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DEVELOPMENT AND APPLICATION OF A DECISION MAKING TOOL FOR FAULT DIAGNOSIS OF TURBOCOMPRESSOR BASED ON BAYESIAN NETWORK AND FAULT TREE

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Abstract
Fault Tree is one of the traditional and conventional approaches used in fault diagnosis. By identifying combinations of faults in a logical framework it's possible to define the structure of the fault tree. The same go with Bayesian networks, but the difference of these probabilistic tools is in their ability to reasoning under uncertainty. Some typical constraints to the fault diagnosis have been eliminated by the conversion to a Bayesian network. This paper shows that information processing has become simple and easy through the use of Bayesian networks. The study presented showed that updating knowledge and exploiting new knowledge does not complicate calculations. The contribution is the structural approach of faults diagnosis of turbo compressor qualitatively and quantitatively, the most likely faults are defined in descending order. The approach presented in this paper has been successfully applied to turbo compressor, which represent vital equipment in petrochemical plant.

Keywords
plant maintenance, prioritization, Bayesian networks, fault tree, diagnosis, turbo-compressor.

Introduction

Detection, diagnosis, and repair are the three key elements to keep industrial systems under control [1]. Monitoring consists of following the behavior of the industrial system, starting with detection (identification, probability of occurrence) and ending with a diagnosis (decision-making). A monitoring system is set up from the starting-up of the industrial system; it is based on an expert evaluation, passage to the limit values of a precursor, or even a poor quality of a product. The nature of the monitoring system depends essentially on the nature of the system and the type of information it contains. Three main types of monitoring approaches can be distinguished [2]: analytical model-based methods, data-driven methods, and knowledge-based methods.

Analytical model-based methods use a model described by mathematical relationships, representing the different physical relationships of the system, obtained by implementation of fundamental laws of various domains (physics, chemistry, electricity, thermodynamics, mechanics, etc.). The objective of this type of approach is to distinguish between residues caused by faults (assignable causes) and residues caused by other sources of variation (random causes). In this case, the presence of fault is detected by applying adequate thresholds on the residues [3].

Currently most industrial systems are more and more automated allowing data recovery. It should also be noted that the amount and variety of data to be processed is so important that an operator cannot directly track each variable in the system. We use data-driven techniques to represent the information expressed by all variables of the system. Some techniques allow detection while others focus on diagnosis [4]. Among these methods, we can notably mention approaches by control cards, principal component analysis and projection in latent structures for the detection phase, whereas for the diagnostic phase, we mainly find classification tools such as discriminate analysis [5], or neural networks [6].

In the absence of an analytical model of the system, the solution for monotoring lies in the exploitation of the qualitative knowledge held by experts on the system under study. Some techniques could be mentioned such as expert systems, FMEA (Failure Mode and Effects Analysis), FMECA (Failure Mode, Effects and Criticality Analysis) [7], as well as fault tree.

In the rest of this article, we are interested in fault tree. Fault tree analysis is a deductive method. Indeed the objective is to determine, from an undesired event defined *a priori*, the sequence of events or combinations of events that can finally lead to this event. This analysis makes it possible to go back from causes to causes until the basic events likely to be at the origin of the undesired event.

Modelling possibilities offered by fault tree, one of the best-known techniques for the analysis of operating safety of critical systems, can be extended relying on Bayesian networks (BNs) [8]. This formalism gives the possibility to make more flexible some typical constraints of BNs. In addition, BNs can be used to represent local dependencies and perform reasoning-based analysis for both diagnostics and prediction [9].

Quantitative and qualitative exploitation of the tree can only be carried out from a reduced tree. Computer software developed over the past ten years makes it possible to automatically determine probabilities throughout the tree. Fault tree combines analytical methods, Monte-Carlo simulation, and decision diagrams. Due to the limited use of Monte-Carlo simulation, the analytical approach is frequently the most used for the determination of probabilities by fault tree. In order to reduce the margin of error due to inaccurate and incomplete primary event data, some authors have recently used fuzzy theory in combination with fault tree [10, 11]. Fault tree, in addition to being limited to evaluating a single output variable, does not allow the representation of several state variables (which is generally the case for safety and risk analysis) [12], however a BN can fill this gap because it has the ability to evaluate several output variables in the same model.

