

Risk and uncertainty analysis of gas pipeline failure and gas combustion consequence

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Abstract Taking into account a general concept of risk parameters and knowing that natural gas provides very significant portion of energy, firstly, it is important to insure that the infrastructure remains as robust and reliable as possible. For this purpose, authors present available statistical information and probabilistic analysis related to failures of natural gas pipelines. Presented historical failure data is used to model age-dependent reliability of pipelines in terms of Bayesian methods, which have advantages of being capable to manage scarcity and rareness of data and of being easily interpretable for engineers. The performed probabilistic analysis enables to investigate uncertainty and failure rates of pipelines when age-dependence is significant and when it is not relevant. The results of age-dependent modeling and analysis of gas pipeline reliability and uncertainty are applied to estimate frequency of combustions due to natural gas release when pipeline failure occurs. Estimated age-dependent combustion frequency is compared and proposed to be used instead of conservative and age-independent estimate. The rupture of a high-pressure natural gas pipeline can lead to consequences that can pose a significant threat to people and property in the close vicinity to the pipeline fault location. The dominant hazard is combustion and thermal radiation from a sustained fire. The second purpose of the paper is to present the combustion consequence assessment and application of probabilistic uncertainty analysis for modeling of gas pipeline combustion effects. The related work

includes performance of the following tasks: to study gas pipeline combustion model, to identify uncertainty of model inputs noting their variation range, and to apply uncertainty and sensitivity analysis for results of this model. The performed uncertainty analysis is the part of safety assessment that focuses on the combustion consequence analysis. Important components of such uncertainty analysis are qualitative and quantitative analysis that identifies the most uncertain parameters of combustion model, assessment of uncertainty, analysis of the impact of uncertain parameters on the modeling results, and communication of the results' uncertainty. As outcome of uncertainty analysis the tolerance limits and distribution function of thermal radiation intensity are given. The measures of uncertainty and sensitivity analysis were estimated and outcomes presented applying software system for uncertainty and sensitivity analysis. Conclusions on the importance of the parameters and sensitivity of the results are obtained using a linear approximation of the model under analysis. The outcome of sensitivity analysis confirms that distance from the fire center has the greatest influence on the heat flux caused by gas pipeline combustion.

Keywords Risk parameters · Natural gas pipelines · Age-dependent reliability · Bayesian inference · Gas combustion · Uncertainty and sensitivity analysis

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1 Introduction

1.1 Relation between risk and uncertainty

The word risk is used in many different senses. Initially, instead of a formal risk definition valid throughout the

paper, some introductory remarks are given to characterise the failure and risk under uncertainty. In this paper the *failure* of a system, component or structure is associated with the event of unintended operation of the system, component or structure such as leakage, rupture, break or loss of pipe operability. The risk, in a general qualitative sense, is defined as the likelihood of the occurrence of undesirable event with severe adverse effect.

For a particular application, the risk measures can be defined in many different ways, thus a careful consideration must be devoted to select the appropriate risk measures. Possibly the most general quantitative definition of risk is given by Kaplan and Garrick (1981), who suggested the definition of risk analysis as consisting answers to the following three questions:

- What can happen? (i.e. What can go wrong?)
- How likely is it that it will happen?
- If it does happen, what are the consequences?

Partly because of the broad variety of contexts in which the risk concepts are applied, different definitions of risk continue to appear in the literature. In order to clarify risk subject there is a need to sort out different meanings by drawing some distinctions between meanings of related words. The notion of risk involves both uncertainty and some kind of loss or damage that might be received (Kaplan and Garrick 1981). Symbolically this distinction can be expressed in the following equation:

$$\text{Risk} = \text{Uncertainty} + \text{Damage}. \quad (1)$$

The issue of risk meaning becomes even clearer, when quantitative definition of *risk* is given precisely in connection to *probability*. As risk depends on what has happened, what is known and not known, this can lead to the ideas of quantitative risk under uncertainty.

To help understand the concept of uncertainty, and to be able to treat uncertainty in a structured manner, many attempts have been made to characterise classes of uncertainty and the underlying sources of uncertainty. Several authors, including Morgan and Henrion (1990) and others, provide more detail regarding sources of uncertainty.

In most of the literature, uncertainty and variability are separated. Uncertainty is due to the assessor's perception of the system. Variability on the other hand is due to the heterogeneity of that system. The Committee on Risk Assessment of Hazardous Air Pollutants (NRC 1994) prefer to use the concepts of model uncertainty and parameter uncertainty as opposed to uncertainty and variability. Model uncertainty arises due to lack of information and gaps in the scientific theory. Uncertainty in parameter estimates arises due to measurement errors, use of generic data, or input data uncertainty.

Uncertainty associated with model formulation and application can be classified as reducible and irreducible (Ang and Tang 1984). Irreducible (random) uncertainty (or variability) is due to inherent randomness in physical phenomena or processes. Collecting data cannot reduce it. Reducible uncertainty is due to lack of knowledge.

In addition, Oberkampf et al. (2000), considered a third type of uncertainty, called error, which is a recognizable deficiency in simulation. Assumptions and simplifications in simulation, and lack of grid convergence, introduce reducible uncertainty and errors. Collecting data or refining models can reduce this type of uncertainty.

In summary, at more fundamental level, two major groups of uncertainty are recognised in most of the literature. On the one hand there is the epistemic (or knowledge-based) uncertainty and on the other the aleatory (or stochastic) uncertainty or variability.

However, epistemic and aleatory uncertainty is not always separated in quantitative estimates of uncertainty. Nikolaidis and Kaplan (1992) studied the relative importance of the random and reducible components of uncertainty in rare events. They concluded that the random part of the uncertainty (variability) tends to become less significant for rare events. Finally, as stated by Winkler (1996): There is no fundamental reason for distinguishing between different types of uncertainty, but it may well be appropriate in assessment process and many practical applications.

In terms of the risk assessment process the uncertainty in the risk can be thought of being manifested as a spread or distribution in the value of the risk estimate. The spread in the risk estimate arises mainly from the spread in two input parameters, namely, the uncertainty in failure probability estimate and the uncertainty in consequence estimate. That's way in two parts of this paper the main focus is set on uncertain failure of pipeline and the consequence of uncertain combustion.

Numerous methods exist for assessing and expressing risk (Covello and Merkhofer 1993) and this impact the perceptions of risk. For example, if death is used as a risk (or consequence) metric, the issues surrounding risk will be related to social, religious, philosophical and various other aspects. One way to avoid the above issues is to avoid the use of death as a metric and define a risk in different way.

In an attempt to avoid some of the above issues associated with assessing and expressing risk, a variety of approaches have been proposed. A number of regulations use one of these approaches, e.g. Environmental Protection Agency uses the following guidelines regarding acceptable risk: A lifetime cancer risk of less than 1×10^{-4} for the most exposed person and a lifetime cancer risk of less than 1×10^{-6} for the average person. Although this and variety of regulations, none of applied approaches is without

problems, and no one approach seems to be dominant or acceptable in all cases.

The consideration of risk uncertainty introduces a probability distribution into the estimated risk. This may undermine the decision as to whether the risk is acceptable or not, particularly if the distribution is wide. Regulatory decisions using risk estimates are go/no go decisions—an activity, design change etc. must be either permitted or not. There is, however, no firm dividing line between acceptable and unacceptable risk and this is due to risk uncertainty.

Of course, one way of preventing decisions difficulties would be to use conservative (pessimistic) assumptions for all of the inputs and hence produce a conservative estimate of the risk. That, however, could well lead to the risk estimate being too large to be acceptable. Hence, it is preferable in comparisons to use an average risk as best point estimate of real value. Besides, due to difficulties in definition of conservative assumptions, there is an increasing interest in risk assessment to replace the conservative evaluation model calculations by best estimate calculations supplemented by a quantitative uncertainty and sensitivity analysis.

