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MULTI SOURCES INFORMATION FUSION BASED ON BAYESIAN NETWORK METHOD TO IMPROVE THE FAULT PREDICTION OF CENTRIFUGAL COMPRESSOR

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Abstract: The centrifugal compressor is an important machine in the oil and gas industry, so the fault prediction of these machines is widely discussed in the literature. Several techniques can and should be used in fault prediction of centrifugal compressors: vibration analysis, non-destructive testing techniques, operating parameters, and other techniques. But in particular cases, these tools are inefficient for making a decision regarding the combined fault diagnosis and prediction. This paper presents a contribution to fault prediction in centrifugal compressor utilizing multi-source information fusion by a Bayesian network. The data fusion does not come from the same source, but rather from vibration analysis, oil analysis, and operating parameters. In addition, the accuracy and ability of fault prediction can be improved compared with the use of data obtained from vibration analysis only or oil analysis. The proposed method accuracy is validated on a BCL 406 type centrifugal compressor. Furthermore, the obtained results showed the effectiveness of the multi-source information fusion by Bayesian network approach gives more accuracy to decision-making in fault prediction and the developed method has an effect in predicting the combined faults.

KEYWORDS: Centrifugal Compressor, Fault prediction, Bayesian Networks, Multi-source information fusion, decision making

1 Introduction

Varieties of metals are being used for large-scale manufacturing / production of products in the industrial sector to meet the global market demand with the possibility of improving the quality at lower costs. Such phenomenon has resulted in the investigation of modern technologies to weld dissimilar metals for large-scale industrial applications. Among the present, Laser Beam Welding of metallic plates offers considerable advantages over the conventional techniques. Some of these advantages include precision of operation, local processing, fast processing time, and low cost [1]. The proper selection of welding parameters is necessary for defect-free welded joints. In addition, high temperature gradients developed in the welded section result in high stress fields in this region, which can limit the practical applications of the welded products. The model study gives physical insight into the welding process, which provides useful information on the process control and stress levels in the welding sections [2].

The centrifugal compressor plays a vital role in large industries such as the petrochemical industry, energy, steel, and metal. Unfortunately, however, uncontrolled operations and breakdowns of the centrifugal compressor can have serious effects on the availability and become a serious obstacle to successful production. Conditional maintenance techniques are highly recommended by centrifugal compressor manufacturers and widely used by operators whose main objective is to avoid accidental failures and long downtimes that cause substantial

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economic losses. Several techniques can and should be used as predictive maintenance programs. Vibration analysis, oil analysis and NDT techniques are the most popular.

The vibration analysis is employed to monitor the centrifugal compressors and detect at earlier the appearance of any faults, to predict the behavior of the device submitted to vibrations, and even to achieve acoustic measures [1]. The applications revolve primarily on monitoring through the use of the monitoring systems on-line or off-line using the sophisticated analyzers of vibration [3]. On the application side, monitoring and fault diagnosis-prediction of centrifugal compressors, for example, requires spectral analysis, order tracking, time recording of the signal, or sometimes envelope detection functions. More and more researchers are using the artificial intelligence technique to automate and facilitate the fault diagnosis in the centrifugal compressors in the field of vibration analysis. Neural networks, fuzzy logic, genetic algorithms [2,4,5] and earlier expert systems [6], are now the most used. These methodologies can be used to evaluate the degradation level and to predict breakdown. In these applications, the robustness of the method plays a decisive role. Artificial intelligence methods for monitoring compressors by vibration analysis are often used in the presence of background noise. They need massive data as inputs in the models, and the computation time must be as short as possible.

In the case of centrifugal compressor monitoring, it is also important to take into account the operating parameters. The integration of information from the supervision system (load, temperature, flow, pressure) can facilitate decision-making while confirming or reversing the conclusions on the nature of the fault. As an example, a thermal imbalance is at once, generating a component of order on a vibration spectrum and temperature rise. Prognostics and health monitoring are also conditions based on oil analysis. In principle, assessment of the contamination or degradation of the oil lubricant could be based on chemical analysis [7]. On the other hand, health assessment of the machine can be done by particle count and wear debris analysis of the lubricant (ferrography).

Associate and fuse several information to develop a system to aid in the decision-making appears as a better solution for the maintenance. However, the information fusion from the same source for the reconstitution of an environment, a state, or multiple sources for decision-making has been supported by researchers from different areas in recent years. In the field of road safety, [8] has fused information using the theory of Dempster-Shafer to improve the temporal response of the drivers monitoring in real-time. In another contribution, the support Vector Machine (SVM) method has been used for the data fusion of a diesel engine fault diagnosis [9]. In this work, the proposed consideration offers predictions argued by probabilities. The information and experience form the basis for decision-making by different kinds of information. Many works developed in this same reflection have been made, but each of these works has its particularity. [10] Has shown that information fusion by the Bayesian network applied to a control system of the commercial environment aircraft has allowed fault isolation at a rate higher than 89%. Other works concern the information fusion by Bayesian networks to improve the maintenance that has been developed in recent years in the use of reliability information, vibration signals, the current signals, or the sensor data [11-14]. Also, industrial systems (static equipment, a rotating machine, a conveyor band; an airplane) have their peculiarities, and the information is not of the same nature and of the same source.

