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Hydraulic Optimization of a Double-channel Pump's Impeller Based on Multi-objective Genetic Algorithm

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Abstract: Computational fluid dynamics (CFD) can give a lot of potentially very useful information for hydraulic optimization design of pumps, however, it cannot directly state what kind of modification should be made to improve such hydrodynamic performance. In this paper, a more convenient and effective approach is proposed by combined using of CFD, multi-objective genetic algorithm (MOGA) and artificial neural networks (ANN) for a double-channel pump's impeller, with maximum head and efficiency set as optimization objectives, four key geometrical parameters including inlet diameter, outlet diameter, exit width and midline wrap angle chosen as optimization parameters. Firstly, a multi-fidelity fitness assignment system in which fitness of impellers serving as training and comparison samples for ANN is evaluated by CFD, meanwhile fitness of impellers generated by MOGA is evaluated by ANN, is established and dramatically reduces the computational expense. Then, a modified MOGA optimization process, in which selection is performed independently in two sub-populations according to two optimization objectives, crossover and mutation is performed afterword in the merged population, is developed to ensure the global optimal solution to be found. Finally, Pareto optimal frontier is found after 500 steps of iterations, and two optimal design schemes are chosen according to the design requirements. The preliminary and optimal design schemes are compared, and the comparing results show that hydraulic performances of both pumps 1 and 2 are improved, with the head and efficiency of pump 1 increased by 5.7% and 5.2%, respectively in the design working conditions, meanwhile shaft power decreased in all working conditions, the head and efficiency of pump 2 increased by 11.7% and 5.9%, respectively while shaft power increased by 5.5%. Inner flow field analyses also show that the backflow phenomenon significantly diminishes at the entrance of the optimal impellers 1 and 2, both the area of vortex and intensity of vortex decreases in the whole flow channel. This paper provides a promising tool to solve the hydraulic optimization problem of pumps' impellers.

Keywords: double-channel pump's impeller, multi-objective genetic algorithm, artificial neural network, computational fluid dynamics(CFD), uniform experiment design method

1 Introduction

Flow loss is the main loss in the fluid machinery, so the optimal design can be established if quantitative calculation of the flow loss can be carried out[1].

Computational fluid dynamics (CFD) can give a lot of potentially very useful information for improving the fluid dynamic design of pumps. Such as SHOJAEEFARD, et al[2], studied effects of some geometric parameters on fluid dynamic characteristics of a centrifugal pump impeller that pumps a viscous fluid by CFD; FAN, et al[3], studied on CFD analysis and design optimization of jet pumps; ZHAO, et al[4], comprehensively studied the inner flow pattern in a double-channel pump by CFD and particle image velocimeter measurement. ZHANG, et al[5], optimized the impeller of a low-specific high speed pump with the CFD method, and the result shows that this optimization method is reasonable and feasible. However, in many cases, CFD does not directly state what kind of modification of geometrical parameters should be made to improve such hydrodynamic performance of pumps. Therefore, combined using of CFD and mathematical optimization design method is a more convenient and effective approach. Such as YAN, et al[6], discussed the prospect of algorithm in the optimization design of blade for centrifugal pump impeller. MURR, et al[7], optimized a multi water-to-water heat pump by combined using of CFD and evolutionary algorithm. WANG, et al[8–9], used CFD and response surface method to optimize a vortex pump and a S-type blade of fire pump respectively. Refs. [10–12] has performed and discussed the optimization problem of centrifugal pumps by combined using of CFD and genetic algorithm (GA). DERAKHSHAN, et al[13], numerically shape optimized a centrifugal pump impeller using the artificial bee colony algorithm. KIM, et al[14], enhanced

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aerodynamic performance of a axial-flow ventilation fan by multi-objective optimization method. Among various mathematical optimization algorithms, multi-objective genetic algorithm (MOGA) is a notable popular global optimization algorithm with good robustness[15].

