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04 May 2026

A Condition Monitoring Based Signal Filtering Approach for Dynamic Time Dependent Safety Assessment of Natural Gas Distribution Process

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Abstract

Condition monitoring of natural gas distribution networks is a fundamental prerequisite for evaluating safety of the operation during the lifetime of the system. Due to the high level of uncertainty in the observed data, predicting the operational reliability of the networks is complicated. Moreover, there is a fluctuation in most of the monitoring data in different time scales, as most of the derived data tend to be of non-stationary nature and are complex to model or forecast. Therefore, a more realistic data driven approach for developing a reliability framework needs to be considered. This paper aims at proposing a probabilistic model to predict the complexity of the non-stationary behaviour in monitoring data. It also aims at developing a novel framework for the time dependent reliability assessment of a natural gas distribution system using condition-monitoring data. To this end a methodology by integrating Empirical Mode Decomposition (EMD) and Hierarchical Bayesian Model (HBM) is developed. The advantages of the methodology are demonstrated through a case study of a Natural Gas Regulating and Metering Station operating in Italy. Based on pressure data acquired from the case study, the model is able to predict overpressure thus directly avoiding unnecessary maintenance and safety consequences.

Keywords

Condition monitoring, Time dependency assumption, Empirical Mode Decomposition (EMD), Hierarchical Bayesian Model (HBM), Noise

1. Introduction

Natural gas operational facilities and distribution networks are associated with potential hazards, which pose a threat not only to the workers, but also to the people living around the facilities. Natural gas is considered as the cleanest burning fossil fuel which supplies more than 20% of energy consumption to the European Union [1]. A great deal of ongoing effort is made to increase the operational reliability of the natural gas networks by considering real-time condition monitoring of their subsystems. For conducting realistic real time monitoring of the networks, identifying the convenient Process Variables (PVs) is necessary to obtain a safe operation.

Different damages such as cumulative damage, fault damage zone, etc. occur gradually or suddenly [2]. Sudden damage is defined as an undetected steady deterioration trend in the system. Therefore, owing to the rise in the components' wear, regular observation of conditions must take place to detect the gradual deterioration [3] and achieve suitable predictive maintenance decisions according to the deterioration trend [4]. Considering the previous researches on Condition Monitoring (CM) in engineering systems, different statistical approaches have been developed to investigate the performance of systems under the associated uncertainties [5-9]. The CM maintenance paradigm has received significant development in recent decades, although a longstanding gap continues to exist as there is still lack of a unified model to capture the effect of noise on the raw data, and also the associated uncertainty with time-variant parameters.

The classical models of time series data [10], such as Auto Regressive Moving Average (ARMA) models, regression methods (e.g. Least Squares Regression (LSR)), and statistical process control (SPC) methods have been widely used by different researchers. For instance, Carden and Brownjohn [11] presented a sound physical basis for forming ARMA models of structural response data. Nair et al. [12] applied ARMA to analytical and experimental outcomes of the American Society of Civil Engineering (ASCE) benchmark structure to detect and locate damaged signals. Pham and Yang [13] proposed the hybrid model of ARMA and generalized autoregressive conditional heteroscedasticity (GARCH) to predict the machine state based on vibration signal. Kruger and Dimitriadis [14] developed fault diagnosis scheme to extract the fault signature by applying local Partial Least Square (PLS) model. Wang et al. [15] presented an application of recursive partial least squares (RPLS) algorithms together with adaptive confidence limits to reduce the number of false alarms. Zhou et al. [16] integrates the statistical process control technology and the Haar wavelet transform for cycle-based waveform signal to detect a process degradation and to estimate the magnitude of mean shifts.

These approaches focused on evaluating the health condition of considered system over time. However, neither of these models are practical for data with non-stationary and nonlinear nature. ARMA models are applicable to stationary time series data without identifying any long term trends. In the application of statistical regression method, the predicted trend is predetermined since the form of the data should be specified prior to performing a prediction. LSR and SPC are subject to the same drawback and need a pre-specified form that representing the trend. In the case of SPC especially, the level of noise is assumed to be small and data are given to be distributed normally.

The raw data collected from observations in condition monitoring of gas pipelines consists of non-stationary trends, short term cycle and noise. As the noise has a complex time-dependent auto-correlation structure, Empirical Mode Decompositions (EMD) is recommended in recent studies as a suitable statistical method to extract the disturbing noises from the time series. EMD has been successfully applied in different fields, from engineering to climate science and tourism challenges, in order to predict the long-term trend of the observed data with a minimum trace of noise. The model is particularly useful for degradation modeling and for gaining useful knowledge for future decision making strategies [17-20].

Li and Pandey [21] presented EMD as a statistical algorithm method for condition monitoring, able to isolate the noise and diagnose the ongoing degradation process by recognizing the long-term trend. Although in previous studies, the noise is extracted from the non-stationary data, the long-term trend is considered as the complement of fluctuation trend which can be either mean trend or a constant. This provides uncertainty in the long-term trend, since the correlation and variability of data is not observed over time. Therefore, an appropriate probability model is necessary to consider the time dependency of the data. HBM is a probabilistic tool which incorporates the information on various types of uncertainties over time. HBM is considering the nonlinear nature of the observed data via Markov Chain Monte Carlo (MCMC) sampling. It has been widely used in different fields including probabilistic risk assessment (PRA) and CM [22-27]. There is also a great deal of research on PRA and CM applying Bayesian inference [28-31]. Likewise, several engineering challenges have been struggled by the extensions of Bayesian approach, i.e., Dynamic Bayesian Network [32-35].

This paper attempts to develop methodology by integrating the EMD and HBM in a systematic framework for dealing with the noise and the uncertainty associated with variability of monitoring data. Given the non-stationary and nonlinear nature of the captured data, the condition of PVs is monitored to predict the likelihood of the variables exceeding the safe operational limit. To this end, nonhomogeneous Poisson process (NHPP) is adopted to model the number of times that PVs pass the safety threshold. A Natural Gas Regulating and Metering Station (NGRMS) operating in Italy is selected as a case study to indicate the advantages of the developed methodology.

The remaining parts of this paper are organized as follows. In section **1**, the aspects of EMD and HBM are treated. The subdivision of methodology is touched upon in section **2**. Section **3** is devoted to the application of the case study, while the conclusion is presented in Section **4**.

