



# A data indicator-based deep belief networks to detect multiple faults in axial piston pumps



Shuhui Wang, Jiawei Xiang\*, Yongteng Zhong, Hesheng Tang

College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou, PR China

## ARTICLE INFO

### Article history:

Received 19 December 2017

Received in revised form 10 April 2018

Accepted 22 April 2018

### Keywords:

Piston pumps

Multiple faults classification

Deep belief networks

Data indicators

Feature learning

## ABSTRACT

Detecting faults in axial piston pumps is of significance to enhance the reliability and security of hydraulic systems. However, it is difficult to detect multiple faults in the hydraulic electromechanical coupling systems because the fault mechanism of some faults is unclear. In this paper, a method using deep belief networks (DBNs) is proposed to detect multiple faults in axial piston pumps. Firstly, for each individual fault, all the data indicators extracted from the raw signals in time domain, frequency domain and time-frequency domain are calculated to construct training and testing samples. Then, the constructed samples are fed into DBNs to classify the multiple faults in axial piston pumps. With restricted Boltzmann machine (RBM) stacked layer by layer, DBNs can automatically learn fault features. Numerical simulations using the benchmark data of five faults in rolling bearings are classified by the present method to select the relative optimal combination of indicators. The classification results are also compared with those commonly used support vector machine (SVM) and artificial neural network (ANN) to manifest the classification accuracy of the present method. Experimental investigations are performed to classify four faults in an axial piston pump. The classification accuracy ratio is 97.40%, which confirms the feasibility and effectiveness of multiple faults detection in axial piston pumps using DBNs.

© 2018 Elsevier Ltd. All rights reserved.

## 1. Introduction

Hydraulic transmission systems are widely used as vital electromechanical equipment in modern industry. The occurrence of faults in the electromechanical equipment may cause potential decreases in productivity, or even catastrophic casualty. Nowadays, condition monitoring of hydraulic systems has attracted more and more attentions [1–5]. Axial piston pumps are key components in hydraulic systems. Failure of the piston pumps is the most frequent cause of unexpected machine shutdown [6–8]. As a matter of fact, more than 50 percent of electromechanical equipment defects are related to pumps faults [7,8]. Therefore, precise and effective diagnosis of piston pumps is of great significance to enhance the security and reliability of hydraulic systems.

Faults in an axial piston pump are commonly occurred to the cylinder block, the valve plate, bearings and pistons, etc. When the piston pumps run, both the mechanical vibrations and working fluids will affect the performance of piston pumps. As a result, most fault diagnosis works are conducted based on the vibration signals [9–12] and discharge pressure signals [13–16]. Wang and Hu [9] applied fuzzy logic principle to recognize conditions of the five-plunger pump. In their method,

\* Corresponding author.

E-mail address: [wxw8627@163.com](mailto:wxw8627@163.com) (J. Xiang).

feature vectors are constructed by envelope spectrum analysis from the vibration signals of pumps, which are employed to detect different faults in the pumps using fuzzy algorithm. Dong and He [10] presented an improved segmental hidden semi-Markov model (HSMM) to identify faults and further predict the health condition of hydraulic pumps. Wavelet packet transform (WPT) is adopted to extract pump fault features. The experimental results show that HSMM-based approach is more efficient in fault state recognition and remaining useful life prediction of the pumps. Chen et al. [11] proposed a fault degradation assessment method for hydraulic motors. WPT is used to analyze the impulsive energy of the vibration signal, and the Kolmogorov–Smirnov (KS) test is further used to detect the piston condition. Jiang et al. [12] developed a vibration-based fusion approach by combining local mean decomposition (LMD) and improved adaptive multiscale morphology analysis (IAMMA) to detect faults in hydraulic pumps. Gao et al. [13] applied a hybrid method using conventional envelope spectral analysis and WPT to detect faults in hydraulic piston pumps based on discharge pressure signals. The agreeable results indicate that WPT is more sensitive and robust in extracting features than the spectral analysis. Zhao et al. [14] introduced intermittent chaos combined with sliding window symbol sequence statistic to detect early faults in hydraulic pumps. Lu et al. [15] developed a two-step fault detection method based on empirical mode decomposition (EMD) and fuzzy C-means clustering. They also investigated fault severity recognition using EMD and feature energy entropy [16].

