An improved ABC algorithm approach for shape optimization of the blood centrifugal pump impeller

Jiaming Wang¹*, Xiaodong Ruan¹ and Xin Fu¹

¹State Key Laboratory of Fluid Power & Mechatronic Systems, Zhejiang University, Hangzhou, Zhejiang, 310007, China

*Corresponding author’s e-mail: wjm0@zju.edu.cn

Abstract. A high efficiency blood centrifugal pump has low blood damage and little energy loss, so it is important to improve hydraulic efficiency by optimizing the design. In this paper, an improved Artificial Bee Colony algorithm combined with the adjoint method (ABCA) is proposed to optimize the blood centrifugal pump impeller. The introduction of gradient information enhances the search performance and the convergence judgment of ABC algorithm. Besides, its random search feature can effectively avoid the adjoint optimization method from trapping in local optimum. The ABCA algorithm are applied to increase the hydraulic efficiency of a self-designed blood pump. After optimization, five design parameters of the impeller are optimized, and hydraulic efficiency of the impeller improves about 3.90%. Compared with ABC algorithm, the ABCA algorithm saves about 58% of calculation time, and its convergence performance is much better than ABC in the middle of the iteration.

1. Introduction

The blood centrifugal pump has been widely used in extracorporeal circulation and auxiliary circulation. Improving the efficiency of the blood pump can not only reduce heat production and prevent blood degeneration, but also reduce the size of the battery and motor. The flow losses in the blood pump blade passage are usually large, so it is necessary to optimize the hydraulic efficiency of the impeller for the blood centrifugal pump. Since there is a complicated relationship between performance and design parameters of impellers, many researchers establish the relationship by CFD [1] and get the optimal designs by optimization algorithms. However, due to the large amount of CFD calculation, some direct optimization algorithms take a lot of computation time. Although, some stochastic algorithms reduce computational costs with surrogate models, the estimation results may deviate from CFD results.

In recent years, because of its fast convergence, the adjoint optimization method is getting wider application in scientific researches [2]. If the boundaries of impeller models are deformed along the directions of surface sensitivities, the objective performance will be optimized. Therefore, it is easy to apply some gradient-based optimization methods, such as the steepest descent method. Since fluid calculation is operated on model mesh, mesh deformation technology is usually used to update geometric models. For example, Liu, Zhang, & Li [3] constructed a high-efficiency aerodynamic optimum design system of blade by using discrete viscous adjoint equation method and radial basis function mesh deformation technology. Although the adjoint optimization method is of high efficiency, it has many weaknesses: (1) It is difficult to determine an appropriate iteration step size, which has a huge influence on the optimization process [4]; (2) After a few iterations, some meshes may have negative volumes, and the boundary may be too rough to meet the design requirements; (3) It is
difficult to bring the modifications back into the CAD process [5]; (4) As a gradient-based algorithm, this surface shape optimization method is easy to trap in local optimum [6]. Despite the defects of adjoint optimization method, the gradient information got by it is of great use. If we introduce it into stochastic algorithm, the convergence rate may be increased. For impeller optimization, both the stochastic algorithm and the adjoint optimization method have obvious advantages and disadvantages. A combination method can avoid their weakness, so an improved ABC algorithm with the adjoint method (ABCA) is proposed. The introduction of gradient information enhances the search performance and the convergence judgment of ABC algorithm, so that the convergence rate can be increased. In our research, both ABCA algorithm and traditional ABC algorithm are applied to optimize the parameters of a blood pump impeller. By comparison, the improvement of impeller design parameters and the characteristic of ABCA algorithm are summarized.

2. Methodology

The ABC algorithm, a stochastic algorithm, is inspired by the intelligent foraging behaviour of bees [7]. It is widely used to optimize design and is quite effective when solving multimodal, high-dimensional engineering problems [8]. In this study, based on the surface shape sensitivity calculated by the adjoint method, the sensitivities of design parameters to hydraulic efficiency is calculated. And then the ABC algorithm is improved with the help of these sensitivities. The following is an introduction and improvement of the ABC algorithm.

The artificial bee colony in the ABC algorithm contains three bees: employed bees, onlookers and scouts [9]. The employed bees and onlookers take charge of searching around the food sources that have been found. Scouts randomly search for new food solutions to expand the scope of exploration. At the beginning of the algorithm process, the employed bees are randomly initialized by Eq. (1), and the solutions and nectar amounts are recorded as the first generation “food sources”.

\[
x_i = x_{\text{min}} + \Psi_i (x_{\text{max}} - x_{\text{min}})
\]

(1)

where \(i \in \{1, 2, \ldots, N\}, \; j \in \{1, 2, \ldots, D\}, \) the number of food sources is \(N\) and, the number of variable elements is \(D\). \(x_j\) represents \(j\)th element of \(i\)th source solution and \(\Psi_i\) is a random number in \([0, 1]\).

