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Seafaring Business and Fault Evaluation of a Floating Platform-Applied Electric Submersible Pump

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Abstract

The growth of the marine safety sector and the general well-being of humanity are directly tied to the health of the ocean economy. In order to keep the machinery on offshore platforms running, electric submersible pumps (ESP) are often employed. While ESP failure may lead to contamination in the water, identifying the problem early can boost the marine economy. Fault detection of ESP systems is becoming more common as nations strive to conform to ocean economics and environmental protection rules. ESP issues have been effectively diagnosed using vibration mechanical models of common failures. The vibration signal is monitored by several sensors in order to perform signal analysis and problem diagnostics in the ESP system. Meanwhile, the difficulty of defect identification would grow if physical sensors were used. In recent years, neural network techniques have been extensively used for ESP fault detection because of their ability to effectively identify electric pump faults using a huge database. In this research, methods are developed based on feature extraction to detect the malfunction of the ESP system, which reduces the number of sensors required and eliminates the need for a huge database. The simulation results demonstrate that the algorithms perform well in meeting the envisioned goals.

1. Introduction

Over the last several decades, worries about energy shortages and pollution have increased. Due to its high discharge head and straightforward management, ESP is attracting increasing interest from researchers. Yang (2004) has studied the characteristics and uses of ESP. Due to the ESP's more complex construction and the somewhat unpleasant working conditions beneath the shaft; the ESP's fault rate during oil production is highly variable. There have been significant investments made to address ESP's flaws. Using spectrometric and discrete wavelet transform data analysis, Liu et al. (2011) proposed the fault diagnosis methods about ESP, and Xi (2008) proposed another method based on vibration detection to study centrifuge pump fault diagnostics. This low-efficiency, card-based technique for ESP fault diagnosis is further complicated by the introduction of human error.

Electric indications from the motor, say Harihara and Parlos (2012) might reveal a faulty pump. Once the link between the pressure-out value of ESP wells and time has been determined, as in the work by Zheng et al. (2012), a mathematical model may be built to enhance the efficiency with which oilfields are developed. Dong (2004) has used the holding pressure diagnostic procedures into the management of a submersible electric pump well in the Bohai Q Oil field. The more severe the defect degree of ESP, the more detrimental the effects of a prolonged pressure-out on production status and efficiency. However, Li et al. (2008, p.121) assessed the production status of the wells in each area and analyzes the appropriate technical measures that should be applied, and the macro-control diagram of ESP is useful to increase the efficiency of ESP well production. After doing a qualitative and quantitative analysis of ESP faults using the FTA technique, the

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fault tree of the ESP may be constructed, as well as the minimal cut sets, minimum route sets, and structural function, as reported by Zhao et al. (2006) and Zhang (2008). Prior to that, Gan et al. (2002) used the data from FMECA and FTA to investigate fault diagnosis and fault prognosis. In addition, Sakthive et al. (2010) reported on mode analysis and feature extraction from vibration signals under both normal and fault circumstances. In addition, Farokhzad (2013) employed a Fast Fourier Transform and an Adaptive Neuro-Fuzzy Inference System to identify pump failure, while Li et al. (2010) used Fuzzy Petri Nets to analyze ESP performance. The pattern recognition model of ESP faults has been established using fuzzy mathematics theory and expert data, however there are still some unknowns due to the limits of establishing the fuzzy connection matrix. Peng (2016) and Wang et al. (2007) identified pumps failure using the neural network, and this technique has been more popular in recent years, allowing for more precise and rapid diagnosis in ESP. In addition, pumps system defects have been identified and diagnosed by Wang (2013) and Rajakarunakaran et al. (2008). Several studies, including ones by Li (2010) and Zhao (2011), found that examining vibration signals was sufficient for defect diagnosis. Prior to that, the properties of motor were studied by Leon et al. (2000). Therefore, an efficient diagnosis of ESP may be implemented via the use of vibration signal analysis, feature extraction from electric pump units, and the development of a typical fault vibration mechanics model. In addition, Behzad et al. (2004) demonstrated a method wherein vibration analysis and motor current signature analysis (MCSA) work together to identify problems and anomalies in mechanical systems. Some more thorough diagnostic approaches exist, in addition to the ones just mentioned. Zhao (2010) and Feng (2007) investigated the state monitoring and fault diagnostic technology and synthetic diagnosis model of ESP, respectively; Mckee (2015) studied the connection between vibration cavitations sensitivity parameter and centrifugal pumps condition.

