Original Research

A dynamic approach for maintenance evaluation and optimization of multistate system

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Abstract
This work presents a quantitative approach on the basis of Dynamic Bayesian Network to model and evaluate the maintenance of multi-state degraded systems and their functional dependencies. The reliability and the availability of system are evaluated taking into account the impact of maintenance repair strategies (perfect repair, imperfect repair and under condition-based maintenance (CBM)). According to transition relationships between the states modeled by the Markov process, a DBN model is established. Using the proposed approach, a DBN model for a separator Z1s system of Sour El-Ghozlane cement plant in Algeria is built and their performances are evaluated. Through the result of diagnostic, for improving the performances of separator, the components E, R and F should give more attention and the results of prediction evaluation show that in comparing with perfect repair strategy, the imperfect repair strategy cannot degrade the performances of separator, whereas the CBM strategy can improve the performances considerably. These results show the utility of this approach and its use in the context of a predictive evaluation process, which allows to offer the opportunity to evaluate the impact of the decisions made on the future performances measurement. In addition, the maintenance managers can optimize and improve maintenance decisions continuously.

Keywords - Availability; Reliability; Dynamic Bayesian Network; Performance evaluation; Maintenance optimization.

1. INTRODUCTION

In advanced process industries, availability and reliability analysis plays a crucial role in ensuring process safety, optimizing the maintenance and increasing production capacity. Cement manufacturing is a complex process that requires rigorous and continuous maintenance strategies adapted to the evolution of the state of systems. In Sour El-Ghozlane cement plant in Algeria, the grinding mill and the separator are essential systems. Placed after the grinding mill, the separator (Z1s) is responsible for the quality of the ground product. This system requires precise conditions to provide a quality product. An increase in faults significantly affects the performance of the system. However, the reliability and the availability evaluation of these systems are more complex due to their multi-state functionality and failure scenarios of their components. The reliability evaluation of the system in operating mode consists of analyzing failures component in order to estimate their impact on system [1].

Traditional analysis methods, such as Failure Modes and Effects Analysis (FMEA), Failure Tree Analysis (FTA) are used to assess systems reliability, when using these methods, it is assumed that the system operates in two states namely; perfect operating state and total failure state. However, in addition to perfect operation state and complete failure, the system can have several intermediate states [2],[3]. Degraded systems are functioning systems whose condition degrades over time, and this degradation can lead to a decrease in their performance and efficiency [4]. Maintenance strategies has a major impact on the evolution of system performance measures including reliability and availability.

In the literature, several models for multi-state systems are used to assess these parameters and see how they evolve over time. Soro et al. [5] Proposed a model for assessing reliability indices and production rate of a degradable multi-state system subject to minimal and imperfect repairs. Meanwhile [6] proposed an optimal replacement policy based on the combination between the Markov model and the Universal Generating Function (UGF), to assess the probability of system states, a quasi-renewal process is used to describe the behavior of the system after imperfect maintenance. Lisnianski et al. [7] presented a multi-state Markov model to predict the reliability of a power-generating unit for a short-time period. Reliability modelling and analysis of a power station under fatal and nonfatal shocks is proposed by [8]. Moreover, in a research proposed by [9], a simulation approach for reliability assessment of complex system subject to stochastic degradation and random shock is applied. Attar et al. [10] proposed a simulation-based optimisation method to solve a multi-objective joint availability-redundancy allocation problem of multi-state system. Gol-Ahmadi and Raissi [11] used another analytic method to estimate reliability of multistate system and predict residual of systems' lifetime under the effect of an out of control noise condition.

Recently, the importance of predictive maintenance and diagnostic techniques has been increased rapidly, Nematkhah et al. [12] presented a multi-attribute decision-making model to choose the most suitable predictive diagnostic method in the conditional monitoring system for the critical machines and measure the total predictive performance score, they applied an integrated DEMATEL-fuzzy ANP approach. Leigh and Dunnett [13] used petri nets to dynamically model maintenance applied to wind turbines.

Bayesian Network (BN) represents another area of research that is widely used in many applications; for maintenance [1], system performance evaluation [14], risk analysis [15][16], diagnosis and prediction analysis [17]. Reasoning from probabilistic graphical models facilitates dealing with both diagnosis and prediction problems [18]. In research [19], a hybrid BN framework is presented to model the availability of renewable systems.

The Dynamic Bayesian Network (DBN) is an extension of BN that models stochastic processes that alter over time. Moreover, in the DBN, a new type of node called temporal nodes which allows to model the random variables over time, all cause-and-effect relationships can be designated by probability distributions [20] [21]. In several studies, DBN represents an appropriate solution for predictive and even diagnostic analysis, as well as for expressing uncertain causal relationships [22]. By translating, the Failure Tree (FT) into DBN, Cai et al. [14] proposed a model based on DBN to analyze and evaluate reliability and availability for a subsea BOP system. Wang et al. [23] Established a stochastic deterioration model for multi-element systems under a conditional based-maintenance strategy. A quantitative risk assessment approach based on DBN that dynamically predict the risk of riser recoil control failure during production test of marine natural gas hydrate is presented by [24]. In another study, a quantitative reliability modelling and analysis of a multi-state system based on a combination of the Markov process and a DBN, taking into account different types of maintenance was proposed by [25]. Adjerid et al. [26] presented an approach to evaluate the performance of an industrial system and studied the effect of different maintenance strategies on system performances. An ArdeBayes methodological approach is proposed by [27] to model a mechanical system based on the method of fault trees. The objective of the present paper is to model a multi-state industrial system with their functional dependencies based on the Markov process and DBN in order to evaluate their performances and optimize maintenance decisions by taking into consideration the perfect repair, the imperfect repair and CBM.

The rest of this paper is organized as follows: Section 2 presents a Bayesian approach for modeling multi-state systems. Section 3 presents the proposed methodology, section 4 analyzes a separator system as a case study, results and discussions are presented in Section 4, and Section 5 summarizes this paper.