In general, once there are faults occurred to the hydraulic electromechanical components, they can be reflected in the measured signals with certain characteristics, e.g., feature frequency. However, the fault excitation impulses are usually too weak to be observed due to the strong noise and other disturbances. Thus, most studies focus on the weak fault impulses enhancement and fault feature extraction using signal processing techniques [17–20]. Fault condition of the pumps can be identified by matching the extracted fault features with the corresponding theoretical fault characteristics. Unfortunately, it has been reported that some different faults have the same feature frequency [13,15]. In addition, the fault mechanism of some faults is unclear, namely it is hard to give such a fault with its corresponding theoretical characteristic [21–23]. Therefore, it is urgent to search for techniques to automatically learn fault features to detect faults in axial piston pumps or other components of hydraulic transmission systems.

Traditional machine learning methods, such as support vector machine (SVM) and artificial neural network (ANN) have enjoyed great success in rotating machinery fault diagnosis [24–28]. Bin et al. [25] combined wavelet packet decomposition (WPD) and empirical mode decomposition (EMD) to extract fault features and then applied ANN for early fault diagnosis. Hajnayeb et al. [26] developed an ANN based system to diagnose faults in a gearbox. Zhang et al. [27] designed a multivariable ensemble-based incremental support vector machine to detect incipient faults in bearings. Jegadeeshwaran and Sugumar [28] proposed a SVM based approach for condition monitoring of hydraulic brakes. However, these intelligent fault diagnosis methods still suffer from obvious shortcomings. The shallow learning architecture is inadequate to learn complicated non-linear relationships and thus has limited representation capacity [29,30]. Deep learning, as a new branch of machine learning, has been shown the excellent ability in learning features from raw signals [31]. Many deep learning models have been extended to rotating machinery fault diagnosis [30,32–34]. The most obvious property of deep learning models is the multiple layer structure. With multiple hidden layers stacked hierarchically, the deep learning model can realize very complicated transformation and abstraction of raw signals. DBNs are a kind of generative deep learning model with powerful feature learning ability. Tamilselvan [35] adopted DBNs to recognize aircraft engine fault conditions. Van et al. [36] employed the Teager-Kaiser energy operator (TKEO) and DBNs to detect faults in reciprocating compressor valve. Shao et al. [33] developed optimized DBNs for rolling element bearing fault diagnosis. Gan et al. [37] introduced DBNs to implement the fault type classification of rolling element bearings. In addition, Zhao et al. [38] extended DBNs to classify analog circuit faults using time series signals. The main advantage of the intelligent diagnosis solution is that DBNs does not rely on manual feature extraction and selection [38].

In this paper, a new fault detection method based on DBNs is proposed to detect multiple faults in axial piston pumps. Firstly, all the data indicators extracted from the raw signals in time domain, frequency domain and time–frequency domain are obtained to characterize the pump health status. Secondly, the training and testing samples are constructed by the relative optimal data indicators. Finally, DBNs are employed to identify the multiple faults in an axial piston pump. Comparing with SVM and ANN, the classification accuracy ratio of the proposed method is manifested by using simulations and experimental investigations.

The remainder of this paper is organized as follows. Section 2 gives a brief review of the basic theory of DBNs. In Section 3, the fault detection method is introduced in details. Simulations using benchmark data are investigated in Section 4. In section 5, the proposed method is applied to analyze the experimental signals from an axial piston pump. Conclusions are drawn in Section 6.

## 2. A basic theory of DBN

DBNs are a kind of neural networks with several hidden layers. The multiple hidden layers allow DBN to learn very complex functions which could then complete data transformation and abstraction by successive learning process. The main architecture of DBNs includes an ensemble of stacked RBMs. Every two-layer neural network composes a RBM. In the present, DBNs are composed by three stacked RBMs and an output layer.

As shown in Fig. 1, the learning process of a DBN consists of two stages: the first stage is pretraining every individual RBM layer by layer in an unsupervised manner; the second stage is to fine tune the whole network using back propagation algo-

Download English Version:

<https://daneshyari.com/en/article/6953739>

Download Persian Version:

<https://daneshyari.com/article/6953739>

[Daneshyari.com](https://daneshyari.com)