In predictive maintenance and based on data retrieved from the monitoring system, it is possible to trace trends or even identify alerts, but practice always hides surprises and decision-making can be accompanied by strong ambiguity and remains uncertain. In this paper, a multi-source information fusion by the Bayesian network is proposed. The information fusion is not from the same source and is mainly from vibration analysis, oil analysis, and the operating parameters. A qualitative analysis will be recommended for the construction of the network structure and quantitative analysis will be based on inference in the proposed Bayesian network. The predictive maintenance program that will be developed as a result of this study will be based on a condition-driven and on the occurrence probability of faults. In practice, a decision support system for a more in-depth analysis allows the predictive analyst to estimate the most likely failure, to make decisions in the event of uncertainty about the existence of combined faults, and to recommend corrective actions to prevent the recurring problem.

2 Tools Used in Compressor Monitoring and Fault Analysis

In the literature, there are several methods and techniques used for fault monitoring and analysis of the compressor, such as the NDT technique [15], and vibration analysis [16]. The latter is one of the most common methods used in the field of monitoring, and it has been relied upon in this paper. In addition to the oil analysis, and the operating parameters. It has already been mentioned that it plays an important role in centrifugal compressor monitoring and fault analysis. .

In this section, the faults that occur in centrifugal compressors are classified according to the analysis techniques (vibration analysis, oil analysis, operating parameters). In addition, in order to facilitate the construction of the Bayesian networks that model the order of causality for prediction purposes, codes have been assigned to the different events. Causality is always checked, starting from the causes and arriving at the effects. Based on [17], the fault name definition is as shown in Tables 1,2, and 3. The a priori probability is also defined using the historical file obtained from the Algerian oil and gas company SONATRACH.

2.1 Vibration analysis

Vibration analysis is one of the most used techniques in fault diagnosis and prediction in rotating machinery [18,19] in general and in compressors specifically [20]. Vibration analysis-based fault detection involves obtaining, extracting, and analyzing centrifugal compressor-related vibration amplitude data under a number of part scenarios, which include Damaged Rotor, Loose Rotor Parts, Piping Strain, and Shaft Misalignment … etc. In a centrifugal compressor, the faults detected by the vibration analysis are classified in Table1.

Table 1 The causes related to vibration analysis.

Effect	**Cause**	**Code**	**a priori probability**
Excessive Vibration		EV	/
	Bent Rotor (Caused by Uneven Heating and Cooling)	BR	0.0009
	Build-up of Deposits on Rotor	BDR	0.01
	Damaged Rotor	DR	0.022
	Dry Gear Coupling	DGC	0.0007
	Excessive Bearing Clearance	EBC	0.0002
	Improperly Assembled Parts	IAP	0.0003
	Liquid “Slugging”	LS	0.04
	Loose or Broken Bolting	LBB	0.00065
	Loose Rotor Parts	LRP	0.0011

	Operating in Critical Speed Range	OCSR	0.0012
	Operating in Surge Region	OSR	0.0002
	Piping Strain	PS	0.009
	Rotor Imbalance	RI	0.00015
	Shaft Misalignment	SM	0.00025
	Sympathetic Vibration	SV	0.0026
	Worn or Damaged Coupling	WDC	0.0001
Units Do Not Stay in Alignment		UNSA	
	Piping Strain	PS	0.009
	Shaft Misalignment	SM	0.00025
Persistent Unloading		PU	
	Bent Rotor (Caused by Uneven Heating and Cooling)	BR	0.0009
	Improperly Assembled Parts	IAP	0.0003
	Liquid "Slugging"	LS	0.004
	Piping Strain	PS	0.009
	Rotor Imbalance	RI	0.0015
	Rough Rotor Shaft Journal Surface	RSJS	0.0001
	Sympathetic Vibration	SV	0.0026
	Warped Foundation or Baseplate	WFB	0.005
Excessive Bearing Oil Drain Temp		EBODT	
	Faulty Temperature Gauge or Switch	FTGS	0.00085
	Poor Oil Condition	POC	0.004
	Rough Rotor Shaft Journal Surface	RSJS	0.0001
	Vibration	V	0.0005
	Warped Damaged Bearing	WDP	0.001

2.2 Oil analysis

The oil analysis technique is one of the classic techniques used in fault diagnosis of mechanical machines [21]. This technique is mainly based on data obtained from oil analysis. Table2 shows the faults that occur in centrifugal compressors, which can be identified or detected using the oil analysis technique, as well as a set of causes that lead to the appearance of these faults.

