On Hierarchical Bayesian based Predictive Maintenance of Autonomous Natural Gas Regulating Operations

Abstract

Safety Improvement of engineering processes, especially Oil & Gas operations, has gained a lot of attention during the last decades. This fundamental vision results in risk remediation programs, minimizing the risks of failure and reducing the associated costs for operation and maintenance. As failures may represent serious threats for both humans and environment, a comprehensive tool is required to employ maintenance and avoid immoderate dangerous consequences. Traditional risk frameworks mainly include estimation approaches, such as Fault Tree (FT) and Event Tree (ET), producing more simplified models than other tools, such as Bayesian inference. They may rely on historical data and generally are not updated by new observations or monitored information. The present work aimes at developing an advanced Risk-Based Maintenance (RBM) methodology for prioritizing maintenance operations, by addressing associated uncertainties through the accident modelling of the process. For this purpose, a Hierarchical Bayesian Approach (HBA) is applied to estimate the failure probabilities of each component while a Failure Mode, Effects and Criticality Analysis is performed to assess the severity. lastly, to make a meaningful difference between different kinds of risk consequences, whether the risk has direct or indirect loss, the cost of failures of components are accounted. The proposed method can be exploited by maintenance engineers, asset managers and policy makers to reduce the downtime periods as well as the risks of on-going operations. To demonstrate the application of the methodology, a Natural Gas Reduction and Measuring Station (NGRMS) is taken into account as a case study.

1. Introduction

Natural gas network is a critical infrastructure and, due to its proximity to urban areas, the consequences of a severe damage to the system could lead to disastrous outcomes, threatening the safety of the near human beings and environment (Jo and Ahn 2002). Although accidents involving natural gas facilities are less common than road or trail accidents (Brito and de Almeida 2009), they still caused several injuries and deaths all over the world in the recent years (Han and Weng 2011, Girgin and Krausmann 2016). Therefore, countermeasures against hazardous conditions need to be adopted to minimize the chances of failures and to reduce the risk arising from a natural gas distribution system breakdown.

One of the most renowned strategies to mitigate the risk, is to set up repeated inspections and maintenance activities. Maintenance, in fact, supports the asset managers to increase the safety and availability of engineering infrastructures. Recently, Iqbal, Tesfamariam et al. (2017) divided different types of maintenance policies into four main categories: corrective, preventive, proactive and predictive. Corrective maintenance is a disused category since it leads to costly breakdown. A quite recent type of maintenance is RBM which prioritizes the maintenance of components basing on the level of the associated risks (Ambühl and Sørensen 2017). Establishing an RBM policy is predictably followed by a gradual decline of the likelihood of system failures and of its consequences related to safety, economy, and environment (Khan and Haddara 2003). Over the last decades many researchers have focused on RBM and on the optimization of maintenance plans, considering the risks arising from failures (Khan and Haddara 2004, Krishnasamy, Khan et al. 2005, Kumar and Maiti 2012, Wang, Cheng et al. 2012). Abbassi, Bhandari et al. 2016 developed a RBM strategy, applied to a power plant. In the first part this methodology uses a BN to assess the level of risk, based on a certain failure scenario, while in the second part a backward analysis is carried out to determine a maintenance plan able to reduce the level of risk according to acceptable criteria.

Within the process of RBM, due to insufficient data and vague characteristics of the events, the probabilistic risk assessment has been accounted as a difficult task (Yuhua and Datao 2005). Accordingly, exploiting historical data is crucial for deepening the understanding of main causes of an unexpected breakdown (Montiel, Vilchez et al. 1996, Papadakis 1999). A great deal of research has been made to reduce the uncertainties associated with failure rate calculations. Moreover, the risk probabilities vary significantly with design factors, maintenance techniques and environmental conditions (Wu, Zhou et al. 2017). Consequently, there is an ongoing effort on risk assessment of engineering processes, including natural gas distribution systems, to optimize the calculations (Jo and Ahn 2005, Sklavounos and Rigas 2006, Han and Weng 2011, Lees 2012, De Rademaeker, Suter et al. 2014, Vianello and Maschio 2014, Pasman 2015). Vianello and Maschio (2014) proposed a quantitative risk assessment methodology applied to a portion of Italian natural gas network. The authors divided the study into three stages: risk identification, estimation of failure frequency and estimation of consequences. This model concluded that the flash fire scenario should be considered the most severe and that the minimum proximity of the pipeline for residential buildings is approximately proportional to the square root of the operating pressure of the pipeline.

Developements of RBM and related risk assessment have been executed by means of different tools such as FT, ET, Bow-tie, Fuzzy logic method (Khan and Haddara 2003, Krishnasamy, Khan et al. 2005, Yuhua and Datao 2005, Makowski and Mannan 2009, Lavasani, Yang et al. 2011, Shahriar, Sadiq et al. 2012, Jamshidi, Yazdani-Chamzini et al. 2013). However, the focus of these studies is limited only to identifying the main causes of the accidents and to assess their risk (Han and Weng 2011) and subsequently the unknown hazards were overlooked. Moreover, FT, ET and BT describe the breakdown process with binary variables. Also, neither of FT, ET and BT can represent the conditional dependencies between the considered failures (Martins, Schleder et al. 2014), which results in being unable to fully grasp the changes in risk during operations. (Khakzad, Khan et al. 2011, Paltrinieri and Khan 2016). To overcame these limitations, Bayesian inference, as both parametric and non-parametric model, has attracted a significant attention from researchers for conducting risk and reliability assessment of complex engineering systems (Khakzad, Khan et al. 2013, Barua, Gao et al. 2016, Kabir, Sadiq et al. 2016, Yu, Khan et al. 2017, Zarei, Azadeh et al. 2017). Khakzad, Khan et al. (2013) compared the application of BT and BN models for a quantitative risk analysis of offshore drilling operations. The results highlighted that BN is more efficient than bow-tie models for probabilistic analysis, since it can consider common failure causes as well as conditional dependencies. Moreover, BN can perform probability updating and sequential learning based on accident precursors data or new available evidence. In another more recent research, Zarei, Azadeh et al. (2017) presented an approach for accident scenarios and risk modelling of natural gas stations. In this work a Failure Mode and Effect Analysis (FMEA) was used for hazard analysis while a BT and BN were employed to model the worst-case scenario and to assess the risk. The results of this study showed that failure of the control system, with the contribution of human error, can trigger an accident in the process and has been identified as the root cause of the worst case scenario. In the past years, the application of BN has been extended also to schedule the maintenance time (Abbassi, Bhandari et al. 2016, Pui, Bhandari et al. 2017, BahooToroody, Abaei et al. 2019a, Leoni, BahooToroody et al. 2019). The paper presented by BahooToroody, Abaei et al. (2019) focuses on the Process Variables (PVs) i.e. pressure, temperature, etc. and assesses how their variations can be used for determining the optimum maintenance schedule. In this work a Dynamic Bayesian Network (DBN) was proposed to model the damage and to estimate the probability of failure. The novelty of this approach is that the perturbations, PVs conditions, reliability of inspection, sensors uncertainty, failure probability, maintenance decision alternatives, utility of maintenance and utility of failure, are all considered for a given time series and in a single Influence Diagram (ID).

