

## Electrical Power Generator Faults Analysis Using Fault Tree and Bayesian Network

Toufik TOUIL<sup>1,2</sup>, Abdelaziz LAKEHAL<sup>3</sup>

<sup>1</sup> LGMM laboratory, Department of Mechanical Engineering, August 20, 1955 University, P.O. Box 26, El-Hadiék Road Skikda 21000, Algeria. e-mail: toufik.touil@bakerhughes.com

<sup>2</sup> Baker Hughes, Algerian Engineering Services Company, 148 chemin de wilaya, Blida, Algeria.

<sup>3</sup> Laboratory of Research on Electromechanical and Dependability, University of Souk Ahras, Algeria, e-mail: a.lakehal@univ-soukahras.dz

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**Abstract:** This paper presents a model to predict Electrical Power Generator (EPG) faults. The fault tree (FT) model is developed and used to help maintenance engineers in fault analysis procedure of this rotating machine. By identifying the main, intermediate and basic events it's possible to construct the FT with logical reasoning. The top dreaded event is defined. By using a Bayesian network (BN) as a complementary tool, fault prediction of the EPG becomes possible and easy. By using the developed BN, the probability of occurrence of the top event (EPG failure) is calculated. Also, by this approach, we can process complex information that causes system faults in an easy and simple way. The essential elements to do this analysis are the reliable and good exploitation of the information previously stored in the system. The use of the BN in combination with the FT gives the possibility of qualitative and quantitative analysis, diagnosis, and prediction of faults from the same Bayesian model. The flexibility of the proposed BN model in this paper allows better and precise decision making. Also, priorities regarding maintenance job are defined and resources are a priori prepared.

**Keywords:** Bayesian network, fault tree, electrical generator, fault prediction, information, maintenance priorities.

### 1. Introduction

Electric Power Generator (EPG) is used in many industrial and energy sectors. However, it can be prone to breakdowns. Faults of these rotating machines can cause serious damage to the economic sector, and in some cases hinder the development of society. Therefore, it is necessary to understand the root causes of EPG faults and providing an effective reference to prevent them. To do this,

this article presents a solution for identifying faults and taking preventive actions with the objective to prevent and minimize the risks of faults by using the fault tree (FT) and the Bayesian Network (BN). The second objective of the proposed solution is to pre-evaluate generator faults in an accurate and efficient manner. The fault prediction plays an important role in the safety systems of power plants and reduces maintenance costs, electricity production losses and increases the life cycle of EPGs.

Previous studies have conducted and proposed various solutions to improve the efficiency of EPGs, identify risks, and assess their impacts on this equipment.

Firstly, traditional analysis methods are used by researchers, such as Failure Mode and Effect Criticality Analysis (FMECA) [1,2], FT analysis [3], and Ishikawa diagram method [4]. However, these methods remain of limited use because they can be costly, not flexible to accommodate unforeseen changes in systems, also provide a false sense of security by overlooking human errors that can contribute to EPG faults. Other studies proposed artificial intelligence methods for industrial systems faults analysis, such as: artificial neural networks for fault diagnosis [5], fuzzy logic [6], and support vector machine [7]. Other authors have used artificial techniques for optimizing EPG operation and improve its availability such as: particle swarm optimization [8] and genetic algorithms [9]. These artificial intelligence techniques are given a strong contribution in the mastering of the EPG function, and they have improved the fault diagnosis and prediction when combined with traditional methods.

Several previous works in the literature show that hybrid fault diagnosis techniques based on traditional techniques and artificial intelligence methods allow better decision making and high performance when they are used together. Akhtar and Kirmani combine the operational failures with fuzzy logic in a Fuzzy Fault Tree model [10]. The contribution shows that the proposed model allows a good assessment of reliability and provides excellent fault analysis. Two traditional methods: FT and FMECA are combined to another traditional method to determine critical component in a diesel generator [11], they have also been utilized for conducting quantitative analyses of biogas plants by integrating them with recursive operability analysis, with a focus on elucidating the roles of procedural errors and component failures [12]. In other contributions, such as a maintenance plan for a turbine of hydroelectric power plant, Reliability-Centered Maintenance (RCM) was combined with FMECA [13] to better understand all potential failure scenarios that can affect industrial machines, while ensuring their reliability. Also, two artificial intelligence methods: genetic algorithm and fuzzy logic are combined to provide an expert system with the capability of anomaly detection and to allow the system to expose network problems autonomously [14].