In this article, we will give a new method of fault diagnosis based on the use of a fault tree and a BN. At the end and before concluding this article, we will show the effectiveness of the proposed tool through a case study of a turbo-compressor (TC).

Fault tree

Fault tree analysis has historically been the first method developed to conduct a systematic risk assessment. Aimed at determining the sequence and combinations of events that can lead to top event taken as a reference, fault tree analysis is now applied in many fields such as aeronautics, nuclear, chemical industry.

Tree construction

Whatever the nature of the basic identified elements, the fault tree analysis is based on the fact that the events are independent (i.e. they will not be split into simpler elements because of lack of available information, there is no interest or simply because it is not possible) and their frequency or probability of occurrence can be evaluated. Thus, the fault tree analysis enables identifying the successions and combinations of events that conduct the basic events up to the selected undesirable event.

Using mathematical and statistical rules, it is theoretically possible to evaluate the probability of occurrence of the final event from the probabilities of the identified basic events. Fault tree analysis of undesirable events begins with a first step which consists in defining the studied undesired event, then the construction of the tree, and finally the exploitation of this tree. To these steps should be added a preliminary step of knowledge of the system. This latter is essential for conducting the analysis and most often requires prior knowledge about faults. The links between the various identified events are made by means of logic gates of type "AND" and "OR", for example (Fig. 1).

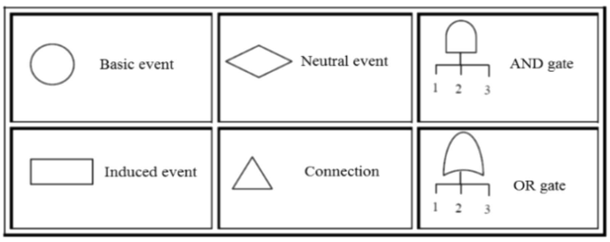


Fig. 1. Main elements of a FT.

Qualitative analysis of faults

The qualitative exploitation of the tree aims to examine in which proportion a fault corresponding to a basic event can spread in the chaining of causes until the final event. For this, we assume that all basic events are equiprobable and we study the routing of events or combinations of events, through the logic gates, up to the final event. Intuitively, a fault propagating through the system by encountering only "OR" gates is likely to lead very quickly to the final event. Conversely, a routing that operates exclusively through "AND" gates indicates that the occurrence of the final event from the basic event or the combination of basic events is less probable, and thus demonstrates better prevention of the final event.

Quantitative analysis of faults

The quantitative exploitation of fault tree aims to estimate, from the probabilities of occurrence of the basic events, the probability of occurrence of the final event as well as intermediate events. This is not an approach that allows obtaining accurately the probability of each event. It must be implemented in order to prioritize the various possible causes and to focus, as a prevention measure, on the most probable causes. In practice, it is often difficult to obtain precise values of probabilities of the basic events. In order to estimate them, it is possible to use databases, expert assessments, tests where possible, and feedback of experience on installation or similar installations.

From the probabilities of the basic events, it is a question of going up in the fault tree by applying the rules represented in the Fig. 2.

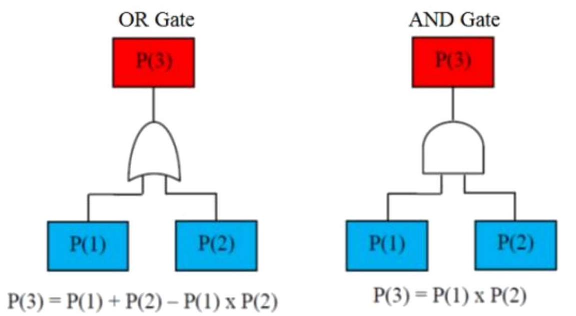


Fig. 2. Quantitative exploitation of a fault tree.

