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Reliability Analysis by Mapping Probabilistic Importance Factors into Bayesian Belief Networks for Making Decision in Water Deluge System

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Liquid petroleum gas (LPG) is one area where catastrophic release scenarios have occurred. For this reason, preventive, and protective barriers have to be installed in order to reduce the occurrence and the severity of these scenarios. This article addresses an analysis of deluge system barrier and proposes a making decision process to ensure a high level of reliability, availability, maintainability, and safety (RAMS) using a robust Reliability Analysis with conditional probabilities. To achieve this RAMS target, a methodology for converting fault tree analysis (FTA) in continuous time using Monte Carlo (MC) simulation to Bayesian belief network (BBN) is developed. The probabilistic importance factors (PIFs) for critical components ranking and decision making are also mapped using BBN inferences in Water Deluge Systems (WDS) with an optimization aim using redundancy or maintenance tasks. This analysis illustrates the helpfulness of mapping PIFs into BBN for making a decision in any critical technological infrastructures. © 2018 American Institute of Chemical Engineers Process Saf Prog 2018

Keywords: Reliability Analysis; Water Deluge System; Probabilistic Importance Factors; FTA; BBN; Monte Carlo Simulation

INTRODUCTION

The oil and gas industries operate a great and complex variety of processes and plants. Where a major accident involving fires, boiling liquid expansion vapour explosions (BLEVEs), vapor cloud explosions (VCEs) [1] and domino effects [2,3] have occurred, with serious damage on human beings, industrial sites, environment, and economy.

The storage area of Liquid petroleum gas (LPG) petroleum industries are one of the areas where these catastrophic scenarios happened because of flammable substances presence in this area. Darbra *et al.* [4] and Abdolhamidzadeh *et al.* [5] showed that 89% of flammable substances were involved in domino accidents. Examples of recent accidents in the LPG facilities, such as release in Virginia, Mississippi USA, Viareggio Italy and others along with their key information's are cited by Al-shanini et *al.* [1]. For this reason, it is very important to insure a high level of safety with organizational improvements and technical devices. Then, the implementation of efficient safety barriers is a usual safety preventive action. One of the typical technical devises used as safety barriers is the Water Deluge systems (WDS) [6–8]. These are able to reduce the occurrence of catastrophic scenarios by mitigation of high temperatures and heat flux. An LPG complex has to be highly reliable and available during all its life because of high probability of fire and domino effect scenarios. Several articles focus on the mitigation of catastrophic scenarios using WDS [9–12] especially in LPG storage areas. The WDS do not only reduce the global heat flux with an existing fire, but reduce the probability for fire or explosion occurrence if released on a gas cloud.

To ensure a very high reliability, availability, maintainability, and Safety (RAMS) of WDS, a large variety of reliability and risk analysis methodologies exist with both qualitative and quantitative proprieties as detailed by Khan *et al.* In the article of "Methods and models in process safety and risk management: Past, present and future" [13]. In aim to ensure safety in the LPG storage area and improve these infrastructures, several methods have been developed. The FTA (Fault Tree Analysis) which is one of the best prominent techniques used by a wide range of industries [14,15], allowed the identification of the potential causes of the WDS design failures based on using reliability engineering theory and Boolean functions.

In order to determine which apparatus or equipment is the most important contributor when a failure occurs in the system, the probabilistic importance factors (PIFs) assessment from FTA is widely applied. The Birnbaum's and Criticality PIFs allowed ranking, adapting new corrective or preventive maintenance tasks and/or design optimization. An extensive review of reliability importance measures is presented in Kuo and Zhu [16]. New measures have also been defined and used in optimization system design. For example, Jussi K. Vaurio has developed several importance factors related to fault diagnostics and for making decision [17,18]. Contini *et al.* proposed method to apply importance factors to multiple FTA and initiating events in FTA [19,20]. Also, Eryilmaz *et al.* proposed

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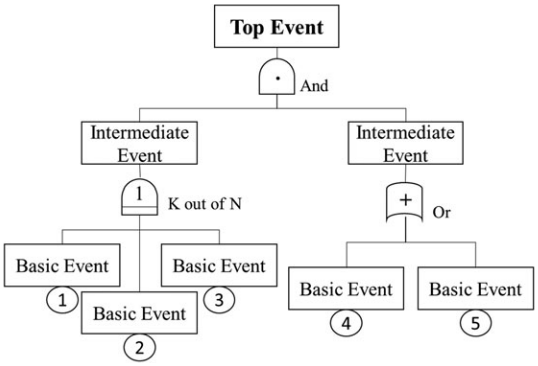


Figure 1. Example of general fault tree structure.

computation of marginal and joint reliability importance for a coherent system with multiple types of dependent components [21].

The standard FTA presents some limits: they are not suitable in reliability analysis for a large system, redundant failures, common cause failures and time depend failures [22–24]. However, different approaches using artificial intelligence in risk analysis [25,26] [27] and with FTA especially were used. For depth and dynamic analysis, several techniques are used with FTA as the binary decision diagrams (BDD) [28–30] used to encode efficiently FTA and calculation of minimal cut sets. The Monte Carlo (MC) simulation is designed for continuous–time models to compute the system reliability in FTA [14,31,32]. In the articles by Freeman and Summers [33,34] MC simulation is used as the baseline method for comparison to results obtained using variance contribution analysis and error propagation methods.

There are other FTA extensions using Petri Nets [35], fuzzy numbers [36], Markov Chains [14], and Neural Networks [37] .

The majority of the previous methods present a limitation which are frequently nondeterministic such as artificial neural networks, multiple regression models, or as the Markov models with limited ability to handle the cause-symptom relationships in fault diagnosis [38,39]. In this case, an important feature of Bayesian Belief Network (BBN) is their ability to represent the probabilistic relationship between causes and symptoms or between symptoms and faults. It can also represent multi-fault and multi-symptom models.

Recently BBN is more and more used in dependability, reliability, maintenance and risk analysis [40] due to the fact that the model can perform forward and predictive analysis as well as diagnostic analysis and design optimization [22].

The BBN for reliability analysis can be achieved by converting the reliability models: Bobbio *et al.*, Lampis *et al.* and Khakzad *et al.* presented an algorithm for converting FTA into BBN [22,24,39]. Kalantarnia *et al.* used Bayesian theory for updating occurrence probability of event tree scenarios [41]. Khakzad *et al.* and Badreddine *et al.* presented a methodology to map bow-tie (combination of a fault tree and an event tree) into Bayesian network for dynamic safety analysis [23,42].

Weber *et al.* compared Bayesian Networks with fault trees, Markov chains, and Petri nets [40].

Many authors used BBN in their work for different industrial fields such as Baoping *et al.'s* model human error on offshore blowouts using pseudo FTA [43], Khakzad *et al.* who used the application of bow-tie and Bayesian network methods in drilling operations [44]. Dongiovanni *et al.* translated fault tree into a Bayesian network for a nuclear plant turbine system [45].

The present study demonstrates a methodology to convert FTA into a corresponding BBN in continuous time using MC simulation. Additionally, the methodology includes PIFs into BBN for building and belief update of the network by using Bayesian inferences for making decision in WDS. It is an experiment of mixing two strong concepts in BNN (inference) and FTA (PIFs analysis). This article also presents a design optimization of WDS using redundancy and maintenance tasks for reducing the losses due to equipment failure by intelligently maintaining the equipment before catastrophic failures occur.

Following this introductory in section one, the rest of this article is organized as follows. The second section gives a brief overview of reliability analysis methods such as FTA, reliability functions, PIFs, BBN, and mapping algorithm from FTA and PIF's to BBN. In the third section, a case study of WDS installed in Algerian LPG storage area is presented while section four applies Reliability modelling of water deluge system, results discussion and design optimization. The last section is devoted to the conclusion of this work and perspectives.

RELIABILITY ANALYSIS

Fault Tree Analysis Techniques and Availability functions

FTA is one of the well-known used techniques in process safety and reliability analysis that graphically depicts failure propagation and logical relationships between root causes and fault paths. The FTA bases are the reliability theory, Boolean algebra and probability theory and provide a quantitative risk analysis (QRA).