However, a large number of offspring individuals will be produced in optimization processes, too much work needs to be done if the fitness value of each individual is evaluated by CFD. Therefore, surrogate models, such as response surface method (RSM) and artificial neural networks (ANN), and so on, are incorporated in many optimization processes as a more economic way to assign the fitness value. MUELLER, et al[16], optimized a radial turbine by combined using of ANN and differential genetic algorithm, setting hydraulic performance and mechanical processing requirements as optimization objectives. A compromised design scheme is found to satisfy both hydraulic and mechanic processing requirements. LOU, et al[17], used the genetic algorithm to optimize the axial compressor blade for multi-criteria optimization design by setting the maximum value of isentropic efficiency and minimum value of maximum stress as optimization objectives. It is proven to be an effective way for the optimization of the turbine machinery blade. ZHANG, et al[18], made Multi-objective shape optimization of helico-axial multiphase pump impeller based on genetic algorithm and ANN.

Based on these works, the relation between geometric parameters and the hydraulic performance of a double-channel pump will be established using ANN in this paper; then hydraulic optimization will be performed on the impeller of the double-channel pump by using CFD, MOGA and ANN simultaneously, to find the optimal geometric parameter combination; Finally, two optimal designs are chosen from the Pareto Front, and compared with the preliminary design to validate this optimization method.

2 Multi-objective Optimization

2.1 Preliminary design

The impeller under investigation is a double-channel pump's impeller, and its design specifications are specific speed of 110.9, flow rate of 50 m^3/h, and head of 10 m at a rotating speed of 1450 r/min[19]. The geometrical parameters of the preliminary impeller (labelled impeller 0), are designed using the traditional velocity modulus method plus the experience of designer, and their values are listed in the second column of Table 1.

2.2 Optimization parameter and design space

Since different geometric parameter influences the hydraulic performance of the impeller to different degrees, first of all, the geometric parameters are screened according to their influence on the hydraulic performance using Design-Expert software. The inlet diameter D_1, exit width B_2, outlet diameter D_2 and wrap angle of the midline φ are sorted to be significant factors, and constitute the optimization parameters in a form as $X=[D_2, D_1, B_2, \varphi]$. The variation range for each optimization parameter is listed in the third column of Table 1.

Table 1. Geometric parameter and value range

Parameter	Initial value	Range
Inlet diameter D_1/mm	85	74/96
Outlet diameter D_2/mm	200	160/220
Exit width B_2/mm	60	74/96
Shroud arc radius R_1/mm	40	R_1=0.5D_1
Hub arc radius R_2/mm	110	R_2=0.5D_2
Shroud angle T_1/(°)	89	89
Hub angle T_2/(°)	90	90
Wrap angle of midline φ/(°)	160	196/228

2.3 Optimization objective

The essence of the hydraulic optimization of the impeller is to improve the head and efficiency, and reduce the shaft power. Since to increase efficiency is equivalent to decrease shaft power in the premise of head unchanged, the optimization in this research becomes a two-objective maximization problem in a form as $F(X)=\max[H(X), \eta(X)]$.

2.4 CFD evaluation

CFD evaluation, which is performed using ANSYS CFX software, is used for the objective function value assignment of impellers in training sample space for ANN and serves as a comparison for ANN evaluation as well.

The whole computational domain is composed of the impeller flow channel, volute flow channel, front and rear pump chamber, extended upstream and downstream channel, and meshed using non-structural tetrahedron grid due to its better adaptability with refinement at the seal ring area, see Fig. 1. The total number of the grid is determined to be 1 659 057 after the grid independency test.

