization goals, and the chord length and the twist angle served as the optimization variables. The cavitation constraint was different from the traditional method in that the judgment criterion of occurrence of cavitation was no longer the minimum pressure coefficient but the maximum stress coefficient. The combination of the artificial neural network and the genetic algorithm not only realized high optimization accuracy but also greatly saved computation time. To verify the validity of the optimization method, a 1 MW turbine was designed, and the optimal solution was chosen from the formed Pareto optimal solution set for modeling, and the new model was compared with the model quoted in the reference. The simulation result shows that the turbine designed using the optimization method not only reduces the surface area of the rotor blade and improves the annual energy output, but also remarkably improves the blades’ cavitation resistance. The optimization analysis and comparison using different cavitation judgment criteria shows that the cavitation resistance of blades obtained using the maximum stress coefficient as the judgment criterion is more advantageous.

KEYWORDS
BEM, cavitation, GA-ANN, multi-objective optimization, tidal current turbine

1 | INTRODUCTION

The demand for energy in today’s world is huge, and it is obvious that traditional fossil energy can no longer meet the needs of the rapid development of the current world economy. Therefore, there is an urgent need to develop new energy resources to adapt to future development. Developing tidal current energy has very broad application prospects.
and market value because it is a renewable, nonpolluting energy with huge reserves. During the last few decades, technologies that directly capture the kinetic energy from tidal-driven marine currents have been developed. Tidal current turbine is an effective device which can directly obtain energy from the ocean with less harmful environmental effects. At present, many new concepts and devices have emerged with the rapidly developing of tidal current technology but horizontal axis tidal current turbine is one of the hottest researches. The design method and theory of tidal current turbine mainly comes from horizontal axis wind turbine. Blade element momentum (BEM) theory is the most widely used which combines momentum theory with blade element theory. The BEM theory is modified by taking the tip loss and hub loss into account after the study by Prandtl. In addition, there are other theories to be applied to design hydraulic turbine such as lifting line theory and Schmitz theory. Melo et al proposed a simplified vortex wake alignment scheme for the lifting line model, which can be easily applied in the analysis of turbine rotors. Wu et al designed high-efficient blades of tidal current turbine by using Schmitz method. As an effective simulation tool, computational fluid dynamics (CFD) which are based on the Reynolds-Averaged Navier-Stokes (RANS) equations, are then performed to evaluate the performance of the rotor both at transient and steady state. Gao et al adapted CFD method to optimize bidirectional flow passage components and lateral inlet/outlet diffusion part of a pumped hydroelectric storage. The BEM-CFD method is an enhanced actuator disk and is able to reduce the computational cost by simulating a time-averaged downstream velocity field.

Unlike wind turbines, cavitation may occur during tidal current turbine operation. The hotspot of cavitation research is the propeller of ships, and cavitation is easy to occur when the horizontal axis turbine is at the high tip-speed ratio. Therefore, the study of cavitation of hydraulic turbines cannot be ignored. The occurrence of cavitation on horizontal axis marine current turbine blades has been investigated by numerical methods in Ref. Kaufmann presents an enhanced semianalytical model that allows the prediction of the performance characteristics including cavitation inception of horizontal axis tidal turbines. Silva PASP designs hydrokinetic turbines using BEM and analysis of cavitation, and this method corrects the blade chord by a modification on the local thrust coefficient in order to prevent cavitation.

Multi-objective optimization algorithm is widely used in the design of hydraulic turbine and wind turbine. Viana et al designed wind turbine blade geometry based on multi-objective optimization using metaheuristics, and the results showed that the output of the design methodology is feasible for manufacturing. Gao et al selected the nondominated sorting genetic algorithm (NSGA-II) to conduct the optimizations, and better optimization results are obtained. The improvements are more significant with more objectives involved, demonstrating that the proposed algorithm can serve as a universal, high performance algorithm for the multi-objective optimization of wind turbine blade design. A series of compromise solutions can be obtained by optimum design method of multi-objective function, and we can choose the appropriate optimal solution according to the different needs of users and different emphasis. Stochastic algorithms mainly include genetic algorithm (GA), particle swarm, and ant algorithm. These algorithms introduce stochastic parameters in the process of searching the optimal solution, which can jump out of the trap of local extremum, so they belong to the global optimization algorithm. Recent studies have mainly focused on maximizing generated power under a given operating condition and use GA or other optimization algorithm. Artificial neural network (ANN) algorithm is an algorithmic mathematical model for distributed parallel information processing, which imitates the behavior of animal neural networks. Artificial neural network develops rapidly. It combines with fuzzy system and GA to form a new intelligent computing, which becomes an important direction of artificial intelligence. Zhang et al adopted the neural network (NN) to approximate the uncertain dynamics, and NNs are considered to be one of the effective methods in many control systems. He et al developed a fuzzy NN learning algorithm to identify the uncertain plant model, and the NN technology is proposed to approximate the uncertain robotic dynamics.

How to reduce the probability of cavitation while improving the efficiency of power generation is the focus of this study. The objective and significance of this research study is to propose and evaluate the performance of the optimum design algorithms. With the increase of tidal current turbine power, the volume and weight of blade will also increase and there has a greater impact on service life so blade area is considered as one of the optimization objectives in this study. At the same time, the energy production (AEP) is also taken as the optimization objective. The possibility of cavitation is considered, and the degree of cavitation is limited in the optimization process and set the maximum stress coefficient as criterion. Artificial neural network and GA are combined for hydraulic turbine optimization. The individual in population sufficiency needs to be evaluated in the process of optimizing solution by GA, so performance parameters for each individual must be obtained. It would be a high computational cost and hard implementation if these data are calculated by CFD, so ANN is lead into this research and combined with GA to solve numerically. The performance parameters of training samples are obtained by CFD, and in the process of optimization, the performance parameters of temporary samples are calculated by ANN. The advantage of this method is that it
not only guarantees the calculation accuracy of the training sample, but also greatly speeds up the optimization process. Finally, a 1 MW tidal current turbine is optimized by the new method, and the performance of optimizing blades and reference blades was evaluated successfully.

