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Prediction Research on Cavitation Performance for Centrifugal Pumps

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ABSTRACT

The present situation about cavitation performance prediction of centrifugal pump is introduced. The primary methods of cavitation performance prediction for centrifugal pumps are summarized, including numerical simulation method and artificial neural network method. Based on the neutral network toolbox of MATLAB7.0, topological structures of artificial neural networks are determined and network models for predicting cavitation performance of centrifugal pumps are established by analyzing the relations between geometric parameters of centrifugal pumps and net positive suction head at designed flow rate, The BP and RBF neural networks are trained by 60 example data, which are obtained from engineering practice and normalized by using neural network toolbox function. The cavitation flow in centrifugal pumps is simulated by using the commercial CFD code FLUENT6.2. A moving reference frame technique is applied to take into account the impeller-volute interaction. The standard k-ε turbulence model, mixture multiphase model and SIMPLEC algorithm are used. Velocity inlet and pressure-outlet are set as boundary conditions. The cavitation performance curves at design condition are predicted by calculating the head under different net positive suction head. The cavitation performances of 3 pumps with the different specific speeds are predicted by using numerical simulation method and neural network method respectively. The predicted values are compared with the tested values, the results show that the predictions by two methods are satisfied, the relative declination of BP and RBF for 3 pumps are 2.87%, 2.55%, 5% and 3.71%, 3.27%, 4.62% respectively. The absolute declinations of numerical simulation method are 0.17m, 0.08m and 0.16m. The advantage and disadvantage of those two methods are compared, The numerical simulation method will take a lot of time to modeling and calculating, but the law of cavitation flow in the centrifugal pumps can be obtained, which are helpful to disclosing the mechanism of cavitation characteristic; The artificial neural networks method needs a great deal of training examples, which are necessary and important to the prediction accuracy, but the math relation between input variables and output variables can be set up by using artificial neural network method, which is useful to optimize the structure of pumps.

Key words: Centrifugal Pump, Cavitation Performance, Performance Prediction, Numerical Simulation, Artificial Neural Network

INTRODUCTION

The development of fluid machinery is confined by the cavitation all the time, the prediction of cavitation performance is one of the main direction of cavitation researches, which can reduce the relative experiment, shorten the design time, and lower the costs. At present, numerical simulation method and artificial neural network method are two primary methods for predicting the cavitation performance of centrifugal pumps [1]. With the rapid development of computer technology and CFD (Computational Fluid Dynamics), the numerical simulation researches of inner cavitation flow in centrifugal pumps are the hot direction and a lot of achievements are obtained. Franklyn [2] simulates the cavitation phenomenon in centrifugal pump and predicts the inception and development of cavitation by using CFD code FULENT6.1. Medvitz, et al [3] analyze the energy performance of centrifugal pumps under developed cavitation by using multitude phases CFD method. Artificial neural networks have recently attracted much attention based on their ability to learn complex, non-linear functions, this method had been applied to predicting the energy performance and cavitation performance of centrifugal pumps [4-6], and the predicting results are satisfied. In this paper, the cavitation performance for 3 centrifugal pumps with different specific speed are predicted by using those two methods, the using conditions and predicting accuracy of those two methods are compared detailedly.

ARTIFICIAL NEURAL NETWORK APPROACH

There are some different types of available network architectures, according to the characters of prediction, the BP (Back-Propagation) networks and RBF (Radial Basis Function) networks are selected to predicting the cavitation performance of centrifugal pumps at design condition. In this paper, BP and RBF networks are arranged in 3 layers, including input layer, hidden layer and output layer. Various neurons are arranged in different layers, In BP network, the processing function among input layer, hidden layer and output layer are function tansig and purelin, the connection weights between input layer and hidden layer, hidden layer and output layer are $IW_{1,1}$, $LW_{2,1}$. In RBF network, the processing functions are function radbas and purelin, the connection weights are W_1 and W_2.

