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# Root Cause Analysis to Identify Physical Causes

G. Medina Oliva<sup>a</sup>, B. Iung<sup>a</sup>, L. Barberá<sup>b</sup>, P. Viveros<sup>c</sup>, T. Ruin<sup>a</sup>

<sup>a</sup>CRAN, Nancy-Université, CNRS, Boulevard des Aiguillettes B.P. 70239 F-54506 Vandœuvre lès Nancy

(e-mail: {[gabriela.medina-oliva](mailto:gabriela.medina-oliva), [benoit.iung](mailto:benoit.iung), [thomas.ruin](mailto:thomas.ruin)}@cran.uhp-nancy.fr)

<sup>b</sup>Department of Industrial Management, School of Engineering, University of Seville, Camino de los Descubrimientos s/n 41092 Seville, Spain

(e-mail: [lbm@esi.us.es](mailto:lbm@esi.us.es))

<sup>c</sup>Department of Industrial Engineering, Universidad Técnica Federico Santa María, Avenida Espana 1680, Valparaiso, Chile

(e-mail: [pablo.viveros@usm.cl](mailto:pablo.viveros@usm.cl))

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**Abstract:** This paper proposes a methodology to develop a root cause analysis (RCA) tool which purpose is to identify the physical bad actors that cause performances deviations of an industrial system. This model is based on the integration of several RCA tools such as fault tree, FMECA and HAZOP. The objective is to evaluate and identify perturbation factors in order to eliminate them and to optimize the enterprise maintenance performances. The methodology is formalized from functional, dysfunctional and informational studies of the technical industrial systems. This methodology is applied, for modeling a water heater system to identify the factors that causes deviation on its reliability and its output flow attributes.

**Keywords:** Bayesian Network, root cause analysis, system performances

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## 1. INTRODUCTION

Several methods have been proposed in the literature for planning activities for industrial plant maintenance. Proactive maintenance utilizes tools such as Root Cause Failure Analysis (RCFA), Failure Modes and Effects Analysis (FMEA), Critical Analysis (CA), Acceptance Testing and Aging Exploration (AE). Some authors even make a distinction and identify a sub-branch in the Proactive Maintenance, called Radical Maintenance (RM), which involves the detection and prediction of root causes of failures, and subsequently take appropriate actions to eliminate the root causes or conditions that lead to them (Gao et al., 2005).

There is a wide variety of tools and methods for determining the root causes of certain events or failures (Barberá et al., 2010). They vary in complexity, quality of information required and applicability of their results. In general, the most commonly used are the 5 Why Analysis, Change Analysis, Current Reality Tree (CRT), Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Pareto Analysis, Bayesian Inference and Ishikawa Diagram. These methodologies have substantial differences, and they can be categorized into qualitative (5 Why Analysis, Ishikawa Diagram, HAZOP, among others) and quantitative (Bayesian Inference, Pareto Analysis, Fault Tree Analysis (Gano, 2007) and (Rossing et al., 2010)). While qualitative methods are generally performed in the form of brainstorming; quantitative methodologies can even use complex mathematical methods. The importance of using Root Cause Analysis tools in Maintenance relies in the need to understand the main causes of failure on which Management or Operations may have some control, so that they can avoid the chronic failure and returning to a specified plan of action.

The flow chart below (Figure 1), based on the work of (Barbera et al., 2010) and (Li and Gao, 2010), shows the location of various methods of root cause analysis in a model of maintenance management by stages. Pareto Analysis is at the stage of critical equipment hierarchization, because in conjunction with the criticality matrix can help to determine which equipments are critical at a systemic level. FMEA can be used at the stage of Weaknesses Analysis of critical equipment, where an assessment of causes, failure modes and effects can be relevant. Critical Analysis helps to determine whether the weaknesses of critical equipment are significant in the system performance. FTA or Bayesian inference can be used to perform a more complex analysis for determining the root causes of equipment failures and critical weak points.

For all the above, it is worth to note that the optimum performance of the methodologies is achieved when used properly for a particular requirement at a specific stage within the framework of the overall maintenance management process.