2. DYNAMIC BAYESIAN METHODOLOGY FOR MODELING A MULTI-STATE SYSTEM

I. Dynamic Bayesian Network

A BN is a probabilistic causal network that allows to graphically represent variables and their probabilistic dependencies. The BN is composed of nodes that are connected by direct arcs; the arcs indicate a causal relationship or dependency between the linked nodes and conditional probability tables (CPTs) that determine how the linked nodes depend on each other. It can describe a multi-state element with a single node, cause-and-effect relationships can be designated by conditional probability distributions, using static or dynamic logical gates the (CPTs) can be obtained [25]. A DBN is an extension parallel to the ordinary BN that allows to explicitly model the temporal evolution of variables over time [28]; each step of time is called a time slice. The probability of transition between two successive slices $P\ (Xt \mid Xt\ -1)$ is expressed by:

$$P\ (X_t \mid X_{t\ -\ 1}) = \prod_{i=1}^{N} P(X_t^i \mid pa(X_t^i))) \qquad (1)$$

Where X_t^i represents the i^{th} node at time t, and $pa\ (X_t^i)$ represents its parent nodes.

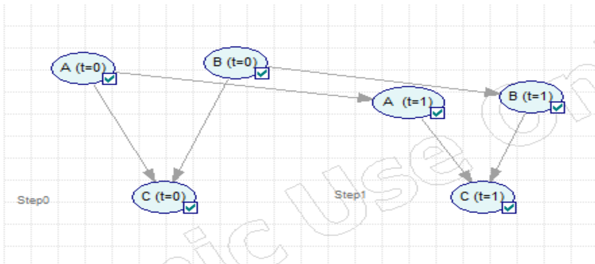

FIGURE 1
A DYNAMIC BAYESIAN NETWORK EXPANDED FROM TIME SLICE 0 TO 1

Figure 1 represents a DBN where intra-slice arcs represent the relationships between nodes (variables A and B) and the relationships between nodes at successive time intervals t0-t1 are represented by arcs between slices. By unrolling the time slices, the probability of joint distribution is obtained by the following expression:

$$P\ (X_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(X_t^i \left| pa(X_t^i)\right) \quad (2)$$

II. Imperfect repair modeling

In DBN modeling, it is assumed that each parent node is a degraded multi-state system; four assumptions are made [5]:

1. The component may have many levels of performances, corresponding to degradation rates, which vary from perfect function to complete failure.
2. The system might fail randomly from any operational state.
3. All transition rates are constant and exponentially distributed.
4. The current degradation state is observable through some system parameters, and the time needed for inspection is negligible.

In the DBN each parent node has four states: perfect state (P1), degraded state1 (DS1), degraded state2 (DS2), fault state (Fault). The perfect state refers to perfect operation; the fault state represents a total failure. The DS1 and DS2 represents the first and second degraded states respectively. At first, each parent node of DBN is in perfect condition, as time passes, the DBN either passes to the DS1 or DS2 states, or proceed to the fault state. When a failure occurs, a repair is needed, the DBN can either return to perfect condition, which is considered a perfect repair, or return to the first or second degraded state, which is considered an imperfect repair. The state transition diagram for four-state component is shown in Figure 2.

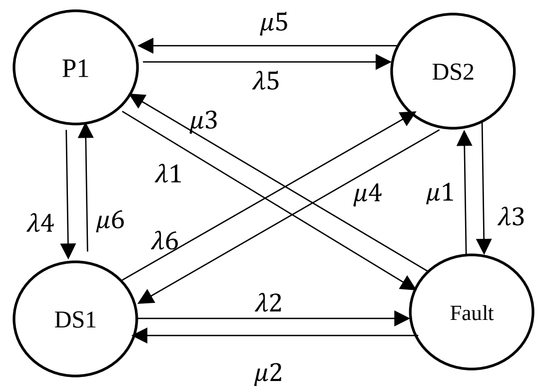

FIGURE 2
TRANSITION STATE DIAGRAM FOR FOUR-STATE COMPONENT

By referring the feedback experience of Sour El-Ghozlane cement plant engineers, the failure rates and repair rates between states for each parent node can be classified: two classes for failure rates, minor failure class ($\lambda3, \lambda4\ and\ \lambda6$) and major failures class ($\lambda1, \lambda2\ and\ \lambda5$). Three classes are distinguished for repair rates between states: minor repair ($\mu1, \mu4\ and\ \mu6$), imperfect repair ($\mu2, \mu5$) and perfect repair($\mu3$). The following equations show how the failure and repair rates are calculated:

$$\lambda1 + \lambda4 + \lambda5 = \lambda s \quad (3)$$
$$\lambda4 = \lambda6 = \lambda3 \quad (4)$$
$$\lambda2 = \lambda5 \quad (5)$$
$$\lambda1 : \lambda4 : \lambda5 = 1:5:4 \quad (6)$$
$$\mu1 + \mu2 + \mu3 = \mu s \quad (7)$$
$$\mu1 = \mu4 = \mu6 \quad (8)$$
$$\mu2 = \mu5 \quad (9)$$

Suppose that at any time $\boldsymbol{t}$ the interval between two consecutive time slices is $\Delta\boldsymbol{t}$. Then, the transition relationships between nodes of the DBN without repair, with perfect repair, imperfect repair and under CBM are present in Tables 1 to 4 respectively.

I. Conditional Probability Tables

Conditional dependencies between variables will be assigned to conditional probability tables (CPTs), in a DB having n parents and m states, in order to determine the CPT for each parent node, it is necessary to define parameters independent. When n is large, traditional models of OR-gate and AND-gate are used to specify as many parameters to quantify relationships in series and parallel systems.