Currently, because of the complexity, needed to treat the physics that occurs during the failure and consequences phenomena, analysts have relied on using sophisticated models for the accidents and their affects. The majority of these models are deterministic in the sense that all the physical parameters used to define geometry, material properties, loadings, etc. as well as the parameters for calculation in the analyses have fixed values. These values usually are chosen by the analysts/engineer as best estimate values. Thus, the results from these analyses do not take into account the range of variation of these parameters or the affect that different combinations of the parameters uncertainty have on the conclusions, drawn from the analyses. In such case the probabilistic aspect of the parameters is neglected.

On other hand, in this work the probabilistic nature of the important parameters are taken into account to provide a more realistic expression of risk under uncertainty. According to the used approach a probabilistic analysis is embed into the deterministic analysis to provide uncertainty analysis capability. The approach for joint deterministic and probabilistic assessment of risk is applied and presented.

1.2 Analysis of the pipeline failure and natural gas combustion

Natural gas is a commonly used energy source. Due to different geographical distributions of natural gas supply sources and consumers, large distances have to be covered

by extensive networks of pipelines delivering natural gas. Since natural gas is a flammable and explosive fuel, it is hazardous and its transportation has inherited risks associated with potential damage. Accidental gas pipeline combustions could lead to extreme destruction and negative consequences for people.

If a constructions or population is exposed to a fire event, such as a defined level of heat radiation for a particular duration, a fatality rate or damage probability could be predicted.

While there is a lot of literature regarding the assessment of damage probability, which is derived statistically, it will be just shortly reviewed as later the focus is set on more specific issues of combustion consequence analysis. In general, fatality rate (or percent fatality) is accounted for using quite basic probit (probability unit) mathematics, which considers normally distributed random variable with a mean of 5 and standard deviation of 1. In the middle of 20th century David Finney wrote a book called Probit Analysis (Finney 1952), having an idea of transforming the sigmoid dose–response curve to a straight line that can then be analyzed by regression either through least squares or maximum likelihood. Today, probit analysis is still the preferred statistical method in expressing dose–response relationships. Besides, in general, if response versus dose data are not normally distributed, Finney (1952) suggests using the logit over the probit transformation. Probit or similar analysis can also be applied to thermal radiation hazards. The parameters for the analysis are established from measurements and/or critically evaluated scientific estimations of he radiation intensity and exposure time. In so called Green book the TNO CPR-16E (1992) provides probit functions for different degree burns as well as lethality from exposure to heat radiation within the infrared part of the spectrum. Other sources and authors, e.g. Lees (1996) or Stephens (2000) for application purposes does not focus on probit analysis, but in table form rather provide relevant dose–response relationships. This is more widely considered in the final sections devoted for combustion consequence analysis after the sections for dose formatting situations or events (i.e. pipeline failures). Uncontrolled release of natural gas or loss of pressure in the network cause unsafe situations due to the potentially combustive mixture of gas and air (Helseth and Holen 2006). Prevailing practice in assessment of such dangerous events is to consider failures rate of pipelines network as constant value. However, due to dynamic operating environment, improvements in maintenance strategies and the use of more advanced materials in the construction of new pipelines as well as in the repair of old ones the real failure rate is age-dependent (Iesmantas and Alzbutas 2011).

The framework to deal with ageing in a coherent way depends on the type of data at hand. Statistical data can be

presented as a pure failure sample, i.e. it can be failure counts in consecutive (but not necessarily equal) time periods, records of component state (failed or not) at specific times, or it might be evolution of component physical degradation characteristics, e.g. crack size.

There is a vast number of references, with models developed specifically to deal with the last type of data, known as degradation models. One of such comprehensive studies is a review of Singpurwalla et al. (2003), where part of this paper is devoted to the stochastic diffusion-based state models and covariate induced hazard rate processes. Also, Yashin and Manton (1997) reviewed available literature on the likelihood construction for covariate induced hazard rate models when two cases are possible: unobserved and observed covariate processes.

As for the first type of statistical data, the most relevant paper to our research is written by Kelly and Smith (2009), where they reviewed a state of the art of probabilistic risk assessment with one of applications being related to ageing and valve leakage. However, they a priori assumed logit model and did not validated it except the comparison with the case where constant failure rate is assumed. In addition, some related papers are due to Colombo et al. (1985), where authors present nonparametric estimation of time-dependent failure rate, or due to Ho (2011), where semi-parametric family of bathtub shaped failure rates is analysed. Although these approaches offer a rich class of failure trend models, it also requires the larger samples of data. It is the price for the flexibility of these models.

If the true failure rate is higher than the value used in reliability and combustion assessment, then inferences made from such evaluation is overly optimistic and leads to underestimated risk. If actual failure rate is lower, then overestimation leads to higher economical costs in risk management. Hence, the first part of this paper is devoted to resolve such issues by employing age-dependent failure rates and then applying the results to estimation of age-dependent probability of combustions. Bayesian methods are used to provide more robust inferences together with more realistic treatment of uncertainties. In Sect. 2.1 the statistical information from international associations is reviewed; in Sect. 2.2 the developed Bayesian models for age-dependent analysis of statistical information is presented; in addition, in Sect. 2.3 these models are applied to age-dependent failure rate and combustion accidents analysis in a case study of natural gas network.

In order to estimate and reduce pipeline failure rate as well as probability and potential damage of natural gas pipelines combustions the good understanding of involved phenomena and ability to model them are also needed. Therefore, the second part of this paper addresses the assessment of consequences due to gas pipeline rupture and hypothetical natural gas combustion. Various mathematical

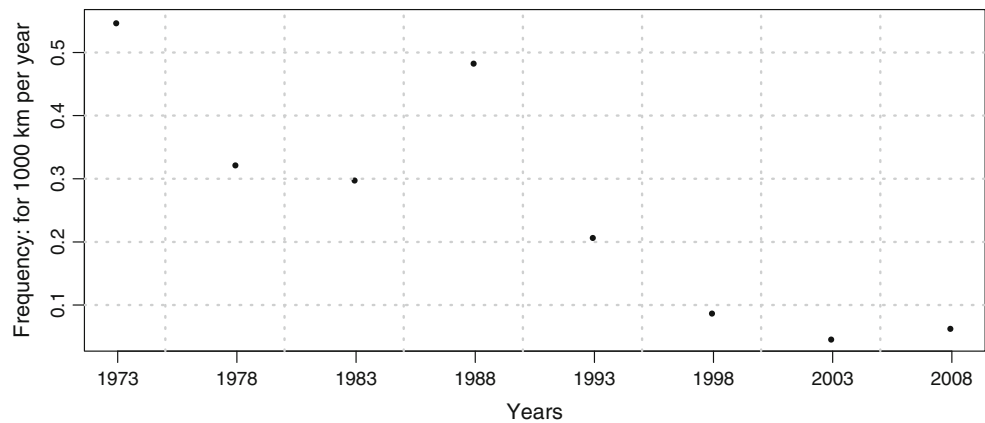
models are described in the methodological part of the work. They help to elucidate the consequences and importance of failures in the gas pipeline networks and assess the size of risky zone reflecting the uncertain distance of potential disaster or hazard area.

Consequences of the natural gas pipeline accident are assessed in this paper considering possible combustion of natural gas, released from the ruptured pipe, assuming that jet flame would be formed and dominant mode of heat transfer would be radiation. In general, radiation heat transfer is a complex topic, more information on which can be found in the books of Siegel and Howell (1991) and Modest (1993). Following the usual assumption and in order to simplify calculations a point source model (Jo and Ahn 2002, Jo and Ahn 2003) is used to describe the radiation intensity of flame thermal energy due to jet fire.