2 | THE MATHEMATICAL MODEL

2.1 | Blade element momentum theory

Blade element theory divides the blade into many microsegments along the extension direction, and then, forces and moments acting on the segments are integral as shown in Figure 1. Blade element momentum theory combines momentum theory and blade element theory. Glauert theory introduces two inducing factors: axial inducing factor $a$ and tangential inducing factor $b$ when calculating axial and tangential losses.

From the momentum theory, the synthetic inflow velocity $V_0$ at blade element is

$$V_0 = \sqrt{V_{x0}^2 + V_{y0}^2} = \sqrt{(1-a)^2 V_1^2 + (1+b)^2 (\Omega r)^2}$$

$$\theta = \alpha + \beta = \arctan \left( \frac{(1-a)V_1}{(1+b)\Omega r} \right)$$

where $V_{x0}$ and $V_{y0}$ are velocity components of flow velocity in X and Y directions, respectively; $\Omega$ is the rotation angular velocity.

The axial thrust acting on the annulus on the plane a of the turbine is as follows

$$dT = \frac{1}{2} B p c V_0^2 C_N dr$$

$$(3)$$

$$dM = \frac{1}{2} B p c V_0^2 C_T r dr$$

$$(4)$$

where $dT$ and $dM$ denote the local thrust and torque, respectively; $p$ and $V_0$ denote the density of seawater and the marine current speed, respectively; $r$ and $dr$ denote the local radius and radius increment, respectively; and $C_N$ and $C_T$ denote the normal force coefficient and tangential force coefficient. $c$ denotes the chord length of airfoil.

Since the turbine is composed of a finite number of blades in reality, on this basis, Prandtl proposes a correction factor $f$ for tip loss.

$$f = \frac{2}{\pi} \arccos \left( \exp \left( -\frac{B}{2} \frac{R-r}{r \sin \theta} \right) \right)$$

$$(5)$$

where $B$ is blade number, $R$ is turbine radius, and $\theta$ is the twist angle.

On the basis of the above modified model, Shen further revised the axial force and tangential force coefficients in impeller blade element and introduced the correction factor.

$$f_1 = \frac{2}{\pi} \cos^{-1} \left( \exp \left( -\frac{g}{2} \frac{B}{r \sin \theta} \right) \right)$$

$$(6)$$

where $g$ is the correction factor.

$$g = \exp \left[ -0.125 (B \lambda - 21) \right] + 0.1$$

$$(7)$$

$$a = \frac{1+2f \sin^2 \theta/(\sigma_1 C_{r f_1})}{1+(f \sin^2 \theta/(\sigma_1 C_{r f_1}))^2}$$

$$b = \frac{1-a}{4f(1-af) \sin \theta \cos \theta / (\sigma_1 C_{r f_1}) + a - 1}$$

Because BEM theory fails when the axial inducing factor is greater than 0.3, it is necessary to correct the thrust of the turbine.

$$dT = 4\pi p V_1^2 \left[ \frac{f^2}{9} + \left( 1 - \frac{2f}{3} \right) a \right] \frac{r dr}{\sin \theta \cos \theta / (\sigma_1 C_{r f_1}) + a - 1}$$

$$a = 1 + \left( \frac{1-2f/3}{2} \right) 4f \sin^2 \theta / (\sigma_1 C_{r f_1})$$

$$b = \frac{1-a}{4f(1-af) \sin \theta \cos \theta / (\sigma_1 C_{r f_1}) + a - 1}$$

2.2 | The criterion of cavitation inception

The practice has proved that it is necessary to consider cavitation in the design of hydraulic turbines. Cavitation occurs because of the existence of meiobar, the water begins to
evaporate, and bubbles are formed when the absolute pressure of water which flowing through the blade surface of a turbine drops to its vaporization pressure. The bubbles are squeezed and burst as water flows into the high-pressure zone. High-frequency surge pressure caused by bubble burst and blade surface will be severely impacted promoting erosion on the blade. When the cavitation develops to a certain extent, it is equivalent to changing the shape of the blade airfoil, which will result in the change of the dynamic characteristics of the turbine and the decrease of its efficiency. The traditional judgment is based on the comparison of pressure coefficient and cavitation number \( \sigma \).

\[
\sigma = \frac{p_\infty - p_v}{0.5\rho V_\infty^2} = \frac{p_{\text{atm}} + \rho g h - p_v}{0.5\rho V_\infty^2} \tag{13}
\]

where \( p_\infty \) and \( V_\infty \) is the static pressure and speed \( \rho \), \( p_v \) is the vapor pressure where \( p_{\text{atm}} \) is the atmospheric pressure, \( g \) is the local gravity, and \( h \) is the distance between free surface and the radial position on the hydrokinetic rotor.

The pressure coefficient \( C_p \) is defined as

\[
C_p = \frac{p - p_\infty}{0.5\rho V_\infty^2} \tag{14}
\]

Traditional criteria for the occurrence of cavitation which is given by

\[
\sigma + C_p \leq 0 \tag{15}
\]

From another point of view, the location where cavitation occurs is where the continuity of liquid is destroyed. The numerical simulation results (shown in Figure 2) show that the position of cavitation inception is changing with the increase of velocity and the experimental results are the same as the simulation results.\(^{37}\) Pressure is not the only basic dynamic variable in a moving incompressible fluid; in Newtonian fluids, the stress state at each point can be determined by the following formula.

\[
P_\Sigma = -pI + 2\mu S \tag{16}
\]

where \( p \) is pressure, \( I \) is unit tensor, \( \mu \) is Viscosity coefficient, and \( S \) is strain rate tensor.