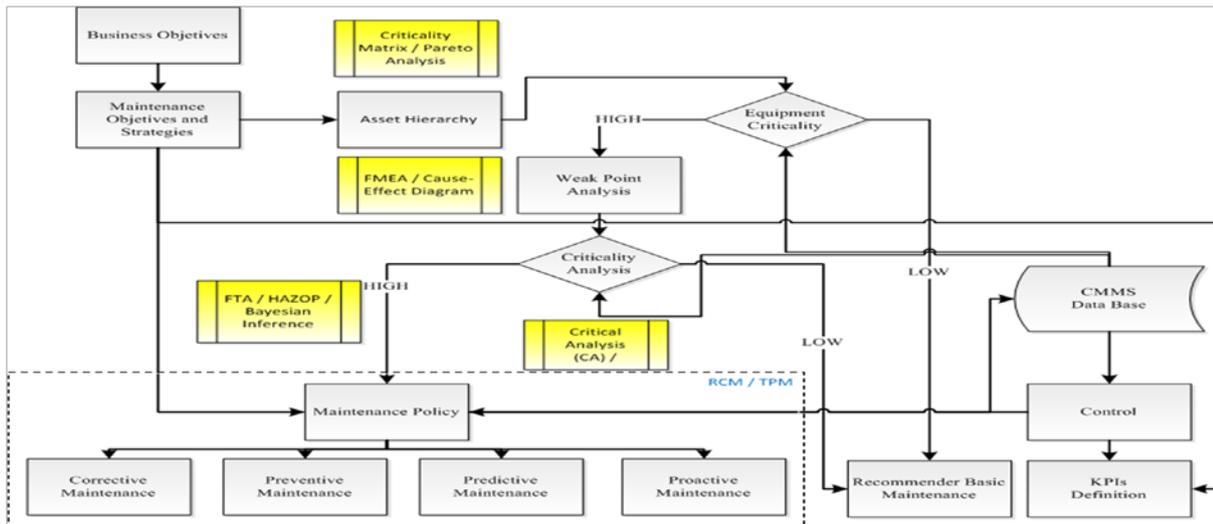


Figure 1. Location of RCA methodologies in Maintenance Management

## 2. ROOT CAUSE ANALYSIS MODELS (RCA)

The root cause of a failure can be defined as the basics causes which can be reasonably identified and on which management has control (Paradies and Busch, 1988). The literature that supports this approach determines that there are three levels of root cause of the failure in a system:

- Physical Root Cause: Equipment failure caused by physical reasons.
- Human Root Cause: Equipment failure caused by human intervention.
- Latent Root Cause: Equipment failure caused by organizational-level decisions that trigger a fault event.

Failure Analysis (FA) or Root Cause Analysis (RCA) consists of examining in detail the items reaching the fault state to determine the root cause of it and improving system reliability (Sikos and Klem, 2010). This process identifies causal factors using a structured approach with techniques designed to achieve a proper orientation, thereby allowing the identification and resolution of problems. Its implementation eliminates or minimizes those root causes that can generate recurrent failures, not focusing on the actual consequences of failure (Doggett, 2004). Within root cause analysis methods, four groups can be distinguished (American Institute of Chemical Engineers, 1992).

Table 1. Classification of RCA techniques in groups, based on their approach

Root Cause Analysis Groups	Description
Deductive	This Approach involves reasoning from general to specific (Example: Fault Tree Analysis).
Inductive	This Approach involves reasoning from individual cases to general conclusions, providing a comprehensive approach (Example: Cause and Effect Analysis Diagram, HAZOP).
Morphological	Method based on the structure of the system under study. It is centered on the potentially dangerous items, focusing on factors that have the greatest influence on the system safety. (Example: Accidents Evolution, Barrier Techniques, Job Safety Analysis).
Non system oriented techniques	Non-oriented concepts and techniques as the previous ones. (Example: Change Analysis, Human Error Study Probability).

Below the most used RCA methodologies in Reliability Engineering are:

- Failure Modes and Effects Analysis and Criticality (FMECA) (Cai and Wu, 2004), (Li and Gao, 2010).
- Fault Tree Analysis (FTA).
- Cause and Effect Diagram (CED) (Doggett, 2004).
- Hazard and operability study HAZOP (Rossing et al., 2010).
- Bayesian Inference.