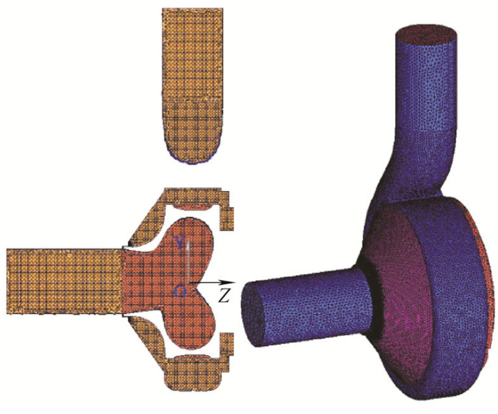

Fig. 1. Computational domain and grid

A uniform inlet flow distribution is assumed by setting the mass flow rate and a turbulence density of 5%. The outlet is assumed to be a free flow outlet without pressure gradient along its flow direction, and static pressure is set to be 0 here as the reference pressure. For wall boundary, non-slip wall boundary condition is imposed, and the logarithmic law is employed to estimate the wall shear stress. The effect of wall roughness is also considered by setting the absolute surface roughness value not zero[20].

Shear stress transport turbulence model is incorporated to simulate the 3D anisotropic turbulence flow in the pump, the rotor-stator interaction of the impeller and volute is handled by the frozen rotor model. Convergence is based on reducing the maximum residuals of all governing equations to less than 10^{-5}.

According to pump's working principle, the head and efficiency can be calculated by Eq. (1) and Eq. (2), respectively:

$$H=\frac{p_{\text{out}}-p_{\text{in}}}{\rho g}, \tag{1}$$

$$\eta=\frac{\rho g Q_{\text{d}} H}{(M_{\text{im}}+M_{\text{s\&h}})\omega/0.97}, \tag{2}$$

where η is the efficiency, H is the head, ρ is the fluid density, Q_{d} is the design flow rate, M_{im} refers to the torque on the impeller, $M_{\text{s\&h}}$ refers to the sum of torque on the shroud and hub, n indicates the impeller rotating speed under rpm, ω is angular velocity, p_{in} and p_{out} is area averaged total pressure at the inlet and outlet.

2.5 ANN evaluation

As introduced before, a large number of child impellers will be produced by MOGA. If their objective function values are all assigned by high fidelity CFD evaluations, the optimization process will be too much CPU time consuming, and even unable to realize. Thus, a low fidelity surrogate model will be built by ANN to evaluate the objective function of child impellers instead of CFD evaluation. The model is built by the following steps.

Firstly, according to the uniform experimental design method, a uniform design table $U_{50}(50^4)$ is designed, which arranges 50 experimental points for a 4-factor, 50-level experiment, and 1/5 of the uniform design table $U_{50}(50^4)$ is shown in Table 2.

Table 2. 1/5 of the normalized uniform design table and objective function values

No.	Optimization parameter				Objective function	
	D_2	D_1	B_2	φ	H	E
1	0.80	0.21	0.56	0.40	0.88	0.63
2	0.84	0.34	0.76	0.02	0.85	0.32
3	0.92	0.47	0.86	0.87	0.96	0.00
4	0.76	0.55	0.20	0.98	0.59	0.51
5	0.73	0.06	0.52	0.19	0.78	0.71
6	0.37	0.09	0.28	0.13	0.41	0.98
7	0.27	0.45	0.22	0.62	0.25	0.80
8	0.63	0.75	0.26	0.04	0.54	0.61
9	0.84	0.70	0.00	0.42	0.49	0.43
10	0.20	0.70	0.50	0.85	0.37	0.49

Secondly, the objective function values of these 50 experimental points in the uniform design table are assigned by CFD evaluation, and listed in Table 2. Note that, the values of optimization parameters and objective function in Table 2 are normalized according to Eq. (3) to make all data vary between 0 and 1:

$$Y_{ji}=\frac{X_{ji}-X_{j\min}}{X_{j\max}-X_{j\min}}, \tag{3}$$

where i and j refers to the index of row and column, $X_{j\min}$ and $X_{j\max}$ refers to the minimal and maximum training sample in j column, and X_{ji} indicates the training sample in i row and j column.

Finally, a three-layer BP neural network with four inputs (D_1, B_2, D_2 and φ) and two outputs (H and η), is built by the initial training samples. S-type and purelin-type transfer functions are constructed for the hidden layer and output layer. A schematic diagram of the three-layer BP neural network is shown in Fig. 2.

