HHT Fuzzy Wavelet Neural Network to Identify Incipient Cavitations in Cooling pump of Engine

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***Abstract*—Incipient cavitations identification is very practical and academic significance for cavity research in cooling pump of engine but it is very complicated. In this paper, a Hilbert-Huang transform(HHT) fuzzy wavelet neural network (FWNN) is proposed for incipient cavitations identification. The main incipient cavitations feature was extracted from entrance pressure fluctuation by the HHT. This FWNN uses wavelet basis function as membership function which shape can be adjusted on line so that the networks have better learning and adaptive ability and at the same time combine the wavelet neural network with fuzzy logical theory to deal with complicated nonlinear, uncertain and fuzzy problem. At last the experiment showed that this identification model can provide fast and reliable incipient cavitations identification with minimum assumptions and minimum requirements for modeling skills.**

***Index Terms*—incipient cavitations identification; Hilbert-Huang transform; fuzzy wavelet neural network; wavelet basis function**

I. Introduction

The water pump is an important part in cooling system of engine, which performances directly impacts on the engine dynamic, economic and durability. The cavitations in water pump are the key reason to result in performance decline, which can be controlled effectively by identifying incipient cavitations. Conventionally, the incipient cavitations were confirmed by measuring pump external performance. At the beginning of cavitations the pump head changes little and the incipient cavitations are unlikely to be diagnosed in time. But when the pump head change distinctly, the cavitations have been very serious. So it is very important to identify incipient cavitations accurately, effectively and in time for engineering practice. Perovic, S, Unsworth, P.J used spectral analysis of their phase current waveform to diagnose Cavitations in Cooling pump of engine [1]. Liu yajun and Hao Dian identified incipient cavitations by analyzing wavelet package theory [2]. But the spectral analysis can't preciously tell the incipient cavitations. The wavelet analysis deal with sample signals as random ones supposing their frequency uniformly distribute in [1]whole band. So they have localization. In this paper, the Hilbert-Huang transform(HHT) is proposed to extract main signal feature from the entrance pressure fluctuation and then combine with the fuzzy wavelet neural network to optimize global parameters and can preciously confirm the incipient cavitations. HHT can dispose nonlinear signal to a series of intrinsic component features which can more reflect signal intrinsic character and the result has more generality [3]. The cavitations occur possibly due to pool running instance or external fuzzy circumstance such as engine and radiator vibration. Fuzzy technology is an effective tool for dealing with complex nonlinear processes that are characterized with ill-defined and uncertain factors. Fuzzy controllers are often used in achieving a desired performance, the rule base of which is created on the base of the knowledge of human experts. However, for some complicated processes, this knowledge may not be sufficient. The FWNN can use their advantage adequately and combined the wavelet neural network with fuzzy logical theory to dispose the complex, uncertain and fuzzy problems. This model was tested that can more accurately and effectively to identify incipient cavitations in water pump than other model such as WNN and BP.

II. Hilbert-Huang Transform

A. Hilbert-Huang Transform Principle

In 1998, Norden E. Huang, who worked in NASA Goddard space flight center, proposed Hilbert-Huang transform(HHT)to process those signals with nonlinear and non-stationary characteristics [4]. The HHT is composed of empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA). The goal of the EMD is to extract a series of IMF from the underlying signal. EMD adopts feature scale parameters based on extremes point [5]. The basic variable described by EMD is instantaneous frequency (IF). The IMF is a function that satisfies two conditions [6]:

1) The number of extrema and zero-crossings of the function must be equal or differ by no more than one. That is that the number of extrema equaled the number of zero points in local group with the symmetry

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characteristics of the upper envelope line and the lower envelope line.

2) The mean at any point of the envelope defined by the local maxima and local minima is zero.

When we have decomposed the signal into a series of IMF, Hilbert transform can be carried out on each IMF to get a series of instantaneous frequency and amplitude

$$z(t) = s(t) + jH(s(t)) = A(t)\exp(j\phi(t)) \quad (1)$$

Where amplitude function:

$$A(t) = \sqrt{s^2(t) + H^2(s(t))} \quad (2)$$

And angle function:

$$\phi(t) = \arctan\frac{H(s(t))}{s(t)} \quad (3)$$

Instantaneous frequency function:

$$f(t) = \frac{1}{2\pi}\frac{d\phi(t)}{dt} \quad (4)$$

In fact, any signal maybe not satisfies these conditions because of its complexity in the process of pump running. Yet, Norden E. Huang supposed that any signal was composed by some different intrinsic modes, which might be linear or nonlinear [8].At any time, a signal might include many intrinsic modes. If these modes overlapped with each other, they might format compound signals. Hence, any signal may be decomposed into infinite IMFs, which could be achieved by the method bellowed.

(1) For any signal $s(t)$, firstly determine all extreme points of $s(t)$ in local group, and then connect these maximal points to format upper envelope line by cubic spline lines. Meanwhile, connect those minimal points to format lower envelope line by cubic spline lines. These two lines envelope all data of the signal.

