Automatic Optimization of Vertical Long-shaft Fire Pump Overload Based on Particle Swarm Optimization Algorithm

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Abstract. As a typical large-flow high-head pump, the vertical long-axis fire pumps have the advantages of rapid startup, superior structure, and strong applicability in multiple occasions. In order to shorten the non-overload optimization cycle, CFturbo, ICEM and CFX are integrated by writing batch processing commands to achieve automatic multi-load and no-load optimization of vertical long-axis fire pumps based on Isight’s multi-disciplinary optimization platform. With the objective of achieving the non-overload characteristics of vertical long-axis fire pumps, the optimal Latin hypercube design is used to spatially sample the design variables of the impeller. After sampling, the particle swarm optimization (PSO) algorithm is used to optimize the design. The results show that, vertical long-axis fire pumps achieve non-overload characteristics within 1.5Q₀ after optimization, while the head and efficiency at the rated operating point are almost unchanged.

1. Introduction
As a typical large-flow high-head pump, vertical long-axis fire pumps have the advantages of rapid startup, superior structure, and strong applicability in multiple occasions [1]. Therefore, they are widely used in Offshore platforms, flood control and drainage, urban water supply, boiler water supply, mines and other fields. With the rise in offshore platform oil development, large-scale terminals and other projects, the demand for vertical long-axis fire pumps continue to increase, which also places higher requirements on their performance. Affected by tides, waves, typhoons, etc., the power of vertical long-axis fire pumps increase extremely with the increase of flow, and it is easy to overload and burn the motor under large flow conditions. Therefore, the development of a vertical long-axis fire pump with no overload performance and high efficiency is the current research focus of the fire industry.

Presently, the domestic and foreign researches on the no-overload performance of centrifugal pumps are mainly concentrated on low specific speed centrifugal pumps [2]. There are few related studies on vertical long-axis fire pumps with medium specific revolutions, and the research on their no-overload characteristics is also non-existent. In recent years, intelligent optimization design has been widely used in all walks of life, and has been proved to be effective by actual engineering tests [3]. Fortunately, there are many cases of applying intelligent optimization algorithms to the optimization design of fluid machinery [4-13], which provides a reference for multi-parameter optimization of fluid machinery.

There are many impeller hydraulic parameters that affect the no-overload performance of vertical long-axis fire pumps. It is difficult and time-consuming to modify one by one. In order to achieve fast and efficient hydraulic optimal design of vertical long-axis fire pumps, this paper uses Isight optimization software to integrate

CFturbo, ICEM with CFX to establish a CFD-based no-overload automatic optimization platform for the vertical long-axis fire pump platform. Combined with the optimal Latin
The Fourth Chinese International Turbomachinery Conference (CITC 2020) 
IOP Conf. Series: Materials Science and Engineering 1081 (2021) 012017 
doi:10.1088/1757-899X/1081/1/012017

hypercube test design and particle swarm optimization algorithm, a vertical long-axis fire pump impeller is optimized for no overload.

2. Computational models and numerical methods

2.1 Computational models
The research object is a vertical single-suction, single-stage guide vane vertical long-axis fire pump with a specific revolution of 157.3. The main parameters are shown in Table 1. The pump structure is mainly composed of a water suction chamber, an impeller and a guide vane.

Table 1. Main parameters of vertical long-axis fire pump

| Parameter     | Parameter name           | Value |
|---------------|--------------------------|-------|
| $Q_0$         | Design flow /m³·h⁻¹       | 864   |
| $H$           | Head /m                  | 43.3  |
| $n$           | Impeller speed/r·min⁻¹    | 1485  |
| $N$           | Number of blades         | 6     |
| $D_1$         | Impeller inlet diameter/m| 0.209 |
| $D_2$         | Impeller outlet diameter/m| 0.383 |
| $b_2$         | Impeller outlet width /m  | 0.0587|

Figure 1. Vertical long-axis fire pump

2.2. Numerical Methods
When the numerical simulation of the model pump is carried out, Creo Parametric 5.0 three-dimensional modeling software is used to perform three-position modeling on the pump inlet and outlet extension, the impeller water body and the space guide vane water body. CFX17.0 is used for steady calculation of the model pump in this research. Considering that this research focuses on the non-overload characteristics of vertical long-axis fire pumps, the RNG k-ε turbulence model is adopted, and the boundary conditions are pressure-inlet and massflow-outlet; the discrete solution is set to the second-order upwind style, and the convergence residual is set to $10^{-5}$.