The neurons number in input layer correspond to dependent input variables of the problem, according to the basic theory of pump cavitation [7], the flow rate at design condition and geometry parameters of impeller inlet which effect the cavitation performance of centrifugal pumps including the diameter of impeller inlet D_j, the width of blade inlet b_1, the curvature radius of shroud at impeller inlet R_1, the inclination of blade inlet $\triangle\beta$, the blade number Z are selected as the input various of artificial neural networks, so the input layer neurons number is 6. The output variables present the cavitation performance for centrifugal pumps, the net positive suction head (NPSH) is taken as the output various of neural network model, so the neurons number of output layer is 1. In BP neural network, for the best network performance, the neurons number of hidden layer must be properly determined using the trial and error procedure [8], by comparing with some values, the neurons number is arranged 16. The architecture of BP neural network is shown in Figure 1. In RBF neural network, the neurons number in hidden layer is determined by the iterative times of training network, neurons adding one after each iterating, the architecture of RBF neural network is shown in Figure 2.

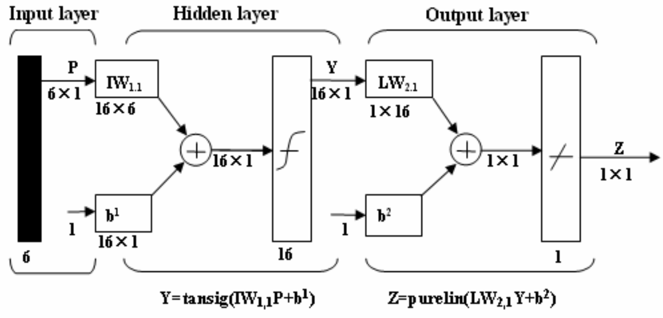


Figure 1 Architecture of BP neural network

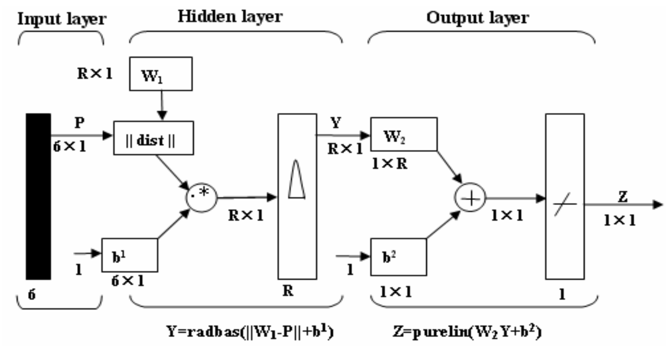


Figure 2 Architecture of RBF neural network

There are 60 sets training data are obtained which are from engineering practice, so they are exact and representative, the partial training data are shown in Table 1. If the raw data are directly applied to the networks， higher valued input variables may tend to suppress the influence of smaller ones. That is to say that the changes in the input value will produce a very small change or no changes in the output value, this affects the network training to a great extent. So the data should be normalized before being presented the neural network such that neural network will give equal priority to all the inputs. Data normalization compresses the range of training data between -1 and 1, the input and output data are normalized by using the neural network toolbox function premnmx and postmnmx, the usage of those functions can refer to reference [9].

Table 1 Partial experimental data for training neural network

NO.	Model type	Input variables						Output variables
		Q/（m^3/h）	Z	$\Delta\beta$/(°)	b_1/mm	R_1/mm	D_j/mm	$NPSH$/m
1	SI6602-1	36.18	5	11	27.4	18	88	2.40
2	2.5GY-2.5	32.40	5	11	21.9	14	65	2.60
3	IS50-32-125	12.50	6	9	20.1	12	48	2.20
4	IS65-50-125	25.00	6	8	24.2	16	65	3.00
5	IS80-65-125	50.00	6	7	30.3	19	76	2.85
6	6BA-8	37.2	5	10	24.8	23.5	54	2.38
7	8BA-12	280.00	6	7	32.3	35	160	4.40
8	IS100-65-200	100.00	6	8	39.1	23	100	3.28

NO.	Model type	Input variables						Output variables
		Q/（m^3/h）	Z	$\Delta\beta$/(°)	b_1 /mm	R_1 /mm	D_j/mm	$NPSH$/m
9	IS125-100-400	200.00	5	9	53.4	31	125	2.70
10	IS200-150-315	400.00	7	7	71.1	47	190	2.80

BP network is established by using neural network toolbox function NEWFF, training function is Trainlm, which updates weights and bias values using a back-propagation algorithm based on Levenberg-marguardt algorithm. Levenberg-Marguardt algorithm contains positive attributes of Gauss-Newton method and gradient descent algorithm [10]. It uses gradient descent to improve on an initial guess for the weights and transforms to the Gauss-Newton method as it approaches the minimum value of the cost function. The training parameters are set as follow: the steps number of iteration are 300, learning efficiency is 0.04 and the target error is 10^{-3}, the performance of network reached requirement after 22 steps, and the curve of model error for BP neural network is shown in Figure 3.