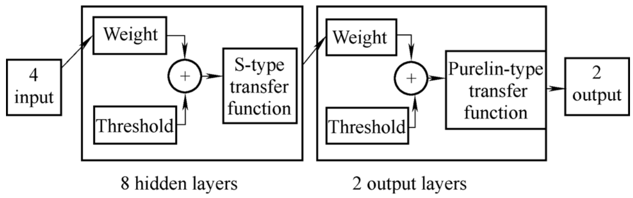

Fig. 2. Schematic diagram of the three-layer BP neural network

2.6 Optimization strategy

The first generation of population of MOGA is generated randomly and has 100 individuals, which are coded by the binary coding method. The fitness value of each individual is assigned by ANN evaluation. Later, the new generations of population are generated by the selection, crossover and mutation operations of MOGA. Note that, since two sub objective functions are under investigation, the traditional genetic algorithm process is modified in this paper. The first generation of population is divided into two sub-populations, and selection is performed independently in each sub population according to corresponding fitness values. Then the selected individuals are merged into a new population, crossover and mutation are performed on it. So the individuals with largest fitness values, named elite members, are selected considering two aspects of the optimization objective. In the following operation, on one hand, they are used to generate new individuals by crossover operator, which ensures their excellent genes can be inherited; On the other hand, they are used to generate new individuals by random mutation, which increases the diversity of the population. This division, selction, combination, crossover and mutation process is repeated until the preset maximum generation number is reached. Finally optimal individuals are selected from the last generation of population.

The complete flow chart of the optimization method developed in this paper is illustrated in Fig. 3, and is composed of the following five main steps: 1) The constitution of the initial training samples; 2) The training of the BP neural network for a low fidelity fitness evaluation model; 3) Generation of new individuals through the modified MOGA's selection, crossover and mutation process; 4) Evaluation of the fitness value of new individuals by ANN; 5) Comparison of the fitness value evaluated by ANN and CFD. If their difference is less than a preset value, then the optimization process ends and individuals of last generation are output and decoded, else the new individuals are added into the training samples, the established BP neural network is retrained, and the above optimization process repeats again. From this process, it is found the number of training samples increases constantly, which increases the accordance of the CFD and ANN evaluation and ensures the optimization direction towards the global true optimum results.

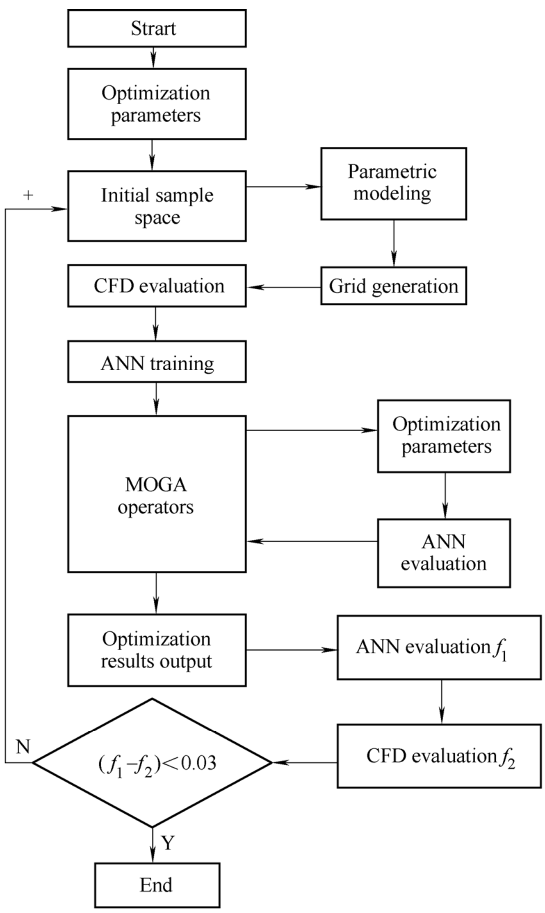

Fig. 3. Flow chart of the optimization

3 Optimization Results and Analyses

3.1 Optimization results

Fig. 4 shows the last generation after 500 steps of iteration, Pareto optimal frontier as well as the chosen two optimal schemes compared with the preliminary scheme. The two optimized impellers, with the head around 10 m, relative higher efficiency and lower shaft power compared with the preliminary one, are labeled as impeller 1 and impeller 2, respectively, and corresponding pumps are labeled as pump 1 and pump 2, respectively. The specific values of the four optimization parameters of the optimized impellers are shown in Table 3.

