Imperfect maintenance modelling by dynamic object oriented Bayesian networks

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Abstract— **The maintenance of complex systems is a discipline that requires great knowledge and great experience. These factors are, unfortunately, not enough: the opportunity to model the system to be maintained and to represent it in the form of a mathematical and probabilistic model, can't be disregarded at all. These composite systems, moreover, are often subject to problems of uncertainty and must operate in multifunctional contexts. So, even the modelling tools must be able to take into account these aspects. In recent years, new probabilistic tools, such as the Dynamic Object oriented Bayesian Networks (DOOBNs), have been developed. They're able, among other things, to estimate the reliability performance of complex systems and have been applied in production plants, machinery and process plants. An usual problem, often occurring, is to correctly represent the process of imperfect maintenance. This is characterized by a recovery of the system that brings it back into an intermediate situation between the minimum repair and perfect repair. The aim of this study is to evaluate how it is possible to use dynamic Bayesian networks to model imperfect maintenance. In particular, first we studied the problem, then a case study on the compressed air production and treatment system of an high speed train was analysed and finally the analytical capabilities of the instrument were assessed. The originality of this work lies in the fact that there are not in the literature DOOBN applications to model imperfect maintenance. The study results were very satisfactory and in the future it will be necessary to better investigate what are the limits and the potentials of the instrument.**

Keyword- Bayesian Networks, Reliability analysis, Maintenance Management.

I. INTRODUCTION

A typical issue for a technical asset manager is to take decisions basing on the analysis of the controlled system. The great complexity of many plants returns the necessity to use new methodologies and tools to support decision-making processes, in order to increase the efficiency and the effectiveness of the engaged actions. Decisions must often be taken without a perfect perception of the state of the system and without essential information, due to uncertainty.

Bayesian Networks (BNs), coming from Artificial intelligence, where were used like a robust and efficient framework for reasoning with uncertain knowledge, can be used as decisions aiding systems, assessing values of the main process performance parameters [1] [2].

The proposal of using BNs as a framework for reliability analysis, has given the rise to a research trend comparing classical reliability formalisms and BNs. The modelling and the analysis of reliability block diagrams [3] and fault-trees [4] [5], have been compared to BNs and it has been shown that these have significant advantages over the traditional frameworks. We will discuss some of these advantages in detail by means of a real-world case study. More recently, other general reliability models have been compared with BN-related formalisms [6]. BNs have found applications in fault finding systems [7], [8], maintenance modelling [9], decision support [10], risk management [11]. Bayesian Networks are also suggested for root cause diagnostic analysis [12] and probabilistic approach to fault diagnostics in combination with multivariate data analysis [13]. Moreover researchers have been using temporal dynamic BNs for the diagnosis and prediction of failures in industrial plants [14].

Nonetheless, big and complicated BNs are difficult to design and to be implemented. This is why the object oriented method, basing on BNs and on a hierarchical breakdown of the model, was so appreciated so far. This resulted in a large number of publications and papers focused on Object oriented Bayesian Networks (OOBNs) [15], [16].

The top down creation of BNs, which needs several levels of abstraction, and the mighty model elaboration procedure for those arrangements that show repetitive structures, make OOBNs very suitable to represent processes and maintenance policies [16]. Complex models are used and both the structure and the parameters can be enriched by means of an analysis of the past experience. Weber [17] suggested a decision procedure basing on a static probabilistic framework that allows to identify faults by an analysis of the system operation and failure. In order to develop diagnosis and maintenance management, we wanted to define a model representing the process performance. This model should allow to evaluate each probability distributions of each state considering both the age of the elements and the maintenance policy adopted.

Since reliability[18] [19], safety and maintenance management [20] [21] are some of the most interesting issues of international scientific research and have been deeply analysed by the authors [22], our interest focused on the verification of the potential of BNs for implementing in the context of industrial plants engineering.

The purpose of this research is to introduce a new Object oriented approach to model the reliability performance of a system within the Dynamic Bayesian Networks (DBNs) model. The probability distribution over the next states was determined by the present state of the system and the maintenance action employed on that state. One of the latest studies [23], presents a methodology that could help in exploiting Dynamic Object Oriented Bayesian Networks (DOOBNs) to describe so multifaceted models and is a good omen for the success of the search.

This paper sows how the dynamic Bayesian networks are able to model different maintenance strategies for industrial plants. This would make it possible to check what are the impacts on the company of the adoption of different maintenance policies, in terms of reliability and availability. The proposed approach matches DOOBNs methods and RBD-BN technique to evaluate, in terms of reliability and other process performance indexes, the impact of decisions on the maintenance of a complex multifunctional system, whose parameters are affected by uncertainty.

This paper is divided into seven sections. The problem statement is presented in section II, where we recall as the belief networks are a graphic and efficient framework for dealing with the complex system modelling. Section III describes the Bayesian networks theory. The modelling approach is explained in section IV, where an original formalisation of the reliability connections and maintenance policies is proposed. The case study and simulation results are developed in section V and VI respectively; finally some discussion and final conclusions are argued in section VII.

II. PROBLEM STATEMENT

In order to gain the higher availability performance from the system it is necessary to define the correct maintenance strategy. The best choice can be properly taken with the help of a decision support system.

Let $U = (X_1, X_2, \dots, X_n)$ be a set of random variables, indicating, for example, symptoms and failures in a fault diagnosis context. Let $p(U)$, represent the probability distribution for U. Moreover, let's consider that the domain of the above mentioned variables is affected by uncertainty. We now would want to represent the complex system just described within a powerful model that, by means of efficient computing algorithms, can infer interesting issues. For example, it would be useful to assess the probability of an unknown variable state by some observed data and a given knowledge of some event.

Graphs are a natural medium for representing information in a compact form which humans can grasp, understand, and use. In particular, the structure of a graphical model clarifies the conditional independencies in the implied probability models, allowing model assessment and revision [24].The main idea behind graphical models, like belief networks, is to represent the independence structure existent in $p(U)$ by an annotated graph.

Each node of the graph corresponds to another variable in U and the edges of the graph reproduce the independence structure in $p(U)$. Therefore, for instance, a probability model with no independence structure is symbolized by a completely connected graph; contrariwise, a model where all variables are independent from each other, is represented by a graph with no arcs connecting any of the other nodes. The graph annotation is realized transforming the underlying probability model $p(U)$ into tables of conditional probabilities, made by deterministic values or rule equations. These factors are saved, in the form of tables, at the single nodes which represent the local dependencies and are used for graph calculations.