Bayesian networks

Bayesian networks also called probabilistic graphical models [13], have been widely used to solve various problems (e.g., diagnosis, classification, fault prediction, risk analysis) [9, 14, 15]. These models are characterized by their ability to process uncertain information and to represent the interdependencies between different variables of a given problem.

The advantage of probabilistic graphical models is the interesting graphical representation using basic models easily understandable and interpretable. Reasoning from probabilistic graphical models facilitates dealing with some problems such as prediction or diagnosis. Moreover, it is known that probabilistic fault analysis has many advantages, because it enables to evaluate the probability of fault of a complex system so that its weak points can be identified. Another advantage of probabilistic graphical models concerns the various developed tools, which participate and facilitate the construction of a model representing a given problem.

In Bayesian methods, *a priori* information, likelihood, and *a posteriori* information are represented by probability distributions. *A priori* probability represents the probability distribution of a knowledge or belief about a subject or variable before the parameter it represents is observed. Likelihood is a function of parameter of a statistical model, reflecting the possibility of observing a variable if these parameters would have a value. *A posteriori* probability is the conditional probability on the collected data by combination of *a priori* probability and likelihood via the Bayes theorem [16]

$$P(A/B) = \frac{P(A).P(B/A)}{P(B)}. \tag{1}$$

Bayesian network consists mainly of nodes and a set of edges. Indicating an edge between two variables implies a direct dependence between these two variables: one is the parent and the other the child. It is necessary to provide the behavior of the child variable in view of the behavior of his parent or parents, if there are several. For this, each node of the network has a table of conditional probabilities. A conditional probability table associated with a node enables to quantify the effect of the parent node(s) on this node: it describes the probabilities associated with the child nodes according to the different values of the parent nodes. For root nodes (without parents), the probability table is no longer conditional and then sets *a priori* probabilities concerning the values of the variable [13].

BNs forbid child to parent(s) dependencies. Thus, the set of variables and edges will form a directed (edges have a direction) and acyclic (no cycle in the graph) graph.

A BN (Fig. 3) is defined by [17]:

- an oriented acyclic graph G, $G = (V, E)$, where V is the set of nodes of G, and E is the set of edges of G;
- a probabilistic space (Ω, Z, P), with a non-empty finite set, Z a set of subspaces of Ω, and P a probability measure on Z with $\mathrm{P}(\Omega) = 1$;
- a set of random variables associated with the nodes of the graph G and defined on (Ω, Z, P), such that:

$$p(V_1, V_2, ..., V_n) = \prod_{i=1}^{n} p(V_i/C(V_i)), \qquad (2)$$

where C (V_i) is the set of parents (or causes) of V_i in the graph G.

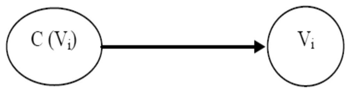


Fig. 3. Graphical representation of a simple BN.

Conversion of the fault tree into a Bayesian network

After building the fault tree, the first step in building a BN from a fault tree is to convert the graphical representation of the fault tree into a BN. The basic graphic elements for a fault tree are the events and logic gates (AND and OR), whereas for the BNs the basic elements are the nodes, that represent the events, and the edges that model the dependencies. There are some methods of transformations of a fault tree into BN, which consist in transforming the logical gates of a fault tree into nodes in the BN. These methods increase the number of nodes and make the calculations complicated and difficult. However the construction adopted in this article consists in transforming the different types of events of a fault tree into nodes in the associated BN, whereas the logical gates AND/OR do not participate in the graphical form of the network [8, 18]. In a BN, the connections between the events of a fault tree will be represented by edges, which translate the dependence between these events, and the relationships will be of "cause-effect" type; the different types of events will be represented by nodes, on the basis that the basic events will be the input nodes, and in the case that an event is repeated in the fault tree, it will be represented by a single node (Fig. 4).

