A Data-Driven Decision Model: A Case Study on Drawworks in Offshore Oil & Gas Industry

Pengyu Zhu

Abstract Offshore installations are complex and need to be maintained properly to sustain expected performance. Critical failures on these installations could pose great threats to productivity, personnel safety, and the environment. The research is designed to suggest some practical solutions for improving decision quality and reliability. During operation and maintenance (O&M) activities, much data are collected, and it is believed that making full use of them has great potential for improving production efficiency, as well as for reducing risks. Drawworks is studied to elaborate a data-driven methodology. The research suggests some practices for identifying and using critical data sets as a driving force to improve decision-making. Both qualitative and quantitative analysis are used during the study. Competence management is also studied as a necessary part of the data-driven decision-making setting.

1 Introduction

Offshore oil & gas (O&G) operations are expensive and generally have higher safety requirements compared to onshore operations. Production safety and availability are largely influenced by the performances and conditions of key equipment of offshore installations. Human decisions play an important role in the process. However, in traditional terms, decisions related to operation and maintenance activities are often made based on experiences. The consistency and quality of experience-based decision practices are questionable [17].

It has been widely acknowledged that data & information have great potentials for improving the quality of decision-making [1, 4, 12]. With the development of sensor technology and digitalization, more and more data are collected and need to be integrated into decision making, but the definition of the most critical data sets, and the integration process are still heavily experience-based. The paper promotes a

P. Zhu (✉)
Cluster on Industrial Asset Management, University of Stavanger, Stavanger, Norway
e-mail: pengyu.zhu@uis.no

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normative approach to help decision-makers gain more control of data and explore the maximum value of them in a systematic way. A critical equipment in offshore drilling is selected and described in Sect. 2. In Sect. 3, the methodology of the data-driven approach is explained. In Sect. 4, the failure mechanism of the selected equipment is studied, and how to establish the contextual data architecture for decision-making is explained.

2 Drawworks

Faller [7] listed the most critical equipment for offshore drilling facility as including top drive (crown block), drawworks, and mud pumps. Drawworks was selected in this study as its criticality in offshore drilling was sometimes overlooked. An operator from North Sea recoded all maintenance activities related to the drawworks between 2004 and 2014. Records showed that 10% of total maintenance activities were corrective maintenance, while the rest was planned maintenance. From the oil operator's point of view, the drawworks was quite reliable. However, a drawwork incident several years back induced a production shutdown for more than two weeks, which caused great economic loss. Drawworks can, in many ways, be the reason for production loss or catastrophic failures that threaten the environment and human lives. Its possible impacts should not be neglected. A system of systems diagram of drawworks is depicted in Fig. 1.

Some essential functions that drawworks perform include: dragging the drill string/casing out of the hole; controlling the speed of drill string/casing; controlling the weight that is applied on the drilling bit; providing a power take-off for the chain-driven rotary table if no other hoisting equipment is installed [6, 14].

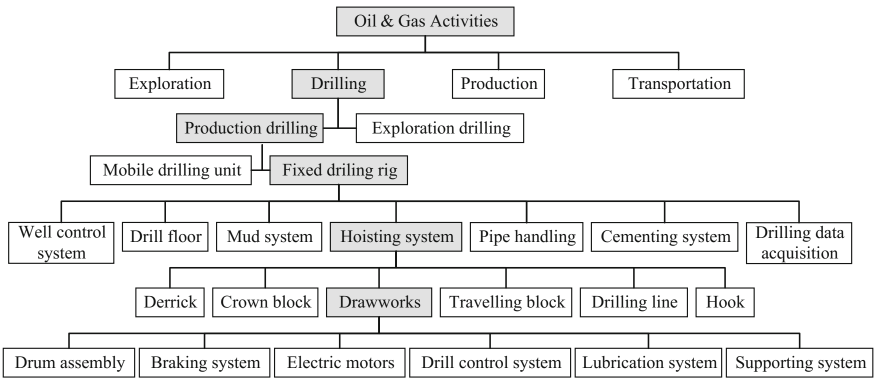

Fig. 1 System of systems. Adapted from [3, 15, 19]

3 Methodology

New sources of data are generated and collected with the development of advanced monitoring technologies and with the increasing requirement on safety. The paper promotes a normative data-driven approach to help improve the contextual awareness and assist decision-makers to define and make use of the right data in decision-making processes.