2. Electric Submersible Pump (ESP)

2.1. ESP Systematic Component

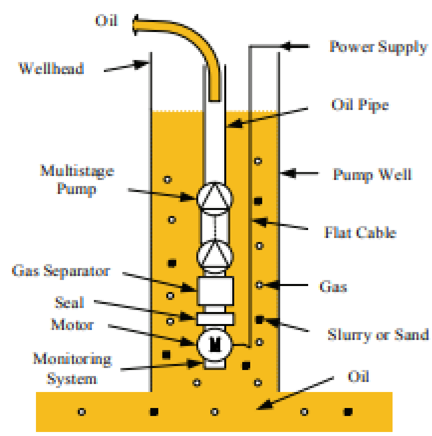

Figure 1: The ESP System Schematic

The downhole system component and the surface equipment component make up the ESP systematic component. Basic ESP downhole system components include the multistage pump, the gas separator, the seal section, the motor, the power cable, and the monitoring system, while the surface equipment (beyond the wellhead) comprises of the motor controller, the converter, the junction box, and the surface cable. As may be seen in Figure 1, several parts serve various purposes. The power line brings electricity from surface machinery to the motor, which in turn runs the multistage pump and seal section. The pump's torque is transferred from the motor via the seal section, which is situated between the pump and the motor. In lieu of a traditional pump intake, the gas separator removes some of the free gas from the fluid being drawn into the pump. The pump is a multistage centrifugal pump that brings the fluid to the surface through the pipe, and the monitoring system is affixed to the motor's base, where it keeps tabs on variables like intake pressure, temperature, discharge pressure, and so on.

2.1. ESP Operation Principle

The fluid within the impeller is pushed to the sides of the impeller along the blade between the flow channels when the motor forces the impeller on the pump shaft to spin at a high speed, thanks to centrifugal force. When the liquid is pushed by the blades, it gains pressure and speed simultaneously. The liquid's kinetic energy is converted to pressure energy as it passes through the impeller and on to the next stage of the pump. The liquid is pumped via a series of impellers, where its pressure is increased until it is strong enough to overcome the resistance in the pump's discharge pipeline. It is almost difficult for the ESP to function in perfect conditions because of the complex well environment and unpredictable pollutants in the well fluids, such as gas, slurry, sand, and so on. The research of defects diagnosis of ESP is required to minimize economic losses and safeguard the marine environment.

3. Fault Detector Design

The flow chart of fault detector can be designed as following figure.

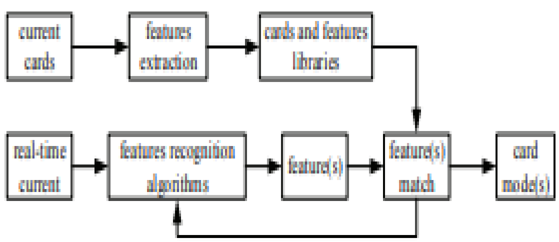

Figure 2: The Schematic Diagram of Fault Detector Design

3.1. Features Extraction

Following the aggregation and analysis of many fault current cards, characteristics such as expectation, variance, and so on are extracted from each card. Table 1 displays the existing mapping relations between cards and characteristics. The expectation, as described by Han and Xie (2006) and Zhang (2015), represents the mean value of the random variable. The variance is another statistic used to quantify the dissimilarity or degree to which a random variable deviates from its expectation.

Card types and their corresponding attributes are mapped out in Table 1.