In addition, some studies have integrated classical analysis methods and BNs such as: FT analysis and BN [15], Fuzzy Fault Tree with BN [16] and FMECA with BN [17]. In the application side there are few research works that discuss the fault diagnosis of EPG systems with BN. In this article FT is combined with a BN to resolve the problematic of fault prediction of these power systems. A mapping of the FT will be shown and a qualitative analysis will be made by the development of the BN structure and finally we try to give a quantitative analysis by inference in the developed BN.

This article is organized as follows: section 2 presents the EPG protection systems to allow a better understanding of the relationship between the system components. In section 3, a brief review of various methods and tools used for diagnosis and prediction of EPG faults, is presented. An application of our approach on EPG is presented in section 4. Finally, some recommendations and conclusions are provided at the end of this paper.

## **2. Generator protection systems description**

Power generation stations play a vital role in human life due to the importance of energy in industry and daily life. To mitigate recurrent system failures and power supply interruptions that result in significant economic losses, many industrial companies in this sector have resorted to innovation and development of control and protection systems for electrical generators.

These systems are specifically designed to prevent various faults that may occur during operation, utilizing a control program equipped with advanced sensors that facilitate the detection of faults and enable the immediate implementation of appropriate decisions.

Most EPGs are rotating machines created and developed with different technologies over time, used to produce electric energy on the one hand and to operate systems (industrial machines) on the other hand, which may be necessary for their proper functioning. In addition, they have several protection systems (*Fig.1*), including the lubricating oil system, cooling and ventilation system, control system, and it is also equipped with sensors that record various parameters such as temperature, vibration, etc. Due to their working conditions, EPGs are subject to unexpected failures that affect their components such as the rotor, bearings, etc.



Figure 1: Schematic diagram of a generator protection system.

To ensure providing a reliable supply of clean and fresh lubrication oil to the generator bearings and removing heat generated by friction, a reliable lubrication oil system is essential for the generator operation. Also, during the generation of electrical energy, heat is produced by eddy currents and Joule losses and by aerodynamic and mechanical friction. This heat must be dispersed to maintain the efficiency of the generator. The cooling and ventilation systems of the generator dissipate heat by cooling the generator and ventilating. Ventilation system is intended to pressurize the generator enclosure to prevent the infiltration of any combustible leakage gas, and to provide cooling airflow through the enclosure. In addition to these systems, a control system includes everything related to the control of voltage, temperature, synchronization, protection relays, and vibrations monitoring.

### 3. Research tools and methodology

There are several commonly used methods for fault and risk analysis, including the following examples: FT analysis, Failure Mode and Effects Analysis (FMEA), Functional Safety Analysis, Quantitative Risk Analysis using BN, etc. The methods used and presented in the rest of this paper are FT and BN.

#### A. FT Analysis

FT analysis is one of the methods developed for systematic fault assessment. FT is used to represent graphically the events that can lead to a system failure, as it is the main reference in the study of industrial machines faults. The FT is based mainly on defining the set of primary events and basic events sequentially, which in turn lead to the occurrence of the undesirable event specified in this study as the fault of the EPG. The connection between the various specified events is carried out by logical gates of type "AND" and "OR", which are used to represent the dependency relationships between the events.

#### B. BN analysis

BN is a probabilistic analysis tool or graphical probabilistic model that allows the representation of cause-and-effect relationships between events that lead to a fault of the system. BN is a powerful tool for modeling complex systems that involve multiple random variables and conditional dependencies between them, allowing for the calculation of the posterior probability of an event based on the prior probability of its causes.

In a BN, each node represents an event, and each link represents a cause-and-effect relationship between events. The probabilities of each event are updated based on the available information (previously stored information). The components of a BN include nodes, arcs, conditional probabilities, conditional probability tables.

