Loughborough University

This item was submitted to Loughborough's Research Repository by the author.
Items in Figshare are protected by copyright, with all rights reserved, unless otherwise indicated.

Profitability, reliability and condition based monitoring of LNG floating platforms: a review

PLEASE CITE THE PUBLISHED VERSION

http://dx.doi.org/10.1016/j.jngse.2015.10.015

PUBLISHER

© The Authors. Published by Elsevier

VERSION

VoR (Version of Record)

PUBLISHER STATEMENT

This work is made available according to the conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) licence. Full details of this licence are available at: https://creativecommons.org/licenses/by-nc-nd/4.0/

LICENCE

CC BY-NC-ND 4.0

REPOSITORY RECORD

Gowid, Samer S.A.A., Roger Dixon, and Saud Ghani. 2019. “Profitability, Reliability and Condition Based Monitoring of LNG Floating Platforms: A Review”. figshare. https://hdl.handle.net/2134/20123.

Journal of Natural Gas Science and Engineering 27 (2015) 1495–1511

Contents lists available at ScienceDirect

Journal of Natural Gas Science and Engineering

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

Profitability, reliability and condition based monitoring of LNG floating platforms: A review

Samer Gowid [a, b, *], Roger Dixon [a], Saud Ghani [b]

[a] School of Electronic, Electrical and Systems Engineering, Faculty of Engineering, Loughborough University, P.O.Box LE11 3TU, Leicestershire, UK
[b] Department of Mechanical and Industrial Engineering, College of Engineering, Qatar University, P.O.Box 2713, Doha, Qatar

ARTICLE INFO

Article history:
Received 28 April 2015
Received in revised form
12 October 2015
Accepted 12 October 2015
Available online 23 October 2015

Keywords:
LNG liquefaction system
Reliability of LNG liquefaction system
Condition based maintenance
Floating
Production
Storage and Offloading platform (FPSO)
Acoustic emission
Vibration signatures

ABSTRACT

The efficiency and profitability of Floating, Production, Storage and Offloading platform (FPSO) terminals depends on various factors such as LNG liquefaction process type, system reliability and maintenance approach. This review is organized along the following research questions: (i) what are the economic benefit of FPSO and how does the liquefaction process type affect its profitability profile?, (ii) how to improve the reliability of the liquefaction system as key section? and finally (iii) what are the major CBM techniques applied on FPSO. The paper concluded the literature and identified the research shortcomings in order to improve profitability, efficiency and availability of FPSOs.

© 2015 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

Natural Gas (NG) is considered as the cleanest fossil fuel and holds several advantages over other energy resources such as the low emittance of harmful products and the high calorific value. In 2014, The International Energy Agency (IEA) predicted that the international demand for energy will increase by 37% and that the demand for Natural Gas (NG) will be more than 50% higher than the 2014 levels by 2040 (World Energy Outlook, 2014). The demand for NG kept increasing annually by 2.7% over the last decade and the global gas demand reached 3284 billion cubic meters (bcm) in 2010. NG came third behind oil and coal with a 21% share in the global primary energy mix. The IEA categorized United states as the first NG consumer as well as the second NG producer (World Energy Outlook, 2011). The U.S. Energy Information Administration (EIA) estimated that there are 2587 trillion cubic feet (Tcf) of technically recoverable NG in the U.S. This amount includes undiscovered, unproved, and unconventional natural gas which could significantly change the American markets of energy supply and use (Annual Energy Outlook, 2010). In the coming decade, NG and nuclear power will be on top of the list of most promising energy resources. However, the confidence of atomic based power generation was shocked due to Fukushima nuclear accident which hit Japan in 2011. This catastrophic accident increased the confidence of NG utilization and gave NG a bigger stake on future energy demand.

In 2013, EIA forecast that during the coming 28 years, NG will overtake coal and will be the world's second most widely utilized fuel after oil. EIA predicted that Liquefied Natural Gas (LNG) will take a bigger stake in overall supply of gas. Since the price of LNG is 50% cheaper than diesel, the economic performance of converting buses, trucks, ships to LNG is assured. Based on the Annual Energy Outlook (AEO) 2013 report and due to the huge demand for electricity, 63% of the new electricity generating capacity from 2012 to 2040 in the Reference case will be based on NG-fired plants, compared to 31% for renewables, 3% for nuclear and 3% for coal as shown in Fig. 1 (Annual Energy Outlook, 2013).

The LNG liquefaction process starts by treatment of dry lean natural gas after the steps of acid gas removal, dehydration, mercury removal, heavy hydrocarbon removal, and optional feed

* Corresponding author. School of Electronic, Electrical and Systems Engineering, Faculty of Engineering, Loughborough University, P.O.Box LE11 3TU, Leicestershire, UK.
E-mail address: samer@qu.edu.qa (S. Gowid).

http://dx.doi.org/10.1016/j.jngse.2015.10.015
1875-5100/© 2015 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

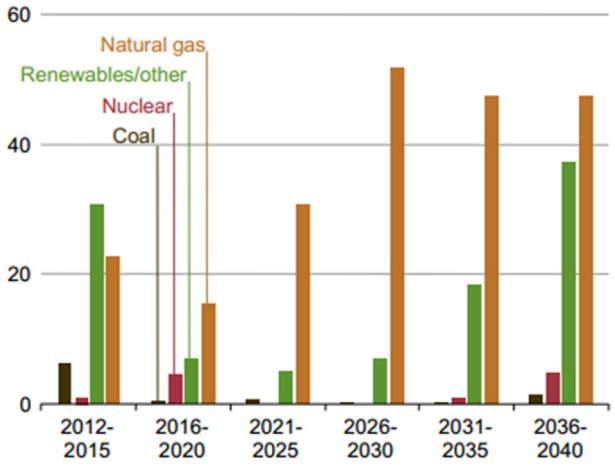


Fig. 1. Electricity generation capacity addition by fuel type (Annual Energy Outlook, 2013).

recompression. Further liquefaction processes involve the three basic processes of NG precooling to about −30 to −40 °C, liquefaction to about −120 to −135 °C, and subcooling to about −140 to −165 °C as shown in Fig. 2 (Bukowski et al., 2011).

The volume of LNG is about 1/600th the volume of NG. LNG is transported to receiving terminals using large ships. The LNG is typically off-loaded and stored into well-insulated storage tanks. In order to supply the NG through domestic pipeline distribution systems, the LNG must be restored to its gaseous form. The conversion process from LNG to NG is known as “regasification” (The Energy Department's Fossil Energy Organization).

LNG can be produced and stored in the sea and then transferred to the world market through carriers using FPSOs. Currently, the demand for FPSO platforms is increasing due to the increasing demand for LNG (Gowid et al., 2013; Haid, 2010).

Liquefaction is considered as the key process on FPSO terminals. The cost of LNG liquefaction plant ranges from 30% to 40% of the overall cost of LNG production plant. Liquefaction system failures may cause serious risk to FPSO terminal and its environment. To maximize the operational availability and minimize the associated cost of the liquefaction system on FPSO, the following factors must be taken into consideration: (i) configuration of system redundancy; (ii) applied maintenance strategy, and (iii) repair plan that takes into consideration that the ship is on the sea, and that spare parts are sometimes not available onboard (Pil et al., 2008). Mixed Refrigerant Cycle (MRC), N2 expander cycle, and Propane Precooled Mixed Refrigerant C3MR process are the three major liquefaction processes. The C3MR process has the highest economic performance and is selected by the majority of FPSOs manufacturers (Li and Ju, 2011).

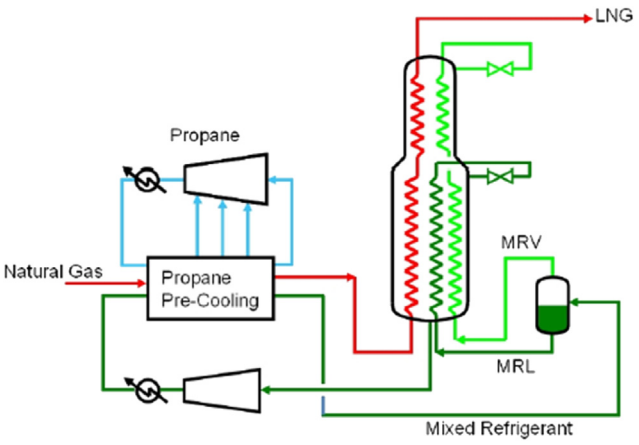


Fig. 2. Air products AP-C3MR™ LNG process (Bukowski et al., 2011).

The profitability of LNG production plant is directly affected by the applied maintenance strategy and LNG liquefaction plant reliability. Liquefaction plant's reliability is strongly related to system redundancy and also to applied maintenance strategy. Hence, reliability and maintenance strategy are the two main factors that increase the reliability and operational availability of C3MR liquefaction process and decrease its associated maintenance cost (Pil et al., 2008; Gowid et al., 2014). The total maintenance cost can be defined as the summation of shutdown cost, Preventive Maintenance (PM) cost and Corrective Maintenance (CM) cost.

Breakdowns in Oil and Gas production systems significantly affect the profitability profile of plants as shutdown and maintenance cost sharply increases with the increasing failure rates. Quick repair of breakdown equipment is critical. Due to the high shutdown and maintenance cost during failures, CBM was introduced to prevent equipment breakdown. With CBM, equipment are continuously monitored in an effort to decrease the repair time and to prevent breakdown (Rienstra, 2005). Unlike preventative maintenance, which is based on servicing a machine at scheduled intervals, CBM is based on equipment conditions such as its operating environment and assigned application (PuraDYN).

Since it is vital to maintain equipment before breakdown, CBM was introduced to prioritize and optimize maintenance resources to maintain the equipment at the right time. A CBM system determines the equipment's health, and acts only when maintenance is necessary. Ideally, CBM will minimize the cost related to spare parts, maintenance and system downtime. Detection of potential degradation and failure and maximization of useful life of a component give CBM a specific advantage over other maintenance strategies (Viktorov, 1967).

Fig. 3 illustrates the relationship between the total maintenance cost and the different maintenance strategies and standby redundancy strategy. The shutdown cost is associated with the production stoppage due to maintenance or failure. The switchover cost is associated with the production stoppage when the production is switched over from a main to a standby system. To ensure that the total maintenance cost is minimal, the standby redundancy strategy should be applied together with an effective CBM system. Hence, as the LNG liquefaction system has the highest failure rates, this review paper will focus on the research work carried out in the field of reliability and CBM of LNG liquefaction systems on LNG floating platforms.

Fig. 4 illustrates the expected maintenance cost reduction due to the application of different maintenance strategies. The Standby maintenance strategy with an effective CBM system has the potential of lowering the maintenance cost to its minimum as the cost of shutdown, switchover, PM will be eliminated.

This paper is divided into five sections. The first section introduces the economic importance of LNG, importance and advantageous of FPSO and CBM system, and the factors that affects the profitability of LNG FPSO. In section two, the economic performance of FPSO is compared to onshore plants. The cost effectiveness of the different types of liquefaction processes on FPSOs is identified and the liquefaction process is described. The reliability of the existing LNG liquefaction processes is investigated and concluded in section three. The most suitable reliability calculation approaches for LNG liquefaction systems are investigated and prioritized based on their performance in solving such reliability