Depending on the type and depth of analysis to be performed, it is necessary to evaluate each method to use only the one that best suits the needs addressed. While all methods have the ability to define the problem in question, Cause and Effect Diagrams do not show any causal relationships between the primary effect and the root causes nor are they able to deliver a clear path to the root causes, as only isolated causes are categorized or sorted into groups which produce a primary effect. However, they have a low level of requests

for information and resources and are relatively easy to use (Gano, 2007). The HAZOP study is an analysis structured as a brainstorming and developed by people highly internalized into the problem to solve, so it is highly dependent on the experience of managers and should be conducted in multiple sessions, requiring time and other resources. Their advantage lies in the plans developed to prevent recurrence (Rossing et al., 2010). The FMEA is effective to find the causes of component failure, however, loses its ability to solve complex problems being unable to establish causal relationships beyond the failure mode being analyzed. The Fault Tree Analysis is a quantitative method that works extremely well in engineering problems, finding causes related to the original design of the system, identifying possible scenarios and selecting appropriate solutions, whenever they do not include human factors (Gano, 2007). For its part, the Bayesian Networks (despite of requiring more resources and have less ease of use) has great ability to establish causal relationships for a large number of variables and is suitable as a support for making decisions to prevent recurrence. Its structure facilitates the combination of prior knowledge, obtained either causally or from observed data. Bayesian networks can be used to find causal relationships, to facilitate understanding and the best way of analyzing the problem and to predict future events (Zitrou et al., 2010), (Ben and Gal, 2007). Below, Table 2 presents a comparative summary table based on a set of criteria for the methods commonly used in RCA.

Table 2. Comparison of several RCA methodologies (Cai and Wu, 2004), (Li and Gao, 2010), (Doggett, 2004), (Dei and Stori, 2005), (Ben and Gal, 2007), (Rossing et al., 2010), (Gano, 2007).

Cause and Effect Analysis	High	✓	✓		✓					✓	
	Low			✓		✓	✓	✓	✓		✓
HAZOP	High	✓		✓	✓	✓	✓		✓		
	Low		✓					✓		✓	✓
Bayesian Networks	High	✓		✓		✓	✓	✓	✓		✓
	Low		✓		✓					✓	
FMEA	High	✓	✓		✓	✓		✓			
	Low			✓			✓		✓	✓	✓
Fault Tree Analysis	High	✓	✓	✓			✓	✓	✓		
	Low				✓	✓				✓	✓
RCA Methodology / Characteristics		Ability to define problems	Easy to use	Information requirements	Experience dependence	Time and Resources consumption	Definition of all causal relationships	Provide paths to root causes	Explain how solutions prevent recurrence	Ability to include human errors	Ability to predict future events

Using a single method may lead to an incomplete analysis, therefore, in some specific cases may be appropriate integration tools Root cause analysis, especially when dealing with complex systems, better results can be achieved (Hitchcock, 2006). In fact one of the common combinations to support the RCA analysis is FMECA and FTA (Li and Gao, 2010).

This research proposes a model representation of the system functioning, malfunctioning, and identification of physical causes of failure based on the integration of Bayesian networks, fault trees, FMEA and HAZOP study based on the statements of certain variables, given its dependencies, may trigger a state or event of failure.

### 3. KNOWLEDGE FORMALISATION

The proposed modeling approach consists, from functioning systemic analysis, (a) in representing the abnormal operation (malfunctioning) (Muller, 2007), (Weber and Jouffe 2006), (b) in representing the informational point of view and then (c) in formalizing and unifying these results in a unique model by means of a Bayesian Network.

#### *System functioning modeling*

The functional modeling of an industrial system consists in formalizing, by qualitative causal relationships, the interactions between the functions performed by each of the sub-systems until the component level (elementary functions). This type of formalization can be supported by a method such as the Structured Analysis and Design Technique (SADT). The system functioning modeling is based on the principle of activity and sub-activities until elementary activities, supported by components, are emerging; plus the notions of system's theory (Mayer, 1996). Each activity (Figure 2) fulfils finality, which is to modify a "product" carried out by the manufacturing system. It produces or consumes flows such as "Having to Do"

(HD) materializing the Input/Output (I/O) finality, “Knowing How to Do” (KHD) materializing the I/O knowledge, “being Able to Do” (AD) representing I/O energies, resources, activity support and finally “Wanting to Do” (WD) materializing the I/O triggers. For example, the output flow WD is a report (RWD) that represents the informational result of the Input HD product flow transformed by the activity.

*System Flow Informational Modeling*

Each flow is characterized by the state of the variables related to its morphologic, spatial or temporal properties of the objects that composed it (i.e. objects and flow of objects) and by the flow variables that are express as the quantity of objects per time unit (such as a flow rate) (Mayer, 1996). So, the state variables and the flow variables can be regroup in one denomination called flow attribute. In that way, to measure the performance of a function, it is assume the hypothesis that it can be evaluated directly from the flow attributes. The object representation allows to identify these flow properties or attributes, and it can be represented on an entity-relationship diagram.