The Bayes theorem is expressed as a formula in probability theory, utilized for the calculation of conditional probabilities. This method systematically adjusts the probabilities in order to obtain more information that may help us avoid total failure of the systems. The Bayesian approach has been widely applied in all fields. From the Bayesian formula, we have (*Fig. 2*):

$$P(A/B) = \frac{P(A \cap B)}{P(B)}, \quad (1)$$

where  $P(A \cap B)$  represents the probability of the intersection of events A and B, i.e., the probability that events A and B occur simultaneously, then

$$P(A \cap B) = P(A) \cdot P(B/A). \quad (2)$$

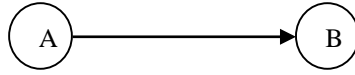


Figure 2: Simple Bayesian network

Substituting (2) into (1), we get:

$$P(A/B) = \frac{P(B/A) \cdot P(A)}{P(B)} \quad (3)$$

$P(A/B)$  is the probability of event A given event B has occurred.

$P(B/A)$  is the probability of event B given event A has occurred.

$P(A)$  is the prior probability of event A.

$P(B)$  is the marginal probability of event B.

Let  $A_1, A_2, \dots, A_n$  be the possible causes of B (Fig.3).

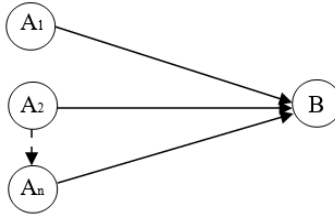


Figure 3: Simple Bayesian network for multiple events and a single effect

Then:

$$P(B) = P(A_1) \cdot P(B/A_1) + P(A_2) \cdot P(B/A_2) + \dots + P(A_n) \cdot P(B/A_n) \quad (4)$$

or equivalently,

$$P(B) = \sum_{i=1}^n P(A_i) \cdot P(B/A_i)$$

### C. Mapping of the FT into a BN

The mapping of the FT into the BN is based on their identical graphical representation. The second reason is that the two tools are given a strong contribution in fault analysis. The common element is the modeling of the relationships between faults that are represented by variables. The FT constructs by nodes, arcs, and logical gates (AND and OR) to display the interdependent relationships between events and their causal effects, while the BN are used to model the probabilistic relationships between system variables by using nodes and arcs to define the top event.

Also, a BN is based on a conditional probability table to calculate posterior probability of each variable during the quantitative phase. One conditional probability table defines quantitatively the relationship between events, but FT analysis requires two formulas to calculate each logic gates. In the case of new information, updating a BN is easier than a fault tree which requires redoing the all calculation throughout the tree. The combination of these methods makes it possible to obtain a more precise and complete probabilistic analysis of the faults to improve the system reliability.

#### **4. Practical application on an electrical power generator**

This section proposes a practical application of the proposed fault analysis approach; the main objective is to determine the degradation indicators of an EPG installed on the power plant production of Boufarik unit in northern Algeria. This plant is made up of three gas turbines totaling an installed capacity of 704.129 MW, and it was commissioned in 2016. It has been connected to the monitoring center of Algerian Electricity Production Company (AEPC) since April 2018.

In the maintenance activities, inspections are made and several repair works are carried out to address issues such as: visual inspection and NDT inspection of all components and replacing destroyed components with new ones. To interpret these found results, this paper presents a concrete example of probabilistic analysis using a combined approach based on FT and BN. It explains how to apply this approach to find out the causes that lead to the EPG faults, and enables us to predict the probability of occurrence of the top event, helps us in simplifying and understanding the results obtained easily, knowing the weaknesses areas in the system, and help taking actions to improve the reliability of the EPG.

Table 1: Basic faults and events of electric generators

Machine	Faults (D)	Causes (C)		
ELECTRICAL GENERATOR	Vibration (D1)	Bearing assembly fault (C1)		
		Vibration monitoring system (C2)	Faulty vibration probe (C21)	
			The monitor (C22)	
		Imbalance fault (C3)		
	Coupling problem (C4)			
	Generator overheating (D2)	Fire (C5)		
		Filters clogged (C6)		
		Cooling fan failure (C7)		
		Dirty air inlet screens (C8)		
		Internal air passage clogged (C9)		
	High temperature accompanied by vibrations (D3)	Electrical protection relays (C10)	Synchronization check (C101)	
			Generator differential (C102)	
			Power return (C103)	
			Loss of excitement (C104)	
			Time over current relay (C105)	
			Over- / underfrequency relay (C106)	
			Overvoltage relay (C107)	
			Undervoltage relay (C108)	
		Ground overvoltage relay (C109)		
		Rotor cooling air holes clogged (C11)		
		Shaft cooling fan broken (C12)		
	Voltage regulator problem (C13)			
	High temperature at the bearings (D4)	Lubrication system (C14)	Oil quality (C141)	
			Motor (C142)	
			Pumps (C143)	Auxiliary pump (C1431)
				Mechanical pump (C1432)
Emergency pump (C1433)				
Oil circuit (Piping) (C144)				
Oil pressure (C145)		High pressure (C1451)		
		Low pressure (C1452)		
Dirty oil inlet filters (C15)				
Faulty temperature sensor (C16)				



