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Fault diagnosis of pipeline and pump unit systems using status coupling analysis

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A R T I C L E   I N F O

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A B S T R A C T

Earlier studies on fault diagnosis of the pipeline and pump unit systems (PPU) relied mainly on independent equipment analyses, which usually lead to false alarms because of the loss of information fusion. The aim of this study is to utilize the status coupling relationship to improve fault detection sensitivity and reduce false alarm rate. A real-time status identification of related equipment step is added between capturing abnormal signals and listing out diagnosis results. For example, when the pipeline pressure fluctuation is found abnormal, a status analysis of pump units is performed immediately, if the pump units are proven to be operational normally, then the pipeline leak alarm is acknowledged valid. The logical reasoning algorithm is used to capture abnormal conditions of pipeline pressures. The pump unit faults are captured by combining information from multiple sources. Field applications show that the proposed method significantly improves the PPU fault detection capability on fault detection sensitive and accuracy.

1. Introduction

Pipelines and pump units in petroleum production and transportation systems (PPTS) function as blood vessels and hearts in human bodies. They play an important role in the reliability and safety of PPTS. Because most pipelines are arranged outside stations, and pump units experienced bad working conditions (extreme temperature, high rotating speed, and high pressure), pipeline leaks and pump unit failures account for the majority of accidents (Taylor, 2003). Most fault diagnosis methods developed so far have dealt faults in pipelines and pump units separately. This may be explained by the fact that fault characteristics and modes differ greatly in pipelines and pump units.

1.1. Background

Pipeline leak detection methods include manual inspections and advanced satellite imagines (Lopes dos Santos et al., 2011). Conventional approaches have some drawbacks, such as a low credibility of fault diagnosis due to lack of efficiently utilizing and integrating specialized knowledge, and a misdiagnosis caused by insufficient attention to the coupling effect analysis. Therefore, the development of a pipeline leak detection method that will greatly enhance detection sensitivity and detection accuracy is highly required. The Reinforcement Learning (RL) was applied to the prediction of the entire control process, because it can acquire experiences and select actions through its interactions with environment (Hu et al., 2011). The essence of RL is autonomous learning algorithm, which does not need prior self-learning knowledge. Furthermore, Negative Pressure Wave (NPW) method has been successfully used on identifying and locating pipeline leaks (Ge et al., 2008; Kaelbing et al., 1996). However, coupling relationships between adjacent segments of the pipeline have been rarely taken into consideration. Several reports suggest that even if the pipeline and pump unit systems (PPU) is under normal operations, some unexpected situations other than oil spill may also cause abnormal pressure waves, i.e. upstream pump stop, load alternating (Veland and Aven, 2013; Sun and Chang, 2014). Therefore, the leak detection sensitivity is usually reduced to eliminate excessive false alarms, which inevitably lead to a decline in capability of small leak detection.

A common approach to detect and identify failures in pump units is to compare to normal signals with abnormal signals (Karassik et al., 1986), which utilize on-line fault monitoring and off-line fault analysis. While the proposed Hidden Markov Models (HMM) could classify and identify the running status of individual

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equipment as well as holistic processes (Ridvan, 2012), and the expert system for real-time fault diagnosis was able to determine failure modes and select proper strategies from memory knowledge bases, abnormal information cannot be fully exploited due to the functional limitation of Supervisory Control and Data Acquisition (SCADA) system (Holmes et al., 2013). Thus, false alarms can be caused, which imply that information fusion in the context of multiple sources will enhance the accuracy of fault diagnosis.

1.2. Status coupling analysis of PPU

Pump units and pipelines separately act as energy providers and transferring channels from perspective of energy transportation. As petroleum is transported in a closed environment, the change of each parameter may create influence on the other parameter (Liang et al., 2013). Previous studies have shown that strong coupling effects exist in pump unit running statuses, pump unit external hydraulic parameters and both ends of pipeline hydraulic parameters. However, studies on coupling effect in PPU have just started, and most of them only consider the internal coupling effects within the equipment itself (Zhang et al., 2012; Du et al., 2012). Recent developments in the complexity of modern process plants have illustrated the need to take account of the multiple-source characteristic of faults to make a more comprehensive and convinced fault diagnosis results.