FTA is a very prominent method that combines qualitative analysis, like minimal cut sets, and quantitative techniques, including a wide variety of stochastic methods to compute failure probabilities. FTA is useful to depict system failure in a simple and understandable manner.

Table 1. Failure probabilities propagated by using standard probabilities equations

Gates	Probability equations
And	$P\,[and\,(X_1, \ldots, X_n) = 1] = P\,[X_1 = 1 \wedge \ldots \wedge X_n = 1] = P\,[X_1 = 1] \times \ldots \times P\,[X_n = 1] \ldots (1)$
Or	$P\,[or\,(X_1, \ldots, X_n) = 1] = 1 - P\,[or\,(X_1, \ldots, X_n) = 0] = 1 - P\,[X_1 = 0 \wedge \ldots \wedge X_n = 0] = 1 - (1 - P\,[X_1 = 1]) \times \ldots \times 1 - (1 - P\,[X_n = 1]) \ldots (2)$
KooN	$P\,[koon\,(X_1, \ldots, X_n) = 1] = P\,[(X_1 = 1 \wedge \ldots \wedge X_k = 1) \vee (X_1 = 1 \wedge \ldots \wedge X_{k-1} = 1 \wedge X_{k+1} = 1) \vee \ldots \vee (X_{n-k} = 1 \wedge \ldots \wedge X_n = 1)] \ldots (3)$

Where: P[$X = 1$] denotes the probability that X is in working state and P[$X = 0$] denotes the probability that X is in failure state, with a condition that, in koon, k is the minimum input in working state (k-out-of-n: G).

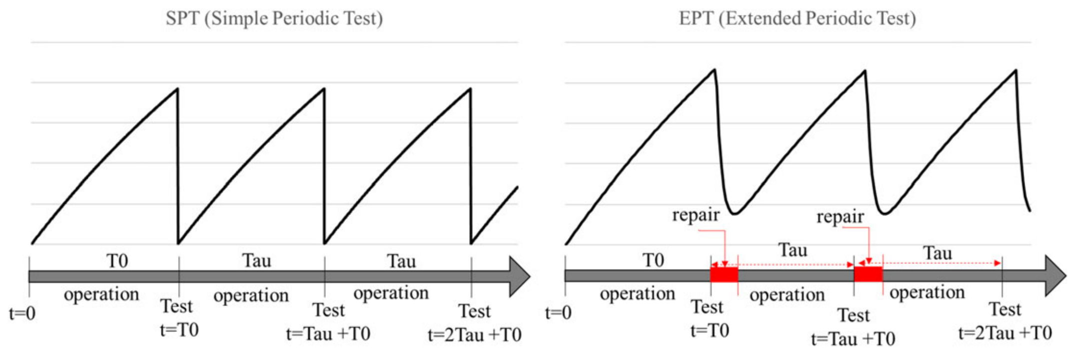


Figure 2. An illustration of the SPT and EPT models evolution in time. [Color figure can be viewed at **wileyonlinelibrary.com**]

Fault Tree Analysis Qualitative Aspect

As a directed acyclic graph (DAG), FTA structure consists of two types of nodes: events and gates (and, or, *k*-out-of-*n*) as shown in Figure 1, which should capture all possible cause-consequence relationships. The events can be divided into basic events which occur spontaneously, the intermediate events which are caused by one or more other events, and the top event which is the event being analyzed. The gates represent how failure in subsystems interacts resulting in failure of the system allowing the top event to occur.

However, The FTA structure algorithm of large and complicated fault tree is generally developed using BDDs [28] to analyze probable common cause failure (CCF), compute minimal cut sets and assess probabilities of root events.

In the present work, therefore, a large FTA of WDS is defined by incorporating the failure modes of system components using BDD.

Fault Tree Analysis Quantitative Aspect

The quantitative calculation of the FTA combines numerical values of basic events to obtain precise and realistic probabilities of system failure using logical gates. For a system of X_1, X_2, …, X_n input basic events, failure probabilities can be easily propagated by using standard probability equations listed in Table 1.

However, for the quantification of the large FTA, several techniques are employed such as the BDD, BBN, fuzzy numbers, Monte Carlo, Markov chain [13,14]. In this article, three reliability functions associated with the failure behavior of components [46] are used to obtain the availability probability that WDS is functioning or not at a given time.

Constant model

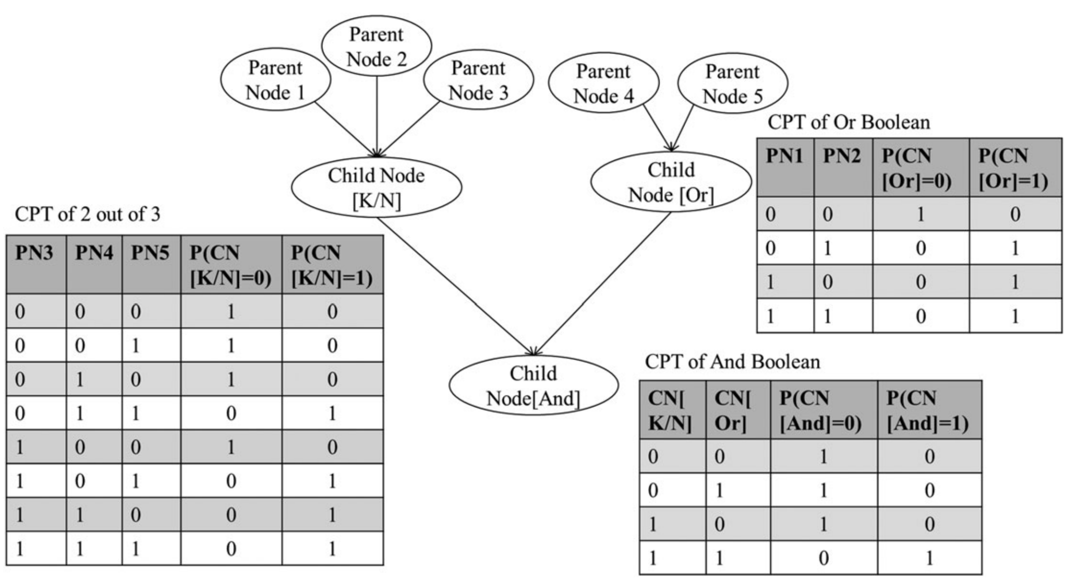
$$Q(t) = q \tag{4}$$

Where: 'q' denotes a constant failure probability.

Simple periodic test model

$$Q(t) = \begin{cases} 1-e^{-\lambda.t}, \text{if } t < t_0 \\ 1-e^{-\lambda.[(t-t_0) mod \tau]}, otherwise \end{cases} \tag{5}$$

Where: 'λ' denotes the failure rate, 'τ' the test period (time interval between two consecutive tests) and 't_0' the date of first test.



CPT of 2 out of 3

PN3	PN4	PN5	P(CN [K/N]=0)	P(CN [K/N]=1)
0	0	0	1	0
0	0	1	1	0
0	1	0	1	0
0	1	1	0	1
1	0	0	1	0
1	0	1	0	1
1	1	0	0	1
1	1	1	0	1

CPT of Or Boolean

PN1	PN2	P(CN [Or]=0)	P(CN [Or]=1)
0	0	1	0
0	1	0	1
1	0	0	1
1	1	0	1

CPT of And Boolean

CN[K/N]	CN[Or]	P(CN [And]=0)	P(CN [And]=1)
0	0	1	0
0	1	1	0
1	0	1	0
1	1	0	1

Figure 3. Example of general Bayesian belief network.