Semi parametric and non-parametric Bayesian inference have found also a wider audience for solving complex engineering problems based on recent development in open source Markov Chain Monte Carlo (MCMC) sampling software packages, i.e., OpenBUGS (Spiegelhalter et al. 2007, Kelly and Smith 2009). This software has been widely exploited to perform advanced Bayesian methods, like HBM as a fully Bayesian state of art, by many researchers (Kelly and Smith 2009, Abaei, Arzaghi et al. 2018, Arzaghi, Abaei et al. 2018). Abaei, Arzaghi et al. (2018) adopted HBM to estimate the probability of a boat to touch the seabed based on the results of dynamic under keel clearance obtained from time-domain hydrodynamic simulations, while Arzaghi, Abaei et al. (2018) proposed an

Ecological Risk Assessment (ERA) method for oil spilling from subsea pipelines using HBM and fugacity model as core tools.

Despite all the ongoing efforts for improving the safety of natural gas distribution system, there is still space for reliable tools able to define proper maintenance actions, based on the level of risk. Moreover, while the pipeline systems have lured a lot of attention, not so much interest has been given to NGRMS. Therefore, the main objective of this paper is to develop a risk-based methodology capable of prioritizing maintenance, in the context of NGRMS. This is essential for ensuring the safety of the operations under limit resource condition and it will help to deal with the uncertainties arising from the process. To this end, HBM is adopted, first to quantify the state-of-knowledge uncertainty associated with predictions of the involved parameters and then to determine the probabilities of failure. The advance of such a model was verified on an actual example of stochastic process of a Natural Gas Regulating and Metering Stations (NGRMS) near Florence, Italy.

1.1 Hierarchical Bayesian Modelling

Every statistical inference starts with data. 'Data' are defined as the observed values of a physical process that may be affected by uncertainty. The process of manipulation, evaluation and organizing data leads to 'Information', while 'Knowledge' is a value-added acquaintance gathered from information. Finally, statistical inference is the process of obtaining a conclusion based on what is known (Kelly and Smith 2009, Abaei, Arzaghi et al. 2018).

HBM is an advanced probabilistic approach that allows inferences to be made based on real-world observations. (El-Gheriani, Khan et al. 2017, BahooToroody, Abaei et al. 2019b). In the current study, Bayes' theorem, given by Eq. 1, is used to perform inference:

$$\pi_1(\theta|x) = \frac{f(x|\theta)\pi_0(\theta)}{\int_\theta f(x|\theta)\pi_0(\theta)d\theta} \tag{1}$$

the unknown parameter of interest is denoted by θ, while $f(x|\theta)$ is called likelihood function. $\pi_0(\theta)$ is known as the prior distribution of θ and $\pi_1(\theta)$ is addressed as the posterior distribution of θ. As stated by Kelly and Smith (2009) the prior distribution for the parameter of interest can be expressed by the Eq. 2 :

$$\pi_0(\theta) = \int_\emptyset \pi_1(\theta|\varphi)\pi_2(\varphi)d\varphi \tag{2}$$

where $\pi_1(\theta|\varphi)$ represents the first-stage prior of the population variability in θ, for a given value of φ. The hyper-prior distribution is denoted by $\pi_2(\varphi)$ and it considers the uncertainty of φ, which, in the most cases, is a vector and its components are called hyper-parameters.

2. Developed Methodology

The sequence of the proposed methodology is illustrated in Fig. 1.