Table 2. Analysis of grid independence

| Scheme | Grid numbers | $H$ /m | $r_H$/% | $\eta$/% | $r_\eta$/% |
|--------|--------------|--------|---------|---------|------------|
| A      | $2.634\times10^6$ | 40.90  | —       | 81.56   | —          |
| B      | $4.160\times10^6$ | 41.95  | 2.56    | 82.59   | 1.26       |
| C      | $5.350\times10^6$ | 42.90  | 2.26    | 84.58   | 2.41       |
| D      | $6.782\times10^6$ | 43.78  | 2.05    | 84.55   | 0.04       |
| E      | $9.219\times10^6$ | 43.83  | 0.11    | 84.52   | 0.04       |
| F      | $1.232\times10^7$ | 43.83  | 0       | 84.71   | 0.22       |
It can be seen from Table 2 that the error of the number of grids of scheme D for the simulation result is less than 1%. Therefore, the scheme of the number of grids of scheme D of 6.782 million was finally selected to start numerical simulation calculation in Figure 3. After analyzing the external characteristic curves of the experiments and simulations, it is found that the two trends are pretty consistent, so the simulation results can be considered reliable.

Figure 2. Structural grid of water body computing domain

Figure 3. Experimental and simulated computing domain externacharacteristic curves

3. Non-overload theory and optimization method

The theory of non-overload centrifugal pump means that when the centrifugal pump works in the full-flow working range, the pump’s flow-axis power curve is saturated: the shaft power has a maximum change with the flow. However, the vertical long-axis fire pump requires no overload within $1.5Q_0$ (the maximum shaft power appears within $1.5Q_0$).

According to the traditional optimization method, the designer repeatedly changes the relevant parameters of the blade and performs numerical simulation calculations based on the calculated performance results in the blade optimization process. This repeated process not only has a long cycle but also has poor economic benefits. Practice has proved that most design schemes made in accordance with traditional design methods have room for improvement, which is not the best design.

This research combines calculation models with modern intelligent optimization algorithms, and applies mathematical methods and computer techniques to the optimization design process. First, design the vertical long-axis fire pump design variables and their value ranges. Secondly, conduct spatial sampling through experimental design to reduce the scope of optimization variables. Finally, use the optimization algorithm to optimize the calculation model. The research uses the Isight optimization platform to fully automate the design process to shorten the optimization cycle and reduce the optimization cost.

3.1. Non-overload constraint equation and optimization parameters

According to the theoretical conditions of the saturated shaft power characteristics of the centrifugal pump, Yuan Shouqi et al. deduced the constraint equations for the design of no overload pumps. They comprehensively considered the influence of geometric parameters on the performance of the pump, then modified the existing centrifugal pump calculation formulas and related coefficients, and finally proposed a more accurate set of constraint equations. According to Yuan Shouqi’s research on the area ratio theory [13], the constraint equations for the non-overload centrifugal pumps (suitable for specific speed $n_s=80-250$) are followed:
In order to ensure that the rated working head efficiency of the original model pump meets the requirements to the greatest extent. The parameters such as the outer diameter of the impeller and the width of the impeller outlet are kept. From the above non-overload constraint equations, it can be deduced that, the overload-free characteristic of the vertical long-axis fire pump is realized by changing the blade inlet placement angle $\beta_1$, reducing the blade outlet placement angle $\beta_2$ and increasing the blade wrap angle $\phi$.\cite{14}

Table 3 shows the range of design variables. In CFturbo’s hydraulic design of vertical long-axis fire pump impellers, three streamlines are used to control the blades. $\beta_{1-a}$, $\beta_{1-b}$ and $\beta_{1-c}$ is the inlet placement angle on the three streamlines; $\beta_{2-a}$, $\beta_{2-b}$ and $\beta_{2-c}$ is the outlet placement angle corresponding to the three flow lines; $\varphi_1$, $\varphi_2$ and $\varphi_3$ is the blade wrap angle corresponding to the three flow lines; in order to reduce the optimization variables, let

$$\begin{align*}
\beta_{1-b} &= \beta_{1-a} - 15.4, \\
\beta_{1-c} &= \beta_{1-a} - 21, \\
\beta_{2-c} &= \beta_{2-b} = \beta_{2-a}, \\
\varphi_3 &= \varphi_2 = \varphi_1.
\end{align*}$$

\[ (2) \]