Table 2 The causes related to oil analysis.

Effect	Cause	Code	a priori probability
Water in Lube Oil		WLO	
	Condensate in Oil Reservoir	COR	0.0005
	Leak In Lube Oil Cooler Tubes or Tube Sheet	LOLCATS	0.02
	Piping Strain	PS	0.009
	Sympathetic Vibration	SV	0.0026
Excessive Bearing Oil Drain Temp		EBODT	
	Faulty Temperature Gauge or Switch	FTGS	0.00085
	Poor Oil Condition	POC	0.004
	Rough Rotor Shaft Journal Surface	RSJS	0.0001
	Vibration	V	0.0005
	Warped Damaged Bearing	WDP	0.001

2.3 Operating parameters

Vibration analysis and oil analysis give a good contribution to fault diagnosis in centrifugal compressors, but there are always faults requiring human intervention to detect, or specialists can easily detect them without resorting to vibration or oil analysis. In this section, we will present the operating parameters fault, which they represented in Table 3.

Table 3 The causes related to operating parameters.

Effect	Cause	Code	a priori probability
Compressor Surges		CS	
	Build-up of Deposits on Diffuser	BDD	0.0023
	Build-up of Deposits on Rotor	BDR	0.01
	Change in System Resistance	CSR	0.001
	Insufficient Flow	IF	0.004
Loss of Discharge Pressure		LDP	
	Compressor Not Up to Speed	CNUS	0.0006
	Excessive Inlet Temperature	EIT	0.003
	Leak In Discharge Piping	LIDP	0.0007
Low Lube Oil Pressure		LLOP	

	Bearing Lube Oil Orifice Missing or Plugged	BLOOM	0.005
	Clogged Oil Strainer/Filter	COS/F	0.0003
	Failure of Both Main and Auxiliary Oil Pumps	FBM	0.001
	Faulty Temperature Gauge or Switch	FTGS	0.00085
	Incorrect Pressure Control Valve Setting	IPCVS	0.0001
	Leak in Oil Pump Suction Piping	LOPSP	0.0035
	Oil Leakage	OL	0.003
	Oil Pump Suction Plugged	OPSP	0.0001
	Oil Reservoir Low Level	ORLL	0.0019
	Operating at Low Speed w/o Auxiliary Oil Pump	OLS	0.0003
	Relief Valve Improperly Set or Stuck Open	RVIS	0.0022
Motor Trips		MT	
	Change in System Resistance	CSR	0.001
	Faulty Temperature Gauge or Switch	FTGS	0.00085
	Improperly Assembled Parts	IAP	0.0003
	Piping Strain	PS	0.009
	Rough Rotor Shaft Journal Surface	RSJS	0.0001
	Warped Foundation or Baseplate	WFB	0.005
	Warped Damaged Bearing	WDP	0.001

3 Bayesian Networks

Bayesian networks can be classified within the category of probabilistic graphical modelling techniques [22]. A directed acyclic graph (DAG) is used to define a Bayesian network. It comprises a series of nodes and arrows, with arrows defining the relationship between the nodes (parent-child) [23]. For more simplicity, we give the example illustrated in figure 1. Bayesian network topology modelling causal relationships, excessive vibration or compressor surge (causes) can damage the compressor (effect). An arrow from an Excessive vibration node "EV" towards a compressor node "CF", means that the variable EV influences the variable CF.

The probability of each variable is given by a conditional probability table. In Table4, for example, if a variable has no node parents, such as EV and CS, its probability distribution is said to be a priori. On the other hand, if the variable has parent nodes, its probability distribution is said to be conditional.

Table 4 Conditional probability table

	EV	True		False	
	CS	True	False	True	False
CF	True	1	1	1	0
	False	0	0	0	1

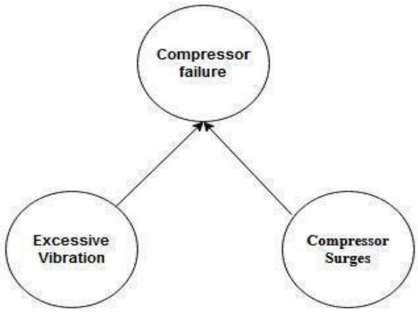

Fig.1 Example of simple Bayesian network

The joint probability calculation for a Bayesian network is given by formula 1 [23]:

$$P(C1, \ldots, Cn) = \prod_{i=1}^{n} P(Ci|parents(Ci)) \qquad (1)$$

An example of a calculation to find the posterior probability is given below, based on conditional probability table (table 4) and formula 1:

P(CF = T) = P(CF = T|EV = T, CS = T) × P(EV = T) × P(CS = T) + P(CF = T|EV = T, CS = F) × P(EV= T) × P(CS = F) + P(CF = T|EV= F, CS = T) × P(EV = F) × P(CS = T) + P(CF = T|EV = F,CS = F) × P(EV = F) × P(CS = F)

The main use of a Bayesian network is to calculate the posterior probabilities, given an observed event.