TABLE I
A TRANSITION RELATIONS BETWEEN STATES WITHOUT REPAIR

	$t+\Delta t$			
t	Perfect	DS1	DS2	Fault
Perfect	$e^{-(\lambda1+\lambda4+\lambda5)\Delta t}$	$\frac{\lambda4}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda5}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda1}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$
DS1	0	$e^{-(\lambda2+\lambda6)\Delta t}$	$\frac{\lambda6}{\lambda2+\lambda6}\times(1-e^{-(\lambda2+\lambda6)\Delta t})$	$\frac{\lambda2}{\lambda2+\lambda6}\times(1-e^{-(\lambda2+\lambda6)\Delta t})$
DS2	0	0	$e^{-\lambda3\Delta t}$	$1-e^{-\lambda3\Delta t}$
Fault	0	0	0	1

TABLE II
A TRANSITION RELATIONS BETWEEN STATES WITH PERFECT REPAIR

	$t+\Delta t$			
t	Perfect	DS1	DS2	Fault
Perfect	$e^{-(\lambda1+\lambda4+\lambda5)\Delta t}$	$\frac{\lambda4}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda5}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda1}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$
DS1	0	$e^{-(\lambda2+\lambda6)\Delta t}$	$\frac{\lambda6}{\lambda2+\lambda6}\times(1-e^{-(\lambda2+\lambda6)\Delta t})$	$\frac{\lambda2}{\lambda2+\lambda6}\times(1-e^{-(\lambda2+\lambda6)\Delta t})$
DS2	0	0	$e^{-\lambda3\Delta t}$	$1-e^{-\lambda3\Delta t}$
Fault	$(1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	0	0	$e^{-(\mu1+\mu2+\mu3)\Delta t}$

TABLE III
A TRANSITION RELATIONS BETWEEN STATES WITH IMPERFECT REPAIR

	$t+\Delta t$			
t	Perfect	DS1	DS2	Fault
Perfect	$e^{-(\lambda1+\lambda4+\lambda5)\Delta t}$	$\frac{\lambda4}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda5}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda1}{\lambda1+\lambda4+\lambda5}\times(1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$
DS1	0	$e^{-(\lambda2+\lambda6)\Delta t}$	$\frac{\lambda6}{\lambda2+\lambda6}\times(1-e^{-(\lambda2+\lambda6)\Delta t})$	$\frac{\lambda2}{\lambda2+\lambda6}\times(1-e^{-(\lambda2+\lambda6)\Delta t})$
DS2	0	0	$e^{-\lambda3\Delta t}$	$1-e^{-\lambda3\Delta t}$
Fault	$\frac{\mu3}{\mu1+\mu2+\mu3}\times(1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	$\frac{\mu2}{\mu1+\mu2+\mu3}\times(1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	$\frac{\mu1}{\mu1+\mu2+\mu3}\times(1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	$e^{-(\mu1+\mu2+\mu3)\Delta t}$

TABLE IV
A TRANSITION RELATIONS BETWEEN STATES WITH CBM

	$t + \Delta t$			
t	Perfect	DS1	DS2	Fault
Perfect	$e^{-(\lambda1+\lambda4+\lambda5)\Delta t}$	$\frac{\lambda4}{\lambda1+\lambda4+\lambda5} \times (1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda5}{\lambda1+\lambda4+\lambda5} \times (1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$	$\frac{\lambda1}{\lambda1+\lambda4+\lambda5} \times (1-e^{-(\lambda1+\lambda4+\lambda5)\Delta t})$
DS1	$\frac{\mu6}{\lambda2+\lambda6+\mu6} \times (1-e^{-(\lambda2+\lambda6+\mu6)\Delta t})$	$e^{-(\lambda2+\lambda6+\mu6)\Delta t}$	$\frac{\lambda6}{\lambda2+\lambda6+\mu6} \times (1-e^{-(\lambda2+\lambda6+\mu6)\Delta t})$	$\frac{\lambda2}{\lambda2+\lambda6+\mu6} \times (1-e^{-(\lambda2+\lambda6+\mu6)\Delta t})$
DS2	$\frac{\mu5}{\lambda3+\mu4+\mu5} \times (1-e^{-(\lambda3+\mu4+\mu5)\Delta t})$	$\frac{\mu4}{\lambda3+\mu4+\mu5} \times (1-e^{-(\lambda3+\mu4+\mu5)\Delta t})$	$e^{-(\lambda3+\mu4+\mu5)\Delta t}$	$\frac{\lambda3}{\lambda3+\mu4+\mu5} \times (1-e^{-(\lambda3+\mu4+\mu5)\Delta t})$
Fault	$\frac{\mu3}{\mu1+\mu2+\mu3} \times (1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	$\frac{\mu2}{\mu1+\mu2+\mu3} \times (1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	$\frac{\mu1}{\mu1+\mu2+\mu3} \times (1-e^{-(\mu1+\mu2+\mu3)\Delta t})$	$e^{-(\mu1+\mu2+\mu3)\Delta t}$

Suppose that for node A, there are n parent node $X1, X2, \ldots, Xn$, and the degradation probability of the node i is P_i.The unreliability of an AND-gate can therefore be calculated by the expression as follows [14]:

$$P(A|X_1, X_1, \ldots, X_1) = \prod_{1<i<n} P_i \quad (10)$$

In the case where the parent nodes are in parallel, the unreliability of an AND gate can be calculated by the expression as follows [14]:

$$P(A|X_1, X_1, \ldots, X_1) = 1 - \prod_{1<i<n}(1 - P_i) \quad (11)$$

3. METHODOLOGY FOR MAINTENANCE EVALUATION AND OPTIMIZATION OF SYSTEM

The proposed methodology for dynamic evaluation of system performances and maintenance optimization flowchart is illustrate in Figure 3, the main steps can be summarized as following:

1. Defining the system and identify the potential failure causes (the construction of fault tree of system): in this step functional decomposition and analysis of system should be studied, collecting the historical necessary data of components, however, domain experts can contribute their opinions.
2. Construction DBN: based on the fault tree which provides an effective prior knowledge, the construction of the DBN model is established.
3. Quantitative analysis: from the collected failure data and domain of Feedback experience (R.E.X) the prior probabilities, failure and repair rates, conditional probabilities tables and the transition probability tables can be estimated.
4. Evaluation and exploitation of results: After assigning the probabilities in the network, the reliability and availability can be evaluated and by diagnostic inference, the critical components leading to system failure could be identify.
5. Optimization maintenance decisions: in this step, by using the results of proposed methodology (prediction/diagnosis analysis and sensitivity analysis) as an effective tool to acquire experience, optimize and improve maintenance decisions continuously.