Having shared the information of current “food sources”, according to Eq. (2), employed bees search for new food sources. And then, some food sources are selected artificial onlookers in light of probability value (\(p_i\) in Eq. (3)), which is determined by fitness. Therefore, new food solutions were generated according to Eq. (2). By employing greedy selection, the “food sources” in each iteration are updated by employed bees and onlookers. If the fitness of a food source has not increased to more than “limit” (a control parameter) times, it will be abandoned. And then the scout searches for a new food source according to Eq. (1).

\[
v_j = x_j + \Phi_j (x_j - x_{\text{min}})
\]

(2)

where \(\Phi_j\) is a random number in \([-1, 1]\) and \(k\) is randomly selected, but different from \(i\).

\[
p_i = \frac{F_i}{\sum_{m} F_m}
\]

(3)

where \(F_i\) is the fitness value of the \(i\)th solution.

Referring to Othmer’s study [10], by adjoint calculation, the gradient between performance function and boundary geometry can be expressed as:

\[
\delta_p J \propto u_i^j \cdot v_i^j
\]

(4)
where $\beta$ represents localized surface normal displacements, and $J$ represents the hydraulic performance of an impeller. $u_j$ and $v_j$ are the tangential adjoint velocity and tangential velocity of grid $j$, which is closest to the surface perturbation.

Then, the shape sensitivity between the performance function and CAD parameters can be calculated by Eq. (5). The term $\delta_\beta$, which is called design velocity, is used to refer specifically to the normal displacement of the model boundary caused by changing a parameter value [11].

$$\delta_\beta = \delta_\beta J \cdot \delta_\alpha \beta$$  \hspace{1cm} (5)

With the help of gradient information, our modified ABC algorithm has three improvements:

1. Employed bees and onlookers look for better routes with clear directions. Replacing Eq. (2) with Eq. (6), the absolute value of $\zeta_{ij}$ in Eq. (6) is a random number between $[0, 1]$, but it is determined by the gradient with adjoint method whether $\zeta_{ij}$ is positive or negative.

$$v_j = x_j + \zeta_{ij} \left| x_j - x_k \right|$$  \hspace{1cm} (6)

2. In the ABC algorithm, a food source is chosen by an onlooker in light of probability value, which is determined by fitness. Similarly, in our algorithm, when the global best solution is selected by employed bees (or onlookers), the variable element selected to change is determined by the probability value associated with the gradient. Detailed operations are as follows: Randomly selecting a variable element $y_k$ and a random number $q$ in $[0, 1]$. If $p_{g_k}$ in Eq. (7) is greater than $q$, this element will be used for optimization, otherwise re-random selection will be carried out until the judgment condition is met.

$$p_{g_k} = \frac{\left| \frac{\partial F}{\partial y_k} \right|}{\sum_{m=1}^{P} \left| \frac{\partial F}{\partial y_m} \right|}$$  \hspace{1cm} (7)

3. The gradient values of solution near the vertex are relatively small. So, an abandoned solution can be judged not only by the control parameter (limitation of times), but also by the gradient value. In our study, the scout bee operates a random search only when a food source has not been updated more than limited times, and all variable gradients of this source are less than 10 times maximum parameter gradient of the global best solution.

3. Application

3.1 Description of the impeller model

In order to reduce the size of motor, the ABCA algorithm is applied to improve the efficiency of a blood centrifugal pump. At the design operation point, the blood pump needs to provide a head of 100mmHg under a flow rate of 5 L/min and a rotate speed of 3000 r/min. The preliminary design fluid model of the pump includes inlet, impeller, volute and outlet fluid models. In the simulation, the RNG k-epsilon Reynolds average stress turbulence model is employed, and the mixed-plane function is used for the rotor-stator interface. The blood is considered to be a single-phase incompressible Newtonian fluid. The density is 1050 kg/m$^3$, and the viscosity is 3.5e-3 kg/m.s. The mass flow rate is set at the inlet plane and average static pressure at the outlet plane. All solid walls are assumed under the no-slip condition. The convergence criterion is $1e^{-5}$.

We have verified the accuracy of the simulation model by performance tests (Figure 1 shows the test platform). The test was repeated 5 times. The accuracy of the pressure transmitters is ±0.5%FS, and the uncertainty data of the head is represented by error bars. Then a comparison between the simulated and tested H-Q characteristic curves is shown in Figure 2. We can see that the simulation errors are less than 5% under the design condition and less than 10% under off-design conditions. Since the errors between simulations and tests are small, the simulation model is of high reliability.
Figure 1. Performance test platform.

Figure 2. Characteristic curves from simulations and tests.

The objective of our study is to improve the impeller efficiency under design conditions, but at the same time the head cannot be less than the minimum value by our design requirements (The head of the impeller should be no less than 120mmHg). The following design parameters of the impeller are selected as optimization variables: inlet diameter \( d_1 \), outlet diameter \( d_2 \), outlet width \( b_2 \), inlet angle \( \beta_1 \), outlet angle \( \beta_2 \), according to Figure 3. In our optimization, 10% maximum variations are set for all design variables.

Figure 3. Design parameters of the impeller.