(2) The mean value of the two envelope lines is denoted by $m_1(t)$, the difference $h_1(t)$ of $s(t)$ and $m_1(t)$ can be written as:

$$s(t) - m(t) = h_1(t) \quad (5)$$

(3) Judge whether $h_1(t)$ is IMF. If $h_1(t)$ satisfies the IMF's condition, let $c_1(t) = h_1(t)$. If $h_1(t)$ doesn't satisfy the IMF's condition, $h_1(t)$ as the original data, the mean value is denoted by $m_{11}(t)$, then calculate

$$\begin{cases} h_{11}(t) = s(t) - m_{11}(t) \\ \cdots \\ h_{1k}(t) = s(t) - m_{1k}(t) \end{cases} \quad (6)$$

Repeat step (1) and (2) until $h_1(t)$ satisfies the IMF's condition. Now, let $c_1(t) = h_{1k}(t)$ as the first IMF which denotes high-frequency component of $s(t)$.

(4) Extract $c_1(t)$ from $s(t)$, then achieve signal $r_1(t)$ without high-frequency component.

$$r_1(t) = s(t) - c_1(t) \quad (7)$$

As the original data, $r_1(t)$ is processed according to the steps (1), (2) and (3) to achieve the second IMF, denoted by $c_2(t)$. Repetitions of procession, n IMF are achieved.

$$\begin{cases} r_1(t) - c_2(t) = r_2(t) \\ \cdots \\ r_{n-1}(t) - c_n(t) = r_n(t) \end{cases} \quad (8)$$

When $c_n(t)$ or $r_n(t)$ satisfies termination condition that $r_n(t)$ becomes a monotonic function, repetition is terminated. From equations (2) and (3), we may have

$$s(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (9)$$

Here, $r_n(t)$ is the residual function that denotes the trend of signal. Yet, each IMF $c_1(t)$, $c_2(t)$, …, $c_n(t)$ denotes different frequency band component from high to low respectively. EMD could decompose the signal into waveform and trend as different scales, and then a series of IMFs with different feature scale are achieved. Each IMF focuses on local characteristic of the signal. Then, features extraction could be more accurate and effective.

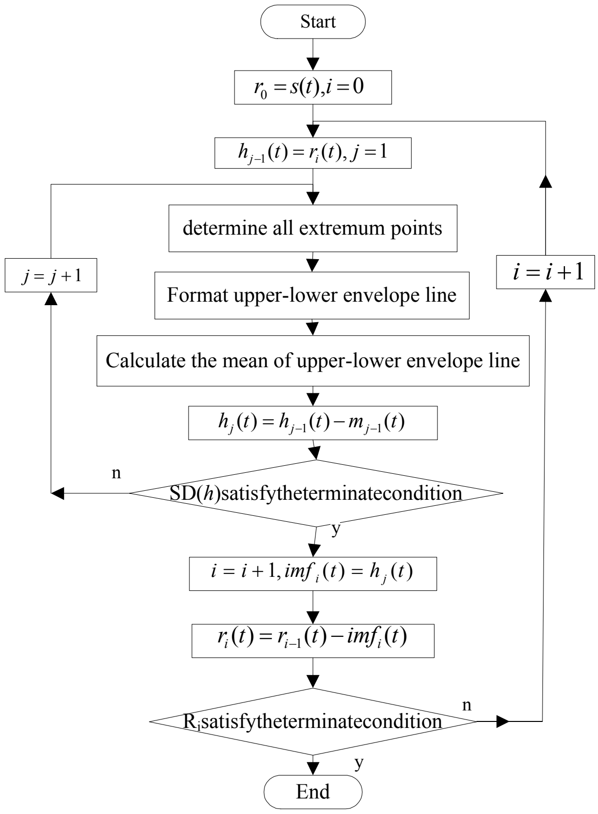


Fig.1 EMD flow chat

B. Extracting Feature Energy from Pressure Signal

When the gas-liquid two-phase flow regime transforms, the differential pressure fluctuation signal can put up different feature. The EMD method can placidly linearize unsteady and nonlinear data and preserve data feature. After decomposed, each component of the pressure fluctuation signal respectively represents a group of steady signals with feature scale. The energy variety of every frequency band represents different feature, the fore eight energy features scale with main information and the remnant function were elected as network feature vectors to identify cavitations. The steps of energy extraction based on EMD were followed as:

(1)Decompose original sample signal of the differential pressure fluctuation and selecting the fore 8 components with main feature scale.

(2)Resolve total energy of each components

$$E_i = \int_{-\infty}^{+\infty} \left|c_i(t)\right|^2 dt \quad (I=1,2,\ldots,8,\mathrm{r}) \tag{10}$$

Where $c_i(t)$ is EMD component

(3)Construct a feature vector with energy as element.

$$T = [E_1, E_2, ..., E_7, E_8, E_r] \tag{11}$$

Because of the bigger energy value, normalize T for subsequent data analysis and disposal. Set:

$$E = (\sum_{i=1}^{8} \left|E_i\right|^2 + E_r)^{1/2} \tag{12}$$

Follow:

$$T' = [E_1 / E, E_2 / E, ..., E_8 / E, E_r / E,] \tag{13}$$

Where the Vector T' is the normalized vector. According to the method above, the normalized data fall in the range [0, 1].