For two-dimensional flow, it can be defined as

\[
S = \begin{bmatrix}
\frac{\partial V_x}{\partial x} & \frac{1}{2} \left( \frac{\partial V_x}{\partial y} + \frac{\partial V_y}{\partial x} \right) \\
\frac{1}{2} \left( \frac{\partial V_y}{\partial y} + \frac{\partial V_x}{\partial x} \right) & \frac{\partial V_y}{\partial y}
\end{bmatrix} = \begin{bmatrix}
S_{11} & S_{12} \\
S_{12} & S_{22}
\end{bmatrix} \tag{17}
\]

In this stress-induced cavitation theory, the initial criterion of cavitation is expressed as

\[
p - 2\mu S_1 < p_v \tag{20}
\]

If the dimensionless form is used to express the occurrence of cavitation, the upper form becomes

\[
C_p - \frac{2\mu S_1}{0.5\rho V_1^2} < -\sigma \tag{21}
\]
Merge $a$ and $b$

$$\frac{p-p_\infty - 2\mu S_1}{0.5 \rho V_i^2} < -\sigma$$  \hspace{1cm} (22)

$$C_f = \frac{2\mu S_1}{0.5 \rho V_i^2}$$  \hspace{1cm} (23)

Then, the criterion of maximum initial stress of cavitation can be expressed as$^{38}$

$$C_p - C_f < -\sigma$$  \hspace{1cm} (24)

As can be seen from Figures 3 and 4, the strain rate in the front section of the airfoil is obviously large, so the effect of shear stress is also great. The distribution of pressure coefficients and stress coefficient along chord length is simulated by CFD when the angle of attack of airfoil is $8^\circ$. Cavitation begins to occur when $\sigma = 1.5$ after the maximum stress criterion is adopted. It was obvious that cavitation occurred ahead of schedule comparing with traditional judgment methods.

### 2.3 Hydro turbine airfoil and hydraulic performance calculation

Currently, tidal turbines and wind turbines are similar in choosing airfoils such as NACA series. In order to meet the requirements of wind turbine operating conditions, many countries have developed their own special airfoils for wind turbines.$^{39,40}$ However, traditional airfoils are difficult to meet the aerodynamic performance of turbines at low Reynolds number. In the current work, s825 hydrofoil was selected because it still has good aerodynamic performance at low Reynolds number. The blade model is built on the basis of S825 airfoil, and the airfoil and blade piecewise diagram is shown in Figure 5.

Performance parameters such as lift and drag coefficients of airfoil were calculated by CFD, as shown in Figures 6 and 7.

The aerodynamic performance parameters of the reference blade are shown in Table 1. Based on the criteria mentioned above, note that $C_p - C_f + \sigma < 0$ in Section 6, and it means that cavitation will occur.

### 3 MULTI-OBJECTIVE OPTIMIZATION

In this study, ANN is applied to the optimization of hydraulic turbines. BP algorithm is the most widely used model algorithm of ANN. The performance parameters of temporary blades are calculated by ANN in the process of optimization, and the performance parameters of training sample blades are still obtained by CFD. In this way, not only ensures the accuracy of training samples, but also greatly reduces the amount of optimization calculation and improves the efficiency of calculation.
3.1 Artificial neural networks model algorithms

Artificial neural networks are more and more widely used because they have many advantages, such as nonlinear mapping ability, no need for accurate mathematical models, and easy to implement parallel computing. Especially, BP algorithm (shown in Figure 8) is applied in many fields which composed of input layer, hidden layer, and output layer. The learning process of the algorithm consists of forward and backward propagation. In the process of forward propagation, the input information is processed layer by layer from the input layer and then transferred to the output layer, and if the expected value is not reached at the output layer, it is turned back to backward propagation.

Set the input mode of the network to be \( x = (x_1, x_2, \ldots, x_n)^T \), hidden layer contains \( h \) units, and the output of the hidden layer is \( y = (y_1, y_2, \ldots, y_h)^T \); the output layer contains \( m \) units, and the output is \( z = (z_1, z_2, \ldots, z_m)^T \), and the target output is \( t = (t_1, t_2, \ldots, t_m)^T \). The transfer function from the hidden layer to the output layer is \( f \), and the transfer function of the output layer is \( g \), we can get it

\[
    y_j = f \left( \sum_{i=1}^{n} w_{ij} x_i - \theta \right) = f \left( \sum_{i=0}^{n} w_{ij} x_i \right) \quad (25)
\]

where \( y_j \) denotes the output of the \( j \) neuron in the hidden layer, \( w_{ij} = \theta, x_0 = -1 \)

\[
    z_k = g \left( \sum_{j=0}^{h} w_{jk} y_j \right) \quad (26)
\]

where \( z_k \) denotes the output of the \( k \) neuron in the hidden layer, and the error between network output and target output is

\[
    \varepsilon = \frac{1}{2} \sum_{k=1}^{m} \left( t_k - z_k^2 \right) \quad (27)
\]

3.2 NSGA-II algorithm

As an efficient global class optimization algorithm, NSGA-II algorithm is undoubtedly the best choice. The algorithm

| Section | \( r/R \) | \( Re \) \( (10^6) \) | \( \sigma \) | \( C_p - C_f \) | \( C \) (m) | Twist angle |
|---------|---------|----------------|--------|--------------|--------|-------------|
| 1       | 0.1     | 2              | 65.395 | -0.9561      | 0.986  | 12.64       |
| 2       | 0.2     | 2              | 20.963 | -1.1236      | 1.277  | 12.56       |
| 3       | 0.3     | 2.5            | 8.578  | -1.2698      | 1.302  | 11.82       |
| 4       | 0.4     | 2.5            | 4.279  | -1.4754      | 1.211  | 10.51       |
| 5       | 0.5     | 3              | 2.146  | -1.5879      | 1.085  | 8.69        |
| 6       | 0.6     | 3              | 1.503  | -1.6384      | 0.959  | 6.55        |
| 7       | 0.7     | 3              | 1.325  | -1.6795      | 0.833  | 4.32        |
| 8       | 0.8     | 2.5            | 1.142  | -1.7078      | 0.686  | 2.37        |
| 9       | 0.9     | 2.5            | 0.987  | -1.7369      | 0.496  | 0.91        |
| 10      | 1.0     | 2              | 0.740  | -1.7523      | 0.252  | 0.51        |
uses real number coding, which is characterized by using fast nondominant sorting method to classify the population and the method of “congestion distance ranking” is introduced to rank the individuals of the same level. It enables individuals in quasi-Pareto domains at all levels to spread to the whole Pareto, maintaining the diversity of the population. The flowchart of NSGA-II algorithm is shown in Figure 9.