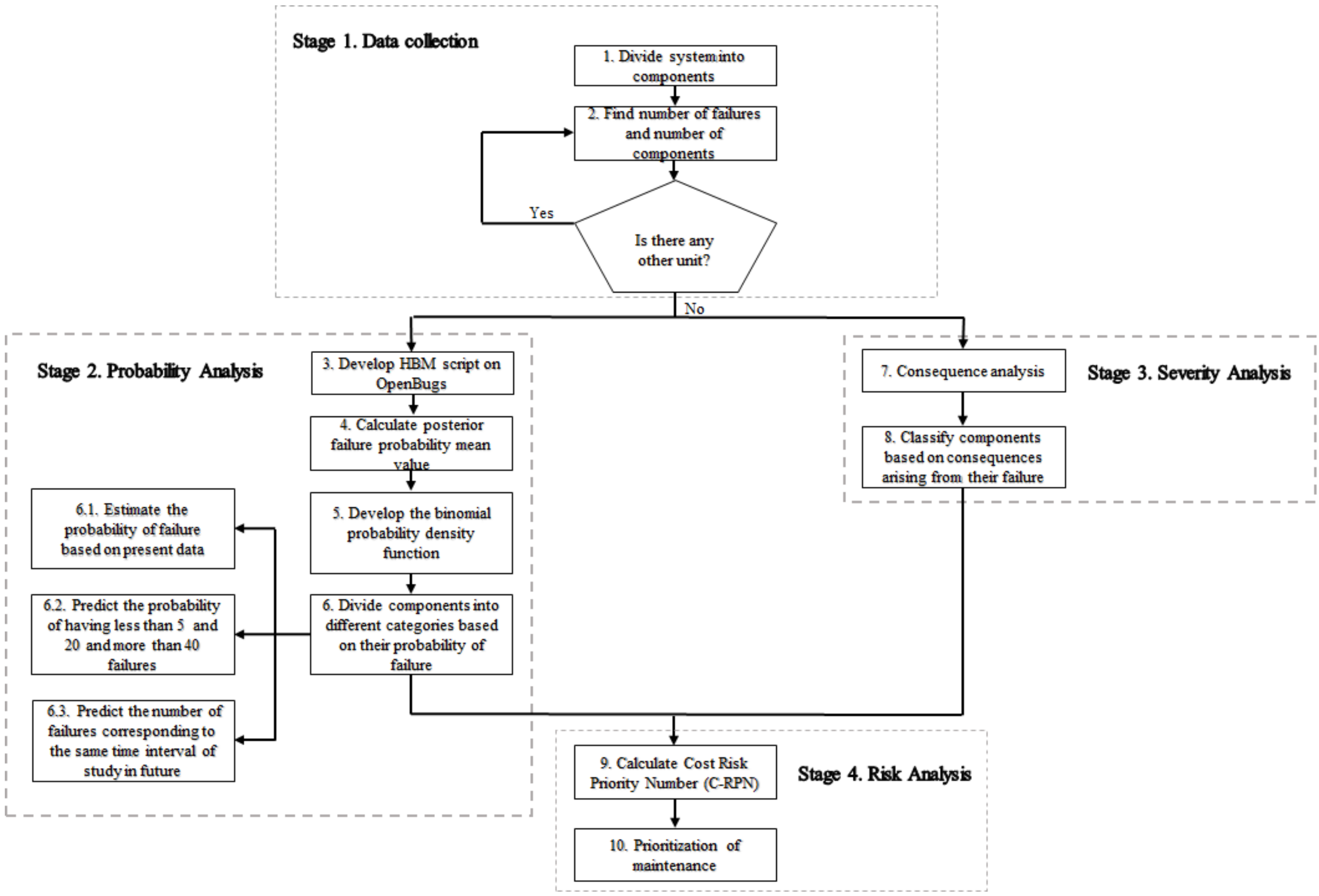


Fig. 1. Proposed RBM framework methodology with hierarchical Bayesian inference.

2.1.Stage 1: Data collection

The first step is to specify the system involved in the RBM study. task analysis in order for the considered system to divide it to its most relevant components and to characterize the quality of interaction between the components is defined within the first step. The second step is to acquire the number of failures as well as the statistical population of each component in the specific time interval of the operational time.

2.2. Stage 2: probability analysis

This stage aimes at conducting probability analysis, starting with the implementation of Hierarchical Bayesian Model (picture 3. of Figure 1) by developing a script in OpenBugs software, followed by the calculation of the mean probability of failure of each component (4.). In order to classify the components into different maintenance type categories (6.), a binomial probability function is specified (5.) and three predictions are carried out (6.1, 6.2, 6.3).

2.3.Stage 3: severity analysis

Based on possible outcomes arising from components' failures, a consequence analysis is performed (7.) and subsequently the components are classified into different effect categories (8.). As is common in risk management, it is proposed to consider four different categories:

1. "Minor": that is the lowest level of severity in which the operations are regarded as safe.
2. "Moderate": that is a low level of severity, considered acceptable for the safety of the operations.
3. "Major": which is a higher level of severity that includes performance loss and loss of primary functions.
4. "Catastrophic": which is the highest level of severity and it comprehends hazardous outcomes such as damages to human beings and environment.

This stage is accounted for severity analysis exploiting to determine the consequences of potential failures. this analysis is conducted using Failure Mode, Effect and Critically Analysis (FMECA).

2.4. Stage 4: risk analysis

Using results from probability and severity analysis, Cost Risk Priority Number (C-RPN) is calculated (9.). Finally, (10.) on the basis of the C-RPN estimate, the most critical components are highlighted, whose maintenance must be a priority.

3. Application of methodology: case study

To demonstrate the applicability of the developed RBM methodology, a case study of 59 NGRMSs (for logistic locations see Fig. 3) operating in Florence area, Italy, is conducted. A detailed discussion on the developed RBM framework is provided in the following sections.

3.1. Scenario development

Within four critical groups of preheating, reduction, measuring and odorization, NGRMSs are designed to fulfil two main tasks: first, to regulate the income pressure of natural gas in order to adapt it for the subsequent utilities and, next, to measure the flow of the regulated gas. Furthermore, the components operating in the aforementioned groups of these stations are listed in Table 1.

Table 1

Groups and components of NGRMS

Group	Component
Reduction	Pressure regulator
	Pilot
	Filter
Measuring	Pressure and temperature gauge
	Calculator
	Meter
	Remote control system
Odorization	THT tank
	THT pipelines
Preheating	Pump
	Boiler
	Water pipe

As a heart of the system, pressure regulator keeps the downstream pipes at a pre-determined pressure while it simultaneously guarantees the required flow. The gas flow is regulated by varying the cross-sectional flow area. The pilots are set up, to have more precision and a faster change of the gas flow. Filters block the impurities, both solid and liquid which are always present in the gas and must be placed upstream the pressure regulator. The measuring group assesses both the flow and its characteristic parameters such as pressure and temperature. The remote control system (RCS) allows to access the data from distance. The preheating group is placed downstream the filter and upstream the pressure regulator lead to prevent the formation of ice in the regulated gas flow. As the temperature decreases along with the reduction of pressure the gas temperature is increased by an exchanger in which there is a flow of hot water, previously heated by a boiler. Last but not least, a very precise quantity of odorizer, which is usually tetrahydrothiphene (THT), must be added to warn of any gas leaks. The system architecture of the NGRMS underlining the relationship amongst components is illustrated in Fig.2.

