



An application of Bayesian Networks to the Performance Analysis of a Process

Philippe Weber, Marie-Christine Suhner

► To cite this version:

Philippe Weber, Marie-Christine Suhner. An application of Bayesian Networks to the Performance Analysis of a Process. Mar 2002, pp.266-273. <hal-00128473>

HAL Id: hal-00128473

<https://hal.science/hal-00128473v1>

Submitted on 1 Feb 2007

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

AN APPLICATION OF BAYESIAN NETWORKS TO THE PERFORMANCE ANALYSIS OF A PROCESS

APPLICATION DES RESEAUX BAYESIENS A L'ANALYSE DES PERFORMANCES D'UN PROCESSUS

Weber P. and Suhner M.-C.

Centre de Recherche en Automatique de Nancy (CRAN), CNRS UMR 7039

Université Henri Poincaré, Nancy 1

2, rue Jean Lamour F-54519 VANDOEUVRE-LES-NANCY Cedex – FRANCE

Email: [philippe.weber,marie-christine.suhner@esstin.uhp-nancy.fr]

Summary

This paper proposes a methodology to develop a decision-making aid system of which purpose is the performance evaluation of a manufacturing process. This model, based on Object Oriented Bayesian Networks (OOBNs), evaluates the overall performance of the system from its implementation and maintains this performance during its operating phase. The added value of the methodology is, at first time, to formalise models from prior knowledge both on the system functioning and malfunctioning. Networks are also built on principles of adaptability and integrate uncertainties on the relationships between causes and effects. In the second time, the aim is to evaluate, in term of performance, the impact of several decisions about maintenance of the system. This is made thanks to the use of the concept of influence diagram allowing the valuation of the cost associated with every decision. The feasibility of this methodology is tested, in an industrial context, thanks to the maintenance aid on a lathe machine.

Résumé

Cette communication propose une méthodologie afin de développer un système d'aide à la décision dont le but est l'évaluation des performances d'un processus manufacturier. Ce modèle, à base de Réseaux Bayésiens Orientés Objets (OOBN), répond à la nécessité d'évaluer la performance globale du système dès sa mise en œuvre et de maintenir cette performance lors de son exploitation. La valeur ajoutée de la méthodologie est, dans un premier temps, de formaliser les modèles à partir de données a priori issues des analyses fonctionnelle et dysfonctionnelle. Les réseaux sont ainsi construits sur des principes d'adaptabilité et intègrent les incertitudes sur les relations de causes à effets entre les variables. Dans un second temps, il s'agit d'évaluer en terme de performance l'impact de différentes décisions liées à la maintenance du système. Ceci est effectué grâce à l'utilisation du concept de diagramme d'influence permettant l'estimation du coût associé à chaque décision. La faisabilité de cette méthodologie est testée, dans un contexte manufacturier, grâce à une application sur la maintenance d'un tour.

Keywords: Decision-making – Performance analysis – Maintenance strategy – Availability – Cost – Object Oriented Bayesian Networks (OOBNs) – Influence Diagram.

Introduction

The improvement of the overall performance of a manufacturing system is an issue to be solved to ensure the optimisation of the Enterprise needs. In that way, the challenge is to control direct and indirect costs of the process compared with its necessary availability. The design choices and the maintenance of the process have impacts on the overall cost, availability, safety and quality of the process. It is important to estimate these impacts in order to optimise their influence during the life cycle. Then during the operating phase, the objective is to compare several alternative maintenance strategies and to determine the combination of alternatives which allows the best compromise between: availability, cost, production quality, safety...

Moreover, recent works on system safety and Bayesian Networks (BNs) have been developed. For example, in [1] a method to achieve Fault Trees using BNs is presented. Nevertheless, large and complex BNs are not easy to design and to maintain. This is the reason why the method proposed within SERENE project [2] is interesting. This method is based on BNs and a hierarchical decomposition of the decision-making model for system safety analysis. Recent publications are focused on the Object Oriented Bayesian Networks (OOBNs) [3], [4] allowing the formalisation of the Bayesian network method used in SERENE. OOBNs are useful to model the process because this method leads to a top down construction of the BNs based on several abstraction levels and supplies a powerful mechanism for the elaboration of models with repetitive structures. Then elementary models are used. The structure and the precision of the elementary model parameters can be increased based on past experience.

Recent software tools like Hugin [5] support object oriented modelling. In addition, an Influence Diagram is defined by adding to the OOBN specific nodes like utility and decision nodes [6]. Influence diagrams are graphical models taking into account cost impacts of several scenarios.

The paper presents a methodology to define a OOBNs and Influence Diagrams model of a process. The model is applied from implementation and during operating phase. The aim is to estimate the overall performance of the process (costs impacts and availability) in regard to several maintenance scenarios. Purpose is to help managers in their decision-making. The proposed methodology has originality on formalising, by means of BNs, the models from prior knowledge on the system functioning and malfunctioning. To show the feasibility and the added value of this methodology, an application is developed on the case of maintenance aid for a lathe machine. Finally, conclusions and prospects are presented.

Definition of Bayesian networks

BNs are a network-based framework for representing and analysing models involving uncertainty [6]. A BN is defined as a set of nodes with different states and a set of directed edges describing the probabilistic dependencies between nodes.

The nodes represent discrete random variables of the process. A Conditional Probability Table (CPT) is associated with each node to quantify the dependencies between random variables as conditional probabilities. A node without parent is called a root node.