4 Building of Elementary Bayesian Networks for Fault Diagnosis of Centrifugal Compressor:

Decision-making concerning an anomaly requires, first of all, an analysis of failure modes in the centrifugal compressor, which will lead to the anomaly's construction of the Bayesian network. The links between the nodes of the network will be a cause-effect type. Continuous line nodes represent the causes and discontinuous line nodes represent the effect. Then it is necessary to estimate the probability of anomalies manifestations based on the information exploitation recorded in the historical files or recovered from the online monitoring systems.

4.1 Building of the BN structure from vibration data:

Built on vibration data, the Bayesian networks shown in figure 2 have two levels. In the first level, we have twenty-two node parents who represent the causes (nodes drawn in a continuous line), and in the second level we have four children's nodes representing the effects (nodes drawn in a discontinuous line). As an example, Bent Rotor (BR) represents the cause and the node Excessive Vibration (EV) represents the effect.

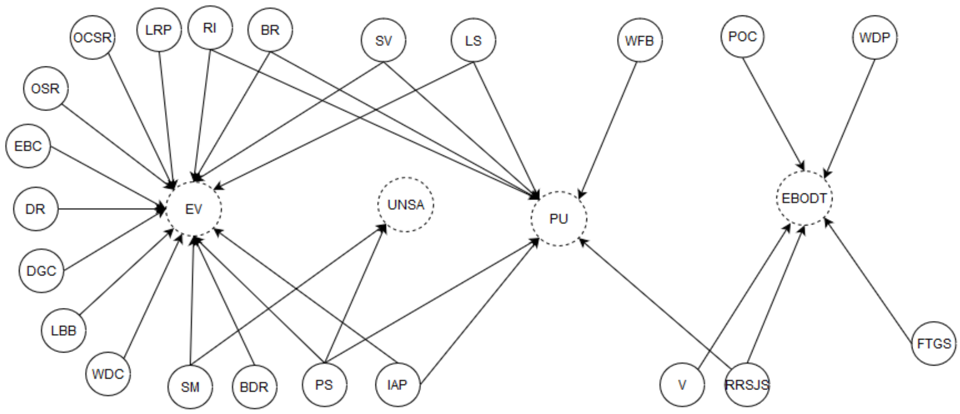

Fig.2 Bayesian network for fault prediction using vibration data.

4.2 Building of the BN structure from oil analysis:

Such as the Bayesian network structure of vibration data. On the basis of data from oil analysis, the Bayesian network represented in figure3 was structured on two levels, and as can be seen in the figure, the causes of the "WLO" fault are completely independent of the causes of the "EBODT" fault.

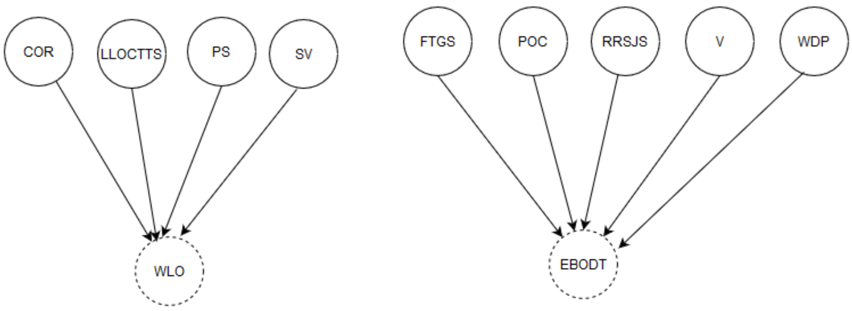

Fig.3 Bayesian network for fault prediction using oil analysis.

4.3 Building of the BN structure from the operating parameters:

Figure 4 represents the Bayesian network structure obtained from the operating parameter shown in table 3. On this network, there are four faults represented by nodes drawn in discontinuous line. CS as an example, this one has four parents' node (cause) BDD, BDR, IF and CSR, if only one cause of these causes is true (exits) that can generate the CS fault.

The essential point is these networks shown in this section are causal networks, which means if one cause takes a state true, the effect also takes a state true. The only case that leads to the fault (effect) not occurring is if all the causes are false. In other words, there is no fault. To illustrate, if "CNUS = True, EIT = True, and LIDP = False," the LDP fault is True (occurs); if "CNUS = False, EIT = False, and LIDP = False," the LDP fault is False (not occurs).