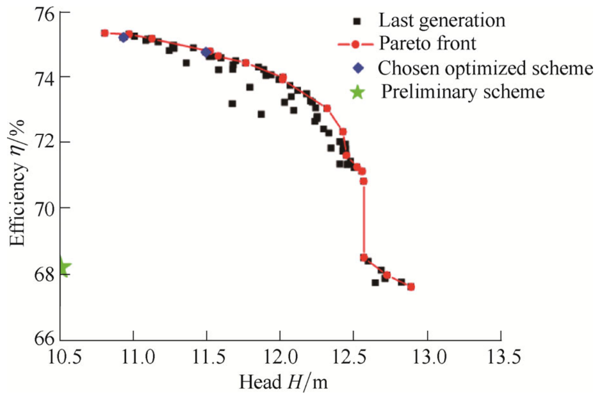

Fig. 4. Pareto Front of the impeller optimization

Table 3. Comparison of the geometric parameters of the optimized and preliminary impellers

Impeller	Outlet diameter D_2/mm	Inlet diameter D_1/mm	Exit width B_2/mm	Midline wrap angle φ/(°)
0	200	85	60	160
1	211	74	40	172
2	211	74	45	176

3.2 Hydraulic performance analyses

Fig. 5 shows the comparison of the characteristic curves of the optimized and preliminary pumps. It is found that compared with the preliminary pump, the head and efficiency of pump 1 increases by 5.2% and 5.7%, respectively under the design working condition, furthermore the shaft power decreases under various working conditions, espeacially declines by 6.2% under the small flow rate working condition. The head and efficiency of pump 2 also increases by 11.7% and 5.9%, respectively under the design working condition, while the shaft power increases by 5.5%.

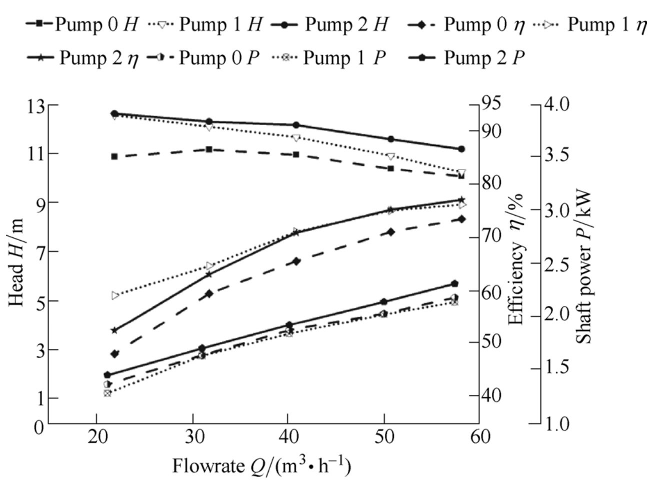

Fig. 5. Comparison of the characteristic curves of the optimized and preliminary pumps

3.3 Inner flow field analyses

Fig. 6 shows the static pressure contours and flow lines on horizontal sections at different relative axial postion D (D=2Z/B_2, where Z refers to the axial coordinate). It is found that there are two symetrical vortices near the blade pressure side at the entrance of the preliminary impeller, with swirl angular velocity in the opposite direction. After comparison, it is observed that these vortices' intensity weakens and their affecting area shrinks in both impeller 1 and impeller 2. Secondary backflow in the adverse pressure gradient direction is also observed near the blade suction side at the entrance of the preliminary impeller, and this phenomenon relieves in impeller 1, while intensifies in impeller 2, especially on the horizontal section at D=−0.33.