The inference aim is to estimate the posterior probability of an event given a set of evidence (selected nodes). It is possible with sequential applications of Bayes' theorem. A probability is assigned to each state of a node. This probability is defined, a priori, for a root node and computed by inference for the others. The computation is based on the probabilities of parents' states and the CPT. For instance, two nodes A and B with each of them two states (S_{-1} and S_{-2}) form the BN in Fig. 1.

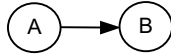


Fig. 1. Basic example of a BN.

Prior probabilities are defined in Table 1.

Table 1. Prior probabilities of node A.

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

The probabilities of the states assigned to B are computed using a CPT. This CPT is defined by the probability of each B state knowing the state of A (Table 2).

Table 2. CPT of node B.

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

Thus, to compute $P(B=S_{B1})$, Eq. (1) is used:

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

The added value of a BN is linked to the computation of the probabilities assigned to a node state, knowing the state of one or several variables. If any state of nodes is defined, then the computation is only based on prior probabilities. However, if knowledge is increasing and some states are defined, the computation takes it into account and all the probabilities are updated. It is then possible to estimate the impacts of a random variable on the process.

Modelling approach

The main interest of BNs appears when the economical aspects of a decision are taken into account. Influence diagrams are thus used for the development of decision models and as an alternative graphical representation of decision trees [7].

The steps of modelling

The model is supposed to be elaborated just before the implementation of the system. The main technological choices are made. But it remains to define the logistics of maintenance which contribute to reach objectives in term of performance: availability and cost.

The construction of the influence diagram is proposed in four steps as follows:

- Elaboration of the structure of the Bayesian network from the functional analysis (SADT¹) and the malfunctioning analysis of the system (FMECA²). At the level of the main function, definition of environment, external resources and overall costs.
- Description of the components: failure causes, availability, cost...
- Selection of decisions from a study of criticality: strategy of maintenance, maintenance organisation...
- Estimation of the impact of the decisions on the characteristics of the components: availability and cost.

From system functioning-malfunctioning representation

The modelling approach consists, from functioning systemic analysis based on SADT¹ graphical representation, in

representing the abnormal operation (malfunctioning) based on FMECA² and then in formalising and unifying these two results in a unique model by means of OOBNs.

The functioning and malfunctioning of the system are dual and must be studied together to control each system variable [8]. It leads, first, to focus on the system functioning in relation to its environment and its internal and external resources. This action can be made using SADT graphical representation. This modelling is based on the principle of function and sub-functions until elementary functions, supported by components, are emerging. Each function (Fig. 2) fulfils an objective, which is to modify a "product" carried out by the manufacturing system. It produces or consumes flows such as "Having to Do" (HD) materialising the Input/Output (I/O) finality and "being Able to Do" (AD) representing I/O energies, resources, activity support. From this step, simplifying assumptions are made to carry out the prospective study until a feasibility phase. Therefore, the output flow is a report (RHD) that represents the informational result of the Input HD product flow transformed by the function. Only the RHD flow is taken into account as output. This flow is an informational view of the function finality, so it is assumed to be the added value on product flow represented in Fig. 2 by the HD flow transformed by the function. It is thus transferred as informational view of physical result through the input flow HD of another function.

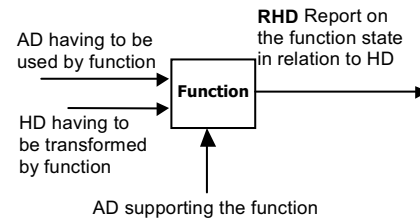


Fig. 2. Flows and Function Representation.

The Bayesian Network representation is based on the functional decomposition of the system. This representation is structured as a tree (Fig. 3). Its root is an OOBN representing the highest abstraction level. The elementary functions represent the lowest functional levels modelled by BNs. The connections between the sub-functions are modelled by logical functions. To model high functional levels, the OOBNs are composed of generic sub-functions.

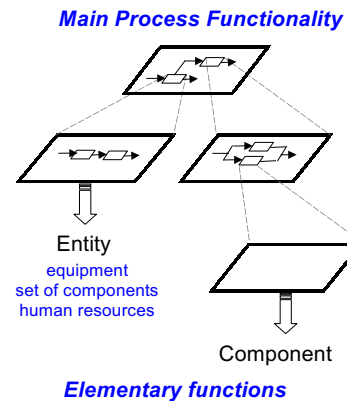


Fig. 3. Functional decomposition.

From this functioning, the malfunctioning is induced [9] by considering that the relationship between these two modes is directly linked to the relationship between the normal and abnormal states of the system. The malfunctioning modelling can be made by means of FMEA study in order to identify the failure or degradation modes of each function, the elements that are at the failure origin (causes) and the possible consequences of these failures (effects).

For example, the RHD flow can take the value "Realised (R)" corresponding to the nominal state of the activity or the values "Not Conform (NC)", "Not Realised (NR)" requiring to identify the causes and the effects associated with these two abnormal states. The failure causes are either external with the function (Input flows) or internal ones because linked to the AD function support flow (components).

¹ Structured Analysis and Design Technique

² Failure Mode, Effects and Criticality Analysis

A whole of states can be thus associated with each component. These states correspond to: nominal operation, failure 1, failure 2...

In the same way, the consequences are observable either on function output flows or on the influence of the component degradation development on itself (to go towards a breakdown state). To sum up, a failure cause leads to a failure mode (e.g. the modification of the function state reported in RHD), which has an effect for the function not to produce nominal flow HD any more. This FMEA study is completed by a FMECA study where each failure mode is characterised by a criticality C (risk priority number) resulting from the product of the three criteria, which are the frequency, the severity and the no detection.