III. IDENTIFICATION WFNN

The neural network and fuzzy theory are two effective identification methods. The fuzzy wavelet neural network (FWNN) integrates the advantages of both fuzzy technique and wavelet neural network and can denote qualitative knowledge. It is capable of self-learning and processing quantificational data. It excels over the normal neural network at learning time, training steps and precision [6].Wavelet transform has the ability to analyze nonstationary signals to discover their local details. Fuzzy logic can reduce the complexity of the data and deal with uncertainty. Their combination can develop a system with fast learning capability that can describe nonlinear systems characterized with uncertainties. Fuzzy neural network can approach any nonlinear system, but its member function is a Gaussian function. Parameter is not easily to adjust. The FWNN with Gaussian function replaced by wavelet function has favorable scale transform and dilation-translation characters. It can learn on smooth function at large scale and on local fantastic function at small scale. The parameters can be easily adjusted.

A. FWNN constructing

FWNN put the basic factors: membership function, fuzzy logical rules, fuzzy mapping and reversal fuzzy mapping and hidden fuzzy rules into relative structure and make it possess learning capability for membership function and fuzzy logical rules. FWNN integrates wavelet and neural network fuzzy model. The kernel of the fuzzy system is the fuzzy knowledge base that consists of the input–output data points of the system interpreted into linguistic fuzzy rules. The consequent parts of fuzzy IF–THEN rules are represented by either a constant or a function. These fuzzy networks do not provide full mapping capabilities, and, in the case of modeling of complex nonlinear processes, may require a high number of rules in order to achieve the desired accuracy. Increasing the number of the rules leads to an increase in the number of neurons in the hidden layer of the network. The use of wavelet (rather than linear) functions are proposed to improve the computational power of the neuron-fuzzy system. The basic configuration of the FWNN system includes a fuzzy rule base, which consists of a collection of fuzzy IF-THEN rules in the following form:

R^l : IF x_1 is F_1^l and ... and x_m is F_m^l THEN y_1 is G_1^l and ... and y_n is G_n^l

where Rl are the lth rule ($1 \le l \le s$), $\{xi\}i=1\ldots m$ the input variables, $\{yj\}j=1\ldots n$ the output variables, $F_i^{\,l}$ are the labels of the fuzzy sets characterized by the membership functions(MF) $\mu_{F_i^l}(x_i)$, $G_1^{\,l}$ are the labels of the fuzzy subsets in the output space.

The structure of FWNN proposed in this paper for identification. It includes four layers structure with an input layer, wavelet layer (membership layer), fuzzy inference and non-fuzzy layer. A schematic diagram of the four-layered FWNN is shown in Fig.2.

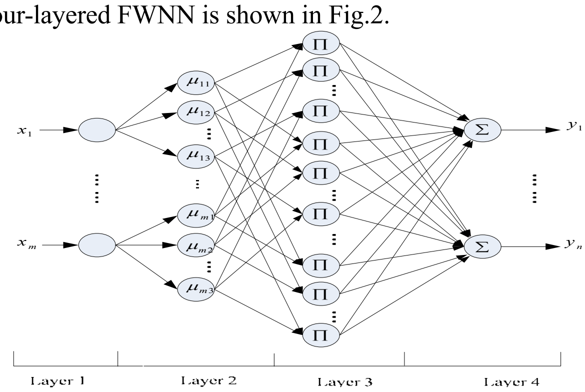


Fig.2. FWNN topology structure for cavitations identification

The first Layer (input layer): In this layer, the number of nodes is equal to the number of input feature energy. These nodes are used for signals feature. For every node i, the net input and the net output are related by

$$I_i^{(1)} = x_i$$

$$O_i^{(1)} = I_i^{(1)} \qquad i = 1,2,..., m, \tag{14}$$

where $I_i^{(1)}$ and $O_i^{(1)}$ denote ith input node and ith output node, respectively.

The second layer (membership layer): In this layer, the input vector is described as fuzzy member and the output is the corresponding membership degree. The wavelet basis function is adopted as the membership function. For every input vector, three linguistic fuzzy variable are adopted as no, just and over. The member relation of Input vector x_i and the corresponding linguistic fuzzy variable is written as:

$$\mu(x_i)=\psi_{a_{ij},b_{ij}}(x_i)=\psi\left(\frac{x_i-b_{ij}}{a_{ij}}\right)=\cos(0.25\bullet\frac{x_i-b_{ij}}{a_{ij}})\bullet\exp\left[-\frac{(x_i-b_{ij})^2}{2a_{ij}^2}\right] \tag{15}$$

where i=1,2,…,m; j=1,2,…,r, r(r=5) represents the number of linguistic values for each input, a_{ij} and b_{ij} are dilation parameter and translation parameter correspondingly.