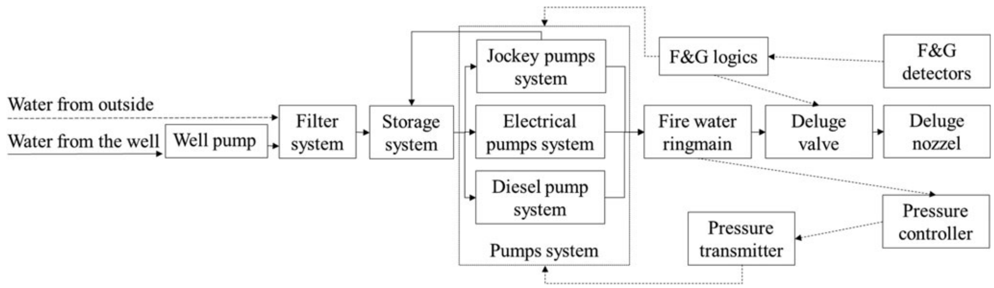


Figure 4. A simplification of deluge system flowchart diagram installed in the storage area of Algerian LPG project.

Extended periodic test model

$$Q(t)=\begin{cases}\dfrac{\lambda}{\lambda+\mu}.\left(1-e^{-(\lambda+\mu).t}\right), \text{if } t<t_0\\ \dfrac{\lambda}{\lambda+\mu}.\left(1-e^{-(\lambda+\mu).[(t-t_0)mod\tau]}\right), otherwise\end{cases} \tag{6}$$

Where: 'λ' denotes the failure rate, 'μ' the repair rate (when the failure has been found during a test), 'τ' the test period (time interval between two consecutive tests) and 't_0' the date of first test.

In The repair phase each component is refurbished with preventive maintenance of good-as-new type which gives its exponential law to zero (as if t = 0), hence the use of the modular in the Eq. 6.

Figure 2 illustrates the evolution of the SPT and EPT models.

MC Simulation is also used in this article to compute availability over an interval time (for continues time), with random failure times and repair times [31,32].

For each probability used in the model, it is possible to introduce an uncertainty on failure rate parameter, and at last, the impact of the uncertainties on the data into the final results is obtained. The estimated failure rate of each component in the system is given under both the multi-sample assumption, and under the assumption of homogeneous data sets. The uncertainty of the failure rate λ is presented as a 90% confidence interval covering 90% of the variation between the multiple samples, such that the true value of λ fulfils: $Pr\,(\lambda_{5\%} \le \lambda < \lambda_{95\%}) = 90\%$.

Normal distribution model

$$f_{\mu,\sigma}(t)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\left(\frac{(t-\mu)^2}{2\sigma^2}\right)} \tag{7}$$

Where: 'μ' is the mean and 'σ' the standard deviation.

Probabilistic Importance Factors

To evaluate which components are the most important contributors in the reliability of a system and improving RAMS in the system, it is very essential to compute PIF.

The PIF of a component depends generally on the location of the component in the system and the reliability of the components. It is natural to compute the relative importance of the individual components for ranking and optimization, however; several PIFs [16,25] have been developed according to their interest. In this article, two of the most important probabilistic factors are discussed.

Birnbaum's Probabilistic Importance Factor

The Birnbaum's importance is the first PIF proposed by Z.W. Birnbaum in 1968 and it only depends on the structure of the system and reliability of the other components.

For a system S with n components, The Birnbaum's PIF for a component i at time t denoted by $I_i^B(t)$ is:

$$I_i^B(t)=\frac{\partial p_s(t)}{\partial p_i(t)} for\ i=1,2,\ldots,n \tag{8}$$

This PIF can be interpreted as the probability that the system S is in an operating state having the component i as the critical component, knowing that i is in operation, either:

$$I_i^B(t)=p_{(s|i)}(t)-p_{(s|\bar{i})}(t) \tag{9}$$

Where:

$p_{(s|i)}(t)$ denotes the conditional probability that the system is failed given that component i has failed and $p_{(s|\bar{i})}(t)$ the

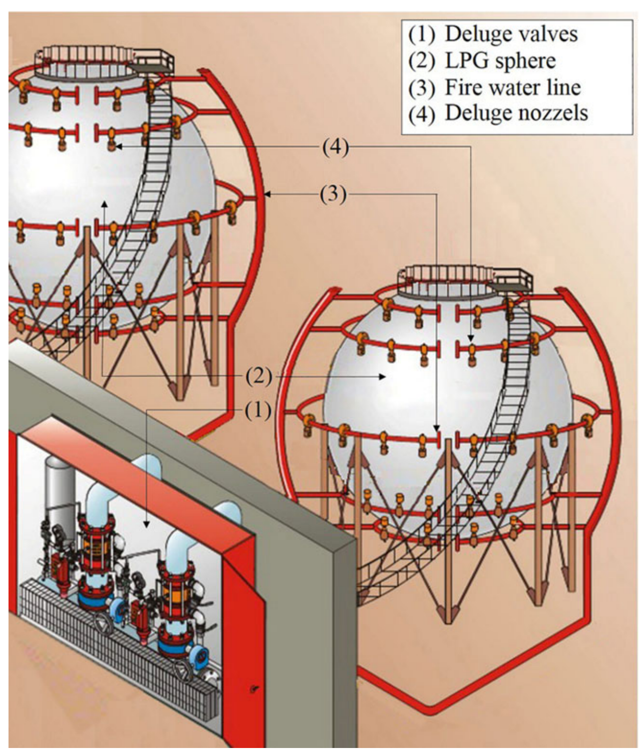


Figure 5. Water deluge network in LPG sphere. [Color figure can be viewed at **wileyonlinelibrary.com**]

conditional probability that the system is failed with component i working.

Components with a very low value of Birnbaum's PIF have a negligible effect on the system reliability and extra efforts finding high quality data for such components maybe considered a waste of time.

Criticality Probabilistic Importance Factor

The criticality PIF is related to Birnbaum's PIF and indicates on which components it is necessary to do actions of component repair, and then, the system will start functioning again.

The component importance measures criticality importance $I_i^{CR}(t)$ of component i at time t is the probability that component i is critical for the system and is failed at time t when the system S is surely failed at time t.

$$I_i^{CR}(t) = \frac{p_i(t)}{p_s(t)} \times I_i^B(t) \, for \; i = 1, 2, \ldots, n \tag{10}$$

The criticality PIF is appropriate to improve system performance by focusing on the truly important components, by allowing avoidance of assigning high importance to components that are very unlikely to occur.

Bayesian Belief Networks Analysis

BBN is a powerful tool in artificial Intelligence to represent uncertain knowledge and dependency in probabilistic systems. A BBN consists of qualitative and quantitative parts. The qualitative par is given by a directed acyclic graph with nodes representing discrete or continuous random variables, and directed arcs (from parent to child) representing causal or influential relationships between variables. The quantitative parts are the conditional probabilistic tables (CPT), which define the probabilistic relationship between each child node and its parents according to Bayes' theorem.