3.3 | Optimization objective

3.3.1 | AEP

Annual power generation as an important acceptance technical index after installation and commissioning of tidal turbine is the main optimization objective. The flow velocity distribution is defined by Weibull probability density function, and the following optimization objective function is established.

\[
\max \text{AEP} = N_h \sum_{i=1}^{n} \left[ F(v_i) - F(v_{i-1}) \right] \cdot \left( \frac{P(v_i) + P(v_{i-1})}{2} \right) \tag{28}
\]

where AEP is average annual power generation, \( N_h \) is hours, \( F(v) \) is Weibull distribution function, \( P(v) \) is output power of hydraulic turbine, and \( v_i \) is the flow velocity value.

Rayleigh distribution and Weibell distribution are commonly used for the velocity distribution function of water flow in the objective function. Weibell distribution is mainly used in practice

\[
F(v) = 1 - \exp \left[ -\left( \frac{v}{c} \right)^k \right] \quad v > 0 \tag{29}
\]

3.3.2 | Minimization of the blade area

The blade size of tidal turbine is getting larger and larger, and the increase of mass will lead to the increase of bearing capacity of the whole supporting structure and reduce the safety and service life of the whole structure. Blades are manufactured from composite materials with varying densities; therefore, the established quality calculation models are not accurate. In this study, blade area was taken as the objective of optimization, because small blade area leads to small mass.

\[
F(X) = \min \left( A_{\text{blade}} \right) \tag{30}
\]

\[
A_{\text{blade}} = B \lim_{x \to 0} \sum_{i=1}^{n} \Delta S = B \int \int dS = B \int \int f(x,y)dr \tag{31}
\]

where \( f(x,y) \) is contour line length equation of blade section along spread direction \( r \), and the function is expressed in the form of calculus.

\[
f(x,y) = \sum_{i=1}^{m} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{32}
\]

where \( x_i \) and \( y_i \) are coordinates of blade section data points in three-dimensional space. According to the principle of geometric transformation, the cross-sectional coordinates of the blade with a length along the extension direction \( r \), \((x, y)\) can be expressed as

\[
x = c \left( x_0 \cos \beta + y_0 \sin \beta \right) \tag{33}
\]

\[
y = c \left( x_0 \sin \beta + y_0 \cos \beta \right) \tag{34}
\]

where \( x \), \( y \) is spatial coordinate points of airfoil along extension \( r \) of blade, \( x_0, y_0 \) is coordinates of airfoil with unit chord length in two-dimensional plane, \( c \) is the chord, and \( \beta \) is twist angle.

3.3.3 | Design variables and constraints

The main determinants of generating capacity and efficiency are the shape of blade surface, chord length, installation
angle, number, and blade length. In order to make the section chord length and twist angle of the main output power section of blade distribute continuously and smoothly along the extension direction, both chord length and torsion angle are defined as Bezier curve distribution. The Bezier curves corresponding to chord length and torsion angle distributions use seven and four control points, respectively, so there are eleven design control variables in total.

\[
\begin{align*}
    c_1' &< c_2' < c_3' < c_4' \\
    c_4' &< c_5 < c_6 < c_7 < c_{\text{max}}' \\
    t_1 &< t_2 < t_3 < t_4 < t_{\text{max}}
\end{align*}
\]  

(35)

where \( c_i \) \((i = 1, 2, \ldots, 7)\) is chord length control point, \( t_i \) \((i = 1, 2, 3, 4)\) is twist angle control point, \( c_{\min}', c_{\max}', c_{\min}, \) and \( c_{\max}\) are minimum and maximum chord lengths defined separately. \( t_{\min} \) and \( t_{\max} \) are minimum and maximum twist angle defined separately.

In order to reduce the degree of cavitation, it is necessary to add cavitation constraints in the optimization process. The criteria for the occurrence of cavitation are as follows.

Define \( F_s \) as cavitation safety factor

\[
\sigma + F_s \left( \frac{C_p}{0.5 \rho V_i^2} \right) \geq 0
\]

(36)

where cavitation safety factor \( F_s \geq 1\)

The constraint range of optimized variables is shown in Table 2.

Based on the modified aerodynamic model, the initial conditions are set and the inducing factors are obtained by iteration. The improved GA is used to solve the optimization problem, and the specific optimization process is shown in Figure 10.

1. Firstly, the blade design parameters and constraint parameter are input. The specific parameters are shown in the table.
2. Random generation of initial population based on input parameters and then blade performance parameters are calculated by ANN.

![FIGURE 10](image-url) The flowchart of multi-objective optimization
3. The Pareto solution filter is used to select the optimal solution, and the Pareto distance of the population is calculated to judge whether it converges or not.

The main design parameters of hydraulic turbines are given in Table 3, and all the parameters of the NSGA-II procedure used are shown in Table 4.