BN model construction

Then, the OOBN is directly built from the dual functioning/malfunctioning analysis presented above leading to a unified representation. To keep the generic function concepts, the inputs are modelled by input nodes defining the random variables associated with the flows AD, HD (Fig. 4). The generic function represented in BN formalism is given in Fig. 4.

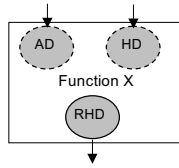


Fig. 4. Generic BN input and output nodes structure.

To model high functional levels, OOBNs are composed of generic sub-functions with the structure defined in Fig. 4. The number of nodes states is adapted and it is possible to duplicate several inputs or outputs nodes (AD, HD...) if the function carries out several missions. Moreover, it is possible to model sub-functions in parallel or in series (Fig. 5).

In Fig. 5, as the generic sub-functions F1 and F2 are in series, the report RHD1 is transferred to F2 through the input flow HD. As the functions F2 and F3 are in parallel, a node OR is linked to RHD2 and RHD3 in order to compute the RHD of the overall function. In this level, only the connections between functions in parallel are defined as CPT.

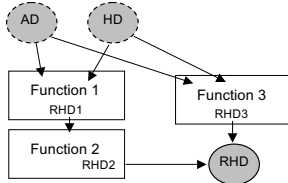


Fig. 5. High level of the functional decomposition.

The CPT of an OR node, for two functions whose RHD2 and RHD3 are composed of three states (R, NC, NR), is defined in Table 3.

Table 3. Conditional Probability Table.

RHD2	R			NC			NR		
RHD3	R	NC	NR	R	NC	NR	R	NC	NR
R	1	1	1	1	0	0	1	0	0
NC	0	0	0	0	1	1	0	1	0
NR	0	0	0	0	0	0	0	0	1

At the level of the main function, environment, external resources and their availability are defined as AD or HD flows.

Description of components and elementary functions

As for functions, a generic model is proposed for components (or for a set of components). The nodes constituting a generic Component BN are (Fig. 6):

- a component node (CMP) or a set of components node according to the model description,
- an utility node (U) modelling the overall cost associated with the component (or the set of components).



Fig. 6. Generic Component BN.

FMEA analysis allows the determination of the failure causes associated with a component (Table 4). So, the states (considered as exhaustive) of a CMP node are, for instance:

- Ok: the component is available,
- C1: the component is unavailable due to cause of failure C1,
- C2: the component is unavailable due to cause of failure C2...

Table 4. FMEA.

Failure Modes	Causes	Effect
Elementary function in mode 1	CMP failure C1	Effect 1
	CMP failure C2	Effect 2

It is now necessary to quantify the probabilities associated with these states. These probabilities depend on the reliability (Weibull model) and the maintainability of each component (strategy of maintenance chosen for this component). The computations are explained in [10].

The model of reliability is a Weibull model Weib (β, η). The parameters β and η are obtained from supplier data, experts' judgement or by operating experience on a similar component. The maintainability is defined according to the maintenance strategy chosen for the component. The strategy is also selected from supplier data experts' judgement or by operating experience on a similar component.

The estimation of probabilities can be made by Bayesian analysis. Then, the prior probabilities associated with CMP node states in the BN are estimated for a given operating time T (Table 5).

Table 5. Component states and probabilities.

CMP	OK (correct operation)	a
	C1 (cause of failure 1)	\bar{a}_{C1}
	C2 (cause of failure 2)	\bar{a}_{C2}

With:

- a : component availability,
- \bar{a}_{C1} : component unavailability due to the cause of failure C1,
- \bar{a}_{C2} : component unavailability due to the cause of failure C2.

\bar{a}_{C1} and \bar{a}_{C2} are deducted from "a" by allocating relative weights θ_1 and θ_2 to failures C1 and C2. θ_1 and θ_2 are calculated, for example, using past data.

$$\bar{a} = 1 - a = \theta_1 \bar{a}_{C1} + \theta_2 \bar{a}_{C2} \quad \text{with} \quad \theta_1 + \theta_2 = 1 \quad (2)$$

The utility node (U) models the component overall cost (Cost). The cost depends on component reliability (occurrence of failure) and maintainability. It contains: repair cost in case of failure, maintenance cost, cost of spares, labour cost... [10].

A CMP node is defined as an output node. Then, probabilities associated with the CMP states are used to compute probabilities of the Elementary Function states related to this component.

If a component is used to realise several sub-functions, the output node CMP of the Component BN appears at the highest level where the component is used. This is made in order to allow inference towards the sub-functions. If a component realises only one sub-function (Elementary Function EF), the output node CMP appears as an AD flow supporting the function (Fig. 2) in a generic sub-functions BN (Fig. 7).

The CMP output nodes are directly linked to the EF nodes representing their functionality. The CMP states are defined by the causes analysed by means of FMEA. The causes are either internal of the low BN level i.e. linked to CMP, or external i.e. linked to the input nodes AD or HD. The common causes are defined in higher hierarchical levels and the information forwards by heritage between the levels through the input and output nodes.

The EF nodes are linked to the CMP nodes and the input nodes leading to compute the RHD states probabilities (Fig. 7). If all the EFs are realised then the RHD is realised.

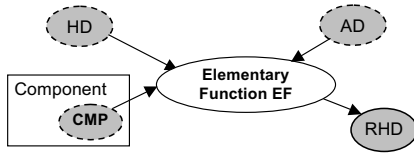


Fig. 7. Low level of the functional decomposition.