*System Malfunctioning Modeling*

The functional model could be used to develop by duality the malfunctioning analysis, whose objectives are to identify the degraded and failure states of the components and of the flows, and then to determine the causes and consequences of these states on the industrial system behavior.

The degradation is spread to the rest of the system through the flow exchanging between processes, according to the **causality principle**:

- The potential cause of the degradation of a process is the deviation of an input flow attribute or the deterioration of its support.
- Contrarily, the potential effect of the degradation of a process is the deviation of an attribute of its output flows or its support (Figure 2).

The industrial system is in degradation or failure mode when there is a flow deviation and/or a deterioration of the supports of the process: the flow deviation is linked to the qualitative or quantitative deviation of a flow attribute compared to its nominal value and the support deterioration is related to the apparition of a physical mechanism of deterioration. When dealing with several functions e.g. two functions, the deviation on the output flow in function 1 (consequence), will become the cause of the deviation of the next output flow function (function 2)... This will lead to causality relations (Figure 3) (Léger and Lung, 1998).

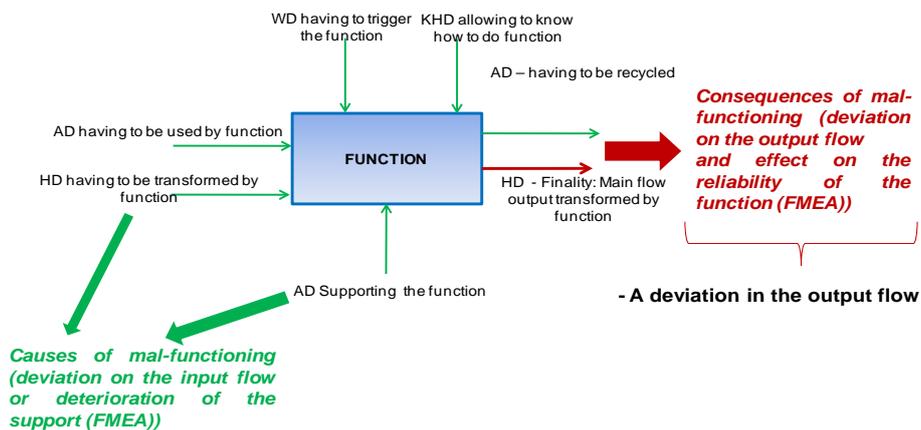


Figure 2. Technical Knowledge Formalization

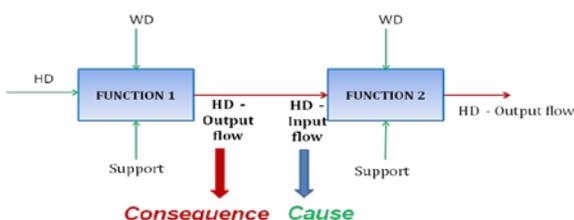


Figure 3. Causality relations between functions levels

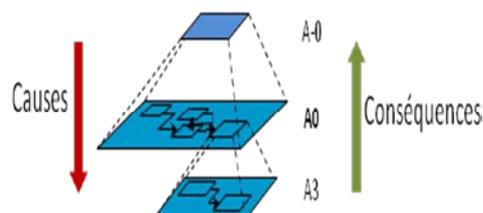


Figure 4. Relations between different abstraction levels

Moreover when dealing with different abstraction levels, the degradation cause in a high abstraction level (e.g. A0) is the degradation on the lower level (e.g. A3) (Figure 3). On the other way, the consequence of degradation in a low abstraction level (e.g. A3), is the degradation of the function of higher abstraction level, in this case the function (e.g. A0).

This relationships defined by Léger and Lung, (1998), leads to a causality chain of flows within a process. This chain will allow us to perform RCA in order to identify the physical causes that produce an event. For this aspect, there are used the following dependability methods:

- FMECA: to model failure modes of the functions, failure modes of the components, failure consequences (impact on the flow and other functions) and the criticality of the failure.
- HAZOP: to model flow deviation, cause of flow deviation and failure consequences (impact on the flow).

The dysfunctional analysis also involves the identification of groups of elementary events or combination of events that lead to a failure event, as well as, the identification of the logical links between essential components to perform the system mission. For this aspect, the following dependability methods are used: Fault tree (FT), reliability block diagram or Bayesian networks (BN) to model the logical links of events or logical links between components.

#### 4. PROPOSITION OF BAYESIAN NETWORKS (BN)

BN appear to be a solution to model complex systems because they perform the factorization of variables joint distribution based on the conditional dependencies. The main objective of BN is to compute the distribution probabilities in a set of variables according to the observation of some variables and the prior knowledge of the others. The principles of this modeling tool are explained in Jensen (1996) and Pearl *et al.* (1988).