Categories of current cards	Change trends of features
Casing gas causes underload shutdown	Uptrend of variance; Periodicity
The gases affect	Variance almost retain the same
Well liquid contain sediment or mechanical impurities	Downtrend of variance
Insufficient liquid supply in oil wells	Downtrend of expectation; Start-up fail again
Insufficient liquid supply and intermittent pumping in oil wells	Downtrend of expectation; Periodicity; Start-up success again
Electric pump impeller wear	Downtrend of expectation;
Motor wear	Uptrend of expectation;
Well liquid contain mud	Uptrend of expectation; Start-up fail again
Electric pump shaft fracture during run-time	Mutation of falling
⋮	⋮

So the expectation and variance of random variables can be described in the following equations:

$$E(X) = \sum_{i=1}^{n} x_i \cdot p_i \qquad (1)$$

$$D(X) = \sum_{i=1}^{n} p_i \cdot (x_i - \mu)^2 \qquad (2)$$

3.2. Features Recognition Algorithms

A variance threshold may be set such that variations that are less than the threshold value are considered normal. Figure 3 shows how recognition algorithms are developed based on the attributes, so we can learn about the cards' defining characteristics. In various failure modes

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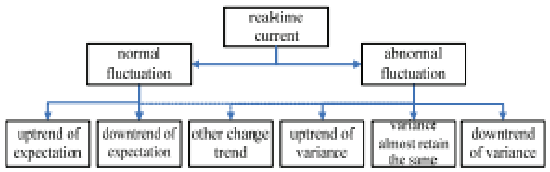


Figure 3: The Schematic Diagram of Features Recognition Algorithms

3.3. Features Match

After running through feature recognition algorithms, the card mode may be determined by comparing its characteristics to those listed in Table 1. If not, we need to do some more work on the algorithm sets and the mapping relation.

4. Simulation Results

Here, we simulate the changing behavior of the retrieved characteristics and the applicability of the strategies described in Section 3 using MATLAB. As was previously indicated, working conditions have a role in determining whether the present normal varies. As a consequence, I've laid out two examples of what the simulation results may look like. First scenario: the current is erratic (not including start-up and power-down). Under load shutdown due to casing gas current is seen in Figure 4. The current card's variance change trend is shown in Figure 5, where it can be seen that the variance is increasing with time. Therefore, the present anomalous fluctuation is becoming more severe, and the working situation may be identified using Table 1.

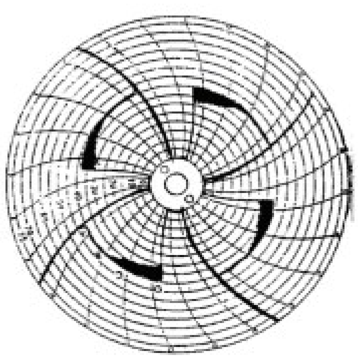
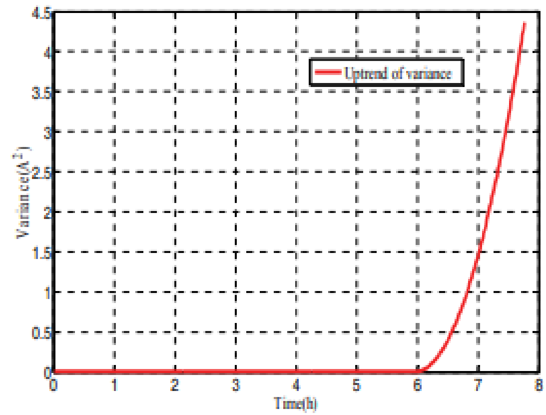


Figure 4: Current Card of Casing Gas Causes Underlo ad Shutdow



Casing gas current card variance trend showing under load shutdown

Figure 6 also illustrates patterns in variance change for many modern cards. It's clear that the present deck has a wide variety of cards with varying variance change trends, including rising and lowering mutations. Table 1 shows the mapping connection that allows us to learn about the various ESP operating situations. This proves that the aforementioned algorithms work.