| Variables | Min | Max | Initial value |
|-----------|-----|-----|--------------|
| $\beta_{1-a}$ (°) | 25.8 | 51.6 | 40.4 |
| $\beta_{1-b}$ (°) | 10.4 | 36.2 | 25 |
| $\beta_{1-c}$ (°) | 4.8 | 30.6 | 19.4 |
| $\beta_{2-a}$ (°) | 21 | 33 | 27 |
| $\beta_{2-b}$ (°) | 21 | 33 | 27 |
| $\beta_{2-c}$ (°) | 21 | 33 | 27 |
| $\varphi_1$ (°) | 110 | 155 | 120 |
| $\varphi_2$ (°) | 110 | 155 | 120 |
| $\varphi_3$ (°) | 110 | 155 | 120 |
3.2 Automatic optimization without overload

3.2.1 Optimal Latin Hypercube Test Design
Figure 4 is a schematic diagram of the optimal Latin hypercube test. The test design provides data samples for the construction of the calculation model. For the test design, the number of tests is required to be as small as possible, and the design space characteristics are fully reflected as much as possible. The optimal Latin hypercube test design method used in this research improves the uniformity of the random Latin hypercube design, so that all test points are distributed as evenly as possible in the design space, and have the ability to fit second-order or non-linear relationships[15].

3.2.2 Automatic Optimization Platform Construction

Parameter modeling is the key to optimal design. In this research, the rotating machine design software CFturbo is used to hydraulically design the impeller. Based on the Isight optimization platform, this research integrates the three-dimensional modeling software Cfturbo, meshing software ICEM and numerical simulation software CFX to optimize the corresponding parameters of the variable blades, and perform multi-parameter optimization with non-overload characteristics.
as the optimization goal. The "design-simulation" integrated automatic optimization platform of the vertical long-axis fire pump is set up, and the integration process is shown in Figure 5.

- Export the file that records the CFturbo design process: imp1.cft-batch, write the parameters to be optimized, and edit the equation (2) to modify the corresponding parameters.
- Establish a batch command for software operation as follows:

| Softwares | Bch commands |
|-----------|--------------|
| CFturbo   | "E:\Program Files\CFturbo 10\CFturbo.exe" -batch imp1.cft-batch |
| icemcfd   | "D:\Program Files (x86) \ANSYS Inc\v170\icemcfd\win64_amd\bin\icemcfd.bat" -batch-script yl xjt.rpl |
| cfx5pre   | "D:\Program Files (x86) \ANSYS Inc\v170\CFX\bin\cfx5pre.exe" -session impeller_h50.pre |
| cfxsolve  | "D:\Program Files (x86) \ANSYS Inc\v170\CFX\bin\cfx5solve.exe" -def C:\Users\Administrator\Desktop\isight_leon\impeller_h50.def -par-local -partition 2 |
| cfxpost   | "D:\Program Files (x86) \ANSYS Inc\v170\CFX\bin\cfx5post.exe" -session impeller_h50.cse |

- Read the efficiency, head and shaft power from the table.txt of the CFX calculation results.
- The running process is shown in Figure 6. Set up and run the test design component to drive the platform automatically, then obtain the numerical simulation results. In order to provide enough sample points for the calculation model, 24 cases are designed using the optimal Latin hypercube, and the specific scheme is automatically generated in the Isight test component.

3.2.3. Particle Swarm Optimization (PSO) Algorithm optimization

Particle swarm optimization is a stochastic optimization algorithm proposed by Kennedy and Eberhart in 1995. It is a bionic algorithm inspired by group behaviors such as bird foraging. The optimization process is based on a particle group, and through iterative calculation, these particles are constantly moved from the decision space to search the space. Information is shared between particles, and speed and position updates are affected by their own experience and group experience, so that particles can move to a better position with the greatest probability. The basic speed and position update formulas are shown in equations (3) and (4):

\[
\begin{align*}
    v_{i+1} &= v_i + c_1 \cdot r_1 \cdot (p_{best,i} - x_i) + c_2 \cdot r_2 \cdot (g_{best} - x_i) \\
    x_{i+1} &= x_i + v_{i+1}
\end{align*}
\]

In the formula, \(x\) is the particle position; \(v\) is the particle velocity; \(c\) is the individual learning factor and group learning factor, generally take 2; \(r\) is a random number between \([0,1]\); \(t\) represents the number of iterations, \(g_{best}\) represents the optimal position of the group, \(p_{best}\) represents the optimal position of the individual.