Fig. 7 and Fig. 8 show relative velocity vectors on cylindrical sections at different relative radius R (R equals to 2r/D_2, where r refers to the cylindrical surface radius.). From Fig. 7, obvious cross flow and recircluation is observed near the entrance of the preliminary impeller. After optimization, cross flow disappears in both impeller 1 and impeller 2, and recirculation weakens obviously at the same time. From Fig. 8, obvious vortex is observed on the cylindrical section at R=0.6 in the preliminary impeller, and disappears in the optimized impellers. As a result, the water can flow into the impeller's out channel more easily, with less secondary flow loss, less shock loss between the water and blade as well.

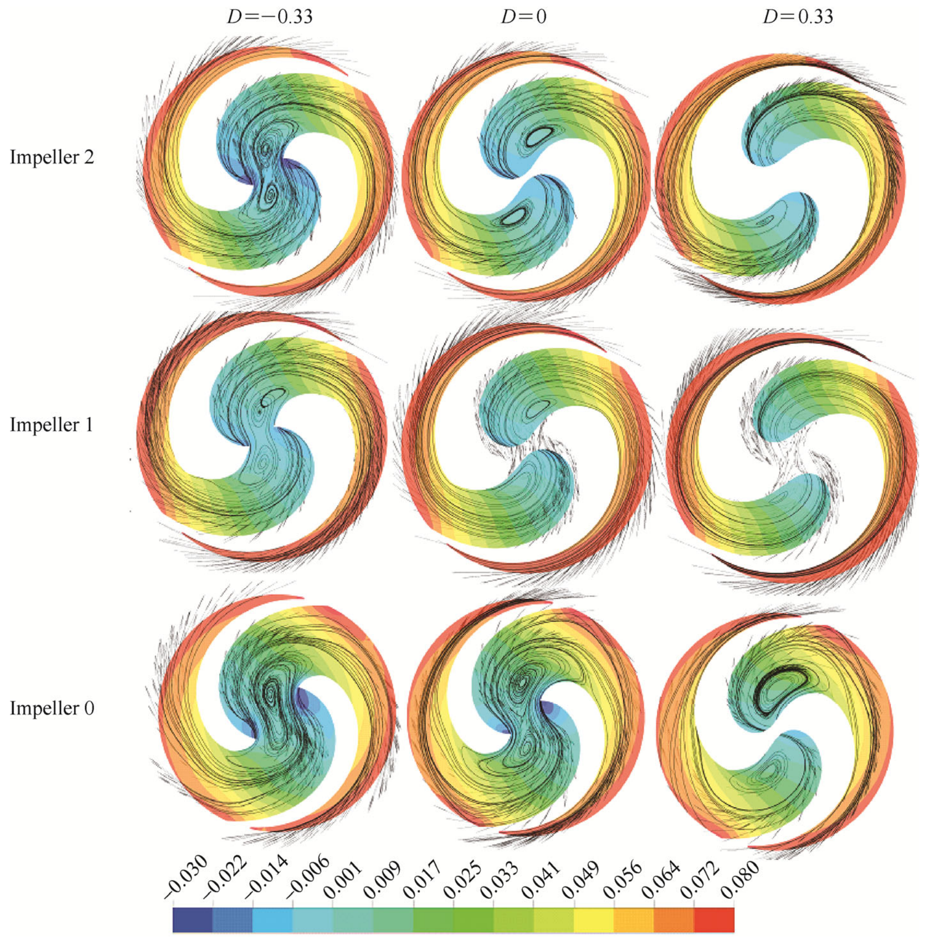

Fig. 6. Static pressure contour and flow lines on different horizontal sections (MPa)