4. INDUSTRIAL APPLICATION OF THE PROPOSED METHODOLOGY

I. *System description*

The separator (Z1s) is a complicated mechanical system, which mainly composed of six components (Engine (E), Fan (F), Reducer (R), Ferrule (L), inflow valve (I), outlet valve (O)) with functional dependencies. It has different kinds of failure modes and a failure of one of its components will result in an unavailability of the system and therefore huge losses for the company. For there, a quantitative method to model and evaluate performances of system, identify the subsystems most contributing to separator's failure and to measure the impact of different maintenance strategies during future missions. Each component has four states: a perfect operating state, two degraded operating states (DS1, DS2) and failure state.

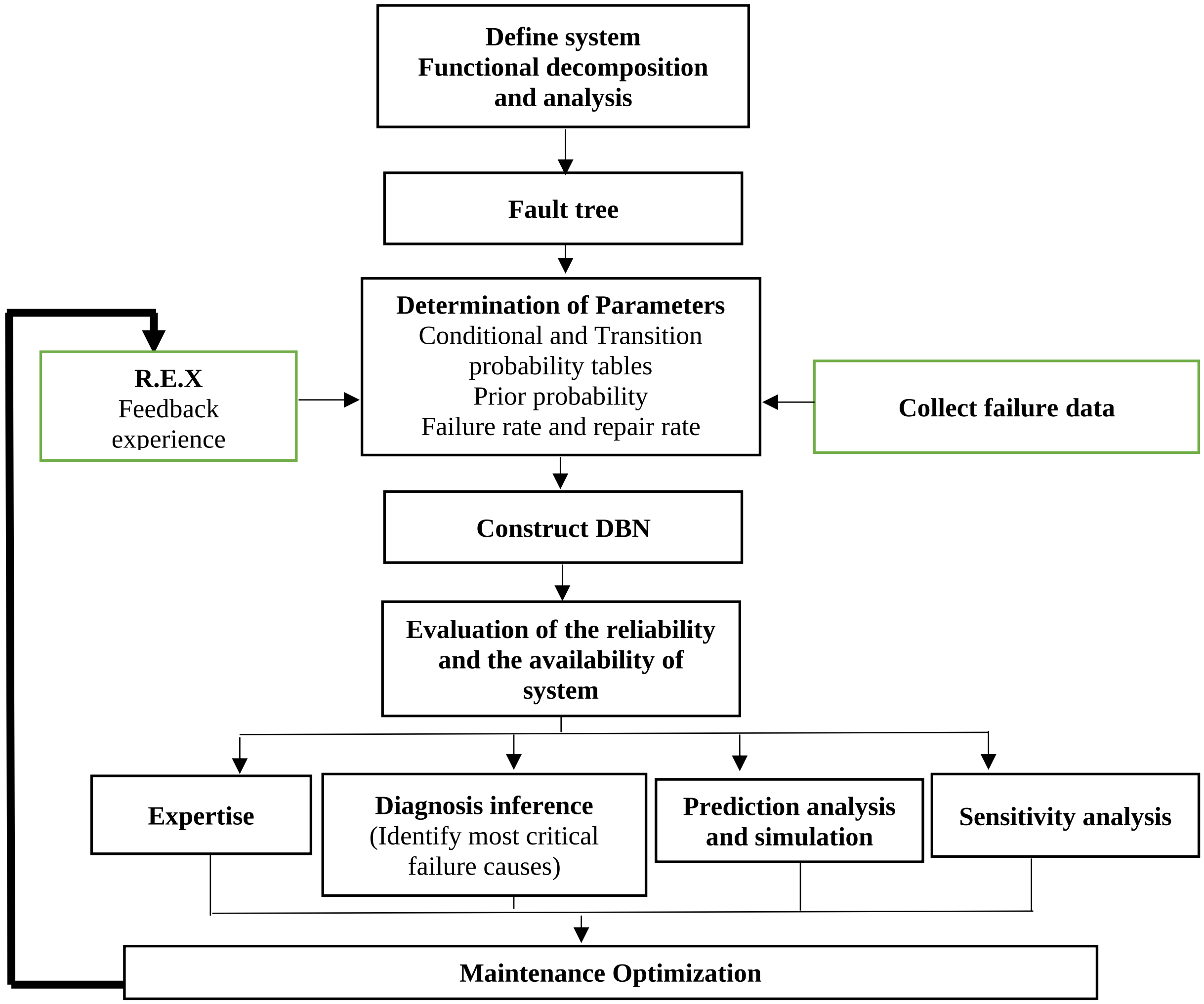

FIGURE 3
FLOWCHART OF PROPOSED METHODOLOGY

Referring to subsystems data and consulting the Sour El-Ghozlane cement plant ‘experts in the domain, the failure rates, repair rates and the degradation probabilities (%) of separator’s components are presented in Table 5.
The architecture of Figure 4 represents the system topology describing the degradation evolution, the black arc represents the temporal evolution, whereas the functional dependence represented by an orange arc. The evolution of the degradation model of the power system is conditioned by the degradation function of their functional dependencies, which are the Engine (E), Reducer (R) and the Fan (F). The architecture of the equivalent DBN model was developed using the GeNIe graphical interface software, taking into account the different states of each node and their functional dependence as illustrated in Figure 5.