The characteristics of the PSO algorithm are as follows:

- The PSO algorithm does not have cross operations and mutation operations like genetic algorithms, but relies on particle speed to complete the search, and in the iterative evolution, only the information of the optimal particle is passed to other particles, and the search speed is fast;
- The PSO algorithm is memorable and can remember the historical optimal position of the particle group and pass it to other particles:
The structure is simple, there are few parameters to be adjusted, and it is easy to implement in engineering. Using real number coding, the variable number of the problem is directly used as the dimension of the particle, which directly points to the problem.

The PSO optimization process is shown in Figure 7. The PSO algorithm is used to optimize the Latin hypercube design after sampling, to find the optimal solution that meets the requirements of no overload as quickly as possible.

Figure 7. PSO optimization process

Figure 8. Comparison of optimization

Table 5 is the geometric parameter table. After the optimization, the shape of the impeller changes greatly, in which the exit edge of the impeller is appropriately inclined, the blade wrap angle increases substantially, the blade inlet placement angle slightly decreases, and the blade outlet placement angle becomes larger, but the head, efficiency and shaft power of the flow design point almost unchanged.

Figure 8 shows the efficiency, head and shaft power curve of the vertical long-axis fire pump before and after optimization. It can be found that after optimization, the vertical long-axis fire pump achieves no overload characteristics within 1.5\(Q_0\), and the head and efficiency at the rated operating point are almost constant. However, it is worth noting that by increasing the blade wrap angle and reducing the blade exit placement angle to achieve no overload performance, the efficiency and head change of the vertical long-axis fire pump under low flow conditions is relatively small. However, under high flow conditions, efficiency and head are reduced to a certain extent.

Table 5. Results of optimization

| Variables   | Initial values | Optimized values | Variables   | Initial values | Optimized values |
|-------------|----------------|------------------|-------------|----------------|------------------|
| \(\beta_{1,a}\) \(^\circ\) | 40.4           | 39.90            | \(\varphi_1\) \(^\circ\) | 120            | 127.96           |
| \(\beta_{1,b}\) \(^\circ\) | 25             | 24.6             | \(\varphi_2\) \(^\circ\) | 120            | 127.96           |
| \(\beta_{1,c}\) \(^\circ\) | 19.6           | 19.2             | \(\varphi_3\) \(^\circ\) | 120            | 127.96           |
| \(\beta_{2,a}\) \(^\circ\) | 27             | 29.79            | \(\eta\) \(\%\)          | 83.56          | 83.38            |
| \(\beta_{2,b}\) \(^\circ\) | 27             | 29.79            | \(H\) \(m\)            | 43.319         | 43.24            |
| \(\beta_{2,c}\) \(^\circ\) | 27             | 29.79            | \(P\) \(kW\)             | 122.02         | 122.06           |
3.3. Pareto graph analysis

In order to understand the contribution of design variables to the efficiency of the vertical long-axis fire pump, a Pareto diagram analysis of the experimental design results is shown in Figure 9. Figure 9 is Analysis graphs of optimization variables in $Q_0$, $1.25Q_0$, and $1.5Q_0$, including Pareto graph and Main effect diagram. The Pareto graph reflects the percentage of the contribution of all inputs to each target in the fitted quadratic regression model of the samples. Its absolute values indicate the significance of the impact on the target, and positive and negative indicate the positive and negative effects on the target. The order of significance of the influence of each design variable on efficiency is as follows: $\varphi_1$, $\varphi_1^2$, $\beta_{2-a}$, $\beta_{1-a}^2$, $\beta_{2-a} \cdot \beta_{1-a}$, $\beta_{2-a} \cdot \varphi_1$, $\beta_{1-a} \cdot \varphi_1$, $\beta_{1-a}$, $\beta_{2-a}$. It can be seen that the non-overload performance of the vertical long-axis fire pump is greatly affected by the blade wrap angle. The blade wrap angle has a large negative effect on the non-overload performance, indicating that the non-overload design of the vertical long-axis fire pump can be appropriately increased; while the blade inlet placement angle has a slight negative effect on the non-overload performance, indicating that the non-overload design of the vertical long-axis fire pump can appropriately increase the blade outlet placement angle; and the blade outlet placement angle has a non-overload performance. The small positive effect shows that appropriately reducing the blade inlet placement angle can achieve the non-overload design of the vertical long-axis fire pump. This conclusion is consistent with the results of the Main effect diagram.