**Algorithm 1 Computation of the blade area**

**Begin**

Require: flow speed, maximum root bending moment. Divide the blade into n sections, compute bending moment by

\[
C_N = C_L \cos \theta + C_D \sin \theta
\]

\[
C_T = C_I \sin \theta + C_D \cos \theta
\]

for \(i=1\) to(number of sections) do

while section number <\(n\) do

compute

\[
A_{\text{blade}} = B \int \sum_{i=1}^{n} \Delta S = B \int f(x, y) \, dr
\]

\[
f(x, y) = \sum_{i=1}^{n} \left( \frac{x_{i+1} - x_i}{2} \right)^2 + \left( y_{i+1} - y_i \right)^2
\]

\[
x = c \left( x_0 \cos \beta + y_0 \sin \beta \right)
\]

\[
y = c \left( x_0 \sin \beta + y_0 \cos \beta \right)
\]

compute

\[
M_{\text{bending}} = \frac{1}{2} \rho B \sum_{i=1}^{n} \left( 1 - \frac{2}{3} \right) \frac{V_k}{r_i} c C_a r_i dr
\]

if \(M_{\text{bending}} > M_{\text{max}}\) then

break while
end if

end for

end procedure

### 3.4 Numerical method

Computational fluid dynamics is a new subject that combines numerical science with computer science. Discrete mathematical equations are used to simulate the problems of hydrodynamics, acoustics, heat transfer, and other related disciplines. The Fluent 14.5 was used in this study and a second-order-accurate finite-volume discretization scheme used to solve the incompressible RANS equations. The SST (shear stress transport) turbulence model was selected to model the turbulence terms of the RANS equations.

#### 3.4.1 Computation domains and grid generation

In the present study, all structured grids were generated using the ICEM grid generation utility in ANSYS 14.5. When creating the flow field, the flow field is divided into external flow field and internal flow field, and the internal flow field is a rotating field. Data exchange between internal and external flow fields by setting interface. The computation domain is a cylinder, and the diameter of the external flow field is five times that of the turbine diameter. Setting velocity entrance boundary conditions on the left side of the fluid field and the outlet condition of flow field is set to pressure outlet. No-slip boundary conditions are imposed at the surface of the blades. The speed and pressure coupling method is set as simple algorithm. Select the entry parameters as the initialization object and set the residual error accuracy to 0.0001. The boundary conditions are also shown in Figure 11.

#### 3.4.2 Verification and validation

The power and thrust coefficients of the rotor are used as the basis for grid independence verification. The simulations are conducted at TSR = 6. Table 5 summarizes the results with different grid resolutions. It can be seen from the table that when the number of grids is 7.38 million and 9.25 million, the results are the closest. Considering the economy of time in the simulation, the grid with 7.38 million elements is chosen for the following simulations.
3.4.3 | Grid influence

The density of grid has a significant impact on the accuracy of calculation, and if the number of grid is large, it will take a lot of time. Grid Coefficient of Blade Boundary Layer “\(y^+\)”. 

\[
y^+ = \frac{\Delta y u_r}{v}
\]  

(37)

where \(u_r\) is the wall friction velocity, \(\Delta y\) is Distance from the first grid node to the wall, and \(v\) is kinematic viscosity coefficient. The flow region is viscous bottom layer when \(y^+ < 5\), and flow is in the logarithmic layer when \(60 < y^+ < 300\).

If \(y^+\) does not match the turbulence model properly, the computational accuracy will be worse if the number of grids is large. SST turbulence model and automatic wall function are used in this study, when \(y^+ < 2\), and the low Reynolds number model can be used to predict turbulent fluctuations with high accuracy. Table 6 gives the grid generation strategy for this study.

4 | OPTIMIZATION RESULTS AND ANALYSIS

4.1 | Optimized results

In order to compare the advantages and disadvantages of the optimal solution set and the reference blade comprehensively, three blades were randomly selected from Pareto optimal solution set, which were small, medium and large in area numbered solution 1 to solution 3, respectively (As shown in Figure 12). The optimized results of the multi-objective problem are a group of results. Improving the performance of one objective function will lead to the performance degradation of another objective function. With the increase of blade area, the annual power generation of the optimized solution increases, showing a monotonous trend, and this is in line with the actual situation.

Table 7 and Figures 13-15 summarize some performance parameters of the selected rotor solutions. By comparing the three blades in the optimization solution with the reference blades, it is found that the maximum power coefficient of the optimized blade is larger than that of the reference blade. The solution 3 has the largest power coefficient, but the increase of blade area is larger, and similarly, solution 1 has a smaller blade area, but the power coefficient increases slightly. The thrust coefficients of the solutions 1-2 optimized blades are smaller than those of the reference blades, and the solution 1 is the smallest. The area of solution 1 decreases the most, but the life of blade decreases. The power coefficient of solution 2 increases about 2.2%, and blade area decreased by about 14.27%. As solution 2 has a superior aerodynamic performance comparing with other optimized blades, area also decreased significantly. It is regarded as the best solution found.
Two sets of optimal solutions are obtained by using different cavitation constraints criteria. The optimized blade with the minimum pressure coefficient as the criterion is named OptA, and similarly, the optimized blade with the maximum stress coefficient as the criterion is named OptB. The blades in the literature\textsuperscript{16} serve as reference blades.

Modeling and comparison of blades based on optimization solution and wire-frame of the blade are shown in Figure 16.

4.2 Discussion of the optimized results

The optimized blade chord length and twist angle distribution are shown in Figure 17, and compared with the blade in literature.\textsuperscript{19} The two optimized blade chord length is obviously smaller than that in the literature in the range of $r/R < 0.75$ especially in the middle of the blade, and optimized blade chord length begins to increase near blade tip which we can draw from the figure. This is because blade tip is the main power generation area, and the reduction of chord length leads to reduction of turbine output power; therefore, the chord length of the optimized blade tip region is larger than that of the reference blade. The blade area is one of the optimization objectives, so the chord length of most areas of the optimized blade is less than that of the reference blade. The optimized blade twist angle presents nonlinear characteristics, as the root of the blade is obviously larger than that in the literature but there was little difference at the tip of the blade. The increase of twist angle will decrease load at blade root.