1.1. Empirical Mode Decomposition

The raw data is an amalgamation of true signal and noise. Noise is introduced to the data by either data gathering instruments such as sensors or system conditions due to concurrent phenomena. Considering the time-dependent auto-correlation structure of noise, filtering processes are complex and in some cases impossible [36]. As an effective filtering method, EMD is introduced based on Hilbert-Huang Transform [37]. According to EMD method, the time series data is decomposed into a set of functions, known as Intrinsic Mode Functions (IMFs) and a trend known as residual term given by Equation 1 [21]:

$$x(t) = \sum_{k=1}^{n} c_k(t) + r(t) \tag{1}$$

where $c_k(t)$ is k-th IMF, n is the number of sifted IMFs and $r(t)$ is the residue which indicates a long term trend in the process. An extensive review of the sifting process to decompose a time series, including wide range of applications in condition monitoring, is provided by [37]. Each IMF can be either random noise or true signal. Thus, the time series is finally decomposed according to Equation 2.

$$x(t) = \sum_{k=1}^{i} c_{T,k}(t) + \sum_{k=1}^{j} c_{N,k}(t) + r(t) \tag{2}$$

where $c_{T,k}(t)$ and $c_{N,k}(t)$ are a k-th IMF of true and noise data, respectively and $r(t)$ is the residue similarly. As suggested by Wu et al. [39] and Li et al. [21], it is necessary to distinguish and filter out the noise from the raw data by conducting a Statistical Significance Test (SST) on the recorded time series of the process. The idea behind the SST is based on evaluating the energy density and the mean period of determined IMFs [36].

1.2. Hierarchical Bayesian Modelling

Observed data, manipulated information, and gathered knowledge are three consecutive steps of making inference throughout a model. Models have two fundamental types; aleatory and deterministic. Aleatory models are themselves imprecisely known and therefore uncertain. Herein, HBM as one of the most advanced of Bayesian statistical methods, can be applied using open source MCMC software packages such as OpenBUGS [38] to describe aleatoric uncertainty. Subsequently, the associated uncertainty with variability of the observations existing among the data source is to be properly represented by the resulting posterior distribution [23] given by Equation 3.

$$\pi_1(\theta|x) = \frac{f(x|\theta)\pi_0(\theta)}{\int_\theta f(x|\theta)\pi_0(\theta)d\theta} \tag{3}$$

where θ is the unknown parameter of interest, $f(x|\theta)$ is the likelihood function, and $\pi_1(\theta|x)$ is the posterior distribution. Hierarchical Bayes utilizes multistage prior distribution for the parameter of interest indicated $\pi_0(\theta)$ [23] as follow:

$$\pi_0(\theta) = \int_\emptyset \pi_1(\theta|\varphi)\, \pi_2(\varphi)d\varphi \tag{4}$$

where, $\pi_1(\theta|x)$ denotes the first-stage prior as the population variability in θ; φ is a vector of hyper-parameters, e.g., $\varphi = (\alpha, \beta)$, while α and β are the shape and scale parameters of a Weibull distribution respectively. The uncertainty in φ is represented by $\pi_2(\theta)$ as the hyper-prior distribution. An informative prior distribution, $\pi_0(\theta)$, is developed using generic data collected from different sources (numerical simulations, experiments or collected from different industrial sectors) to estimate the posterior distribution [28].

2. Methodology: Time Dependent Reliability Assessment

To predict the existing health condition of the gas distribution, an integrated approach is proposed to conform EMD and HBM in a unified framework. Although EMD is ideally appropriate for analyzing data of non-stationary and nonlinear nature, it still cannot resolve the most complex cases, e.g., nonlinear process in which the noise also has the same time-scale as the signal [36]. Accordingly, to model the remaining uncertainty in noise extracted time series data, HBM is adopted. The developed methodology eliminates random noise emerging from monitored data and reduces the uncertainty involved in the engineering process. The developed methodology includes two different parts, as presented in **Fig. 1**. A detailed description of these parts is provided in the following sections. The developed framework in this study could be used in different engineering contexts to compute the failure rates. It would also be a base for further development on risk-based maintenance scheduling optimization.

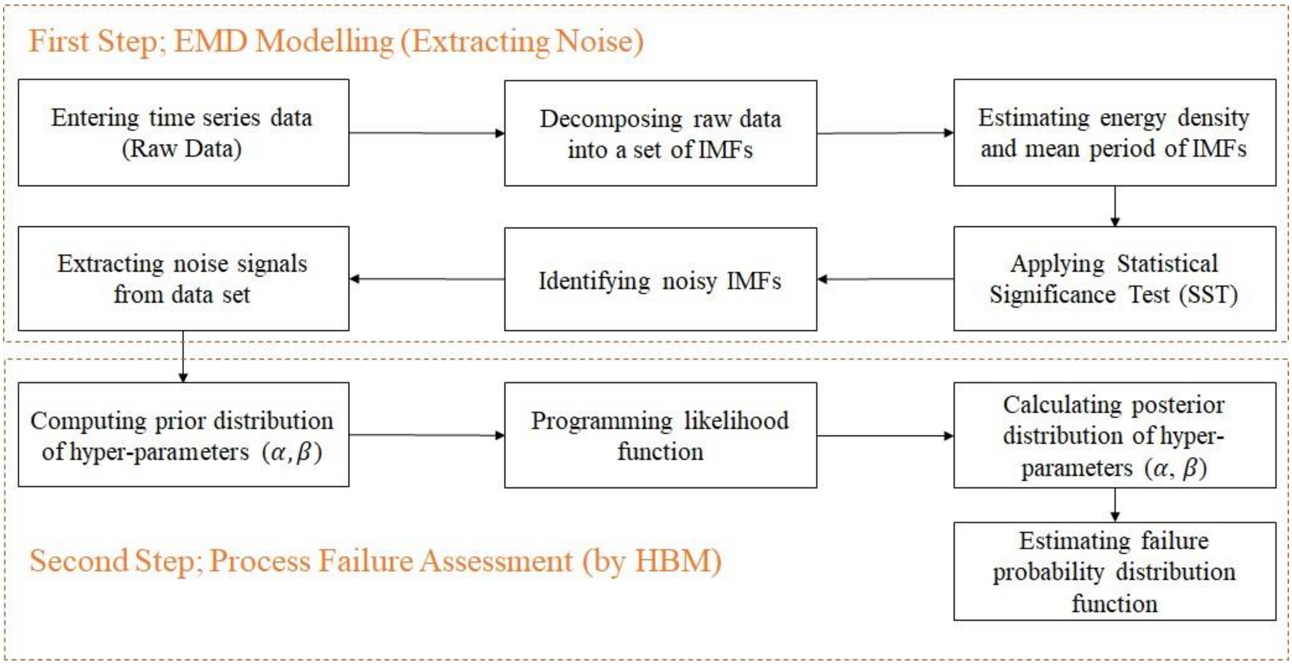


Fig.1. Developed methodology for time dependent reliability assessment of gas distribution networks