Except for cases with a few variables, the $p(U)$ is very difficult to handle considering the model probability structure. For instance, a system with no independence structure and N binary variables requires the declaration of 2^N probability values. Moreover, computations of certain probabilities posterior to some observed evidence, may also tend to go up exponentially in N. For these reasons such models might result actually useless.

The most powerful and used belief networks are the Bayesian ones that provide a graphic and efficient framework and algorithm for dealing with the above mentioned issues. They are a robust graphic formalism that can easily fit complex systems affected by uncertainty. They can manage uncertainty through the analysis of the interactions between causes and effects [25].

The nodes of BNn represent propositional interesting variables (for example, the pressure of an appliance, an attribute of a device, the occurrence of some event) and the oriented arcs designate causal or informational dependencies among connected variables. Such node relationships are quantified by the conditional probabilities, given the parents, evaluated for each node. [18].

III. METHODS

A. Bayesian networks syntaxes and semantics

A growing need in the industrial sector is to have suitable decision support systems. These are required in several areas, for instance in the energy resolutions [26], in management choices [2], and in maintenance issues [10]. Bayesian networks can be used as a valuable support system for engineering problems. Bayesian networks are directed acyclic graphs, often referred as DAGs. A Bayesian network is defined by a couple $G = \{(N, A), P\}$, where (N, A) represent respectively the collection of nodes and the group of arcs. P is the discrete probabilities distribution associated to each node. Let us consider a simple case of network, as visible in Figure 1.

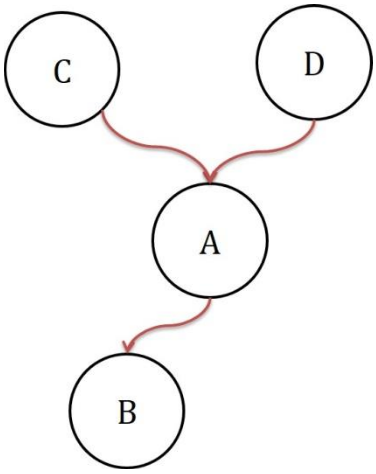


Fig. 1. A simple Bayesian network. Nodes C and D are "parents" of A, while B is a "leaf"

Like in a family tree, the parents of a node are defined as the set of nodes pointing to it; nodes C and D are parents of node A and a conventional indication for the set of parents of A is $Pa(A)$. Then, you can identify the "root" nodes, that are all the ones which don't have parents, as C and D; moreover there are the "leaf" nodes, that are all those which don't have any child, like B: this latter node doesn't have any causal influence on any other one.

For every node which has parents, the P distribution is a conditional probability function, determining the stochastic dependency of a node from its parents. For every child there must be, at least, one parent.

Let us define X as a discrete random variable expressing the state of a node $n \in N$, where N is the set of the network's nodes. The X variable can assume M mutually exclusive states that could be collected by the vector $S_n = \{S_n^1, S_n^2, \dots S_n^M\}$. For instance, if the fourth node has three possible states (A, B, C) with probabilities of $(20\%, 50\%, 30\%)$, we'll have $S_4 = \{S_4^1, S_4^2, S_4^3\} = \{A, B, C\}$.

The vector π_n denotes a probability distribution over these states, where $\pi_n(S_n^m)$ is the marginal probability of n being in state S_n^m and $\pi_n = \{\pi_n(S_n^1), \pi_n(S_n^2), \dots, \pi_n(S_n^M)\}$ signifies the probability of each of the M states of n and $\sum_{k=1}^{M} \pi_n(S_n^k) = 1$. In the previous example, we'll have again $\pi_4 = \{\pi_4(A), \pi_4(B), \pi_4(C)\} = \{20\%, 50\%, 30\%\}$.

The P set, that is the group of conditioned probabilities describing a node, is illustrated by the Conditional Probabilities Table (called CPT). For every node there's a CPT. The CPT of a node n_j is then defined by the conditional probabilities $p(n_j|n_i)$ over each n_{jj} state knowing its parents' states n_i, so its CPT is defined as a matrix $P\left(n_j \middle| pa(n_i)\right)$.

The conditional probability values, filling the CPTs of every node, come from the information and knowledge of the observed system. As the knowledge increases thanks to more field data, experts experience and database information, consequently the CPTs redaction is more precise and the inference is more reliable.

The Bayesian network's nodes are the variables, the arcs are the dependence relationships and the CPTs define the values of them [27].

B. The Bayesian networks inference

The statistical inference is the capability of forecasting an event, basing on observations. In the Bayesian networks, the inference permits to evaluate the probability of the states of some interesting nodes, thanks to the observation of some other nodes. If it wasn't possible to make any observation, the probability estimate of the interesting nodes might be made on the basis of the a-priori probability knowledge of the sole root nodes. Any information coming out from an observation may be formalised as a strong or weak evidence.

A strong evidence of the X random variable indicates that the node $n \in N$ is undoubtedly in one of its possible M states $S_n = \{S_n^1, S_n^2, \dots S_n^M\}$.

A weak evidence is involved when the knowledge is not certain. It's a set of new values for the root nodes probabilities. A weak evidence of a node n permits to update the a-priori probability values for the possible states of n.

By means of observations, in the Bayesian networks, it is possible to have four kinds of inference: diagnostic inference (from the effects to the causes), causal inference (from the cause to the effects), intercausal inference (among common causes of an affect), mixed inference (a combination of the previous).

The inference process is gained thanks to an algorithm able to update the probabilities of the network nodes, after having assigned a status to some variables as a result of an observation.

Several inference algorithms might be operated to calculate the marginal probabilities: the best known is based on the use of a junction tree [28]. Inference in BNs then allows to take into account any observation of the state variables to update the probabilities of all the other variables. If there's not any event observation, the calculation relies only on the *a priori* probabilities. When there are observations of real events, these are included into the network and all the remaining probabilities are consequently updated [29].

C. The dynamic Bayesian networks

The Dynamic Bayesian Networks (DBNs) are BNs that including a temporal dimension. They have the CPTs with time dependent parameters, instead of constant values. From the operating point of view, they are hard to implement and there are two possible solutions so far.

The first one is called "time dependent arc", where the concept of time is inserted by means of an inference [30]. It is feasible to calculate the probability distribution of any variable X_i at time step k, founding only on the chances of the $k-1$ time step. In such a way, the probabilities at the $k+1$ time stage, are estimated using following inferences.

Consider now a network with only two time slices, such as defined in Figure 2. The first part on the left comprehends the nodes describing the present time step $(k-1)$ while the right part represents the subsequent time step (k). Any external evidence will be introduced only in the current time step. The time development of calculation is achieved by setting the calculated marginal probabilities of the node at time k as evidences for its equivalent node in the preceding time step.

