Artificial neural network for the performance improvement of a centrifugal pump

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Abstract. Performance improvement is very important to the energy saving of the pumps and industrial pumping systems. To increase the efficiency at design point, an artificial neural network is applied to construct a non-linear function with high accuracy between the optimization objective and design variables of the impeller, then particle swarm optimization is used to globally optimize the mathematical model. A database consists of 200 sets of impellers generated from Latin Hypercube Sampling method and corresponding efficiencies obtained from numerical simulation. A whole computational domain considering the leakage between the impeller and suction is calculated with SST k-ω turbulence model. Design variables are the distribution of blade angle is controlled by fourth-order Bézier curve with six points. The results show that the numerical performance curve has a faithful agreement with the experimental data. The approximate function can predict the optimization objective with high R-square 0.9311. The pump efficiency at design point is 0.12% higher than the original one. The velocity streamline distribution in the impeller illustrate the optimization eliminates the flow separation at the pressure side of impeller blade.

1 Introduction

Energy consumptions of pumps accounts for 10% of global power share. Centrifugal pumps are widely used in electricity industries, chemical industries, agricultures and so on. Therefore, it is necessary to improve the pump performance using effective optimization method. Replacing the optimal centrifugal pumps of the original ones can reach an obvious target of saving energy.

Comparing with the traditional trail-and-error method, combination the optimization method with the numerical simulation for pump performance improvement can shorten development cycle, numerical and experimental resources. Application of surrogate models to optimize engineering problems is very effective. It is convenient for engineers to build an approximate function to describe the relationship between the objectives and variables. The common surrogate models are response surface model [1], Kriging model [2] and artificial neural network [3]. Response surface model can be linear and second-order function. Kriging model is combination of regression function with correlation function. Artificial neural network is very useful tool to fit the nonlinear relationship based on “learning process”. As is known, the pump performance doesn’t have accurate relationship with the geometrical parameters due to the unsteady flow in pumps, especially under off-design conditions. Thus, it is suitable to build complex mathematical function between the pump performance and geometrical parameters using artificial neural network.

Derakhshan et al [4] optimized a centrifugal Berkeh 32-160 pump impeller’s shape with artificial neural network and artificial bee colony algorithm. The efficiency and head at design point is optimized...
as objectives with improvement of 3.59% and 6.89m respectively. Duan et al [5] combined improved back-propagation neural network with the non-dominated sorting genetic algorithm-II for improving the efficiency and head of a minipump at design point. Besides, it pointed out that blade outlet angle and inlet diameter had great influence the head and efficiency respectively. Shim et al [6] used Kriging models to build approximate functions for three optimization objectives of a centrifugal pump and achieved Pareto-optimal designs with multi-objective genetic algorithm. The optimized impeller improved the pump performance and reliability. Suh et al [7] applied a second-order response surface model to construct surrogate function of efficiency of a multiphase pump. After that, the research group continued to improve the pressure and efficiency of the second stage of the multiphase pump using response surface model and non-dominant sorting genetic algorithm [8]. Miao et al [9] improved the efficiency and cavitation performance of axial-flow pump using Group method of data handling (GMDH) polynomial neural networks and modified particle swarm optimization.

The function could be supposed to be multimodal because different combination of parameters can obtain the same pump performance at design point. Thus, the global optimization algorithms are more appropriate than local optimization ones. Particle swarm optimization is one of nature-inspired swarm intelligence algorithms, proposed by Eberhart and Kennedy in 1995 [10]. This algorithm origins from the searching food of birds. It can be improved to apply in unconstrained and constrained optimization problems [11-12].

An optimization method of combination of artificial neural network with particle swarm optimization for a centrifugal pump performance improvement is proposed and automatically executed with the software Matlab. Artificial neural network is applied to construct non-linear function between the efficiency at design point and impeller blade angle distribution. The best efficiency and combination of design variables are achieved with particle swarm optimization on the approximate model.

2 Computational model and numerical simulation

2.1 Centrifugal pump

The centrifugal pump investigated is single stage and single suction (figure 1). The flow rate and head at design point are 50m$^3$/h and 34m respectively. The rotating speed is 2900 r/min and specific speed $n_s$ is 81.5. The main parameters of the centrifugal pump are listed in table 1.

![Figure 1. Structural drawing of a centrifugal pump](image)

2.2 Mesh generation

The whole computational domain consists of inlet pipe, impeller, front chamber, rear chamber, volute and clearance. All the parts except for the impeller are generated with structured mesh using ICEM. The structured mesh of the impeller is automatically generated using TurboGrid, due to the automatic
optimization on the performance in the next section. The detailed mesh is shown in figure 2. The total number of computational mesh is about 4 million.

