2016 3rd International Conference on Social Science (ICSS 2016)
ISBN: 978-1-60595-410-3

Spatial Dimension Analysis based on Real-time Signal: Safety Evaluation Improvement of Pipeline and Pump System

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Keywords: Partial Dimension Analysis, Real-Time Signal, Safety Evaluation, Pipeline and Pump System.

Abstract. This paper, describing a pipeline and pump system (PPS) as a set of interconnected network with real-time signal updating, presents a spatial dimension analysis (SDA). It is conceived as a scheme that pumps and pipelines run involving a firm relationship between each other, specially, in problems where detecting the precise status of abnormal changes is the main goal. Negative Pressure Wave method based on logical inference is applied to extract abnormal signals captured from the supervisory control and data acquisition. We use Local Mean Decomposition combined with Cubic B-Spline Interpolation (CLMD) to reduce the singular points of the instantaneous frequency avoiding spectrum distortions. SDA can determine the trend of the system and be applied to achieve better estimation accuracy of state variables.

Introduction

Traditional methods for detecting the running status of pipeline and pump system are challenged by issues requiring comprehensive and precise analysis of obtained information. A large proportion of those methods are connected with monitoring pipelines and pumps as separated entities and may not provide the analysis taking into account the influence on each other. In a reviewed work[1], there exists a strong coupling effect between pipeline and pump. Therefore, it is significantly less accuracy without taking into account the influence on each other. Inspired by aforementioned approaches, this paper analyzed real-time signal in a spatial dimension for pipelines and pumps.

There has been a several general principles pertaining to the problem of real-time performance monitoring and evaluating involved in the pipeline system. The mass approaches available for detecting pipeline failure can be classified into hardware and software based methods[2]. As for hardware-based methods, optical fibers or special sensors (acoustic sensor, chemical sensor, etc.) are used to capture the changes in surrounding environment due to pipe leak. In the software-based techniques, software packages are used to continuously monitor process variables such as pressure or flow rate to signal the generation of pinpoint leaks. Now a method so-called negative pressure wave (NPW) (which is sensible to serious leaks) has found to be the most prevalent one with leak identified by detecting pressure changes at the both ends using installed pressure transducers. A diagnosis model was established mixing the evaluation for condition monitoring, failure prediction and performance degradation, which considered both the influence of installation and also operation factors on mechanical dynamics[3]. A kind of monitoring method for operation states of a critical sub-system was developed to detect the potential dangers[4]. Due to its neglecting of external interference that may be caused by other sub-systems. So this method will provoke a high probability of misdiagnosis. Another method, named pressure gradient method has proved to be effective for localization of weak leaks. In this method, leak localization can be done by measuring the pressure gradient near inlet and outlet of the duct and utilizing the mathematical formula derived from continuity and momentum equation in terms of pressure gradients, inlet and outlet pressure and length of pipe[5-7]. An approach that combines rough set theory and support vector machine (SVM) in conjunction with artificial bee colony algorithm has been applied to improve the accuracy with reduced time of prediction of leaks along the pipeline carrying crude oil and liquid fuels[8-9].

Methods for pipeline and pump safety evaluation differ greatly from the failure mode, characteristic, detection and analysis. A large proportion of those methods usually adopt independently research or fault analyzing in single dimension approaches for pipelines and pumps. Therefore, this paper implements SDA for safety status estimation of PPS. NPVLR has been used to extract abnormal signals of running pipelines and pumps that will be used in SDA. In order to reduce the singular points of the instantaneous frequency, the obtained signals are processing with Local Mean Decomposition (LMD) combined with Cubic B-Spline Interpolation (CBI) named as CLMD. With the specifications or realities in the safety evaluation, space dimension are applied to achieve better estimation accuracy of state variables. We focus on analysis and evaluation of PPS for safety running, which identifies the system abnormality trends and failure influences having a significant effect on performance.

Brief Description of the SDA

The purpose of SDA is to evaluate the system performance by analyzing the dynamic data from pipelines and pumps in real-time. In general, SDA includes the following four steps:

- Capture the abnormal signals during the running conditions (such as temperature, pressure, vibration and flow and so on).
- Hydraulic characteristic research: deduce the functional relationship by correlating pressure of both upstream and downstream.
- Signal processing: the real-time data is analyzed with the method of CLMD to realize accurate fault diagnosis.
- Spatial dimension: spatial transference of state variables is used to estimate other related state variables. And from this point of view, the dynamic data evaluation method for PPS is built.

A Scheme of Capturing Abnormal Signals based on Logical Inference Algorithm

Capture of Abnormal Pipeline Pressure

The traditional pipeline leak detection based on NPV can be divided into two stages, which are abnormal pipeline pressure capturing and leak pattern recognizing for abnormal data. Real-time ability of the operation system will be affected greatly by the complexity of the leak identification algorithm and the large amount of system resource usage. So the proposed new testing method is called negative pressure wave method based on logical reasoning (NPVLR) to reduce computation load and improve online performance, which includes the following three steps:

- Noise reduction: the real-time pressure data is processed with the method of threshold value judgment to reduce noises.
- Extract data characteristic indexes(such as rising edge numbers, declining edge numbers and deviation values between the first point and final point and so on).
- Capture signs of abnormal pressure fluctuations based logical inference.