In Fig. 4, the FT model is established where EPG fault is the top event. Four common faults are intermediate events ( $D1, D2, D3$  and  $D4$ ). Also,  $C_i$  ( $i = 1, \dots, 16$ ) code is used to represent basic events.

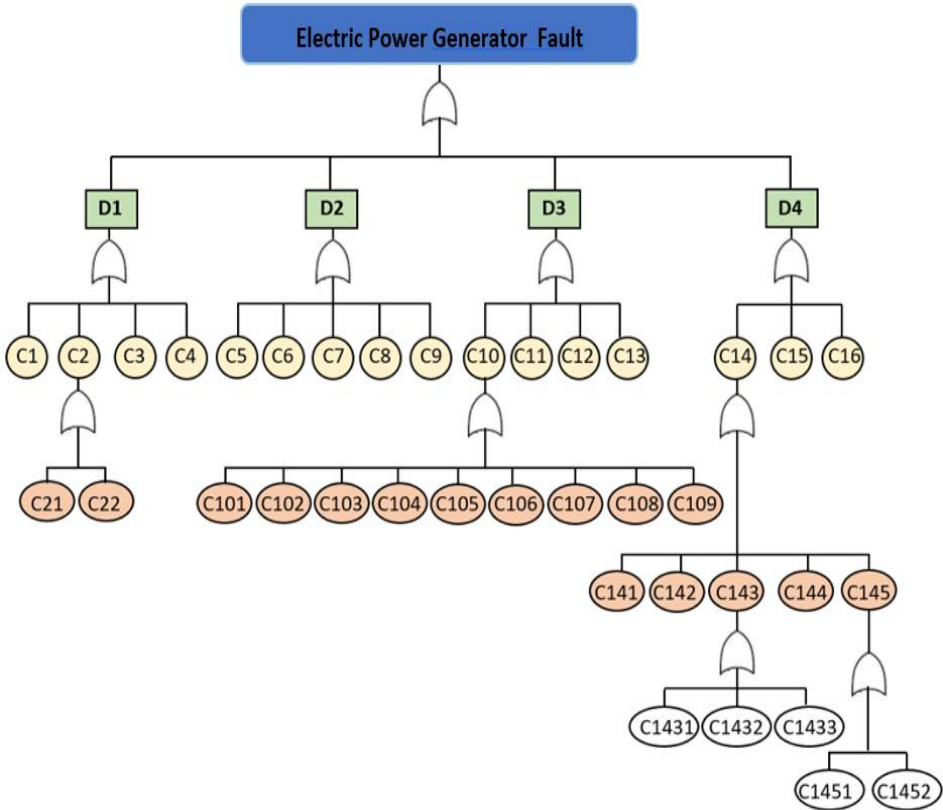


Figure 4: Fault tree diagram of an electrical generator

To complete the transposition of the FT in the space of probabilities, the following parameters must also be provided:

- If the cause  $D$  has no direct cause,  $P(D)$  will be defined. In the case where the cause  $D$  takes two states: true and false, we have to define the probabilities of the two logical values  $P(D = True)$  and  $P(D = False)$ .
- Also, If the effect EPG has a single direct cause  $D$ , we have to define  $P(G/D)$ , i.e., the four values  $P(EPG = T/D = T), P(EPG = T/D = F), P(EPG = F/D = T), P(EPG = F/D = F)$ .
- If the effect EPG has two direct causes  $D1$  and  $D2$  we have to define  $P(EPG/D1, D2)$ , that is to say the eight values:

$P(EPG = T/D1 = T, D2 = T), P(EPG = T/D1 = T, D2 = F), P(EPG = T/D1 = F, D2 = T), P(EPG = T/D1 = F, D2 = F), P(EPG = F/D1 = T, D2 = T), P(EPG = F/D1 = T, D2 = F), P(EPG = F/D1 = F, D2 = T), P(EPG = F/D1 = F, D2 = F).$

How to compute the probability of the main event  $D1$ , which has the secondary causes  $C1, C2, C3$  and  $C4$ ? First, we compute the probabilities of all events produced by secondary causes for example  $C2$  which in turn contains two secondary causes  $C21$  and  $C22$ , whose values are given in the Table 2.

$$\begin{aligned}
 P(C2 = T) &= P(C2/C21, C22) & (5) \\
 &= P(C2 = T/C21 = T, C22 = T) \cdot P(C21 = T) \cdot P(C22 = T) \\
 &\quad + P(C2 = T/C21 = T, C22 = F) \cdot P(C21 = T) \cdot P(C22 = F) \\
 &\quad + P(C2 = T/C21 = F, C22 = T) \cdot P(C21 = F) \cdot P(C22 = T) \\
 &\quad + P(C2 = T/C21 = F, C22 = F) \cdot P(C21 = F) \cdot P(C22 = F) \\
 &= (1 \times 0.0003 \times 0.0002) + (1 \times 0.0003 \times 0.9998) + (1 \times 0.9997 \times 0.0002) \\
 &\quad + (0 \times 0.9997 \times 0.9998) = 0.00000006 + 0.00029994 + 0.00019994 + \\
 &0 \approx 0.0005.
 \end{aligned}$$

Therefore, the value of  $P(C2)$  is 0.0005.

Having  $C1, C2, C3$  and  $C4$ , we can easily compute the value of  $D1$ , that is,

$$\begin{aligned}
 P(D1 = T) &= P(D1/C1, C2, C3, C4) = & (6) \\
 &= P(D1=T/C1=T, C2=T, C3=T, C4=T) \cdot P(C1=T) \cdot P(C2=T) \cdot P(C3=T) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=T, C2=T, C3=T, C4=F) \cdot P(C1=T) \cdot P(C2=T) \cdot P(C3=T) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=T, C2=T, C3=F, C4=T) \cdot P(C1=T) \cdot P(C2=T) \cdot P(C3=F) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=T, C2=T, C3=F, C4=F) \cdot P(C1=T) \cdot P(C2=T) \cdot P(C3=F) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=T, C2=F, C3=T, C4=T) \cdot P(C1=T) \cdot P(C2=F) \cdot P(C3=T) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=T, C2=F, C3=T, C4=F) \cdot P(C1=T) \cdot P(C2=F) \cdot P(C3=T) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=T, C2=F, C3=F, C4=T) \cdot P(C1=T) \cdot P(C2=F) \cdot P(C3=F) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=T, C2=F, C3=F, C4=F) \cdot P(C1=T) \cdot P(C2=F) \cdot P(C3=F) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=F, C2=T, C3=T, C4=T) \cdot P(C1=F) \cdot P(C2=T) \cdot P(C3=T) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=F, C2=T, C3=T, C4=F) \cdot P(C1=F) \cdot P(C2=T) \cdot P(C3=T) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=F, C2=T, C3=F, C4=T) \cdot P(C1=F) \cdot P(C2=T) \cdot P(C3=F) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=F, C2=T, C3=F, C4=F) \cdot P(C1=F) \cdot P(C2=T) \cdot P(C3=F) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=F, C2=F, C3=T, C4=T) \cdot P(C1=F) \cdot P(C2=F) \cdot P(C3=T) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=F, C2=F, C3=T, C4=F) \cdot P(C1=F) \cdot P(C2=F) \cdot P(C3=T) \cdot P(C4=F) \\
 &\quad + P(D1=T/C1=F, C2=F, C3=F, C4=T) \cdot P(C1=F) \cdot P(C2=F) \cdot P(C3=F) \cdot P(C4=T) \\
 &\quad + P(D1=T/C1=F, C2=F, C3=F, C4=F) \cdot P(C1=F) \cdot P(C2=F) \cdot P(C3=F) \cdot P(C4=F) \\
 &\quad \approx 0.0019
 \end{aligned}$$

In the same way, we calculate the remaining causes ( $D2, D3$  and  $D4$ ). The difficulty arises from the expanding number of combinations for which the probabilities need to be defined.