The EF states are defined by failure modes. For instance, the EF nodes in the BN take the following states:

- Realised (R),
- Not Conform or partially realised (NC),
- Not Realised (NR).

No prior probability is associated with these states because they are calculated according to the states of their parents i.e. the internal causes (CMP node states) and the external causes (AD and HD input node states).

The CPT of the EF is defined thanks to the columns of the causes and the modes of the FMEA analysis (Table 6).

Table 6. Elementary Function CPT.

AD		R			NC			NR
CMP		OK	C1	C2	OK	C1	C2	*
EF	R	1	0.2	0	0	0	0	0
	NC	0	0.8	0	1	0.2	0	0
	NR	0	0	1	0	0.8	1	1

The probabilities link causes to EF modes. Nevertheless, the power of the BNs representation is that a combination of causes (for instance AD=R and CMP=C1) can lead to several failure modes with different probabilities modelling thus the uncertainty (0.8 and 0.2, for instance in Table 6).

Selection of decisions associated with components

The use of the Influence diagram allows the simulation of several scenarios in order to take into account decisions about maintenance strategy on a component, for example.

But, it is necessary to select the critical components on which one wants to modify the maintenance strategy.

In particular, the criterion C (Criticality) issued from FMECA analysis can be used to determine the critical components. Obviously, the expert' opinion can also be taken into account.

When a decision is allocated to a component, the model becomes (Fig. 8):

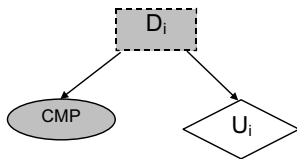


Fig. 8. Component Influence Diagram.

The decision associated with CMP is modelled as a Decision node (D_i) with several mutually exclusive states:

$$D_i = (d_i^1, \dots, d_i^j, \dots, d_i^n) \quad (3)$$

In the decision-making problem, the decision can, for example, take two states: "Corrective Maintenance (CM)" or "Preventive Maintenance (PM)".

According to the decision, the utility node (U_i) associated with the component is updated. If the decision is "CM", then U_i is equal to $Cost_{CM}$. If the decision "PM" is chosen, then $Cost_{PM}$ affects U_i . Probabilities associated with component states are also updated.

Component node CPT and utility node are computed, according to every decision, in the same way as in the generic Component BN (Table 7, Table 8 and Table 9).

Table 7. Component Decision table.

Decision node D_i	
CM	PM

Table 8. Component Utility table.

Utility node U_i	
CM	PM
$Cost_{CM}$	$Cost_{PM}$

Table 9. Component CPT.

Component node CPT		
Decision	CM	PM
OK	a_{CM}	a_{PM}
C1	$\bar{a}_{CM,C1}$	$\bar{a}_{PM,C1}$
C2	$\bar{a}_{CM,C2}$	$\bar{a}_{PM,C2}$

Overall cost impact

The system unavailability cost is computed using an approximation presented by [11]. Considering that the production is proportional to system availability, the losses are due to the system unavailability.

Financial impacts are defined from Fixed costs (FC) which are constant, production costs (PC) and sale volume (SV) whose depend on the RHD_0 states.

Assuming an operating time and the availability equal to 1, the maximum benefits due to the production sale are defined as sv_{Max} , the energy and the raw materials costs pc_{Max} and the uncompressed charges fc .

The main function RHD_0 is a random variable defined over several states: (x_1, \dots, x_n) . Therefore, specific production costs pc and specific sale volume sv are associated with each RHD_0 state.

Fig. 9 represents the influence diagram which evaluates the financial impacts associated with the RHD_0 states where utilities nodes represent FC, PC and SV.

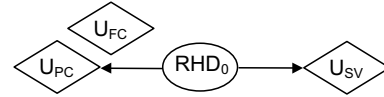


Fig. 9. Financial impacts of the system availability.

The probabilities of the RHD_0 states depend on the system structure with its redundancy and the components availability.

Considering independent components and a coherent system, BNs model the logic and the redundancy of the system. Then, BN inference estimates the states probabilities of the main function.

Use of the model: performance analysis of the process according to decisions

Simulation of several scenarios

The objective of the decision-making problem is to compare several alternative solutions (combination of decisions).

The Influence Diagram inference evaluates the financial impacts according to m decisions D_i ($i = 1 \dots m$) (Eq. (3)) allowing the research of the optimal solution.

For each combination of decisions D_i , the Expected Utility EU function (benefit) is computed by Eq. (4).

$$EU(d_1, \dots, d_i, \dots, d_m) = \sum_{x_k \in RHD_0} P(x_k | e) \cdot U_{PC}(x_k) + \sum_{x_k \in RHD_0} P(x_k | e) \cdot U_{SV}(x_k) + U_{FC} + \sum_{i=1}^m U_i(d_i) \quad (4)$$

With e the evidence.

Thanks to the influence diagram, it is also possible to estimate overall availability and overall benefit by imposing the state of one or several decisions.