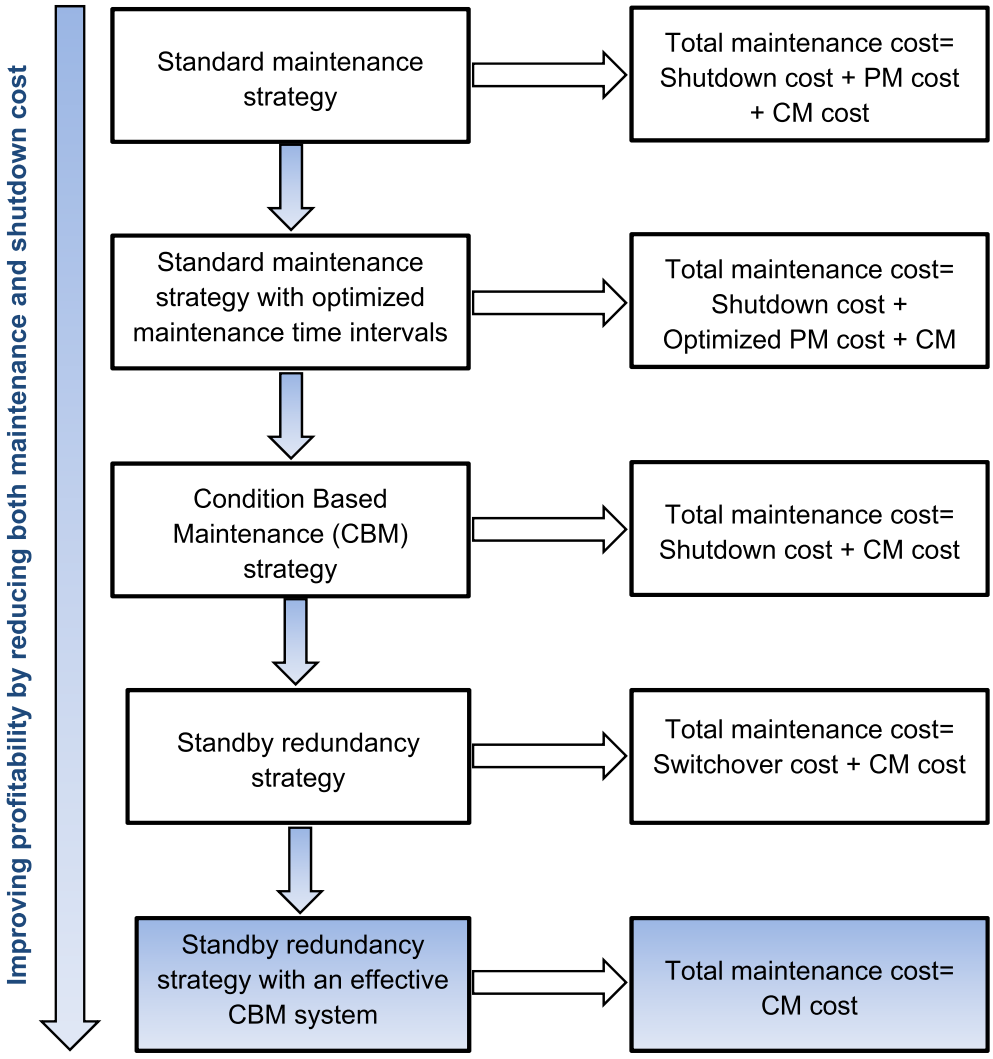


Fig. 3. Effect of applied maintenance strategy on total maintenance cost.

problems. Section four reviews the literature of CBM systems applied to rotating equipment and identifies their advantages and disadvantages. Finally the last section is a conclusion and a presentation of the research gaps that should be bridged to improve the efficiency and profitability of FPSOs.

2. Floating Production, Storage and Offloading platform (FPSO)

This section contains a survey of the benefits of FPSO. FPSO is a recent unit that can be effectively and realistically utilized for exploitation and utilization of marginal and offshore gas fields, where a pipeline network is not available, with a small number of wells and with limited recoverable reserves. FPSO is a floating LNG production plant that can produce and store LNG in the sea. The offloading facilities on FPSO allows the transfer of LNG product to LNG carriers and then to world markets. The LNG-FPSO is not only compact and mobile but can also be reused in other offshore fields (Yan and Yonglin, 2008). Fig. 5 shows a typical LNG-FPSO terminal. The main disadvantages of current FPSOs are (a) the low LNG production capacity (3.5 MTA), (b) the poor reliability of onboard centrifugal equipment and (c) the inherited difficulties in operation and maintenance logistics due to offshore location remoteness (T.

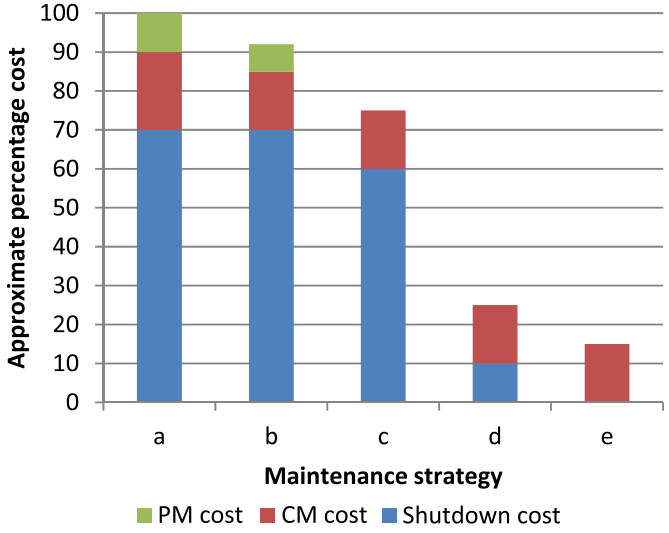


Fig. 4. Illustrative chart for the maintenance cost variation between the following proposed maintenance strategies: (a) Standard maintenance strategy, (b) Standard maintenance strategy with optimized PM, (c) Condition Based Maintenance strategy, (d) Standby redundancy strategy and (e) Standby redundancy strategy with an effective CBM system.

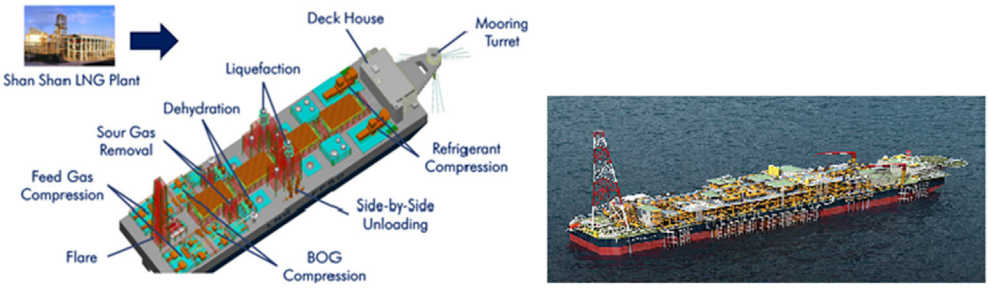


Fig. 5. Sanha – World's first LNG FPSO Terminal (Yan and Yonglin, 2008).

N. O. I. A. (OLF), 2011).

Yan and Yonglin, 2008 and Haid, 2010 reported the potential benefits of LNG FPSO and compared it to onshore LNG plants. It was concluded that the FPSO is cost effective and favorable for LNG production. In summary, the benefits of using the onshore LNG plants against the offshore FPSO terminals were compared and the researchers highlighted the extra benefits of using FPSO in current LNG industry. The cost and operational effectiveness of offshore terminals were demonstrated. The following points conclude the benefits of FPSOs (Gowid et al., 2013; Haid, 2010):

(i) up to 40% cost saving
(ii) shorter time to market
(iii) high utilization flexibility
(iv) compact in size
(v) Early production

3. LNG liquefaction system processes

This section provides a survey of the type and reliability of LNG liquefaction system processes. The section is organized into major LNG liquefaction process, Section 3.1 and LNG liquefaction system reliability, Section 3.2.

3.1. Major LNG liquefaction system processes

Liquefaction is the key process on floating LNG platforms and the profitability of FPSOs is directly affected by the availability of this system. There are three major LNG liquefaction processes namely Propane Pre-Cooled Mixed Refrigerant cycle (C3MR), Mixed Refrigerant cycle (MR) and Nitrogen Expander cycle (N2 expander). Although of the numerous advantages of N2 expander system, the C3MR process remains on top of the list of most utilized process due to its high economic process performance. Further research should be made to develop an LNG liquefaction process that combines the advantages of both of C3MR and N2 liquefaction processes.

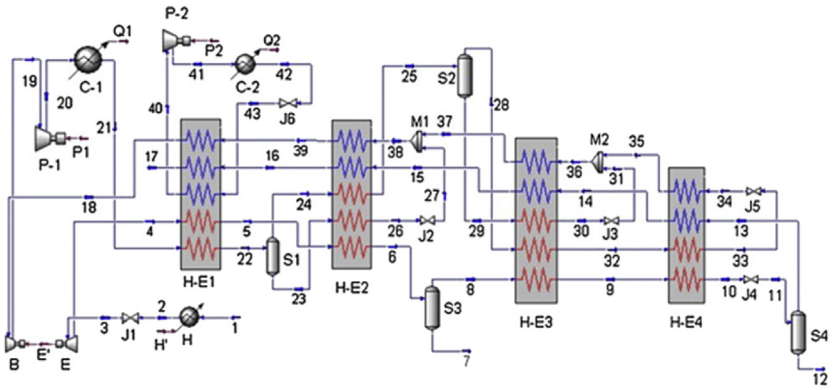
In a research study by Li and Ju (2011), three major LNG liquefaction processes were analyzed and systematically assessed. In the study, the C3MR, MR and N2 expander processes were investigated for the special offshore associated gases in South China Sea. These processes were analyzed and compared considering factors like performance parameters, economic performance, layout, sensitivity to motion, suitability to different gas resources, safety and operability, accounting for the features of the floating production, storage and offloading unit for liquefied natural gas (LNG-FPSO) in marine environment. A typical pre-cooled mixed refrigerant process is shown in Fig. 6. The process starts by lowering the raw natural gas pressure and temperature via a turboexpander (E). The low pressure mixed refrigerants are compressed by a centrifugal compressor (P-1) and then precooled via a simple propane cooling system (P-2). The natural gas is then cooled down through four huge series LNG heat exchangers (H-E1, H-E2, H-E3 and H-E4) to a very low temperature of approximately −165 °C. The liquefied form of natural gas is achieved when the output of the heat exchangers is throttled to the storage pressure. The booster/turbo expander set is employed in this system and the work recovered from the turboexpander (E) is utilized to drive the booster (B). The pipes lines are numbered according to the normal sequence of processes.

The result indicated that C3MR has the highest economic performance. The process based on N2 expander has the highest energy consumption and the poorest economic performance. Irrespective of these two points, the process has much more advantages over C3MR and MR for offshore application as it is simpler and more compact. The N2 expander requires less deck area, less sensitive to LNG FPSO motion, has better suitability for other gas resources, has higher safety and is easier to operate. Fig. 7 illustrates that, although the various benefits of N2 expander process, the C3MR and C3MR/split MR (precooled MR) remained the most popular liquefaction process in 2013, accounting for 66% of the total capacity of on service LNG trains (WorldLNG report, 2014).

Based on the World LNG report, the pre-cooled MR processes such as C3MR and Dual Mixed Refrigerants (DMR) have the highest process efficiency while the N2 process has the lowest process efficiency. In terms of production capacity, the precooled MR process has the largest capacity that normally ranges from about 1 to 5 + MTPA. While the capacities of other liquefaction processes are limited to about 1–2 MTPA per train. The advantages of the N2 process is that it uses entirely nonflammable refrigerant and is insensitive to vessel motions which makes it the safest LNG liquefaction process (Bukowski et al, 2013). It can be concluded from the previous research that there are various LNG liquefaction processes such as C3MR, MR, DMR, N_2 expander and Cascade are currently utilized (Li and Ju, 2011; Bukowski et al, 2013). The C3MR and DMR LNG liquefaction processes have the highest economic performance, and most of land-based LNG facilities use this type of process in the production of LNG.

The summary of the previous related work reviewed in this section is as follows:-

- The cost and operational effectiveness of FPSOs make it more preferable than onshore plants
- The features that affect the selection of FPSO LNG liquefaction processes are (a) process efficiency, (b) production capacity, (c) safety and (d) impact of vessel motion.
- C3MR liquefaction process has the highest process efficiency and most of LNG onshore plants utilize this process in the production of LNG.
- N2 liquefaction process is the safest LNG liquefaction process as the N2 refrigerant is nonflammable and the process is not sensitive to vessel motions.



H-E1, H-E2, H-E3 and H-E4, LNG heat exchangers; S1, S2, S3 and S4, separators; M1 and M2, Mixers; P-1 and P-2, compressors; C-1 and C-2, after coolers; H, heater; B and E, booster/turbo expander; J1-J6, valves; P1, P2, Q1, Q2, E' and H', energy; numbers of 1-43, pipelines.

Fig. 6. C3MR LNG liquefaction process (Li and Ju, 2011).

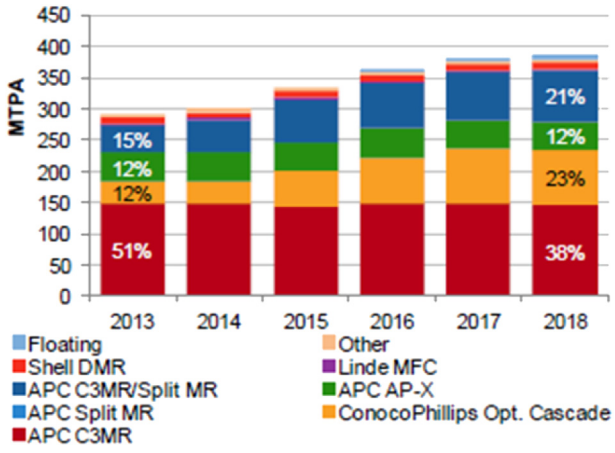


Fig. 7. Liquefaction capacity by LNG process type (WorldLNG report, 2014).