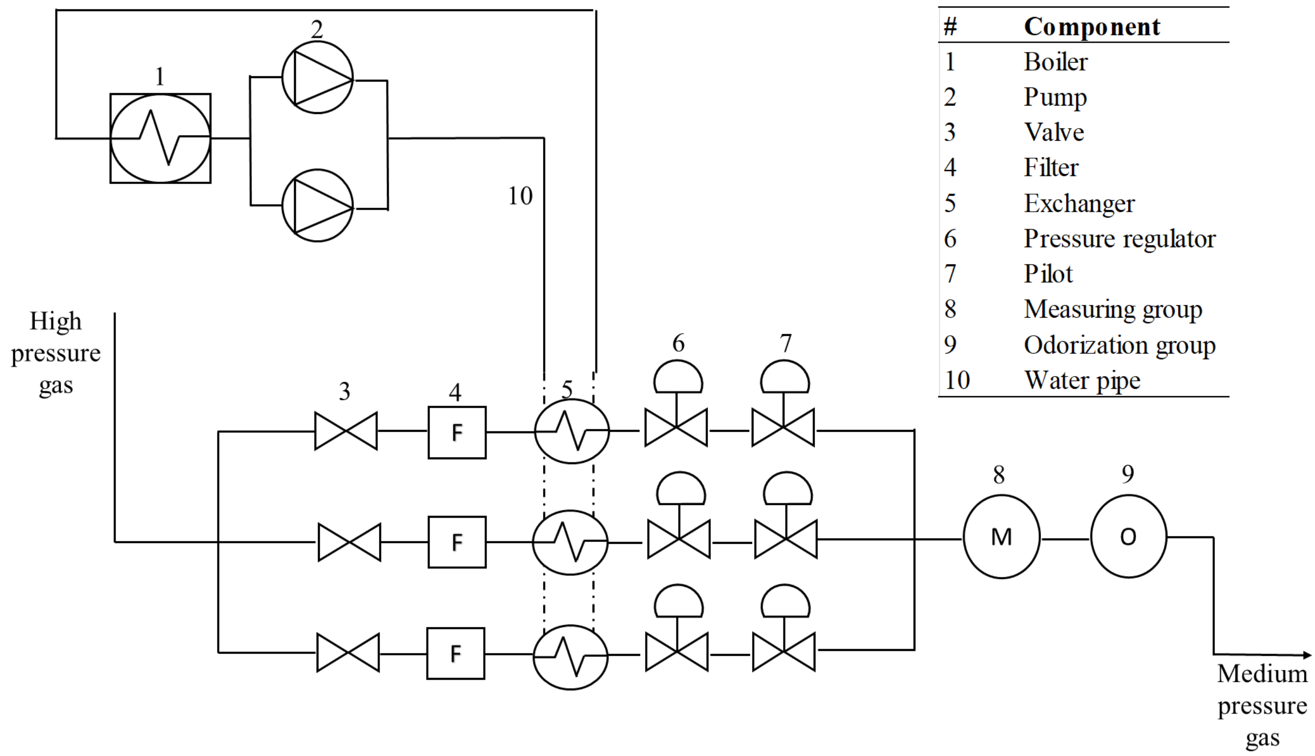


Fig. 2. a typical architecture of the NGRMS

Table 2 shows the number of components installed, the number of failures and the population surveyed. The values are derived from 59 NGRMS and cover a period of six years.

Table 2

Number of failures and population number of NGRMS' main components

Component	Number of failures	Number of components	Population
Pressure Regulator	17	248	543120
Pilots	6	496	1086240
Filter	12	124	271560
RCS	19	59	129210
meter	7	108	236520
PTG	65	59	129210
Calculator	47	59	129210
THT tank	7	59	129210
THT pipelines	3	59	129210
Pump	38	108	236520
Boiler	23	108	236520
Water pipe	25	59	129210

3.2. Probability analysis; Beta-Binomial model

On the basis of the aforementioned observations (shown in Table 2) a Beta-Binomial model was defined. To this end, HBM was used to formulate the likelihood function. Among a number of likelihood functions, a binomial aleatory failure model was accounted for writing the script in Openbugs software:

$$P(k) = \binom{n}{k} p^k (1-p)^{n-k} \tag{3}$$

where n and k are respectively the number of trials and the number of successes, which, in this case, are safety incidents,. $P(k)$ represents the binomial distribution $B(n, p)$, where p is the probability of success in a single trial. $\binom{n}{k}$ also denotes the binomial coefficient.

Accordingly, as beta function is the conjugate prior for the binomial distribution, meaning that the prior and posterior distributions belong to the same functional type, beta function, it was chosen as the prior distribution, stated by:

$$f(p) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} \propto Cp^{\alpha-1}(1-p)^{\beta-1} \tag{4}$$

Where α and β are the hyper-parameters of the model. The BN adopted to find the posterior distribution of p, achieved by Eq. 5, is illustrated in Fig.3, where X stands for the number of failures and n represents the population number. Both X and n are listed in Table 2 for each component, respectively as the number of successes and the number of trials.

The posterior distribution adopted in this paper is illustrated in Eq.5

$$f(p|D) \propto Cp^k(1-p)^{n-k}p^{\alpha-1}(1-p)^{\beta-1} \; \frac{p^{k+\alpha-1}(1-p)^{n-k+\beta-1}\Gamma(\alpha+\beta+n)}{\Gamma(\alpha+k)\Gamma(\beta+n-l)} \tag{5}$$

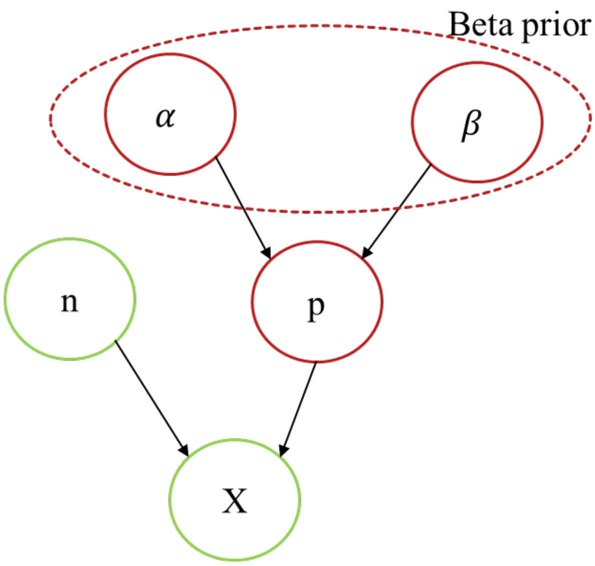


Fig. 3. BN to calculate the mean value of posterior probabilities of failure. Red and green nodes represent respectively the unknown and known parameters

With MCMC sampling from likelihood function and prior distribution, the Bayesian inference predicted the posterior distribution of hyper-parameters. To this end, three chains with 10^5 iterations through each of chains has been simulated. Using the Jeffery prior, dbeta (0.5,0.5), led to the predicted mean values mined from the posterior beta distribution (listed in table 3).

