Mechanical Systems and Signal Processing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Centrifugal compressor fault diagnosis based on qualitative simulation and thermal parameters

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A R T I C L E I N F O

Article history:
Received 1 June 2015
Received in revised form
24 February 2016
Accepted 24 March 2016

Keywords:
Centrifugal compressor
Thermal parameters
Qualitative simulation
Fault diagnosis

A B S T R A C T

This paper concerns fault diagnosis of centrifugal compressor based on thermal parameters. An improved qualitative simulation (QSIM) based fault diagnosis method is proposed to diagnose the faults of centrifugal compressor in a gas-steam combined-cycle power plant (CCPP). The qualitative models under normal and two faulty conditions have been built through the analysis of the principle of centrifugal compressor. To solve the problem of qualitative description of the observations of system variables, a qualitative trend extraction algorithm is applied to extract the trends of the observations. For qualitative states matching, a sliding window based matching strategy which consists of variables operating ranges constraints and qualitative constraints is proposed. The matching results are used to determine which QSIM model is more consistent with the running state of system. The correct diagnosis of two typical faults: seal leakage and valve stuck in the centrifugal compressor has validated the targeted performance of the proposed method, showing the advantages of fault roots containing in thermal parameters.

1. Introduction

Centrifugal compressors are essential equipments which are widely used in industrial applications, such as petrochemical industry, metallurgy, power plant, nature gas transportation and so on [1,2]. They are mainly used for increasing the pressure of compressed gases in order to maintain the production process. Centrifugal compressors usually have high running speed, large gas flow and high power, and operate continuously for a long period. Once the units fail or emergency shutdown, it often causes huge economic losses and threatens the production safety. Therefore, it makes great sense to monitor and analyze the parameters of compressors and timely to diagnose when the faults occur and why they occur for the stable and safe operation of centrifugal compressors.

Over the past several decades, the researches on fault detection and diagnosis (FDD) methods of centrifugal compressors and other turbine equipments have attracted a lot of attentions and made many progresses. [3–6] present the feature extraction method of vibration signals using time frequency techniques for fault diagnosis of rotating machinery. Model-based FDD methods have been employed for centrifugal chiller system and gas turbine [7,8]. Fuzzy logic based FDD methods are also developed for diagnosis of gas turbine [9,10] and centrifugal compressor [11]. In [12–14], model-free approaches based on principal component analysis (PCA) and canonical variate analysis (CVA) are concerned for FDD of centrifugal chiller systems and multi-shaft centrifugal compressor. The application of machine learning methods like artificial neural

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http://dx.doi.org/10.1016/j.ymssp.2016.03.018
0888-3270/

networks (ANN) and support vector machine (SVM) in rotating machinery fault diagnosis are presented in [15,16].

Most of the fault diagnosis methods developed for centrifugal compressors mainly focus on the mechanical faults of compressors (like rotor imbalance, rotor misalignment, shaft bending, etc) through analyzing the vibration signals of shaft system [3–6]. At the same time, the diagnosis systems about the faults related to the thermal parameters (i.e. impeller fouling, seal wear, increase of impeller tip clearance, etc) are quite few. Generally, when a fault occurs in the gas flow path, the thermal parameters (i.e. temperature, pressure, mass flow) will change rapidly, and the vibration parameters usually have an evident change when the fault developed to a more serious situation. Therefore, the abnormal variations of thermal parameters can often be treated as the precursor of unexpected mechanical faults. Though analyzing the variations of thermal parameters, we can predict the occurrence of faults and take effective measures and immediate actions. Meanwhile, a variety of sensors are installed for real time collections of the thermal parameters of compressors, which carry valuable information about the actual conditions of the gas flow path.

Different methods for turbine machinery fault diagnosis based on thermal parameters have been presented in [8,15,17]. However, none of them is targeted at centrifugal compressor. Meanwhile, the fault mechanisms and their features are usually difficult to obtain without utilizing the principle of centrifugal compressor. This may result in inaccurate diagnosis results when these isolation and classification methods are applied to centrifugal compressors.

In this paper, an improved qualitative simulation (QSIM) based fault diagnosis method based on the thermal parameters of centrifugal compressor is proposed. QSIM models under normal and two faulty conditions have been built through the analysis of the principle of centrifugal compressor. In order to unify the different description ways of variables between QSIM models and actual system, an adaptive qualitative trend extraction algorithm is adopted to extract the dynamic behaviors of variables' observations. A sliding window based matching strategy is also proposed to calculate the final diagnosis results.

The rest of the paper is organized as follows: in Section 2, the details of fault diagnosis method based on our improved QSIM method are presented. In Section 3, centrifugal compressors in gas-steam combined-cycle power plant (CCPP) gas system is introduced in brief, and QSIM models under normal and two faulty conditions are deduced from the Greitzer compressor model. Section 4 shows the diagnosis results of the proposed fault diagnosis method. In the last section, the conclusion of the paper is discussed.

2. QSIM based fault diagnosis method

2.1. The QSIM method

Qualitative simulation method was proposed by B. Kuipers in 1986 [18]. Utilizing the experiential knowledge and first principles of system, QSIM models can be built by a set of variables representing the physical parameters of the system, and a set of qualitative constraints describing how these variables related to each other. The qualitative behaviors of system can be obtained through qualitative reasoning of the QSIM model.

The qualitative state of a variable is represented by Qs(qval, qdir), where qval stands for the qualitative value and qdir for the direction of change. An ordered set of relevant critical qualitative values a variable can take(called landmarks) defines a quantity space. Qval is either a single landmark or an interval between consecutive landmarks. Qdir={inc, std, dec}, representing the direction of change are increasing, steady and decreasing, respectively. The qualitative constraints are two- or three-place relations on the variables, including arithmetic relations ADD(X, Y, Z), MULT(X, Y, Z), differential relation DERIV (X,Y), and functional relations $M^+(X, Y)$, $M^-(X, Y)$ which specify that X and Y have the same or opposite direction of change, respectively. The qualitative constraints can describe the structure of system, and represent the "deep" knowledge of the system.

According to the definition of qualitative constraints, the combinations of directions of variable change that satisfy each constraint are summarized in Tables 1–3. The symbols "+", "−", "0" and "?" represent the direction of change are increasing, decreasing, steady and uncertain, respectively. Given that the variables involved in this paper are positive, the values of variables X, Y and Z in these tables are all positive.

Table 1
The qualitative influence of ADD and MULT.

Z \ X / Y	+	0	-
+	+	+	?
0	+	0	-
-	?	-	-