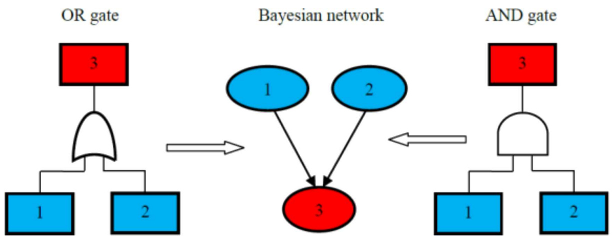
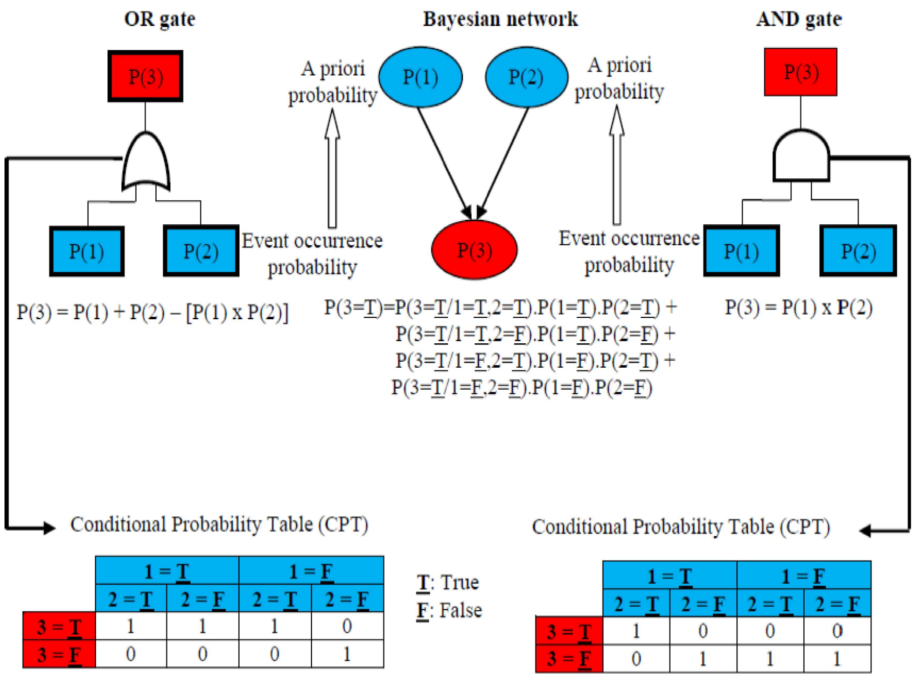


Fig. 4. Graphical conversion of a fault tree into BN.

The calculation of probabilities represents the second step in the construction of the BN from a fault tree. It consists of assigning the probabilities of occurrence of the basic (primary) events of the fault tree to the root nodes as *a priori* probabilities. In the case of induced (intermediate) events and the adverse event (top of the tree, final event), the associated probabilities will be calculated on the basis of the calculation of the conditional probabilities (Fig. 5).



	1 = T		1 = F	
	2 = T	2 = F	2 = T	2 = F
3 = T	1	1	1	0
3 = F	0	0	0	1

	1 = T		1 = F	
	2 = T	2 = F	2 = T	2 = F
3 = T	1	0	0	0
3 = F	0	1	1	1

Fig. 5. Numerical conversion of a fault tree into a BN

Analysis of faults of a turbocompressor

Description of the equipment

The turbo-compressor (TC) studied is used for the compression of the gas, which, in turn, is the basis for the production of liquefied natural gas. It consists of three machines: a multi-stage condensing steam turbine in which the steam passes through several stages, one behind the other, in order to reach an economical use of its energy, coupled to an axial compressor, consisting of two groups of stages, which is in turn connected to a gas turbine, whose rotor is common for the compressor and the gas turbine.

The rotor of the compressor and that of the steam turbine rest in sliding bearings regulated and lubricated by lubricating oil. They are axially fixed in two thrust bearings, one on the compressor side and the other on the steam turbine side (Fig. 6). The compact type oil system provides not only the oil for the bearings and other lubrication points of the machines and their accessories, but also the driving oil for the regulators and positioners, which makes the oil circuit complex.