Table 3

Posterior mean probability of failure of NGRMS' main components

Component	**Posterior mean probability of failure**
Pressure Regulator	0,00003462
Pilots	0,00001291
Filter	0,00005363
RCS	0,0001519
Meter	0,00004226
PTG	0,0005089
Calculator	0,0001609
THT tank	0,00006795
THT pipelines	0,0000357
Pump	0,0001694
Boiler	0,0001067
Water pipe	0,0002072
Reduction Group	1,618E-08

Odorization Group	6,244E-08
Measuring Group	6,302E-08
Preheating Group	3,857E-08
NGRMS	6,574E-15

The calculation revealed that the components with the highest probability of failure are the PTG and the pump, with posterior mean value of 0,0005089 and 0,0001694, respectively. On the contrary, the pressure regulator has the lowest probabilities of failure: 0,00003462. At this stage, the posterior distributions can be updated as soon as new data or information regarding number of failures become available.

Given the predicted posterior mean probabilities of failure, as the probabilities of success in a binomial distribution, resulted in the developed binomial probability density functions plotted in Fig. 4. It appears that the PTG has a distribution focused around the highest value, while the distribution centered around the lowest value belongs to THT tank.

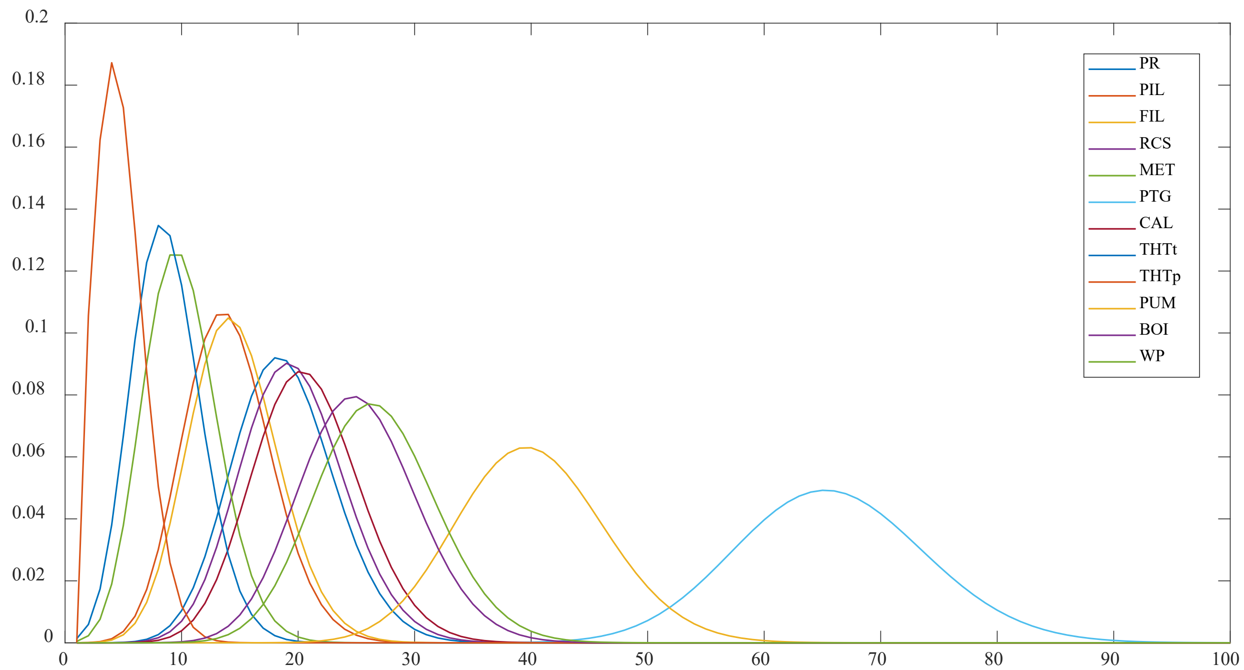


Fig. 4 Binomial probability density functions of NGRMS' main components

Once the average posterior probability of failure has been calculated, it is possible to analyse the observed conditions of the system. Results can be viewed in Fig 5 and in Table 4. Having exactly three failures in six years for the THT, we geta probability of 16%, while 7 failures for the THT tank occur with a probability of 12% during the same period of time. On the other side, the probability of getting exactly 47 failures for the calculator and 6 failures for the pilots are equal to 3,14E-05% and 0,8% respectively. The rest of the components is characterized by a probability between 6% and 9% of having the exact number of failures as the previous 6 years of operations.