The study began with the identification of critical failure modes and mechanisms of drawworks that had the severest impacts on production, safety, or the environment. Failure modes and symptoms analysis (FMSA) and fault tree analysis (FTA) were implemented to study the failure logic and symptoms. This process helped define the critical parts/systems that the data architecture could be built around, and provided a reasoning logic for decision-making, both qualitatively and quantitatively. The definition and collection of various data sets and dissemination of data were explained with a case study. In the end, the paper studied the role and competence of personnel in the new decision setting.

4 Case Study Results and Analysis

4.1 Failure Modes and Symptoms of Drawworks

Failure modes and symptom analysis (FMSA) is a systematic risk analysis tool, where failure modes, causes, local effect, and system effect are identified, following the guidelines defined by ISO [11]. FMSA analysis was performed at the component level of drawworks, and more than 80 failure modes were analysed [19]. The highest-ranking failure modes are listed in Table 1.

In the analysis, shutdowns of the whole system or threats to human safety or environment were all considered unacceptable. The analysis used the monitoring priority number (MPN) as an indicator to help prioritize the monitoring sequence of failure modes. The formula for calculating MPN is [10]:

$$\mathrm{MPN} = \mathrm{DET} \times \mathrm{SEV} \times \mathrm{DGN} \times \mathrm{PGN} \tag{1}$$

where, DET refers to probability of detection, SEV is severity of failure, DGN is diagnosis confidence, and PGN is prognosis confidence. The numbers for DET, SEV, DGN and PGN in the table are assigned subjectively from 1 to 5, which represents the degree of confidence from weak to strong. According to the definition of MPN, the higher its value is, the higher is its monitoring priority [10].

Table 1 Part of FMSA analysis.

FMSA of drawworks

System	Failure symptoms	Failure mode	Cause of failure	Local effect	System effect	DET	SEV	DGN	PGN	MPN
Drum assembly	Breakage of wireline	Structure deficiency	Off-design service: fatigue, or over holding weight	Possible drop of load, failure of drawworks	Drop of load	4	5	4	4	320
Braking system	Fast wearing of brake discs	Load drop	Maintenance error	Insufficient braking	Insufficient braking, drop of load	4	5	4	4	320
Braking system	Breakage	Structure deficiency	Off-design service: fatigue, or over holding weight	Possible drop of load, faliure of drawworks	Drop of load	4	5	4	4	320
Braking system	Brake power is not enough	Failure to stop on demand	Operation error: disconnection, loose items	Insufficient braking	Insufficient braking, drop of load	4	5	4	4	320
Braking system	Brake functions improperly	Failure to stop on demand	Maintenance error: pneumatic system error	Unexpected braking, failure to brake	Delayed drilling, drop of load	4	5	4	4	320
Electric motors	Unstable power output	Erratic output	Maintenance error	Decreased capacity of power output	Threat of ho isting/ lowering safety	4	5	4	4	320

(continued)

Table 1 (continued)

FMSA of drawworks

System	Failure symptoms	Failure mode	Cause of failure	Local effect	System effect	DET	SEV	DGN	PGN	MPN
Electric motors	Unstable power output	High output	Management error	Higher speed than expected	Threat of hoisting/ lowering safety	4	5	4	4	320
Drill control system	Switch failure	Failure to function on demand	Operating error: short/open circuit, or earth isolation problem	Loss of control of drawworks drilline/ braking system	Emergency braking triggered unexpected during ho isting/ lowering operation	4	5	4	4	320
Drill control system	Failure to respond on command	Failure to function on demand	Operating error	Loss of control of drawworks drilline/ braking system	Drop of load/ travelling block	4	5	4	4	320
Lubrication system	No rise in pressure	Internal leakage	Maintenance error	Loss of function of pumping	Stop of production due to automatic utilization of emergency braking	4	5	4	4	320

Adapted from Zhu [19]

4.2 Fault Tree and Reliability

In this paper, both qualitative and quantitative reliability analysis were needed for decision-making. Due to the limited reliability data from OREDA [16], electric motor was used to illustrate the process. There are two redundant electric motors in drawworks. The fault tree analysis (FTA) is depicted in Fig. 2.