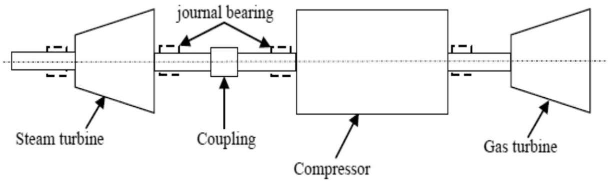


Fig. 6. Synoptic diagram of the equipment.

Fault tree analysis

To begin the construction of the TC associated TF, a codification for the different events is presented in Table 1, as well as the associated probabilities of occurrence.

To construct the fault tree, the undesired event begins with events and proceeds to their causes until basic the components are reached. The undesired event is the shutdown of the TC (see Fig. 7). In practice, to build our fault tree, it is necessary to find out

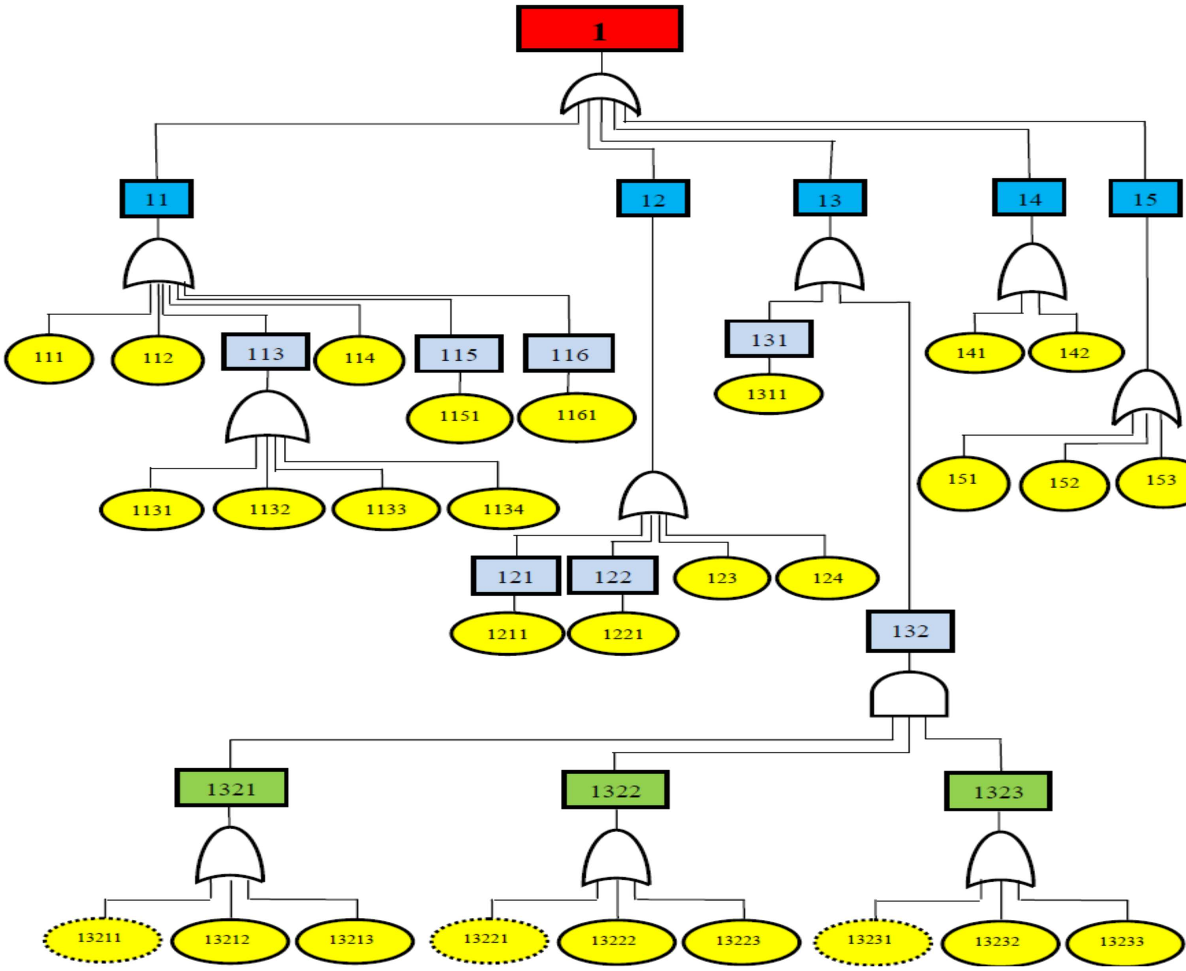


Fig. 7. Fault tree of a turbo-compressor.

Table 1
Different events and their associated probabilities of occurrence.

N°	Event	Code	Probability	a posteriori Probability
01	Turbo-compressor off	1	OR Gate	0.0340
02	Passage to vibrations limit values	11	OR Gate	0.0120
03	Faulty vibration sensor	111	0.0020	0.0020
04	OR Faulty Transmitter	112	0.0001	0.0001
05	OR Out of balance	113	OR Gate	0.0060
06	OR Presence of water in steam	1131	0.0018	0.0018
07	OR Broken blade	1132	0.0010	0.0010
08	OR Deformation of rotor	1133	0.0009	0.0009
09	OR Poor steam filtration	1134	0.0020	0.0020
10	OR Incorrect setting of the threshold	114	0.0001	0.0001
11	OR Bearing wear	115	0.0040	0.0040
12	Bad lubrication	1151	0.0040	0.0040
13	OR Axial displacement	116	0.0001	0.0001
14	Deterioration of the balancing piston	1161	0.0001	0.0001
15	OR Overspeed	12	OR Gate	0.0120
16	Mechanical overspeed	121	0.0030	0.0030
17	Process problem	1211	0.0030	0.0030
18	OR Electrical overspeed	122	0.0001	0.0001
19	Faulty Transmitter	1221	0.0001	0.0001
20	OR Faulty speed sensor	123	0.0025	0.0025
21	OR Misinterpretation	124	0.006	0.0060
22	OR Insufficient oil pressure	13	OR Gate	0.0070