*Recall of BN characteristics:* A BN is a directed acyclic graph (DAG) in which the nodes represent the system variables and the arcs symbolize the dependencies or the cause-effect relationships among the variables. A BN is defined by a set of nodes and a set of directed arcs. A probability is associated to each state of the node. This probability is defined, *a priori* for a root node and computed by inference for the others.



Figure 5. Basic example of a BN

A	$S_{A1}$	$P(A=S_{A1})$
	$S_{A2}$	$P(A=S_{A2})$

Table 3. A Priori probabilities of the node A

The computation is based on the probabilities of the parents' states and the conditional probability table (CPT). For instance, let's consider two nodes A and B; with two states ( $S_{*1}$  and  $S_{*2}$ ) each; structuring the BN (Figure 5). The *a priori* probabilities of node A are defined as (Table 3). A CPT is associated to node B. This CPT defines the conditional probabilities  $P(B|A)$  attached to node B with a parent A, to define the probability distributions over the states of B given the states of A.

This CPT is defined by the probability of each state of B given the state of A (Table 4).

		A	$S_{A1}$	$S_{A2}$
B	$S_{B1}$		$P(B=S_{B1} A=S_{A1})$	$P(B=S_{B1} A=S_{A2})$
	$S_{B2}$		$P(B=S_{B2} A=S_{A1})$	$P(B=S_{B2} A=S_{A2})$

Table 4. CPT of the node B given the node A.

Thus, the BN inference computes the marginal distribution  $P(B=S_{B1})$ :

$$P(B = S_{B1}) = P(B = S_{B1}|A = S_{A1}).P(A = S_{A1}) + P(B = S_{B1}|A = S_{A2}).P(A = S_{A2}) \quad (1)$$

BN establishes cause-effect relationships between these factors for modeling their interactions. For example, BN can model the effect of maintenance actions and barriers' impact on the global system risk analysis (Leger, 2009). Besides, a general inference mechanism that permits the propagation as well as the diagnostic is used to collect and to incorporate the new information (evidences) gathered in a study. The Bayes' theorem is the heart of this mechanism and allows updating a set of events' probabilities according to the observed facts and the BN structure. To compare BN with other root cause analysis method such as the Fault Tree (FT), when multiple failures can potentially affect the components with several different consequences on the system (which is usually the case for risk and dependability analyses), the model needs a

representation of multiple state variables. In this context, FT are not suitable. Another constraint is that the FT model is limited to assess just one top event. In contrast BN allow similar capabilities to the FT with the advantages of a multi-state variable modeling and the ability to assess several output variables in the same model. Castillo *et al.*, (1997), Bobbio *et al.*, (2001), and Mahadevan *et al.*, (2001) present a relevant contribution in which they explain how FT can be translated to BN, maintaining its Boolean behavior.

During the process operation, when there are abnormal changes in the conditions and they are not identified and corrected, they can generate events known as failures. A causal representation of the facts through the BN generates a chain of events and transitions, which are interesting for Root Cause Analysis under uncertainty and for the purpose of supporting decision making on appropriate corrective.

Bayesian networks have proved being useful for a wide variety of predictive and monitoring purposes. Related applications have been documented in the medical and image processing, among other areas (Dei and Stori, 2005), (Medina et al., 2009). In manufacturing has also been used as a method of monitoring and diagnosis in real time to identify component failures in multi-stage process (Wolbrecht et al., 2000).

#### 4.1. Quantification of the causality relationships: Unification in a BN model

To model the different aspects of a system in a BN, it is required to take into account the different types of knowledge previously identified. Also, to integrate this knowledge within a BN, it is incorporated as new variables of a network or as a part of the required information to complete a conditional probabilities table (CPT) for these variables. The knowledge integration is based on the following rules:

- 1.- Formalization of the network structure from the functional analysis (input and output variables of a process). The input and output variables are defined from the functional analysis (different kinds of input flows on the SADT) and from the informational analysis (input flow attributes on the entity-relationship diagram).
- 2.- Definition of the input and output variable states, as it is described in the malfunctioning analysis. The states of input and output variables are defined on the malfunctioning system analyses of the system, such as failure modes or flow deviations (methods FMEA or HAZOP).
- 3.- Definition of the conditional probabilities given in the malfunctioning analysis (logical links between components), combinatory logic or expertise.