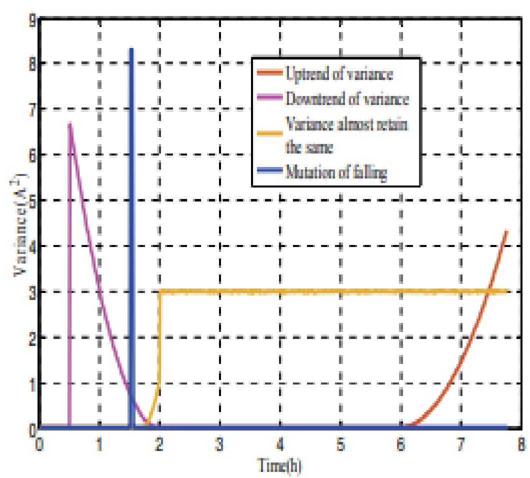


Figure 6: Trends in the Variance Change of Various Currently Available Cards

Second scenario: the current exhibits typical fluctuations, although with discernible shifts. Figure 7 depicts the motor wear current card, and Figure 8 depicts the expected change trend of current card, both of which illustrate that the current is steadily rising as time passes.

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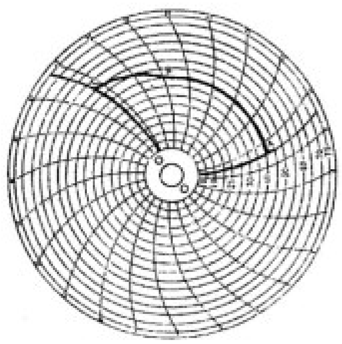

Figure 7: Current Card of Motor Wear

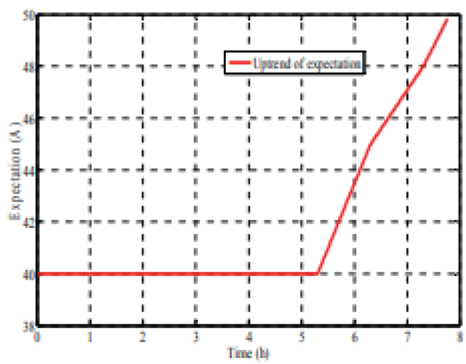

Figure 8: Expectation Change Trend of Current Card of Motor Wear

As shown in Figure 9, expectation has two types of change, uptrend and downtrend respectively. Besides, two or more current cards have the same change tendency of expectation, and other features, such as periodicity in Table 1, need to be taken into consideration now, so the different faults can also be judged correctly.

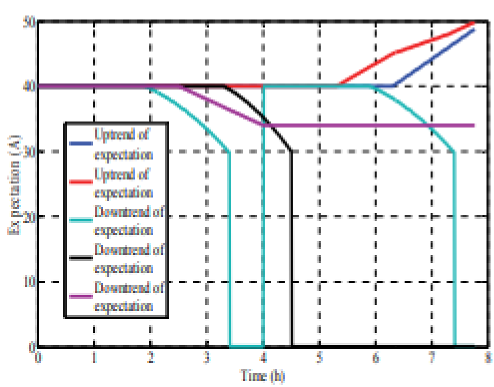

Figure 9: Expectation Change Trends of Different Current Cards

The algorithms designed based on the features extraction can recognize the different working conditions of ESP quite well. In addition, to better diagnose the fault of ESP, the mapping relations between current cards and features in Table 1 need to be gradually perfected.

5. Conclusions

In this research, we provide methods based on feature extraction that aims to solve the issues of human error and delayed fault detection in ESPs, with the goal of preventing costly financial losses. To further verify the practicality of the methods and ensure that the simulation results can satisfy the aims, two scenarios are simulated in MATLAB depending on whether the current is normal or not fluctuating. We'll do further study and refinement of the algorithms to cut down on losses to the ocean economy. Future studies will investigate the feasibility of using alternative fault diagnostic techniques, such as combining the approaches of Tao et al. (2012) and Durham et al. (1990) to collect noise and vibration signals via sensors, analyze a large database, and apply the neural network method to diagnose ESP failures. This would help to both grow the ocean economy and better protect the marine environment. Meanwhile, we'll look at the ESP system discussed by Li et al. (2003) and try to enhance the ESP simulation model performance developed by Thorsten et al. (1999). There will also be an increase in the number of experiments conducted concerning the ESP faults diagnosis system and cutting-edge fault diagnostics techniques (Karimi, 2011; Yin et al., 2014; Zhang et al., 2010; Chadli et al., 2013).

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