Research Article

Optimization for Cavitation Inception Performance of Pump-Turbine in Pump Mode Based on Genetic Algorithm

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Cavitation is a negative factor of hydraulic machinery because of its undesirable effects on the operation stability and safety. For reversible pump-turbines, the improvement of cavitation inception performance in pump mode is very important due to the strict requirements. The geometry of blade leading edge is crucial for the local flow separation which affects the scale and position of pressure drop. Hence, the optimization of leading edge shape is helpful for the improvement of cavitation inception performance. Based on the genetic algorithm, optimization under multiple flow rate conditions was conducted by modifying the leading edge ellipse ratio and blade thickness on the front 20% meanline. By using CFD simulation, optimization was completed with obvious improvements on the cavitation inception performance. CFD results show that the pressure drop location had moved downstream with the increase of the minimum pressure coefficient. Experimental verifications also got an obvious enhancement of cavitation inception performance. The stability and safety was improved by moving the cavitation inception curve out of the operating range. This optimization is proved applicable and effective for the engineering applications of reversible pump-turbines.

1. Introduction

Cavitation is a common dangerous phenomenon in hydraulic machinery, usually causing vibration, noise, and damage. As a consequence, it affects the stability and safety seriously. Reversible pump-turbines usually have higher speeds and heads than typical centrifugal pumps and are more likely to experience large-scale cavitation with tremendous negative impacts. Moreover, the cavitation coefficient in pump-mode is much greater than that in turbine-mode. Often, critical cavitation data are obtained by measuring the external characteristics. However, before the conditions reach the “critical cavitation” conditions, in the impeller, the actual extent of the cavitation is already quite serious. For the above reasons, the cavitation inception in pump-mode is often regarded as the crucial factor. Hence, improving the cavitation inception performance of a reversible pump-turbine is obviously important in engineering applications.

For pumps, the minimum pressure point is usually located in the leading edge (LE) of the blade. As a consequence,

the inception cavitation often manifests as LE cavitation. LE cavitation in hydraulic turbomachinery has received great attention and been widely investigated by researchers based on experiments and CFD simulations [1–5]. Arakeri [6] pointed out that the cavitation inception at LE is related to the position of flow separation. Flow separation occurs when the boundary layer lifts off or separates from the surface due to the geometry [7, 8]. In practical applications, researchers modified the geometry of LE to improve cavitation performances of pumps and inducers [9–11]. But targeted optimization for the cavitation inception performance of pump-turbine is still unresolved in engineering applications.

As a common optimization method, the genetic algorithm (GA) is famous for its global optimization and parallel computing capabilities [12] and has been applied to the dynamics optimizations of pumps, compressors, and wind turbines [13–15]. In this study, GA is used to search the optimal LE geometry to improve the cavitation inception performance of pump-turbine in pump mode. The optimized pump-turbine model is expected to change the position of

FIGURE 1: Meridional shape of pump-turbine impeller.

TABLE 1: Specification of the performance and geometry parameters.

Parameters	Values
Performance	
Design flow rate Q_d	450 kg/s
Design head H_d	54 m
Rotational speed n	1200 r/min
Geometry	
Blade number Z	9
Leading edge hub diameter D_{h1}	140 mm
Leading edge shroud diameter D_{s1}	300 mm
Trailing edge diameter D_2	514 mm
Outflow width b_2	57.2 mm

local separation especially under off-design conditions, slow down the dramatic pressure drop near LE, and enhance the safety and stability of pump-turbine units.

2. Application Example

2.1. Model and Parameterization. In this study, a pump-turbine which has seriously bad cavitation performance was put into optimization. This pump-turbine has a 9-blade mixed flow impeller whose meridional shape is shown in Figure 1. Moreover, the details of performance parameters and geometry parameters are shown in Table 1.

As the optimized object, the LE geometry was parameterized for controlling. Figure 2 shows the parameterization of LE shape. The thickness values on the front 20% meanline and the LE ellipse were controlled. So there were 6 parameters including the thickness at 0%, 4%, 8%, 12%, and 16% meanline length and the LE ellipse ratio. To apply the GA, the original values and variation range of all the 6 parameters were determined and shown in Table 2.

FIGURE 2: Parameterization of leading edge shape.

TABLE 2: Original values and variation range of controlling parameters.

Parameters	Original values	Variation range
Ellipse ratio	3	1~5
Thickness at 0%	1.058 mm	1.058~4.058 mm
Thickness at 4%	4.664 mm	2.664~6.664 mm
Thickness at 8%	5.911 mm	3.911~9.911 mm
Thickness at 12%	6.613 mm	4.613~10.613 mm
Thickness at 16%	6.967 mm	4.967~10.967 mm

2.2. Optimization Method. After the parameterization of LE geometry of impeller, the initial generation was created randomly in the variation range with 10 individuals. These individuals were encoded with 42-digit binary code (7 digits for each parameter). The binary code and the parameter values could be converted following the rule below:

$$x = a + x' \frac{b - a}{2^n - 1}, \quad (1)$$

where x is the decimal value of parameter, a and b are the lower and upper limit of the variation range, n is the digit number of binary code per parameter (here $n = 7$), and x' is the corresponding decimal value of the binary code. The binary code had a numerical precision of 0.1 for the ellipse ratio, 0.024 for the thickness at 0%, and 0.047 for the thickness at other locations.