$$P(A|B) = (P(A) \times P(B|A))/P(B) \tag{11}$$

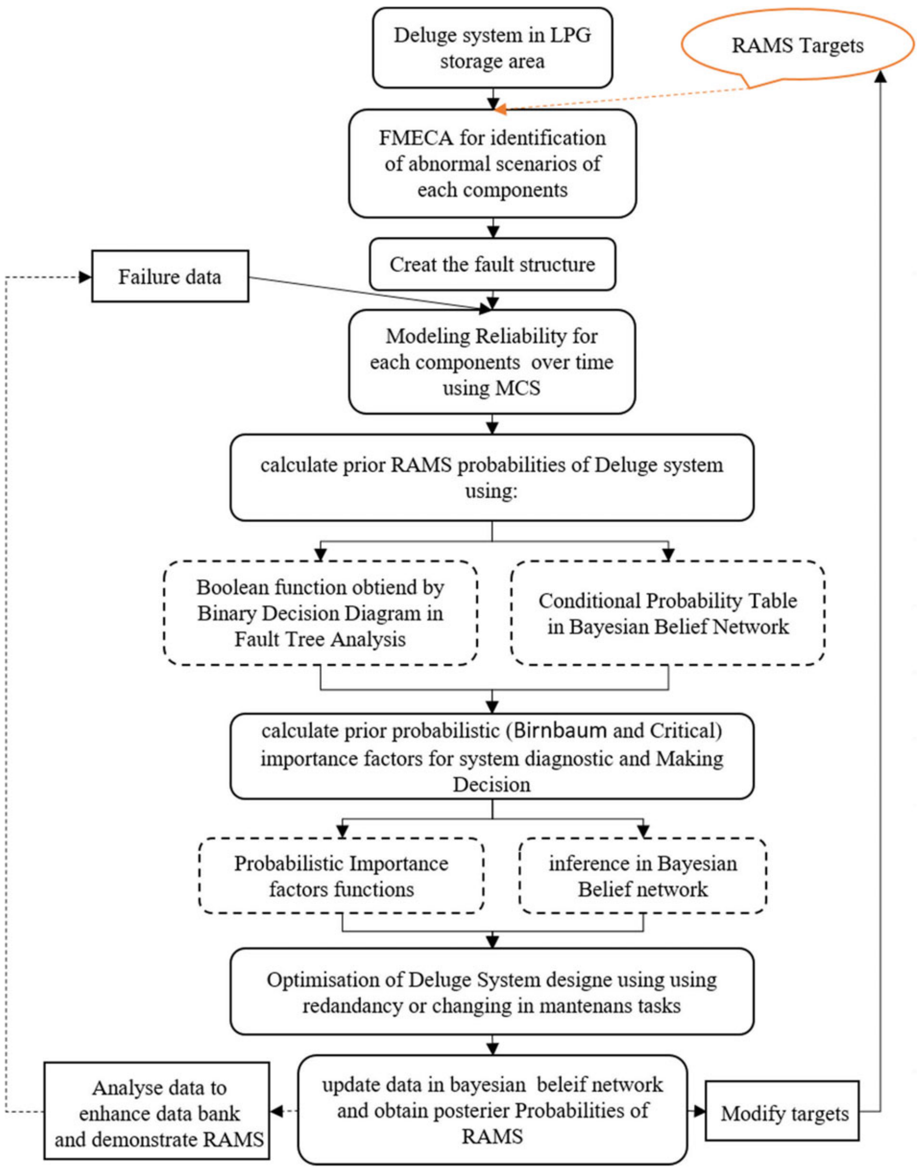


Figure 6. Reliability Analysis methodology of water deluge system. [Color figure can be viewed at **wileyonlinelibrary.com**]

Table 2. Data of water deluge system components from OREDA [49]

Node	Component	Parameters (λ, σ), τ, t_0 (SPT) (λ, σ), μ, τ, t_0 (EPT)	Model	U(t = 87600 *h*)
N1	Deluge valve fail to open on demand	P (1)=5.223E-3	Constant	5.2230E-03
N2	Nozzle spray blockage or reduced flow	P (2)=1.0E-6	Constant	1.0000E-06
N3, N4, N5	Flam detector 1, 2, 3/	(5.9E-7, 5.9E-7), 3.39E5, 4	SPT	5.4959E-02
N6, N9/N12, N15/N18	Failure of jokey 1, 2/electrical 1, 2/diesel pump	(1.7E-6, 2.48E-6), 2E-2, 1.471E5, 1.471E5	EPT	1.4520E-01
N7, N10, N13, N16, N31	Failure of electrical motor 1, 2, 3, 4, 5	(1.473E-6, 1.123E-5), 1.054E-2, 1.697 E4, 1.697 E4	EPT	4.0325E-02
N8	Failure of pressure sensor	(5.3E-6, 7.55E-6), 3.774E4, 48	SPT	6.8165E-02
N11, N14, N17, N19	Pump fail to start on demand	P(11, 14, 17, 19) = 2.84E-3	Constant	2.8400E-03
N20	Failure in diesel engine	(1.466E-5, 1.274E-5), 0.1639, 1.705E4, 1.705E4	EPT	3.3083E-02
N21	Rupture of tank A	P (21)=2.89E-7	Constant	2.8900E-07
N22	Manuel valve leakage in closed position	(5.074E-5, 5.074E-5), 8.403E-2, 4.927E3, 4.927E3	EPT	1.7580E-01
N23	Human error	P (23)=0.01	Constant	1.0000E-02
N24, N25	Filter A/B fail	(3.805E-5, 3.805E-5), 6.897E-2, 6.57E3	EPT	7.7608E-02
N26, N29	Glob valve1/2 leakage	(6.34E-6, 1.996E-5), 3.704E-2, 3.943E4, 3.943E4	EPT	8.9987E-02
N27	Failure in the level sensor	(9.2E-7, 1.26E-6), 2.174E5, 48	SPT	8.3636E-02
N28, N33	Automatic valve1/2/fail to open	(5.93E-6, 5.93E-6), 0.1667, 42160,42160	EPT	1.9734E-02
N30	Well pump failure	(1.026E-5, 9.32E-6), 6.258E-3, 2.437E4, 2.437E4	EPT	1.4430E-01
N32	Well pump fail to start on demand	P (32)= 6E-3	Constant	6.0000E-03

SPT (Simple Periodic Test), EPT (Extended Periodic Test)

Where: $P(A|B)$ is the probability of event A occurring given that we have witnessed event B, $P(A)$ is the probability of event A, $P(B|A)$ is the probability of event B occurring given that we have witnessed event A and $P(B)$ is the probability of event B.

The Figure 3 shows an example of BBN with CPT of different Boolean gates. Together, the qualitative and the quantitative parts encode all relevant information contained in a full joint probability model.

BBN is widely used [40] in Reliability analysis it allowed the study of the systems behavior of (functional and dysfunctional analysis) components observation in complex systems.

In this article, BBNs are used as an alternative method of FTA to use it in a depth probabilistic analysis using algorithms proposed in these articles [22,24,39] as described in the next section.

The advantage of BBNs over traditional methods is that BBNs can compute not only the probability of the top event given the leaves, but also the probability of the leaves given the top event, where a failure has surely occurred, and is able to find which leaves are most like causes. Additional evidence can also be given, such as certain leaves known to have not failed.

Mapping Algorithm

Mapping FTA by BBN

A number of recent studies have attempted to use BN's to provide models and analysis of complex systems. In particular, FTs are converted into BBN because there is a clear correspondence between them.

FTA can be converted to BBN for a depth probabilistic analysis and using inferences. Mapping algorithm of converting FT to BBN is based on the work of [22,24,39] and achieved performing the following step.

1. Each basic event and top event of FTA is translated to parent node and child node, respectively in corresponding BBN
2. For each parent node in BBN, it is assigned the same failure probability over time of the corresponding basis event in FTA.
3. The relationships between basic events "And, Or, *k*-out-of-*n*" in FTA are converted into equivalent CPT in BBN.

Figures 1 and 3 show the translation of general FTA structure into BBN with CPTs for all types of corresponding Boolean gates.

Mapping PIF by BBN

The posterior probability can be also computed in a BN for a single component, for a subset of components or for all components except the ones to which evidence has been assigned. When the fault is given as evidence, the posterior probability of each component gives the criticality of each of them and the posterior probability of a sub-system gives the criticality of the sub-system in causing the system failure.