The conditional probabilities are related to the combinatory logic, to the frequency of failures defined on the malfunctioning analysis or to the expert's judgment. Moreover, to calculate the conditional probability of support of a function which is supported by two or more parallel components, it is possible to obtain the reliability of the support (AD support flow) of this function by means of a dynamic bayesian network, fault tree or a reliability block diagram.

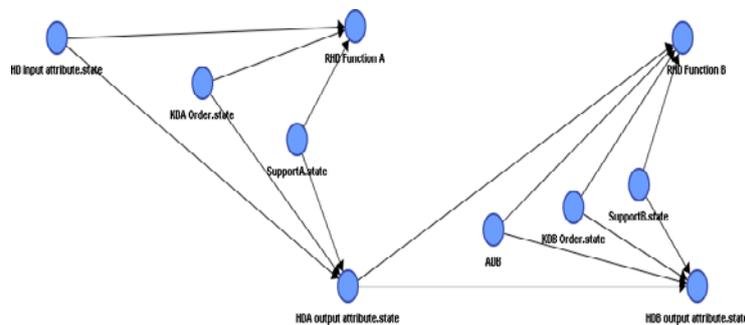


Figure 6: Network structure from functional and informational analyses

In Figure 7 it is shown how to integrate in a CPT the variables and the conditional probabilities according to the different system' point of view: functioning view, malfunctioning view and the informational view.

Also, it is important to know that:

- To represent the input flow (energy, information or material flow) of a function, there could be several variables for each flow.

- To define an output flow, there are necessary several CPT based on the input flows. There must be one CPT for each output flow.

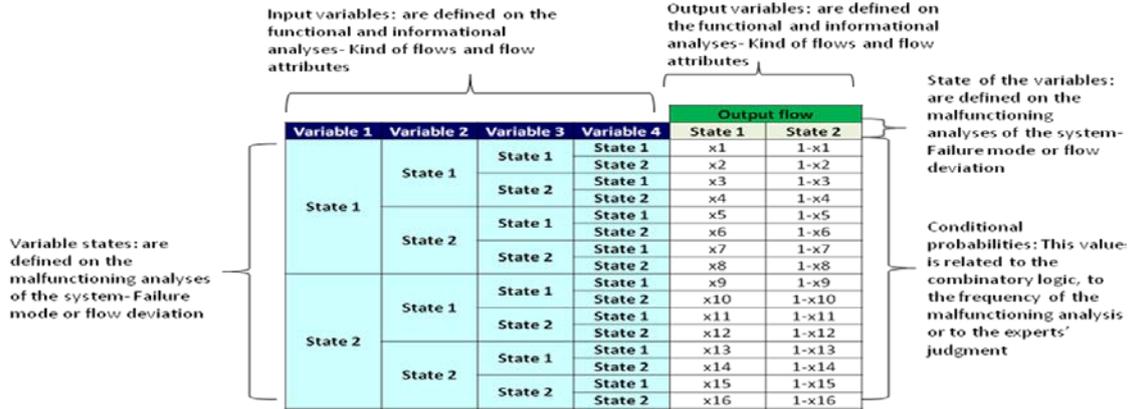


Figure 7: Knowledge integration in a CPT

#### 4.2. BN as a tool for the identifying the physical Root Cause Failure

Once the problems with highest significance and less expected effort are identified (Crespo, 2008), a diagnostic phase should be started. The BN allow to verify which are the most probable variables that cause a problem are. The idea is to verify which input flows are more likely to be in an abnormal functioning that caused performances deviations.

### 5. APPLICATION

To show the feasibility of the proposed knowledge formalization and the integration of the different kinds of knowledge into a BN, an application is illustrated. A classical example of a water heater process is presented in order to assess the reliability and the compliance of the output flow attributes. The objective of the thermal process (shown in Figure 8) is to ensure a constant water flow rate with a given temperature. The process is composed of a tank equipped with two heating resistors R1 and R2. The system inputs are the water flow rate  $Q_i$ , the water temperature  $T_i$  and the heater electric power  $P$  that is controlled by a computer. After measuring process parameters by the corresponding sensors, the outputs are the water flow rate  $Q_o$  and the temperature  $T$ .

#### System Functioning Modeling: SADT model

Figure 9 presents the diagram A-0 of the SADT related to the process. This figure depicts the interaction between the process and the external environment through the AD, HD and RHD flows. The main functionality of the process is to provide warm water.