The best compromise is obtained for the maximum benefit corresponding to the optimal decisions:

$$\text{Opt}(D_1, \dots, D_i, \dots, D_m | e) = \arg \max_{d_i \in D_1, \dots, d_m \in D_m} EU(d_1, \dots, d_i, \dots, d_m) \quad (5)$$

Thus, the overall availability of the system can be estimated:

$$P(RHD_0 = R | \text{Opt}(D_1, \dots, D_i, \dots, D_m), e) \quad (6)$$

Use of the model in operation

A prognosis model

After the decisions choices, BN model defined above can be used as a prognosis model. The BN model allows the analysis of the degradation influences on the functions states. This analysis is based on the simulation of a component failure, a common cause or an unconformity of a sub-function. The objective is to forecast the impacts of failures on the functions. It is then possible to analyse the upstream and downstream consequences on the whole system. For example, if a component failure is supposed, an evidence is defined as for instance $P(\text{CMP}=\text{C1}) = 1$. Then the probabilities associated with sub-functions are updated after the BN inference. The RHD of each function relates the failure impacts on each functional level.

Operating experience

During the operating phase, the probabilities and the costs have to be updated. So, the availability and the benefit can be evaluated taking account these new data, by Bayesian analysis, for example. It is then possible to confirm or not the implemented decisions.

Application

To show the feasibility and the added value of this methodology, an application has been developed on a lathe machine to aid the decision on maintenance strategy. The level A0 "to produce" of the functional analysis of the system is presented in Fig. 10. This level is composed of three main functions ("to grip the part", "to manufacture" and "to loosen the part"). Each function is decomposed until a level allowing a connection with the real components of the lathe system. For example, the function "to manufacture" is decomposed into generic sub-functions such as "to put in rotation", "to machine". The function "to put in rotation" is supported by the MOTOR of the LATHE.

The software used to build BNs model is Hugin [5].

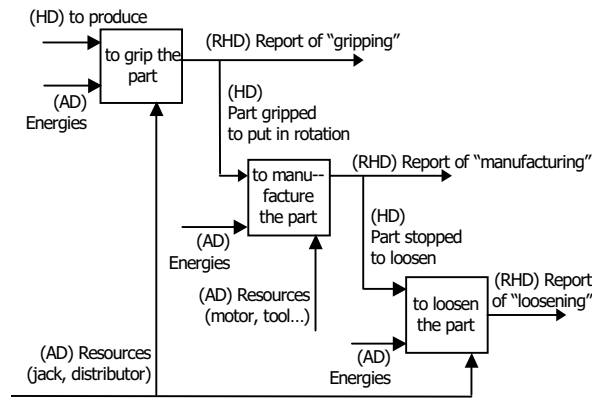


Fig. 10. Level 0 of the LATHE function analysis.

BNs Model

Level 0 - Function "to produce" (Fig. 11).

The BN represents high level of the functional decomposition of the system. Input nodes are in grey (dotted line): AD (electric and pneumatic power) and HD ("to produce"). The sub-functions are represented as sub-BN (framed nodes): "to grip the part", "to manufacture the part" and "to loosen the part". The sub-BN input nodes are linked to AD and HD, and the output node represents the RHD of the sub-function. Two decision nodes represent the decisions concerning the resources JACK and DISTRIBUTOR used by the sub-functions "to grip the part" and "to loosen the part". And they are propagated into the lower hierarchical level. The node "RHD producing" (RHD₀) depends on the output node "RHD loosening the part". Because the process functionality is "to produce" the parts, and the last function made before to consider the part produced is "to loosen the part".

The evaluation of the overall effectiveness is represented by the three utilities nodes: SV, PC and FC. Table 10, Table 11 and Table 12 present utility tables of nodes SV, PC and FC.

The Sales Volume (SV) depends on the state of RHD₀ because in this application several levels of quality of production are considered (Table 10).

Table 10. SV Utility Table.

RHD ₀	R	NC	NR
SV	1,000,000	800,000	0

The maximum of the Sales Volume is obtained if RHD₀ is in the state "R" (Realised) corresponding to the best quality of the production. If RHD₀ is in state "NC" (Not Conform) then the Sales Volume is decreased.

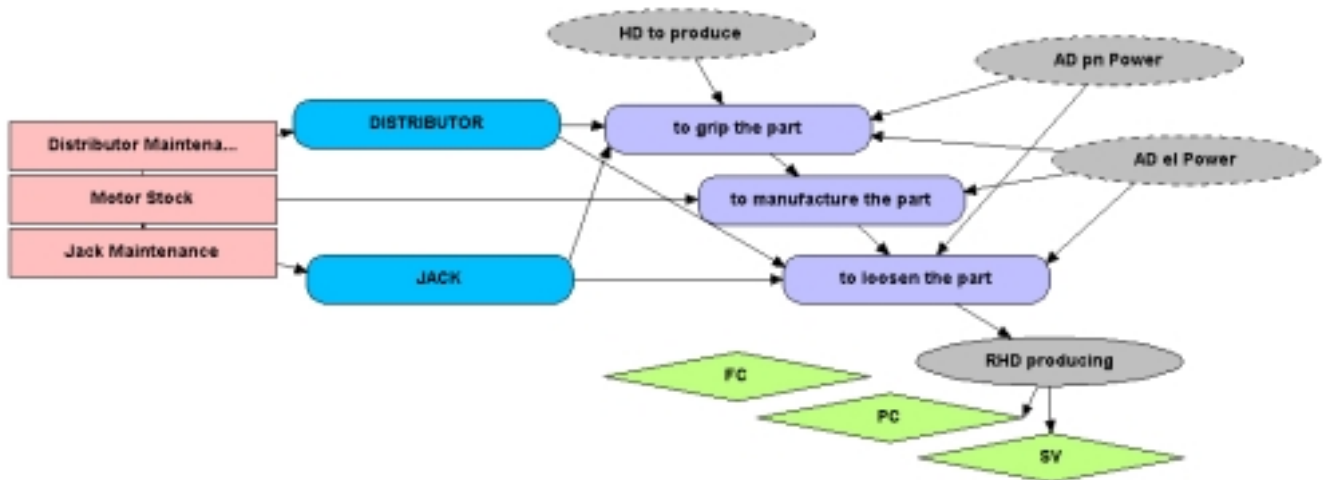


Fig. 11. Level 0 - High BN representing the main function "to produce".