The relation between the input and output is represented as

$$I_{ij}^{(2)}=O_i^{(1)}$$

$$O_{ij}^{(2)}=\mu_{ij}(I_{ij}^{(2)})=\cos(0.25\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}})\bullet\exp\left[-\frac{(O_i^{(1)}-b_{ij})^2}{2a_{ij}^2}\right] \tag{16}$$

where i=1,2,…,m; j=1,2,…,r.

The third layer (rule layer): this fuzzy inference layer completes fuzzy operation with fuzzy logical rules. The number of nodes corresponds to the number of rules .Each node represents one fuzzy rule. Here, to calculate the values of the output signals of the layer AND (min) operation is used. The normal AND (min) operation includes intersection calculation and algebraic calculation.

If intersection is used [11-14], we have

$$O_i^{(3)}=\min(O_{1i_1}^{(2)},O_{2i_2}^{(2)},\ldots,O_{mi_m}^{(2)}) \tag{17}$$

On the other hand, if algebraic operation is used, we have

$$O_i^{(3)}=O_{1i_1}^{(2)}O_{2i_2}^{(2)}\ldots O_{mi_m}^{(2)} \tag{18}$$

Each node in this layer is denoted by $\prod$, the relation between the input and output is represented as

$$I_i^{(3)}=O_{1i_1}^{(2)}*O_{2i_2}^{(2)}*\ldots*O_{mi_m}^{(2)}=\min\{O_{1i_1}^{(2)},O_{2i_2}^{(2)},\ldots,O_{mi_m}^{(2)}\} \tag{19}$$

The net output is written as

$$O_i^{(3)}=I_i^{(3)} \tag{20}$$

where i=1,2,…,s, $s=\prod_{i=1}^{m}r^m=\prod_{i=1}^{m}5^m$

The fourth layer (non-fuzzy layer): this layer is to cancel the fuzzy factors of output. Nodes in this layer represent the output variables of the system.

$$I_i^{(4)}=\sum_{j=1}^{S}W_{ij}O_j^{(3)} \tag{21}$$

The net output is written as

$$Y_i=O_i^{(4)}=I_i^{(4)}$$

$$i=1,2,\ldots,n \qquad j=1,2,\ldots,s \tag{22}$$

where w_{ij} are the connection weights, Y_i represents the ith output to the node of layer 4.

B. Training Algorithm for FWNN

In this study, a gradient-descent (GD) learning algorithm with adaptive learning rate is adopted. The latter guarantees the convergence and speeds up the learning of the network. In addition, a momentum is used to speed-up the learning process. The parameter to be trained are the parameters of wavelets (a_{ij}, b_{ij}, w_{ij}, i = 1, . . . , n, j = 1, . . . , m) in the consequent part. The initial values are generated randomly.

Here, the gradient descent learning algorithm with adaptive learning rate is introduced. The learning error function can be written as

$$E=\frac{1}{2}(D-Y)^T(D-Y) \tag{23}$$

where D is the desired output acquired from specialists, and Y is the FWNN's current output, Y=[y_1 , y_2,…, y_n].

The weights in the output layer are trained by:

$$\Delta W_{ij}=-\frac{\partial E}{\partial W_{ij}}=-\frac{\partial E}{\partial O_i^{(4)}}\bullet\frac{\partial O_i^{(4)}}{\partial I_i^{(4)}}\bullet\frac{\partial I_i^{(4)}}{\partial W_{ij}}=(D_i-Y_i)\bullet O_j^{(3)} \tag{24}$$

The weights of the output layer are updated according to the following equation:

$$W_{ij}(t+1)=W_{ij}(t)+\eta\bullet\Delta W_{ij}=W_{ij}+\eta\bullet(D_i-Y_i)\bullet O_j^{(3)} \tag{25}$$

where i=1,2,…,n; j=1,2,…,s; η is the learning-rate parameter.

One of the important problems in learning algorithms is the convergence. The convergence of the gradient descent method depends on the selection of the initial values of the learning rate and the momentum term. Usually, these values are selected in the interval [0–1]. A large value of the learning rate may lead to non-stable learning; a small value of learning rate leads to slow learning speed. In this paper, an adaptive approach is used for updating these parameters.

For this fuzzy wavelet neural network, which is very important is to select wavelet base which is decided by actual situation. At present, many wavelet function can be supplied such as Morlet，Harr，Mexican Hat and Meyer. Morlet wavelet has been chosen to serve as an adoption basis function [10] which has been proved to be concise and applicable.

$$\psi_{a,b}(t)=\cos(0.25t_z)e^{-\frac{t_z^2}{2}} \tag{26}$$

where $t_z=(t-b)/a$

$$\psi_{a,b}'(t)=-\left(0.25\sin(0.25t_z)\exp(-\frac{t_z^2}{2})+\cos(0.25t_z)\exp(-\frac{t_z^2}{2})t_z\right) \tag{27}$$