2.1. EMD Modelling

Appropriate signal processing techniques must be applied for acquiring and processing the raw data to estimate the states of the system. The acquired raw data is generated either from engineering PVs, such as pressure, or environmental conditions such as temperature. The EMD is adopted in developed methodology to extract the random noise from nonstationary and nonlinear raw data. To this end, the considered time series data is decomposed into its IMFs and a long term trend. Considering mean period and energy density of each IMF, the SST will be carried out correspondingly. Mean period of the kth IMF, T_k , is given by Equation 5.

$$T_k = \frac{m}{P_k} \tag{5}$$

where m is the number of raw data points and P_k indicates number of peaks in the kth IMF, c_k . The general properties of the energy density is considered as function of period for the data [36] and is given by Equation 6.

$$E_k = \frac{1}{m} \sum_{j}^{m} |c_k(j)|^2 \tag{6}$$

where E_k is the energy density of the kth IMF. Similar to the mean period, m denotes the number of data points and $c_1(j), \dots, c_n(j), j = 1, \dots, m$ are n IMFs. In order to identify the noisy IMFs, the SST is applied based on mean and variance of the IMFs which are represented by mean period and energy density, respectively. According to previous conducted studies, there are two substantial beliefs for selecting the first IMF as the main source of the noise in the process [32, 36, 39]. One belief is that the first IMF has the highest order of fluctuations, and the second one is the mean period (T_1) and energy density (E_1) are not much affected by the sampling uncertainty. Wu et al. [39] proposed a hypothesis test for any kth IMF in which the Null Hypothesis is that an IMF, $c_k, k = 2, \dots, n$, is a noisy IMF and the test statistics is ($\ln E_k + \ln T_k$). The confidence interval of this hypothesis is defined by Equation 7.

$$\ln \left(\frac{1}{3} E_1\right) + \ln T_1 < \ln E_k + \ln T_k < \ln (3 E_1) + \ln T_1 \tag{7}$$

Given this SST, noise signals and true signals are those IMFs for which the Null Hypothesis is rejected and accepted, respectively. After identifying and removing the noisy IMFs, the combination of remaining IMFs and the trend function will result in the noise separated signal. This signal will be then used as the input for the second part of the methodology for investigating the exceedance times and frequencies.

2.2. Process Failure Assessment

An operational limit should be taken into account to preserve the process in a safe condition during the operation. For this purpose, the times that the operation enters the unsafe zone is recorded considering the noise separated data. These observations are given as the input for predicting the likelihood of safety threshold exceedances. To model the uncertainty in a process, it is more realistic to indicate the correlation of monitoring data in a time series. Unlike a renewal process, that presumes that the inter-arrival times of an observation data are independently and identically distributed (iid), Nonhomogeneous Poisson Process (NHPP) is based on the assumption that i^{th} time-step (t_i) is dependent on the value in previous time-step, t_{i-1}. Therefore, in this study, the exceedance rate of safety limit, $\lambda(t)$, in a time series is modeled by NHPP. Consequently, the expected number of exceedances through the specific time interval, $[t_n, t_{n+1}]$ in the process, $E(NE)$, is given by Equation 8.

$$E(NE) = \int_{t_n}^{t_{n+1}} \lambda(t)dt \tag{8}$$

where an appropriate function for $\lambda(t)$ must be determined to represent the rate of exceedance limit accordingly. To develop an appropriate function for the exceedance rate of safety limit, power-law, log-linear and linear models are recommended by previous researchers [23, 40]. In order to predict the nonlinearity of random process more precisely in comparison with linear modelling, the power-law is taken into account for this study (see Equation 9) as suggested by different researchers [23, 27].

$$\lambda(t) = \frac{\alpha}{\beta}(\frac{t}{\beta})^{\alpha-1} \tag{9}$$

Constant model (Equation 10) and linear model (Equation 11) are conjugate to power-law function; considering power-law function, the constant model can be included by $\alpha = 1$.

$$\lambda(t) = \frac{1}{\beta} \tag{10}$$

and by $\alpha = 2$, the linear model can be produced which is typically addressed by:

$$\lambda(t) = \alpha + \beta t \tag{11}$$

The time to first exceedance of safety limit based on the power-low process generates a Weibull distribution, (t, β, α) , with shape parameter, α, and scale parameter, β, given by Equation 12 [23].

$$f(t, \beta, \alpha) = \frac{\alpha}{\beta}(\frac{t_1}{\beta})^{\alpha-1} \exp[-(t_1/\beta)^{\alpha}] \tag{12}$$

The observation process will be performed by conducting a failure-truncated approach as recommended by [23]. In order to reflect the dependency of times in which the PV exceeds the safety limit, a conditional probability must be defined for each desired time interval $[t_{i-1}, t_i]$ by using Equation 13 [41].

$$f(t_i|t_{i-1}) = f(t_i|T_i > t_{i-1}) = \frac{f(t_i)}{\Pr(T_i > t_{i-1})} \tag{13}$$

where T_i is the observed exceedances time of the safety limit for a considered PV. Consequently, the truncated Weibull distribution based on the power law function, Equation 14 would be achieved.

$$f(t_i|t_{i-1}) = \frac{\alpha}{\beta^{\alpha}}(t_i)^{\alpha-1}\exp[-\left(\frac{t_i}{\beta}\right)^{\alpha} + \left(\frac{t_{i-1}}{\beta}\right)^{\alpha} \tag{14}$$

where, $i = 2, \dots, n$, and subsequently the likelihood function is given by using Equation 15.

$$f(t_1, t_2, \dots, t_n|\alpha, \beta) = f(t_1)\prod_{i-2}^{n} f(t_i|t_{i-1}) \tag{15}$$

α and β are modelled by HBM to represent the population variability of exceedances time of the safety limits in an operation. It is worth noting that α and β as the hyper-parameters are independent, prior to the observation of the data. Once, an operational variable is observed, these parameters would be dependent. Using Openbugs, the marginal posterior distributions as well as statistics of hyper-parameters are executed by MCMC sampling from their joint distribution. The likelihood function provided by using Equation 15 is not pre-programmed into Openbugs. While, as suggested by [23], it is possible to create a vector of n array which is assigned to a generic distribution with parameter, φ. By defining $\varphi = log(likelihood)$ given by Equation 16 and considering samples of α and β from the prior distribution in Equation 17, Openbugs can update the parameters in the likelihood function (phi) [27].

$$\varphi = \log(\alpha) - \alpha \times \log(\beta) + (\alpha - 1)\log(t_i) - (t_n/\beta)^{\alpha}/n \qquad (16)$$

where t_n and t_i are the last and i^{th} observation of the exceedances event in the simulation, respectively, and n is the vector size. Diffusive Gamma distribution is applied independently for the prior distribution of hyper-parameters, α and β, as suggested by [42].

$$\begin{cases} \alpha \sim Gamma(0.0001{,}0.0001) \\ \beta \sim Gamma(0.0001{,}0.0001) \end{cases} \qquad (17)$$

MCMC sampling for $i = 1, \ldots, n$ leads to estimating the updated posterior distribution of hyper-parameters (α, β).