3.2. LNG liquefaction system reliability

The reliability of LNG liquefaction plant is of high importance as it directly affects both profitability and safety on FPSOs. Failure rates of liquefaction systems on LNG floating platform are high (OREDA, 2009) and the repair times for these failures takes longer time than onshore repairs. All liquefaction system components are exposed to wear out which results in increasing the failure rates with time if no maintenance is carried out (Rausand and Hyland, 2004). The research papers that are summarized below (in Section 3.2.1) introduced reliability analysis as used in the oil and gas industry for a number of different types of terminals and discuss the different reliability analysis methods utilized to calculate the reliability of systems. This sets the context for the reliability work later in this paper, as does the comparison of Markov versus Fault Tree methods which follows in Section 3.2.2.

3.2.1. Reliability in oil and gas industry – state of art

Many authors have considered applying reliability analysis to the oil and gas industry. For example, a number of books introduce the subject (Calixto, 2012; Peters, 2014). Researchers from academia and industry have also shown an interest in the area with papers addressing both the system level issues (Pil et al., 2008; Aven, 1987; Cheng et al., 2009; Gu and Ju, 2011) and issues with particular components in the industry such as gas turbines (Sarkar et al., 2012), compressors (Miranda and Meira, 2008), induction motors (Thorsen et al., 1995), pipelines (Yuhva and Datao, 2005), and bearings (Caroni, 2002). However, many of these studies are indirectly relevant to this study.

Although there are a large number of researches investigated the reliability in different areas, a research gap is observed in studying the reliability and in introducing the redundancy to LNG liquefaction systems. Pil et al. (2008) assessed the reliability of Boil-off Gas (BoG) Systems on LNG carriers with a focus on maintenance strategies and redundancy optimization. The objectives of the work were to: (i) consider and asses the feasibility, reliability and operational availability of the usual LNG re-liquefaction plant options for installation on a large LNG carrier; (ii) evaluate the financial benefits for either total or partial redundancies of the re-liquefaction plant and confirm the preferred option for large LNG carriers, and (iii) offer the basic strategy for establishing a maintenance policy for the LNG re-liquefaction plant. A typical liquefaction and re-liquefaction plant diagram is shown in Fig. 8. The figure shows the BoG (solid line) exciting the cargo tank and entering the preparation system, where the mist droplets are eliminated before compression. The BoG is cooled, if it need be. The BoG is then compressed and sent to the BoG liquefaction, in this case, a cold box, where the BoG is liquefied after indirect contact with cooled nitrogen gas in a cryogenic heat exchanger. To minimize the investment cost, efforts were made in combing the LNG re-liquefaction plant with a Gas Combustion Unit (GCU) rather than introducing various redundancies in the LNG re-liquefaction plant. Results showed that in the assumption of no repair on board, the redundant system was more economical and efficient than the GCU. The argument for choosing the redundant system was reinforced by the fact that the implantation of full onboard corrective maintenance is most likely impossible. Regarding the maintenance strategies, results showed that both the Preventive Maintenance (PM) and the Corrective Maintenance (CM) cost were significantly higher than flaring. The reason for this was that the system availability is relatively high even without introducing the redundancy on the N2 compressor system. It is clear that this type of approach could be extended to the LNG liquefaction systems.

Gowid et al. (2014) assessed and optimized the system reliability and preventive maintenance intervals of propane pre-cooled mixed refrigerant (C3MR) liquefaction system on FPSO. The authors developed a Markov model for the C3MR liquefaction system,

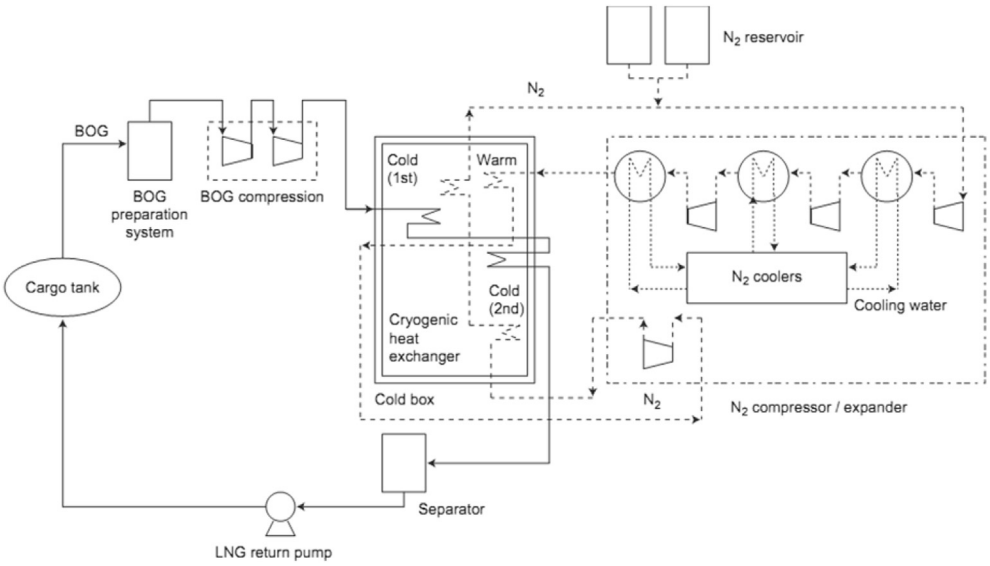


Fig. 8. Typical liquefaction and re-liquefaction plant diagram (Pil et al., 2008).

optimized the associated preventive maintenance cost and introduced system redundancy. The cost analysis demonstrated the cost effectiveness of introducing a 100% standby system for the primary liquefaction system. The application of such redundancy scheme will increase the system availability from 85.30% to 97.81% as well as it will increase the annual profitability by 187.65 million USD (from 1279.5 million USD to 1467.15 million USD and based on an LNG price of 50 USD/Mt). The results of this study needs to be supported by further studies on the reliability and cost effectiveness of the introduction of redundancy to LNG liquefaction plants. Further researches should be carried out to study the reliability and redundancy introduction to all LNG liquefaction systems.

3.2.2. *Reliability calculation methods*

Markov Analysis (MA) and Fault Tree Analysis (FTA) are two well proven analysis techniques that are utilized in systems reliability calculation. Complexity of design and accuracy of results are the major parameters that should be taken into account before deciding the most suitable analysis technique for the system (The Energy Department's Fossil Energy Organization).

MA is a technique developed by Andrei Markov to calculate the availability and reliability of systems with dependent components. The analysis is based on state transition diagram that identifies all system discrete states as well as all possible transitions between these states. MA model is time dependent and considers the transition rates which make this method favorable for calculating the reliability of time dependent systems (Pukite and Pukite, 1998). FTA is an analytical logic technique developed in Bell Telephone Laboratories to calculate the availability and reliability of systems. The analysis is based on fault tree diagram which is built top-down and takes system discrete state as top event and components states as basic events. Logic gates (AND and OR) are then utilized to interconnect the events and conditions (Stamatics, 2014). Although this technique does not consider the transition time from one state to another, its simplicity in modeling and calculating the reliability of complex system makes it preferred than MA.

Andrew and Ericson (2000) compared the accuracy of reliability calculation techniques. Table 1 shows that Fault Tree Analysis (FTA) and Markov Approach (MA) yielded the same result for series, parallel and hot standby systems. The MA and FTA reliability equations for full monitoring, sequence parallel, and cold/warm standby systems were different, making the result of FTA an approximation. Although it was believed that MA produces more accurate results than FTA, this work stated that the FTA is accurate and that, for many design complexities, FTA produces similar results accuracy as MA. In addition, the authors observed that FTA is much easier in modeling large systems and yielded acceptable results. Table 1 concludes the summary of results.

Table 1
Comparison between FTA and MA results accuracy (Andrew and Ericson, 2000).

Consideration	FTA	MA
1. Models undesired events	√	Partially
2. Models probability	√	√
3. Models unavailability	√	√
4. Series system	√	√
5. Parallel system	√	√
6. Sequence parallel system	Approx.	√
7. Full monitor system	Approx.	√
8. Partial monitor system	Approx.	√
9. Standby redundancy system	Approx.	Difficult
10. Repair	√	√
11. Latency	√	√
12. Large models	Approx.	√
13. Dependencies	√	No
14. Coverage	√	√
15. Easy to follow model	√	No
16. Easy to document process	√	No

Norm Fuqua (2003) observed that fault trees and reliability block diagrams are widely utilized in predicting safety of complex systems, maintainability and reliability but they cannot accurately model the behavior of dynamic systems. The author found that the MA technique is best in analyzing dynamic systems and referred this to the capability of MA technique in analyzing complex, faults tolerant, highly distributed and dynamic systems. The conclusion of Andrew and Ericson (2000) and Norm Fuqua (2003) is in agreement and showed that the effectiveness of both techniques depends on the size and type of system. The studies concluded that FTA is easier in modeling large systems and that Markov gives a better accuracy in calculating the reliability of dynamic systems such as sequential and cold/worm standby systems.

Ridley and Andrews (1999) presented an improved model for reliability calculation of standby dependencies and sequential

systems using FTA and MA. Two new gates were introduced into the fault tree diagram to allow reliability calculation of standby and sequential systems using MA. Both FTA and MA were utilized to outline the new model. The authors extended the FTA to allow an accurate reliability calculation for both standby and sequential systems. The main disadvantage of FTA is that it gives an approximation when used to calculate reliability of dependent systems while the main disadvantage of MA is the complexity of the construction of Markov state transition diagram. The new model overcame the drawbacks of both FTA and MA by improving the accuracy of FTA and by significantly reducing the complexity of MA. Pil et al. (2008) modeled the BoG and N2 compressor systems using Markov approach. For each of these two systems, a redundant standby system of the same type is added. Because of the unique ability of MA in handling dynamic cases, it was used to calculate the reliability of the system. Cheng et al. (2009) selected the FTA technique to calculate the reliability of the Emergency Shutdown System (ESD). The authors found that FTA is widely utilized for providing logical functional relationships between system components and subsystems and for identifying the root causes of the undesired system failures. Pil et al. and Cheng et al. utilized the MA and FTA approaches in modeling the BoG and ESD systems. Kwang et al. used the MA in modeling the BoG system taking into account the time dependent transition rates (dynamic systems) while Cheng et al. utilized the FTA approach because of its proven effectiveness in modeling complex and big system.

The summary of the previous related work reviewed in this section is as follows:-

- The introduction of a 100% standby system to BoG liquefaction process significantly improved the system reliability.
- Markov chain approach is preferred over FTA in calculating the reliability of time dependent (dynamic) systems such as sequential and standby redundancy systems but the complexity of the construction of Markov state transition diagram makes it difficult to implement on big systems.
- There are a very few research papers addressing the reliability optimization of C3MR LNG liquefaction plants. A research gap was identified in investigating the system reliability of MRC and N2 expander LNG liquefaction plants on FPSOs.

4. Condition based maintenance of rotating equipment

This section contains a survey of the recent techniques and results of CBM systems. The section is organized into typical CBM systems, value and challenges, Section 4.1, model based diagnostics technique, Section 4.2.1 and signal based diagnostics technique, Section 4.2.2 and features selection techniques, Section 4.3.

Condition based monitoring is a process that utilizes the most appropriate technology and sensors to record a number of characteristics or parameters of equipment. Condition Based Maintenance (CBM) is a maintenance strategy that utilizes the monitoring process to decide what kind of maintenance should be carried out. This can be achieved by analyzing various measurable data in relation to operating machines. CBM detects early changes in characteristics, parameters and trends, to identify the deteriorating component's state prior to failure. This helps to enable rectification without incurring the disadvantages resulting from loss of production due to unplanned shutdowns. In contrast, fault diagnostic processes identify the faulty component along with the cause of the fault after the occurrence.

Many authors have considered developing CBM systems for rotating machinery. A number of these research papers assessed the suitability of implementation of various condition based maintenance techniques to the fault detection of rotating equipment such as sound, vibration, process information and AE and are summarized below (in Sections 4.2.2.1 and 4.2.2.2). Other research papers investigated on the advantages of utilizing mutli-fault detection techniques and these research papers are summarized in Section 4.2.2.2. However, no researchers have developed a "lookup table" that characterizes the best techniques and signal features for the fault detection of rotating equipment. Automated features selection process has a key role in CBM systems and come next to the selection of the most appropriate fault detection technique. Therefore, as summarized in Section 4.3, many researchers have developed different approaches to select the best sets of signal features to improve the detection of faults and to decrease the developing cost and time of the features selection process. However, the existing features selection approaches still in need of development in terms of accuracy and development time.