1.3. Research method

This paper proposes a novel fault diagnosis method to diagnose the faults in PPU based on integrated monitoring of process data and coupling effect analysis. There are three basic procedures for the study. First, abnormal equipment signals are captured through the analysis of signal feature extraction. Second, a real-time status model of related equipment is built to trace the causes of abnormalities (whether the abnormalities caused by failures of the equipment itself or unstable statuses of the related equipment), and the procedure for model building includes building standard status databases for the equipment running under different conditions, and obtaining equipment real-time monitoring information and comparing real-time monitoring results with the standard statuses. Third, the validation of false alarms is determined.

2. Method

2.1. Capturing abnormal conditions for PPU

Diagnosis of mechanical faults is to identify the running statuses of equipment (Poole et al., 1987). The framework for the diagnosis is presented in terms of three key elements: capturing characteristic signals (vibration, noise, temperature and pressure), extracting fault symptoms from characteristic signals and identifying possible faults. Based on attributes associated with the data and prior knowledge of pipeline leaks and pump unit faults, real-time parameters in PPU are divided into five categories (Table 1).

Table 1
PPU data acquisition items and categories.

Category	Items of pump units	Items of pipelines
Vibration	Motor end tile vibration	
	Pump end tile vibration	
Temperature	Pump middle tile temperature	Station inlet temperature
	Pump case temperature	Station outlet temperature
	Motor A phase temperature	
Pressure	Pump inlet pressure	Station inlet pressure
	Pump outlet pressure	Station outlet pressure
	Manifold inlet pressure	
Status	Pump running status	
	Pump driven-end leaking status	
Electricity	Motor electric current	
	Motor electric pressure	

2.1.1. Capturing abnormal pipeline pressures using Negative Pressure Wave (NPW) with logical reasoning algorithm

NPW method procedure is in two steps: capture of pipeline pressures and recognition of leak patterns. As the real-time capture capability of signals is greatly affected by the complexity of leak identification algorithms, and the leak alarm function can only be triggered when abnormal pipeline pressures are identified, it is accordingly important to improve the capture method of abnormal pipeline pressures to increase the leak detection sensitivity.

This paper develops an embedded logical reasoning algorithm NPW to capture abnormal pipeline pressures with regard to the features of smooth fluctuation in long transportation pipelines. Three major steps of the proposed method are noise reduction, extraction of characteristic indices and capturing of abnormal pressure fluctuations. As the whole process requires less calculation, it is suitable for on-line applications. Fig. 1 shows the flowchart of the method.

2.1.2. Capturing abnormal signals of pump units

Because the aim of the function of commonly used SCADA system is just to identify simple threshold values of real-time parameters (Anastasio et al., 1998), it is difficult to detect hidden faults of the pump units. Although hidden faults do not impact normal productions of the current system, long-time existence of hidden faults without awareness may damage the equipment and eventually lead to accidents. Therefore, it is necessary to capture the symptoms of hidden faults. The status data of pump units comes from different collecting points and covers a specified period of time. A temporary (the duration will be 1s–5 s) real-time data buffer is set up in the system memory to store these process data (Fig. 2). In the proposed monitoring and alarm diagram of pump units, the diagnosis of hidden faults can be viewed as a real-time program because the data buffer is within a short time range, which contributes to the efficiency of fault diagnosis. False alarm is set off when a few characteristic indices of several status parameters exceed the threshold scope and continue for a certain time based on multi-source information fusion (Cai et al., 2014), and here the threshold should be smaller than the one set by the SCADA system. This offered a high level of diagnosis accuracy. The study mainly deals with time domain indices of process data due to the real-time requirements. Aiming at concisely reflecting comprehensive hidden information, Table 2 summarized these time domain characteristic indices.

2.1.3. Case study: capturing abnormal signals of pump units using multi-source information fusion

The parameter waveforms depicted in Fig. 3 are from four vibration processes of one abnormal running condition, and these vibration signals are collected from four testing ends of bearings located in both ends of the motor and the pump. Table 3 lists the results of time domain characteristic indices of the vibration process parameters. Because the maximum amplitude value of the vibration signal is 2.17 mm/s failing to reach the alarm limit value 3.5 mm/s, the SCADA system does not set off any false alarm. However, through the analysis of characteristic indices in Table 3, indices such as kurtosis, variance and peak-to-peak value have been above the standard values for more than 5 min, if the situation continues, the equipment could be damaged by impact forces, that is, hidden faults exist in the pump units.