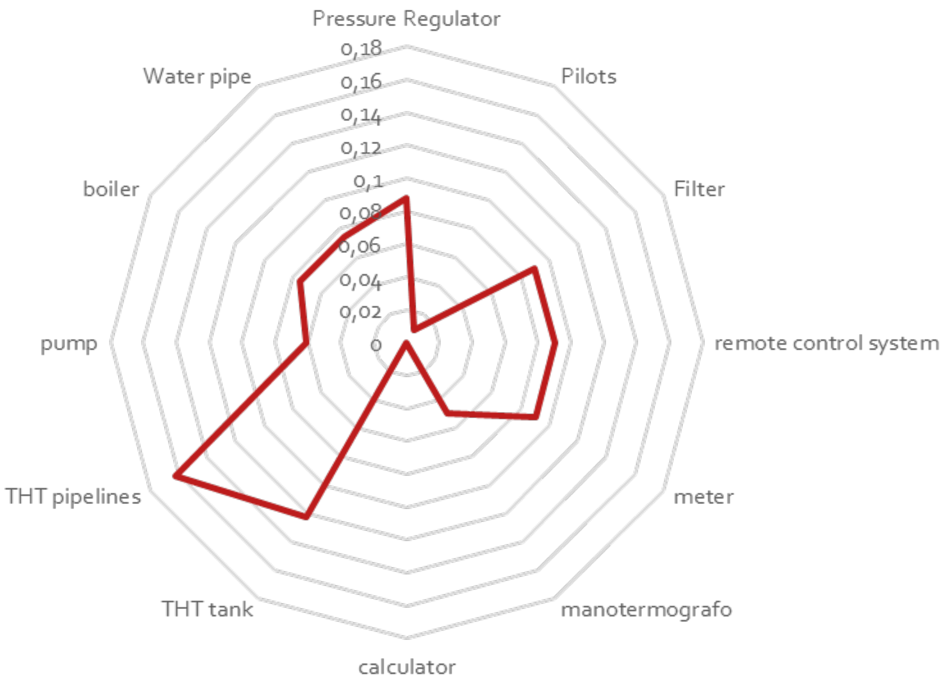


Fig. 5. Radar graph of the probabilities of failure based on actual data

Table 4

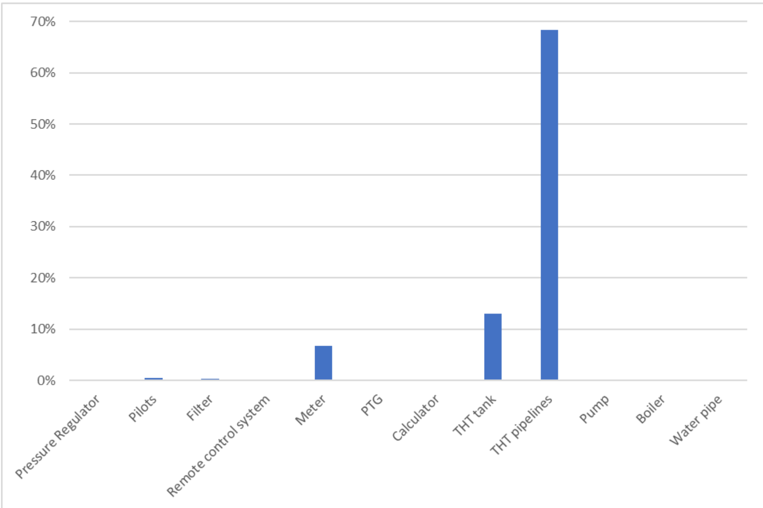
Actual probabilities of failure of NGRMS' main components

Component	Number of failures	Actual probability of failure
Pressure Regulator	17	0,088057642
Pilots	6	0,008580268
Filter	12	0,089947422
RCS	19	0,09021181
Meter	7	0,09020493
PTG	65	0,049217028
Calculator	47	3,13599E-07
THT tank	7	0,122729187
THT pipelines	3	0,162341728
Pump	38	0,061170827
Boiler	23	0,074836274
Water pipe	25	0,07489807

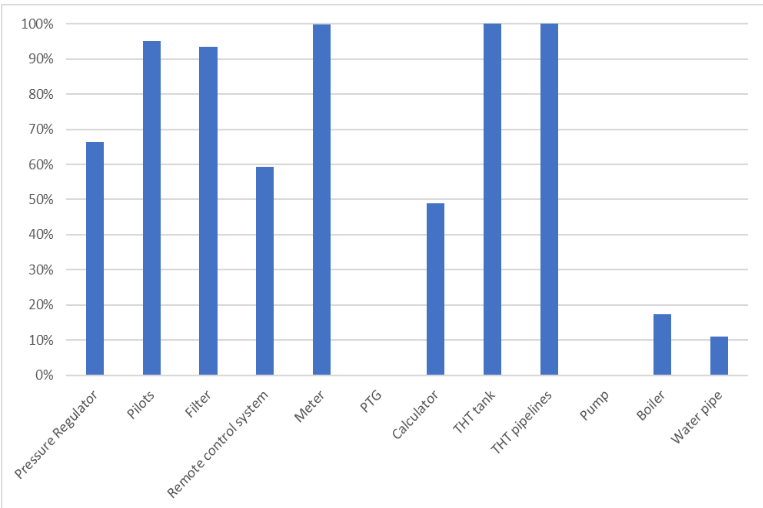
Cumulative binomial distribution, shown in Eq. 6 is adopted to predict the probability of having a certain number of failures, k, during a period of 6 years :

$$P(x \leq k) = \sum_{i=0}^{k} \binom{n}{i} p^{i} (1-p)^{n-i} \quad (6)$$

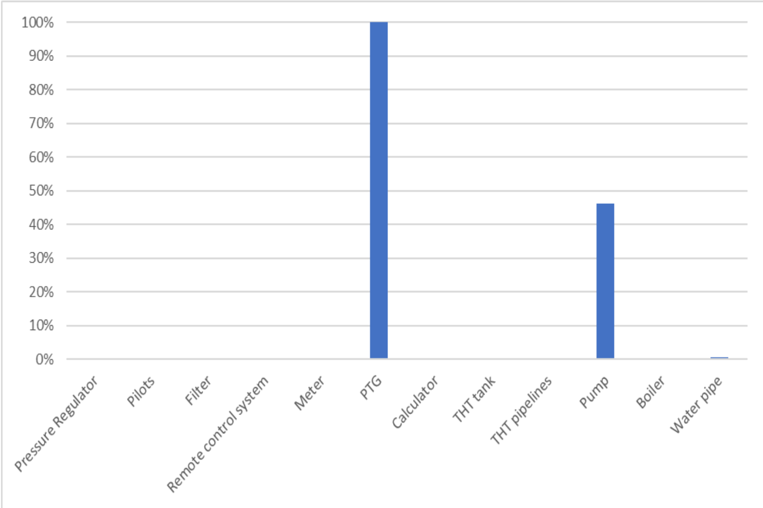
Where $P(x \leq k)$ is the probability of getting k or less successes, given as safety incidents, n is the number of trials and p is the single trial probability of success. Accordingly, in order to analyse the process, three different conditions of having less than 5 and 20 and more than 40 failures was investigated. The associated results can be observed in Table 5 and Fig. 6 (a), (b) and (c).