4.1. Typical CBM systems, value potential and challenges

Maintenance cost is a significant part of the operating cost of production or manufacturing plants. Depending on particular industry, maintenance cost can represent 10–40% of the cost of final product. Distinct from preventive maintenance strategy, Condition Based Maintenance helps to reduce or eliminate unnecessary repairs, increase the profit by reducing maintenance cost and prevent disastrous machine failures (Hurdle et al., 2009; Lampis and Andrews, 2009). CBM relies on mechanical condition's regular monitoring of different trains of actual equipment. Operating efficiency of equipment train will guarantee maximum repair intervals and will lower the cost and frequency of unscheduled maintenance. Significant improvements may be achieved in: unexpected machine failures, maintenance cost, repair downtime, and spare parts inventory. In fact, CBM is a condition-driven preventive maintenance approach that minimizes the maintenance cost and maximizes the operational availability of systems (IAEA-TECDOC-1551, 2007). Thus, an ongoing effort is made to shift from PM to CBM.

Effective fault detection techniques are essential to implement the maintenance strategy of CBM. The efficiency of these techniques depends on the accuracy of identifying the correlation between fault situations and signal features using different fault detection techniques such as machine process information, vibration, sound and acoustic emission. Many fault detection techniques have been proposed in this field. Each technique has its own merits and demerits. Fault diagnostic is still a challenging problem as a numerous fault situations can possibly affect the accuracy of detection due to the improper selection of signal features' sets or due to the existence of fault interference and noise.

Fig. 9 shows a typical CBM system which continuously monitors the status of system components and acts only when a component is about to fail. The process starts by reading the signals coming from sensors through a data acquisition system. The received signals are then passed to a features extraction algorithm to extract the best features of signals and then pass them to a fault diagnostic/decision making algorithm. The Decision making algorithm is trained using a set of machine fault signatures which is collected through either signal based or model based techniques. After the decision making algorithm being trained, the algorithm compares the signal features of the current machine condition with the signal features of the fault signature. Then, a real-time decision (faulty of healthy) will be made based on the current condition of system components. Effective fault diagnostic algorithms will also determine the faulty components and the fault type.

Fig. 10 illustrates the features selection process using signal based diagnostics technique. The experimental determination of the best features sets of different machine fault signatures consists of three major processes. The first process is to determine the most

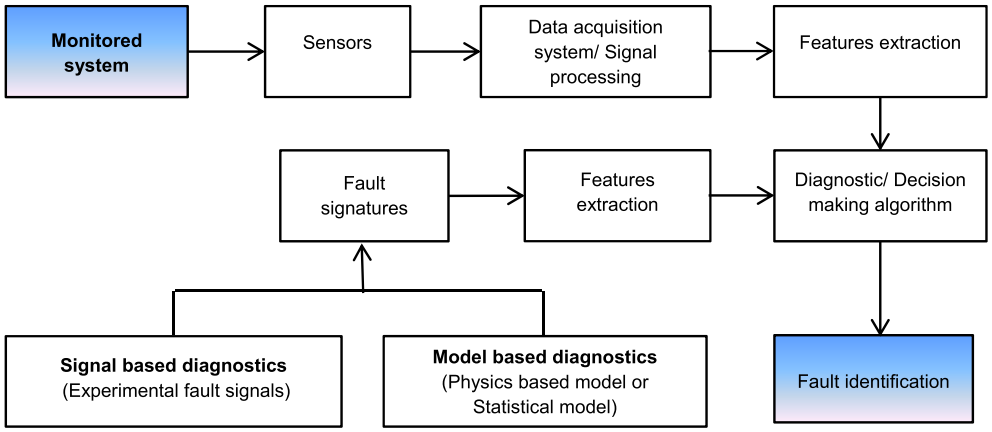


Fig. 9. A typical CBM system.

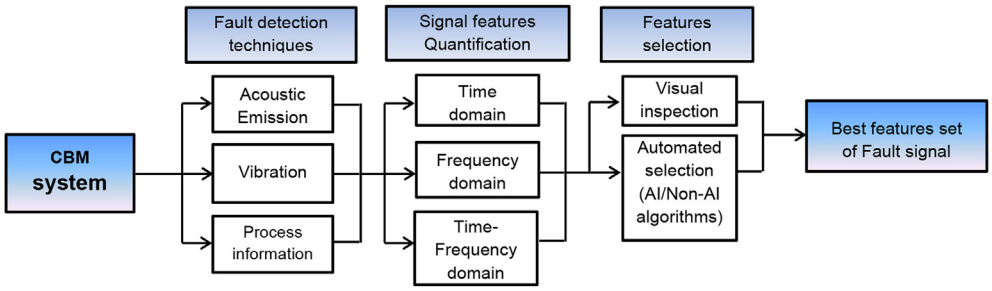


Fig. 10. Selection process of best features set of machine fault signal using signal based diagnostic technique.

suitable fault detection technique or combination for diagnosing faults in machine, the second process is to select the features type that would give the largest differences between different fault patterns (time domain, frequency domain or time frequency domain feature), and the last phase is to process and analyze the signal to select the best set of features for the automated detection of machine condition.

4.2. Diagnostic techniques

Fault Diagnostic process is divided into four stages; detection, diagnostic, identification and then prognosis of faults. The fault is to be detected when a change in condition parameters is observed. The fault diagnostic includes two main processes; the first process is the fault identification and the second process is the fault isolation to determine the location of the faulty component. The fault can be diagnosed through a quantitative comparison between different machine condition patterns. The fault identification process provides information about the size of fault and the time of fault onset while the prognosis provides a long term prediction for industrial applications. Arguably, due to the stochastic processes that failure events are yet to occur, the formulation of prognosis is more complex than diagnostic (Galka and Tabaszewski, 2011). The diagnostic technique can be effectively assessed based on the following factors (a) detectability of fault, (b) effect of noise on fault detection and (c) fault can be easily distinguished from other known and unknown faults. This section reviews the major fault diagnostics techniques of CBM systems. The section is organized into model based technique, Section 4.2.1 and signal based technique, Section 4.2.2.

4.2.1. Model based technique

Models utilized for fault diagnostic are categorized into physics based models, Section 4.2.1.1 and statistical models, Section 4.2.1.2.

4.2.1.1. Physics based models. Physics based models usually utilize mathematical models that are directly related to physics parameters that have direct or indirect effect on the health of system components. The diagnostic process is based on the values of residuals which are commonly generated using Kalman Filters, Interacting Multiple Models and Parity Relations (Yan, 2015). Fig. 11 shows a typical physics based model for CBM systems. The physics based model approach helps understanding the physics of the system and hence enhancing the model based on the comprehension of system deterioration. However, the difficulties associated with this technique are that the developed model is to be validated using a large number of actual data sets and the model development process requires special knowledge with mathematics and theories relevant to the monitored system.

Ginzinger (2010) presented a model based condition monitoring of auxiliary bearing. A multibody simulation environment was utilized in the modeling of the rotor system shown in Fig. 12. A number of fault simulation parameters were optimized to align the simulation results with the measurements. Two different faults were successfully identified based on the developed model.

Charles et al. (2008) developed two models to simulate both wheel-rail profile and low adhesion contact. The results of the simulation were fed into a CBM system to monitor the condition of wheel-rail interface. Ugechi et al. (2009) proposed a model based condition monitoring to diagnostic faults in centrifugal pumps. The model was validated using vibration data of a centrifugal pump. Guo and Parker (2010) developed a model based condition monitoring of planetary gear tooth wedging of a wind turbine system.

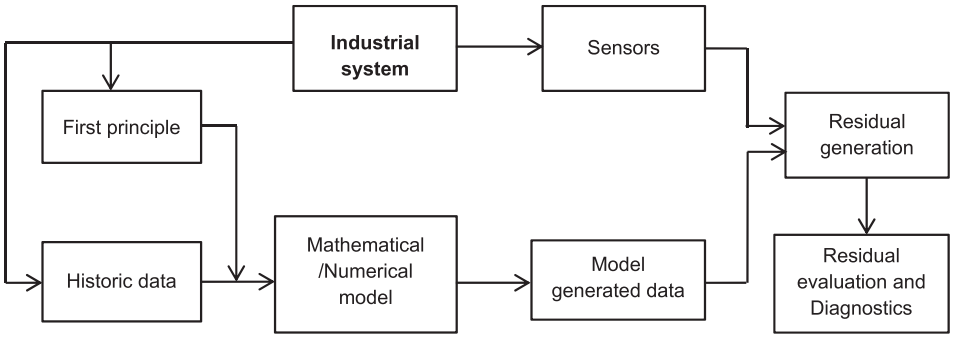


Fig. 11. Flowchart of a typical physics based model for CBM systems (Yan, 2015).

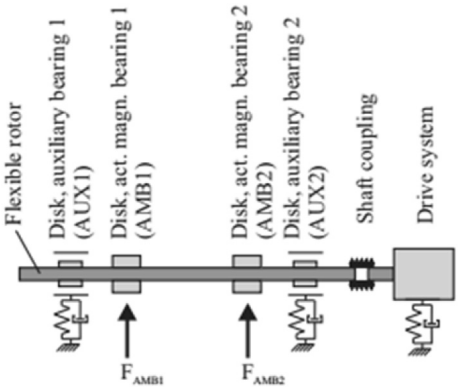


Fig. 12. Modeling of auxiliary bearing dynamic response (Ginzinger, 2010).

The model shown in Fig. 13 was utilized to predict vibration signals resulting from the nonlinear tooth wedging behavior. The model also considered back-side contact, tooth separation and bearing clearance. It can be observed that Guo and parker verified the analytical model using a non-verified finite element solution. Further investigations should be carried to apply the results of this study to an actual wind turbine system.

In real world, for all model based approaches, serious modeling inaccuracies occurring due to parameters drift. The majority of the developed models are linear and cannot handle non-linear systems. Linearization of non-linear systems results in a significant effectiveness reduction of the technique. The modeling of full scale process is difficult as it includes a number of non-linear relationships which increases the computational complexity and hence error (Venkatasubramanian et al., 2003).

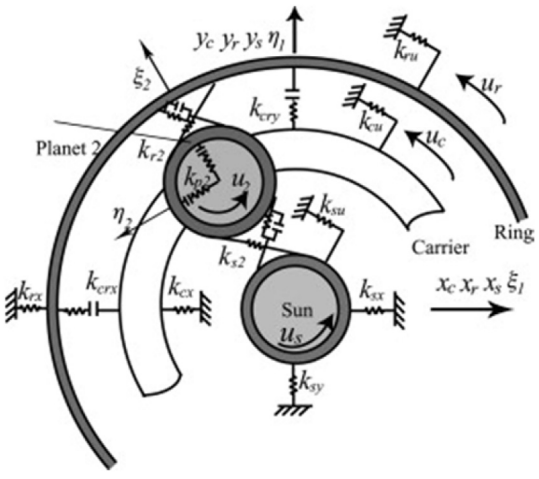


Fig. 13. 2D dynamic model of planetary gear lumped parameter (Guo and Parker, 2010).

4.2.1.2. Statistical models. Statistical models are based on statistical time series measurements. In faulty conditions, statistical parameters such as mean and standard deviations values deviate from their benchmark values. Multivariate statistical techniques such as Principal Component Analysis (PCA) and Partial Least Square (PLS) proved their effectiveness in compressing the data and in handling correlation and noise to effectively extract true information. The main function of these techniques is to transform a large number of process related variables to a smaller set of uncorrelated variables (Venkatasubramanian et al., 2003).

Hurdle et al. (2009) and Lampis and Andrews (2009) developed two CBM approaches based on the available historical data. The first approach was based on FTA while the second approach was based on Bayesian Belief Networks (BBNs). Both approaches utilized the historical data for training and then performed the detection by comparing the current system performance to the historical data of sensors. The BBNs approach had more advantages over FTA as it ranked all possible faulty components based on their failure probabilities while FTA identified a single component only. Although Hundle et al. and Lampis et al. demonstrated the effectiveness of these FTA and BBNs, the fault diagnostic performance was not properly determined. Shang et al. (2009) investigated implementation difficulties of intelligent diagnostic on reciprocating compressors due to the lack of actual fault samples. Thus, the authors proposed Support Vector Machine (SVM) technique that is based on statistical learning theory in order to overcome that deficiency and to prove a new way for diagnostic technology. The approach was implemented into an intelligent diagnostic which can accurately recognize faults and in a rapid way. The main disadvantage of this work is that the model has not been verified due to the lack of actual fault signatures. Percentage difference between the addressed machine conditions' signals features was not determined. Quantification of differences between machine conditions' signal features can be utilized in measuring the certainty\confidence level of CBM approaches. Galka and Tabaszewski (2011) utilized the lifetime historical data in diagnostics of machines. The symptom value fluctuations were utilized for machine learning. An energy processor model was developed to verify the results of this study. It can be observed that Galka and Tabaswewski did not verify the developed model. The main advantage of having a model of the system is that it can allow the simulation of numerous faults and this can help investigating the fault interference issue.