Table 2: A priori and a posteriori probabilities of the basic events (C1– C16)

Basic Events		A priori probabilities	A posteriori Probabilities		Probability of failure	
C1		0.0009	0.0009		D1= 0.0019	
C2	C21	0.0003	0.0005			
	C22	0.0002				
C3		0.0002	0.0002			
C4		0.0003	0.0003			
C5		0.0001	0.0001		D2=0.0016	
C6		0.0004	0.0004			
C7		0.0006	0.0006			
C8		0.0003	0.0003			
C9		0.0002	0.0002			
C10	C101	0.0001	0.0017		D3=0.0026	
	C102	0.0002				
	C103	0.0003				
	C104	0.0001				
	C105	0.0002				
	C106	0.0004				
	C107	0.0004				
	C108	0.0005				
	C109	0.0002				
C11		0.0001	0.0001			
C12		0.0003	0.0003			
C13		0.0005	0.0005			
C14	C141	0.0003	0.0009		D4= 0.0054	
		C142				0.0006
	C143	C1431	0.0008	0.0014		
		C1432	0.0001			
		C1433	0.0005			
	C144		0.0009	0.0009		
	C145	C1451	0.0003	0.0007		
C1452		0.0004				
C15		0.0009	0.0009			
C16		0.0006	0.0006			

Four primary variables ( $D1, D2, D3$  and  $D4$ ) represent the factors that conduct to the top event (electric power generator fault), each of these variables is connected to other variables in hierarchical order. In addition, the BN contains a

quantitative description of the behavior of the variables, which are expressed using a posteriori probability of the prior data previously stored by the experts.

From the Table 2, by using the values obtained from the four events calculated previously ( $D1, D2, D3$  and  $D4$ ), the top event can be calculated as follows:

$$P(EPG) = P(EPG/D1, D2, D3, D4) = \sum_{i=1}^4 P(EPG/Di).P(Di), \quad (7)$$

therefore

$$P(EPG) = P(EPG/D1).P(D1) + P(EPG/D2).P(D2) + P(EPG/D3).P(D3) + P(EPG/D4).P(D4)$$

From relationship (4), we have

$$P(EPG/Di).P(Di) = P(EPG \cap Di), \text{ for } i = 1, \dots, 4. \quad (8)$$

From Table 2, we have

$$P(EPG \cap D1) = 0.0019, P(EPG \cap D2) = 0.0016, P(EPG \cap D3) = 0.0026$$

and  $P(EPG \cap D4) = 0.0054$ .

It follows from these results that

$$P(EPG) = 0.0019 + 0.0016 + 0.0026 + 0.0054 = 0.0115.$$

From the BN of *Fig. 5*, we have calculated that the probability of occurrence of the undesirable event, which is the shutdown of EPG, is 1.2%. This probability is temporarily acceptable in terms of quantity, but from an economic point of view, and also given the importance of electricity in the life of the population, it is necessary to address the sources of the faults before they create other problems, by identifying the weaknesses and taking corrective measures to reduce the probabilities of faults. Therefore, we must return to the FT to find out the causes of top impact on the EPG, using Table 2, which gives us an approximate view of the probability of each event occurring (quantitative description of each event). The contribution of each of the main events ( $D1, \dots, D4$ ) to the total failure rate can be expressed in percent.

For instance, the probability of 0.0019 of the first main event “ $D1$ ” represents a 17% contribution to the total failure rate of 1.15%. According to the results shown in Table 2, we conclude that the prediction of occurrence of a posteriori probability of bearings ( $D4$ ) due to the high temperature and lubrication system, the most important factor as it ranks first in EPG fault approximately with 49%. High temperature accompanied by vibrations ( $D3$ ) also plays a significant role, but to a lesser extent as they contribute about 23% to EPG fault. EPG overheating

(D2) and vibration (D1) contribute less to the system fault, by rates of 14% and 17% respectively.

Due to the importance and strategic role of the EPG in the community, in order to improve its operational safety, the maintenance team is required to reduce the occurrence probability of the top events. This is done by focusing on the main events, such as reducing vibrations and temperature increases at the bearings, by conducting preventive checks to reduce them, such as checking the lubricating oil system (pumps, filters, and pipes). Also, it is important to take corrective actions for other events that are less harmful to the system. By making these corrections, it is possible to raise the efficiency of the EPG and reduce the exorbitant maintenance costs, in addition to increasing the energy production, and this is what the power units aspire for.