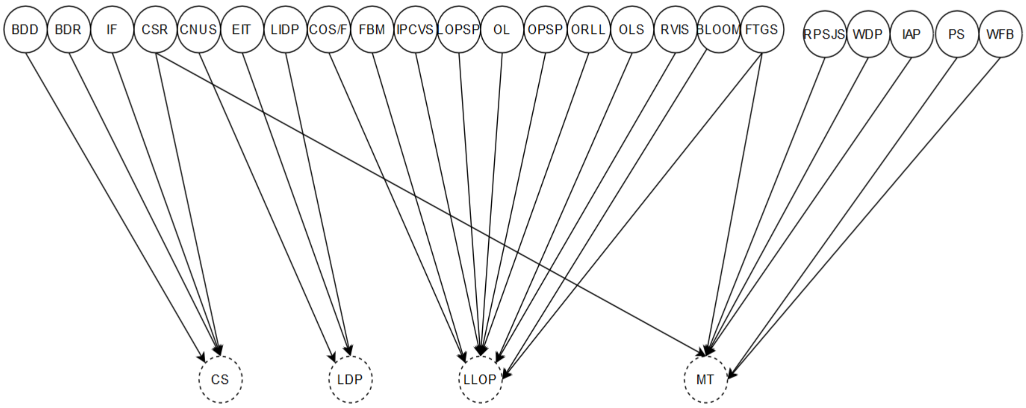

Fig.4 Bayesian network for fault prediction using operating parameters

5 Application on Faults Prediction of Centrifugal Compressor

This study was conducted on the centrifugal compressor type BCL 406, and table 5 shows the operating characteristics of this centrifugal compressor.

Table 5 characteristic of the centrifugal compressor

Parameters	**Compressor**
Debit	99400 N3/h
Suction pressure	30 Bar
Discharge pressure	80 Bar
Suction temperature	50 C
Discharge temperature	150 C
Absorbed power	5504 Kw
Rotation speed	10323 r/min
Max speed	10375 r/min

In this section, and in order to improve the fault prediction of the centrifugal compressor, we are using the Bayesian network method to fuse the fault prediction obtained from vibration data and oil analysis and the operating parameters.

5.1 Multi-source information fusion:

The process of multi-source information fusion for centrifugal compressor in this study done through the following steps: Get information of the faults in the centrifugal compressor. Classify and sort the information of faults obtained from the centrifugal compressor. Information is classified an according to its fault prediction method, and various types of faults are ruled as independent of each other. Finally, fuse all the information of fault prediction to achieve a final decision.

The Bayesian network-based centrifugal compressor information fusion model was applied to study fault prediction was presented in the figure 5 below. To simplify the problem, different methods have been used for fault prediction in centrifugal compressors, such as vibration analysis and oil analysis. Thus, the results obtained would have different characteristics if they were submitted to the multi-source information fusion model based on Bayesian networks. This process should produce fault prediction results with more precision, that is to say, obtain more complete and reliable results, which could provide a basis for the prediction of faults in centrifugal compressors and decision-making.

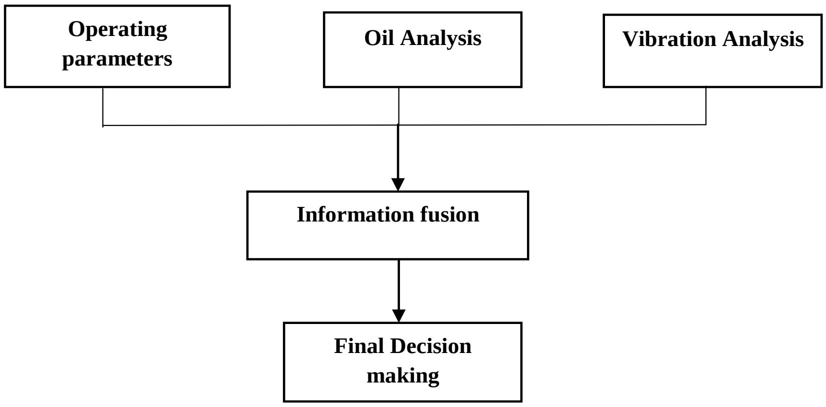

Fig.5 The multi-source Information fusion algorithm.

The entire fault prediction model is shown in Figure 6 was generated by combining the sub-models of figures 2, 3, and 4. Taking as an example the two causes "Poor Oil Condition POC" and "Warped Damaged Bearing WDP", are not only created the fault Excessive Bearing Oil Drain Temp "EBODT" but also generates the fault Excessive Vibration,

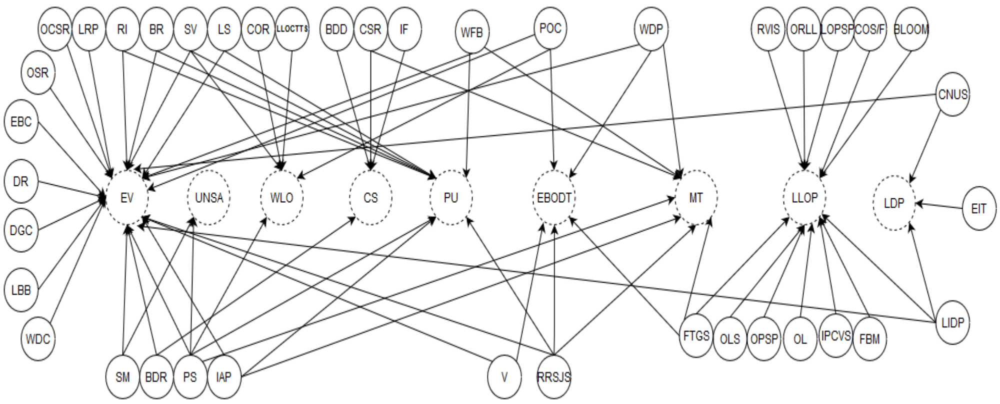

Fig.6 Bayesian network for fault prediction of centrifugal compressor.