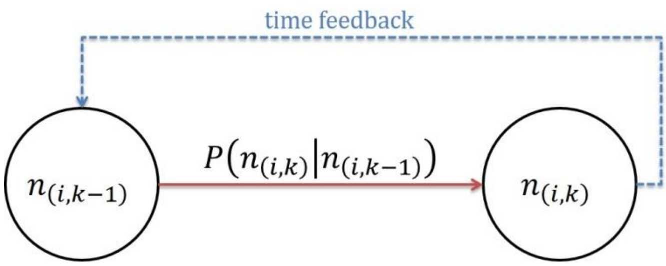


Fig. 2. The time dependent arc. The node on the left corresponds to time $k-1$, while the node on the right is the same node, but a time k

This compactness is based on the following assumptions: the described process is Markovian, i.e. the variables of time step t depend only on the variables of the preceding time step $t-1$ and the system is time invariant, i.e. the probability tables do not evolve with respect to time [31].

This last assumption is overcome thanks to the second solution, that is called "time dependent node". It is possible by modifying the probability distributions, according to the value of the current time step by means of equations. The time node is a parameter node representing the time flow and its values, positive and integer, are used in the probability distribution equations.

This is not a typical Bayesian network node. It is always disconnected, that is even the nodes that use it in their equation are not graphically connected to it and the corresponding probability tables don't reference it explicitly as parent. There are only the probability values that depend directly on it.

During the temporal inference, after each time increment, the probability distributions described by the equations that use this parameter are updated. The use of this parameter transforms the network into a dynamic Bayesian one.

The inference in the dynamic networks is not as simple as in the case of the static Bayesian networks, i.e. the inference based on a junction tree is exact for static networks, but approximate in the dynamic case at each time step. So it could be helpful to introduce some Monte Carlo inference based simulations, that would give approximate results in static and dynamic cases, but the approximation is of the same order in both configurations. That is to say, the approximation is not related to the dependence of the nodes but it's only due the randomness of the simulation.

D. The object oriented Bayesian networks

If we consider a system represented by many variables, their implementation within Bayesian networks models might be a very complex task. Anyway this hard implementation is a far more simple task compared to the solution of other methods.

In order to approach this aspect, a new peculiar kind of Bayesian networks has been defined, as previously said, called Object Oriented Bayesian Network. An OOBN is a network that, beyond the previously described nodes, contains some link nodes, called instance nodes whose function, is to connect with each other some portions of a bigger network. In such a way it is possible to represent a complex network as a series of small ones that can be managed, joint by the instance nodes.

The modelling is based on the breaking down of the network structure in hierarchical levels [32]. The overall function is split into basic functions and sub-functions, often referred to as elementary function.

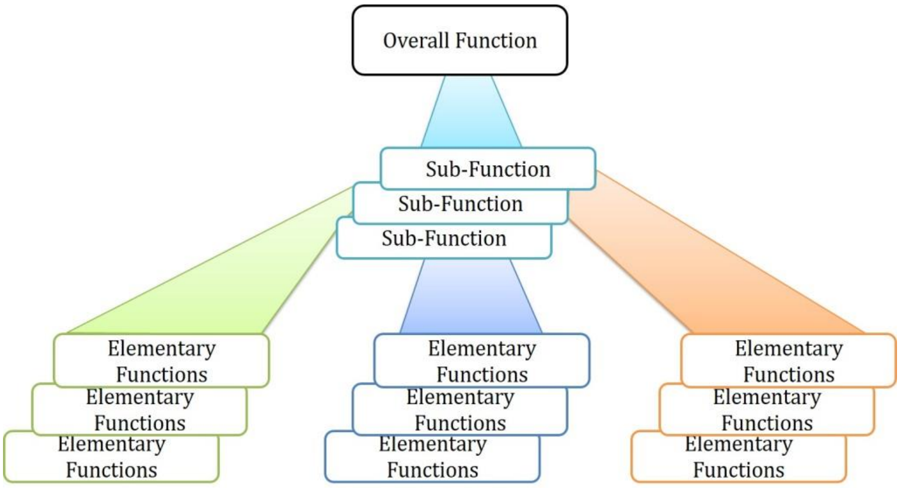


Fig. 3. The functional decomposition. The network in broken in hierarchical levels: overall, sub and elementary functions.

Every function represents an elementary process of the system.

This representation permits to decentralise and to structure the knowledge with little dimension networks that are more manageable and computable. Thanks to this simplification, the object oriented Bayesian networks are easily used to model industrial systems.

As already seen with the dynamic Bayesian networks, also the object oriented ones have their corresponding dynamic model, called DOOBNs. The difference between the two types is that the first one uses static models while the second one a dynamic approach.

IV. Modelling approach

A. SADT representation

Modelling a complex system requires a methodology that will help to detail the BN structure and the variables states. Structured Analysis and Design Technique (SADT) and Reliability Block Diagram (RBD) are methods that are often used in practice; therefore, we will formalise the BN from this knowledge representation[33]. This approach, trough SADT graphical representation, allows to highlight the system functioning inside its setting and to consider its interconnections with the internal and external resources. SADT is based on the principle of functional decomposition of the system into functions, sub-functions end elementary functions.

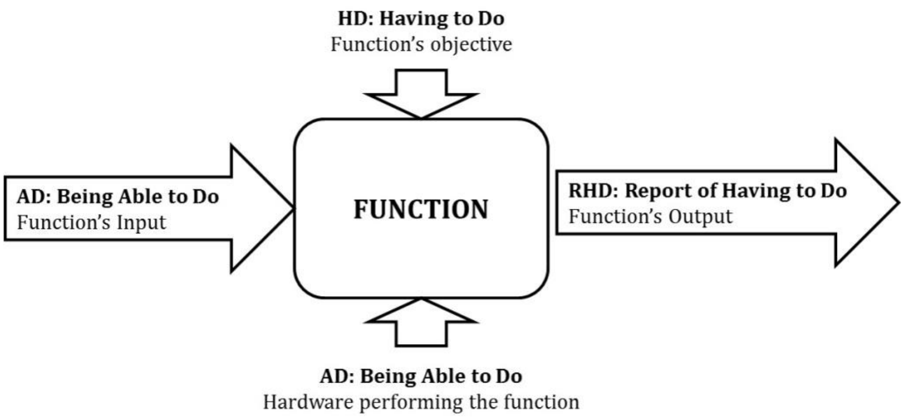


Fig. 4. The Structured Analysis and Design Technique (SADT). This representation shows how an Elementary Function is modelled a complex system representing the modification of an input.