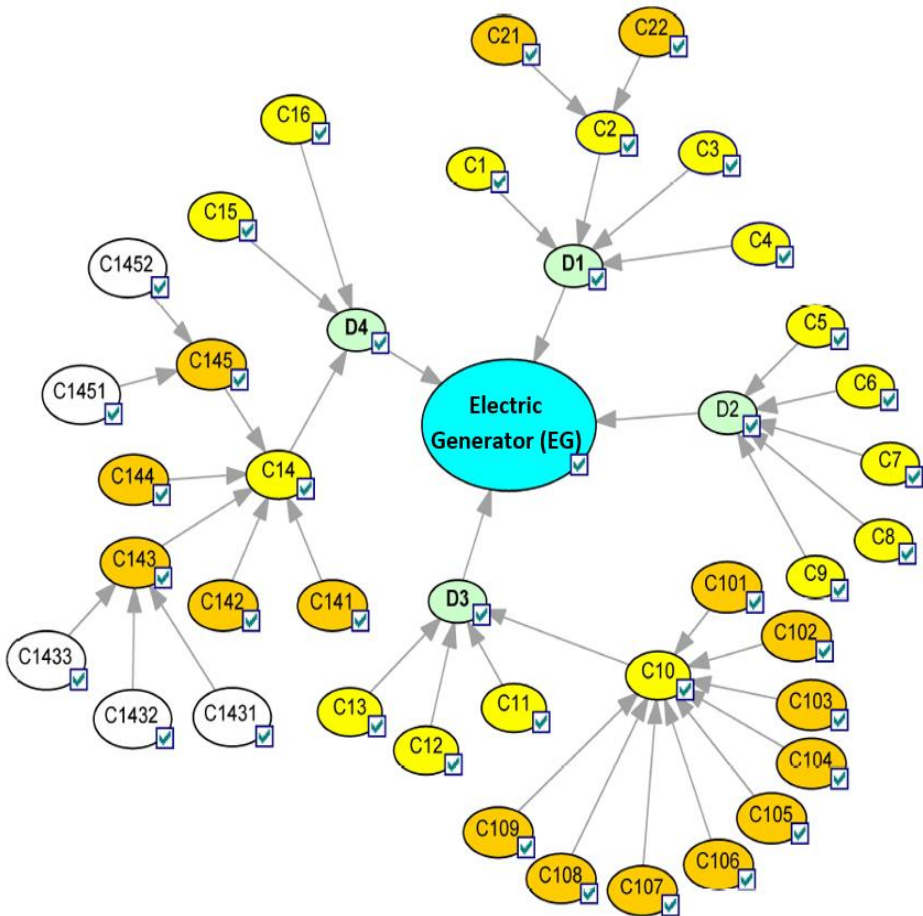


Figure5: Bayesian network of electric power generator fault

## 5. Conclusion

In this study, a probabilistic analysis of EPG faults was performed, firstly using FT analysis to know all the main and secondary causes that could lead to EPG fault. After listing all faults in Table 1 based on initial data collected by operators and maintenance experts, by the proposed approach of integrating the FT and BN it becomes easy for us to calculate all the a posteriori probability leading to the prediction of occurrence of the EPG fault. The results obtained, shown in Table 2, indicate that EPG failure is primarily attributed to the high temperature at the bearings (**D4**), accounting for approximately 49% of failures. Subsequently, high temperature accompanied by vibrations (**D3**) is identified as another significant factor, contributing to failure at an approximate rate of 23%. In contrast, generator overheating (**D2**) and vibrations (**D1**) are recognized as causative factors at lower rates, estimated at 14% and 17%, respectively. Based on the results obtained, the proposed method simplifies complex industrial models, especially those that are challenging for failure analysis. This method helps to identify fragile branches in the FT, which is crucial to understanding the main causes of system failure. Also, it allows the maintenance team to evaluate potential faults and take preventive measures to avoid or reduce them. In conclusion, the goal of this approach is to improve the reliability of the EPG and of the entire system.

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