Training the dilation factor and translation factor, and the modification of a_{ij} and b_{ij} are expressed as:

$$\Delta a_{ij}=-\frac{\partial E}{\partial a_{ij}}=-\frac{\partial E}{\partial O_l^{(4)}}\bullet\frac{\partial O_l^{(4)}}{\partial I_l^{(4)}}\bullet\frac{\partial I_l^{(4)}}{\partial O_k^{(3)}}\bullet\frac{\partial O_k^{(3)}}{\partial I_k^{(3)}}\bullet\frac{\partial I_k^{(3)}}{\partial O_{ij}^{(2)}}\bullet\frac{\partial O_{ij}^{(2)}}{\partial I_{ij}^{(2)}}\bullet\frac{\partial I_{ij}^{(2)}}{\partial a_{ij}}$$
$$=2\sum_l\left[(D_l-Y_l)\bullet\sum_{k_1,\ldots,k_{i-1},k_{i+1},\ldots,k_m}(O_{1k_1}*\ldots*O_{i-1k_{i-1}}*O_{i+1k_{i+1}}*\ldots*O_{mk_m})\bullet W_{lk}\right]\bullet\left[-\frac{(O_i^{(1)}-b_{ij})^2}{2a_{ij}^2}\right]$$
$$\bullet\exp\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}^2}\bullet\left[0.25\sin(0.25\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}})+\cos(0.25\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}})\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}}\right] \tag{28}$$

$$\Delta b_{ij}=-\frac{\partial E}{\partial b_{ij}}=-\frac{\partial E}{\partial O_l^{(4)}}\bullet\frac{\partial O_l^{(4)}}{\partial I_l^{(4)}}\bullet\frac{\partial I_l^{(4)}}{\partial O_k^{(3)}}\bullet\frac{\partial O_k^{(3)}}{\partial I_k^{(3)}}\bullet\frac{\partial I_k^{(3)}}{\partial O_{ij}^{(2)}}\bullet\frac{\partial O_{ij}^{(2)}}{\partial I_{ij}^{(2)}}\bullet\frac{\partial I_{ij}^{(2)}}{\partial b_{ij}}$$
$$=2\sum_l\left[(D_l-Y_l)\bullet\sum_{k_1,\ldots,k_{i-1},k_{i+1},\ldots,k_m}(O_{1k_1}*\ldots*O_{i-1k_{i-1}}*O_{i+1k_{i+1}}*\ldots*O_{mk_m})\bullet W_{lk}\right]$$
$$\bullet\exp\left[-\frac{(O_i^{(1)}-b_{ij})^2}{2a_{ij}^2}\right]\bullet\frac{1}{a_{ij}}\bullet\left[0.25\sin(0.25\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}})+\right.$$
$$\left.\cos(0.25\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}})\bullet\frac{O_i^{(1)}-b_{ij}}{a_{ij}}\right] \tag{29}$$

Then the wavelet node parameters are updated as follows:

$$a_{ij}(t+1) = a_{ij}(t) + \eta \Delta a_{ij} \quad (30)$$

$$b_{ij}(t+1) = b_{ij}(t) + \eta \Delta b_{ij} \quad (31)$$

where i=1,2,…,m; j=1,2,…,r; k=1,2,…,s; l=1,2,…,n; η is the learning rate. We let the learning rate η vary to improve the speed of convergence, as well as the learning performance.

IV. HT FWNN Identification System Experiment Analysis

Test system is composed of data sampling and data processing. Data sampling is hard part of the system which consists of signal measure and data sampling as Fig.3. signal measure is made up of pressure signal picker as PD-23 difference transformer from Switzerland KELER company, its capacity 0～10kPa, output 1V～5V,precision 0.5%, frequency more than 1000Hz. It has adequate precision and desirable dynamic response characters. The data sampling is composed of computer, IMP3595A data sampling card, IMP35951C data sampling transformer and data line, power supply. Sampling frequency is 1000—10000Hz. It was set as 1000Hz. IMP data sampler has an intelligent input-output top. Every IMP of system does not only contain microprocessor and logical array door, but also EPROM and RAM. So, it is capable of processing data and programming. Meanwhile, every IMP can make some data pretreatment by inner intrinsic software and delivery part data processed by main computer to data sampler in addition to complete data sampling and communication.

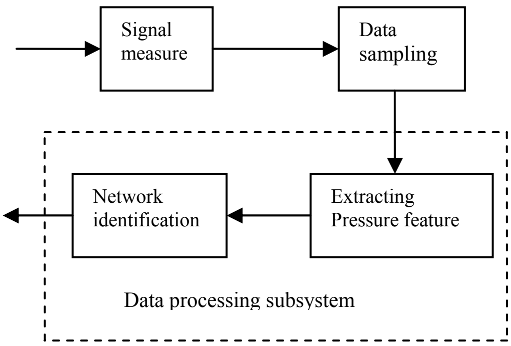
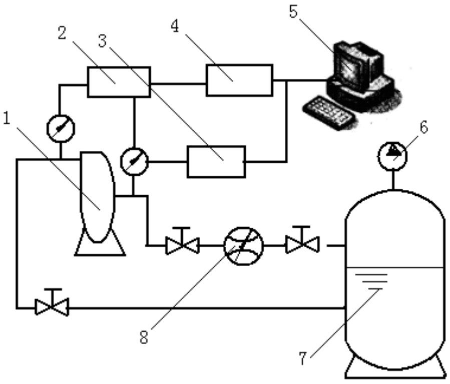