23	Oil pressure < 8.26 bar	131	0.0070	0.0070
24	Impurity in the circuit	1311	0.0070	0.0070
25	OR No oil pressure	132	AND Gate	0.0010
26	First motor pump P1 shutdown	1321	OR Gate	0.0040
27	Power outage	13211	0.0002	0.0002
28	OR Motor short circuit	13212	0.0019	0.0019
29	OR Pump cavitation	13213	0.0015	0.0015
30	AND Second motor pump P2 shutdown (same as P1)	1322	OR Gate	0.0030
31	Power outage	13221	0.0002	0.0002
32	OR Motor short circuit	13222	0.0018	0.0018
33	OR Pump cavitation	13223	0.0010	0.0010
34	AND Third motor pump P3 shutdown (same as P1 and P2)	1323	OR Gate	0.0010
35	Power outage	13231	0.0002	0.0002
36	OR Motor short circuit	13232	0.0001	0.0001
37	OR Pump cavitation	13233	0.0001	0.0001
38	OR Emergency shutdown	14	OR Gate	0.0010
39	Control system adjustment drift	141	0.0002	0.0002
40	OR Manual control of the system	142	0.0001	0.0001
41	OR Anti-surge valve does not open	15	OR Gate	0.0030
42	Faulty surge limiter	151	0.0003	0.0003
43	OR Faulty valve	152	0.0001	0.0001
44	OR Faulty limit switch	153	0.0027	0.0027

the necessary and sufficient causes for the machine shutdown; this solution allows identifying a certain number of intermediate events, which will constitute the first level of the tree. Following the same principle, we obtain the second level, i.e. we look for the causes necessary for the intermediate event to appear. *A priori* probabilities of faults are defined by using the experience feedback and the history file of the turbo-compressor. Operators and maintenance engineers play an important role in defining these *a priori* probabilities. From the reliability of the *a priori* information depends the results of the fault diagnosis and analysis.