As for jet fire simulation, in literature a variety of approaches can be found. Extensive review of jet (and other types) fire research and modelling can be found in works of Lees (1996). Here a short overview of main jet simulation approaches is presented. One of the earliest models was developed by Hawthorne et al. (1949). They modelled jet as an inverted cone, with length and width calculated using correlations for turbulent diffusive flame. A model developed by Brzustowski and Sommer (1973) for the flare modelling is also used for jet modelling. It is based on correlations obtained experimentally by Brzustowski and colleagues. Using it the flare diameter is calculated from selected Mach number. Another model intended to calculate heat flux reaching target near the flame was developed by Craven (1972). It uses mentioned Hawthorne et al. (1949) model to calculate flame dimensions, but radiant heat flux is assumed to be equal to $1,600 \text{ kW/m}^2$ and has a set of view factors for various target positions relative to the flame and ground. However, this method is suitable for the turbulent flames mainly and intended for the design and not for the hazard assessment. Another approach was proposed by Hustad and Sonju (1986), where flame dimensions are correlated with flame's Froude number. Finally Carter (1991) proposed a model of a jet flame on a gas pipeline where flame is treated as a multiple source radiator. Each source is assumed to radiate a spherical surface. Then distances and periods of time related to various injuries to people and damage to buildings are estimated according to obtained intensities.

The assessment of shock wave or pressure peak strength of hypothetical explosion, i.e. detonation of the released gas is not presented in this paper as this event is less likely. The chance of such an event is extremely low in the case of methane gas, because of its buoyancy, unless obstacles for the gas dispersion were present. Bull et al. (1976) demonstrated experimentally extreme difficulty of detonating unconfined methane-air clouds and later numerical study

Fig. 1 UKOP failure rate estimates of every 5 years



by Boni et al. (1978), showed that unconfined stoichiometric methane–air mixture would need 10 t of tetryl explosive mass to initiate detonation. Thus, the dominant hazard due to natural gas release after rupture of pipeline is thermal radiation from a sustained jet fire, i.e. deflagration.

One of the main purposes of the performed work is to introduce a model for the assessment of heat flux due to gas pipeline combustion, identify uncertainties of the model inputs noting their distribution and variation range, and also apply uncertainty and sensitivity analysis to the model. At first, the assessment methods and models of pipeline rupture consequences related to the combustion of the released natural gas are considered (Uspuras et al. 2012) and summarised in Sect. 3 of this paper.

In addition, in Sect. 3.1 an example of the models application for hazard consequence assessment is presented. Having a number of uncertain parameters in considered models, firstly, the conservative values have been used for the initial assessment. Then, the approach of uncertainty analysis (uncertainty assessment with sensitivity analysis) on the impact of these parameters was being introduced and demonstrated with practical implementation presented in Sects. 3.2 and 3.3. Uncertainty analysis of hazard can also be treated as part of safety assessment that focuses on the assessment of best point estimates and uncertainty interval estimates of hazard consequences.

2 Uncertain failure rates of gas pipeline

2.1 Review of statistical information

United Kingdom Onshore Pipeline Operators’ Association (UKOPA) in its report for year 2009 (Arunakumar 2009) presents age-dependent statistical mean estimates of failure rate (i.e. failure frequency per year), which were calculated for every 5 years in 1969–2008 period (Fig. 1).

Failure rate mean estimate for the last 5 years (from 2004 till 2008) is 0.064 events for 1,000 km per year, while

Table 1 Distribution of pipeline failure frequency

Category	Failure frequency per 1 year (for 1 km)
Wall thickness less than 5 mm	4E–4
Wall thickness less than 10 mm	1.7E–4
Wall thickness less than 15 mm	8.1E–5
Wall thickness higher than 15 mm	4.1E–5

general mean estimate of 1962–2008 period is 0.242 events for 1,000 km per year. There is an increase over the last 5 year incident rate, but it is within the expected variation shown over the last ten years. EGIG (European Gas Pipelines Incident Data Group) in its report (EGIG 2007) for period from 1970 till 2007 reports final failure frequency equal to 3.7E–4. Overall length of pipeline network was 129,719 km. In 1,172 events registered in EGIG database 11 ended with human injuries or death.

EGIG has investigated the relationship between the age of the pipelines and their failure frequencies to determine whether older pipelines fail, due to corrosion, more often than more recently constructed pipelines. The influence of the age of the pipelines, i.e. the age and construction year class (EGIG 2007) on their failure frequencies has been studied.

Early constructed pipelines had a higher failure frequency due to corrosion, in their early years, than recently constructed pipelines. In recent years, due to improved maintenance, the age of pipelines is no longer major influence on the occurrence of corrosion failures. Still, for offshore or submarine gas pipelines and pipes in process plants the different types of corrosion may be one of the dominant failure mechanisms with various probability distributions (known as priors), which leads to 40 % of the accidental hydrocarbon releases to the environment (Thodi et al. 2009).

Distribution (Table 1) of failure frequency per year according to pipe wall thickness and other characteristics

useful for failure rate modelling and analysis is presented in 2010 year report of The International Association of Oil & Gas Producers (OPG 2010).

2.2 Bayesian modeling of failure data

Bayesian methods are well known to have robustness properties in outliers' problems and are well-suited for analysis of sparse and small data samples. As example, the potential benefits of the Bayesian approach comparing with the usual maximum likelihood estimate method is numerically demonstrated by Ahn et al. (2007). As it was mentioned previously Bayesian methods are also well suited for the estimation of dynamic hazard rate. In this section the developed methodology for age-dependent failure data analysis is presented very briefly.

Applying Bayesian inference, additionally, there is a need to deal with changes of age-dependant parameter as a continuous process. This can be partially overcome by considering ageing (or degradation) as step-wise process, which is constant in some period of time and has value jump in other period. Mathematically this can be expressed as a jump process:

$$d(t) = \sum_{i=1}^{N-1} 1_{\{t_i < t < t_{i+1}\}} d(t_i), \quad (2)$$

where $d(t)$ is any model of characteristic under consideration and constant $d(t_i)$ is value of characteristics at each time period t_i ; N —number of time intervals.

Model of characteristic $d(t)$ can have any functional form. It can be linear, Weibull, or some other form. Depending on adopted formula, $d(t)$ will be based on vector of parameters $\Theta = \{\theta_1, \dots, \theta_m\}$:

$$d(t) = d(t, \Theta). \quad (3)$$

If prior knowledge and beliefs about object parameters is represented by probability density distribution $\pi(\Theta)$ and statistical observations has likelihood $f(y|d(t))$, then, according to Bayes theorem, age-dependent beliefs about systems degradation or failure rate is expressed as posterior distribution:

$$\pi(\Theta|y, t) = \frac{\pi(\Theta)f(y|d(t, \Theta))}{\int_{\Omega} \pi(\Theta)f(y|d(t, \Theta))d\Theta}. \quad (4)$$

2.3 Failure rate estimation case study

In this part of paper age-dependent reliability and combustion assessment is carried out applying Bayesian methods and general rate trend models.

Suppose, the age-dependant failure rate (Fig. 1) follows decreasing trend function d and data is generated by

Gaussian nonlinear regression model (Y_t) with unknown dispersion σ^2 , then Bayesian model is expressed as follows:

$$Y_t \sim N(d(t, a, b, c), \sigma^2); d(t, a, b, c) = a + \frac{b}{1+t} + c^t, t = \overline{1, 8}; \\ (a, b, c) \sim Uniform([0, K]^3), \quad (5)$$

where K is some large constant (we used $K = 1,000$), ensuring that large enough space of states is explored by MCMC (Markov Chains Monte Carlo) i.e. a family of specific algorithms, which allows generation of random number distributed by some distribution law, known up to constant (Gilks et al. 1996). Uniform prior distributions for regression parameters (a, b, c) are ascribed since no prior information is available to make any prior judgments about the values of parameters.

In the next two subsections calculations and discussion for age-dependent failure rate and combustion probability will be presented separately.