TABLE V
PARAMETERS OF THE SEPARATOR (Z1S) SUBSYSTEMS

Subsystems	Failure rate λ(week)	Repair rate μ(week)	Degraded state 1 (%)	Degraded state 2 (%)
Engine (E)	0.0591	0.39	4	8
Fan (F)	0.0096	0.16	2.5	7.5
Reducer (R)	0.1063	0.41	5	7.7
Ferrule (L)	0.0625	0.20	2.8	3.2
inflow valve (I)	0.0197	0.25	5	9
outlet valve (O)	0.0197	0.22	5	9

II. Reliability and Availability Evaluation

Over time, failures can occur at any time either minor or major. Take the example of the valve subsystem (Figure 6), failure rates and repair rates between the states of each node can be calculated using equations (3)-(9). Subsequently, the transition relationships between consecutive nodes in all three cases can be calculated using tables [1-4]. The reliability and availability of the valve subsystem node is determined, as shown in Figure 8.

From Table 4 the degradation probability of the inflow valve and the outlet valve are:

$P(Valve\ subsystem = fault|Inflow\ valve = DS1) = 5\%$

$P(Valve\ subsystem = fault|Inflow\ valve = DS2) = 9\%$

$P(Valve\ subsystem = fault|Outlet\ valve = DS1) = 5\%$

$P(Valve\ subsystem = fault|Outlet\ valve = DS2) = 9\%$

Using equation 10, the CPT of valve as subsystem is calculated as follows the table 6.

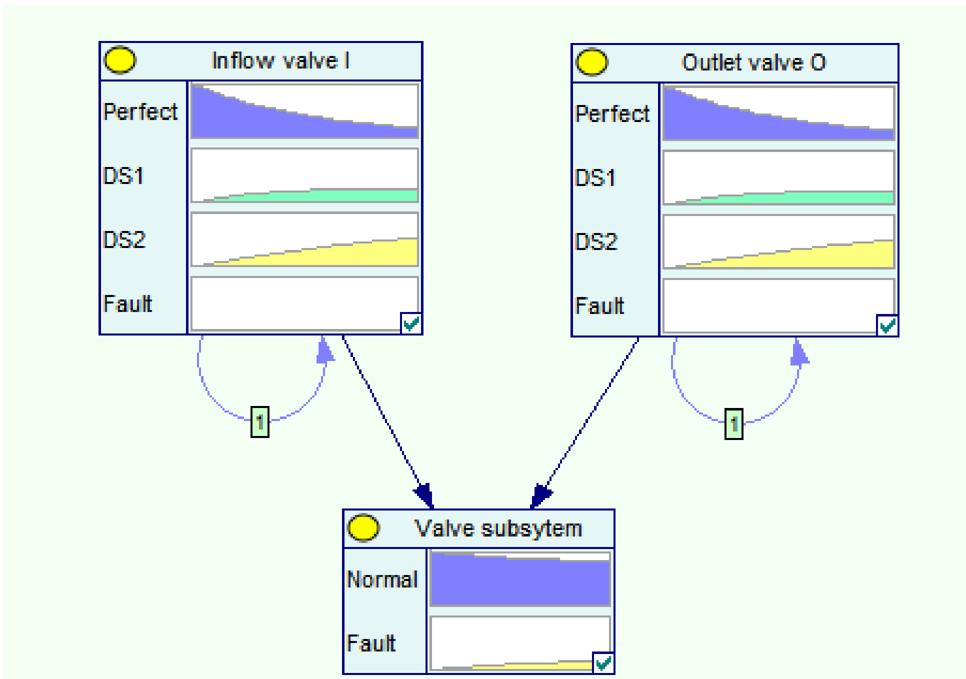

FIGURE 6
DBN OF THE VALVE SUBSYSTEM

As Figure 7 indicates, it is obvious that as time progresses, the dynamic reliability decreases to almost 45% in about 40th week. With repair, the availability of valve decreases, in the case of a perfect repair, it reaches a value of about 86% in the 40th week. When imperfect repairs are considered, it reaches a value of 83.5% in about 40th week. The CBM maintains a high availability level of 91.81% at approximately the 40th week. It can be seen that perfect and imperfect repairs can improve the performances of the valve subsystem and that imperfect repair does not significantly affect availability compared to perfect repair, and the CBM can maintain the valve subsystem at a stable higher level of availability in comparison with imperfect repair.

TABLE VI
CPT OF VALVE SUBSYSTEMS

Outlet valve I				Outlet valve O				Valve subsystem	
Perfect	**DS1**	**DS 2**	**Fault**	**Perfect**	**DS1**	**DS2**	**Fault**	**Normal**	**Fault**
1	0	0	0	1	0	0	0	1	0
1	0	0	0	0	1	0	0	0.9500	0.0500
1	0	0	0	0	0	1	0	0.9100	0.0900
1	0	0	0	0	0	0	1	0	1
0	1	0	0	1	0	0	0	0.9500	0.0500
0	1	0	0	0	1	0	0	0.9025	0.0975
0	1	0	0	0	0	1	0	0.8645	0.1355
0	1	0	0	0	0	0	1	0	1
0	0	1	0	1	0	0	0	0.9100	0.0900
0	0	1	0	0	1	0	0	0.8645	0.1355
0	0	1	0	0	0	1	0	0.8281	0.1719
0	0	1	0	0	0	0	1	0	1
0	0	0	1	1	0	0	0	0	1
0	0	0	1	0	1	0	0	0	1
0	0	0	1	0	0	1	0	0	1
0	0	0	1	0	0	0	1	0	1