Fig.3 Cavitations identification system structure chat

A. Experiment structure

The water pump cavitations experiment structure was adopted as Fig. 4. The normal speed of pump is 3000rpm, charge Q=18m^3 / h, the number of blade z=7; The work medium is water. The entrance section introduced transparent organic glasses convenient for watching the cavitations of pump entrance. During the test processing, firstly regulated pump charge to prescriptive amount and keep it. When the pump run at normal and the pressure difference of input-output was stable, the entrance pressure at normal running (the vacuum pressure was zero) was considered as reference point and then adjust vacuum pump to change entrance pressure. Meanwhile noting the cavitations condition and external character curve, the pressure fluctuation value at entrance was picked in real-time at the pump head descended to none, 3% and 6% respectively.



1 test pump, 2 pressure transform meter, 3 data picker1, 4 data picker2, 5 computer, 6 vacuum pump 7 water tank, 8 vortex flow meter

Fig.4 The water pump cavitations experiment

B. Data disposing and feature extracting

Fig.5, Fig.6 and Fig.7 are pressure signal composing figure at the pump head descended to none, 3% and 6% respectively. From figures, EMD decomposed pressure signal to eight IMF components and a residual function. The different IMF component included different time scale which displayed signal features at different differentiating rate. The part of every layer energy values were calculated by (10) shown as table 1, the corresponding normalized values were written in table 2.

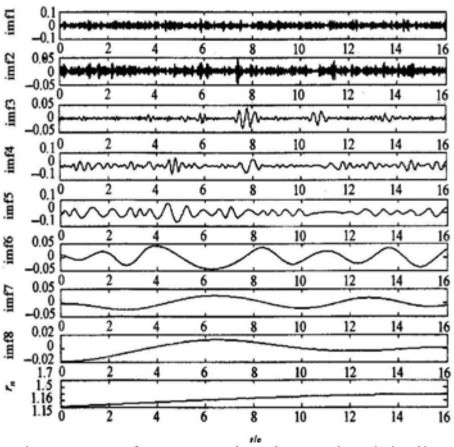


Fig.5 IMFs of pressure signal at no head decline

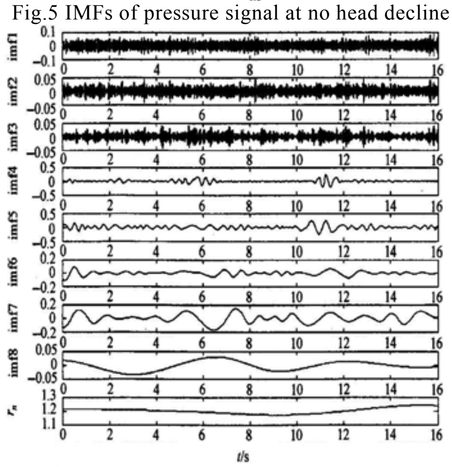


Fig.6 IMFs of pressure signal at 3% head decline

Table 1 the fore feature energy and remnant function energy value

E1	E2	E3	E4	E5	E6	E7	E8	r
1.2949	0.8108	0.3797	0.2877	0.1589	0.1234	0.0995	0.0465	2.9082
1.8368	1.8802	1.4236	1.333	0.713	0.6965	0.1567	0.0105	1.2902
1.6558	1.2289	0.9216	0.8311	0.6504	0.3765	0.4560	0.0201	2.0451
2.6989	1.8221	1.5897	1.3110	0.8394	0.5563	0.2042	0.0854	1.8946
1.1755	1.2389	1.0422	0.9609	0.6313	0.5285	0.4366	0.0665	1.9625
1.9100	1.1342	1.8600	0.6875	0.6101	0.4490	0.1032	0.0672	1.8399
1.9302	1.2564	1.0760	1.0010	0.8749	0.4548	0.4043	0.0977	2.1084
1.7989	1.1371	0.9199	0.5103	0.2406	0.1287	0.0977	0.0318	1.6692
2.187	1.1916	1.1437	0.8157	0.7220	0.2454	0.0920	0.0612	2.2227
1.6910	0.9272	0.8442	0.5307	0.2448	0.0937	0.0370	0.0027	2.1736
1.4392	1.3643	1.2802	0.9240	0.3849	0.0803	0.0891	0.0783	1.5113
1.5449	1.2164	1.2110	0.9372	0.6563	0.6265	0.5274	0.0973	1.3434
2.5723	1.9423	1.5321	0.9909	0.8269	0.7881	0.5260	0.0680	2.7540
0.9203	0.542	0.3700	0.4554	0.3454	0.3031	0.2136	0.0467	2.2241
1.6911	1.2982	1.2609	1.2145	1.1614	0.9756	0.3894	0.0323	3.2611