5.2 Inference in the proposed Bayesian network model:

Referring to the historical file of a centrifugal compressor, a priori probabilities have been defined and given by tables 1, 2 and 3. The second step consists of defining the conditional probability tables (CPT). These tables quantify the relationship between causes and effects. An example of a conditional probability table (CPT) is given in Table 6.

Table 6 Conditional probability table for the UNSA failure.

	PS	T		F	
	SM	T	F	T	F
UNSA	True	1	1	1	0
	False	0	0	0	1

T = True, F = False.

An example of a UNSA failure probability calculation with both True and False states is shown below:

P(UNSA = T) = P(UNSA = T|PS = T, SM = T) × P(PS = T) × P(SM = T) + P(UNSA = T|PS = T, SM = F) × P(PS= T) × P(SM = F) + P(UNSA = T|PS= F, SM = T) × P(PS = F) × P(SM = T) + P(UNSA = T|PS = F,SM = F) × P(PS = F) × P(SM = F)

= (1 × 0.009 × 0.00025) + (1 × 0.009 × 0.99975) + (1 × 0.991 × 0.00025) + (0 × 0.991 × 0.99975) = 0.00000225+ 0.00899775+ 0.00024775 + 0 =0.00925.

With the same method, it is possible to calculate the other failure probabilities. When the number of nodes becomes very large, the calculation becomes complicated. For this reason, we have created a program under Matlab to facilitate the calculation.

Figure 7 shows the results obtained from vibration analysis data. Moreover, as we can see, the probability of occurrence of the "Vibration Excessive EV" fault is 8.645%, and for the Persistent Unloading "PI" fault it's 5.723% One can consider that the probability of occurrence of one of these faults is important compared to the two other faults, "UNSA" and "EBODT".

As shown in figure 8, the probability of fault occurrence for "Water in Lube Oil" is greater than 3%, and it can be seen that the fault "EBODT" can be diagnosed using oil analysis or vibration analysis, but its appearance in fault prediction of the centrifugal compressor is not significant compared to other faults, with the probability of occurrence for the "EBODT" fault being 0.644%.

In the case of operating parameters, as shown in Figure 9, the probability of the presence of a "Compressor surge (CS)" fault is 1.721% and this value was almost the same for the "Motor Trips (MT)" fault it is 1.716%, and for the other "Loss of Discharge Pressure (LDP)" and, "Low Lube Oil Pressure (LLOP)" faults is 0.430% and 0.811% respectively.