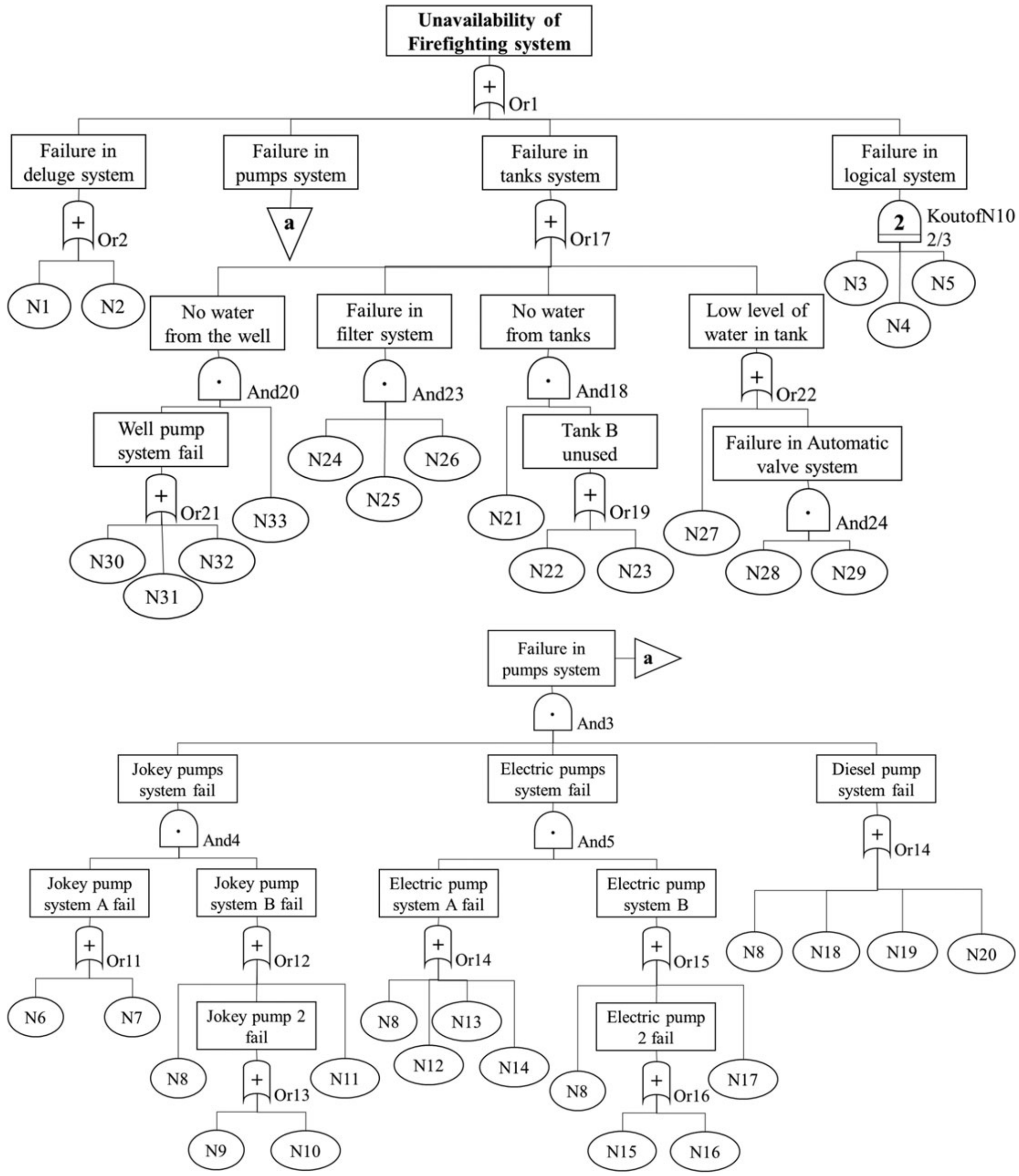


Figure 7. The fault tree structure of water deluge system with the extension of failure in pumps system in (a), where basic events names are listed in Table 2

From this reasoning, Birnbaum's measure can be calculated in terms of posterior probability by inferences in the network. For Birnbaum's PIF equation it will be:

$$I_i^B(t) = p_{(s=yes\,|\,i=yes)}(t) - p_{(s=yes\,|\,i=no)}(t) \qquad (12)$$

In addition, as results the criticality PIF will be.

$$I_i^{Cr}(t) = \frac{\left[p_{(s=yes\,|\,i=yes)}(t) - p_{(s=yes\,|\,i=no)}(t)\right].p_i(t)}{p_s(t)} \qquad (13)$$

Where: $p_{(s\,=\,yes\,\,|\,\,i\,=\,yes)}(t)$ denotes the probability that the system fails given that component '*i*' has failed at time 't' and $p_{(s\,=\,yes\,\,|\,\,i\,=\,no)}(t)$ denotes the probability that the system fails with that component '*i*' working at time '*t*' this probabilities are obtained using inferences in the BBN.

$p_i(t)$ the probability of the component '*i*' at time '*t*' and $p_s(t)$ the probability of the System '*s*' at time '*t*'.

CASE STUDY: WATER DELUGE SYSTEM

The process facility of the LPG storage area needs highly reliable Deluge System according to "the National Fire Protection Association standards [6–8] due to catastrophe scenarios that happened causing material damage and personnel risk.

When improving the RAMS of WDS design in LPG storage area, several robust and making decision methods need to be taken into account. In order to implement the methodology described in previous sections, the WDS installed in the storage area of LPG project in the south of Algeria was selected.

Table 3. Logical gates and subsystems

Node	Name	U(t = 87600 *h*)
Or1	Unavailability of firefighting system	0.1132
Or2	Failure in deluge system	5.2210E-3
And3	Failure in pumps system	1.2764E-2
And4	Jokey pumps system fail	4.3972E-2
And5	Electric pumps system fail	0.1008
Or6	Diesel pump system fail	0.2481
KooN10	Failure in flam logical system	8.6211E-3
Or11	Jokey pump system A fail	0.1797
Or12	Jokey pump system B fail	0.2453
Or13	Jokey pump 2 fail	0.1881
Or14	Electric pump system A fail	0.2474
Or15	Electric pump system B do not star	0.2393
Or16	Electric pump 2 fail	0.1811
Or17	Failure of tanks system	8.9160E-2
And18	No water from tanks	5.3194E-8
Or19	Tank B unused	0.1841
And20	No water from the well	3.6516E-3
Or21	Well pump system fail	0.1823
Or22	Low level of water in tank	8.5331E-2
And23	Failure in filter system	5.6092E-4
And24	Failure in automatic valve system	1.8535E-3

The choice of this site is due to its localization near to other oil and gas sites and its sensibility to the economy of this country. For these reasons, the WDS installed must be able to protect it from all dangerous and catastrophic scenarios.

The deluge system is assumed to supply, on demand by vote system of 2-out-of-3 detectors, water at a controlled pressure to the LPG storage area in order to reduce the heat load from a fire. Therefore, it is evident that the reliability of the WDS has to be high to obtain sufficient heat load capacity. Figure 4 displays a flowchart diagram of the main function within this WDS which is to supply the LPG storage area.

The water coming from the well and outside of the site is stored in two tanks with a capacity of 14000 m^3 each one. Several redundant pump systems [two jockey pumps (2 × 100%) 8 barg, two electrical pumps (2 × 50) 10 barg, diesel pump] are in standby mode and provide water supply to the ring-main on demand [47,48]. In order to distribute the firewater to all fire-fighting equipment in the site, the ring-main is constantly pressurized at eight barg by the jockey pump. In case of a gas or fire situation, the Fire and Gas (F&G) logics will dispatch a signal to the electrical pumps and deluge valve to start. When deluge valve skid to the fire area will open, water flows through the deluge nozzles. In order to maintain the pressure level in ring-main, pressure devices are installed. Figure 5 shows an explicative picture of some WDS components installed in the LPG sphere.

RELIABILITY MODELLING OF DELUGE SYSTEM

The quantitative methods of reliability analysis used in this article are summarized in the flowchart in Figure 6. A "Failure Mode Effect and Criticality Analysis method" (FMECA) is required to stat the reliability study. FMECA is a very efficient method, which is engaged to explore and identify the effects, probability, failure rate, criticality, consequences, how to avoid, how to detect and how to mitigate the effects of the failure or malfunctions of each individual components in the deluge system. Table 2 identifies which part of the system has to be included for in-depth probabilistic study, and gives the information such as failure mode, probability and failure rate from many sources such as knowledge-base, expert judgments or OREDA– Offshore Reliability Database [49].

FTA for WDS

In accordance with the results obtained from FMECA, a FTA model in Figure 7 (with extension of failure in pumps system in (a)) is used for analyzing how the effectiveness over time of the WDS ensures a high RAMS. The top event of the tree is "Unavailability of Firefighting system" chosen to study the WDS and to analyze how the system supplied it in water. According to the structure complexity, and to clarify the representation, the FT is split up into four major subsystems: the pumps system, deluge valve, tanks system, and logical system. These subsystems contribute directly to the top event and are connected to the top event through an Or-gate.