In the same way, the Production Costs (PC) utility table is defined by three columns (Table 11). But we consider here that production costs are independent of quality. Therefore, the value in the columns corresponding to "R" and "NC" are equal to the maximum of the production costs.

Table 11. PC Utility Table.

RHD ₀	R	NC	NR
PC	-200,000	-200,000	0

Table 12. FC Utility Table.

FC	-500,000
----	----------

Table 12 represents the Fixed Costs (FC), which are independent from the states of RHD₀ and from the other variables and decisions.

Level 01 - Function "to manufacture" (Fig. 12) and Level 011 - "to put in rotation" (Fig. 13).

The function "to manufacture" the part is composed by two sub-functions: "to put in rotation" and "to machine". The inputs and the outputs of these two sub-functions are clearly represented in Fig. 12. For instance, the inputs of the sub-function "to put in rotation" are "HD to put in rotation" and "AD el Power", and the output is "RHD putting in rotation". The level 011 sub-function "to put in rotation" is an Elementary Function. The BN model of this sub-function is presented in Fig. 13. The node "to put in rotation" represents the function. The model of the component MOTOR appears in this elementary function. The conditional probability table of the node is based on the logic of the system. In this case, the CPT of the elementary function "to put in rotation" (Table 13) is equivalent to a noisy OR.

The decisions "Motor Stock" (motor in stock or not) and "Motor maintenance" (corrective maintenance or preventive maintenance with several periods) are defined as inputs of level 011. Decisions come from the upper level and are propagated to the lower level, which is the component MOTOR.

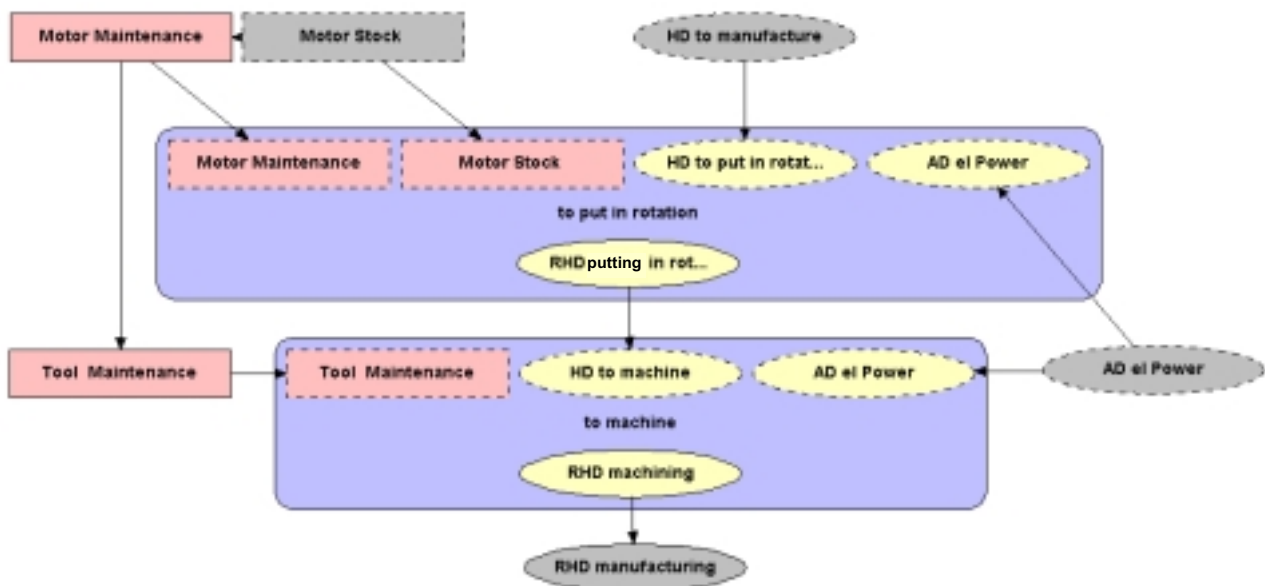


Fig. 12. Level 01 - BN representing the function "to manufacture".

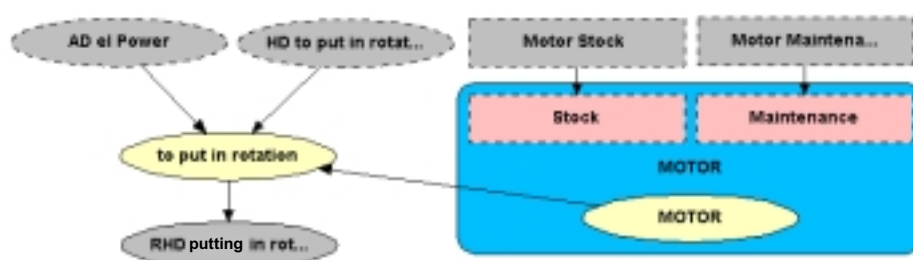


Fig. 13. Level 011 - BN representing the elementary function "to put in rotation".