In general, statistical models are easier than explicit system models. Although statistical models are powerful in revealing the

presence of abnormality, the fact that they do not have a fault signature for each fault makes fault isolation process difficult. However, Enhanced PCA showed some improvement on the differentiation between different process conditions (Miller, 2006).

4.2.2. Signal based technique

Several fault diagnostic systems provide real-time or continuous monitoring of rotating plant equipment for CBM. These diagnostic systems utilize either statistical or experimental data sets for training. They vary from simple devices such as vibration switches that can produce alarm signals as well as machine shutdown information, to highly sophisticated multi-channel monitoring devices that include time to frequency domain conversion, expert data analysis and features extraction algorithms in order to detect various machine faults as well as to evaluate the severity of each fault. These systems detect and isolate faults in order to ensure a smooth and safe machine operation. The learning process of CBM can be performed using either historical or experimental data.

4.2.2.1. Condition based maintenance using sound, mechanical vibration and process information techniques. The previous research on condition based maintenance using sound levels, mechanical vibration and process information is reviewed in this section. Toprak and Iftar (2007) utilized the sound pressure level to diagnose machine faults. The authors studied five faults of compressors that are among the most common faults. A Multilayer Perceptron Network (MLPN) was proposed to identify the five faults. The MLPN was trained using the back propagation algorithm. Training and testing data were obtained by Sound Pressure Level (SPL) measurements of ten selected compressors. Recordings and measurements were carried out in a semi-anechoic sound test room with 12 microphones. Two different techniques were utilized in data analysis. In the first approach, the weighted average of all 12 microphones' measurements was used. The second technique separately used all data from individual microphone; this means larger data files and more computation time for the MLPN training, when compared to the first approach. As shown in Table 2, each fault was precisely identified using the second approach when a sufficient training was performed.

Toprak and Iftar's research stated that separate utilization of each microphone data technique is more accurate than using the weighted average SPL of the 12 microphones if sufficient training is performed. The authors managed to demonstrate their proposed approach but the high ratio between the training and testing datasets and the high computing time and cost were the main disadvantage of this work.

Condition based maintenance using vibration signatures is one of the major fault detection techniques. Spectral and time domain features are the main vibration signal analysis methods. Vibrations of machines usually result from dynamic forces due to moving structures and parts. Different machine conditions can be detected by identifying their corresponding fault symptoms, for example, mechanical vibration, changes in process parameters such as temperature, efficiency and air borne noise (Scheer, 2014). Detections in vibration analysis show a repetitive motion of the surfaces on rotating or oscillating machines. This repetitive motion may be caused by an unbalance, a misalignment, a resonance, electrical effects, rolling element bearing faults, or any number of other causes. To determine the current and future operating condition of the machine, it is vitally important to know the previous degradation pattern and the history of the machine. The major vibration characteristics of rotating equipment are displacement, velocity acceleration, Frequency, and phase angle (IAEA-TECDOC-1551, 2007). In vibration spectra, “low” and “high” frequency ranges can be observed. The various types of vibration frequencies in a rotating machine are directly related to the geometry and the operating speed of the machine. By knowing the relationship between the frequencies and the type of defect, vibration analysts can define the cause and severity of faults or problem conditions. The low vibration range contains component frequencies produced by rotational motion (harmonics). While the high vibration range contains component frequencies resulting from the interaction between fluid-flow system and medium flow. In a power steam turbine, blade frequency range (latter) is typically from a few hundred hertz to about 10–20 kHz, depending on the turbine design (Boller et al., 2009; Orlowski, 1989). Shang et al. (2009) introduced a SVM-based intelligent diagnostic system for reciprocating compressors. This approach was utilized due to the lack of actual fault signatures of the different fault situations for compressors. The main disadvantage of this approach is that the difference in values between the addressed machine condition signals' features is unknown. The quantification of differences between machine condition signals' features can be utilized in determining the certainty/confidence level of CBM approaches. Wang and Hu (2006) utilized the vibration technique to investigate ambiguities and uncertainties that exist among pump failures and faults symptoms. A new approach for solving the existing problems of pump fault diagnostic was presented. Fuzzy logic was used to model the ambiguity and uncertainty relationship between different pump faults, analyze the fuzzy at different phases of fault diagnostic, and determine the frequency spectrum that represents the addressed pump faults. Analysis of the vibration signals of the pump was made to extract the diagnostic features from the spectra. The fuzzy membership function, that was necessary for the pump fault diagnostic, was then created using condition variables based dynamic signal processing. Fig. 14 shows two vibration spectra for the faulty device. The authors concluded that the addressed faults were detected according to de-fuzzy diagnostic criteria and through a fuzzy comprehensive discrimination. It can be concluded that the traditional spectral vibration signature technique is a

Table 2
Summary of the experiments results (Toprak and Iftar, 2007).

	Analysis	# of Training data set	# of Test data set	# of Success	# of Failures
1st Approach	1	30	30	30	0
	2	60	6	6	0
	3	30	30	14	16
	4	54	6	3	3
	5	54	6	3	3
2nd Approach	6	30	30	20	10
	7	30	30	19	11
	8	54	6	6	0
	9	54	6	6	0
	10	54	6	6	0
	11	54	6	6	0

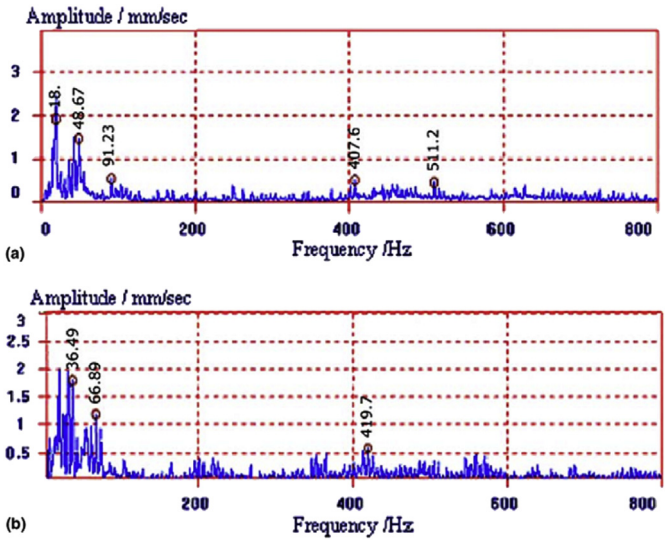


Fig. 14. Two frequency spectra represent (a) sample fault, (b) second fault with the same sample fault on the second inlet valve (Wang and Hu, 2006).

difficult approach for the diagnostic of pump faults. The difficulty comes from the fact that the differences between various faults symptoms and events are uncertain. Thus, the authors established a new fuzzy membership function in order to address the interference problem. However, the accuracy of the proposed technique is not quantified and it is not clear whether the proposed approach completely addressed the problem. Furthermore, the work did not investigate the problem of faults interference that strongly affects the vibration signals.

Liao and Huang (2010) observed that windowing the signals in Fourier Transfer causes misrepresentation of vibration signals and frequency distribution spectra were not clear enough for shock vibration. Furthermore, it was difficult to extract good spectral features because of the distribution of frequency sidebands in frequency modulation. Auto-Regressive analysis (AR) was utilized to analyze the signals in time domain. The differences between AR coefficients were calculated by deducting the AR coefficients of faulty centrifugal compressor signals from healthy centrifugal compressor signal. Neural network was trained to model the relationship between faults and AR coefficients differences. The diagnostic results obtained by using neural network with difference of AR coefficients were better than the results of neural network with AR coefficients and distance approaches. It can be concluded that time series analysis has advantages over frequency domain analysis and that the accuracy of neural network with differences of AR coefficients is better than the accuracy of neural network with AR coefficients. The detection accuracy was not reported in numeric and no concurrent faults were emulated to investigate the fault interference issue.

Condition based maintenance using process information demonstrated its effectiveness in diagnosing a number of machine faults. The fault detection performance is directly affected by the selection of proper information in addition to the utilization of an effective decision making algorithm such as decision table and Fuzzy logic based algorithms (Hafaifa, March 2010; Elha et al., March 2010). Zanoli et al. (2010) proposed a fault detection method for a compression process that is built in the Integrated Gasification and Combined Cycle (IGCC) part of a refinement plant. Single and multiple faults were considered that may cause sensor reading errors in the process actuators. Principal Component Analysis (PCA) is used in a multivariable data-driven approach to monitor chemical process performance. A procedure to determine number of principal components ANOVA was proposed. Faults detection and isolation were tested and validated on the plant. Hafaifa (2010) presented a method for compression system fault diagnostic using Fuzzy Fault Detection and Isolation (FDI). It is an alternative to the compression systems supervision task using model-based FDI along with self-tuning of surge measurements with appropriate corrective actions. By combining this approach with fuzzy logic, it was possible to devise a fault-isolation system based on a given incidence matrix. The experimental results confirmed the effectiveness of the proposed approach. Elha et al. (2010) studied practical usage of two different CBM techniques. Namely, Dynamic Cylinder Pressure (DCP) and crankshaft Instantaneous Angular Speed (IAS). Conventional transducers for machine monitoring were utilized in their experiments. The authors proposed a monitoring technique for valves faults detection in reciprocating compressors. DCP and IAS were used to build two truth tables that show the cases in which each method can be applied. The two truth tables were merged into one decision table. This combination provided a unique and reliable method of detection and diagnostic of each individual fault in the compressor. Zanoli et al. (2010), Hafaifa (2010) and Elha et al. (2010) utilized the process information technique to detect faults in machines. The authors addressed the selection of signal features and decision making algorithm through different approaches. Namely PCA, fuzzy logic and a decision table approach based on two truth tables. The disadvantages of Hafaifa et al. and Elhaj et al. 's researches are that they did not consider multiple faults and hence they did not investigate the issue of fault interference. Elha et al. (2010) did not determine the fault diagnostic performance of the proposed diagnostic approach. In addition, this approach was validated for use with compressor valves but it is not known whether it will accurately diagnose main compressor faults such as bearing faults.

Condition based maintenance using two or more combined techniques demonstrated a better performance in detecting machine faults. Schulthesis et al. (2007) studied different techniques used in machine heath condition monitoring. They compared the online versus periodic monitoring and proven versus effective techniques. The following techniques were found to be effective: ultrasound vibration, mechanical vibration, temperature, rod run out, and pressure velocity measurements. The measurements on the crankshaft case and on the crosshead piece of each cylinder were proven to be effective. For gas leaks, ultrasonic vibration measurement was preferable over mechanical vibration. The online monitoring was effective in decreasing the chance of catastrophic failures and maintenance and shutdown cost. It can be concluded that the combination of two or more monitoring techniques maximizes the efficiency and accuracy of diagnosing faults in reciprocating compressors. Moreover, the appropriate fault detection technique must be selected based on the type of fault.

The summary of the previous related work reviewed in this section is as follows:-

- Utilization of Sound pressure, ultrasound vibration, mechanical vibration, and process information techniques such as temperature, rod run out, pressure velocity techniques are effective in detecting rotating machinery faults.
- Vibration spectral features are utilized for detecting faults in rotating equipment
- Uncertainties and ambiguities between fault symptoms and events of rotating equipment such as pumps made the diagnostic information harder to isolate off the vibration signal.
- Combination of two or more CBM techniques maximizes the accuracy of diagnosing faults in reciprocating compressors.

4.2.2.2. Condition based maintenance using acoustic emission technique. Currently, the majority of current CBM systems utilize the vibration technique in detecting faulty components although most of fault vibration signatures change with load and speed and are affected by strong harmonics and interferences. Thus, CBM systems usually result in false indication of faults or in an inaccurate severity assessment for an existing fault. The main concerns of most CBM studies are the accuracy of the evaluation of machine condition, the identification fault severity, and the prediction of machine remaining life under a broad range of machine operating states. The relationships that exist between machine conditions and machine process, vibration and Acoustic Emission (AE) can be integrated into machine fault models during fault identification to assess fault severity.