In order to ensure the accuracy of the results, the performance of turbine was calculated using the BEM method ($Re = 2.0 \times 10^5$) again and the results were compared with those of CFD. The power coefficients of the optimized blade and the reference blade are compared as shown in Figure 18 predicted by CFD and BEM, corresponding to TSRs from 2 to 10. The CFD result shows that the reference blade achieves the maximum output power when the tip-speed ratio is about 7, the optimized blade is about 6.5, and the maximum increase is about 2.51%. The power coefficient of the optimized blade is slightly lower than that of the reference blade when the tip velocity ratio is less than 5. The power coefficient predicted by BEM follows a similar trend to that of the CFD, but the predicted value is larger than of the CFD. The optimized blade power coefficient increases by 1.48% compared with the reference blade. The maximum power coefficient of

\begin{table}[h]
\centering
\caption{Comparison of performance parameter for different cases}
\begin{tabular}{|c|c|c|}
\hline
Case & $C_{p_{\text{max}}}$ (BEM) & $S$ (m$^2$) \\
\hline
Ref & 0.481 & 48.247 \\
Solution 1 & 0.482 & 28.361 \\
Solution 2 & 0.492 & 41.359 \\
Solution 3 & 0.494 & 82.154 \\
\hline
\end{tabular}
\end{table}
optimized blade A is slightly larger than that of blade B predicted by BEM and CFD. The output power of the optimized blade is larger at high tip-speed ratio and slightly lower than that of the reference blade at small tip-speed ratio as shown in Figure 19.

The torque coefficient and thrust coefficient of the optimized blade and the reference blade predicted by CFD and BEM are shown in Figures 20 and 21. The predicted results of the two methods are similar that the torque coefficient increases first and then decreases with increasing TSR over the entire evaluated range of TSRs. Torque coefficient drops sharply, and the predicted value of BEM is higher than that of CFD method when TSR < 5. Torque coefficients of two optimized blades are larger than those of reference blades when TSR < 7, increased by about 1.5%. According to the variation of thrust coefficient, the optimized turbine thrust decreases obviously, and the maximum reduction was 1.3% when TSR < 9. There is a higher thrust coefficient value calculated by BEM, and both methods predict similar curves. In addition, the reduction of thrust will increase blade life and reduce its cost. Which of the two methods are more accurate needs to be verified by later experiments.

According to the results of comprehensive optimization, both of the optimized blades achieve the design objectives.

As can be seen from Figure 22 and Table 8, the average annual power generation of the two optimized blades has been increased, with a maximum increase of 2.21%. The blade area has been reduced by about 13%, meaning that the quality of blades is also greatly reduced so the fatigue life of blades will be increased accordingly.

5 | CAVITATION PREDICTION

Computational fluid dynamics is widely used in predicting cavitation of rotating machinery. This method is a numerical simulation under the control of the basic flow equation, and through this numerical simulation, the distribution of basic physical quantities at various positions in the complex flow...
field of hydraulic turbine and the variation of these physical quantities with time can be obtained.

5.1 Cavitation model

At present, most of the commonly used cavitation models are based on Rayleigh-Plesset (R-P) model.\textsuperscript{45} The R-P model describes the growth of vapor in liquids.

\begin{equation}
R_B \frac{d^2 R_B}{dt^2} + \frac{3}{2} \left( \frac{dR_B}{dt} \right)^2 + \frac{2\sigma_S}{\rho_l R_B} = \frac{p_v - p}{\rho_f} \tag{38}
\end{equation}

where $R_B$ is cavity diameter, $p_v$ is cavitation pressure, $p$ is liquid pressure, $\rho_f$ is liquid density, and $\sigma_S$ is surface liquid tension coefficient.

If the secondary phase and surface tension terms are neglected, they are simplified to

\begin{equation}
\frac{dR_B}{dt} = \sqrt{\frac{2}{3} \frac{p_v - p}{\rho_f}} \tag{39}
\end{equation}

Bubble volume change rate can be calculated by

\begin{equation}
\frac{dV_B}{dt} = \frac{d}{dt} \left( \frac{4}{3} \pi R_B^3 \right) = 4\pi R_B^2 \sqrt{\frac{2}{3} \frac{p_v - p}{\rho_f}} \tag{40}
\end{equation}

Bubble mass change rate

\begin{equation}
\frac{dm_B}{dt} = \rho_v \frac{dV_B}{dt} = 4\pi R_B^2 \rho_v \sqrt{\frac{2}{3} \frac{p_v - p}{\rho_f}} \tag{41}
\end{equation}
Singhal cavitation model is used in this study which is based on bubble dynamics. The mass fractions of gas and liquid phases are taken as the parameters for solving the transport equation and considering turbulence and incompressible gas content including void formation and transport, velocity, and pressure.

\[
\dot{m}_e^+ = C_e \frac{k}{S_F} \rho_v \rho_t \left[ \frac{2 \rho_{sat} - p}{3 \rho_t} \right]^{1/2} (1 - f) \tag{42}
\]

\[
\dot{m}_e^- = C_e \frac{k}{S_F} \rho_v \rho_t \left[ \frac{2 p - \rho_{sat}}{3 \rho_t} \right]^{1/2} f \tag{43}
\]

where \( f \) is volume fraction of gas phase, \( k \) is unit mass turbulence energy, and \( S_F \) is surface tension.