![Figure 9. Analysis graphs of optimization variable in $Q_0$, $1.25Q_0$ and $1.5Q_0$.](image)

4. Inflow Characteristics Analysis

![Figure 10. Comparison of the static pressure distribution in the middle section of the front and rear impellers in $Q_0$.](image)
Figure 11. Comparison of the relative velocity distribution in the middle section of the front and rear impellers in $1.5Q_0$

Figure 10 is a comparison of the static pressure distribution of design flow in the middle section of the impeller. Compared with the initial impeller, the optimized impeller wrap angle increases, the exit placement angle decreases, the blade length increases, and the constraint on the flow field is enhanced [16]. Compared to initial impeller, pressure gradient in the impeller inlet and outlet, blade working surface and back of optimized impeller is almost the same.

Figure 11 is a comparison of the relative speed distribution of design flow in the middle section of the impeller. Compared with the initial impeller, the relative velocity distribution at the impeller inlet, blade working surface and back of optimized impeller is almost the same, and only the speed at the outlet is significantly increased. This indicates that the water velocity at the exit of the impeller is increased, and the ability of the impeller to convert mechanical energy into kinetic energy of water is improved.

Figure 12. Pressure monitoring points

(a) Initial plan in $Q_0$ (b) Initial plan in $1.5Q_0$
Figure 13. Pressure pulsation diagram of blade pressure surface

Figure 14. Pressure pulsation diagram of blade suction surface

For unsteady calculation, the time step is $1/180T$ and the total time is $10T$. The last $4T$ data is selected to do the pressure analysis. The distribution of pressure monitoring points is shown in Figure 12. The red balls are the pressure surface monitoring points, from the blade inlet to the outlet direction, respectively PA1, PA2, PA3, PA4, PA5. The yellow balls are the suction surface monitoring point, from the blade inlet to the outlet direction, respectively SA1, SA2, SA3, SA4, SA5.

Since the pressure fluctuation at the position of the monitoring point in the pump is very small relative to the pressure value itself at this point, the dimensionless pressure coefficient $C_p$ is introduced in this paper, which can reduce the effect of static pressure to a certain extent and at the
same time make the pressure at each monitoring point. The observation of the value is more intuitive and convenient. The calculation formula of $C_p$ is as formula (5):

$$C_p = \left( \frac{p_i - \bar{p}}{0.5 \rho u_2^2} \right)$$

(5)

Among them: $p_i$ represents the instantaneous pressure of the monitoring point; $\bar{p}$ represents the average value of all pressure data obtained at the monitoring point; $u_2$ represents the outlet circumferential speed of the impeller; $\rho$ represents the fluid density.

Fig. 13 is the pressure pulsation diagram of the initial model and optimized model at the blade pressure surface of $Q_0$ and $1.5Q_0$, and Fig. 14 is the pulsation diagram of the initial model and optimized model at the blade suction surface in $Q_0$ and $1.5Q_0$. The pressure pulsation is very stable after $15f_0$, so we focus on analyzing the pressure pulsation before $15f_0$. The optimization model shows that the pressure pulsation on the pressure surface and the suction surface decreases significantly in $Q_0$, while the pressure pulsation amplitude on the pressure surface and suction surface does not change significantly in $1.5Q_0$, which also verifies that the optimization model achieves no overload characteristics in $1.5Q_0$. It sacrifices part of the efficiency of large flow.

5. Conclusion

The self-editing batch processing command integrates CFturbo, ICEM and CFX to establish a CFD automatic optimization platform for vertical long-axis fire pumps based on Isight. The platform is used to optimize the impeller of the vertical long-axis fire pump with a specific speed of 157, which can realize the non-overload optimization. The conclusions are as followed:

- Use the optimal Latin hypercube test design to uniformly sample and reduce the range of optimized variables, and then optimize the calculation model by PSO algorithm to obtain a set of optimal geometric parameters. The vertical long-axis fire pump achieves non-overload characteristics within $1.5Q_0$, and the head and efficiency of the rated point is almost unchanged.

- Based on the Pareto diagram analysis, the primary and secondary sequence of the design variable's impact on the objective function is obtained. The impeller wrap angle has a greater impact on the non-overload performance of the vertical long-axis fire pump. Researchers should focus on the impeller wrap angle when designing the vertical long-axis fire pump without overload.

- By comparing the internal flow characteristics of the original model and the optimized model, the impeller wrap angle of the optimized model is increased, the outlet placement angle is reduced, the blade length is increased, the binding force on the flow field is enhanced, and the flow channel diffusion capacity is reduced, while achieving the non-overload characteristics, a part of the efficiency of large flow is sacrificed.
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