Based on the resulted Weibull distribution, $f(t, \beta, \alpha)$, the failure probability distribution function for each PV will be predicted. This process could be repeated for each PV to control the operation and enhance the operational reliability of a system.

3. Application to a Case Study

Application of the proposed framework is explained by using a practical example of stochastic deterioration process of Natural Gas Regulating and Metering Stations (NGRMS) operating in Italy. Matlab and Openbugs are the available tools applied in this study for execution of the proposed method. The following sections provide a detailed discussion on application of each part of the proposed methodology to the case study.

3.1.Scenario development

NGRMS are set up in a distribution system and are fed by transmission pipelines. They are designed in five main sections; inlet, filter, metering, regulator, and outlet. The basic functions of a NGRMS are to reduce the pressure and to measure the gas flow by regulators and metering devices, respectively. NGRMS are designed with redundant parts to ensure that if one part fails, the entire system will not stop. **Fig. 2** illustrates a typical NGRMS scheme.

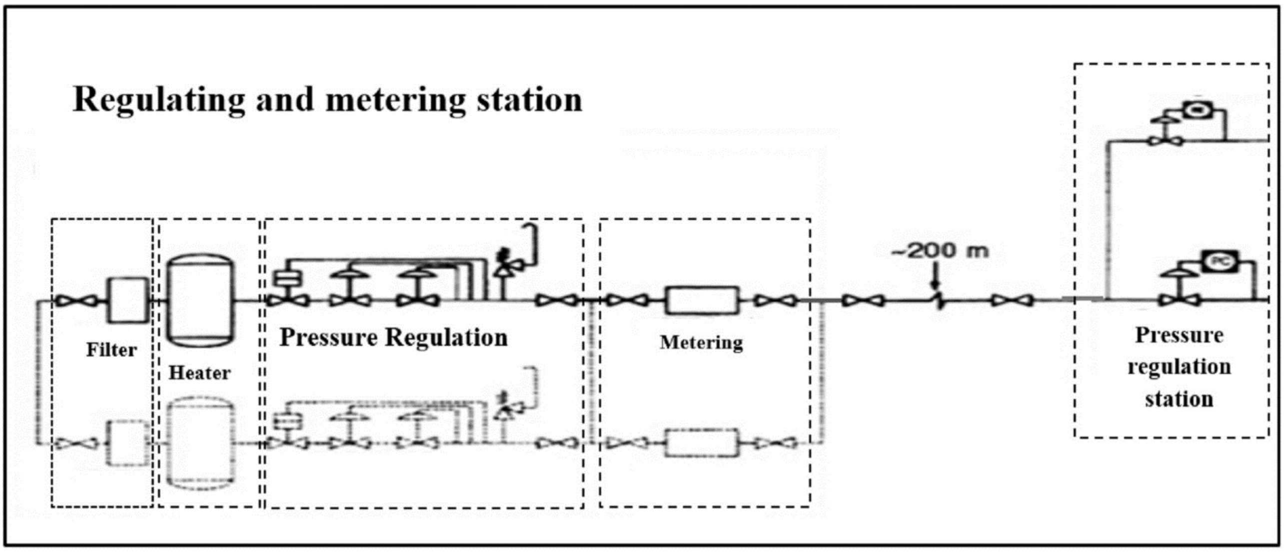


Fig. 2. Typical plan of Natural Gas Regulating and Metering Station [43]

In this study, the pressure is a selected PV to extract the noise and to analyze the potential deterioration process by means of predicting the performance of the network over time.

3.2.EMD modelling of pressure data

The condition monitoring data collected from NGRMS are depicted in **Fig. 3**. This historical data consists of pressure values gathered over 108 weeks and would be used as raw data to extract the noise.

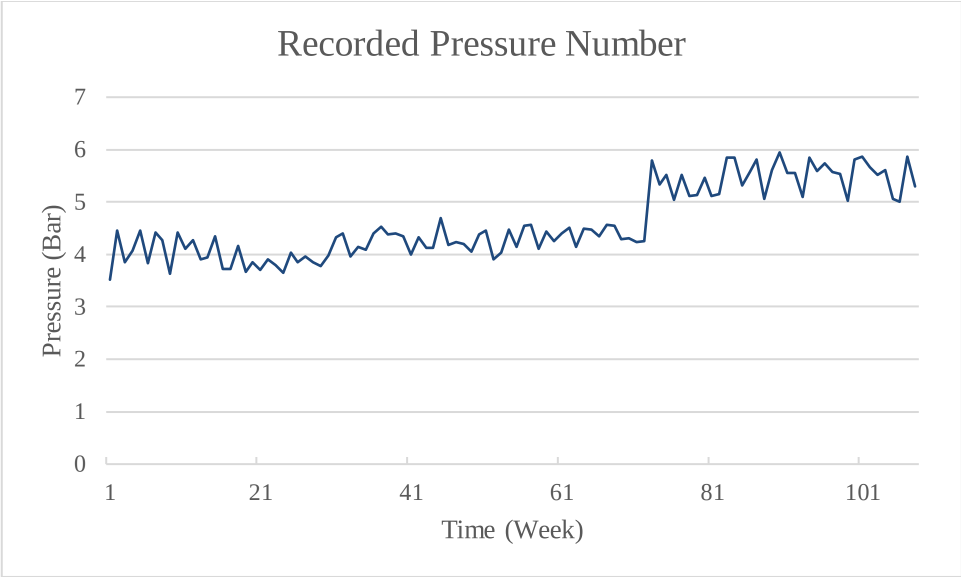
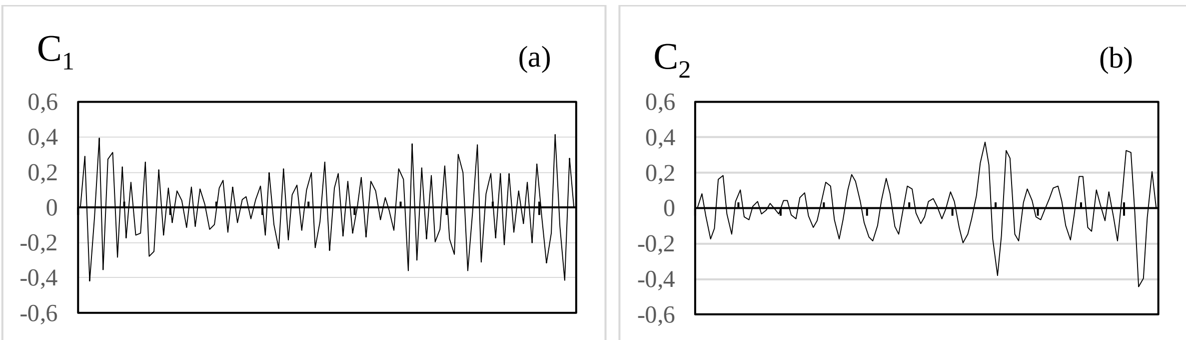