(a)



(b)



(c)

Fig. 6. Clustered column chart of NGRMS' main components' probabilities of having less than 5 failures (a), less than 20 failures (b) and more than 40 failures (c).

Table 5

NGRMS' main components' probabilities of having less than 5 failures, less than 20 failures and more than 40 failures.

Component	**P(k ≤ 5)**	**P(k ≤ 20)**	**P(k ≥ 40)**
Pressure Regulator	0,000178062	0,664151518	6,37318E-06
Pilots	0,005445434	0,951421387	3,8032E-09
Filter	0,003771095	0,933962743	1,06297E-08
RCS	9,54773E-05	0,592192015	1,67677E-05
Meter	0,067258651	0,998420817	1,74749E-13
PTG	3,02696E-22	3,67679E-11	0,99957092
Calculator	3,91467E-05	0,489273157	5,83481E-05
THT tank	0,12972164	0,999679752	2,77556E-15
THT pipelines	0,683551671	0,999999979	0
Pump	3,883E-12	0,000355429	0,462267322
Boiler	1,15242E-06	0,173480275	0,00239217
Water pipe	3,28878E-07	0,109123256	0,006303059

Scrutinizing the probabilities of having less than five failures reflected that THT pipelines and THT tank have the highest probabilities of failing at most 5 times, respectively equal to 68% and 13%. Followed the meter characterized by a probability of almost 7%, while for the other components is very unlikely to obtain less than 5 failures during 6 years of operations. Next, the probability of getting less than 20 failures underlined that aside from two components, PTG and Pump, the other components, pilots, filter, meter, THT tank, THT pipelines, are expected to experience at most 20 failures by a probability of 90%. Finally, the probability of having more than 40 failure events depicts that the PTG and the pump have the only relevant probabilities of more than 99% and 46% respectively, while the rest of components are characterized by a probability of lower than 1%. Overall, based on this study, it can be inferred that among the observed components, THT pipeline and PTG are the components predicting to have the lowest and highest number of safety incidents. For the purpose of quantifying higher level of uncertainties, the inverse cumulative binomial distribution, illustrated in Eq. 7, is established.

$$F(u; n, p) = k \tag{7}$$

Where n is the number of trial, p is the probability of success of the single trial, k is the smallest integer such as that:

$$u \leq \sum_{i=1}^{k} \binom{n}{k} p^{i} (1-p)^{n-i} \tag{8}$$

u is the probability of getting k or less successes, given as safety incidents, in n trials. Accounting the cumulative probabilities as 5%, 50% and 95%, the corresponding number of successes were derived. The outcomes arising from the calculations are shown in Table 6, Fig. 7:

Table 6

Number of failures corresponding to cumulative probabilities of 5%, 50% and 95%

Component	5%	50%	95%
Pressure Regulator	12	19	26
Pilots	8	14	20
Filter	9	14	21
RCS	13	19	27
Meter	5	10	15
PTG	53	66	79
Calculator	14	21	29
THT tank	4	9	14
THT pipelines	1	4	8
Pump	30	40	51
Boiler	17	25	34
Water pipe	19	27	36

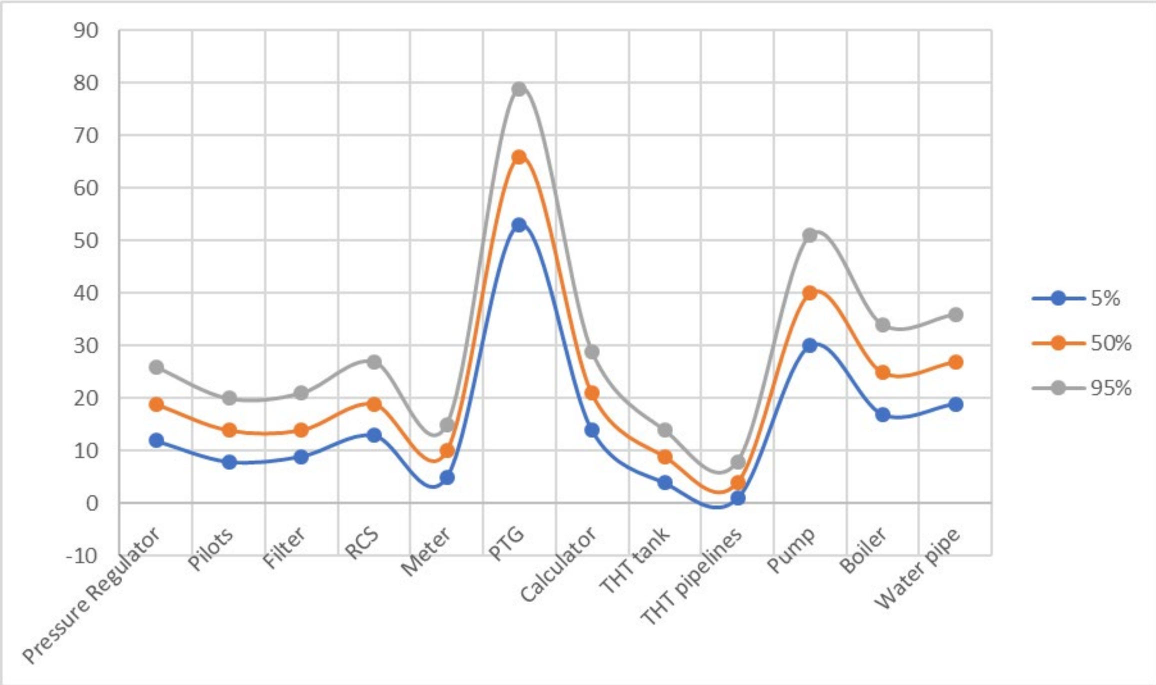


Fig.7. Expected number of failures corresponding to cumulative probability of 5%, 50% and 95%

In accordance with Cumulative binomial modelling, the inverse binomial predicted that the PTG is expected to fail more than other components, between 53 and 79 times with a confidence interval of 90%. following to PTG, pump is characterized by a number of failures between 30 and 51 with the same confidence interval. On the contrary THT pipelines and THT tank are the components that require less maintenance efforts as THT pipelines is expected to have between 1 and 8 maintenance actions, while the THT tank is foreseen to fail between 4 to 14 times.