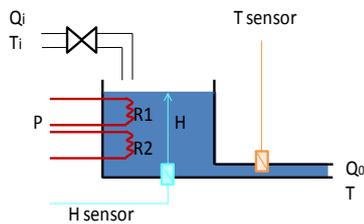


Figure 8: Water heater process

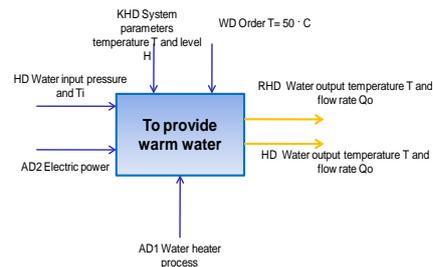


Figure 9: Diagram A-0 of the SADT

Then the diagram A0 describes the four functions that are necessary to perform the main task of the system:

- to transform pressure into  $Q_i$  (A1),
- to control  $V$  and  $P$  (A2),
- to transform  $Q_i$  into  $H$  and  $T_i$  into  $T$  (A3),
- to transform  $H$  into  $Q_o$  (A4).

When decomposing function A3 'to transform  $Q_i$  into  $H$  and  $T_i$  into  $T$ ' one of the elementary functions is "to heat water" supported by the component HEATING RESISTOR. The input flows of the function are: HD storage water, AD electric power, WD order  $T$ , AD heating resistors. The output flows are represented by the RHD water temperature  $T$  and the HD water temperature  $T$ .

*System Malfunctioning Modelling: FMEA, HAZOP, dynamic bayesian networks.*

For this case, the study is applied to the function “to heat water”, so the component of this function is indexed in the FMEA analysis (Table 5). The failure modes of the component are defined as well as their effects. The causes are linked with the component states or the unavailability of the electric energy required to supply the component.

Then, it is necessary to study the possibilities of flow deviation and their causalities through an HAZOP study (Table 6). The flow deviation is linked to the qualitative or quantitative variation of an attribute compared to its nominal value and it is a complementary study of the FMEA since the mal-functioning of an industrial system is caused when there is a flow deviation (HAZOP) and/or a deterioration of the supports of the process (FMEA). Since the heating resistors “R1” and “R2” work on parallel to fulfill the function “to heat water”, it is possible to obtain the reliability of the support (AD support flow) of this function. The state of each heating resistor was defined as follow: 80% is available, 5% works in a maximum level, 5% there is power loss in it and 10% the heating resistor is unavailable. So with this information, it is possible to build a dynamic bayesian network as shown in the Figure 10.

The result of support reliability of the function “to heat” shows that the AD support flow of this function is available 92% of the time, 5% works in a maximum level, 0,75% there is power loss in them and 2,25% the heating resistors are unavailable (results obtained with the software Bayesialab). Moreover, it could be possible to use fault trees or reliability block diagrams in these cases. They can describe the logical links of events in order to obtain the reliability of the support of a function in cases where there are redundancy or k/n relations between components. Their limitation is that they represent boolean variables, that is why it was not appropriated for this example.

FMEA					HAZOP- Water heating system				
Function	Element	Failure Mode	Effects	Causes	Products	Properties	Deviations	Causes	Consequences
To heat water from $T_i$ to $T$	Heating resistor	Maximum level of heat	Temperature higher than desired	T sensor is down Maximum level of heat for the heater resistor.	Storage water	Level	More	H sensor is down More rate flow of $Q_i$	Water spill More outgoing flow $> Q_o$
		No heating	No temperature changed	The heating resistor does not heat. No electric power (AD2) Deviation in the storage water (HD) No Order T (KD) T sensor is down			Less	H sensor is down Less rate flow of $Q_i$ Leak of water of tank	Less outgoing flow $< Q_o$
Heating power loss	Temperature lower than desired	Power loss in the heating resistor	T sensor is down Power loss in the heating resistor	Temperature	More		T sensor is down Maximum level of heat in heat resistor	Higher outgoing temperature in $Q_o$	
						Less	T sensor is down Heating resistor is down	Lower outgoing temperature in $Q_o$	

Failure modes of the function

State of the supports

Flow deviation

Table 5: Extract of the FMEA of the function “to heat water”

Table 6: Extract of the HAZOP of the function “to heat water”

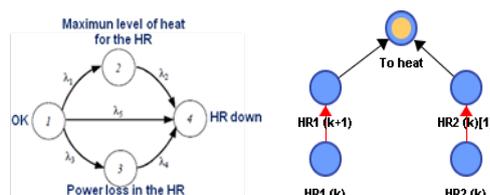


Figure 10: DBN of the parallel heating resistors

*System Flow Informational Modeling: Entity-relationship diagram*

The informational point of view let identify the flow properties and attributes (Figure 11).