2.3.1 Age-dependent failure rate of natural gas pipelines network

MCMC simulation of stated model allows estimation of posterior distribution of regression parameters (a, b, c) and of dispersion parameter sigma σ (Figs. 2, 3). These posterior distributions (probability density functions) represent updated state of knowledge about variability (i.e. the best estimate e.g. mean value and level of uncertainty) of model parameters.

Point estimates and Bayesian confidence intervals, representing uncertainty about parameters after data analysis are presented in Table 2.

It is worth to notice that Bayesian confidence intervals have different meaning compared to frequentists confidence intervals: Bayesian confidence intervals reflects probability (e.g. 0.95) of being in that interval while frequentists confidence intervals represents long-run frequency to “fall” into calculated interval. For frequentists, at every new sample the probability of the fact that parameter will be in previously computed confidence interval is either 1 or 0. Usually, which is a mistake, frequentists confidence intervals are interpreted as Bayesian confidence intervals.

Estimated mean failure rate of pipeline network under consideration is shown in Fig. 4.

Failure rate model (4) with one term equal to constant a considered in this analysis is a deliberate choice. Despite continuously improving maintenance strategies of natural gas transition network, it is unrealistic that failure rate will become equal to zero, so it is reasonable to analyze failure rate trend function with some limiting constant a .

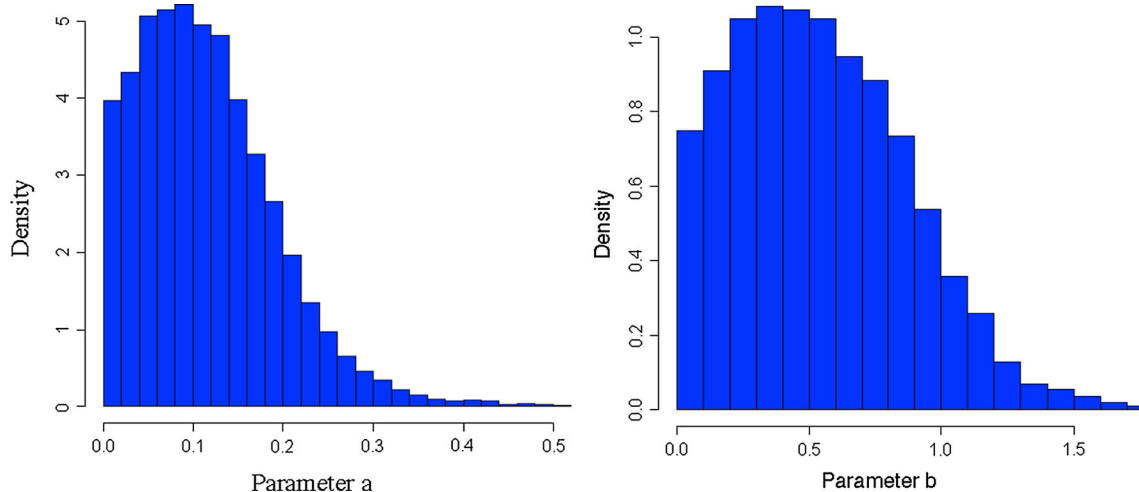


Fig. 2 Posterior distributions of regression parameters **a** and **b**

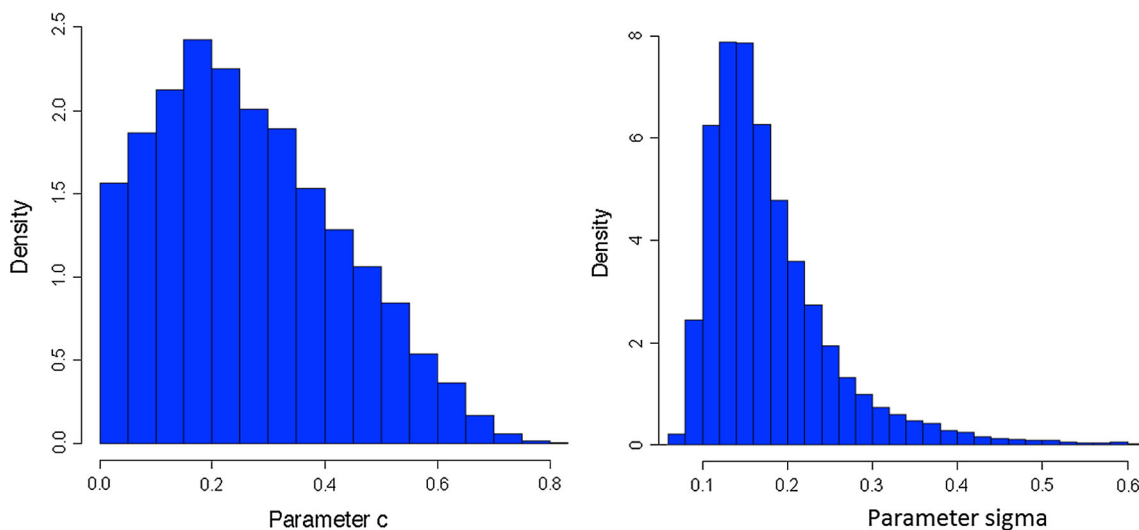


Fig. 3 Posterior distributions of regression parameter **c** and model standard deviation

Table 2 Bayesian point and interval estimates

Parameter	Mean	95 % confidence interval
<i>a</i>	0.11	[0.0059; 0.2549]
<i>b</i>	0.52	[0.0350; 1.1682]
<i>c</i>	0.26	[0.0215; 0.6112]
sigma	0.16	[0.0917; 0.2925]

As it is usually the case in reliability analysis, useful lifetime is of interest, i.e. system operation with constant failure rate. We will dismiss the case when ageing of system manifests, since it is highly unlikely, because of previously mentioned reasons for decreasing failure rate.

Further, in this section we will estimate time moment t^* , when failure rate approaches limiting constant a (say, with

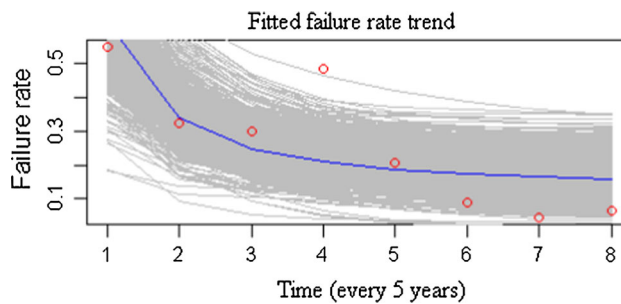


Fig. 4 Bayesian and frequentists estimates for age-dependent failure rate regression curve

error $\varepsilon = 0.01$) and whole lifetime of pipeline network can be divided into two sections: with decreasing and constant failure rate.

Table 3 Parameter values

Parameters	Value
λ	3.7E−4
f_s	0.32
f_t	0.25
f_d	0.1
f_w	0.5

If time moment t^* is such that $|\lambda(t^*) - a| \leq \varepsilon$ or $|\frac{b}{1+t^*} + c^{t^*}| \leq 0.01$, then approximate solution is $t^* = 51$ time periods, which is equal to $5 \cdot 51 = 255$ years.

Hence failure rate of gas grid settles down after quite long time and, since predictions for such time period would be very inaccurate, there is no reason to further analyze constant failure rate segment. Such segmentation would be useful in case when failure rate would approach constant value after relatively short time period (e.g. 10 years).

Failure rate estimate of UKOP natural gas transmission grid allows more advanced improvement of whole energy network reliability assessment and enables making more accurate predictions decisions. Well established practice to use constant failure rate for whole system lifetime when assessing reliability is harmful in terms of underestimated risk.

In addition to more accurate and coherent reliability analysis, we believe that incorporation of age-dependencies in maintenance and inspection optimization (Alzbutas et al. 2003) would also lead to more realistic results. However, we leave age-dependent maintenance optimization in light of ageing of components and systems for future works.