Fig. 3. Pressure data collected from the NGRMS

Applying the EMD method on the empirical time series data led to 6 IMFs and a residual trend (see **Fig. 4**). In order to discriminate noisy IMFs from actual signals, statistical significance test (SST) was taken based on energy density and mean period. **Table 1** gives the energy density and the mean period of each IMF. Based on the application of the SST, the first two IMFs, c_1 and c_2 were recognized as noise signals (see **Fig. 5**). So the four remaining IMFs, $c_3 - c_6$, are actual signals.

The long term trend function illustrates that the pressure values are increasing over time. However, since correlation modelling between data are not considered, this trend is not reliable.



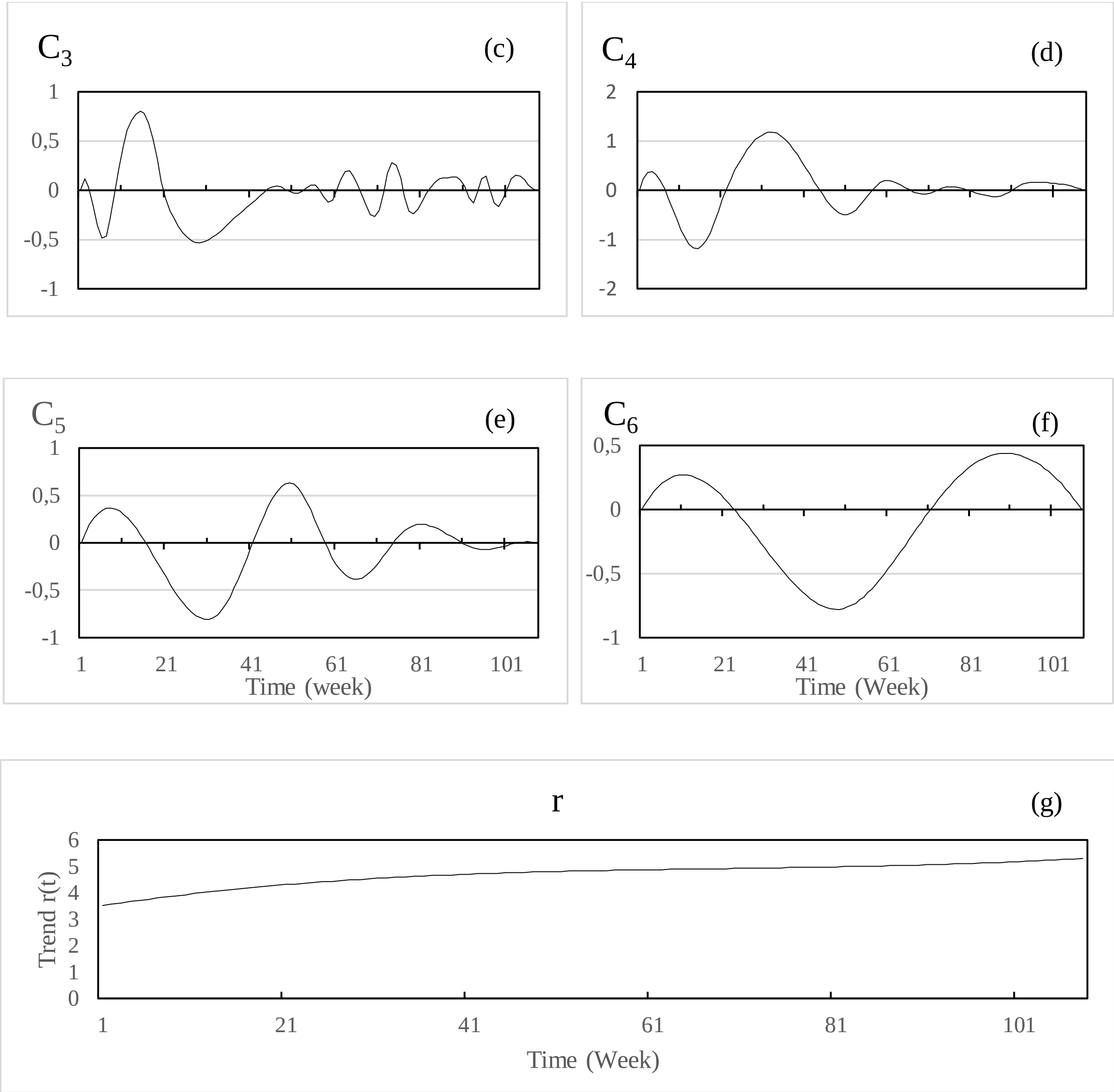


Fig. 4. Estimated IMFs (C_1, C_2, C_3, C_4, C_5, C_6) and the residue function (r) of pressure in time series