The components of the subsystems are listed in Table 2, and are connected using 'and', 'or' and '*k*-out-of-*n*' gates, with their failure probabilities over time obtained using data listed in Table 3 and by performing different reliability functions as defined in section *Fault Tree Analysis Quantitative Aspect* according to the state of the components. The approximation

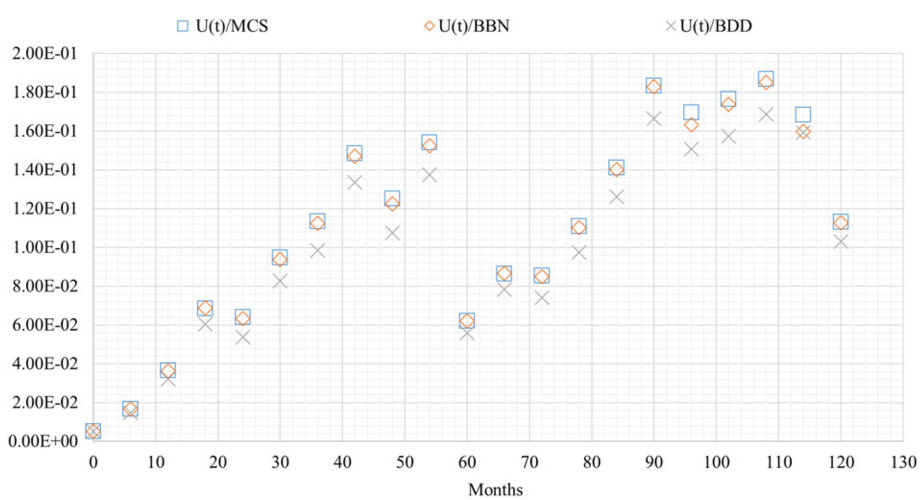


Figure 8. Deluge system unavailability computed using BDD Monte Carlo and BBN over 120 months. [Color figure can be viewed at **wileyonlinelibrary.com**]

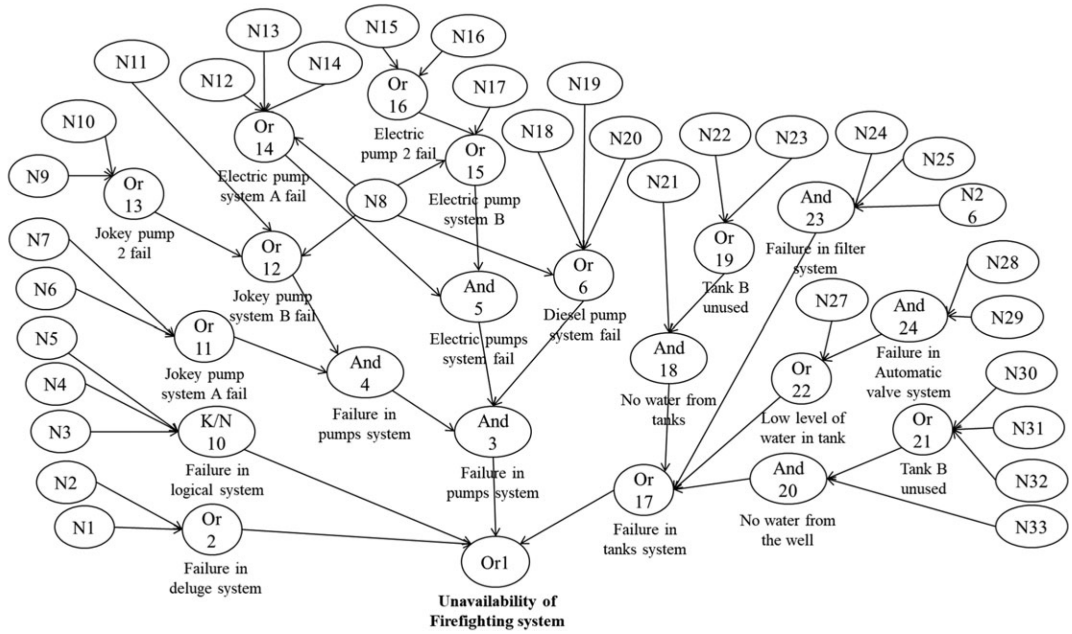


Figure 9. Bayesian belief network structure of water deluge system unavailability, where parent nodes are listed in Table 2.

Table 4. Number of minimal cut sets and their contribution in the top event with example of high unavailability in each order at $t = 87600$ *h*

Order	Number	Probability of products (%)	Examples: Products	Examples: Probability of products
1	3	79.93	N27	7.739E-02
2	11	19.66	N6,N8	8.575E-03
3	1	0.33	N24,N25,N26	3.434E-04
5	162	0.07	N6,N9,N12,N15,N18	5.071E-05

of results in continuous time are obtained using MC simulation for each component taking into consideration the dispersion interval 90% as recommended in [49] and 600 simulations; the average of results convergence being verified.

Then, the failure probabilities of the intermediate events and the unavailability of Firefighting system in LPG storage area are calculated by Boolean expression obtained from using BDD.

The results of WDS unavailability obtained using GRIF® software over a mission time of 87600 h by BDD and MC simulation are shown and compared in Figure 8. The average probability of estimated unavailability is 0.1107 with an approximated reliability of 0.7327.

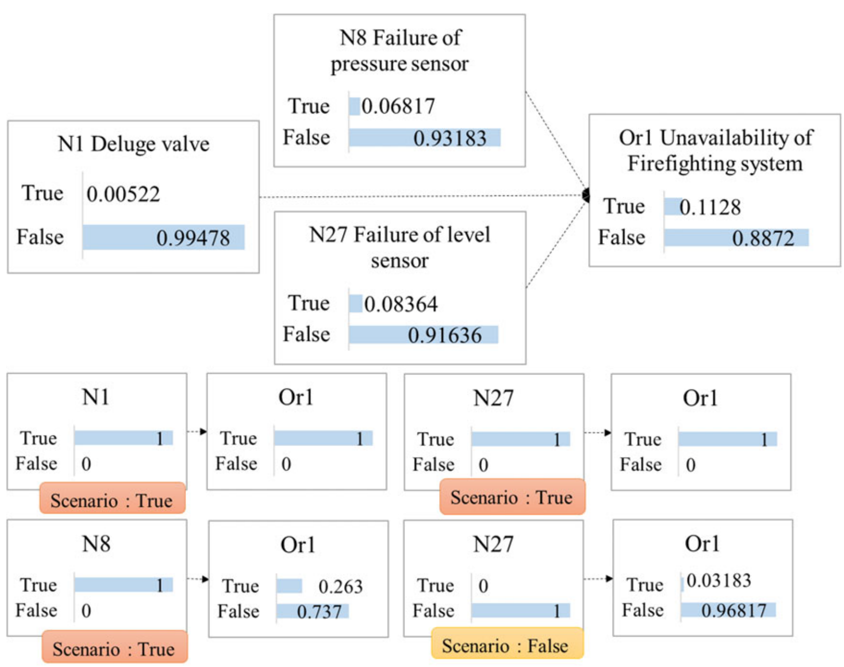


Figure 10. Example of unavailability results a t = 87600 h before and after inference of most critical components. [Color figure can be viewed at **wileyonlinelibrary.com**]

Table 5. Comparison between importance factors obtained using binary decision diagrams and Bayesian belief network of probabilistic importance factors for ranked components.