As mentioned above, the minimum pressure coefficient $C_{p-\min}$ in the impeller was chosen as the fitness function to evaluate the cavitation inception performance. To compare the minimum pressure between different impeller geometries, the dimensionless pressure coefficient C_p was defined and is shown below:

$$C_p = \frac{2(p - p_\infty)}{\rho V_\infty^2}, \quad (2)$$

where p is the pressure, p_∞ and V_∞ are the reference pressure and velocity, and ρ is the density of water. The reference pressure and velocity values were acquired at the impeller inlet.

In this study, three different operating conditions including 360 kg/s, 450 kg/s (the design condition, Q_d), and 540 kg/s were taken into consideration. The fitness function F is defined as follows:

$$F = \sum_i w_i C_{pi-\min}, \quad (3)$$

FIGURE 3: Schematic map of domain, mesh, and boundary conditions.

where i denotes the number of operating conditions which is 3 in this study. The argument w_i is the weight of C_{pi-min} under different conditions. Because of the worse cavitation performance under off-design conditions, w_1 (the weight of $Q_d = 450$ kg/s) was set as 0.2 and w_2 (the weight of 360 kg/s) and w_3 (the weight of 540 kg/s) were set as 0.4.

Considering the nonlinearity in this study, computational fluid dynamics (CFD) tools were used as the solver of fitness function. So, modeling and meshing of the flow domain were proceeded before the solving. A single blade passage was modeled as the flow domain. Then, structural hexahedral elements were used in the meshing of domain. A mesh independence check was conducted to guarantee the computational accuracy. The mesh schemes from 11935 to 57750 nodes were checked by comparing the minimum pressure coefficient C_{pi-min} on the blade surfaces under the design condition. The variation of C_{pi-min} value became less than 1% when the mesh node increased to 44537. Moreover, the y^+ value was controlled within the range of 16 to 583 by setting the height of near-wall mesh elements to 3 mm. So, wall function could be used in the CFD solving of near-wall region. Finally, the mesh scheme with about 45000 mesh nodes was used. The Reynolds Averaged Navier-Stokes equations were solved with SST $k-\omega$ turbulence model [16]. In the definition of boundary conditions, the impeller inflow was set as mass flow inlet. The impeller outflow was set as pressure outlet with the static pressure of 0 Pa. Impeller hub, shroud, and blades were set as no slip wall. Rotational periodic boundaries were given for the simplification of simulation. The schematic map of domain, mesh, and boundary conditions are shown in Figure 3.

After the CFD simulation processes, the individual who had the lowest F value was eliminated and the vacancy was filled by the copy of the sample who had the highest F value. In the setting of genetic operations, the crossover rate was set as 0.65 and the mutation rate was set as 0.1. Optimization would converge when the residual of the fitness function of

the best individual became less than 1×10^{-3} . The schematic map of the whole optimization process is shown in Figure 4.

2.3. Optimization Monitoring and Results. In the solving of fitness function for all the 10 individuals, optimization was running in a parallel way. Every impeller individual was simulated in a standalone CFD progress. Then, fitness function values were transferred to a terminal machine for the genetic operations. The monitoring of fitness function F of all the 10 individuals is shown in Figure 5. After 20 generations, the optimization converged with the F values increasing to a higher level. Individual-9 who has the highest F value was chosen as the final optimized impeller. The comparisons of LE geometry between the optimized and the original impeller are shown in Figure 6.

3. Verifications and Analysis

3.1. Cavitation Inception Performance. To verify the improvement of cavitation inception performance, both the original and optimized impellers were put into cavitation experiments and CFD simulations. The cavitation inception experiments were conducted on the hydraulic test rig shown in Figure 7. The high-speed camera was used as the measurement device of cavitation bubbles. A “3-bubble” criterion was used to identify cavitation inception. By lowering the ambient pressure with the vacuum pump, cavitation bubbles occurred near the blade LE as shown in Figure 7(b). When 3 bubbles appeared, the cavitation inception coefficient C_{oi} was recorded which is defined as

$$C_{oi} = \frac{NPSH_r}{H} = \frac{(p_s/\rho g + V_s^2/2g - p_v/\rho g)}{H}, \quad (4)$$

where ρ is the density of water, g is the acceleration of gravity, p_v is the vapor pressure, p_s and V_s denote the pressure and velocity at the reference position (impeller inflow), and H denotes the head of pump-turbine.