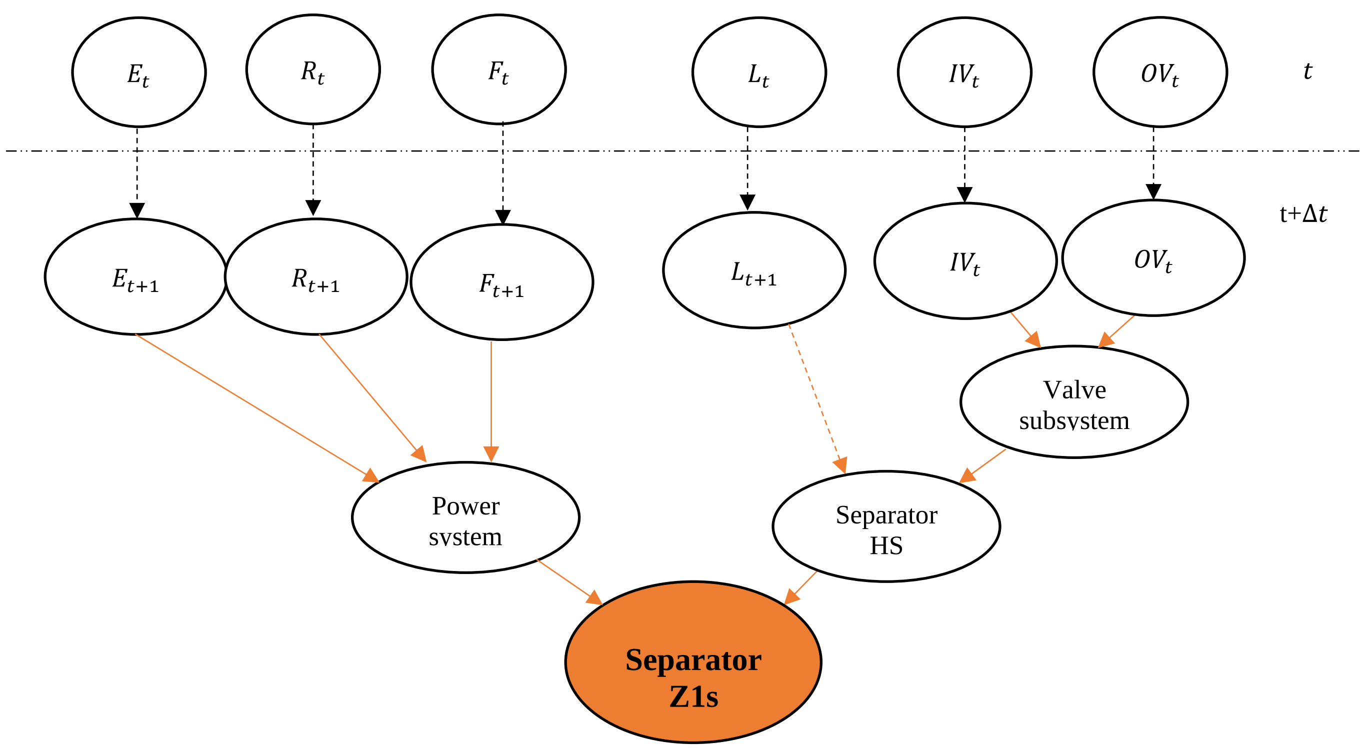

FIGURE 4
PROPOSED MODEL OF THE GLOBAL SYSTEM WITH FUNCTIONAL DEPENDENCIES FROM T TO $t + \Delta t$

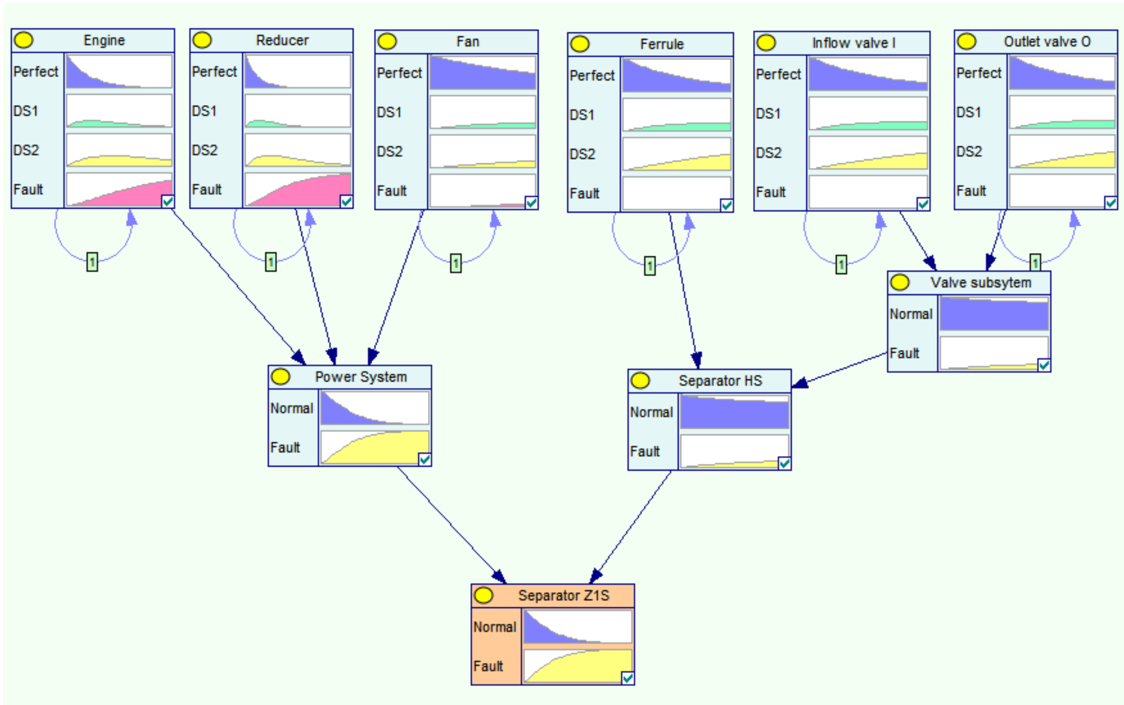

FIGURE 5
DBN OF THE GLOBAL SYSTEM

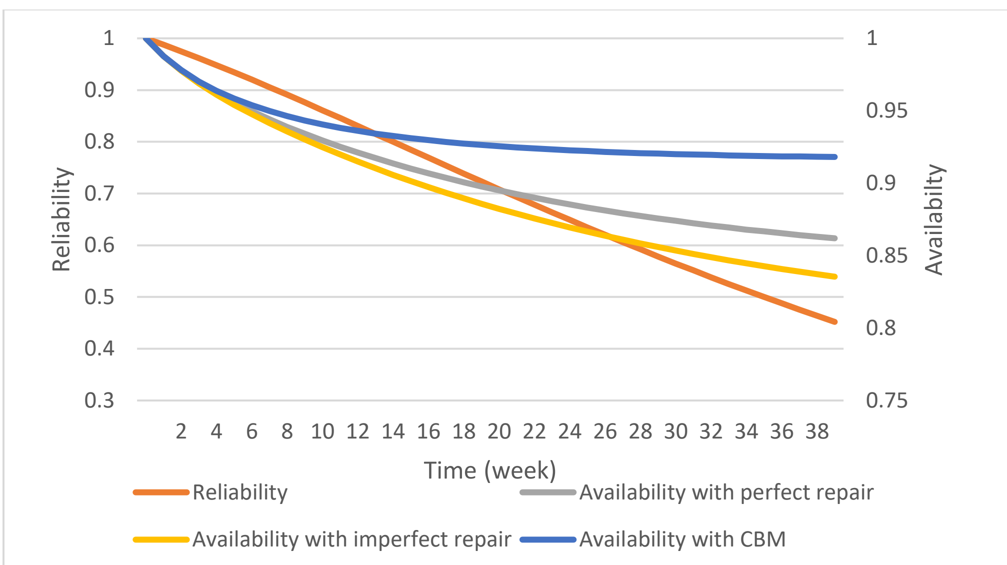

FIGURE 7
THE RELIABILITY AND AVAILABILITY OF THE VALVE SUBSYSTEM

5. RESULTS AND DISCUSSION

I. DBN for the global system

In the same way, now we can build the overall system network and study the influence of subsystems on the separator's state and measure the impact of maintenance strategies on overall performances. Figure 9 shows the global DBN extended over time without repair. Each node initially is in perfect functioning state (perfect =100%), over time, the degradation begins. According to the failures rate, repairs rate and the functional dependence, the probabilities of each subsystem evolve differently from the other. For the separator, two modality are chosen namely (Normal) and failure (fault).

The performance evaluation of the system is examined using DBN, the evolution of reliability and availability with respect to a perfect, imperfect repair and under CBM are represented in the Figure 8. As mentioned, over time, reliability and availability decrease. Reliability drops to about 0 in the 41th week and the availability reaches the values of 56% and 