Each Elementary Function (see Figure 4) means a change of the product, which is made by the system. The function creates or uses flows as "Having to Do" (HD) in order to transform its input into the desired output requiring the "being Able to Do" (AD) element, such as energies, resources, support. Moreover, the output flow is a report (Report of Having to Do, RHD) that represents the function state in relation to HD. The output flow is the proper functioning of the inspected function, that is its reliability. Only the RHD flow is properly considered as output of the function. This output is transferred, as input flow, to another function.

B. Equivalent relationship: RBDs-BNs

In this study special attention was paid to the representation of the logical connection of the physical components. As above mentioned one of the entries of an elementary function (EF) are the AD basic elements. As figure 4 shows, one of the AD elements are the physical components that contribute to perform their relative EF function [23].

In figure 5, it's shown how an RBD connection can be converted into an equivalent BN and how assumptions should be made in the new formalism. Figure 5 also shows the conversion of a parallel and a series RBD model into equivalent networks, following BNs model. Parent nodes *A* and *B* are assigned 'a-priori' probabilities for their two states: working-faulty (equivalent to the failure rates of each component). The child node *C* (representing the functionality of the system) is assigned its CPT depending on the logical connections. Since, the parallel and series connections represent deterministic relationships, all the entries of the corresponding CPT are either 0 or 1.

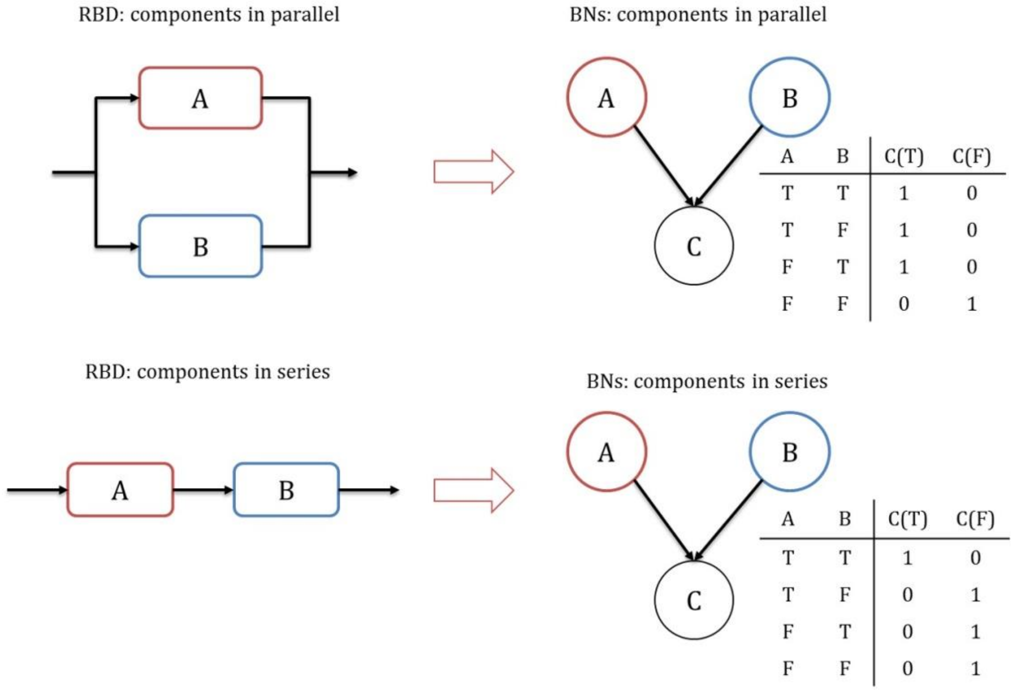


Fig. 5. RBD and BNs representation. The picture shows how to convert a reliability block diagram basic structure (like series and parallel arrangement) into a Bayesian network

This type of representation gives also another opportunity. Let's consider two or more components, like a set of pumps. They could be working in parallel or in series depending on the mission that they have to fulfil. A lot of complex systems are modelled by this feature. These types of dynamic performance can be defined like an intermediate behaviour between the two classical logical connections and can be easily modelled by node *C* thanks to an appropriate CPT.

C. Maintenance Policies

In this section, is described the approach used to model the planned maintenance operations for mechanical equipment.

There are two extreme maintenance approaches: the "perfect repair" and the "minimal repair" [22]. In the first case the component is considered to be "as good as new", that is to say its failure rate will be the same of a new item. This goal is usually achieved by means of a substitution. The minimal repair, on the contrary, leaves an item, after its inspection, "as bad as old". In other words, the failure rate isn't restored to a lower value. This kind of operations doesn't improve the system from a reliability point of view.

There is also an intermediate situation called "imperfect repair" with some reduction of the item failure rate but not a complete renewal. Another strategy is the no preventive maintenance option, applied for those cases in which there wouldn't be enough benefits compared with the problems and costs of any intervention made before the failure. Each one of the three types of maintenance previously described requires its own shaping in a Bayesian network. Our work's result shows how such modelling can be helpful in maintenance management issues.

1) Item without maintenance

The modelling of such items was made with the use of government equations (hence with the time dependent node), whose reliability function is a decreasing monotonic one. Let us consider an item whose failure probability density function is distributed as a normal and characterized by no maintenance activities. In Figure 6 its reliability function is plotted by a dash-dotted line.

The results of reliability calculation in this Bayesian network model are exactly as the theoretical function should be (see Eq.1):

$$R(t) = e^{-\int_0^t \lambda(\tau) d\tau} \qquad (1)$$

2) Item "with perfect repair"

This kind of maintenance was modelled following time based interventions, as required from the scheduled maintenance plan. In the object oriented Bayesian network, the node of the item restores its reliability to 100% every time that a maintenance operation is held, with a time step $t = T_1$. So the $R(t)$ is the same within every T_1 period.

The reliability function can increase and go back to the 100% because we are sure that every T_1 time interval, the system will be as good as new, thanks to the maintenance actions.

The analytical expression of the reliability, in the dynamic Bayesian network, is as follows.

$$R(t) = e^{-\lambda\left[t - int\left(\frac{1}{T_1}\right) \cdot T_1\right]} \qquad (2)$$

where the $\left[t - int\left(\frac{1}{T_1}\right) \cdot T_1\right]$ factor is introduced to describe the recurrence.

In Figure 6 the reliability of an item with a perfect maintenance strategy is plotted by a continuous line, repeating each T_1 time interval. In this example the maintenance actions are made every T_1=2500 time units.