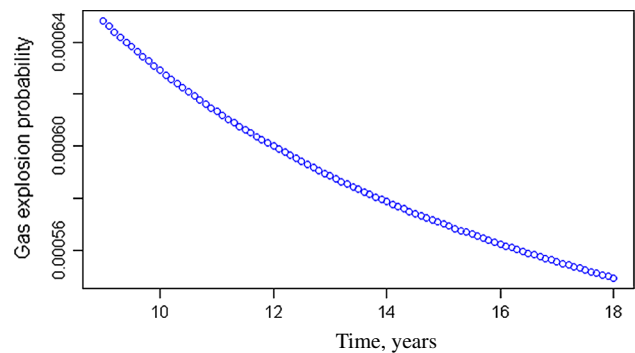
As a consequence of ageing phenomena incorporation into whole reliability assessment picture, the risk assessment related to network accidents (such as gas leakage combustions) is more realistic and provides better-informed decisions. This will be shown in the next subsection, where age-dependent natural gas combustion probability will be estimated for pipeline close to hazardous object.

2.3.2 Age-dependent combustion probability of gas pipelines network

The usual practice to calculate combustion probability near to Nuclear Power Plant (NPP) is to use constant pipeline failure rate NUREG-CR-4550/SAND86-2084 1990):

$$P = \lambda \cdot D \cdot f_s \cdot f_t \cdot f_d \cdot f_w, \quad (6)$$

where λ is pipeline failure frequency, D is pipeline length, close to NPP, f_s is hazardous pipeline accidents frequency, f_t —frequency of accidents related to technical works

**Fig. 5** Age-dependent gas combustion probability near to nuclear power plant

performed close to site, f_d unnoticed and unrepaired accidents, f_w —ratio of adverse weather conditions.

Further we will use estimates, introduced in (EGIG 2007; NUREG-CR-4550/SAND86-2084 1990) and presented in Table 3.

Suppose, that $D = 1$ km, then probability of natural gas combustion near to NPP site is $P = 1.48 \times 10^{-6}$. However, the use of constant pipeline failure frequency can lead to overestimated or underestimated (depending whether actual failure rate is higher or lower than mean value) gas combustion probability. So, to improve the accuracy of combustion probability estimate and to better evaluate the risk, pipeline causes to NPP, age-dependent failure rate should be used.

Using previously estimated failure rate $\lambda(t) = 0.11 + 0.52/(1+t) + 0.26^t$ the function of age-dependent probability of gas combustion near to assumed NPP is similar to the one in Fig. 5.

The differences between combustion probability estimates from constant and age-dependent failure rate models are quite different. In fact, gas combustion probability when taking into account age-dependencies is about 400 times higher compared to estimate from constant rate model.

Actually, the estimation approach used for gas combustion probability is quite universal, because the hazardous object which is close to pipeline grid doesn't necessarily have to be NPP; it can be a hydro power plant, housing developments or other objects.

3 Modeling of gas pipeline combustion

3.1 Models for the assessment of combustion consequences

The assessment of combustion consequence is mainly based on a model developed by Stephens (2000). In the model it is assumed that combustion would occur in the

Table 4 Heat flux and time needed to cause various damage to humans

Heat flux, I (W/m^2)	Time (s) to blister threshold, $tI^{1.33} = 210 - tI^{1.33} = 700$	Time (s) to 1 % mortality, $tI^{1.33} = 1,060$	Time (s) to 50 % mortality, $tI^{1.33} = 2,300$	Time (s) to 100 % mortality, $tI^{1.33} = 3,500$
4,320	30.0–100.0	151.4	328.5	499.9
10,680	9.0–30.0	45.4	98.6	150.0
14,590	5.9–19.8	30.0	65.1	99.1
26,120	2.7–9.1	13.8	30.0	45.7
35,820	1.8–6.0	9.1	19.7	30.0

Table 5 Heat flux intervals relating to selected damage to humans

Heat flux (W/m^2)	Damage	Interval label
35,820–...	100 % mortality	A
26,120–35,820	50–100 % mortality	B
14,590–26,120	0–50 % mortality	C
4,320–14,590	Blisters	D
0–4,320	No damage	E

form of the sustained jet fire. The heat flux radiated by this fire and its impact are estimated using a simple point-source model, described in this section. The obtained heat flux is used to assess the damage it could possibly cause, and to estimate the time needed to cause the given damage.

If one chose a time period during which any person receiving flame radiation would be able to find a shelter, it is possible to directly relate intensity of radiation and the worst possible impact on the health. Usually, the damage from the thermal radiation is estimated (Tables 4, 5) using the models (Stephens 2000), which relate the possible damage to humans, the received heat flux and the exposure time.

This time period may be selected to be equal to 30 s, on the assumption that the affected person would be able to travel a distance of about 60 m during this period (Stephens 2000). Table 5 shows intervals of approximate heat flux relating it to different damage levels in this case.

For buildings, analogous models, which relate radiation intensity and time needed for ignition of wooden construction, exist as well. However, one important difference compared to human damage models is present in building damage models—there is heat flux threshold below which no ignition would occur (Jo and Ahn 2002). Furthermore, buildings cannot run for shelter, therefore no time limit can be assumed for the damage but the time to put out the fire. Using Bilo and Kinsman model of the time to piloted ignition of the wooden structure (Jo and Ahn 2003) and conservatively assuming that time needed to put out the fire is 24 h, the heat flux value of $14,760 \text{ W}/\text{m}^2$ is obtained (thus the threshold value is $\sim 15,000 \text{ W}/\text{m}^2$).

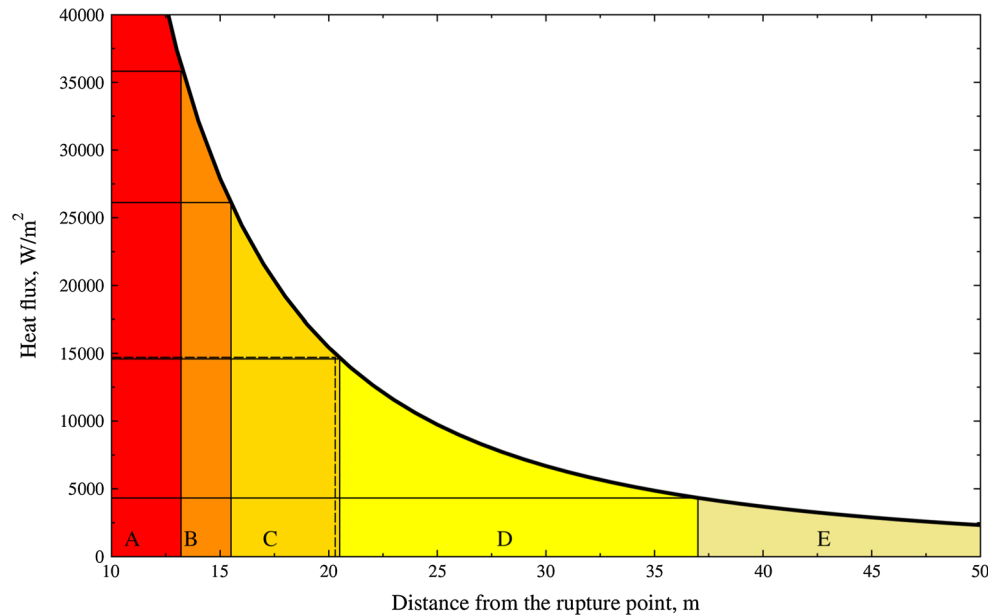
In order to estimate a heat flux radiated by the combustion, it is used a jet fire model. A jet flame is modeled as a point source of thermal radiation situated at the ground level. This simplifying approximation yields a lower accuracy than would a model of multiple point sources spread along the assumed length of the flame yield; however it greatly simplifies the calculations. Furthermore, result obtained with this approximation is conservative in relation to the damage receptor, which is at the low height compared to the real flame. Should the need arose to evaluate the radiation intensity in greater accuracy, it would be possible to disperse this single point source into the multiple point sources, and integrate their radiation received by the receptor e.g., Carter jet flame model (Jo and Ahn 2002). However, in such a case more detailed analysis would be required to consider possible jet and receptor lengths and shapes. The heat flux I (W/m^2), radiated by a point source at the distance r (m) from it, is

$$I(r) = F\tau \frac{Q}{4\pi r^2}, \tag{7}$$

where F is the fraction of the released heat which is radiated, τ is the atmospheric transmissivity and Q [W] is the net heat release rate of the combustion.