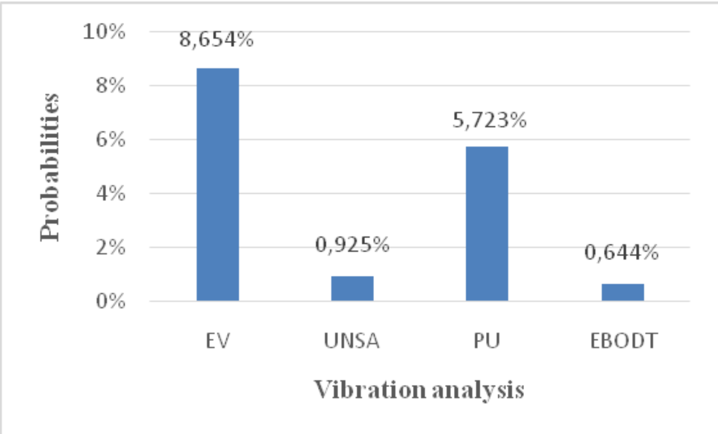

Fig.7 Results of vibration analysis

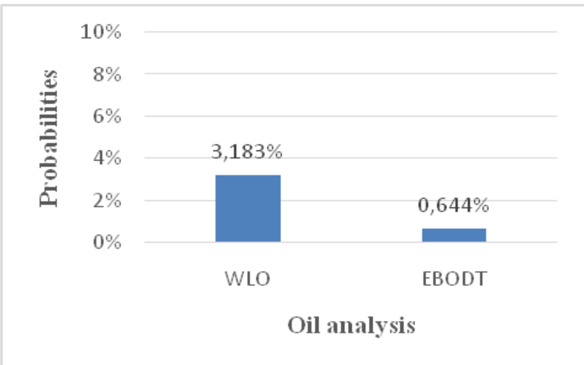

Fig.8 Results of oil analysis

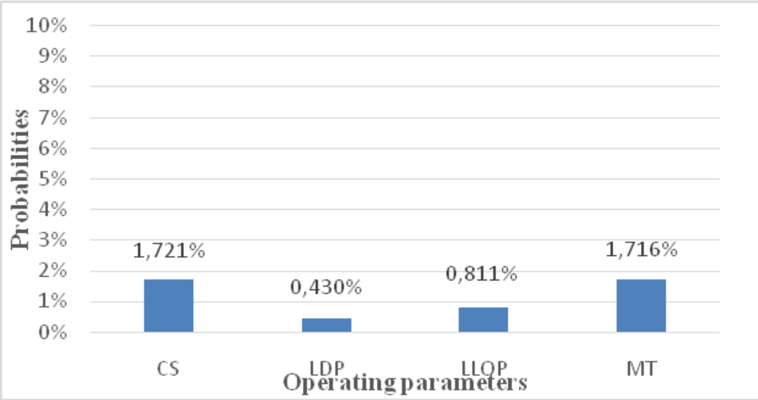

Fig.9 Results of operating parameters

For the multi-source information fusion, "vibration analysis, oil analysis and operating parameters data" are presented in figure 10. From the results obtained, it can be said that the probability of occurrence of the EV fault is at a value of 9.908% and it is the fault that most affects centrifugal compressor operating. Taking the PU fault, it can be seen that the probability value represents 5.273% and 3.570 % represents the probability of the WLO fault. Compared with the rest of the faults, we note that the probability of occurring one of the three faults is very important, as the probability of occurrence of each fault is UNSA represents 0.925% and CS 1.721%, 0.430 for the LDP fault, LLOP its 0.875% and EBODT 0.644%. Finally, the MT fault represents 1.716% in fault prediction of centrifugal compressors.

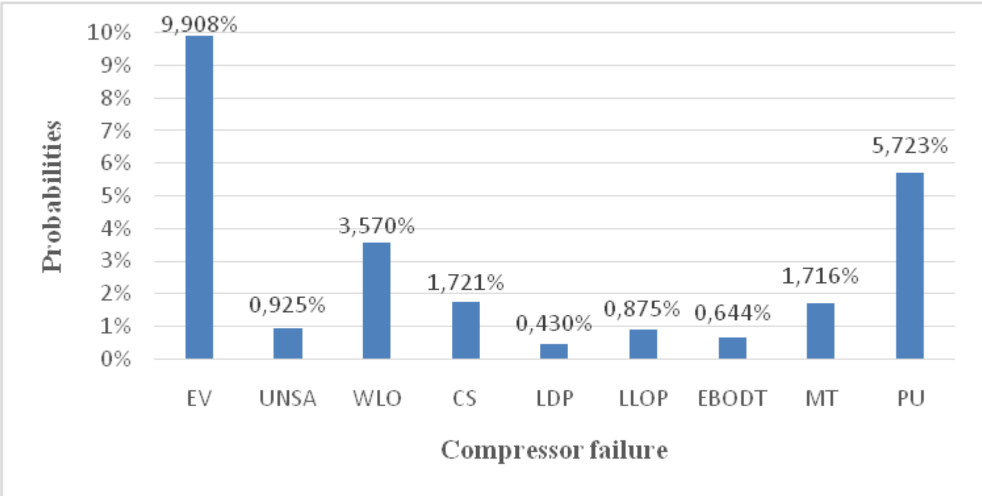

Fig.10 Results of multi-source information fusion.

Predictive maintenance is generally based on data collected from monitoring systems. It is possible to trace trends and even alerts. Decision-making remains ambiguous and uncertain because in practice there are always surprises. The results of this study show that the use of the data obtained from vibration analysis can only be used to make a decision. However, it is still uncertain and not accurate. Furthermore, other findings were obtained by using the data from the oil analysis and operating parameters several times, but the decision-making was uncertain and ambiguous.

The fault prediction model using evidence from only vibration analysis data or oil analysis only is not accurate enough for combined faults. As an example, the faults "POC" It cannot be detected by vibration analysis, but it causes an excessive vibration fault in the centrifugal compressor. Our findings on multi-source information fusion by the Bayesian network at least hint that there are some combined faults that cannot be detected by using vibration analysis or oil analysis only and this supports the hypothesis presented in this paper.

In addition, figure 11 shows the comparison between the vibration analysis and oil analysis fault prediction methods and the operational parameters individually with the multi-source information fusion proposed method. Moreover, it seems clear that the proposed method gives more accurate and reliable fault prediction results, especially when it comes to Excessive Vibration "EV" and Water in Lub Oil "WLO" faults. Finally, it can be concluded that the advantage of the multi-source information fusion by the Bayesian network method gives more accuracy in fault prediction in centrifugal compressors and the decision-making and reduces ambiguity for the combined faults.