Table 2 the normalized values in table 1

e1	e2	e3	e4	e5	e6	e7	e8	er
0.3891	0.2436	0.1141	0.0864	0.0477	0.0370	0.0299	0.0139	0.8740
0.5018	0.5137	0.3889	0.3642	0.1948	0.1903	0.0428	0.0028	0.3525
0.5050	0.3748	0.2811	0.2535	0.1983	0.1148	0.1390	0.0061	0.6238
0.6111	0.4125	0.3599	0.2968	0.1900	0.1259	0.0462	0.0193	0.4290
0.3783	0.3988	0.3354	0.3093	0.2032	0.1701	0.1405	0.0214	0.6317
0.5330	0.3165	0.5190	0.1918	0.1702	0.1252	0.0287	0.0187	0.5134
0.5342	0.3477	0.2978	0.2770	0.2421	0.1258	0.1118	0.0270	0.5835
0.6167	0.3898	0.3153	0.1749	0.0824	0.0441	0.0334	0.0109	0.5722
0.5906	0.3218	0.3088	0.2202	0.1949	0.0662	0.0248	0.0165	0.6002
0.5483	0.3006	0.2737	0.1721	0.0793	0.0303	0.0119	0.0008	0.7049
0.4830	0.4578	0.4296	0.3101	0.1291	0.0269	0.0299	0.0262	0.5072
0.5113	0.4026	0.4008	0.3102	0.2172	0.2073	0.1745	0.0322	0.4446
0.5376	0.4059	0.3202	0.2071	0.1728	0.1647	0.1099	0.0142	0.5756
0.3557	0.2095	0.1430	0.1760	0.1335	0.1171	0.0825	0.0180	0.8598
0.3717	0.2853	0.2771	0.2669	0.2552	0.2144	0.0855	0.0070	0.7168

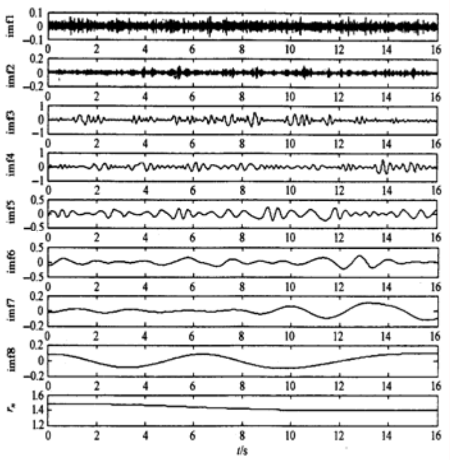


Fig.7 IMFs of pressure signal at 3% head decline

C. Membership function

According to table 2, the sets of sample in Table1 can be normalized between 0 and 1. These normalized vectors are used as input and output of fuzzy sets. Described as Section Ⅲ, the relative identifying knowledge is necessary to be expressed to fuzzy mode rules when constructing FWNN identification of cavitations system and then by which the new learning and training samples can be constructed. So, three fuzzy sets are used for fuzzy identification rules, corresponding to no cavitations, just cavitations, over cavitations (labeled as n, j, and o respectively). Morlet wavelet function is chosen as the membership functions for these three fuzzy sets. Here, the three fuzzy sets for the input and output linguistic variables of the FWNN identification system have both been designed in the same range of [0,1] (Fig. 8). $b_{i1} = 0$, $b_{i2} = 0.5$, $b_{i3} = 1$. Once the shape of the fuzzy sets is given, the relationship between input and output variables of the FWNN based identification system is defined by a set of linguistic statements that are called fuzzy rules.

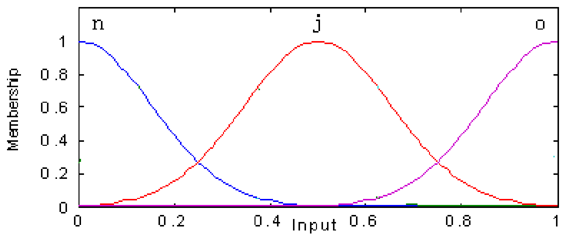


Fig.8 The wavelet based membership functions

D. Network training and determination

Network initialization initializing the wavelet network parameters is an important issue. A random initialization of all the parameters to small random values (as usually done with neural networks) is not desirable since this may make some wavelets too local (small dilations) and make the components of the gradient of the cost function very small in areas of interest.

In [14], a method was proposed for dilation and translation initialization. This work uses this method to initialize the dilation aj and translation bj. In general, one wants to take advantage of the input space domains where the wavelets are not zero. According to the wavelet theory, given the t* as the center of the time domain, $\Delta\psi$ as the radius of the mother wavelet, the time domain so can be written as:

$$\left[b + at^{*} - a\Delta\psi, b + at^{*} + a\Delta\psi\right] \tag{32}$$

In order to guarantee that the wavelets extend initially over the whole input domain, the initialization of the dilation and translation parameters must agree to the following equation:

$$\begin{cases} b_j + a_j t^{*} - a_j \Delta\psi = \sum_{i=1}^{I} w_{ji} x_{i\min} \\ b_j + a_j t^{*} + a_j \Delta\psi = \sum_{i=1}^{I} w_{ji} x_{i\max} \end{cases} \tag{33}$$