According to Carter jet flame model (Jo and Ahn 2002), the radiated fraction of heat F in general depends on several factors: efficiency of combustion, soot formation and heat losses and for jet flames is a function of the fuel and orifice diameters. The atmospheric transmissivity coefficient τ for considered reaction can be calculated according to empirical correlation of Wayne (1991). F together with τ is expressing the emissivity factor X_g . The heat release rate Q itself is a product of the combustion rate C of the fuel and the heat of combustion H_c (J/kg) for the given fuel (usually given in tables). To simplify the model an assumption is made that, considering the gas pipelines, the combustion rate C of the fuel is equal to the effective gas release rate W_e (kg/s) from the pipe rupture multiplied by the combustion efficiency factor η , which accounts for combustion completeness (fraction of the released gas, which is combusted). Then the resulting equation of the heat flux received by the damage receptor is given by

Fig. 6 Heat flux and damage intervals calculated for the example case



$$I(r) = X_g \frac{W_e \eta H_c}{4\pi r^2}. \quad (8)$$

The effective gas release rate W_e varies in time. Beginning from its peak value it decreases and just after a few seconds a fraction of the peak value is left, which is further decreasing. Initial (peak) gas flow value W can be estimated using equation of Crane (2009):

$$W = C_d \frac{\pi d^2}{4} p \frac{\varphi}{a_0}, \quad \varphi = \gamma \left(\frac{2}{\gamma + 1} \right)^{\frac{\gamma+1}{2(\gamma-1)}}, \quad a_0 = \sqrt{\frac{\gamma R T}{m}}, \quad (9)$$

where C_d is the gas discharge coefficient, d —the diameter of the opening, in the conservative case of full-bore (guillotine rupture) equal to the diameter of the pipe (m), p —the pressure difference (Pa), γ —the specific heat ratio ($\cong 1.306$ for methane), a_0 —the sound speed in the gas (m/s), R —gas constant equal to 8.31 [J/(K mol)], T —gas temperature (K), and m —gas molecular weight (g/mol) ($\cong 16$ g/mol for methane).

The varying gas flow W will cause the flame size and radiation intensity to vary accordingly. The peak value of the thermal radiation intensity is not known beforehand and depends on the time interval between the rupture and the ignition. In the presented model varying gas flow W is modeled by constant effective gas flow $W_e = 2\lambda W$, where λ is the flow reduction coefficient (release rate decay factor) and 2 is required to account for gas flow from both ends of the ruptured pipe. Values of λ used in the analogous studies are, e.g. 0.25 (Kuprewicz 2003) and 0.33 (Jo and Ahn 2003). More conservative value of 0.5 can be also used for the safety assessment as it may likely yield a representative steady state approximation to the release rate for typical pipelines (Jo and Ahn 2003).

3.1.1 Example of modeling and assessment

In the simple example of the combustion consequence model application the considered object is a part of a natural gas pipeline considered as one pipe of 10 km length. Its inner diameter is 0.18 m, pressure 0.6 MPa. The gas inside the pipe is methane (100 % concentration assumed) and 50 % air humidity, 273 K temperature, 0.3 fraction of heat radiated and 0.62 gas discharge coefficient were assumed. Then using the expressions of heat flux I and effective gas release rate W_e the damage intervals (A, B, C, D, E) and heat flux dependency on the distance from the rupture place in this pipe is obtained (Fig. 6). Dashed line in the middle of C interval corresponds to the obtained maximum distance for the building damage.

Following this example, it is possible to apply the model in the assessment of consequences of gas supply systems or gas pipeline ruptures, which are important for the justification of pipeline location or selection of site for new potentially dangerous buildings or other objects, which may be affected by possible combustion.

3.2 Approach of uncertainty analysis

The approach suggested for uncertainty and sensitivity analysis is based on specific concepts and tools of probability calculus and statistics. The uncertainty analysis, in addition to uncertainty estimation, includes the identification of the potentially important contributors to the uncertainty of the model output and the quantification of the respective state of knowledge by subjective probability distributions (Hofer 1999). In general, a part of initially conservative assumptions used in the model can be related

to the unavoidable aleatory (stochastic) uncertainties of physical process. In addition, for another part of uncertain input of the model, its probability distribution expresses how well input is known (i.e. epistemic uncertainty). The probabilistic sensitivity analysis, as final part of the uncertainty analysis, can be used to identify uncertain parameters, which mainly contribute to the variations of results and in order to see the uncertain input's combined influence on the output.

3.2.1 Sampling and uncertainty measures

The initial quantitative uncertainty estimation can be expressed using quantiles or percentiles (as example 5 and 95 %) of the probability distribution. Knowing distribution law and its parameters, it is possible to estimate the mean, standard deviation, median, quantiles and other point estimates as well as confidence intervals. In practice, quantiles of output can be estimated using Monte Carlo simulations with a specified number of runs after input sampling.

In addition, the impact of possible sampling error on the output can be considered and related to the number of runs. This can be done by computing (α, β) statistical tolerance limit (or two sided limits treated as interval). This limit (or interval) separate at least $100 \cdot \alpha\%$ part of all possible output with at least a β probability as confidence level. In other words, this means that, with the β probability, $100 \cdot \alpha\%$ part of all possible output will be separated by the specified statistical tolerance limit (or will be in the considered statistical tolerance interval).

According to the classical statistical approach, the confidence statement expresses the possible influence of the fact that only a limited number of model runs have been performed. For example, according to Wilks formula (Hofer 1999), 93 runs are sufficient to have a (0.95, 0.95) statistical tolerance interval. The required number n_1 of runs for one sided (α, β) tolerance limit and correspondingly the number n_2 for (α, β) tolerance interval can be expressed as follows:

$$n_1 \geq \ln(1 - \beta) / \ln(\alpha), \quad (10)$$

$$n_2 \geq (\ln(1 - \beta) - \ln((n_2/\alpha) + 1 - n_2)) / \ln(\alpha). \quad (11)$$

The advantage of such approach is that, the minimum number of model runs needed is independent of the number of uncertain quantities taken into account and depends only on the two quantities α and β described above.

3.2.2 Uncertain output sensitivity analysis

In general, outputs from models are subject to uncertainty. Usually uncertainty estimation can provide a statement about the separated or combined influence of potentially

important uncertainty (aleatory and epistemic) sources on the model output. Often more important, to analyze uncertainty providing quantitative sensitivity statements that rank the uncertain inputs with respect to their contribution to the model output uncertainty. In a frame of uncertainty analysis the purpose of the considered sensitivity analysis is:

- a) to analyze uncertain output sensitivity to the uncertain inputs, and
- b) to identify, which inputs mostly influence the model output.

In general, sensitivity analysis is used not only to analyze uncertainty, but also to examine which epistemic uncertainty sources are better to control.

In order to rank uncertain parameters according to their contribution to model output uncertainty, standardized regression coefficients (SRCs) can be chosen from the many other sensitivity measures available. They are capable of indicating the direction of the contribution (negative means inverse proportion). SRC is supposed to tell by how many standard deviations the model result will change if the uncertain input is changed by one standard deviation.