3.3. Risk Analysis

Based on aforementioned severity classification through section 2.3, the C-RPN is calculated by taking the cost of the failure (C), the severity of effect (S) and the occurrence probability (O) into consideration, as shown in Eq. 9:

$$C - RPN = C * S * O \tag{9}$$

Where S and O are integer given by Table 7 and Table 8 respectively. To make a difference between the failure consequences e.g., whether given failure has a reputation loss or asset loss, the cost associated with failures has been viewed for each component. Costs provided by industry (ESTRA, 2016) are transformed into dimensionless values through the pump failure cost with a failure cost of 10,000€. It emerges that the components characterized by the highest cost are the THT tank and the THT pipelines (a THT leakage can plague the air of a huge area). On the other side the pump failure has the lowest cost, followed by the boiler and the water pipe. Costs related to the calculator, PTG and meter failures are mainly due to legislative penalties. RCS failure has the highest cost among the measuring system components. At last the cost of failures of pilot, pressure regulator and filter failures are mostly characterized by the costs of the components.

Table 7

Likelihood criteria ranking

Occurrence	Occurrence probability	Component
1	<1 in 30,000	Pilot
2	1 in 25,000	Pressure regulator, THT pipelines
3	1 in 20,000	Meter
4	1 in 10,000	Filter, THT tank
5	1 in 5,000	RCS, calculator, boiler, pump
6	1 in 3,000	Water pipe
7	1 in 2,000	
8	1 in 1,000	PTG
9	1 in 500	
10	1 in 20	

Table 8

Consequence criteria ranking

Severity	Severity of effect	Component
1	No effect	
2	Very minor effect on production	Water pipe, PTG
3	Minor effect on production	Pump, meter, calculator
4	Small effect on production, repair not required	
5	Moderate effect on production, repair required	Boiler
6	Component performance is degraded	RCS
7	Component is severely affected, NGRMS may not operate	Filter
8	Component is inoperable with loss of primary function	Pilot, pressure regulator
9	Failure involves hazardous outcomes	THT tank, THT pipelines
10	Failure is hazardous and occurs without warning, NGRMS operation is suspended	

Based on S and O the components can be inserted into the risk matrix shown in Table 9:

Table 9

Adopted risk matrix

		Consequences									
		1	2	3	4	5	6	7	8	9	10
Likelihood	10	31	35	65	67	70	74	91	93	96	100
	9	30	34	39	66	69	73	78	92	95	99
	8	29	33	38	43	68	72	77	82	94	98
	7	7	32	37	42	47	71	76	81	86	97
	6	6	13	36	41	46	51	75	80	85	90
	5	5	12	18	40	45	50	55	79	84	89
	4	4	11	17	22	44	49	54	59	83	88
	3	3	10	16	21	25	48	53	58	62	87
	2	2	9	15	20	24	27	52	57	61	64
	1	1	8	14	19	23	26	28	56	60	63

The predicted posterior mean value of probability of failure for each component, stated through Table 3 was accounted to determine their likelihood criteria. Assuming each failure of the components as a failure mode, the consequences arising from a failure were found via FMECA. Accordingly, the likelihood criteria ranking noted as occurrence, the consequence criteria ranking stated as severity, the risk matrix number, the cost and finally the C-RPN of each component are listed in Table 10.

Table 10

Occurrence (O), Severity (S), risk matrix number (RM), dimensionless cost and C-RPN for each component

Component	**O**	**S**	**RM**	**Dimensionless Cost**	**C-RPN**
Pressure Regulator	2	8	57	4	64
Pilot	1	8	56	4	32
Filter	4	7	54	2	56
RCS	5	6	50	6	180
Meter	3	3	16	10	90
PTG	6	2	13	2	24
Calculator	5	3	18	2	30
THT tank	4	9	83	33	1188
THT pipelines	2	9	61	33	594
Pump	5	3	18	1	15
Boiler	5	5	45	5	125
Water pipe	8	2	33	7	112

Based on the estimated C-RPN, components are classified into three different categories as shown in Table 11:

1. Critical components: components with high C-RPN of more than 500
2. Emergent components: components with medium C-RPN of more than 100 and less than 500
3. Immaterial components: components with low C-RPN of less than 100

Table 13

Critical Components (high C-RPN), Emergent Components (medium C-RPN) and Immaterial Components (low C-RPN)

Critical components	Emergent Components	Immaterial Components
THT tank	RCS	Pressure regulator
THT pipelines	Boiler	Pilot
	Water pipe	Filter
		Meter
		PTG
		Calculator
		Pump

With a striking difference of C-RPN, THT tank and THT pipelines have been evaluated as critical components. Accordingly, odorization group has been given as the most critical group since both components belong to this group. To avoid big losses, either reputational or physical, the maintenance of these two components has to be prioritized. On the other side, with lowest C-RPN, filter, PTG, calculator, pump, pressure regulator, meter and pilot have been characterized as immaterial components. Finally, RCS, boiler and water pipe are included in the intermediate group due to their medium C-RPN. These components can be treated as the critical components or the immaterial components depending on the maintenance policies.

5. Conclusions

This paper presents a novel methodology capable of prioritizing maintenance actions based on the risks arising from failures. NGRMS was chosen as a case study to prove the applicability and show the advantages of the proposed framework. The occurrence analysis conducted via HBM and the severity analysis performed by FMECA are the main parts of present study. In the first part useful information about future number of failures are gathered to estimate the efforts that the different components require. In the last part, through a combination of cost, occurrence and severity the C-RPN is calculated for each component and based on their respective values the components are divided into three different categories. The three classes underline which are the most critical components whose maintenance has to be prioritize for minimizing operation risks. Further development could include Non-Homogeneous Poisson Process (NHPP) calculation, considering correlation between data.

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