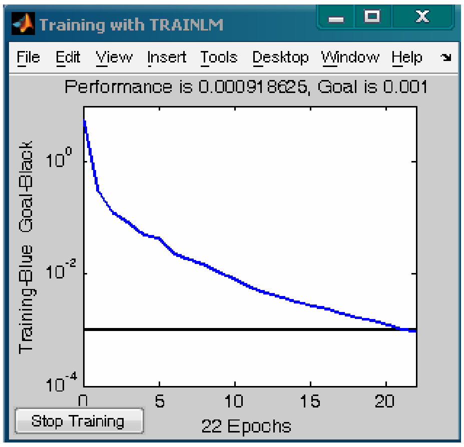


Figure 3 Curve of model error for BP network

In MATLAB, neural network toolbox function NEWRB is used for implementing the RBF neural network. NEWRB sets up neural network using iterative method; the numbers of neuron in hidden layer is zero at first, than adding one after once iteration. During the iteration, network simulates and finds out input sample vector which are corresponding with the maximize output errors, than radial basis adding one neuron and the weights are set as the input vector, at last, arriving the minimize error by amending the weight of linearity layer. The training parameters are set as follow: the target error is 10^{-3}, the expansion constant is 0.75, the maximize neurons are 100 and the indication frequency of iterative process is 1. After 57 steps, the network reaches performance requirement, and the curve of model error for BP neural network is shown in Figure 4.

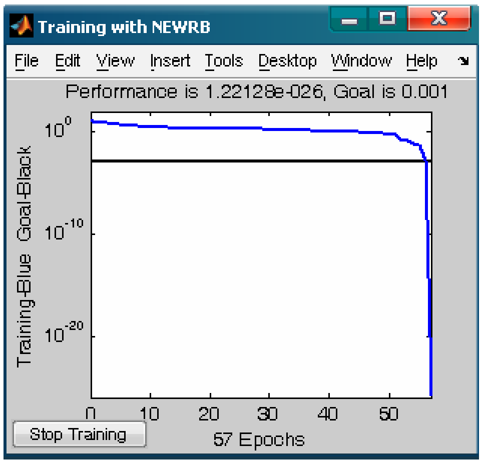


Figure 4 Curve of model error of RBF network

The cavitation performances of 3 pumps are predicted by using the toolbox function SIM on the best-trained network, the input variables of the 3 pumps are not the training data. The predicting values are compared with the real values; results are shown in the Table 2.

Table 2 Comparison between experimental data and prediction value

NO.	Model type	n_s	Input variables						Real values	BP prediction values	RBF prediction values
			Q/(m^3/h)	Z	$\Delta\beta$/°	b_1 /mm	R_1 /mm	D_j/mm	$NPSH$/m	$NPSH$/m	$NPSH$/m
1	50B54	45.95	24.75	5	10	21.3	20	50	3.5	3.4	3.37
2	8B-12	86.44	46.15	5	7	49.2	25	116	2.75	2.68	2.84
3	8B-18	129.80	43.20	6	4	67.8	28	160	2.6	2.47	2.72

From the table 2, it can be obtained that the relative declination of BP network and RBF network for 3 pumps are 2.87%, 2.55%, 5% and 3.71%, 3.27%, 4.62% respectively. The prediction accuracy of BP network and RBF network are satisfied. So the predicting method based on artificial neural network is available, which can provide reference for the engineering practice. But the predicting accuracy of neural network is dependent on the quantity and quality of training samples. The more samples you obtained, the more predicting accuracy you will get. In this paper, there are only 60 set data for training network, with the increasing of quantity and quality of training samples, the better predicting results will be obtained.