FIGURE 4: Schematic map of optimization process.

FIGURE 5: Monitoring of fitness function F of all the 10 individuals.

In the cavitation inception simulations, mass transfer was turned on to make the cavitation happen. The saturation pressure is set to 3500 Pa under the reference pressure of 1 Atm. By lowering the pressure value at impeller outlet,

cavitation occurred in the impeller. The cavitation inception criterion was set as an average vapor volume fraction of 0.01% in the impeller domain. Figure 8 shows the experimental and numerical $C_{\sigma i}$ values under different flow rate conditions.

FIGURE 6: Comparison of LE geometry between the optimized and the original impeller.

FIGURE 7: Measurement of the cavitation inception in the test rig.

As shown in Figure 8, if the $C_{\sigma i}$ curve goes across the operating range, cavitation would happen because the pressure may drop below the vapor pressure. Experimental data show that the $C_{\sigma i}$ curve went across the range under off-design conditions before optimization. After optimizing the blade LE shape, even the $C_{\sigma i}$ value increased under the design flow rate condition ($Q = 450 \text{ kg/s}$)

and the cavitation inception had also been improved because $C_{\sigma i}$ decreased under all the off-design conditions with the curve getting out of the range. It is necessary to study the mechanism of cavitation inception performance optimization. As shown in Figure 8, the numerical simulation had obtained a consistent variation tendency of $C_{\sigma i}$ with the experimental data. So, it is reasonable to study

FIGURE 8: Cavitation coefficient $C_{\sigma i}$ by experiment and numerical simulation.

and analyze the flow details through the CFD simulation results.

3.2. Pressure Drop at Leading Edge. To study the flow details near blade LE, the velocity vectors and pressure contour on the spanwise 50% surface under the design condition are plotted in Figure 9. Seen from the vectors, fluid flowed around the blade LE and separated from the side surface. Adverse pressure gradient generated and induced the pressure drop. Before optimization, the pressure drop was very abrupt because of the mutational geometry. After optimization, the impeller got a bigger thickness around the LE. Hence, the pressure drop became gentle with the minimum pressure point moving downstream. To analyze the pressure drop in detail, the pressure coefficient C_p distributions on the front 2% meanline are plotted in Figure 10.

Seen from Figure 10, pressure drop occurred on the front 2% meanline on the spanwise 20%, 50%, and 80% surfaces. As illustrated in Figure 10, the minimum pressure coefficient $C_{p-\min}$ increased under all the 3 flow rate conditions except on the spanwise 50% surface of $Q = 450 \text{ kg/s}$ condition. This is due to the setting of weight of $C_{pi-\min}$ under different conditions in the fitness function (3). In this optimization, it focused more on the cavitation inception performance under off-design conditions. Even the cavitation coefficient $C_{\sigma i}$ increased at the flow rate of $Q = 450 \text{ kg/s}$ after optimization (shown in Figure 8); this optimization was also globally successful for improving the cavitation inception performance under the poor-performing conditions.

3.3. Impacts on Hydrodynamic Performances. Considering the impacts on external characteristics after the optimization

(a) Original

(b) Optimized

FIGURE 9: Flow separation and pressure drop at blade LE on spanwise 50% surface.

of LE shape, additional studies were carried out by analyzing the variation of head and efficiency. Figure 11 shows the comparison curves of head H and efficiency η between original impeller and optimized impeller. In Figure 11, the CFD head values are the impeller head and the experimental head is the head of the whole passage. The CFD efficiency is the hydraulic efficiency of the impeller and the experimental efficiency is the total efficiency of the whole passage. Both H and η decreased after the optimization of LE. However, CFD H and experimental H changed by less than 0.986% and 1.059%, respectively. Also, CFD η and experiment η decreased by less than 0.237% and 0.180%, respectively. There were just little changes on the head and efficiency. It means that the optimization was applicable and effective.

4. Conclusion

With the genetic algorithm, the optimization on cavitation inception performance of a pump-turbine in pump mode had been conducted. The geometry of LE had been modified

FIGURE 10: Pressure coefficient C_p distributions on the front 2% meanline.

FIGURE 11: Comparison curves of head and efficiency.

after optimization. By both the CFD simulation and the verification experiment, the optimization had been proved effective with conclusions drawn as follows.

As a widely used optimization method, the genetic algorithm was used in this study to solve the nonlinear problem. After optimization, the impeller got a better cavitation performance than before. The optimization was helpful to control the local separation. With the optimized LE geometry, flow separation near leading edge was weakened and postponed to downstream. The tendency of pressure drop became gentle especially under the off-design conditions. Moreover, the minimum pressure coefficients $C_{p-\min}$ increased after optimization. Hence, this optimization was proved excellent for improving the cavitation inception performance of pump-turbines in pump mode. It is reasonable and applicable for relevant engineering applications.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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