48% in the 40th week for the system with perfect repair and imperfect repair, respectively. When CBM is considered, the availability improves significantly and reaches a high level 65% in about the 40th week. Clearly, the availability with perfect and imperfect repairs is evolving almost identically. Based on these results, it has been noted that these strategies can improve the separator (Z1s) performances, while imperfect repair compared to perfect repair cannot degrade the system performance significantly and in comparison, the CBM with other strategies. This later can maintain the system at a stable higher level of availability.

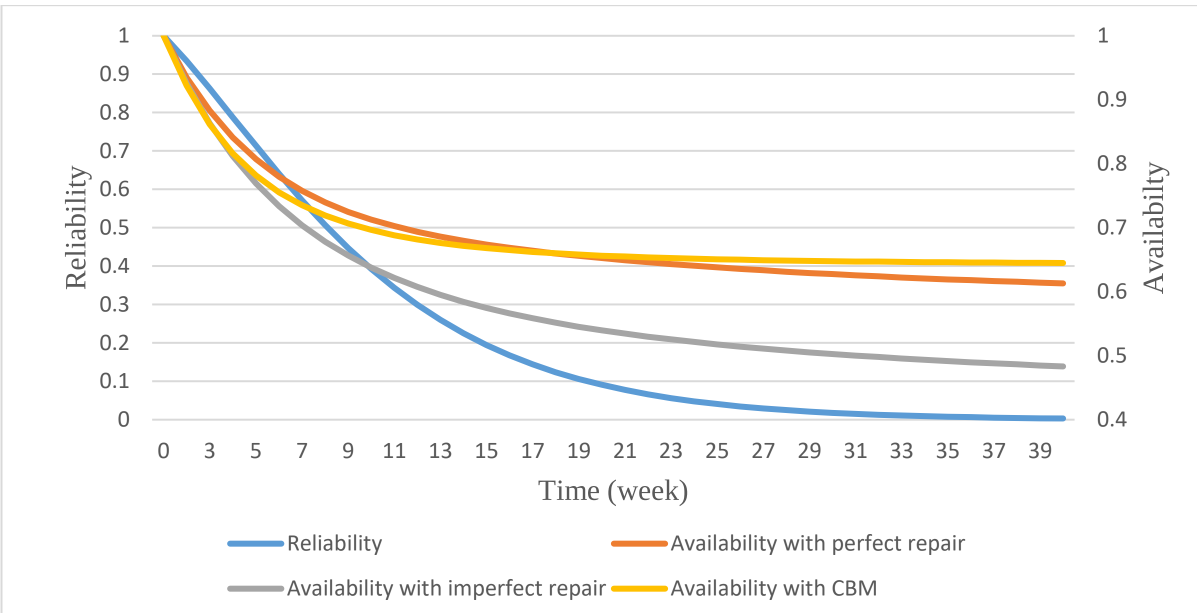

FIGURE 8
THE RELIABILITY AND AVAILABILITY OF THE SEPARATOR (Z1S)

II. Diagnostic Inference

The application of the diagnostic inference method (backward analysis) is used to determine the causes that have a significant impact on the failure of the top event [29]. By adopting this technique in the inference of our DBN model. The new belief over the entire network will be reflected, as a result, critical subsystems are quickly identified and the posterior probabilities of each event at different time slices can be calculated. It can provides useful information about the necessary preventive measures that could be taken to prevent the separator failure.