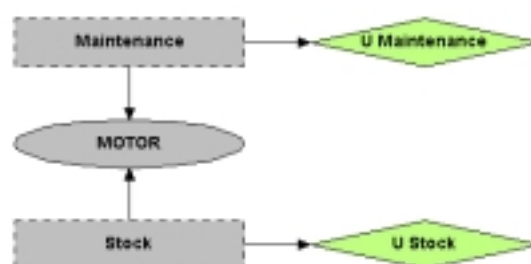


Fig. 14. Level 0111 - BN representing the component MOTOR.

Table 13. CPT of the elementary function “to put in rotation”.

MOTOR		OK									HS								
AD el Power		R			NC			NR			R			NC			NR		
HD to put in...		R	NC	NR	R	NC	NR	R	NC	NR	R	NC	NR	R	NC	NR	R	NC	NR
to put in rotation	R	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	NC	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	NR	0	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 14. First inference.

	HD	RHD				
	to produce	gripping	putting in rotation	machining	loosening	producing
R	1.000	0.910	0.825	0.814	0.812	0.812
NC	0.000	0.042	0.115	0.116	0.080	0.080
NR	0.000	0.048	0.060	0.070	0.108	0.108

Level 0111 - Component MOTOR (Fig. 14).

The BN in Fig. 14 represents the component MOTOR. Decisions about Maintenance strategy are decomposed in two decision nodes. The first corresponds to the periodicity of the preventive maintenance “Maintenance”, and the second corresponds to the stock strategy “Stock”.

According to these decisions, the availability of the component is computed. The Stock strategy and the periodicity of the preventive Maintenance influence the motor availability as it is presented in Fig. 15. Different values of this availability are reported in the MOTOR CPT corresponding to the possible and plausible decisions about preventive maintenance period.

Fig. 16 presents MOTOR costs in regard to the periodicity of the preventive maintenance. These costs are used to determine the utility table “U Maintenance” according to the states of the “Maintenance” decision node. “U Maintenance” node is independent of the “Stock” decision node. Nevertheless, the stock has a fixed cost depending on its decision states: “stock the motor” or “don’t stock the motor”. This cost is used to define the utility table of the node “U Stock”.

MOTOR has two states: “OK” or “HS” corresponding to the availability or the unavailability of the component.

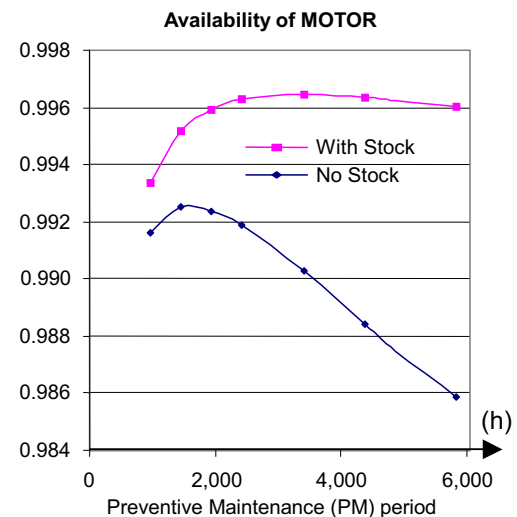


Fig. 15. Availability of MOTOR component.

Use of the model**First inference.**

The prior probabilities associated with the states of variables representing the availability of the functions are computed with an inference of the BN according to the decisions (choice of maintenance strategy).

The first simulation is performed, for example, with a corrective maintenance strategy, and without stocking the motor. The HD “to produce” and RHD of each sub-function are presented in Table 14.

Thus, according to the characteristics of availability used for the components, 82.8 % of the parts are produced, 1.8 % of the parts are produced with no conformities and 15.2 % are not produced. The expected benefit in this configuration of decisions is equal to 131,000. This value is used in the following as a reference level, and the decisions impacts are given like a percentage of variation of the benefit.

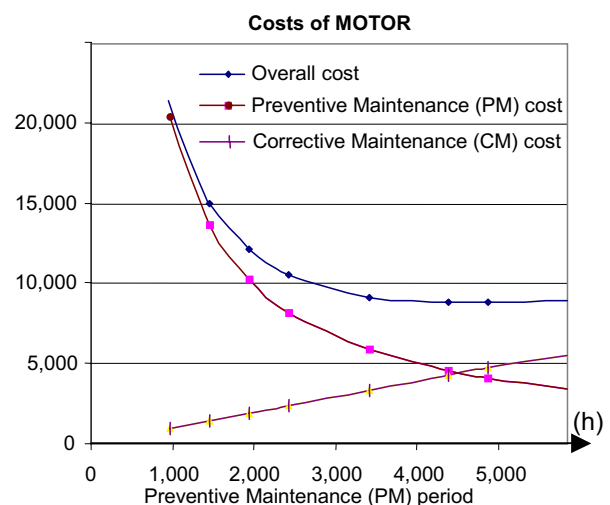


Fig. 16. Costs of MOTOR component.

Simulation of different scenarios.

The results of the simulations with different scenarios are presented in Table 15, Table 16 and Table 17 (487 h = 1 month). The increase in expected utility function is presented in percentage of the reference level (131,000); a positive percentage relates an increase in the benefit.

Strategy 1:

Decisions are given in order to maximise the availability of each component (local maximum availability).

Table 15. Local maximum availability.

Components	Decisions	RHD Producing	
DITRIBUTOR	PM 3,896 h	R	83.10 %
JACK	PM 585 h	NC	7.56 %
MOTOR	PM 3,409 h	NR	9.34 %
TOOL	PM 487 h	Expected utility	
		+ 8.2 %	

Strategy 2:

Decisions are given in order to minimise the costs of each component (local minimum costs).