The fluctuation characteristic changes in companies of different pipelines under normal transport condition. Consequently, threshold value schemes should be developed in the process of logic inference program. In the module design process of capturing abnormal sign, the inferential analysis is actually only focused on the data within the present “rectangular window” (rectangle's width represents the length of time, rectangle's height represents pressure) that will moves backward every specific length of time. When the present “rectangular window” reaches the positions including a significant pressure curve turning, the judgment result of “abnormal pressure” will be obtained, which utility concept is called the “rectangular window discriminate method”. The algorithm flowchart for capturing pipeline abnormal pressure based on NPVLR is shown in Fig. 1.

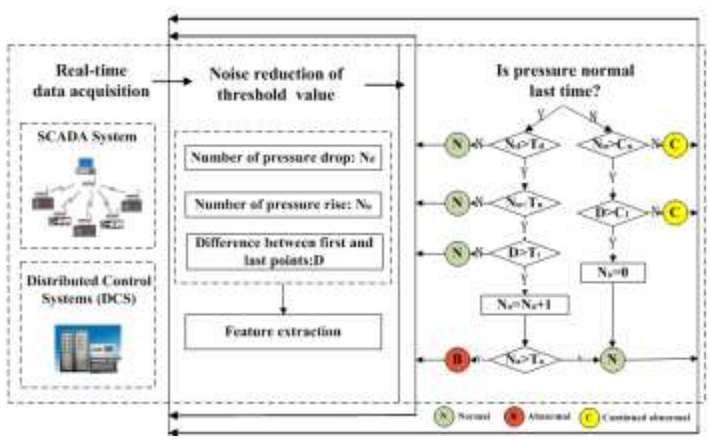

Figure 1. Flowchart of capturing abnormal pressure using logical reasoning algorithm (Td: Number of pressure drop. Tu: Number of pressure rise. Tt: Difference between first and last points. Cu: Number of pressure rise in cancel process. C1: Difference between first and last points in cancel process. Na: Continuous abnormal number. Ta: Abnormal number).

Dynamic Capture of Abnormal Pump States

A pump performance analysis requires to integrated process data from different collecting points or a segment during a specified time period. As shown in Fig.2, if the abnormal capture focusing on single point alone cannot meet requirements fully, so a real-time data buffer of short-term is set up in the system memory.

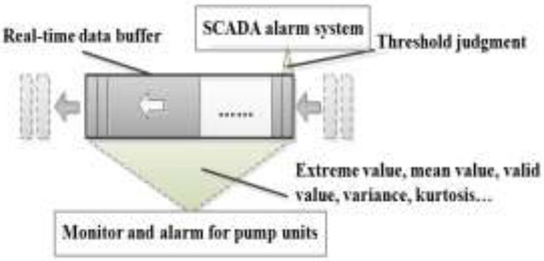

Figure 2. Diagram of pump units fault monitoring and alarm.

An evaluation method for implementing a pump abnormal capture based logic inference can be described as follows: Abnormalities will be obtained when characteristic indexes from state variables are beyond scope of the threshold value for a certain time period. Otherwise, the pump unit is in smooth running. It is meaning to mention that the threshold value intended to be implemented as the scope should be under the threshold valued set by supervisory control and data acquisition system (SCADA). Trigging the function of abnormal capture requires both multiple characteristic indexes over the threshold value and multiple state variables involving, which is so-called multi-source information fusion in analyzing process. In addition, failure modes between the judgment of abnormal capture and the list of equipment failure are similar in conditions associated with symptoms.

The Validation of Abnormal Capture based on Logical Inference

In this validation process, due to the real-time feature and the simplicity of the failure inference algorithm, the objects being studied in this research are centered on time domain indexes of process data. The selected indexes are intended to reflect the hidden information of pumps, which includes characteristic indexes as demonstrated in Table 1. And, the abnormal pumps wave patterns, which is captured by vibration performed in four testing ends (include motor-driven end and pump-driven end), is depicted in Fig. 3. The time domain characteristic index of the vibration process parameters are specified in Table 2.

Table 1. Time-domain characteristics of the unit process data.

No.	Formula	Basis of selection	Note
1	$x_{\max} = \max(x_i)$	High- high alarm	
2	$x_{\min} = \min(x_i)$	Low- low alarm	
3	$x_{\mathrm{pp}} = x_{\max} - x_{\min}$	Fluctuation monitor	
4	$x_{\mathrm{rms}} = \mathrm{mean}(x_i^2)$	Fluctuation monitor, well stability.	$\mathrm{mean}(\bullet)$ Arithmetic mean function
5	$\beta = \mathrm{mean}(x_i^4)$	Pulse monitor	
6	$D = \mathrm{mean}(\sum(x_i - \bar{x})^2)$	Fluctuation monitor	
7	$CL_f = x_{\max} / x_{\mathrm{r}}$	Pulse & Fluctuation monitor	$x_{\mathrm{r}} = \left(\mathrm{mean}(\lvert x_i \rvert)\right)^2$
8	$K_f = \beta / (x_{\mathrm{rms}})^4$	Small pulse monitor, well sensitivity	Non-dimensional