NUMERICAL SIMULATION APPROACH

The 3-D models of calculation zone of the impellers, volutes and suctions are produced by professional software Pro/E, GAMBIT, the preprocessor of FLUENT, is used to generate the grid of these models and grid quality is checked. Science the geometry of the pump is very complex, tetrahedron mesh is used for the generation and “EquiAngle Skew” and “EquiSize Skew” of the grid are all less than 0.85, so the grid quality is good. The cavitation flow is simulated by using CFD code FLUENT6.2, a moving reference frame technique is applied to take into account the impeller-volute interaction. The standard k-ε turbulence model, mixture multiphase model and SIMPLEC algorithm are chosen in FLUENT, convergence precision of residuals is 10^{-5}. Velocity inlet and pressure-outlet are set as boundary conditions, the cavitation condition of centrifugal pumps is adjusted by changing the output pressure. Wall boundary condition: no slip condition is enforced on wall surface and standard wall functions are applied to adjacent region. In order to improve the rapidity of convergence and stability of calculation, the calculation results of single phase and steady flow are initialed for cavitation flow.

The head and net positive suction head of centrifugal pump can be obtained by the following equations:

$$H = \frac{P_{out} - P_{in}}{\rho g}, \quad NPSH = \frac{P_{in} - P_{v}}{\rho g}$$

Where p_{out} is the out total pressure, p_{in} is the inlet pressure, p_{v} is the vapor pressure, ρ is density of the fluid, and g is the acceleration due to gravity.

The predicting curve of cavitation performance is obtained by calculating the head and net positive suction head of centrifugal pump under different output pressure. The necessary cavitation margin is the net positive head when the head decrease 3%, according to the specification of America hydraulic standard association.

The cavitation performance of 3 pumps is predicted by using numerical simulation method, the relative parameters of those pump are shown in Table 3, and the cavitation performance of those pumps have been predicted by using neural network methods.

Table 3 The relative parameters of model pumps

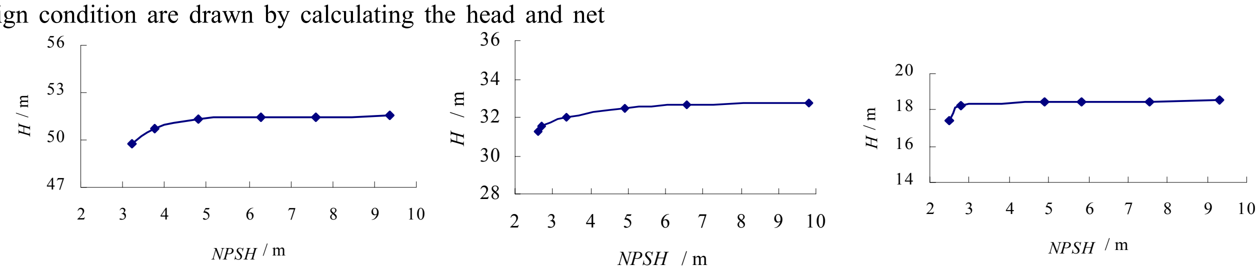
No.	n_s	Q /(m^3/h)	H /m	$NPSH$ /m	Z	$\Delta\beta$ /°	b_1 /mm	R_1 /mm	D_j /mm	D_2 /mm	b_2 /mm	D_3 /mm	b_3 /mm
1	45.95	24.75	51.06	3.5	5	10	21.3	20	50	209	4	214	12
2	86.44	46.15	33.31	2.75	5	7	24.3	12	71	168	10	180	23
3	129.80	43.20	18.45	2.6	6	4	25.7	9	73	132	12	140	24

The 3D entity diagrams of calculation zone for 3 pumps are shown in Figure.5.

pump 1 pump2 pump3

Figure 5 3D entity diagram of calculation zone

According to CFD cavitation performance predicting model, the cavitation performance predicting curves of 3 pumps at design condition are drawn by calculating the head and net positive suction head of pumps under different output pressure, which are shown in Figure 6.



pump1 pump2 pump3

Figure 6 Cavitation performance prediction curve on design condition

From Figure 6, it can be known that the change regular of head is keeping constant at first and than descending with the decrease of *NPSH,* the alter tendency of cavitation performance curve is from gradual falling to steep dropping with the increasing of specific speed. This is accordance with the practical situation. The necessary cavitation margins of 3 pumps are 3.33m, 2.83m, 2.76m, which are obtained by using interpolation method basing on Figure 6. The absolute declinations are 0.17m, 0.08m and 0.16m respectively. The predicting results are available.