Table 1. Energy density and mean period of IMFs for pressure data

***kth* IMF**	**E_k [(mgKOH/g)^2]**	**T_k (week)**
1	0.0398	2.7
2	0.0203	4.909
3	0.0800	12
4	0.2578	21.6
5	0.1277	27

6	0.1659	54

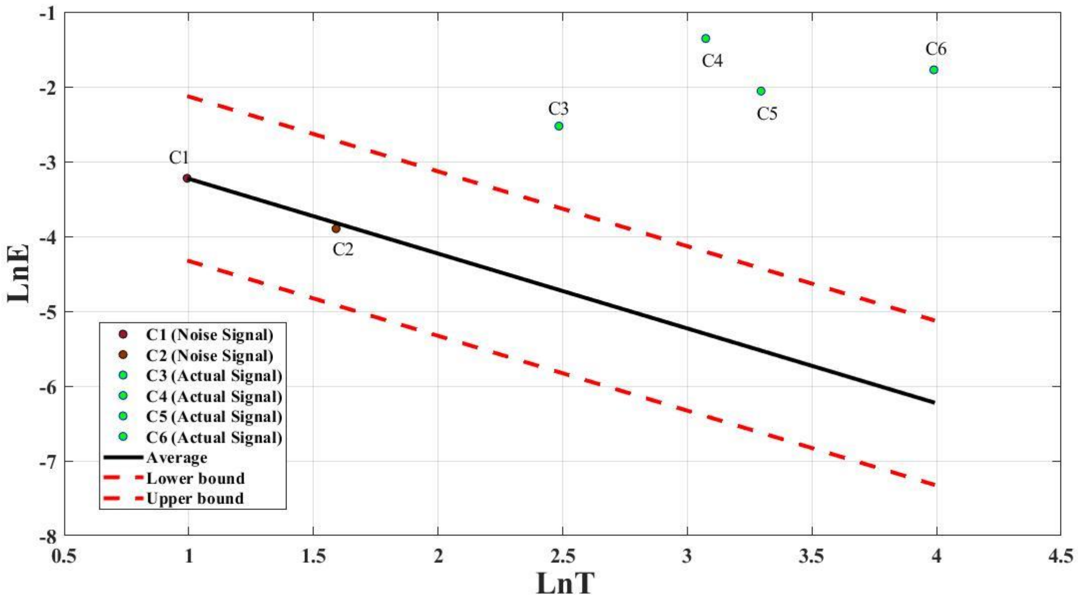


Fig. 5. SST adopted to the decomposed IMFs of pressure data to identify the noise signals

The total noise signals extracted from the raw data are depicted in **Fig. 6**. A comparison between mean and standard deviations of noise signals and actual signals (presented in **Table 2**) proved that EMD is remarkably effective for extracting the noise. **Fig. 7** shows this comparison by true signal (defined as a summation of noise signals and actual signals) and noise separated signal in time series.

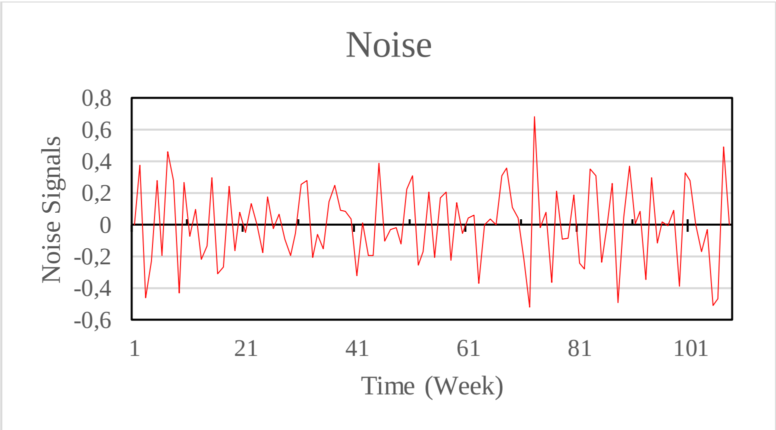


Fig. 6. The superimposed noisy signals extracted by EMD

Table 2. Statistical Summary of the noise and true signals derived from EMD

Signal	Mean	Standard deviation
Noise separated signal	-0.0875	0.4478
True signal	-0.0855	0.5003

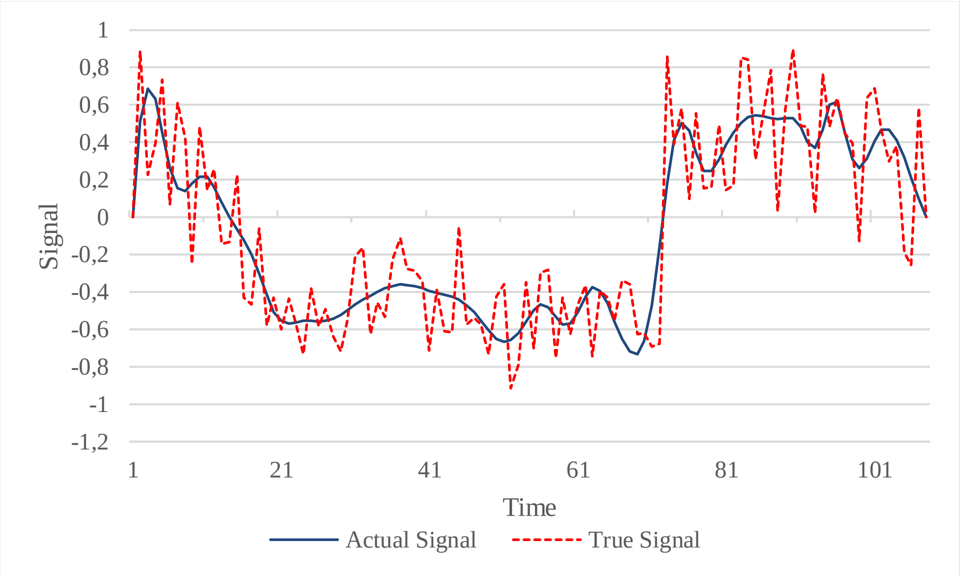


Fig. 7. Comparison of True Signal (actual signal and noise signal) and actual signal (noise separated signal)

In order to estimate the Noise Separated Signal (NSS), the noisy IMFs were removed from the monitoring data and then the remaining IMFs (C3 to C6) and long term trend function (r) are subsequently superimposed. **Fig. 8** represents the NSS graph along with raw monitoring data and trend function. The NSS is the final filtered signal which is considered as the input for the failure assessment of the process in the second part of the framework.