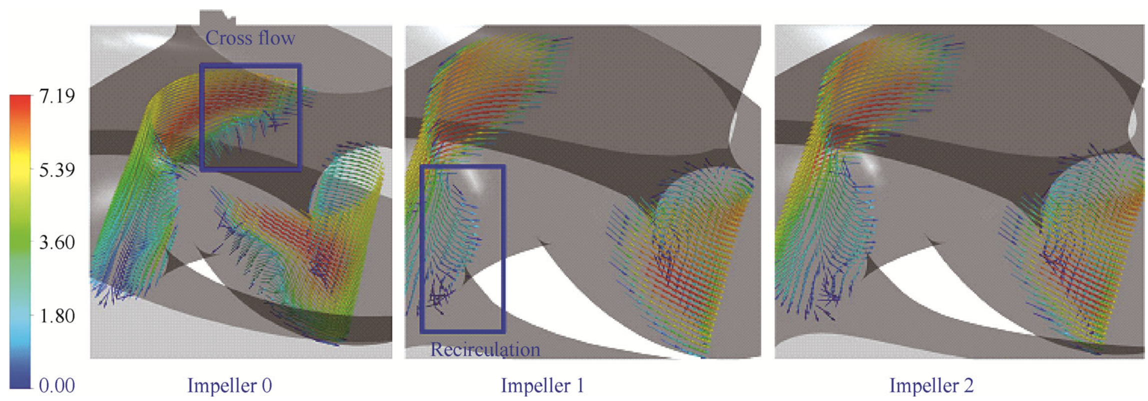

Fig. 7. Relative velocity vectors on the cylindrical section at R=0.1 (m/s)

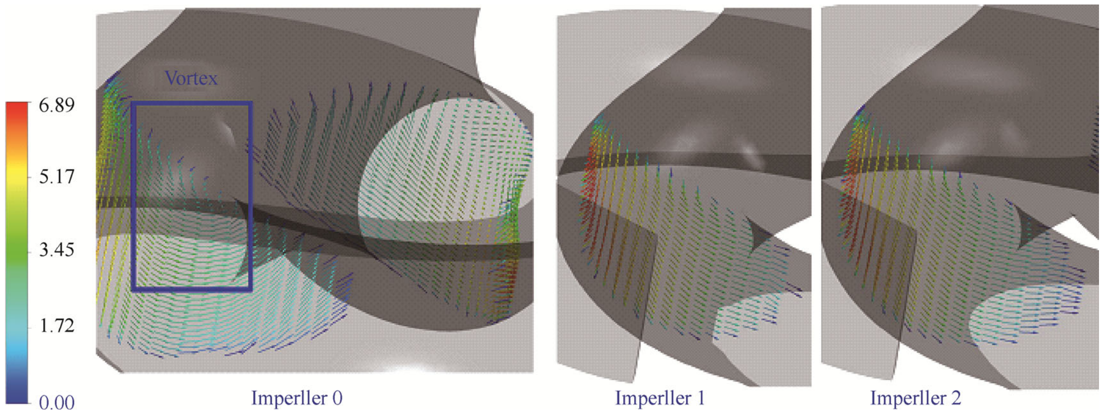

Fig. 8. Relative velocity vectors on the cylindrical section at R=0.6 (m/s)

4 Conclusions

(1) The uniform experiment design method is more suitable to establish performance prediction model with ANN. Compared with other experiment design methods, it requires fewer samples to train ANN while the precision kept same.

(2) A multi-objective genetic algorithm based hydraulic shape design optimization method for the double-channel pump's impeller has been successfully developed in this paper. The two objectives of the optimization are addressed by implementing a modified optimization process with repeated division, selection, combination, crossover and mutation, which not only ensures excellent genes of elite parent individuals to be inherited, but also increases the diversity of population to find the global true optimal solution.

(3) The computational expense of whole optimization process is greatly reduced by implementing multi-fidelity fitness assignment method, both CFD and ANN method.

(4) This optimization method can not only be used in the hydraulic performance optimization of the double channel pump, but also offers a promising tool to hydraulic optimization problems of other pumps, while reducing the dependence on the experience of designers, shortening design cycle and reducing design costs in the near future.

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