The critical saturated vapor pressure is

\[
P_V = P_{sat} + \frac{P_{turb}}{2} \tag{44}
\]

where \( P_{turb} = 0.39 k \), \( P_{sat} \) is saturated vapor pressure.

we can rewrite Equations (42) and (43) and the ultimate interphase transmission relationship

\[
\dot{m}_e^+ = C_e \frac{k}{S_F} \rho_v \rho_t \left[ \frac{2 \rho_v - p}{3 \rho_t} \right]^{1/2} (1 - f) \tag{45}
\]

| Table 9 Calculation conditions |
|-----------------------------|
| Condition                  | Values           |
| Cavitation model           | Singhal         |
| Turbulence model           | SST             |
| Pressure of vapor (\( \rho_v \)) | 3540 Pa         |
| Surface of blade           | No-slip wall    |
| Computational model        | MRF             |

5.2 Validation using CFD

Select a group of optimized blade compared with reference, and taking the size of cavitation area as the criterion to judge the merits and demerits of blades. It can be seen from the numerical simulation results (shown in Figures 23 and 24) that at different rotational speeds, the optimized blade cavitation area is significantly smaller than that of the reference blade with the increase of rotational speed; the effect of optimizing blade cavitation suppression is more obvious. In addition, the blade optimized with the maximum stress coefficient as the criterion of cavitation discrimination is more obvious in cavitation suppression. This is due to when the maximum stress criterion is adopted, cavitation will occur at a larger number of cavitations, that is, cavitation will occur ahead of time, and cavitation suppression will also occur ahead of time in the process of optimization.

The pressure distribution (\( n = 14 \) rpm) on the back of the blade is shown in Figure 25, it can be observed that the nearer the blade tip is, the greater the negative pressure will be generated on the back flow surface. This is also the area where cavitation is most likely to occur; the negative pressure region of optimized blade is smaller than that of reference blade.

6 CONCLUSIONS

In the present study, the tidal current turbine blade calculation model is established, with annual power generation and blade area as optimization design objectives,
cavitation as constraints condition, and blade chord length and twist angle as design variables; the mathematical model and method of turbine optimization are put forward in the end. Artificial neural network combined with improved GA is applied to the optimization process, and in this way, it not only improves the calculation accuracy, but also saves a lot of calculation time. Aiming at the reference blade, the optimum design of the 1 MW turbine blade is carried out, and the shape parameters, structural characteristics, and hydrodynamic performance of the blade before and after optimization are compared and analyzed.

1. For different criteria for cavitation discrimination, algorithms can inhibit the occurrence of cavitation to a certain extent. The optimized blade which taking the maximum stress coefficient as the criterion of cavitation has more obvious cavitation suppression effect.

2. All optimized blades increase the annual power generation, while the blade area decreases significantly comparing with reference blade, which means that the blade quality also decreases correspondingly, so the service life is increased and the cost is reduced, achieving design objectives and requirements.

This research enriches the theory and design method of turbine, and the main work needs to be done in the future is summarized as follows: (a) apply other optimization algorithms and comparing with GA, to find an optimal combination algorithm with higher accuracy and faster speed; (b) other simulation models should be added to enrich simulation method; and (c) relevant experimental work is needed to verify the simulation results.

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CONFLICT OF INTEREST

The authors declared that there is no conflict of interest.

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REFERENCES

1. Zhou Z, Benbouzid M, Charpentier J-F, Scuiller F, Tang T. Developments in large marine current turbine technologies – a review. Renew Sustain Energy Rev. 2017;71:852-858.
1. Yuce MI, Muratoglu A. Hydro-kinetic energy conversion systems: a technology status review. Renew Sustain Energy Rev. 2015;43:72-82.

2. Tahani M, Babayan N, Astaraei FR, Moghadam A. Multi objective optimization of horizontal axis tidal current turbines, using Meta heuristics algorithms. Energy Convers Manage. 2015;103:487-498.

3. Zeiner-Gundersen HD. Turbine design and field development concepts for tidal, ocean, and river applications. Energy Sci Eng. 2015;3(1):27-42.

4. Jahangir K, Bhuyan GouriS. Ocean e-nergy: Global Technology Development Status. Final Technical Report IEA-OES; 2009.

5. Noruzi R, Vahidzadeh M, Riasi A. Design, analysis and predicting hydrokinetic performance of a horizontal marine current axial turbine by consideration of turbine installation depth. Ocean Eng. 2015;108:789-798.

6. Xu Q, Liu H, Lin Y, et al. Development and experiment of a 60 kW horizontal-axis marine current power system. Energy. 2015;88:149-156.

7. Melo DB, Baltazar J, Falcão de Campos J. A numerical wake alignment method for horizontal axis wind turbines with the lifting line theory. J Wind Eng Ind Aerodynam. 2018;174:382-390.

8. Wu B, Zhang X, Chen J, Xu M, Li S, Li G. Design of high-efficient and universally applicable blades of tidal stream turbine. Appl Energy. 2012;98:512-523.

9. Xu Q, Liu H, Lin Y, et al. Development and experiment of a 60 kW horizontal-axis marine current power system. Energy. 2015;88:149-156.

10. Melo DB, Baltazar J, Falcão de Campos J. A numerical wake alignment method for horizontal axis wind turbines with the lifting line theory. J Wind Eng Ind Aerodynam. 2018;174:382-390.

11. Wu B, Zhang X, Chen J, Xu M, Li S, Li G. Design of high-efficient and universally applicable blades of tidal stream turbine. Energy. 2013;60:187-194.

12. Tian W, Mao Z, Ding H. Design, test and numerical simulation of a low-speed horizontal axis hydrokinetic turbine. Int J Naval Archit Ocean Eng. 2018;10:782-793.

13. Eilsakka MM, Ingham DB, Ma L, Pourkashanian M. CFD analysis of the angle of attack for a vertical axis wind turbine blade. Energy Convers Manage. 2019;182:154-165.

14. Gao X, Tian Y, Sun B. Shape optimization of bi-directional flow passage components based on a genetic algorithm and computational fluid dynamics. Eng Optim. 2018;50(8):1287-1303.