**Table 1. Main geometrical parameters of the centrifugal pump**

| Parameters               | Value  |
|--------------------------|--------|
| Inlet diameter of impeller $D_1$ | 74mm   |
| Outlet diameter of impeller $D_2$ | 174mm  |
| Blade outlet width $b_2$        | 12mm   |
| Blade number $Z$                | 6      |
| Blade outlet angle $\beta_2$     | 30°    |
| Wrap angle $\phi$               | 140°   |
| Diameter of volute $D_3$        | 184mm  |
| Inlet width of volute $b_3$     | 20mm   |

**Figure 2.** Detailed structured mesh of whole computational domain

### 2.3 Numerical simulation

Considering the water in the centrifugal pump be three dimensional, incompressible and viscous, Sheer Stress Turbulence (SST $k-\omega$) model is used to enclose the N-S equations. The inlet and outlet boundaries are respectively set as total pressure and mass flow rate. The interface between the rotor and stator is “Frozen Rotor”, while the interface between the stator and stator is “None”. The maximum iterations are 500 and the residual error of convergence is less than $10^{-5}$.

### 3 Optimization method

Figure 3 shows that an automatic optimization process for pump efficiency improvement at design point is proposed based on Matlab 2017b. Firstly, the blade angle distribution of the impeller is designed with fourth-order Bézier curve with six points. The positions of six points are set as design variables. Secondly, Latin Hypercube Sampling method is applied to produce 200 impellers randomly distributed in the designed space within the boundaries of design variables. Thirdly, the efficiencies of 200 cases are calculated with ANSYS CFX 18 automatically executed by Matlab (figure 4). Fourthly, a nonlinear mathematical function based on artificial neural network is built between the objective and design variables. Finally, particle swarm optimization is used to search the global best value of the approximate function and obtain the best combination of 5 design variables.

#### 3.1 Design variables

The blade angle distribution can affect the fluid velocity streamline from the inlet to outlet of impeller. The other geometrical parameters of impeller are fixed in order to match the impeller with the pump body. The blade angle distribution (span=0.5, span of 1 means shroud and span of 0 represents hub) is controlled with Bézier curve with six points (red points in figure 5). The six points are uniformly distributed in $x$ axial direction and the $y$ values are set design variables. The lower and upper bounds are listed in Table 2. The first and last variables are blade inlet and outlet angle respectively and the angle is measured from the axial direction. Due to requirement of enough data for construction of nonlinear function, 200 cases of impeller are randomly generated with Latin Hypercube method [13], which is a
very useful experiment design method to create discrete points in design space. Some of the designed combination of variables are listed in Table 3.

![Flowchart](image)

**Figure 3.** Optimization method of the impeller based on artificial neural network

![Numerical Simulation](image)

**Figure 4.** Numerical simulation based on Workbench controlled by Matlab

**Figure 5.** Numerical simulation based on Workbench controlled by Matlab

| Table 2. The range of design variables |
|----------------------------------------|
| Bound | y₁ | y₂ | y₃ | y₄ | y₅ | y₆ |
| lower  | 50 | 40 | 40 | 40 | 40 | 55 |
| upper  | 70 | 80 | 80 | 80 | 80 | 65 |
Table 3. Some of 200 impellers and calculated efficiencies

| No. | $y_1$ | $y_2$ | $y_3$ | $y_4$ | $y_5$ | $y_6$ | $\eta$ |
|-----|-------|-------|-------|-------|-------|-------|-------|
| 1   | 51.43 | 41.05 | 74.37 | 43.56 | 48.90 | 63.57 | 72.73 |
| 2   | 67.67 | 72.89 | 42.70 | 69.98 | 49.81 | 64.58 | 73.18 |
| 3   | 58.28 | 40.67 | 78.43 | 58.47 | 58.22 | 72.15 |
| 4   | 68.98 | 52.15 | 74.88 | 58.75 | 63.84 | 73.08 |
| 5   | 62.14 | 45.48 | 76.74 | 59.43 | 58.22 | 72.15 |
| 6   | 50.94 | 58.83 | 65.93 | 56.99 | 64.23 | 73.08 |
| 7   | 54.41 | 40.67 | 78.43 | 58.47 | 58.22 | 72.15 |
| 8   | 53.20 | 40.67 | 78.43 | 58.47 | 58.22 | 72.15 |
| 9   | 59.52 | 62.79 | 44.66 | 63.76 | 64.23 | 73.08 |
| 10  | 68.24 | 45.21 | 71.47 | 50.58 | 49.08 | 60.36 |
| 191 | 62.61 | 44.02 | 68.87 | 41.99 | 48.60 | 59.97 |
| 192 | 66.41 | 72.31 | 48.14 | 56.65 | 71.47 |
| 193 | 63.54 | 44.73 | 43.73 | 75.07 | 56.84 | 73.06 |
| 194 | 52.35 | 59.66 | 41.90 | 60.97 | 72.47 |
| 195 | 65.16 | 68.45 | 43.35 | 59.50 | 72.51 |
| 196 | 51.86 | 79.82 | 48.45 | 72.39 | 58.14 | 71.57 |
| 197 | 62.38 | 64.79 | 55.12 | 50.73 | 60.12 | 72.21 |
| 198 | 67.91 | 49.84 | 51.41 | 57.01 | 59.38 | 72.71 |
| 199 | 54.75 | 61.57 | 46.28 | 58.57 | 63.93 | 73.35 |
| 200 | 54.01 | 60.63 | 64.73 | 51.03 | 52.71 | 59.54 | 72.46 |