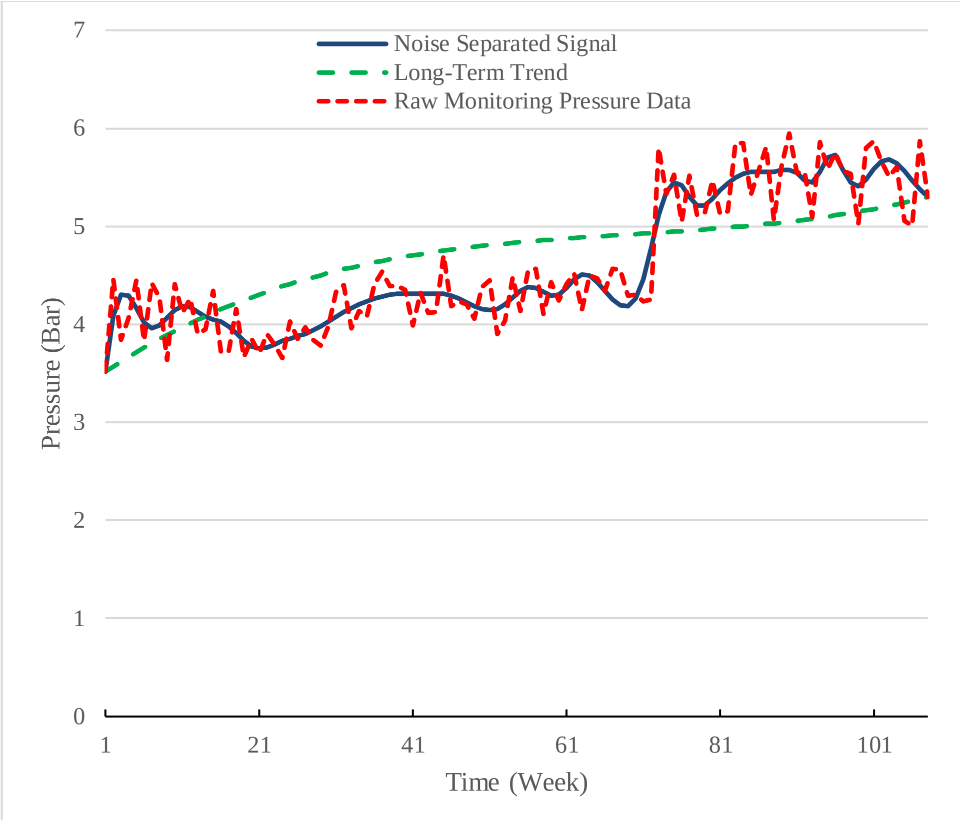


Fig. 8. Pressure time series data after noise separation

3.3. Failure assessment: Hierarchical Bayesian Model

In order to evaluate performance of the operation over time, a safety limit was assigned according to the Italian National Gas distribution regulations [44]. Based on the characteristics of the selected NGRMS, an output pressure bound of [4,5] bar, was determined as the safety limit. Considering the noise separated pressure data, the number of times that the pressure exceeded safety limit were recorded. These observations were then entered into the HBM in order to estimate the likelihood function and calculate the posterior probability of the Weibull parameters, α and β. To this end, three chains were used by the MCMC simulation to check the convergence and to predict the posterior distribution of the parameters (α , β). Each chain started from a separate point with 300E+03 iterations, so a total number of 900E+03 iterations was established. **Fig. 9** illustrates the iteration history of the shape parameter, α. The results for the estimated posterior probability of α, as well as the correlation between Weibull parameters (α , β) are plotted in **Fig. 10**. Furthermore, the summary of estimated marginal posterior distribution for α , β and the expected value for the First Time to Exceed (FTE) of safe limit are listed in **Table 3**. FTE is interpreted as the first sign of gradual degradation in the process.

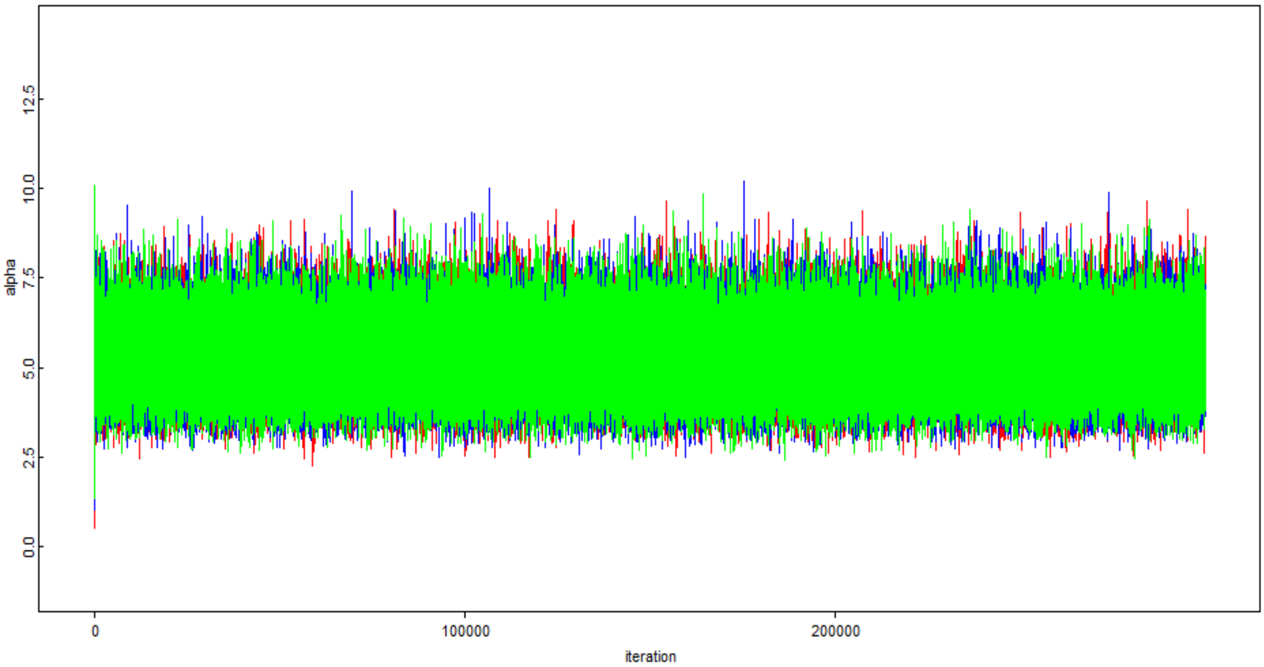


Fig. 9. Iteration history of three chains for posterior estimation of shape parameter