Reliability and sensitivity analysis was implemented based on the FTA. Reliability data of electric motor was found in OREDA [16]. Failures of different parts was assumed to be exponentially distributed with parameter λ. Mean time to failure (MTTF) equals $1/\lambda$. The reliability of component i is calculated:

$$p_i = \frac{MTTF_i}{MTTR_i + MTTF_i} = \frac{MTTF_i}{MTTR_i + (1/\lambda_i)} \tag{2}$$

Terje Aven [2] suggested that Birnbaum's measurement could be appropriate in the context of oil production, as small changes in operation and maintenance performance might induce a large change in system reliability. The use of Birnbaum's measurement has been elaborated by some researchers [9, 18]. The importance of component i is calculated [5]:

$$I_i^B = h(1_i, p) - h(0_i, p) \tag{3}$$

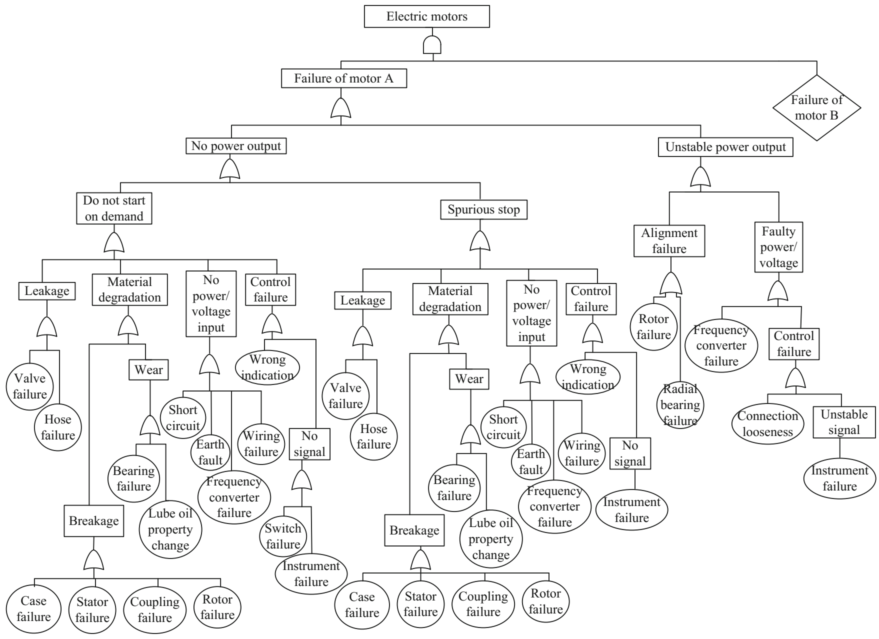

Fig. 2 FTA of electric motor in drawworks system [19]

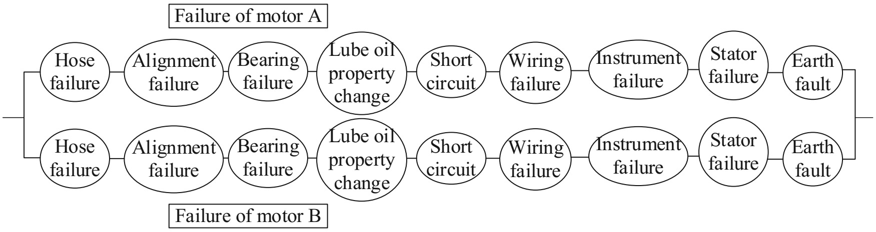

Fig. 3 Reliability diagram for electric motors. Adapted from Zhu [19]

where I^B is the measurement of importance for component i, $h(1_i, p)$ is the overall system reliability when component i is in its best condition, and $h(0_i, p)$ is the overall system reliability when component i fails.