3.2 Artificial neural network

Artificial neural network imitates the transmission of human’s neuron. It can build strong nonlinear relationship between the outputs and inputs using activation functions. The common activation functions are sigmoid function and tanh function. As shown in figure 6, the neural network consists of input layer, hidden layer and output layer. Activation function is used between the hidden layer and input layer, while linear function is used between the output layer and hidden layer. The number of coefficients in the artificial neural network is determined by the number of design variables of input layer and neurons of hidden layer. According to the structure of neural network, the mathematical function of artificial neural network is written as equation (1), activation function tanh is described as equation (2) and the linear function is names as equation (3).

$$y = g \left( \sum_{j=1}^{m} w_j^2 \times f \left( \sum_{i=1}^{n} w_i^j x_i + b_j \right) \right) + b^2$$  \hspace{1cm} (1)

$$f(x) = \frac{1}{2} \left( 1 + e^{-2x} \right) - 1$$  \hspace{1cm} (2)

$$g(x) = ax + b$$  \hspace{1cm} (3)

where $w$ is weight coefficient, $b$ is threshold. Superscript 1 represents the coefficients from the first layer to the second layer, superscript 2 represents the coefficients from the hidden layer to the output layer.

According to the equation (1), to construct accurate nonlinear function, the number of impellers is more than $(m+2) \times n + 1$. Considering 70% of the data used for construction of function and the other data for validation, the number of neurons is set as 5, 7, 9 and 11 and the accuracy of the artificial neural network with different number of neurons are compared.
3.3 Particle swarm optimization

Particle swarm optimization is one of the swarm intelligence algorithms and it origins from the process of birds searching food using acoustics of echolocation. Recently, particle swarm optimization is becoming a popular optimization tool to solve problems in engineering fields due to the easy and comprehensible mathematical structure. The mathematical functions of the movement of birds are defined as followed:

\[ v_{i,t+1} = v_{i,t} + c_1 \times \text{rand}_{i,t} \times (pbest_i - x_{i,t}) + c_2 \times \text{rand}_{2,t} \times (gbest - x_{i,t}) \]  
\[ x_{i,t+1} = x_{i,t} + v_{i,t+1} \]

where \( v \) is the velocity, \( x \) is the position, \( c_1 \) is the local velocity coefficient of learning from the personal best position pbest, \( c_2 \) is the social velocity coefficient of learning from the global best position gbest, \( \text{rand} \) is a random number within \([0,1]\).

4 Results and discussions

4.1 Validation of numerical results

The performance curve of the centrifugal pump is measured in a closed test rig at National Research Center of Pumps, Jiangsu University (figure 7). The flow rate is measured by LWGY-65 turbine flowmeter with accuracy of 0.2%. The inlet and outlet pressure is tested using static pressure sensor produced by WIKA and both of the accuracy are 0.25%. The torque is acquired with SGDN-50 torque sensor with a high accuracy of 0.05%. The performance data is collected with LabView from NI USB-6343 data acquisition card. According to the 10 times of repeated measurement of performance at design point, the total uncertainty is \( \pm 0.56\% \), the comparison of numerical performance data with the experimental one is shown in figure 8. The tendency of performance curve from steady simulation can achieve a great agreement with the experimental results. The simulated head and efficiency are 35.1m and 73.80%. The deviations of head and efficiency at design point are 6.84% and 3.7%. Therefore, the optimization on performance improvement based on numerical simulation can be reliable.
4.2 Artificial neural network optimization

The number of neurons in the hidden layer can have great influence on the prediction accuracy of artificial neural network. Figure 9 compares the R-square of 4 kinds of artificial neural network. The artificial neural network with 7 neurons in the hidden layer can obtain the highest accuracy of efficiency at design point with R-square of 0.9311, while the approximate model with 5 and 11 neurons have lowest accuracy. The low number of neuron could lead to underfitting and the high number of neuron may cause overfitting of the data. Thus, the final artificial neural network with 7 neurons are decided for the optimization on efficiency of centrifugal pump.