AE is defined as the science that deals with the generation, the transmission, the reception and the effects of sound. It is the demonstrable physical or air-borne sound that can manifest itself as; a signal on mechanical objects, the pressure waves associated with leaking vapor or gasses, or the humming of electrical equipment. Acoustics technology includes frequencies that can be as low as 2 Hz or that can be as high as mega-Hertz range. Acoustic testing which includes sensor selection, signal filtration and amplification and low and high pass filters can be used to diagnose machine condition (IAEA-TECDOC-1551, 2007). AE provides indicative data on levels of friction, rubbing, random impacting, and energy produced by the machine at the location of sensor. Ultrasonic monitoring is useful as a first line defense instrument as the collection of information is relatively fast and inexpensive. Ultrasonic monitoring detects the onset of faults in comparison with other techniques (Rienstra, 2005; UE Systems INC). Hence, ultrasound is utilized to perform preliminary diagnoses and to alert changes in machine condition. It should be noted that surface defects such as cracks and scratches attenuate Rayleigh waves. Moreover, the surface finish of metals can also influence attenuation (Mba and Rao, 2006). AE sensors cover a wide frequency range from 40 kHz to 1 MHz. The time domain waveforms associated with AE is of two types; burst and continuous. A continuous AE signal refers to a waveform where transient bursts are not differentiable. Both waveform types are associated with rotating machinery. For instance, a continuous type emission may be as a result of turbulent fluid flow within a pipe while a burst type could be associated with transient rolling action of meshing gears (Miller and Mclntire, 1994).

For rotating machinery, typical background operational noise is of a continuous type. The most commonly measured AE parameters for diagnostic are amplitude, Root Mean Square (RMS), energy, kurtosis, Crest Factor (CF), counts and events. Observations of the frequency spectrum, whilst informative for traditional non-destructive evaluation, found to have a limited success in machinery monitoring. This is primarily due to the broad frequencies associated with the sources of generation of AE in rotating machinery. For example, the transient impulse associated with the breakage of contacting surface asperities experiencing relative motion will excite a broad frequency range (Mathews, 1983). Unlike mechanical vibration technique, AE technique is less affected by noise and detects the faults in their early stages such as friction in bearing. High frequency AE signals are produced by rotating machinery due to frictional forces and are often masked by low frequency vibrations and ambient plant noise (Mathews, 1983). As the defect size increased, AE RMS, maximum amplitude and kurtosis values increased, however, observations of corresponding parameters from vibration measurements were disappointing (Al-Ghamd and Mba, 2006). Tandon and Nakra (1990) investigated the suitability of AE peak amplitudes and counts method for the detection of bearing outer race defects using a resonant type transducer. The AE counts increased with rotational speed and load. However, although AE peak amplitudes provided an indication of defects irrespective of the defect size, AE counts didn't provide any indication when the defect was less than 250 μm in diameter. The authors disagree with Al-Ghamd and Mba (2006) regarding the effect of defect size on the AE maximum amplitude. The research of Al-Ghamd and Mba was more detailed and the authors emulated different crack sizes and observed the increase in AE amplitudes. Rogers (1979) utilized the AE technique for monitoring the condition of slow rotating anti-friction slew bearings in cranes. The AE CBM technique was found better than vibration CBM technique as it gave better results. Grinding of the metal fragments in the bearing, rubbing of the crack faces and impacts between the damaged parts and the rolling elements in the loaded zone were identified as sources of detectable AE signatures. Schoess (2000) presented results of an assessment of six different but relevant technologies for onboard monitoring of a railcar bearing. It was concluded that the AE technique offered the highest potential advantage. Rogers and Schoess demonstrated the potential advantage of AE based condition based maintenance technique for the fault detection of bearings. However, Rogers focused on kurtosis parameter only and did not investigate the other time domain and frequency domain signal analysis methods.

Neill et al. (1997) described how AE techniques could be implemented as a condition-based maintenance strategy to monitor the inlet and outlet valves of reciprocating compressors. AE sensor required very little space and was non-intrusive, which was a major benefit in hostile conditions. The results revealed the practical deployment of AE sensors for condition monitoring applications. Alfayez and Mba (2005) presented a case study on the application of high frequency acoustic emissions as a means of detecting early stages of loss of mechanical integrity in low speed Rotating Biological Contactor (RBC). RBC was used for sewage treatment in small communities and rotates at approximately 1 rpm. The stub shaft of RBC was fractured. The potential of AE for diagnosing serious mechanical defects was demonstrated while vibration technique was found ineffective. Gill et al., Alfayez and Mba highlighted the effectiveness of AE based fault detection techniques for the detection of both reciprocating compressor and mechanical integrity faults. AE technique was found more informative than vibration technique. The study did not investigate nor compare other time domain parameters. Dane (1998) discovered that ultrasonic flow measurement offered significant advantages over the widely utilized turbine instruments. These instruments were known to be positively biased by at least 5% due to the inherently nonlinear aerodynamics. The response of AE signal to velocity fluctuations is not affected by the rotor inertia of turbine due to the fact that the nonlinear aerodynamics doesn't affect the AE signals. Puttmer (2006) proved that AE sensors could play an important role in condition monitoring of machinery. The author developed a CBM system for reciprocating positive displacement pumps and stated that the AE technique was found better than the vibration technique, in particular in noisy environment. Schulthesis et al. (2007) showed that the ultrasonic is the preferred approach in valve condition analysis. Ultrasonic energy is often associated with gas leaks, so a valve that leaks is a strong generator of ultrasonic energy. Ultrasonic measurements are usually taken in conjunction with compressor pressure-volume analysis. Goodman (2010) referred the effectiveness of ultrasonic to the fact that most leakage problems in addition to all operating equipment produce a broad range of sound. High frequency ultrasonic components of these sounds are extremely short wave in nature. These short wave signals are directional and it is relatively easy to determine their exact location. This can be achieved by separating these signals from operating equipment and background plant noises. Moreover,

the directional nature of ultrasound allows these potential warning signals to be detected on the onset of faults and before they are detected by infrared or vibration techniques. Dane, Puttmer, Schulthesis et al. and Goodman demonstrated that AE based CBM systems are effective in detecting a number of machine faults. The authors demonstrated that the AE technique responds well to flow velocity fluctuations and gas leaks.

In practice, the generalization capacity outside the training fault signature is considered as a limitation of signal based technique (Venkatasubramanian et al., 2003). Fault interference is one of the major disadvantages of the signal based technique. Thus, the signatures of faults change and sometimes the fault is masked due to the interaction between different fault signals. This issue can be solved by avoiding talking decisions if there are no similar fault patterns in that region or by increasing the number of samples/fault patterns to specify all possible faults explicitly including the combination and degradation of all fault conditions, which is considered very difficult. However, in case of no similar fault patterns and in case of multiple faults, this technique will effectively detect abnormalities in operation but with a limited ability to classify the unique fault.

The summary of the previous related work reviewed in this section is as follows:-

- The issues of fault interference and noise represent the main obstacles in implementing CBM systems.
- AE is more effective than mechanical vibration technique in detecting faults at their early stages such as friction in bearing. Also, it is less affected by noise and by nonlinear aerodynamics of rotors.
- AE proved its effectiveness over the mechanical vibration technique in detecting the size of cracks.
- Most commonly measured AE parameters for diagnostic are amplitude, RMS, Energy, kurtosis, crest factor, counts and events.
- The collective utilization of several fault detection techniques and signal features improve the accuracy of fault diagnostic.

4.3. Features selection techniques

Currently, the majority of fault diagnostic systems are based on two features selection techniques. The first technique is based on the traditional time and frequency analyses while the second technique is based on Artificial Intelligence (AI) which takes neural network method as a representative. The traditional techniques have a reasonable performance in detecting faults but need a prior knowledge in addition to a numerous fault samples. The artificial intelligence techniques also have a reasonable performance but need a high computational time and cost and the accuracy of the results are always dependent on various design parameters and these design parameters should be set based on the training and testing sets. The global structure of the generally used monitoring system can be divided into the following three main sequential processes: data collection, followed by data acquisition which includes the calculation of statistical functions and values in both time and frequency domains and ending up by automated fault diagnostic. The automated fault diagnostic is the most difficult phase and is still under development. Fault diagnostic approaches should undergo continuous development to adapt to the necessities of industrial applications and to avoid the dependency on operators (Scheer et al., 2003). Frequency domain signal analysis technique is essential when using vibration or AE based monitoring. For vibration based monitoring, the magnitude of vibration signal is basically utilized for establishing the severity of the vibration while the frequency content is utilized for identifying the cause or origin. The AE based method is widely used for monitoring the condition of rotating machinery. Compared to traditional vibration based methods, the high frequency approach of AE has the advantage of a significant improvement in signal to noise ratio (Wang, 2008).

Since the Artificial Neural Network (ANN) architecture and connections weights significantly affect the performance of the ANN network, it is desirable to identify the best possible set of ANN design parameters. As shown in Fig. 15, the performance of the ANN technique is directly affected by the following major design parameters (a) type and size of the training algorithm in addition to the values of the training algorithm parameters, (b) number of training cycles (Epochs) and (c) the number of hidden NN layers in addition to the number of neurons in each layer. Although one hidden layer is always sufficient to approximate any continuous function, the use of two hidden layers can improve the generalization in complex problems (Lima et al., 2012).

Chan and Gu (2012) investigated the accuracy of Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN AI approaches and observed that the accuracy increased when the design parameters were optimized in terms of number of training epochs, number of Membership Functions (MF) of ANFIS per input, number of ANN neurons, and type of transfer function for ANN. The values of these design parameters were obtained by over 50 runs and with final fuzzy if-then rules of 81 for ANFIS based turbine cycle model. Saxena and Saad (2006) proposed the utilization of Genetic Algorithm (GA) with ANN for identifying near optimal feature set for ANN fault diagnostic systems. Nine bearing health conditions were simulated; eight bearings with different crack sizes in addition to a healthy bearing. The cracks were constructed using an Electric Discharge Machine (EDM). Three accelerometers and one AE sensor were utilized. Five features options were set as inputs for the GA namely statistical features, statistical on sum and difference signals, spectral features and all features together. The FFT analysis was based on 32 values for each signal. The results showed that the technique of using GAs for selecting an optimal feature set for a classification application of ANNs is powerful and that the collective use of all features is at its best. The GA optimized the best combination based on the performance obtained directly from the success of classifier and the mean classification success was 99.94%. Based on Chan and Gu's investigation and on the Fuzzy Interference System (FIS) structure and parameters adjustment theory, the ANFIS is complex as the number of membership function, number of training cycles (epochs) and number of rules must be set. The accuracy of prediction mainly depends on the design parameters which usually depend on the training and testing data sets. Hence, every time the training data sets change, the design parameters should be adjusted to ensure the maximum accuracy. Consequently, this increases both complexity and computation time and

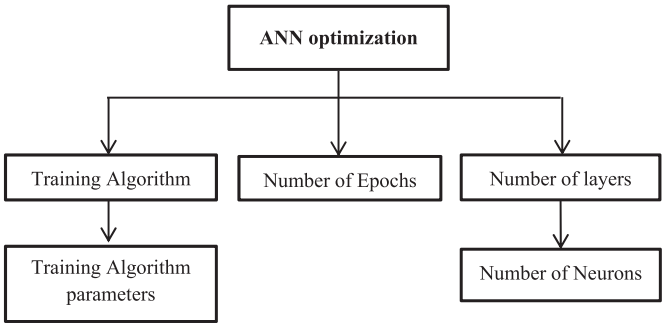


Fig. 15. ANN optimization design parameters.

cost of AI based approaches. The algorithm developed by Saxena and Saad included the FFT in the analysis but it doesn't change the number of segments to better distinguish the fault. The number of segments should be automatically changed based on the number of faults and based on the difference between the values in order to optimize the detection of different faults. Moreover, the FIS algorithm was not tested for the diagnostic of simultaneous faults. The authors did not investigate the effectiveness of the proposed algorithm in selecting the best feature set for multiple-fault classifier and in investigating the issue of fault interference.

The Support Vector Machine (SVM) is an artificial intelligence method based on the principle of statistical learning theory and was utilized for both feature selection and classification processes. The SVM method is utilized for both feature selection and classification (Vapnik, 1999). Meng et al. (2012) presented a new condition monitoring and analysis method for small samples studies such as reactor coolant pump based on SVM. The data were passed through a multi-band FIR filter to eliminate the noise and useless frequency. Kernel principal component analysis was utilized to decrease the dimension of the vector, processing time and accuracy. This method is used as multiple- classifier and can separate the different machine conditions successfully. Gryllias et al. (2009) developed an SVM based features selector for the selection of optimal features due to the lack of actual experimental data. The input features were divided into two groups: (a) Time domain statistical features such as RMS, SK, VAR and kurtosis, (b) spectral features such as energy values calculated at specific frequency bands of the demodulated and measured signals. The main contribution of this work is that the SVM training was based on a model that considers the dynamic behavior of defective rolling element bearings. This enabled the SVM to select a set of good features without the need of having experimental data of defective bearings. The approach developed by Meng and Feng was not validated for the detection of simultaneous faults (unbalance and friction faults). The authors did not investigate the effectiveness of the proposed technique in distinguishing machine multiple faults. Gryllias et al. did not consider the fault interference problem and only studied the occurrence of a single fault. Finding the dynamic equation of each component is difficult and consumes time. The performance of the proposed CBM approach was not verified experimentally. Moreover, this approach will not help minimize the development cost and time of CBM systems.