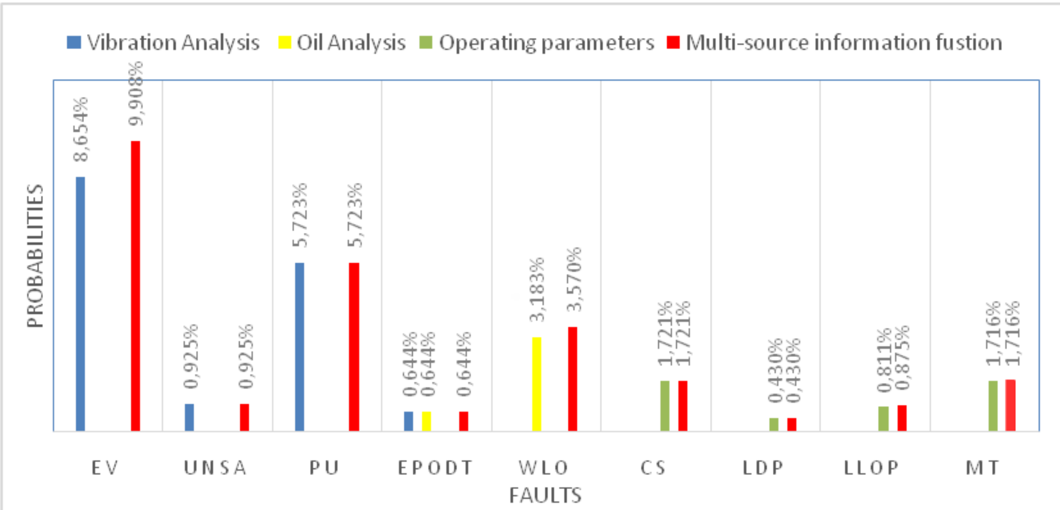

Fig.11 Comparison of the obtained results.

5.3 Comparison with other artificial intelligence methods:

The developed Bayesian networks in this paper have some advantage over other artificial intelligence methods. In terms of graphical models, it can be seen that the Bayesian networks represented in this work are easy to understand even by non-professionals compared to artificial neuron networks (ANN) [25], and support vector machines (SVM) [26] also, fuzzy logic (FL) [27], and expert systems. In addition, this model is compatible with all centrifugal compressors but it must change the probabilities a priori for each one.

Figure 12 depicts a comparison of the Bayesian network and the previously mentioned Artificial Intelligence methods, which reveals a preference for the Bayesian network in both graphical representation and probability calculation.

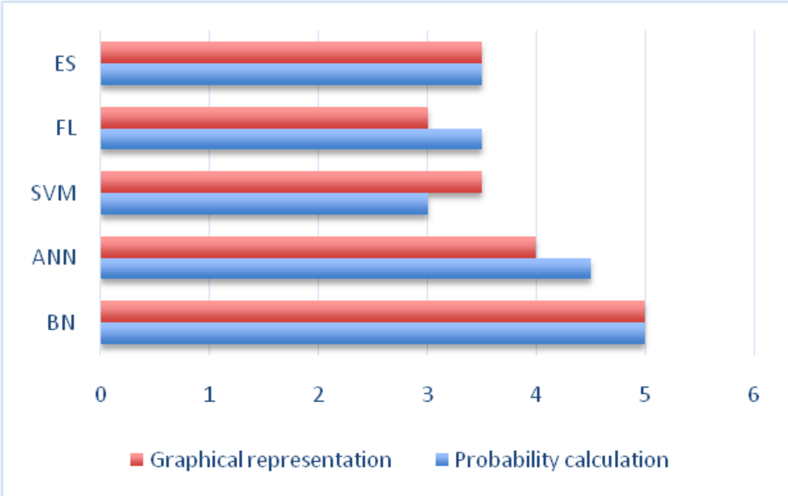

Fig.12 Comparison of BN and other AI method
5= Very high, 4 = high, 3 = low, 2 = very low.

CONCLUSION

A Bayesian network has been developed in this study based on multi-source information fusion, in order to improve the fault prediction in the centrifugal compressor and make a strong contribution to decision-making. In addition, the feasibility and effectiveness of the developed method were verified by a real case study of a centrifugal compressor. Based on the results, it can be concluded that the developed method for fault prediction in the centrifugal compressor has been very successful. The comparison of the obtained results shows that the use of multi-source information fusion by the Bayesian network is more accurate to fault prediction than vibration and oil analysis separately. Furthermore, the developed method gives more accuracy in decision-making and makes it a certainty in the case of combined faults, and removes ambiguity and uncertainty. The proposed method is generalized and could be applied to fault prediction on any centrifugal compressor, not just the one studied in this study. The only problem to consider and manage would be defining the parameters, which are specific for each machine.

Acknowledgements

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