Amirkabir Journal of Mechanical Engineering

Amirkabir J. Mech. Eng., 52(3) (2020) 181-184
DOI: 10.22060/mej.2018.13622.5686

Identification of Cavitation Phenomenon in Centrifugal Pump by Artificial Immune Network Method

S. M. Matloobi, M. Riahi*, H. Sadeghi

Mechanical Engineering Department, Iran University of Science and Technology, Tehran, Iran

ABSTRACT: Reduce the cost of unscheduled shutdown and enhance the reliability of systems, is one of the important goals for various industries that could be achieved by condition monitoring. Cavitation is a common phenomenon in centrifugal pumps which causes the damage and its true identification in early stage is too important. In this paper cavitation is identified by use of artificial immune net that is modeled on the function of the human immune system. For this purpose, after data collection by a laboratory setup and extraction of various features, feature selection and dimensions reduction were done by artificial immune method and then with artificial immune net method, the system condition was identified. Finally, the results of this study were compared with the principal component analysis method and the results of nonlinear supportive vector machine, multi-layer artificial neural network, K-means and fuzzy C-means clustering.

Review History:

Received:11/4/2017
Revised:2/20/2018
Accepted:3/11/2018
Available Online:3/13/2018

Keywords:

Condition monitoring
Cavitation
Artificial immune net
ClonalG

1- Introduction

Centrifugal pumps are one of the most important of rotary machines that widely used and are especially used in the transmission of fluids. Cavitation is one of the most undesirable phenomena in centrifugal pumps, which can cause serious damage to the components of the pump. Generally, the formation of bubbles reduces the effective cross section of fluid transfer and thus reduces the hydraulic efficiency of the pump, Also, the explosion of bubbles near the surface of the metal results in severe local stress and damage to parts of the pump, including the impeller blade by corrosion and erosion, as well as increasing the noise and vibration of the pump.

In some studies vibration signal has also been used to detect cavitation, in reference [1] analysis of vibration signal in time domain has been used, in this reference, it has been shown that the Root Mean Square (RMS) value of a signal that represents the amount of signal energy is roughly constant in normal conditions and during cavitation, but the maximum amplitude of the signal increases, therefore, the ratio of maximum amplitude to RMS or crest factor is used to detect cavitation. Also in reference [2] the extracted features of the vibration signal in the time and frequency domain are used as inputs of a multilayer neural network for this purpose.

In order to increase the accuracy and speed of condition monitoring, intelligent systems are used for decision making, these systems are trained by initial data and can accurately identify the failure occurrence in the early stages, many of these intelligent systems include algorithms inspired by nature or human body system such as ants colony, neural networks, genetic algorithms, and so on. One of this methods is the Artificial Immune System (AIS) algorithm that is inspired from the human body and used for optimization problems over the past few years, this algorithm is modeled base on human immune systems that can identify all types of germs and separate them from body cells, and the results showed that this algorithm is capable for fault detection problem. In this study, several features are extracted from vibration and motor current sensor data and data fusion at the feature level are done, finally, the artificial immune network algorithm is used to determine the status of a multi-stage centrifugal pump and cavitation detection.

*Corresponding author's email: riahi@iust.ac.ir

2- Methodology

In pumps, the cavitation refers to a dynamic process that involves the formation of bubbles within the fluid, growth and eventually bursting them, there are two type of bubbles that formed inside the liquid: vapor bubbles and air bubbles [3].

Artificial immune method is one of the machine learning algorithm that can be used in optimization and pattern recognition problems, which has been given attention for engineering problems in recent years. This algorithm is inspired by the body's immune system, and various models have been proposed for this purpose, some of these models include: negative selection algorithm, clonal selection algorithm, immune network algorithm and so on.

The immune net algorithm is based on the immune net theory, in the immune network theory (Idiotope network), which was proposed by Jerne (1974), the immune system is considered a dynamic system [4]; In this theory it is suggested that the immune system, even in the absence of a stimulus, has a dynamic behavior. An Artificial Immune Network (AIN) is a computational model that is inspired from nature; the ideas and concepts of the immune network theory, which involves the relationship between B cells (mutating and suppressing each other), duplication and mutation, are used in this model, In an artificial immune network, other than affinity to antigens there are other criteria for antibodies. The main evaluation criterion in an artificial immune network is the amount of antibody stimulation based on an antibody's affinity with antigens, affinity with other antibodies and affinity of other antibodies with it. If an antibody detects another antibody or antigen, it is stimulated; however, the detection of another antibody has negative effects on it. The amount of stimulation of an antibody is generally obtained from the following equation [20]:

$$S = N_{st} - N_{sup} + A_g \quad (1)$$

where N_{st} is the amount of antibody stimulation by the network, N_{sup} is the amount of antibody network deterrence and A_g is the amount of antibody stimulation by antigen.

Fig. 1. Experimental setup

Because of the high computational cost of this relationship, various algorithms provided for it use simplified versions of this equation.