Samhouri et al. (2009) proposed a new approach based on the combination of the axial vibration time signal features of carnallite surge tank pump namely RMS, variance, skewness, kurtosis, and normalized sixth central moment. These features were utilized as inputs to both *Adaptive* ANFIS and ANN. Three different faults with three different fault codes were simulated. A total of 92 runs were conducted; 73 runs for training and 19 runs for testing. The comparison showed that the adoption of the time root mean square and variance features achieved the minimum fault prediction errors for both ANFIS and ANN. The trapezoidal membership function in ANFIS achieved a fault prediction accuracy of 95%, while the cascade forward back-propagation ANN achieved a better fault prediction accuracy of 99%. Gupta and Wadhwani (2012) proposed a robust Genetic Programming (GP) based feature selector for the selection of best features from large features data set for bearing fault classification. ANN classifier was utilized for the recognition of fault patterns. Vibration time domain features were extracted from the statistical measures of Median, RMS, crest factor, histogram Lower Bound (LB), histogram Upper Bound (UB), Entropy (ENT), Skewness (SK), Kurtosis (KT), Variance (VAR), Shape Factor (SHF), Impulse Factor (IMF), and Clearance Factor (CLF). Experimental data were collected for four bearings conditions namely healthy, defective outer race, defective inner race and defective ball fault condition. The algorithm was utilized to effectively select a smaller subset of features. All of the eight features were selected by GP and yielded a detection accuracy of 99.99%. Zhao et al. (2010) addressed the limitation of existing spectral feature selection algorithms in handling redundant features. Since redundant features can have significant adverse effect on learning performance, the authors proposed a novel spectral feature selection algorithm of an embedded model. The proposed algorithm evaluated the utility of a set of features jointly and efficiently removed redundant features. The algorithm was based on sparse multi-output regression with L2;1-norm constraint. The algorithm yielded an average feature selection redundancy rate of 0.24. This rate is much less than the redundancy rates of the existing spectral features algorithms. Samhouri et al. observed the effectiveness of the ANN technique over the ANFIS technique. The authors neither addressed the fault types nor utilized the spectral analysis technique as one of the major vibration analysis techniques. As no multiple-fault simulations were carried out, the effectiveness of the proposed approach in distinguishing simultaneous faults is not demonstrated. Zaho et al. demonstrated that the existing spectral features selections algorithms such as Laplacian Score, Fisher score and trace ratio failed to handle the problem of redundant features identification. It can be observed that the existing algorithms evaluate features individually and cannot identify redundant features.

In recent years, several studies on bearing fault diagnostic using wavelet analysis were conducted. Lin (2000) used the wavelet analysis and varied the shape factor of the Morlet wavelet to achieve the minimum wavelet entropy for bearing fault feature selection. Qiu et al. (2006) used the Shannon entropy and singular value decomposition to optimize the wavelet entropy and kurtosis parameters. Bozchalooi (2007) introduced the smoothness index to guide the parameter selection of the complex Morlet wavelet for de-nosing bearing fault signal. Wang et al. (2013) proposed a novel Adaptive Wavelet Stripping Algorithm (AWSA) to extract the simulated transients from bearing fault signals. A comparison between periodic multi-transient model and AWSA was carried out to show that the proposed approach is better in selecting the random characteristics of real transients. An enhanced AWSA was also developed to reduce the computing time. Shen et al. (2010) proposed an automated sensory feature selection method to reduce the development time and cost of condition based monitoring systems for machining operations. Force, acceleration, sound and acoustic emission sensors were utilized for the detection of high-speed milling operations. Time domain, frequency domain and wavelet analysis techniques were employed to analyze the measured signals. Gradual tool wear was used for evaluating the proposed self-learning automated sensory feature selection method. The results showed that the proposed method can be applied through an automated and self-learning monitoring process for the selection of the most suitable sensors. Gowid et al. (2015) proposed an automated FFT based features selection approach. In comparison to the existing AI features selection tools, this algorithm managed to significantly increase the detection accuracy as well as to reduce the development time and cost. The approach is based on a smart segmentation algorithm which divides the frequency spectrum into a number of equal segments. The segment number and size are calculated to maximize the differences between different fault signatures. The algorithm yielded a detection accuracy of 100% and managed to reduce both of computation time and development time to a few seconds. It can be concluded that Lin, Qu, Wang et al. and Shen et al. proposed effective bearing fault detection techniques based on wavelet analysis technique while Gowid et al. proposed an automated features selection approach based on AE spectral features with a confidence level that quantifies the percentage differences between

the selected features of different fault patterns.

The complexity of ANN technique comes from the fact that its performance is significantly affected by a large number of design parameters (Lima et al., 2012). The development time and cost of ANN based CBM technique is high due to the need for the optimization of all design parameters which should be customized based on the training data sets and the accuracy is not guaranteed to be 100%. There is no quantitative factor that can be utilized to measure the percentage difference between different fault patterns and hence to better evaluate the certainty of the classification. Many approaches such as SVM AWSA and GA were utilized to improve the accuracy of ANN based features selection algorithm and to reduce its computing time.

The summary of the previous related work reviewed in this section is as follows:-

- The majority of the existing automated features selection tools utilize artificial intelligence methods such as ANN, ANFIS, GA and SVM while other tools utilize various spectral feature selection algorithms.
- The main disadvantages of the artificial intelligence based methods are the high computing cost and the high developing time. The detection accuracy of these methods is strongly related to the values of their various design parameters.
- Existing spectral features selection algorithms cannot identify the redundant features which negatively affects the learning process as well as the accuracy of fault detection.
- The FFT analysis is key in vibration and acoustic based monitoring. With exception to the research done by Gowid et al. (2015), a research gap was identified in developing an effective automated, non-artificial intelligence, fast and systematic FFT-based features selections algorithms for CBM systems.

5. Conclusion and research directions

Reviewing the previous related work, it is apparent that there is a considerable research effort on the importance of FPSO, LNG liquefaction process performance, BoG system reliability, reliability calculation approaches, fault diagnostic techniques and automated features selection algorithms. The work highlighted the shortcomings and identified research gaps that adversely affect the performance of existing FPSOs. The followings conclude the major findings of the review:

1. The cost and operating performance of FPSOs demonstrated the effectiveness of FPSO over LNG onshore plants (Sections 1 and 2).
2. Most of LNG plants utilize the C3MR LNG liquefaction process for its high economic performance (Section 3.1).
3. There is a research gap in investigating the reliability of C3MR LNG liquefaction plant on FPSOs (Section 3.1).
4. Markov chain approach is preferred over FTA for calculating the reliability of time dependent system such as standby redundancy systems but the approach is more difficult due to the fact that MA takes into account the time dependent transition rates (Section 3.2).
5. Due to the various advantages of CBM systems, there is an on ongoing effort to shift from PM to CBM (Section 4.1).
6. There are few studies that compared the major fault detection techniques for the condition based maintenance of high speed centrifugal equipment (Section 4).
7. For developing an effective CBM systems for LNG Liquefaction plants, the followings should be considered:
   a) Although the physics based model helps to understand the physics of the system, serious modeling inaccuracies would occur due to parameters drift. Linearization of non-linear systems results in a significant effectiveness reduction of the technique.
   b) Statistical models are easier compared to physics based models. They are powerful in revealing the presence of abnormality. Nevertheless, the non-existence of fault signatures for each fault makes the fault isolation process difficult.
   c) The generalization capacity outside the training fault signatures is considered as a limitation of signal based technique. Fault interference issue is one of the major disadvantages of this technique.
   d) As frequency domain signal analysis technique is key in vibration and acoustic based monitoring. There is a research gap in developing automated, non-artificial intelligence, robust fast and systematic FFT-based features selections algorithms (Section 4.3).
   e) CBM strategy proved its effectiveness in maximizing the profitability and availability of plants (Section 4.1).
   f) Mechanical vibration, ultrasound vibration, temperature, rod runout and pressure velocity measurements techniques are utilized in detecting the faulty components/units. The inherited issue of faults interference and noise represent the main drawbacks in implementing the CBM strategy (Section 4.2.2.1).
   g) AE is more effective than the mechanical vibration technique in detecting faults at their early stages such as friction in bearing. In addition, AE is less affected by noise (Section 4.2.2.2).
   h) AE is more effective than mechanical vibration technique in detecting gas leaks (Section 4.2.2.1).
   i) AE proved its effectiveness over the mechanical vibration technique in detecting the size of cracks (Section 4.2.2.2).
   j) The most commonly measured AE parameters for fault diagnostic are amplitude, RMS, Energy, kurtosis, crest factor, counts and events (Section 4.2.2.2).
   k) The combination of several fault detection techniques and signal features improves the diagnostic accuracy of faults (Section 4.2.2.2).
   l) The existing automated features selections techniques either select redundant features which affect the learning process or have high development cost and time as the majority of these techniques are based on non-systematic complex artificial intelligence approaches such as SVM, ANN and ANFIS. Moreover, the utilization of such approaches needs a prior theoretical and rule base knowledge and gives different accuracies based on the values of various optimization parameters such as the number of training data sets, the number of membership functions, the number training cycles (epochs) and the classification rules (Section 4.3).

Further research should be carried out to develop an enhanced LNG liquefaction system that capitalize the advantages of both C3MR and N2 liquefaction systems or by improving the economic performance of the N2 liquefaction process. The reliability and redundancy introductions to various offshore liquefaction systems should undergo further studies to increase the availability, and hence, the profitability of LNG floating plants. Further development of CBM systems is needed to reliably and efficiently diagnose all machine conditions. Fault interference issue needs more research efforts. False alarms are a common problem of current CBM systems. Thus, more studies on the isolation of noise and on the combination of two or more fault detection techniques and features will help ensure the robustness of the CBM algorithm. The features selection algorithm should undergo more research to enhance and automate the selection of best features set. Alternative methods to

ANN based features selection and fault diagnostic methods should be introduced to overcome high development and high computing time and cost. Otherwise, an automated optimization algorithm should be proposed to significantly decrease the development time and effort of ANN based algorithm and to decrease the computing time and cost as well.

References

Al-Ghamd, A., Mba, D., 2006. Comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size. Mech. Syst. Signal Process. 20 (7), 1537–1571.

Alfayez, L., Mba, D., 2005. Detection of incipient cavitation and determination of the best efficiency point for centrifugal pumps using acoustic emission. J. Process Mech. Eng. 219 (1), 327–344.

Andrew, J., Ericson, C., September 2000. Fault tree and markov analysis applied to various design complexities. In: Proceedings of the 18th International System Safety Conference, Texas, USA.

Annual Energy Outlook 2010, 2010. U.S. Energy Information Administration.

Annual Energy Outlook 2013, 2013. U.S. Energy Information Administration.

Aven, T., 1987. Availability evaluation of oil/gas production and transportation systems. Relibaility Eng. 18 (1), 35–44.

Boller, C., Chang, F., Fujino, Y., 2009. Encyclopedia of Structural Health Monitoring. John Wiley & Sons, Chichester.

Bozchalooi, M., 2007. A smoothness index-guided approach to wavelet parameters election in signal de-noising and fault detection. J. Sound Vib. 308, 246–267.

Bukowski, J., Liu, Y., Boccella, S., Leo, K., October 2011. Innovations in natural gas liquefaction technology. In: International Gas Union Research Conference, Seoul.

Bukowski, J., et al., 2013. Natural Gas Liquefaction Technology for Floating LNG Facilities. Air Products and Chemicals Inc.

C. e. a. Scheer, Quality control using vibration and acoustic signatures. Available at: http://www.aaende.org.ar/ingles/sitio/biblioteca/material/T-040.pdf, Accessed Feb. 2014.

Calixto, E., 2012. Gas and Oil Reliability Engineering: Modeling and Analysis, first ed. Gulf Professional Publishing, USA.

Caroni, C., 2002. Modeling the reliability of ball bearings. J. Statistics Educ. 10 (3).

Chan, Y., Gu, S., 2012. Modeling of turbine cycles using a Neuro-Fuzzy based approach to predict turbine-generator output for nuclear power plants. Energies 5 (1), 101–118.

