deep-learning based identification of inducer cavitation instability

|  |  |  |
| --- | --- | --- |
| Youngkuk YoonDepartment of Mechanical EngineeringSeoul National Universitytruesky1218@snu.ac.kr | Sang Hyeon LeeDepartment of Mechanical EngineeringSeoul National Universitybear11235@snu.ac.kr | Seung Jin SongDepartment of Mechanical EngineeringSeoul National Universitysjsong@snu.ac.kr |

Abstract

A deep-learning based method is introduced to detect and identify the inducer cavitation instability. To identify alternate blade cavitation, which is a common cavitation instability occurs at two-bladed inducer, raw unsteady pressure data under equal length cavitation (symmetric development of cavity, not an instability) and alternate blade cavitation are used as train data sets. These train data sets construct the neural network which can label the unknown data set as with or without cavitation instability. In the present research, after the training process of the neural network, the network provided high (over 80%) identification ratio of the alternate blade cavitation and also showed robustness against random noise.

introduction

Inducer cavitation instabilities manifest themselves as various frequency peaks located above and below the shaft frequency harmonics with certain spatial mode and propagating direction. To identify and categorize those instabilities, multi-point unsteady pressure measurement has been widely used. With at least five circumferential measurement points in general, their frequency, spatial mode (usually first or second modes are observed), and propagating direction can be fully identified. However, even though the spatial and temporal Fourier transformation provides the exact mathematical decomposition of the raw unsteady pressure signals, the classification of frequency characteristics into different instabilities are still done manually. Therefore, the criteria between different instability should be determined a priori, and visual inspection of the Fourier transformation results should be continuously accompanied. This interrupts the rapid decision procedure at real-time instability detection, and furthermore, unknown anomalies under new operating condition or machine cannot be classified directly. Therefore, with the aid of deep-learning based method, the identification and categorization of the instabilities should be done automatically. Thus, on this ground, the present research conducted the preliminary study which tests the ability of the neural network that whether it can capture the different frequency characteristics of the raw data with supervision.

RESULTS and DISCUSSION

Firstly, the neural network is constructed as Fig. 1. The raw data for two-bladed inducer, which are unsteady pressure measurements obtained at five measurements points under sample rate of 2kS/s, with and without alternate blade cavitation are used as an input of the network. Then, using the 3, 5, and 7 kernel, data is reduced to a certain degree. By passing the fully connected hidden layer, the data are classified into two groups, with and without alternate blade cavitation. 500 data sets each for with and without alternate blade cavitation are used for training the weight and bias of the network. After the training, unknown data sets which have been previously classified manually are used as an input. Also, synthetic data sets, which are constructed, based on the frequency characteristic of the alternate blade cavitation, but with 5% of random Gaussian noises, are used as an input. The identification ratio (the number of correctly answered set divided by the number of total test sets) was larger than 80%. Considering the existence of noise and small number of training sets, the network can be said to have a good ability to detect the different frequency characteristic of the raw time series data. However, further developments should be eventually done. The classification process should be done automatically without supervision. Key anomalies should be identified without the pre-defined answer. This allows detecting and classifying the instabilities even though the experiments are conducted under new operating condition or new machine, and the present method can be applied to provide criteria for the unknown instabilities.

|  |
| --- |
|  |
| **Figure 1. Configuration of Instability Identifying Neural Network** |