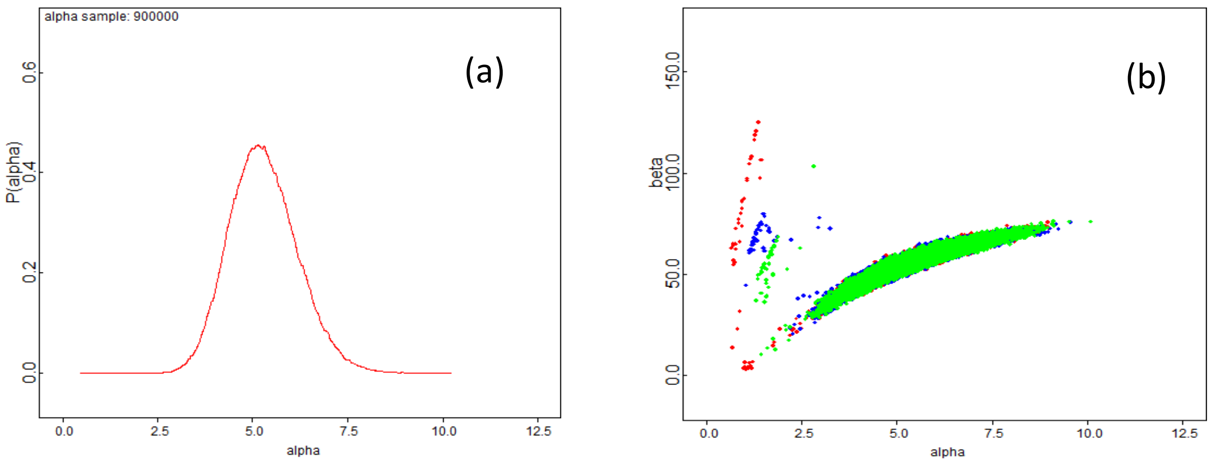


Fig. 10. Posterior distribution of Weibull shape parameter, α (a) and the correlation between α and β, (b)

The posterior mean value of α is 5.29 with a 95% credible interval of (3.68, 7.17). The shape parameter value is higher than one, inferring the number of times entering into unsafe limits for pressure, are increasing with time. The statistics for the posterior β, were evaluated as a mean value of 54.36 with a 95% credible interval of (40.59, 66.19). Thereby, probability of pressure exceedance of safe limit in NGRMS operation is computed according to the estimated uncertainties; and the cumulative density function (CDF) illustrated in **Fig. 11**. The lower and upper percentile of FTE accounted for were 36.62 % and 61.996 %, respectively. The expected value of FTE was estimated at 50.07 week which means the first exceedance is expected to occur in the 50th week.

Owing to relaxing the renewal process assumption (constant failure rate) and taking the time dependency of the observed data into account, the proposed framework can model the pressure exceedance from the safety limit more precisely.

Table 3 Statistical summary of the Weibull parameters

	α			β			FTTF		
	mean	2.5 percentile	97.5 percentile	mean	2.5 percentile	97.5 percentile	mean	2.5 percentile	97.5 percentile
HBM	5.293	3.683	7.176	54.36	40.59	66.19	50.075	36.621	61.996

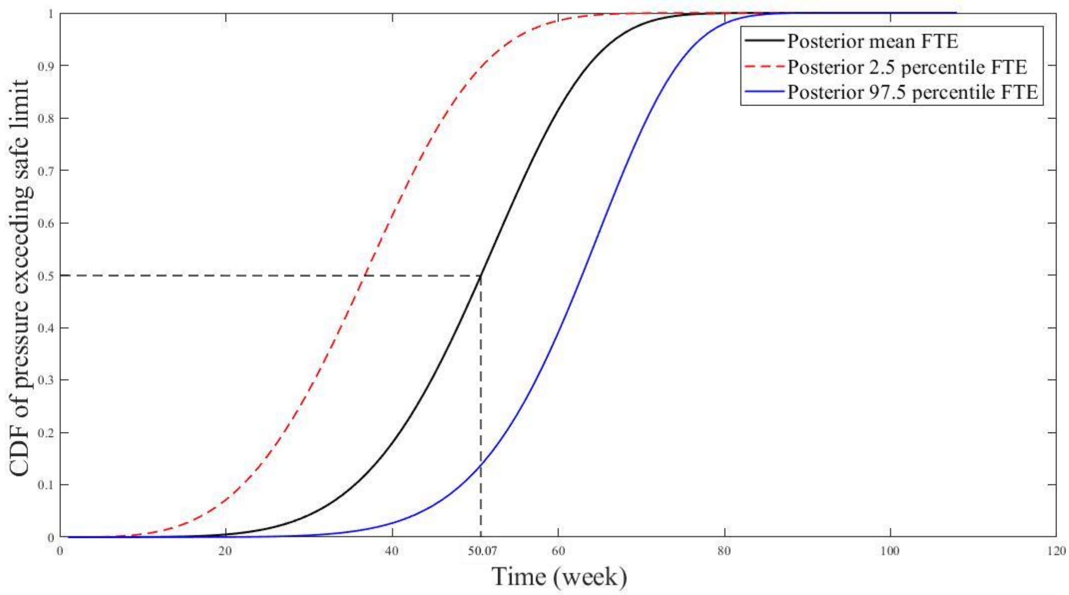


Fig. 11. CDF of pressure exceedance of the recognized safety limit for the selected NGRMS

4. Conclusion

The uncertainties associated with the deterioration of natural gas distribution networks require a sound condition monitoring methodology for reliability assessment. This paper presented a methodology for time dependent reliability assessment of engineering operations by considering a strategy for noise reduction in monitoring demanding parameters. For this purpose, condition monitoring of an NGRMS subject to degradation was selected to simply explain the application of the developed methodology. Pressure was considered as the PV for observing and modelling the associated uncertainty throughout the process. The considered data had nonlinear and non-stationary nature, so it could not be analyzed by a standard method, e.g., SPC or LSR. Subsequently, in order to remove the noise from the raw data in the observation process, EMD was selected as the statistical tool to filter out the data. During the sifting process, the raw data in the time series were decomposed into a set of IMFs, while the noisy IMFs were identified by conducting the SST approach. Later, a Bayesian predictive tool was employed to model the associated uncertainties influenced on the process over the operational time. The results show that the expected time for exceeding the safe limit is 50 weeks with a credible interval of (38, 64) weeks for the 2.5 and 97.5 percentile of estimated distribution, respectively. The predicted exceedance distributions facilitate the exploration of the onset of deterioration. The developed methodology is capable of being considered as a predictive tool for estimating lifetime condition of an engineering process, and regarded as a platform for future decision making analysis to improve asset integrity management of an industrial operation.

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