### 3.2 Program specification

Because of the computational limitations, a single channel model of the impeller was used. In our study, the hydraulic efficiency function, Eq. (8), was substituted into the adjoint equations. Fluid calculations were operated on the OpenFOAM (an open source software) \[12\]. An “adjointSensitivityFoam” function was written to get surface sensitivities, and then the parameter sensitivities were calculated with software CAESES.

\[
\eta = \frac{Q \Delta P}{n \cdot 2\pi \cdot 60 \cdot T}.
\]  

(8)
The optimization algorithm was written in C language, and the main control parameters in this study were set as: the colony size is 20 (the number of employed bees is 10. The number of onlookers is 10. The number of scout bees is one.). The maximum number of generations is 500. The control parameter to abandon the food source is 50. It should be noted that, in the iterative loop, it is unnecessary to solve the adjoint equations in all impeller models. Because of the greedy selection, better source solutions are saved. The adjoint solving is only required for these solutions. The experiments were carried out by ABC algorithm and new improved ABC algorithm. The whole process was operated on a workstation with Intel Core Xeon e5 chip, 2.4GHz of speed and 100GB of RAM memory.

3.3 Optimization results
The convergence histories by ABC algorithm and ABCA method are shown in Figure 4, and the optimization results of the impeller are listed in Table 4. After improvement, the hydraulic efficiency of the impeller improves about 3.90%, from 28.54% to 32.44%. The inlet diameter increases by 3.50%, the outlet diameter decreases by 1.81%, the outlet width decreases by 8.18%, the inlet angle increases by 13.97% and the outlet angle decreases by 18.88%. Inlet and outlet angle change more than other parameters, which indicates that the angular distribution of the blade has a great impact on the hydraulic efficiency. The geometries of initial and optimized impellers are compared in Figure 5, which shows the blade profile and the meridian channel of the impeller. The optimization results obtained by ABC algorithm and ABCA method are similar. Compared with the original ABC algorithm, the ABCA method saves about 58% of calculation time.

![Figure 4. The iterative curve.](image)

![Table 1. Results of optimization by ABC algorithm and ABCA method.](image)

| Parameter | Initial | ABC | ABCA | Radio of change |
|-----------|---------|-----|------|-----------------|
| Step      | 0       | 2583| 793  | -69.30%         |
| Time      | 0h      | 24.3h| 10.2h| -58.02%         |
| d1        | 12mm    | 12.40mm| 12.42mm| +3.50%         |
| d2        | 42mm    | 41.24mm| 41.24mm| -1.81%         |
| b2        | 5.5mm   | 5.05mm| 5.05mm| -8.18%         |
| β1        | 32°     | 27.49°| 27.53°| +13.97%        |
| β2        | 24°     | 19.43°| 19.47°| -18.88%        |
| H         | 122.29mm| 120.04mm| 120.01mm| -1.86%       |
| η         | 28.54%  | 32.45%| 32.44%| +13.67%        |

From Figure 4, it can be seen that the advantages of the new approach are not obvious in the first few steps. This is mainly because the samples have not covered the entire design space, and the effect of gradient acceleration is very small. In order to further improve the method, the adjoint solver cannot
be performed at this stage. In the middle of the iterative process, the improved method shows an obvious feature of rapid optimization. While at the later stage of iteration, target performance remains stable. Applying the adjoint-based optimization method directly to convergence results may help us find better solutions. Due to the adjoint solution, the time costed by each iteration step is longer than ABC algorithm. However, as described in section 3.2, we do not carry out the adjoint solver in the samples that do not replace the original samples. Therefore, as listed in Table 2, the calculation time per step this method takes does not double as ABC algorithm.

The velocity streamlines of the impellers are shown in Figure 6. Due to the flow separation, vortices are generated in each blade passage. After optimization, the vortex near the pressure surface disappears, and the reflux phenomenon is improved. It is indicated that the flow loss is reduced, resulting in the improvement in hydraulic efficiency.

Figure 5. The geometry comparison of initial and optimized impellers.

Figure 6. The internal streamlines of the initial impeller (a) and the optimized impeller (b) at span.

4. Conclusion
In this study, a modified ABC algorithm is developed to optimize the hydraulic efficiency of a blood centrifugal impeller. This method combines the original ABC algorithm with the adjoint solver, which provides gradient acceleration for the entire optimization process. After improvement, the inlet diameter, outlet diameter, outlet width, inlet angle and outlet angle of the impeller are optimized. Since the variations of inlet and outlet angle are more than those of other parameters, they are key parameters for improving hydraulic efficiency. It can be found in flow field analysis, through optimization, the reflux phenomenon is improved, and the flow loss in the channel is reduced. The simulation results show that the impeller hydraulic efficiency is increased by 3.90%. Compared with the original ABC algorithm, the improved method saves about 58% of calculation time. Therefore, combining the ABC algorithm with the adjoint method is an efficient method for shape optimization.
of the blood centrifugal pump impeller, and its convergence performance is much better than traditional ABC algorithm in the middle of the iteration.

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