In this case, the basic events in the fault tree were considered independent from each other, and the state of each component was set to be binary (either fail or function). A simplified reliability block diagram (shown in Fig. 3) was depicted based on the FTA, which were later used for reliability calculation. For the parts that were not recorded in the OREDA handbook, the reliability numbers were rounded up to 1 for simplification.

The results of Birnbaum's importance were shown in Table 2. The highlighted component (instrument failure) was the one that had the highest potential influence on the system reliability of the electric motor. It was thus suggested that maintenance in relation to the instrument parts be prioritized for continuous monitoring and preventive maintenance planning.

From the reliability analysis, it is noticeable that the difference of importance between the components/parts are small, but the difference can be big in other systems. Operators are recommended to establish and use their own databases to serve the purpose in addition to the reliability data from industry data base.

Table 2 Reliability calculation results with Birnbaum's importance measurement

Component	Failure rate (λ)	MTTF	MTTR	I^B
Bearing	4.128	242,247	1.4	0.000308867
Hose/pipe	0.458	2,183,329	2.6	0.000308865
Short circuit	0.916	1,091,665	7.5	0.000308867
Open circuit	0.458	2,183,329	7.3	0.000308866
Earth fault	0.916	1,091,665	6.7	0.000308867
Instrument failure	**10.094**	**99,069**	**15.3**	**0.000308913**
Alignment failure	0.916	1,091,665	5.1	0.000308866
Oil property change	0.916	1,091,665	4.2	0.000308866
Wiring failure	3.67	272,480	29.9	0.000308899
Stator failure	1.374	727,777	9.5	0.000308869

Adapted from Zhu [19]

4.3 Development of Data Architecture

Various data sources are created during the design, operation and maintenance of systems. How to manage data efficiently and effectively needs to be addressed. Different decision-makers have different needs and requirements on data. An integrated architecture to identify and access key data sets is a key element of data-driven decision-making. Liyanage [13] introduced a conceptual data architecture, where he discussed how key data sets should be defined in a holistic manner and how data should be disseminated depending on the specific context. In this section, the establishment of the data architecture of drawworks is explained in two main parts, which are data definition and data dissemination.

Definition of Data Sets

Project data include the system, location and field in which the drawworks is operated. ISO [11] defines the characteristics and attributes in defining and collecting equipment data, failure data, and maintenance data. Equipment data include the manufacturing information of the drawworks, its operating mode, operating power, the location of its applications and so on. Failure data needs to be recorded with the correct identification and with a time tag. Failure modes, possible causes, and potential consequences could be identified with the help of FTA and FMSA. In addition, it is suggested that failure data from both the operator and drawworks' suppliers are recorded and shared for a better understanding of the system. As proposed by ISO [11], maintenance data should cover the category of maintenance activity, the item maintained, the resources and manpower used, the impact from maintenance, downtime and so on. There can be overlappings of events between failure data and maintenance data, but they are stored with different criteria and serve different purposes. Reliability analysis, as explained in Sect. 4.2, uses failure history or industry database as the basis for calculation.

Building a contextual database is the key part of the data architecture and plays a critical role in O&M decision-making. The use of FMSA analysis explains how key monitoring parameters are defined, as discussed in Sect. 4.1. Table 3 shows the use of FMSA as a platform for discussing the technical options of gaining condition data. Alternative methods may exist to collect specific data, and the decision as to which method is more efficient and cost-effective belongs to the operator. The identifications of failure symptoms and failure mechanisms is helpful in implementing diagnosis and prognosis of the system.