The nodes in yellow in Fig. 7 represent the causes or the basic events of the top event represented with the red color (shutdown of the TC), the other nodes (green and blue) represent the intermediate events of the various levels, and the nodes in dotted lines represent a common cause. Probabilities are assigned to the different basic events on the fault tree (see Table 1).

After analysis by fault tree, we find the probability of occurrence of the top event P (shutdown of the TC) $= P(1) = 0.034$, which is worth 3.4%. This probability is quantitatively acceptable, but since the machine is strategic and in view of optimizing the operational safety, it is still necessary to identify the main causes and minimize this percentage.

Fault tree studies are limited to minimizing the probability of occurrence, and identifying the fragile branches of the tree in order to carry out corrective actions. Under such situations and in addition to the frequency (probability), another main element should be considered: severity. The variables are binary (works/does not work), and adding a new state is very difficult with this tool. For example, the elimination of the basic event $P(1311) = 0$ is possible by increasing the oil analysis sampling frequency, which gives $P(1) = 0.027$.

To use this new information it is required to redo all the calculation in the tree. In addition, it is possible to use a fault tree only from a reduced tree.

Modeling using a Bayesian network

Modeling using a BN, obtained from a fault tree, starts with the graphical transformation (Fig. 4), the nodes, in yellow in Fig. 8, represent the parents (causes), and the other nodes represent the children (consequences). The dotted nodes of Fig. 7, which represent the same cause, will be represented by a single node on a BN; the other nodes of the BN represent the same nodes of the fault tree with the same levels.

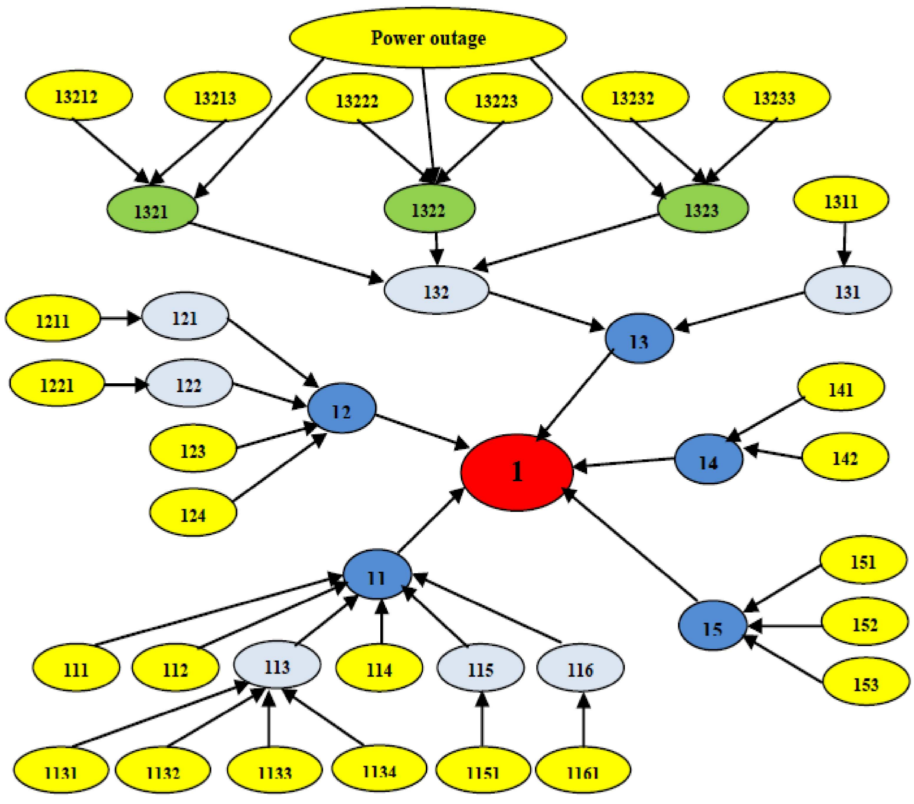


Fig. 8. Bayesian network associated to the turbo-compressor fault tree.