Charles, G., Goodall, R., Dixon, R., 2008. Model-based condition monitoring at the wheel–rail interface. Veh. Syst. Dyn. 46, 451–430.

Cheng, S., Lin, B., Hsu, B., Shu, M., 2009. Fault-tree analysis for liquefied natural gas terminal emergency shutdown system. Expert Syst. Appl. – Elsevier 36 (9), 11918–11924.

Dane, J., April 1998. Ultrasonic measurement of unsteady gas flow. Flow. Meas. Instrum. – Elsevier 8 (3), 183–190.

Elha, M., Almrabet, M., Rgeai, M., Ethiwesh, I., March 2010. A combined practical approach to condition monitoring of reciprocating compressors using IAS and dynamic pressure. World Acad. Sci. Eng. Technol. 39 (1), 186–192.

Fuqua, N., 2003. The Applicability of Makov analysis Method to the Reliability, Maintainability and Safety, vol. 10(2). Reliability Analysis Center.

Galka, T., Tabaszewski, M., 2011. An application of statistical symptoms in machine condition diagnostics. Mech. Syst. Signal Process. 25 (1), 253–265.

Ginzinger, L. e. a., 2010. Model-based condition based monitoring of an auxiliary bearing following contact events. In: Proceeding of MOVIC, Tokyo.

Goodman, A., March 2010. Utilizing airborne/structure borne ultrasound for condition monitoring predictive maintenance inspections. Compressionjobs.com.

Gowid, S., Dixon, R., Ghani, R., 2013. Assessment of liquefaction systems' process performance on LNG floating export terminals. In: International Conference on Mechanical, Automotive and Aerospace Engineering, 2–4 July, Kuala Lumpur, Malaysia.

Gowid, S., Dixon, R., Ghani, S., 2014. Optimization of reliability and maintenance of liquefaction system on FLNG terminals using Markov modelling. Int. J. Qual. Reliab. Manag. 31 (3), 293–310.

Gowid, S., Dixon, R., Ghani, S., 2015. A novel robust automated FFT-based segmentation and features selection algorithm for acoustic emission condition based monitoring systems. Appl. Acoust. 88 (1), 66–74.

Gryllias, K., Yiakopoulos, C., Antoniadis, I., 2009. Automated diagnostic approaches for defective rolling element bearings using minimal training pattern classification methods. In: Engineering Asset Lifecycle Management - Proceedings of the 4th World Congress on Engineering Asset Management, WCEAM, pp. 862–876.

Gu, Y., Ju, Y., January 2011. Effect of parameters on performance of LNG-FPSO offloading system in offshore associated gas fields. Appl. Energy 8 (1), 417.

Guo, Yi, Parker, Robert G., 2010. Dynamic modeling and analysis of a spur planetary gear involving tooth wedging and bearing clearance nonlinearity. Eur. J. Mech. – A Solids 29 (6), 1022–1033.

Gupta, P., Wadhwani, S., 2012. Feature selection by genetic programming, and artificial neural network-based machine condition monitoring. Int. J. Eng. Innov. Technol. (IJEIT) 1, 177–181.

Hafaifa, G., March 2010. Robust fuzzy fault detection and isolation approach applied to surge in centrifugal compressor modeling and control. Fuzzy Inf. Eng. 2 (1), 49–73.

Haid, M., 2010. Small and Mid-scale LNG FPSO. In: 15th TGE Symposium, Shanghai China.

Hurdle, E., Bartlett, L., Andrews, J., 2009. Fault diagnostics of dynamic system operation using a fault tree based method. Reliab. Eng. Syst. Saf. 94 (9), 1371–1380.

IAEA-TECDOC-1551 Implementation Strategies and Tools for Condition Based Maintenance at Nuclear Power Plants, May 2007. International Atomic Energy Agency.

Lampis, M., Andrews, J., 2009. Bayesian belief networks for system fault diagnostics. Qual. Reliab. Eng. Int. 25 (4), 409–426.

Li, Q., Ju, Y., January 2011. Design and analysis of liquefaction process for offshore associated gas resources. J. Appl. Therm. Eng. 30 (16), 417.

Liao, H., Huang, Z., 2010. The fault diagnosis for centrifugal compressor based on time series analysis with neutral network. In: Proceedings of the 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE), Chengdu, China, August.

Lima, T., Silva, A., Ludermir, T., 2012. Selection and fusion of neural networks via differential evolution. In: Advances in Artificial Intelligence - IBERAMIA 2012. Springer, Colombia, pp. 153–155.

Lin, L., 2000. Feature extraction based on Morlet wavelet and its application for mechanical fault diagnosis. J. Sound Vib. 234, 135–148.

Mathews, J., 1983. Acoustic Emission, third ed. Gordon and Breach Science Publishers Inc, USA.

Mba, D., Rao, R., 2006. Development of acoustic emission technology for condition monitoring and diagnosis of rotating machines; bearings, pumps,gearboxes, engines and rotating structures. Shock Vib. Dig. 38 (1), 3–16.

Meng, Q., Meng, Q., Feng, W., 2012. A new application of support vector machine method: condition monitoring and analysis of reactor coolant pump, 25th International Congress on Condition Monitoring and Diagnostic Engineering J. Phys. Conf. Ser. 364.

Miller, J., 2006. Statistical signatures used with principal component analysis for fault detection and isolation in a continuous reactor. J. Chemom. 20, 34–42.

Miller, K., Mclntire, P., 1994. Non-destructive Testing Handbook, third ed. American Society of Non-destructive testing, USA.

Miranda, M., Meira, O., 2008. Life cycle assessment of turbomahcinery for offshore applications – updated with field data. In: Proceding of the 37th Turbomachinery Symposium, Turbomachinery Laboratory. Texas A&M University, Texas, pp. 103–110.

Neill, G., Brown, E., Steel, J., Standford, P., Reuben, R., June 1997. Detection of recirculation in pumps using acousticemission. In: Proceedings of the 11th International Conference on Condition Monitoring and Diagnostic Engineering Management, Tasmania, Australia.

OREDA, 2009. Handbook, Offshore Reliability Data Handbook, fifth ed., vol. 1

Orlowski, Z., 1989. Vibrodiagnostics of steam turbines. In: Proceedings of the Institute of Power Engineering, Warszawa.

Peters, R., 2014. Reliable Maintenance Planning, Estimating, and Scheduling, first ed. Gulf professional publishing, USA.

Pil, C., Rausand, M., Vatn, J., September 2008. Reliability assessment of reliquefaction systems on LNG carriers. Reliab. Eng. Syst. Saf. 93 (9).

Pukite, J., Pukite, P., 1998. Modeling for Reliability Analysis: Markov Modeling for Reliability, Maintainability, Safety, and Supportability Analyses of Complex Systems. Wiley-IEEE Press.

PuraDYN, (avilable at: http://www.puradyn.com/products/ConditionBasedMaintenance-CBM.html).

Puttmer, A., June 2006. New applications for ultrasonic sensors in process industries. Ultrasonics 46 (1), 1379–1383.

Qiu, J., Lee, J., Lin, J., Yu, G., 2006. Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics. J. Sound Vib. 289, 1066–1090.

Rausand, M., Hyland, A., 2004. System Reliability Theory: Models, Statistical Methods, and Applications, second ed. Wiley, , New York.

Ridley, L., Andrews, J., 1999. Opitmal design of systems with standby dependencies. Qual. Reliab. Eng. Int. 15 (2), 103–110.

Rienstra, A., 2005. Predictive Maintenance for the Masses. Airbone Ultrasonic, SDT North America.

Rienstra, A., 2005. Predictive Maintenance for the Masses. Airbone Ultrasonic, SDT North America.

Rogers, L., April 1979. The application of vibration analysis and acoustic emission source location to on-line condition monitoring of anti-friction bearings. J. Tribol. Int. 12 (2), 51–58.

Samhouri, M., Al-Ghandoor, A., Alhaj-Ali, S., Hi, I., 2009. An intelligent machine condition monitoring system using time-based analysis: neuro-fuzzy versus neural network. Jordan J. Mech. Ind. Eng. 3, 294–305.

Sarkar, A., Behera, D., Kumar, S., Singha, M., 2012. Reliability assessment of Rukhia Gas Turbine power plant in Tripura. Int. J. Curr. Eng. Technol. 2 (1), 184–195.

Saxena, A., Saad, A., 2006. Genetic algorithms for artificial neural net-based condition monitoring system design for rotatin mechanical systems. Adv. Soft Comput. 34, 135–149.

Scheer, C., Südmersen, U., Reimche, W., Bach, W., 2003. Quality Control Using Vibration and Acoustic Signatures. Rio de Janeiro - RJ – Brasil.

Schoess, J., June 2000. Development and application of stress-wave acoustic diagnostics for roller bearings. In: Proceedings of SPIE - the International Society for Optical Engineering, California, USA.

Schulthesis, S., Lickteig, C., Parchewsky, R., September 2007. Reciprocating compressor condition monitoring. In: Proceedings of the 36th Turbo Machinery Symposium, Texas, USA.
Shang, F., Jong, L., Yabin, Z., November 2009. Fault diagnosis system for reciprocating air compressor based on support vector machine. In: Proceedings of the 2009 International Workshop on Information Security and Applications, Qingdao, China.
Shen, Z., He, N., Li, L., 2010. An intelligent monitoring system with the capability of automated features selection. J. Harbin Inst. Technol. 42 (9), 1495–1499.
Stamatics, D., 2014. Introduction to Risk and Failures: Tools and Methodologies. Taylor & Francis Group.
T. N. O. I. A. (OLF), 2011. 10 Year Operability Survey of Norwegian FPSOs.
Tandon, N., Nakra, B., August 1990. Defect detection of rolling element bearings by acoustic emission method. J. Acoust. Emiss. 9 (1), 25–28.
The Energy Department's F The Energy Department's Fossil Energy Organization, USA, (available at: http://energy.gov/fe/about-us).
Thorsen, O., Coll, N., Dalva, M., 1995. A survey of faults on induction motors in offshore oil industry, petrochemical industry, gas terminals, and oil refineries. Ind. Appl. IEEE Trans. 31 (5), 1186–1196.
Toprak, S., Iftar, A., October 2007. Fault diagnosis on hermetic compressors based on sound measurements. In: Proceedings of the 16th IEEE International Conference on Control Applications Part of IEEE Multi-conference on Systems and Control, Singapore, Singapore.
W. l. M. o. t. f. U. u. d. instruments, UE Systems INC, (available at: http://www.uesystems.eu/applications/ultrasonic-bearing-mechanical-inspection).
Ugechi, C., Ogbonnaya, E., Lilliy, M., Ogaji, S., Probert, S., 2009. Condition-based diagnostic approach for predicting the maintenance requirements of machinery. Engineering 1, 177–187.
Vapnik, V., 1999. An overview of statistical learning theory. IEEE Trans. Neural Netw. 10.
Venkatasubramanian, V., Rengaswamy, R., Kavuri, S., Yin, K., 2003. A review of process fault detection and diagnosis - Part III: process history based methods. Comput. Chem. Eng. 27, 327–346.
Viktorov, I., 1967. Rayleigh and Lamb Waves: Physical Theory and Application. Plenum Press, New York, USA.
Wang, W., 2008. Complex system maintenance handbook. Springer Series Reliability Engineering.
Wang, J., Hu, H., 2006. Vibration-based fault diagnosis of pump using fuzzy technique. Meas. – Elsevier 39 (2), 176–185.
Wang, D., Shen, C., Tse, P., 2013. A novel adaptive wavelet stripping algorithm for extracting the transients caused by bearing localized faults. J. Sound Vib. 332, 6871–6890.
World Energy Outlook 2011, 2011. International Energy Agency.
World Energy Outlook 2014, 2014. International Energy Agency.
World LNG report, 2014. International Gas Union.
Yan, J., 2015. Machinery Prognostics and Prognosis Oriented Maintenance Management. Wiley.
Yan, G., Yonglin, J., 2008. LNG-FPSO: offshore LNG solution. Front. Energy Power Eng. China 2 (3), 249–255.
Yuhva, D., Datao, Y., 2005. Estimation of failure probability of oil and gas transmission pipelines by fuzzy fault tree analysis. J. Loss Prev. Process Ind. 18 (2), 83–88.
Zanoli, S., Astalfi, G., Barboni, L., June 2010. Applications of fault diagnosis techniques for a multi-shaft centrifugal compressor. In: Proceedings of the 18th Mediterranean Conference on Control & Automation, Marrakech, Morocco.
Zhao, Z., Wang, L., Liu, H., 2010. Efficient spectral feature selection with minimum redundancy. In: Proceedings of the Twenty-fourth AAAI Conference on Artificial Intelligence, Georgia, USA.