4.3 Global optimization on artificial neural network based on particle swarm optimization

The particle swarm optimization is applied to globally optimize the approximate function of efficiency at design point. The particle swarm optimization modified by Ardizzon et al [14] is adopted for optimization on the artificial neural network. The population size is 40 and total iterations is 1000. The particle swarm optimization can have fast speed for global search. After the iteration reaches about 40, the best efficiency predicted is 74.97% (figure 10). The combination of the design variables is 50, 61.68, 40, 80, 68.64 and 65. The comparison of impeller blade shape is shown in figure 11. The green and red represent the optimal and original impellers. The blade inlet angel becomes bigger and the impeller inlet area is larger than that of original one. The blade angle distribution at the suction side of optimal impeller changes faster than that of original one. The blade shape becomes smoother, corresponding with regular pattern of the water. Therefore, the application of particle swarm optimization can shorten the optimization process based on artificial neural network.
The optimal impeller is rebuilt using BladeGen and the numerical simulation is done with the same settings. The optimal head and efficiency are 33.6m and 73.92%, 1.5m lower and 0.12% higher than those of original pump. Meanwhile, the deviation of efficiency between simulation and prediction is 1.05%. Therefore, the optimal impeller can reach a little better pump efficiency at design point. The velocity streamline in the impeller are compared in figure 12. It can be obvious that the light flow separation occurs in the pressure side of original impeller, optimization make the blade shape become smoother, corresponding with regular pattern of the fluid.
5 Conclusions
An automatic optimization method combining the artificial neural network and particle swarm optimization based on MATLAB is proposed to improve the efficiency of a centrifugal pump at design point. The pump performance curve achieved from numerical simulation on whole computational domain has good agreement with the experimental data. The careful conclusions can be drawn as followed:

1) The number of the neurons affects the prediction accuracy of artificial neural network. The approximate model with 7 neurons can obtain the highest accuracy with R-square of 0.9311. The deviation of pump efficiency between prediction and simulation is only 1.05%.

2) The optimization method improves 0.12% of pump efficiency and the flow separation at the pressure side of impeller blade disappears in the optimal pump, reducing the hydraulic loss in the impeller.

3) The combination of artificial neural network with particle swarm optimization can effectively improve the efficiency of optimization process. The further work will be focus on the optimization of multi-point efficiencies of the centrifugal pump with multi-objective algorithms.

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Reference
[1] Bezerra M A, Santelli R E, Oliveira E P, Villar L S and Escaleira L A 2008 Response surface methodology (RSM) as a tool for optimization in analytical chemistry Talanta 5 965-77.
[2] Kleijnen J P C. Kriging metamodeling in simulation: A review. European journal of operational research, 2009, 192(3): 707-716.
[3] Murata N, Yoshizawa S, Amari S 1994 Network information criterion-determining the number of hidden units for an artificial neural network model. IEEE Transactions on Neural Networks 6 865-72.
[4] Derakhshan S, Pourmahdavi M, Abdolahnejad E, Reihani A and Ojaghi A 2013 Numerical shape optimization of a centrifugal pump impeller using artificial bee colony algorithm Computers & Fluids 81 145-51.
[5] Duan B, Luo M, Yuan C and Luo X 2015 Multi-objective hydraulic optimization and analysis in a minipump. Science bulletin 17 1517-26.
[6] Shim H S, Kim K Y, Choi Y S 2018 Three-Objective Optimization of a Centrifugal Pump to Reduce Flow Recirculation and Cavitation. Journal of Fluids Engineering. 9 091202.
[7] Suh J W, Kim J H, Choi Y S, et al 2017 A study on numerical optimization and performance verification.
of multiphase pump for offshore plant. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy* **5** 382-97.

[8] Suh J W, Kim J H, Choi Y S, Joo W G and Lee K Y 2017 Multi-Objective Optimization of the Hydrodynamic Performance of the Second Stage of a Multi-Phase Pump. *Energies* **9** 1334.

[9] Miao F, Park H S, Kim C and Ahn S 2015 Swarm intelligence based on modified PSO algorithm for the optimization of axial-flow pump impeller. *Journal of Mechanical Science and Technology* **11** 4867-76.

[10] Eberhart R C and Kennedy J 1995 Particle swarm optimization. *Proceedings of the IEEE international conference on neural networks* **4** 1942-48.

[11] Fan S K S and Zahara E 2007 A hybrid simplex search and particle swarm optimization for unconstrained optimization. *European Journal of Operational Research* **2** 527-48.

[12] Parsopoulos K E and Vrahatis M N 2002 Particle swarm optimization method for constrained optimization problems. *Intelligent Technologies–Theory and Application: New Trends in Intelligent Technologies* **1** 214-20.

[13] McKay M D, Beckman R J and Conover W J 1979 Comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* **2** 239-45.

[14] Ardizzon G, Cavazzini G and Pavesi G 2015 Adaptive acceleration coefficients for a new search diversification strategy in particle swarm optimization algorithms. *Information Sciences* **299** 337-78.