15. GaoX, Zhu et al. CFD optimization process of a lateral inlet/outlet diffusion part of a pumped hydroelectric storage based on optimal surrogate models. Processes. 2019;7(4):204.

16. Goundar JN, Ahmed MR, Lee YH. Numerical and experimental studies on hydrofoils for marine current turbines. Renewable Energy. 2012;42:173-179.

17. Edmunds M, Williams AJ, Masters I, Croft TN. An enhanced disk averaged CFD model for the simulation of horizontal axis tidal turbines. Renewable Energy. 2017;101:67-81.

18. Singh PM, Choi YD. Shape design and numerical analysis on a 1MW tidal current turbine for the south-western coast of Korea. Renewable Energy. 2014;68:485-493.

19. Usar D, Bal S. Cavitation simulation on horizontal axis marine current turbines. Renewable Energy. 2015;80:15-25.

20. Kaufmanna N, Carolus TH, Starzmann R. An enhanced and validated performance and cavitation prediction model for horizontal axis tidal turbines. Int J Marine Energy. 2017;19:145-163.

21. Silva P, Shinomiya LD, De Oliveira TF, et al. Analysis of cavitation for the optimized design of hydrokinetic turbines using BEM. Appl Energy. 2016;185:1281-1291.

22. Xavier V, José G, Sinalvo M, et al. Wind turbine blade geometry design based on multi-objective optimization using metaheuristics. Energy. 2018;162:645-658.

23. Poloni C, Giurgevich A, OnestiL. Hybridization of a multi-objective genetic algorithm, a neural network and classical optimizer for a complex design problem in fluid dynamics. Comput Methods Appl Mech Eng. 2000;186(2-4):403-420.

24. Shen X, Chen J-G, Zhu X-C, Liu P-Y, Du Z-H. Multi-objective optimization of wind turbine blades using lifting surface method. Energy. 2015;90:1111-1121.

25. Fischer GR, KipourosT, SavillAM. Multi-objective optimization of horizontal axis wind turbine structure and energy production using airfoil and blade properties as design variables. Renewable Energy. 2014;62:506-515.

26. Sale D, Jonkman J, Musial W. Hydrodynamic optimization method and design code for stall-regulated hydrokinetic turbine rotors. In: ASME 28th International Conference on Ocean, Offshore, and Arctic Engineering. Hawaii, Honolulu; 2009.

27. Jureczko M, Pawlak M, Mezyk A. Optimization of wind turbine blades. J Mater Process Technol. 2005;167(2):463-471.

28. Bavanish B, Thyagarajan K. Optimization of power coefficient on a horizontal axis wind turbine using BEM theory. Renew Sustain Energy Rev. 2013;26:169-182.

29. Gao X, Tian Y, Sun B. Multi-objective optimization design of bi-directional flow passage components using RSM and NSGA II: a case study of inlet/outlet diffusion segment in pumped storage power station. Renewable Energy. 2018;115:999-1013.

30. Cichocki A, Unbehauen R. Neural Networks for Optimization and Signal Processing. New York, NY: Wiley and Sons Press; 1993:2-10.

31. Abutunis A, Hussein R, Chandrashekharra K. A neural network approach to enhance blade element momentum theory performance for horizontal axis hydrokinetic turbine application. Renewable Energy. 2019;136:1281-1293.

32. Zhang S, Dong Y, Ouyang Y, Yin Z, Peng K. Adaptive neural control for robotic manipulators with output constraints and uncertainties. IEEE Trans Neural Networks Learning Syst. 2018;29(11):5554-5564.

33. He W, Dong Y. Adaptive fuzzy neural network control for a constrained robot using impedance learning. IEEE Trans Neural Networks Learning Syst. 2018;30(1):97-1186.

34. He W, Li Z, Dong Y, Zhao T. Design and adaptive control for an upper limb robotic exoskeleton in presence of input saturation. IEEE Trans Neural Networks Learning Syst. 2019;30(1):97-108.

35. Shen WZ, Mikkelsen R, Sørensen JN, Bak C. Tip loss corrections for wind turbine computations. Wind Energy. 2010;8(4):457-475.

36. Bouziad Y. Physical Modeling of Leading Edge Cavitation: Computational Methodologies and Application to Hydraulic Machinery. Doctoral Thesis No. 3353, EPFL, Lausanne, Switzerland; 2009.

37. Liu C, Wang Y, Zhang Z. Maximum tensile stress criterion and application of cavitation inception. J Huazhong Univ Sci Technol (Natural Science Edition). 2011;39(12):54-57.

38. Selig MS, Mc Granahan BD. Wind tunnel aerodynamic tests of six airfoils for use on small wind turbines. NREL/SR-500-34515; 2004.
40. Fuglsang P, Bak C, Gaunaa M, Antoniou I. Design and verification of the Risø-B1 airfoil family for wind turbines. *J Sol Energy Eng*. 2004;126(4):1002-1010.

41. Zhang Y, Zheng H, Liu J, Zhao J, Sun P. An anomaly identification model for wind turbine state parameters. *J Clean Prod*. 2018;195:1214-1227.

42. Jing G, Du W, Guo Y. Studies on prediction of separation percent in electro dialysis process via BP neural networks and improved BP algorithms. *Desalination*. 2012;291(1-3):78-93.

43. Shafaghat R, Hosseinalipour SM, Nouri NM, Lashgari I. Shape optimization of two-dimensional cavitators insupercavitating flows, using NSGA II algorithm. *Appl Ocean Res*. 2008;30(4):305-310.

44. Zhu GJ, Guo PC, Luo XQ, et al. The multi-objective optimization of the horizontal-axis marine current turbine based on NSGA-II algorithm. *IOP Conf Ser: Earth Environ Sci*. 2012;15(4):042039.

45. And M, Prosperetti A. Bubble dynamics and cavitation. *Ann Rev Fluid Mech*. 2003;9(1):145-185.

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