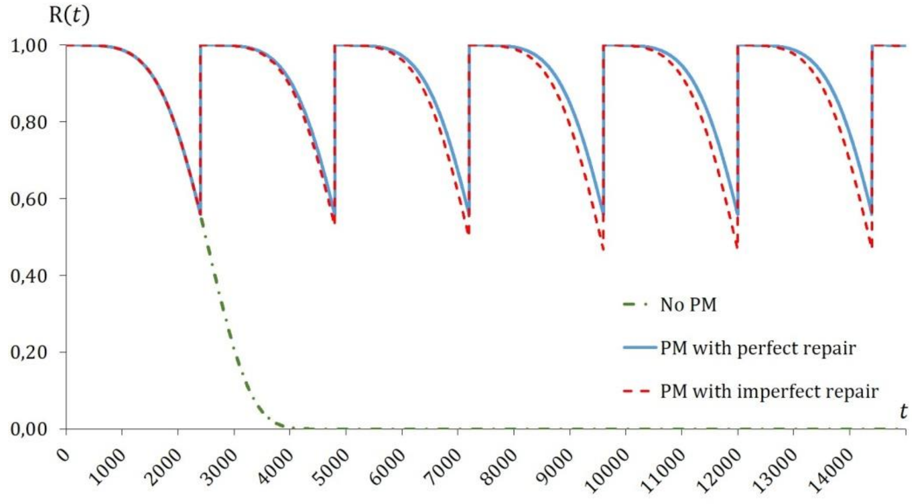
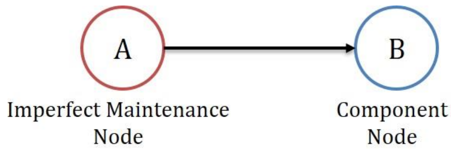


Fig. 6. Alternative maintenance choices. The picture shows the reliability functions of the system in three different cases: without preventive maintenance, with preventive maintenance and perfect repair, with preventive maintenance and minimal repair.

3) Item with "imperfect repair"

In a system there are many items that are maintained with servicing or cleaning actions. In multicomponent systems, in the same way, it could be replaces a single component, leaving all the others unchanged. In such cases the failure rate may decrease, but won't become as low as it was when the unit was new. The imperfect maintenance is modelled adding a certain quantity of operating hours to a new. In order to represent imperfect repair inside a DOOBN, another node is required. It must acquire distinct values as the time goes by. In Figure 6 the result of a reliability evaluation are shown by an hatched line. As clearly visible, every time that a maintenance operation occurs, the reliability becomes 100% but, this time, its decrease is faster as the item gets older.

Now, in order to analyse how we could model an item with imperfect repair, let us consider two nodes, A and B.



$$\mathrm{P}(A|t) = if \begin{pmatrix} 0<t<T_0 \\ T_0<t<T_1 \\ T_1<t<T_2 \end{pmatrix} \text{then} \begin{pmatrix} A=0 \\ A=1 \\ A=2 \end{pmatrix} \qquad \mathrm{P}(B|A,t) = if \begin{pmatrix} A=0 \\ A=0 \\ A=1 \\ A=1 \\ A=2 \\ A=2 \end{pmatrix} \text{then} \begin{pmatrix} B(\text{true})=R_{T_1}(t) \\ B(\text{false})=F_{T_0}(t) \\ B(\text{true})=R_{T_1}(t) \\ B(\text{false})=F_{T_1}(t) \\ B(\text{true})=R_{T_2}(t) \\ B(\text{false})=F_{T_2}(t) \end{pmatrix}$$

Fig. 7. Imperfect Repair Model. According to the type of maintenance performed (node A) the network calculates the probabilities of the component (node B) of being working or faulty.

Node A is the imperfect maintenance node and it can assume, for example, three different states $(0, 1, 2)$ depending on the time variable. They represent the three different maintenance levels concerning the component B. In Figure 7 the logic conditions, that rule the imperfect maintenance node, are shown. The imperfect maintenance node has got as many values as the maintenance levels.

Node B is the component node. It can assume two different states (true and false) depending on A's state; they are ruled each one by three different equations.

After having illustrated the approach developed to model a complex system within BNs formalism, in the following sections we will describe the application and the analysis results derived from a real case study.

V. 5. APPLICATION

The case study selected to test the proposed method, is the compressed air system of an Italian high speed train: the compressed air production and treatment facility (CPTF). Each train is provided with two of these groups that produce drained and stripped air at an operating pressure between 9 and 10 bar. The system, composed approximately by thirty elements, is divided in two subsystems: the unit of compressed air production (left side of Figure 8) and air conditioning unit (right side of Figure 8).

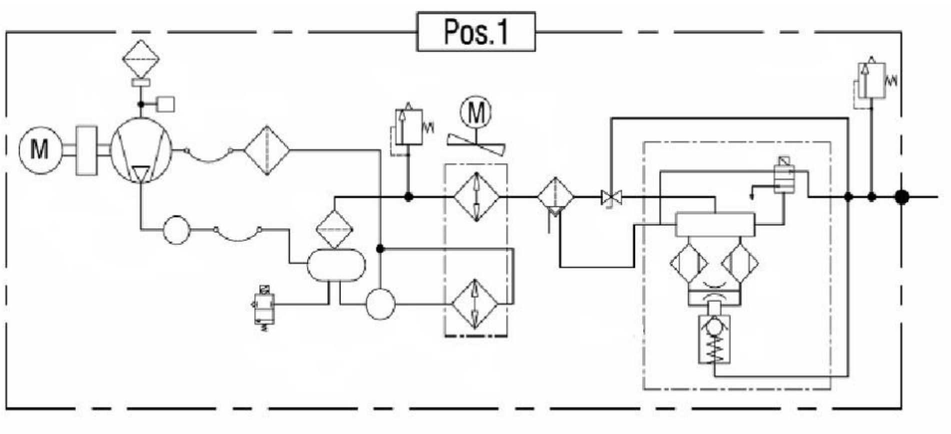


Fig. 8. Piping & Instrumentation Diagram of the CPTF system. In the left part of the diagram are shown the components necessary for the production of compressed air, in the middle are shown the devices for the oil-air mixture treatment while in the right part there are air treatment appliances.

The reliability functions, such as failure rates have been deduced through the analysis of the computerized maintenance management system, used by the owner. The database information, have been first statistically treated to obtain the time distributions of breakdowns and maintenance activities. These operations associated to a deep analysis and study of the system and of its functioning was presented in a previous work [34].

The first step, to apply OOBNs methodology, was the system tasks identification. Three main plant functions were defined as mixture compression, mixture treatment, air treatment. Each one was then split into elementary functions and for each function the input / output flows were identified according to the SADT approach.

The higher level of the system decomposition, with the three function above described, is shown in Figure 9.