Additionally, the correlation ratios (CRs) can be computed. The ordinary CR is the square root of the quotient of the variance of the conditional mean value of the model output (conditioned on the uncertain input) divided by the total variance of the model output due to all uncertain input taken into account. It serves as a measure, how one uncertain model specification was quantified through a set of alternative specifications. The CR quantifies degrees of inputs and output relationship.

How well this is achieved in practice depends on the degree of linearity between the model output and the uncertain input. In case the number of uncertainties is large and the sample size is small, spurious correlations can play a non-negligible role. The effect of spurious correlations on sensitivity measures may be investigated if the estimates of SRCs and correlation coefficients are compared (Hofer 1999).

3.3 Uncertainty analysis of combustion consequences

3.3.1 Parameters' uncertainty analysis

To estimate the uncertainty of model output, at first it is necessary to estimate the uncertainty of parameters describing variation range and probability distribution. This section describes the parameters of the model which were defined according to the statistical data.

As example, qualitatively analyzed data from 1969 to 2010 year on the largest USA natural gas pipeline accidents when a fire/explosion or released gas could cause an

Table 6 Data of pipelines, which have experienced accidents, characteristics

Year	Diameter d (inch)	Pressure p (sig)	Diameter d (m)	Pressure p (Pa)
1969	14	789	0.3556	5,439,966
1974	30	718	0.7620	4,950,438
1974	13	497	0.3239	3,426,696
1976	20	770	0.5080	5,308,965
1982	20	820	0.5080	5,653,703
1984	30	1,016	0.7620	7,005,076
1985	30	990	0.7620	6,825,812
1986	30	987	0.7620	6,805,128
1994	36	970	0.9144	6,687,917
2000	30	675	0.7620	4,653,963
2001	24	817	0.6096	5,633,019
2002	36	974	0.9144	6,715,496
2003	26	647	0.6604	4,460,910
2005	36	824	0.9144	5,681,282
2006	24	572	0.6096	3,943,803
2008	30	799	0.7620	5,508,913
2009	24	784	0.6096	5,405,492
2009	24	762	0.6096	5,253,807
2009	42	1197	1.0668	8,253,028
2010	36	950	0.9144	6,550,022
2010	30	671	0.7620	4,626,384

Table 7 Goodness-of-fit test for normal distribution

Parameter	Kolmogorov–Smirnov statistic (D)	p value
Diameter	0.1855	0.058
Pressure	0.1577	0.150

explosion were identified and collected (Table 6) from different sources (Kuprewicz 2003; PHMSA 2012; WIKI 2012).

Data of pipeline diameter and pressure values (also converted to SI units) were also quantitatively analyzed with a help of software system SAS. The goodness-of-fit test for normal distribution was performed and distribution parameters as well as quantiles of this distribution were estimated.

The goodness-of-fit test for normal distribution is reflected in Table 7. The performed test expresses examination of the hypothesis that the pipeline characteristics (diameter and pressure) values are normally distributed. In both cases the hypothesis of normal distribution is accepted because the Kolmogorov–Smirnov statistics D is outside the critical region and the p value is greater than the significance level ($\alpha = 0.05$).

Table 8 Statistical characteristics of diameter and pressure

Characteristic	Diameter d (m)	Pressure p (Pa)
Mean	0.7073	5,655,345
Std. deviation	0.1887	1,150,838
Minimal value	0.3239	3,426,696
Maximal value	1.0668	8,253,028

Statistical characteristic of pipeline diameter and pressure estimates are presented in Table 8. The value of effective hole diameter of considered gas pipelines is distributed in the interval [0.3239, 1.0668] with the mean of 0.7073 and standard deviation of 0.1887, and the pressure value is distributed in the interval [3426696, 8253028] with the mean of 5655345 and standard deviation of 1150838.

Another parameter of gas release model (13) is discharge coefficient C_d . On the basis of possible assumptions for orifice meter (The Engineering Toolbox 2012) C_d can be distributed on the interval [0.60, 0.64], but the parameter values mostly focused on the middle of it, i.e. on 0.62 (Jo and Ahn 2003). Thus, the normal distribution of this parameter was assumed with mean 0.62 and distribution in a range of two-sigma reflecting that 95.45 % of the values would be inside the interval [0.60, 0.64]. Then a standard deviation would be approximately equal to 0.01.

The following parameter of gas release model (13) is the specific heat ratio γ for methane because the considered natural gas is mainly from methane. As it varies between 1.304 and 1.320 without any known preference, so we assume that it varies uniformly in the range between 1.304 and 1.320.

For the gas release estimation according to the equations (13) the sound speed in the gas a_0 is depended on the gas temperature T . As a high-pressure natural gas pipeline is usually installed under the ground (>0.8 m depth), the gas temperature T variation in underground pipeline is related to variation of air temperature. It is known that the temperature at depth of 1 meter during the winter can be from 0 to 7 °C. During the summer the temperature can reach 18 °C. Thus, gas temperature changes can be in a range between 273 and 291 K and a normal distribution of this parameter was assumed with mean 282 and distribution in a range of two-sigma reflecting that 95.45 % of the values would be inside the interval [273, 291]. Then a standard deviation would be approximately equal to 4.50.

The release rate decay factor λ also affects the effective release rate W_e , given that even immediate ignition will require several seconds for the establishment of the assumed radiation conditions and given further that a fatal dose of thermal radiation can be received from a pipeline fire in well under 1 min. A rate decay factor in the range of

Table 9 Minimal and maximal values of thermal intensity parameters

Symbol of parameter	Full name of parameter	Minimal value	Maximal value
H_c	Heat of combustion for methane	5.00×10^7 (J/kg)	5.55×10^7 (J/kg)
η	Combustion efficiency factor	0.13	0.35
X_g	Emissivity factor	0.17	0.30

0.20–0.50 will likely yield a representative steady state approximation to the release rate for typical pipelines (Jo and Ahn 2003). This parameter values usually are focused on the center of the range. Thus, a normal distribution of this parameter was assumed with the mean 0.35 and distribution in a range of two-sigma reflecting that 95.45 % of the values would be inside the interval [0.20, 0.50]. Then standard a deviation would be 0.075.

Regarding parameters of the thermal radiation intensity (heat flux) model (11), such as the heat of combustion for methane H_c , the combustion efficiency factor η and the emissivity factor X_g , only the minimum and maximum are known and are given in Table 9.

To define the relevant variation of the distance from fire center r the additional calculations were conducted. The minimum values and the maximum values of all previously described parameters were taken and by changing r the radiation intensity I values were obtained and compared with relevant limits. Knowing that approximately $15,000 \text{ W/m}^2$ limit of thermal radiation intensity may ignite the wooden constructions and this can cause the 1 % mortality in 30 s (see Table 1), it is calculated that the distance from combustion center in range of [26.142,

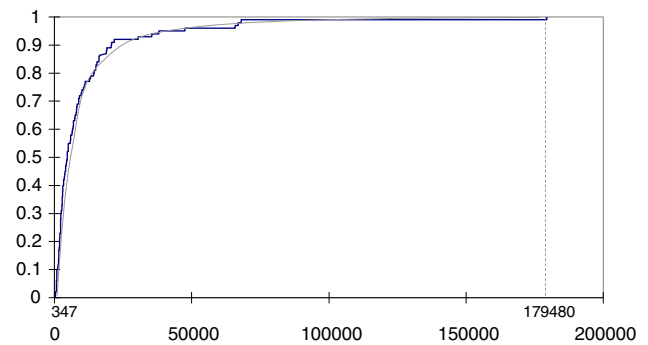


Fig. 7 Probabilistic distribution function of model output I (W/m^2)

510.270] should be considered as an option, which in extreme conditions may pose a risky consequences.

Based on all above assumptions, the information regarding the uncertainty of parameters is summarized in the following Table 10.