Level Sensor					
	$I_i^B(t)$		$I_i^{Cr}(t)$		
time	BDD	BBN	BDD	BBN	RE (%)
0	9.948E-01	9.948E-01	0	0	
4380	9.876E-01	9.876E-01	2.648E-01	2.640E-01	0.32
8760	9.716E-01	9.722E-01	2.416E-01	2.394E-01	0.91
13140	9.430E-01	9.440E-01	1.885E-01	1.848E-01	2.00
17520	9.530E-01	9.535E-01	2.843E-01	2.682E-01	5.65
21900	9.250E-01	9.267E-01	2.252E-01	2.196E-01	2.49
26280	9.111E-01	9.118E-01	2.235E-01	2.156E-01	3.55
30660	8.780E-01	8.802E-01	1.854E-01	1.849E-01	0.26
35040	9.085E-01	9.094E-01	2.716E-01	2.607E-01	4.01
39420	8.823E-01	8.824E-01	2.314E-01	2.282E-01	1.42
43800	9.801E-01	9.806E-01	6.919E-01	6.876E-01	0.62
48180	9.577E-01	9.592E-01	5.317E-01	5.290E-01	0.52
52560	9.647E-01	9.650E-01	6.177E-01	5.883E-01	4.75
56940	9.410E-01	9.424E-01	4.978E-01	4.779E-01	4.00
61320	9.120E-01	9.146E-01	4.016E-01	3.914E-01	2.55
65700	8.700E-01	8.731E-01	3.116E-01	3.059E-01	1.84
70080	8.904E-01	8.978E-01	3.748E-01	3.741E-01	0.17
74460	8.880E-01	8.902E-01	3.794E-01	3.685E-01	2.88
78840	8.819E-01	8.820E-01	3.708E-01	3.619E-01	2.41
83220	8.998E-01	9.129E-01	4.196E-01	4.554E-01	7.85
87600	9.671E-01	9.682E-01	7.295E-01	7.178E-01	1.60
RE = 2.37					
Pressure Sensor					
0	0	0	0	0	
4380	6.947E-02	7.055E-02	1.047E-01	1.073E-01	2.54
8760	1.302E-01	1.321E-01	1.826E-01	1.814E-01	0.67
13140	1.811E-01	1.835E-01	2.049E-01	1.965E-01	4.14
17520	4.045E-02	3.873E-02	5.844E-02	5.844E-02	0.01
21900	1.002E-01	9.985E-02	1.272E-01	1.245E-01	2.16
26280	1.545E-01	1.547E-01	2.013E-01	1.889E-01	6.18
30660	1.982E-01	1.994E-01	2.248E-01	2.124E-01	5.51
35040	7.314E-02	7.016E-02	1.034E-01	1.002E-01	3.16
39420	1.238E-01	1.221E-01	7.410E-03	7.830E-03	5.33
43800	1.923E-01	1.911E-01	1.046E-01	1.079E-01	3.10
48180	2.366E-01	2.363E-01	1.607E-01	1.616E-01	0.55
52560	1.106E-01	1.059E-01	1.015E-01	1.023E-01	0.77
56940	1.633E-01	1.601E-01	1.537E-01	1.510E-01	1.77
61320	2.075E-01	2.056E-01	1.888E-01	1.831E-01	3.02
65700	2.412E-01	2.403E-01	1.999E-01	1.904E-01	4.75
70080	1.314E-01	1.270E-01	1.271E-01	1.275E-01	0.29
74460	1.818E-01	1.779E-01	1.958E-01	1.861E-01	5.00
78840	2.158E-01	2.131E-01	2.196E-02	2.262E-02	2.91
83220	2.600E-01	2.618E-01	6.516E-02	7.284E-02	10.53
87600	1.677E-01	1.612E-01	9.381E-02	9.740E-02	3.69
RE = 3.15					
Deluge Valve					
0	1	1	9.998E-01	9.998E-01	0.00
4380	9.879E-01	9.884E-01	3.480E-01	3.075E-01	11.62
8760	9.671E-01	9.686E-01	1.575E-01	1.386E-01	11.98
13140	9.340E-01	9.362E-01	8.164E-02	7.120E-02	12.79
17520	9.393E-01	9.414E-01	9.207E-02	7.745E-02	15.88
21900	9.073E-01	9.109E-01	5.818E-02	5.068E-02	12.90
26280	8.893E-01	8.922E-01	4.801E-02	4.144E-02	13.69
30660	8.529E-01	8.575E-01	3.406E-02	3.046E-02	10.58
35040	8.783E-01	8.820E-01	4.357E-02	3.757E-02	13.77
39420	8.489E-01	8.521E-01	3.292E-02	2.921E-02	11.27

(Continues)

Table 5. Continued

Deluge Valve					
43800	9.384E-01	9.428E-01	8.839E-02	7.921E-02	10.39
48180	9.126E-01	9.182E-01	6.163E-02	5.539E-02	10.12
52560	9.148E-01	9.197E-01	6.548E-02	5.646E-02	13.78
56940	8.882E-01	8.943E-01	4.861E-02	4.233E-02	12.93
61320	8.568E-01	8.643E-01	3.634E-02	3.218E-02	11.44
65700	8.134E-01	8.215E-01	2.626E-02	2.347E-02	10.62
70080	8.287E-01	8.411E-01	2.955E-02	2.691E-02	8.92
74460	8.227E-01	8.304E-01	2.809E-02	2.494E-02	11.22
78840	8.133E-01	8.193E-01	2.588E-02	2.313E-02	10.62
83220	8.257E-01	8.445E-01	2.769E-02	2.758E-02	0.41
87600	8.834E-01	8.919E-01	4.564E-02	4.129E-02	9.51
RE = 10.69					
Automatic valve 2					
0	5.970E-03	5.970E-03	0	0	
4380	1.077E-01	1.101E-01	1.859E-01	1.720E-01	7.51
8760	1.940E-01	1.982E-01	3.092E-01	2.784E-01	9.95
13140	2.647E-01	2.700E-01	3.387E-01	2.957E-01	12.71
17520	1.694E-01	1.742E-01	3.111E-01	2.692E-01	13.48
21900	2.424E-01	2.482E-01	3.646E-01	3.173E-01	12.99
26280	1.309E-01	1.336E-01	2.019E-01	1.674E-01	17.10
30660	2.037E-01	2.080E-01	2.672E-01	2.278E-01	14.73
35040	1.124E-01	1.157E-01	1.958E-01	1.700E-01	13.18
39420	1.895E-01	1.938E-01	2.926E-01	2.527E-01	13.64
43800	2.727E-01	2.791E-01	4.824E-02	4.465E-02	7.43
48180	3.307E-01	3.381E-01	1.537E-01	1.395E-01	9.24
52560	6.195E-02	6.369E-02	4.984E-02	4.517E-02	9.37
56940	1.466E-01	1.505E-01	1.287E-01	1.144E-01	11.14
61320	2.168E-01	2.223E-01	1.911E-01	1.686E-01	11.76
65700	2.714E-01	2.779E-01	2.233E-01	1.945E-01	12.89
70080	1.934E-01	2.003E-01	2.015E-01	1.823E-01	9.52
74460	8.928E-02	9.148E-02	1.043E-01	8.853E-02	15.16
78840	1.663E-01	1.702E-01	2.027E-01	1.723E-01	15.01
83220	2.421E-01	2.511E-01	3.459E-01	3.223E-01	6.83
87600	1.575E-01	1.626E-01	2.970E-02	2.844E-02	4.24
RE = 10.85					

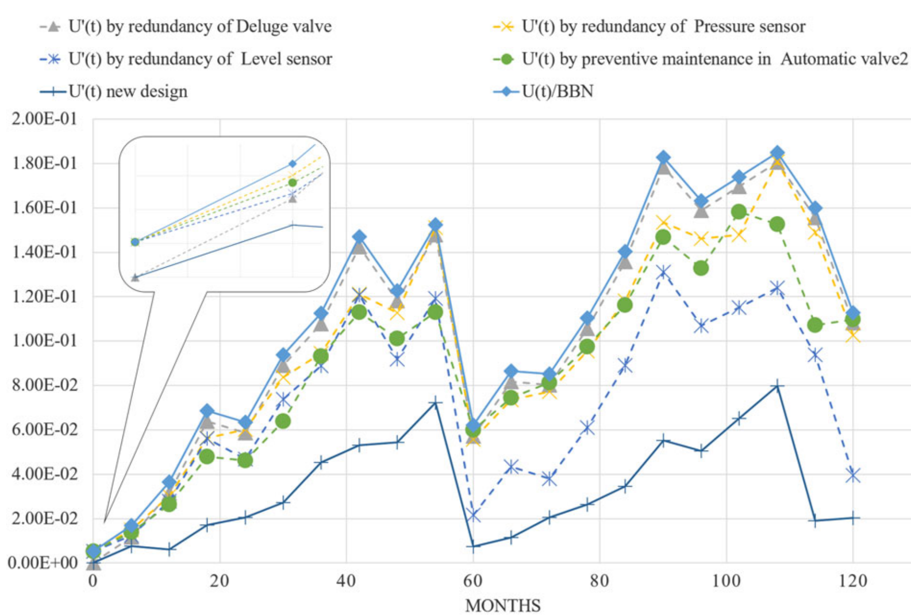


Figure 11. Water deluge system unavailabilities after design optimization. [Color figure can be viewed at **wileyonlinelibrary.com**]

The mission time of 87600 h was used in the calculation while taking into account that the WDS is available on demand whatever scenarios, and this is due to:

1. Redundancy of important components, if the first component is in repair phase the second replaces it;
2. Periodic tests and maintenance devices;
3. Repair phase, when failure is detected components are returning in good as new state.