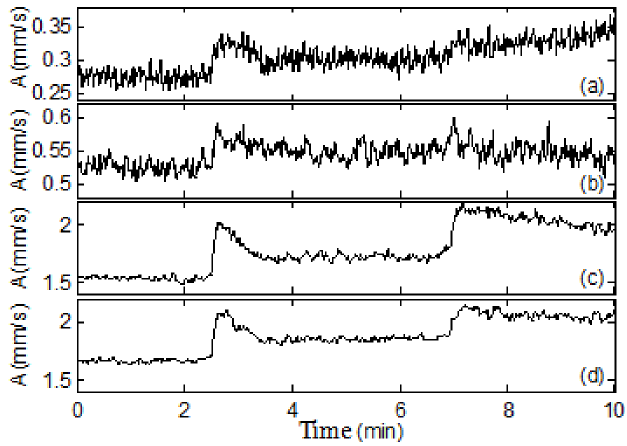

Figure 3. Bearing vibration of the pump unit (a) Motor driven end (b) Motor non-driven end (c) Pump driven end (d) Pump non-driven end

Table 2. Time-domain characteristics of some unit parameters.

Item	**Vibration of motor driven end**	**Vibration of motor non-driven end**	**Pump of motor driven end**	**Pump of motor non-driven end**
Maximum	0.3695	0.6	2.1766	2.1484
Minimum	0.2562	0.5047	1.475	1.6234
Peak-to-peak value	0.1133	0.0953	0.7016	0.525
Root-mean-square value	0.30576	0.54507	1.7934	1.8802
Kurtosis	0.0089	0.0886	10.8782	12.8307
Variance	0.0005	0.0003	0.0406	0.0238
Margin index	1.2085	1.1008	1.2136	1.1426
Kurtosis index	1.0225	1.0037	1.0515	1.0266

Table 2 shows the maximum amplitude value of the vibration signal is 2.17mm/s failing to reach the setting alarm limit of 3.5mm/s. It seems like that SCADA system neglected the abnormality. The bearing vibration amplitude of the pumps is not large based on the analysis of above index items. Though, indexes such as kurtosis, variance and peak-to-peak value are excessive excess for a long-term continues (more than 5 minutes), and this impact often leading to equipment damage in the long-term belongs in hidden failure domain. This means that the abnormal capture is required and effective. Furthermore, comparing to the condition monitoring of the SCADA system, the proposed method for pump abnormal monitoring seems to be more effective to deeply mining state data for tremendous information investigating of hidden failure.

Spatial Dimension Analysis for Safety Evaluation of PPS

For PPS problems, in the first category, a pump may fail to deliver liquid, develop insufficient pressure or symptoms of mechanical difficulties. In the second category, a pipeline may develop breakage of some parts. There is a definite interdependence between some difficulties of both categories. For example, a leak at the running pipeline must be classified as the second category, but it will result in a reduction of the net pump capacity, a hydraulic symptom, without necessarily causing a mechanical breakdown or even excessive vibration. And, correct evaluation of PPS needs to consider cross-effects of pump and pipeline features, and due to nonlinear, time-varying behavior and imprecise measurement information of the systems it is necessary to deal with the failures with precise mathematical equations. Though, there are uncertainties and ambiguities about the failure causes. There for, a developed local Mean Decomposition (LMD) and support vector regression machine (SVR), which deal with vague information based on signal analysis and machine learning could be applied to improve the precision of evaluation.

Discussion and Conclusion

Most of the conventional failure diagnosis, safety evaluation or fault warning to date for pipeline and pump networks, have in general failed to perform optimally within the restrictions of response time, robustness, reliability, sensitivity and accuracy. The proposed SDA effectively addresses the issues of acceptable response time, accuracy and effectiveness, offering a suitable and action effective method to pipeline and pump system safety evaluating.

The proposed SDA method is effective to evaluate the PPS performance by capturing and analyzing the dynamic data. Actually, from the signal and features, the knowledge was acquired (linguistic information was extracted) through the interactive impact of the abnormality on the both pipelines and pumps parameters. And, through CLMD-based signal processing and decomposition with a rule of CBI, the accuracy and efficiency of data analysis are improved. For the dynamic spatial dimension model, CDE-SVR is illustrated in the paper, the proposed evaluation method shows satisfied performance in the failure reasons, inference and alarm time comparison with field failure reports. The implementation of the proposed approach in the petrochemical industry would result in reduction of potential hazards and accident loss, which plays an important role in the safety evaluation of PPS.

Acknowledgment

Project supported by Science and Technology Innovation Foundation from Beijing Institute of Petrochemical Technology (No.15031862005/014 and 15031862005/016); Sudents scientific research and entrepreneurial action plan (URT16032082001/163) projects in Beijing colleges of Beijing Institute of Petrochemical Technology.

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