The prior and posterior probabilities of the basic events at T=24 week with CBM strategy are determined, as shown in Figure 9. It is noted that the subsystems :"Engine(E)", "Reducer (R)", and "Ferrule (L)" are the most influential factors leading to the possible separator failure because, they have the highest increasing probabilities and significant posterior probabilities. Therefore, based on diagnosis results, more attention should to be paid to these subsystems to further reduce the risk of failure.

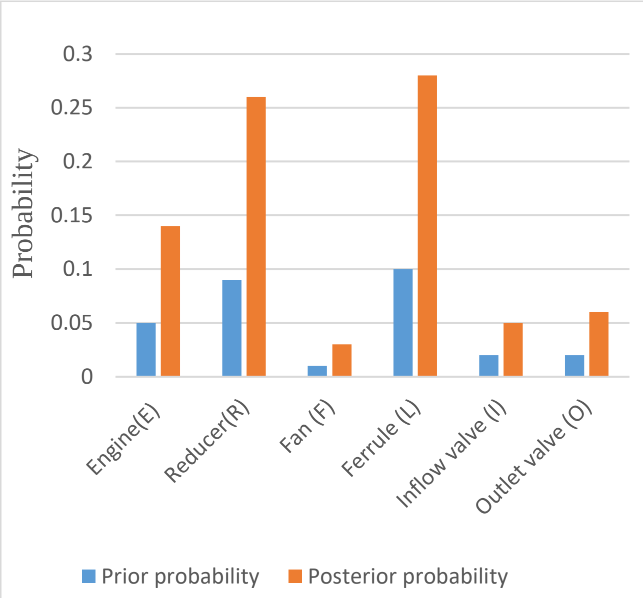

FIGURE 9
COMPARISON BETWEEN POSTERIOR AND PRIOR PROBABILITIES FOR BASIC EVENTS AT T = 24 WEEK UNDER CBM

III. *Sensitivity analysis*

In this study, to test the proposed model, a sensitivity analysis must be carried out to prove that this model is a reasonable representation and to guarantee that its robustness. if the result obtained will be sensitive i.e. it will not show abrupt variations in case of minor change in the input parameters, then the model is robust [30]. It is assumed that the failure rates of critical subsystems are subject to a variation of ±10%. The effects of these variations on the probability of system failure are shown in Figure 10.

In this figure, when the failure rate of the Engine subsystem is increased to 110%, the probability of separator failure increased from 35.51% to 35.71%. When increasing the failure rate of both subsystems Engine and Reducer to 110%, the probability of separator failure increased from 35.71% to 39.16%. When the failure rates of critical subsystems Engine, Reducer and Ferrule were increased to 110%, the probability of separator failure increased from 39.16% to 40.05%. In addition, by increasing failure rates of subsystems Engine, Reducer, Ferrule, Inflow and Outlet valve to 110%, the probability of separator failure increased from 40.05% to 40.58%.
Reducing failure rates of critical subsystems will reduce the failure probability of the top event in the same way. As expected, in this case, a slight modification in the failure rate for critical subsystems induces the probability of separator failure in a reasonable way, thus giving a validation of this model.

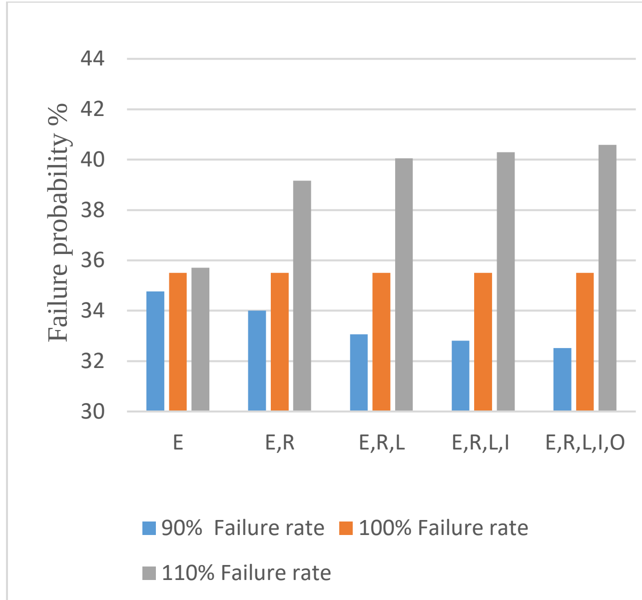

FIGURE 10
THE EFFECT OF CHANGES IN FAILURE RATE OF CRITICAL COMPONENTS ON FAILURE PROBABILITY OF SEPARATOR (Z1S)

6. CONCLUSION

In this article, a methodology based on DBN was developed to evaluate and optimize the performance measurements of a multi-state system taking into account the different repair strategies. A separator (Z1s) system of Sour El-Ghozlane cement plant is analyzed to show how this approach can be effectively manipulated to answer several problems concerning the identification of influencing factors (diagnosis), the analysis of the relationship between system components, predictive assessment of the dynamic failure probability, and measuring the effect of repair and maintenance strategies on system performances. The main conclusions of this study can be presented as follow:

- Dynamic analysis indicates that the repairs strategies can improve the performance of the separator (Z1s), while an imperfect repair does not significantly degrade performance compared to the perfect repair.
- In order to improve the availability of system, CBM strategy can maintain the system at a stable

higher level of availability in comparison to imperfect repair strategy.

- Diagnostic inference four critical subsystems, including the Engine, Reducer and Ferrule are identified as contributors leading to system failure, based on diagnosis, we should pay more attention to these subsystems to further reduce the risk of separator failure.
- The analysis results obtained from this study can provide a decision support tool and a very useful information base. Moreover, the proposed methodology can serve engineers to optimize and improve maintenance decisions continuously.
- A sensitivity analysis allows us to validate and show that modeling based on DBN is correct and rational.

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