Not every elementary function was described, according to the failure rates: the lower ones had a little influence in the overall reliability. For instance, the oil filtering EF wasn't represented in the model, for its low failure rate.

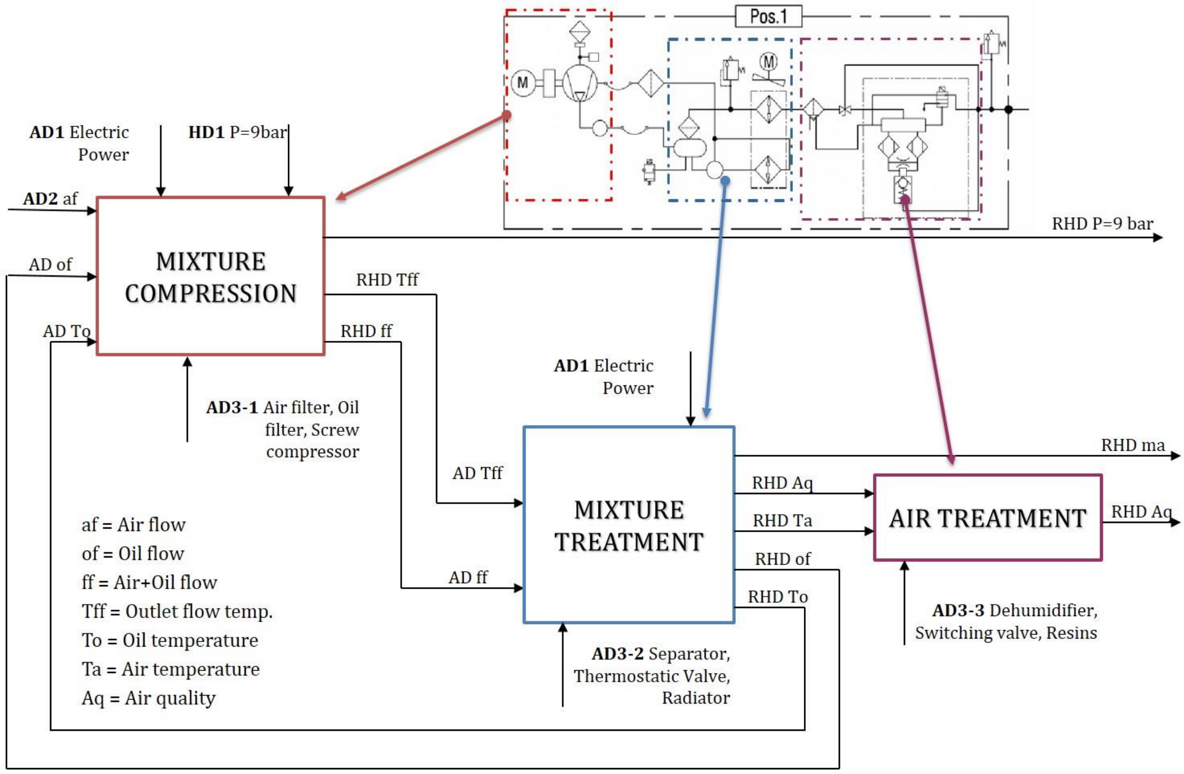


Fig. 9. SADT representation of the plant. Each one of the three phases of the process of the CPTF group, was represented by a block, according to the Structured Analysis and Design Technique.

After this step, all the elements were transposed in a Bayesian network; I/O parameters, functions and components were modelled by nodes, while dependencies and relationships by arcs. This approach generated small networks for each elementary function. Finally, they were all joined together, to obtain the whole system model, using some nodes that represent both an output for a function and an input for another one. The corresponding DOOBN is shown in Figure 10.

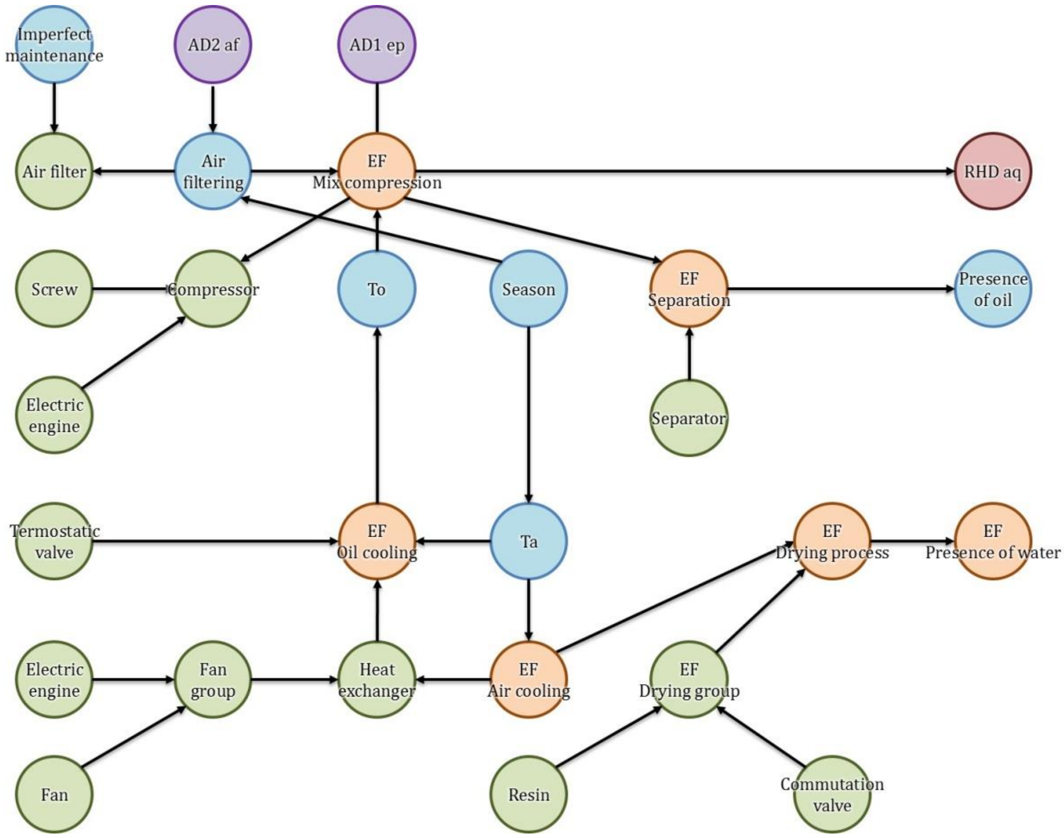


Fig. 10. The Bayesian network. The above picture shows how the air treatment group was modelled by means of a Bayesian approach. This is the full representation of the system. As clearly visible, the graphical representation is very helpful to understand the system functions and the relationships among the nodes.