The numerical conversion from fault tree to BN is based on the calculation of probabilities and conditional probabilities of the variables. We assume that the variables are binary of "True/False" type, the probabilities attributed to the basic events of fault tree will be assigned in a similar manner in BN, these probabilities, called *a priori*, are the input parameters of the network. The evaluation of the probability of occurrence of an intermediate event is done by conditional probability calculation (see Table 1), and by transformation of AND/OR logic gates into conditional probability tables (Fig. 5).

From the BN, shown in Fig. 8, and the *a posteriori* probabilities, shown in the last column of Table 1, the following can be noticed:

- The probability of occurrence of the undesired top event is identical to that calculated by the fault tree, $P(1) = 0.034$;
- With our BN, it is possible to represent and evaluate $P(1) = P$ (TC shutdown) and $1 - P(1) =$ (TC operation) in the same model, and on any hierarchical level of the network;
- Regarding the TC availability, the resolution allows to foresee the resulting probability of the event (1), knowing the elementary probabilities (Pi) of the intermediate events, and to reveal the most important nodes of the network that affect the resulting probability. So for diagnosis, it is necessary to move towards the events to take into account as a priority during tests and for troubleshooting diagrams. From Table 1, events (11) and (12) are the most probable and should be treated first;
- With our BN, we have been able to simulate the event (131) by a continuous variable, which is not possible with the fault tree. Consequently, this gives us the possibility to define alarm and danger thresholds for oil pressure.

The events (13211), (13221), and (13223) modeled by three variables if the fault tree are modeled by a single variable (power outage) on the BN.

Centerpiece of the maintenance plan is the inventory of the most likely intermediate causes (causes 11, 12, 13, 14, 15) in order to list all the interventions to be carried out on the turbo-compressor including periodicity and resources. Table 2 lists a ranking of the most likely intermediate causes and which should be prioritized.

The inference process in the developed Bayesian network updates these probabilities and consequently allows the automatic updating of the turbo-compressor maintenance plan. The next phase is the establishment of the interventions planning which makes it possible to represent in a global and synthetic way the maintenance activity on the turbo-compressor.

Table 2
Most likely causes of faults.

Cause	*A posterior* probability	Priority
Passage to vibrations limit values	0.0120	1
Overspeed	0.0120	1
Insufficient oil pressure	0.0070	2
Anti-surge valve does not open	0.0030	3
Emergency shutdown	0.0010	4

Conclusions

BNs, presented in this article, deal with discrete and continuous variables, whereas fault tree deals with discrete variables. Furthermore, fault tree only works with binary variables; although there are several applications where several fault states are considered. To reduce this constraint, in the case of fault trees, logic gates and variables are added; this will make the graphical representation more bulky and complicates the calculations. Conversely for a BN, we need to adjust only the input data in the conditional probability table.

Fault tree is a fault analysis method that allows, due to its qualitative and quantitative aspect, setting up scenarios of events leading to a top event (TC shutdown). On the other hand, a BN is more suitable for diagnosis because it gives, for example, an explanation to a fault related to the system under study. Furthermore, the inference in a BN, by means of calculation of the *a posteriori* joint probability of the different variables, can fill the insufficiency of a fault tree in the case of diagnosis.

The paper presents the advantages of Bayesian networks over the fault tree in fault diagnosis, the mapping process and the construction of a Bayesian network from a fault tree, and the exploitation of the inference results for the prioritization of maintenance actions. The study presented this paper allows to maintenance practitioners to develop informed maintenance plans. The modes of operation of the maintenance department must therefore integrate this quantitative analysis into the automatic examination of the validity of the maintenance plan. Also, this study can be consolidated by a preliminary study of faults by FMECA, in order to analyze the severity of the various faults. Finally, it can be used in risk analysis.

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