Table 16. Local minimum costs.

Components	Decisions	RHD Producing	
DITRIBUTOR	CM	R	82.96 %
JACK	PM 877 h	NC	7.66 %
MOTOR	CM	NR	9.38 %
TOOL	PM 682 h	Expected utility	
		+ 11.4 %	

Strategy 3:

Decisions are given in order to maximise the expected utility function. This decision corresponds to the best compromise between system overall cost and system availability.

Table 17. Global maximisation of the expected utility function.

Components	Decisions	RHD Producing	
DITRIBUTOR	PM 3,896 h	R	83.07 %
JACK	PM 730 h	NC	7.60 %
MOTOR	CM	NR	9.33 %
TOOL	PM 682 h	Expected utility	
		+ 12.0 %	

To conclude this application, the model presented allows the comparison of different strategies. The local minimisation of the component costs or the local maximisation of the availability of the component leads to an increase in the benefit less important than the overall optimisation of the expected utility function computed from a set of decisions.

Conclusion and further work

The proposed model, based on the functioning and malfunctioning studies carried out during design phase, makes it possible to build easily the structure of the BN. This structure is based on several levels of abstraction carried out from a generic formalism.

The added value of BNs is linked to the computation of the probabilities assigned to a node state, knowing the state of one or several variables. It is then possible to estimate the impacts of a random variable on the process. So, the networks are built by incorporating uncertainties on the relationships between causes and effects to be more consistent with system reality.

First, the phase of quantification of BNs is based on experts' judgement or on the basis of previous projects. The experts' interrogation requires an important work and is not very easy but it is a crucial stage. However, estimated values of parameters don't need a lot of accuracy because the aim of the analysis is to compare solutions among them. It is also necessary to associate with all probabilities an uncertainty in order to undertake studies of sensitivity.

In the second time, probabilities are updated thanks to the data of operating experience, by Bayesian analysis for example.

Operating experience data will enable to refine the probabilities contained in the CPT by training.

The model is based on parameters linked to the economical impact of decisions and is simple and easy to construct. Moreover, it allows the aggregation of the availability parameters, classically computed with complex model, and the knowledge of the financier. The use of the influence diagram in order to simulate the impact of a decision (or an evidence) on the overall performance of the system is easy.

The networks can also be used in design [12] to validate the effectiveness of the corrective actions suggested following the FMECA analysis or during the exploitation of the system for the diagnosis [13].

BNs constitute a powerful tool for decision-making aid in maintenance. The model combines a priori approach in design and a posterior approach in operation.

It remains to improve the automatic generation of BNs starting from model SADT and FMECA analysis. It is also necessary to validate the model by applying it to a real system in order to show industrial feasibility and to confirm its added value compared to the traditional computerised decision-making systems.

Acknowledgements

We would like to thank Mr B. lung for having made available the documentation on the Lathe allowing the application of the proposed method.

References

- [1] Bobbio A., L. Portinale, M. Minichino and E. Ciancamerla (2001). Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. *Reliability Engineering and System Safety*, 71, 249-260.
- [2] Bouissou M., F. Martin and A. Ourghanlian (1999). Assessment of a Safety-Critical System Including Software: A Bayesian Belief Network for Evidence Sources. *RAMS'99 Reliability and Maintainability Symposium*, Washington, USA.
- [3] Bangso O. and P.-H. Wullemmin (2000). Top-down construction and repetitive structures representation in Bayesian Networks. *Thirteenth International Florida Artificial Intelligence Research Symposium Conference*, Florida, USA.
- [4] Bangso O. and P.-H. Wullemmin (2000). *Object Oriented Bayesian Networks A framework for topdown specification of Large Bayesian Networks and repetitive structures*. AALBORG University Technical report, (p29), September.
- [5] Software Hugin (<http://www.hugin.com/>).
- [6] Jensen F.V. (1996). *An Introduction to Bayesian Networks*. UCL Press, London.
- [7] Jensen F.V. (2001). *Bayesian Networks and Decision Graphs*. Springer-Verlag, New-York.
- [8] Léger J-B., B. lung, A. Ferro De Beca and J. Pinoteau (1999). An innovative approach for new Distributed Maintenance System: application to Hydro Power Plants of the REMAFEX project. *Computers in Industry*, 38, issue 2, 133-150.
- [9] Léger J-B. and B. lung (1998). Methodological approach to modelling of degradation detection and failure diagnosis in complex production system. *Ninth international workshop on Principles of Diagnosis*, Cap Cod, Massachusetts, 209-216.
- [10] Weber P. and M.C. Suhner (2001). Aide au choix de stratégie de maintenance par simulation de réseaux bayésiens. *4^{ème} Congrès international pluridisciplinaire Qualité et Sécurité de fonctionnement, Qualita 2001*, Annecy, France, 302-307.
- [11] Fougrouse S. and J. Germain (1992). *Pratique de la maintenance industrielle par le coût global*. AFNOR, Paris.
- [12] Weber P. and M.C. Suhner (2001). System architecture design based on a Bayesian Networks method. *Xth International Symposium on Applied Stochastic Models and Data Analysis*, Compiègne (France), June 12-15, 1004-1009.
- [13] Weber P., M.C. Suhner and B. lung (2001). System approach-based Bayesian Network to aid maintenance of manufacturing process. *6th IFAC Symposium on Cost Oriented Automation, Low Cost Automation*, Berlin, Germany, Oct. 8-9.