Dissemination of Data

The basic principle of data dissemination is to make sure that the right people have access to the right data at the right time [8]. In the data architecture, data are used for both common and specific purposes. Common use data include project data, equipment data, industry database, and so on. These kinds of data provide the basic information of drawworks' operating context and environment and should be available and accessible for all personnel involved. Specific data include failure

Table 3 Approaches to gain condition awareness, based on FMSA analysis

System	Drum assembly	Braking system	Braking system	Braking system	Braking system	Electric motors	Electric motors	Drill control system	Drill control system	Lubrication system
Failure symptoms	Breakage of wireline	Fast wearing of brake discs	Breakage	Brake power is not enough	Brake functions improperly	Unstable power output	Unstable power output	Switch failure	Failure to respond on command	No rise in pressure
Condition awareness	Visual inspection	Visual inspection	Visual inspection	Test	Test	Torque monitoring	Torque monitoring	Visual inspection	Test	Pressure monitoring

data, maintenance data, reliability data, and contextual data of the drawworks. These data sets are directly connected to the history, condition and performance of the drawworks. Not all personnel need to access and understand these data sets, but these data are critical for maintenance engineers, drilling engineers, and so on, to gain context awareness, to optimize maintenance plans, and to implemented critical tasks.

In the case, condition monitoring system has not been applied with full scale on drawworks. One challenge was the lack of definition of critical parameters to monitor. Another major challenge was the lack of platform to integrate these data into decision-making. With the help of FMSA, the first challenge can be easily solved by analysing the components/sub-systems with the highest value on MPN and Birnbaum's importance measurement. For the second challenge, FTA results can be used as the platform for decision-making, both logically and with quantitative analysis.

4.4 Extended Competence Management

Three disciplines are involved in the O&M activities regarding drawworks, including drilling, maintenance, and safety. Based on the observations, employees with roles and responsibilities related to drawworks have been working in their positions for many years. The knowledge and competence of each discipline were observed to be specialized but comprehensive related to the tasks they performed.

However, the complexity of the conditions in which the drawworks is operated still keeps growing, even though the field has been developed for a long time. New sensors and equipment have been added, and new levels of safety and production performance are expected. The interconnections of different data sets, the knowledge from different domain experts and the decision alternatives are increasing. Making informed decisions in the way they used to do is becoming more and more challenging. There is a trend of different disciplines being expected to become multi-disciplinary to improve work performance [13]. In the new context, drilling engineers may be expected to understand safety concerns, as well as financial costs, from example. Companies need to realize that extended competence can play a key role in realizing the full value of the new data architecture, as well as in improving decision-making quality.

5 Discussion and Conclusion

The industry is moving towards an era with great appreciation of data and information. Decision makers are expected to continuously define critical data sets and to make efficient and informed decisions with the right data. A pressure vessel

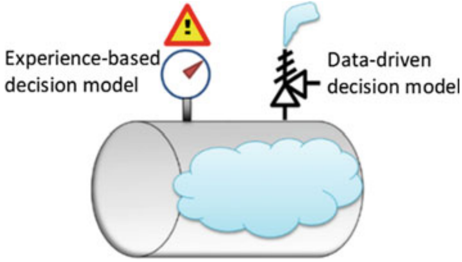

Fig. 4 Pressure vessel model for experience-based and data-driven decision model

model is used to illustrate the value of the data-driven decision method compared to traditional experience-based decision model, as shown in Fig. 4.

In the pressure vessel model in Fig. 4, either pressure gauge or pressure relief valve can be installed to respond to a possible overpressure scenario. The traditional experience-based decision model is just like the pressure gauge in the model, which only means something when someone with the right experience happens to notice it and knows how to react to it. The suggested data-driven approach is like the pressure relief valve, which comes with a whole solution for decision-makers, with the context awareness, failure modes and mechanisms, diagnosis, and consequences displayed and explained.

The paper promotes a normative approach to help decision-makers define the scope of key data sets as well as the process to establish a contextual data architecture for decision-making. The analysis tools that are used in the approach are known to most decision-makers in the offshore O&G industry sector, which makes the approach relatively simpler to be implemented. The method aims to provide some practices to help decision-makers gain control and confidence when too much data can become overwhelming and confusing. The approach can be used to assess other critical equipment or systems with simple adaptations.

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