Some nodes, representing the output variables of the system, were added at the end. For instance the air flow quality "Aq" was divided in two variables: oil presence, water presence. In such a way, the two main pollutants of the compressed air were highlighted, since they are caused by different events.

VI. RESULTS

A very important role, in terms of inference and calculation, is played by the time window settings. In our study a 32000 hour time (5 years and 6 months) was chosen. This selection was made in order to compare the results with the real maintenance plan. A general maintenance, consisting of the substitution of all the items, is was every 29000 hours, after which the plant may be considered as good as new.

The system performance were analysed from two different points of view: the compressed air flow and the compressed air quality. As said, the latter was split into two more output nodes: "water presence" and "oil presence". Each one of these can assume one of three possible states which are shown in Table I.

TABLE I
Main output parameters of compressed air flow and compressed air quality

Output parameter		
Compressed air flow	**Compressed air quality**	
	Compressed air with condensate	*Compressed air with oil*
regular compressed air flow	no water	no oil
regular compressed air flow with temperature rising	small quantity of water	small quantity of oil
no flow	great quantity of water	great quantity of oil

In Figure 11 the probabilities of the three states "regular compressed air flow", "no water in c.a." and "no oil in c.a." are shown.

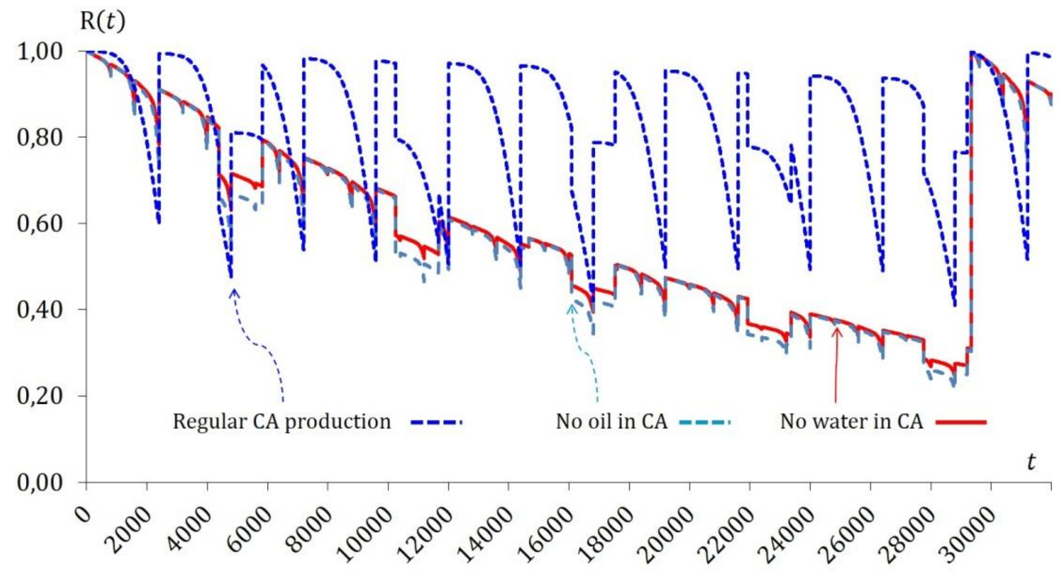


Fig. 11. Probabilities of correct operation. The Bayesian network produced the graph of the probabilities of good production.

The effects of maintenance actions are clearly visible as discontinuity points. As better visible in Figure 12 where the average seasonal performance is plotted, there are two different trends: the one of the “regular air flow” and the “no oil in c.a.” and the one of the “no water in c.a.” events.

The reason of this difference is due to the failure causes, similar for the last two nodes.

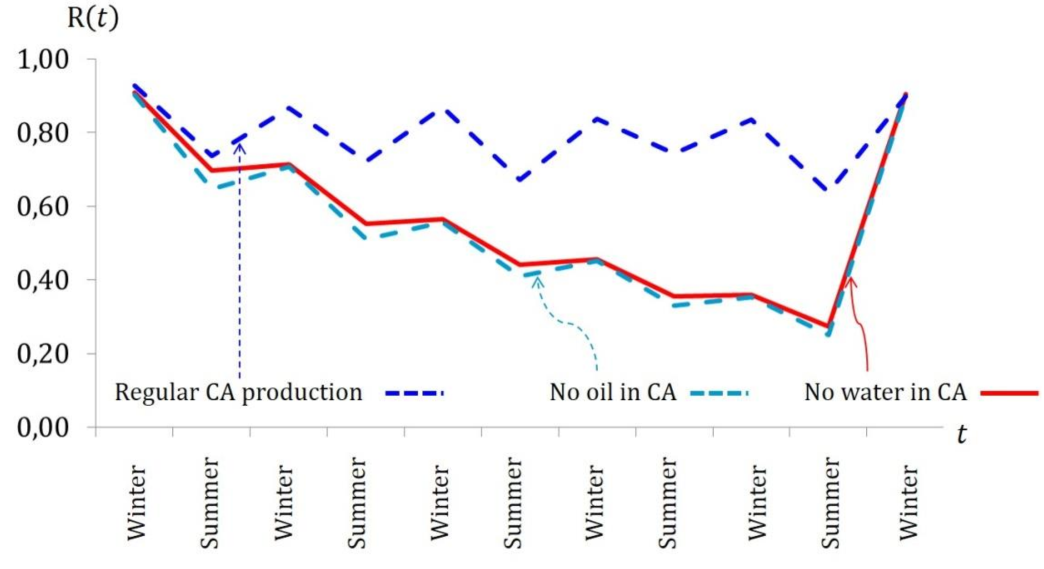


Fig. 12. Average values of correct operation probabilities. The average values, evaluated for the winter and summer semesters, show more clearly their trends..

The above diagram also shows the difference of probabilities between cold and hot seasons. Actually, it’s proved that the system works with different reliability performance in winter and in summer time.

VII. DISCUSSION AND CONCLUSIONS

As is clear from the results,, the proposed methodology is able to compare in a simple way a wide and set of different maintenance configurations in order to optimise service intervals and activities. A good proof of the capability of this approach, can be the evaluation of its effectiveness in comparing alternative maintenance plans. Let’s consider two different maintenance plans: the one proposed by the manufacturer and applied by the owner only in the first years of operations and the one currently in force on the plant.

Figure 13 shows the probability of correct operation for the main process performance index: “regular compressed air flow”. In the graph the seasonal average probabilities are plotted: the lower line is related to the actual maintenance plan and the upper describes the manufacturer's plan. The difference is appraisable only after the end of the 3rd year, moment in which the two maintenance plans begin to differ significantly.