The distribution condition of bubble under cavitation occurrence can be obtained by using CFD method to predicting cavitation performance of centrifugal pumps at design condition. In this paper, the numerical simulation results of model pump 2 will be given. In Figure 7, the volume distribution of bubble on middle section of impeller under different *NPSH* are shown, the symbol Φ represents volume fraction of bubble. When Φ=0, there is no air phase in volume, when Φ=1, the volume is filled of air phase.

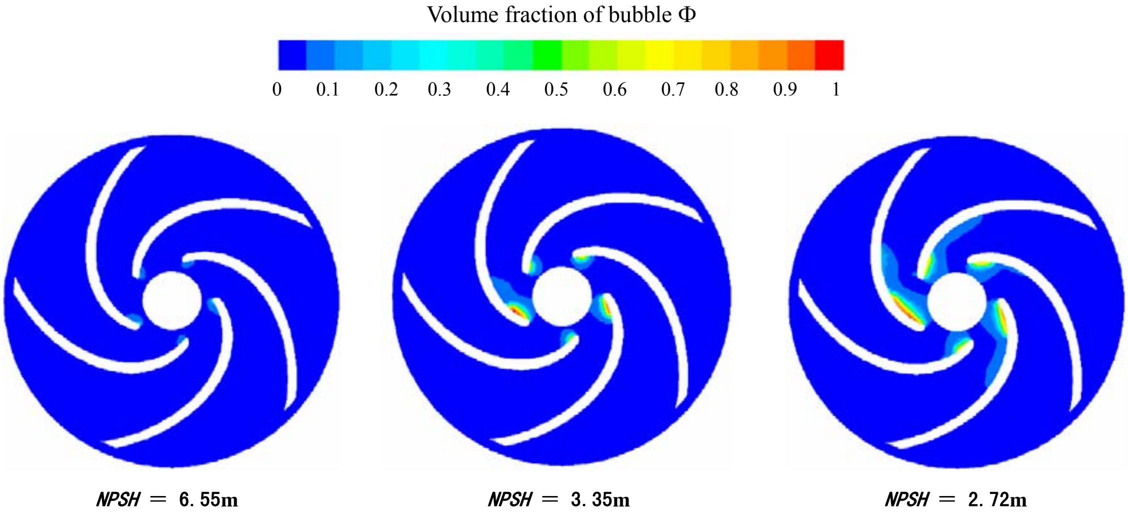


Fig.7 Volume distribution on middle section of impellers under different *NPSH*

From Figure 7, it can be seen clearly that the volume fraction of bubble on middle section of impeller channel increases and extends along the streamline direction on suction side of blades. The channels of impeller are clogged seriously when *NPSH*=2.72m, which causes head of pumps decreases. In addition, the volume distributions of bubbles in different channels is varied, which may be arised from the asymmetry of interior flied of pump because of coupling between impeller and casing[11].

CONCLUSION

In this paper, the cavitation performance of 3 pumps with different specific speed are predicted by using neural network methods and numerical simulation method respectively, and the predicting results approach real value extremely, which can provide reference for engineering practice. But there are limitations for those two methods. The numerical simulation method will take a lot of time to modeling and calculating, but the regularity of cavitation flow in the centrifugal pumps can be obtained, which are helpful to disclosing the mechanism of cavitation characteristic; The artificial neural networks method needs a great deal of training data, which are important to the prediction accuracy, but the math relation between input variables and output variables can be set up by using artificial neural network method, which is useful to optimize the structure design of pumps. So in order to obtain the accurate predicting results, the two methods should be selected according to physical circumstance.

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NOMENCLATURE

g	Gravitational acceleration
H	Head
N	Rotation speed
n_s	Specific speed3.65$n(Q)^{0.5}/H^{0.75}$(r/min, m^3/s, m)
Q	Flow rate
Z	Blade number
b_1	blade inlet width
b_2	Blade outlet width
b_3	Volute inlet width
D_j	Impeller inlet diameter
D_2	Impeller outlet diameter
D_3	Volute inlet diameter
R_1	Curvature radius of shroud at impeller inlet

Greek symbols

$\Delta\beta$	Blade inlet inclination
ρ	Fluid density

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