3- Experimental Data Collection

In this study, closing the inlet valve applied to create cavitation and investigate its effects, for this purpose, a valve is placed at the outlet of the main tank, which closes it, causing the loss of inlet pressure and the creation of cavitation (Fig. 1), this is done by closing the valve in 6 steps. The first step is related to the normal conditions of the pump and the inlet valve is completely open. In two next steps, the outlet valve is closed gradually, in these steps, although flow rate (fluid velocity) is constant, but other performance parameters of the pump, such as the output head and the motor current, will be changed, particular in the third step indicates the start of the suction cavitation in pump. In the fourth step, the effects of cavitation on vibrations, motor current and pump performance parameters are clearly observed. In the next two steps, the amount of flow rate decreases and the output head drops significantly, it is indication of the development of cavitation and increase in the percentage of air in the system. At the final step, air bubbles are observed in the transparent section of the tube, indicating a complete development of the cavitation in the pump.

4- Results and Discussion

After collecting the required data with the help of different sensors, at the first it was necessary to determine initiation of cavitation phenomenon and its development steps, for this purpose pressure sensor data have been used. As mentioned in the previous section, with the initiation of cavitation, the operational parameters of the pump would be changed. In this study, a 3% drop in the pump head is considered as a sign of the cavitation and a severe drop in the output head are considered as signs of development.

In this study, 26 different features of vibration and current signals were extracted in three times, frequency and time-frequency domain and finally 3 features are selected by AIN

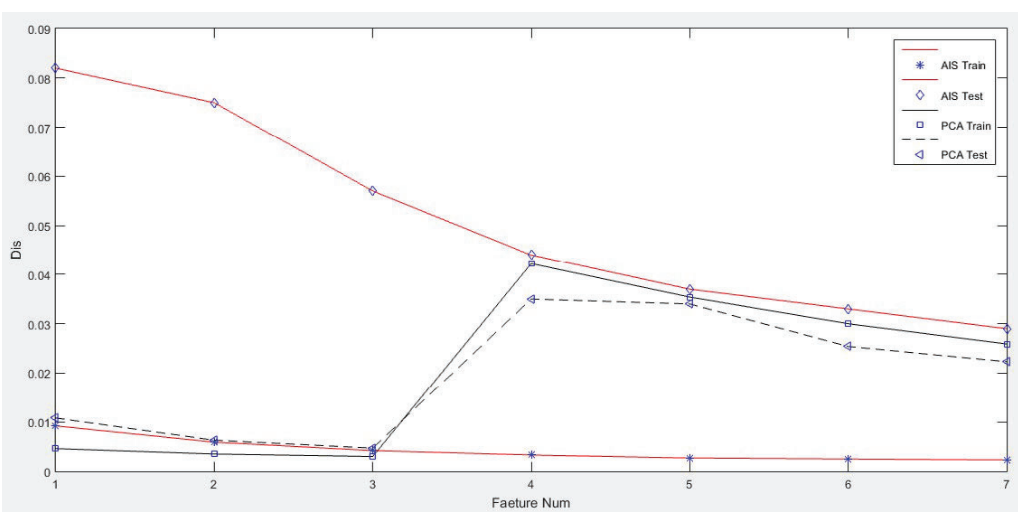

Fig. 2. The error of best combination for the different number of features obtained by the AIS and principal component analysis (PCA) method

Table 1. Results of system condition identification by different methods

Classification Method	Percentage error for detection of training data for AIS features	Percentage error for detection of training data for PCA features	Percentage error for detection of test data for AIS features	Percentage error for detection of test data for PCA features
Non- SVM Linear	3	4.33	23.33	23.33
K-means	36	46.7	48.9	63.33
Fuzzy C-Means	37	49.66	41.11	53.33
AIN	5.5	42.66	6.8	35.55
multilayer perceptron	7.35	10.66	8.47	11.86

method for fault detection.

As seen in Fig. 2, with increasing number of features up to 4, the distance significantly decreases, especially for the test section, but with a further increase in the number of features, the distance reduction is not significant.

5- Conclusions

Comparing the results of the immune network algorithm with other methods shows that the accuracy of the nonlinear supportive vector machine method for the training data is somewhat higher, but for the test data, the error rate of this method is much lower than the other methods. This is indicative of the ability of this method to identify new modes (similar to the human immune system's ability to deal with new ones), therefore, this method can be used to identify the system's condition with suitable accuracy.

References

[**1**] S. C. Li, *Cavitation of Hydraulic Machinery*. Imperial College Press, **2000**.

[**2**] M. R. Nasiri, M. J. Mahjoob, and H. Vahid-Alizadeh, "Vibration Signature Analysis for Detecting Cavitation in Centrifugal Pumps using N eural Networks," **2011**, pp. **632–635**.

[**3**] F. Bastos and F. Rachid, "Modeling gaseous and vaporous cavitation in liquidflows within the context of the thermodynamics of irreversible processes," International .Jour of Non-Linear .Mech, vol. **65**, pp: **245–252, 2014**.

[**4**] Jerne, N.K., Towards a Network Theory of the Immune System, in Annals of Immunology**1974**: Newyork-USA. p. **373-389**.