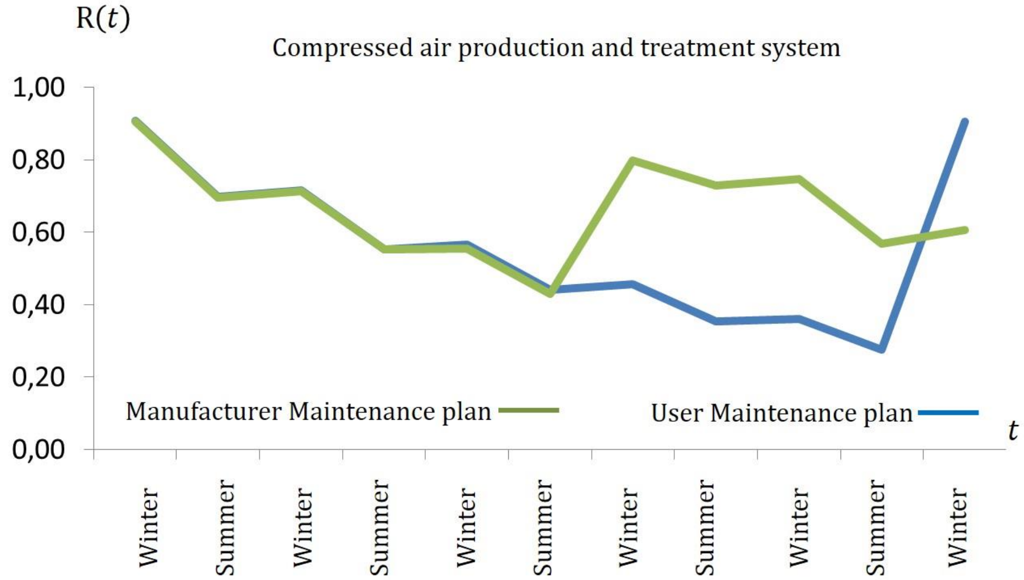


Fig. 13. Probability of having a regular production of compressed air. In this graph the seasonal average probabilities of correct operation for the main process performance (regular compressed air flow) index are plotted.

Both plans have two maintenance levels. The first step is composed by on-line operations while the second one is made by off-line actions. The main difference is the frequency of the second one: the interventions of the manufacturer's plan are twice the ones of the user's plan.

While in the first three years the performance indexes are roughly equal, since the two preventive maintenance plans have got the same frequency for the first operation level, after four years the manufacturer and user plans start to diverge and also the performance parameters turn away in a significant way.

Otherwise, as it is shown in Figure 14, the probability of the event "no water in c.a." is similar for the two maintenance configurations. This quality air flow parameter is influenced by components with similar maintenance activities.

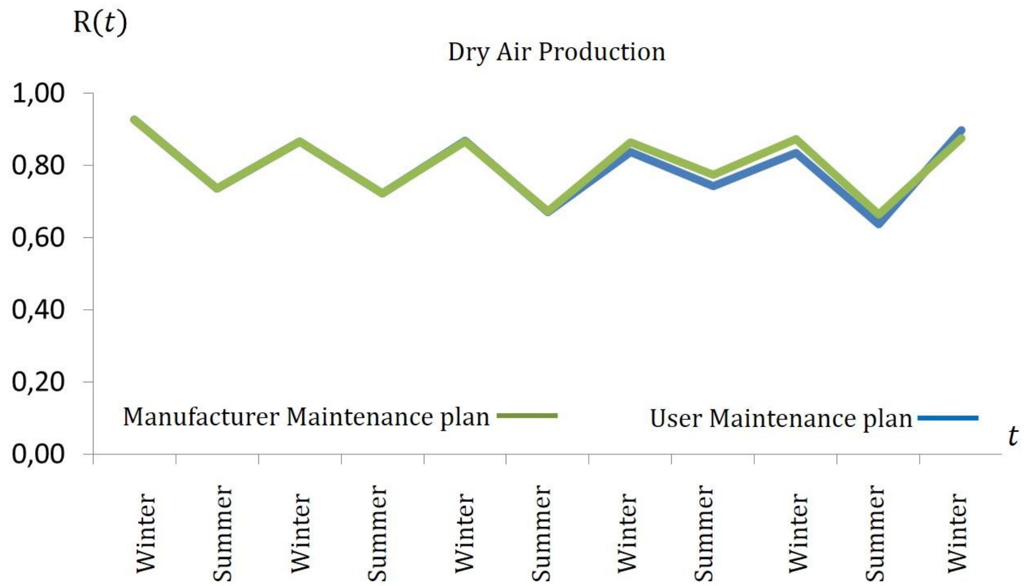


Fig. 14. Probability of not having water in the produced compressed air. In this graph the seasonal average probabilities of having dry compressed air are shown. We can notice that the difference of performance between the two maintenance policies is very small.

The comparison between the two maintenance schedules highlights different results, in terms of performance, for the three main indexes. This is due to the different maintenance planning of each single component of the plants. The instrument, therefore, provides a measure of reliability performance of each of the two scenarios. In this way, it becomes much less complex to compare the two alternatives.

To sum up, it's possible to establish that the approach proposed represents an helpful way to use Bayesian tools for maintenance management. The proposed method, based on SADT graphical representation and RBD diagram formalized in the dynamic object oriented Bayesian networks, easily allows designing the probability functions of complex systems states affected by uncertainty. This approach turns out to be a convincing solution as concerns the modelling of complex. The results of this work, roughly corresponding to the field data, don't pretend to validate the BNs as reliability evaluators, but aim to show how they can also fit the new domain of maintenance policies management.

As a conclusion it's important to highlight the added value of this work. First of all a new approach to model imperfect maintenance plans was presented. This permits to the network to be more tight to many real maintenance situations.

Another interesting result is the use of the time dependent node (with its government equation) instead of the time dependent arc. The benefit is the capability of representing many probability functions and not only the exponential one, so it allows to consider a wider set of items. Moreover the analysis confirms the power of Bayesian networks, in representing series and parallel logical connections, as the Reliability Block Diagrams.

Concluding, this paper shows that DOOBNs represent a very powerful tool for decision-making in maintenance management and interesting comparisons between different maintenance strategies can be performed. In future works, in order to improve this modelling technique, we will have to define the boundaries to which extend the modelling approach and to refine the assessment of the failure rate of an imperfect maintenance. The modelling of corrective maintenance activities, inspection plans and diagnostic systems will be our goals in order to represent a wider set of management strategies achieving a more complete decision aiding system.

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