Due to the complexity of the FT, it has to be noted that the number of the minimal cut sets of the fault events whose occurrence at the same time ensures that the unavailability of the system occurs is 177:

Table 4 shows the number of minimal cut sets and the contribution percentages by order, where the minimal cut sets order are "1," "2," "3," and "5". Examples of minimal cut sets with high unavailability in each order at $t = 87600$ can be also seen and as remarks the first minimal cut sets ranked in order 5 are related with pumps system, where it is important to be supervised and controlled as recommended in NFPA 25 [46].

Analyzing WDS Using BBN

A BBN has been developed for analysing the unavailability of deluge system with a depth probabilistic model, as shown in Figure 9 by converting the FTA model in Figure 7 using the algorithm described in section Mapping FTA by BBN.

All the events in fault tree are converted into components parent nodes. The logical nodes are obtained using conditional probabilities table CPT. All nodes have states yes and no.

For the first analysis, in order to compare results between FTA and BBN, all components' faults give the same failure probability over time. Therefore, the unavailability graphs obtained with the three methods are represented in Figure 8. A small gap between BDD points and others can be noticed, the mean square error between BBN and MC simulation results being about 6.78273E-06. This prior results obtained by the BBN are obtained with AgenaRisk ® software.

PIF of WDS Mapped into BBN

The Birnbaum's PIF used to rank the components representing the maximum increase in risk when components are failed compared to when components are working. As results, four components were selected for this study, the most influencing in the state of the system: deluge valve, level sensor, automatic valve 2 and pressure sensor. Then, the selected components using Birnbaum's PIF allows the calculation of their critical PIF over 87600 h for analysis more precisely the behavior of each component beyond their Mean time to failure (MTTF) to obtain the component that is particularly suitable for prioritizing the decision in optimization actions. To take the right decision insuring a high level of RAMS at real time, it is very important to obtain this importance factors using BBN.

Using algorithm proposed in section Mapping PIF by BBN, the PIF can be calculated in terms of posterior probability. An evidence tolerance of 1% and inferences of WDS components with "true" or "false" scenarios are considered. The posterior probability gives a factor by which each node contributes to the system failure. The example in Figure 10 shows the results of system unavailability at $t = 87600$ h obtained by inferencing in the system network using conditional probabilities knowing that the selected components are in failure and / or in operating state. Then, it is observed that the unavailability of the system is 11.28%, but when one of deluge valve or pressure sensor are in failure state, the system is unavailable with 100%, and when level sensor is in failure state the system is unavailable with 25.30%. However, these inferences in the system network informed which components influence directly in the system unavailability and must be selected for a PIF studies.

The PIFs are obtained from inference results and using Eq. 12 for Birnbaum's PIF and Eq. 13 for critical PIF.

The results of PIFs mapped into BBN obtained for the four selected components are listed and validated with results obtained using BDD in Table 5. A relative error is also calculated between the two methods of criticality PIF. It can be observed from this table that the value of Birnbaum's PIF obtained by the BDD and BBN for each one of the components over time are note significantly different. However, in the case of criticality PIF, the differences between the two methods are relatively small in some components such as "level sensor with a mean relative error of 2.37%, and pressure sensor with 3.15%". An important difference is observed in the other components with "10.69% for deluge valve and 10.85% in automatic valve 2 Table 5". The practical explanations for these differences are related to the relative errors of the system unavailability value obtained in Figure 8 that are used to calculate criticality PIF in Eq. 13. The position of the component in the network and the value after inference in BBN are also considered.

Making-Decision and Updating Design

Once the results of PIF mapped in BBN are obtained and through the expert opinion, the BBN is used for making-decision to optimize the WDS design by adapting the network and updating probabilities. From results of criticality PIF in Table 5, it is clear that each component contributes in the system unavailability at a knowing time interval. A redundancy for the components 'deluge valve, pressure control system and level control system' is required by creating new nodes in parallel to those already existing in the network. The probabilities value of automatic valve 2 node is updated by changing in parameter of maintenance task. This design change has to be a principal target to maximize the RAMS of WDS.

Figure 11 illustrates the contribution of making-decision in the optimization of the WDS performance and how the design change of each component contributes by redundancy or changing of maintenance task of other components in increasing the availability of the system. Furthermore, the redundancy of deluge valve plays a very important part to prevent against system failure on demand. The pressure system redundancy is also one of the key elements in this optimization because it controls the pumps system. All these important changes increase the availability of the WDS. As an example, for $t = 0$, the value of WDS unavailability decreases from $5.22\ 10^{-3}$ to $2.8251\ 10^{-5}$, mainly due to the importance of deluge valve. At $t = 43800$ h, the value of the unavailability decreases from $6.2163\ 10^{-2}$ to $7.3665\ 10^{-3}$, and, at $t = 87600$ h the system availability increases from $8.8720\ 10^{-1}$ to $9.7976\ 10^{-1}$.

CONCLUSION

The current article demonstrated how Bayesian belief networks can be helpful for a depth study in reliability analysis for a sensitive safety system that are difficult to analyze, technically complicated need a high level of RAMS. This article also illustrated how to modelling water deluge system unavailability one of the most important safety system implemented in LPG storage area with a fault tree for a better manipulating dependencies between components. Probabilistic importance factors were mapped using Bayesian belief network for decision-making in design optimization and compared with factors calculated using a deterministic approach.

Additionally, effectiveness and adequacy of mapping PIFs using BBN have been improved on the basis of prior results comparison with posterior results obtained after design changing. The design changes using BBN show that the components ranked by PIFs mapped by BBN contribute most to the system unavailability. Hence, to improve RAMS of the WDS, the focus should be on the better reliability of components by changing in parameters of maintenance tasks and by introducing redundancy in other components. The design optimization in this article has brought as results increasing in WDS availability, thus ensuring high safety in LPG storage area.

For future works, the developments could be focused on using Monte Carlo Markov Chains (MCMC) by dynamic Bayesian networks algorithms in reliability analysis, and also studying multi-state node behaviors and comparing results obtained by BBN and Universal Generating Function (UGF) using python programming.

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ABBREVIATIONS

BBN	Bayesian Belief Network
BDD	Binary Decision Diagrams
BLEV	Boiling Liquid Expansion Vapour Explosion
CCF	Common Cause Failure
CPT	Conditional Probabilistic Tables
DAG	Directed Acyclic Graph
FMECA	Failure Mode Effect and Criticality Analysis
FTA	Fault Tree Analysis
LPG	Liquid Petroleum Gas
LPT	extended periodic test
MC	Monte Carlo simulation
MCMC	Monte Carlo Markov Chains
MTTF	Mean Time to Failure
NFPA	National Fire Protection Association
OREDA	Offshore Reliability Data
PIFs	Probabilistic Importance Factors
QRA	Quantitative Risk Analysis
RAMS	Reliability, Availability, Maintainability, and Safety
SPT	Simple Periodic Test
UGF	Universal Generating Function
VCE	Vapor Cloud Explosion
WDS	Water Deluge Systems

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