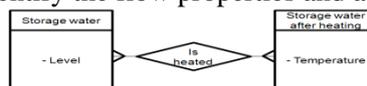


Figure 11: Extract of the entity-relationship representation of the flows of the “to heat water” function

*Unification of Technical knowledge in a PRM model*

Finally, it is shown the integration of the previous kinds of knowledge within the CPT of the variable: “water temperature” and its transformation into the SKOOB language (Figure 12).

Input variables: defined on the functional and informational analyses				Output variable: defined on the functional and informational analyses		
KD Order T	Water level H	Heating resistor	AD2 Electric power	Water temperature		
				OK	More	Less
OK	Ok	OK	OK	100	0	0
OK	Ok	OK	NOK	0	0	100
OK	Ok	Maximun level of heat	OK	0	100	0
OK	Ok	Maximun level of heat	NOK	0	0	100
OK	Ok	No heating	OK	0	0	100
OK	Ok	No heating	NOK	0	0	100

Input variables' states: defined on the malfunctioning analyses- FMEA and HAZOP

Output variables' states: defined on the malfunctioning analyses- FMEA and HAZOP

Conditional probabilities: Related to the combinatory logic and experts' judgement

Figure 12: Knowledge integration of the variable “Water temperature” in a CPT

This part of the CPT shows the link between the information integration available in the CPT and a part of the SKOOB language that allows to convert knowledge into a PRM.

*a. As a diagnosis model:*

The diagnosis starts when the “RWD to heat water” is in abnormal functioning (state= maximum level of heating) for example. Initially, the input flows are checked to see which is the variable that has more probability of been in an abnormal functioning. For this case the water level has a probability of been in an non-nominal state of 4,03%, the electric power has 0%, the order T 0% and the heating resistors of 99,59%. The checking leads suspect that the heating resistors are the most probable cause that the function is not realized, because its probability of been in an abnormal functioning is the highest (99,59%) (Figure 13).

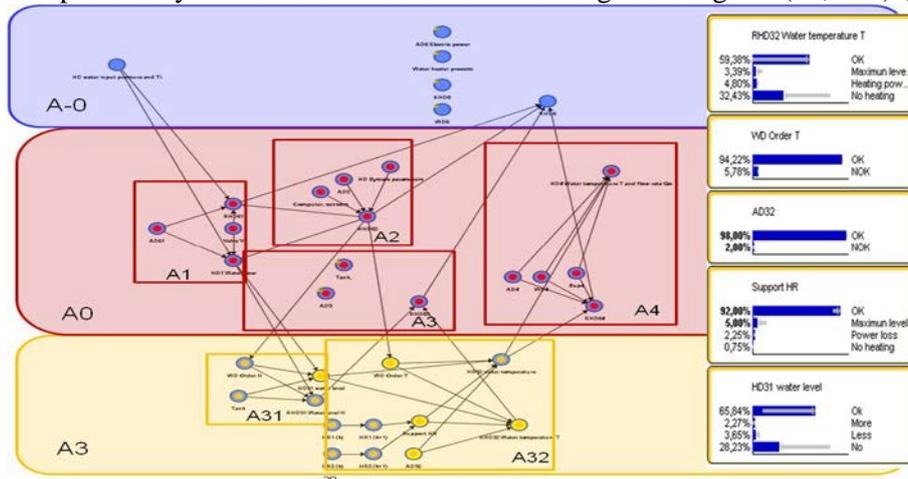


Figure 13. Bayesian Network of the water heater process

**6. CONCLUSIONS AND FURTHER WORK**

The proposed model based on the functioning (SADT), malfunctioning (FMECA, HAZOP analysis, 2TBN, FT) and informational studies (entity- relationship diagram) help to improve the automatic generation of a causality chain to identify the main causes that produce performances deviations. Also this methodology helps to integrate deductive and inductive methods that complement the information in order to improve the identification of “bad actors” affecting the system.

The difference of the BN when comparing with other classical methods is their capacity to represent this model allow to deal with issues such as prediction or diagnostic optimization, data analysis of feedback experience, deviation detection and model updating and multi-state elements. However, this methodology is a first step to identify physical causes in order to improve performances on the weak points of high impact equipments. There are other kinds of causes that also impact the performances such as the human and latent causes, so as further work; some other factors should be incorporated in the model such as human and latent causes.

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