Thus

$$\begin{cases} a_j = \dfrac{\sum_{i=1}^{I} w_{ji} x_{i\max} - \sum_{i=1}^{I} w_{ji} x_{i\min}}{2\Delta\psi} \\ b_j = \dfrac{\sum_{i=1}^{I} w_{ji} x_{i\max}(\Delta\psi - t^{*}) + \sum_{i=1}^{I} w_{ji} x_{i\min}(\Delta\psi + t^{*})}{2\Delta\psi} \end{cases} \tag{34}$$

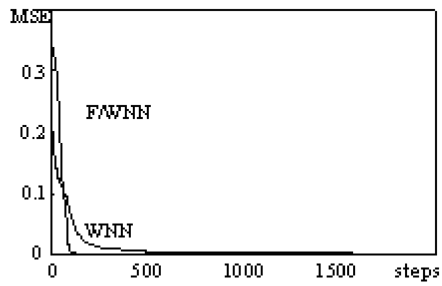
The choice of the learning rate factor η has an important effect on stability and convergence rate. If it is too small, too many steps are needed to reach an acceptable solution. On the contrary, a large learning rate may possibly lead to skip the optimal solution and cause oscillation. In the experiment, η are initialized to 0.9.

The choice of the weights is less critical: these parameters are initialized to small random values.

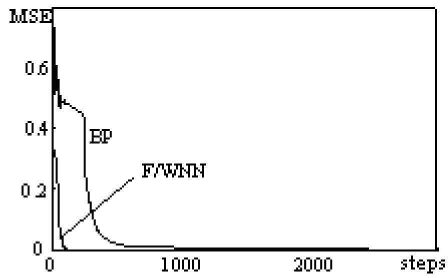
Network training and determination In the experiment, 200 groups of sample data are acquired on Fig 3. 160 groups of the data are used as the training sets, the remaining 40 groups are used as the validate sets. Expecting output error threshold is 0.001. Sample vectors are used as input and output of FWNN. After all possible normal operating modes of the identification are learned, the system enters the identification stage.

FWNN start as a network of nodes arranged in four layers--the input, membership layer, rule layer, fuzzy-cancelling layer. The input and fuzzy-cancelling and rule layers serve as nodes to buffer input and fuzzy-cancelling for the model, respectively, and the membership layer serves to provide a means for input relations to be represented in the output. Here, the network construction used for cavitations identification consists of 9 inputs corresponding to the 8 feature energy value and residual energy value that have been given (listed in table2), and one outputs corresponding to one unknown condition.

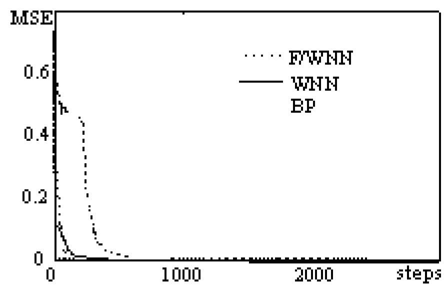
To demonstrate the performance of the FWNN-based approach on cavitations classification, comparisons are made with two types of artificial neural networks, namely wavelet neural networks and BP networks. Fig.9, demonstrate the training history and the performance of the FWNN, WNN and BP networks by using GD algorithm respectively. Table3 are the comparison results of FWNN, WNN and BP methods on identification. The second column in this table lists the identification accuracy on the 40 actual sample data. The third column in this table lists the average number of error function identification used during training, until running terminated with the network converged or the epochs exceeding the maximum epochs. Compared with the BP method, the FWNN method has more than 4.0% improvement on the identification accuracy, and compared with the WNN method, the FWNN method has 2% improvement on the identification accuracy. The test results confirm that, in all compared cases, the proposed FWNN method has a better capability for generalization than the other methods.



(a) The compare between FWNN and WNN



(b) The compare between FWNN and BP



(c) The compare among FWNN ,WNN and BP

Fig.9 Convergence curves for ANNs

Table3 Comparisons of FWNN, WNN and BP method

Method	Estimation accuracy (%)	Sum error	The number of Training steps
BP	92.0	0.001	2490
WNN	94.0	0.001	1550
FWNN	96.0	0.001	135

From the comparison of various methods, it can be seen that, the FWNN method outperformed all the other construction. The FWNN construction is decidedly superior, the errors are smaller than the WNN and BP construction. Another benefit of the FWNN approach is the reduced training time and steps of training.

V. CONCLUSION

Experiment result showed that onefold neural network was adopted to identify the cavitations in the water pump, the precision is very low and can't satisfy controlling the water pump in time and accurately. But the method introduced above that the sample signals are preprocessed by HHT firstly and then identified by FWNN can not only attain higher precision but also speed up the identification.

Based on fuzzy neural network, a FWNN model was build and used the wavelet function as subjection function according to favorable scale transform and dilate translation characters. This model can be used as incipient cavitations identifier. After simulation, it is shown that at the same condition the FWNN model structure is simple, learning algorithms effective and identifying capacity high comparing with other approaches such as WNN and BP.

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