The table above expresses that the specific heat ratio of gas (γ), the combustion efficiency factor (η), emissivity factor (X_g), the heat of combustion for methane (H_c) are distributed uniformly in between minimum and maximum values, while the other parameter values are more concentrated around the middle of the range, and are characterized by normal distribution. According to the information (see table above) 100 combinations of different parameter values were generated and used for heat flux uncertainty analysis.

3.3.2 Uncertainty analysis of model results

Various parameters of natural gas pipeline combustion model are not exactly known, or in different circumstances acquire different values. Thus, the uncertainty analysis was performed using Software system for Uncertainty and

Table 10 Information of uncertain parameters used to estimate the heat flux

No.	Symbol, unit	Full name of parameter	Further notation	Distrib.	Parameters of distribution		Minimal value	Maximal value
1	C_d	Discharge coefficient	C_d	Normal	$m = 0.62$	$\sigma = 0.01$	0.60	0.64
2	d (m)	Effective hole diameter	d	Normal	$m = 0.70727$	$\sigma = 0.18871$	0.3239	1.0668
3	p (Pa)	Pressure differential	p	Normal	$m = 5,655,340$	$\sigma = 1,150,840$	3,426,700	8,253,030
4	γ	Specific heat ratio of gas	Gama	Uniform	$a = 1.304$	$b = 1.32$	1.304	1.32
5	T (K)	Gas temperature	T	Normal	$m = 282$	$\sigma = 4.50$	273	291
6	λ	Release rate decay factor	Lambda	Normal	$m = 0.35$	$\sigma = 0.075$	0.20	0.50
7	r (m)	Distance from fire center	r	Normal	$m = 268.206$	$\sigma = 121.031$	26.142	510.270
8	η	Combustion efficiency factor	eta	Uniform	$a = 0.13$	$b = 0.35$	0.13	0.35
9	X_g	Emissivity factor	X_g	Uniform	$a = 0.17$	$b = 0.30$	0.17	0.30
10	H_c (J/kg)	Heat of combustion for methane	H_c	Uniform	$a = 5.00 \times 10^7$	$b = 5.55 \times 10^7$	5.00×10^7	5.55×10^7

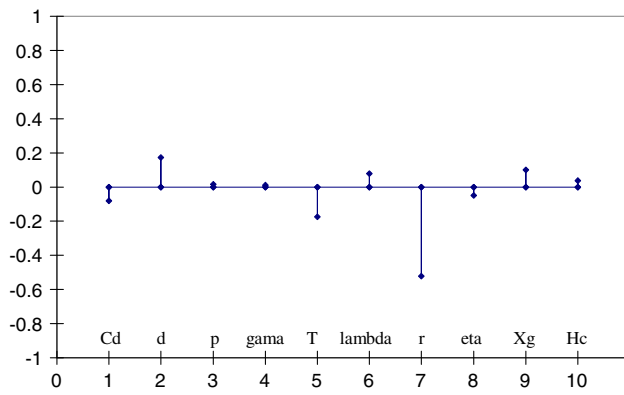


Fig. 8 Sensitivity measures expressed as standard regression coefficients

Table 11 Probabilistic characteristics of model output I (W/m^2)

Probabilistic characteristics	Value
Mean	10,957
Standard deviation	21,499
Median	46,724
Mode	2,360
Minimum	347
Maximum	179,480
(0.95, 0.95) tolerance limit	(347, 179480)
One-sided lower (0.95, 0.95) tolerance limit	382
One-sided upper (0.95, 0.95) tolerance limit	68,104

Sensitivity Analysis SUSA (Krzykacs et al. 1994) and applying previously described analysis methods of statistical data analysis and probabilistic characteristics estimation.

According to inequality (15) based on Wilks' formula the number of model output calculations for (0.95, 0.95) tolerance interval estimation should be at least 93. For more conservative estimation 100 calculations were performed using all ten uncertain parameters, which were changed independently from each other and the variation of the thermal radiation intensity was obtained. The estimated and fitted (in grey) probabilistic distribution of model output and estimates of two-sided (0.95, 0.95) tolerance interval are presented in Figs. 7 and 8.

According to this estimation, the minimum and maximum of flame thermal radiation intensity is 347 and 179,480 correspondingly, and with a probability 0.95, 95 percent of the model outputs fall into the range (347, 179480). Also one-sided lower and upper (0.95, 0.95) tolerance limit was calculated. They show that considering only a single limit with the probability of 0.95, 95 percent of the model outputs will not be less than 382 or exceed the 68,140 limit. In addition, the probabilistic distribution

function fitting was performed and showed that model output is close to Gamma distribution. The most important probabilistic characteristics of model output are presented in Table 11.

Looking at the distribution or the difference between median and mode there is possible to note that the most of the model output are focused on the lower values, as it is typical for Gamma distribution.

3.3.3 Sensitivity analysis of uncertain results

To identify the influence of uncertain parameters to the uncertainty of model result, i.e. estimate of the thermal radiation intensity, the sensitivity analysis was performed. It enables to identify the parameters, which are the most important in order to decrease the uncertainty interval and get more precise mean and other point estimates of the result.

The calculated standard regression coefficients (SRCs) in relation to separate parameters show that the SRC related to the distance from the fire center has the highest absolute value 0.523. This means that the uncertain distance is the most important parameter considering the uncertainty of model result. A negative sign of SRC indicates that the greater value of the distance from the fire center determines a lower value of result, i.e. the thermal radiation intensity. Therefore, for the more precise estimation, the distance (r) from the gas combustion should be specified with lower variation or even without it. Also, it is possible to note that the remaining measures for other parameters are quite weak or even negligible (e.g. for gas pressure).

The assumption that SRCs can be treated as sensitivity measures is based on the assumption that determination coefficient of model is close to one. However, in this case the model is not linear and determination coefficient is 0.411. The value of determination coefficient expresses only the rate of uncertainty in linear model results, which can be explained by uncertainty of model parameters.

In spite of this, Pearson correlation coefficients as alternative sensitivity measures, also confirm the interpretation of previous sensitivity analysis and prove that the uncertainty of thermal radiation intensity is mostly influenced by the specification of distance from combustion center. In this case the coefficient for this parameter in absolute value is close to 0.5 and indicates a moderate strength relationship between this parameter and the model result.

The partial correlation coefficients in addition provide a measure of the linear relationship between the model output and the input variable, i.e. parameter, when the effects of other variables are excluded. These coefficients also confirm the previous interpretations of sensitivity analysis.

The coefficient for the same parameter (r) which was dominant considering SRCs confirms its highest linear effect on the model output. The partial correlation coefficient for the distance from the combustion center is -0.544 . Although other coefficients values are slightly different, all of them show that the uncertainty relationship between the other parameters and model output is weak.

The Spearman correlation coefficients and empirical correlation coefficients also demonstrates that the distance from combustion center had the significant influence on the model results, but in addition more strongly emphasize the importance of uncertainty of effective hole diameter (d) of gas pipeline. The Spearman correlation coefficient for the distance from fire center and for effective hole diameter is -0.762 and 0.420 correspondingly. Between the diameter and the model result is a direct relationship, but between the distance and the model result is an inverse relationship.

4 Summary and conclusions

Taking into account the general concept of risk parameters, firstly, the available statistical data of natural gas pipeline grid were presented in this paper and used to estimate age-dependent failure rate and gas combustion probability.

Bayesian methods allowed more robust estimation of age-dependent failure rate parameters; furthermore, uncertainties of these parameters were also obtained and used to estimate Bayesian confidence intervals, which are more easily understandable (compared to frequentists confidence intervals).

Estimated time point when failure rate decreases to constant value (with some error ε) showed that there is no necessity to divide failure rate into two segments: strictly decreasing and constant failure rate.

Age-dependent failure rate is advantageous for development of maintenance strategies of pipeline grid, also for evaluating risk at different network points—this can be done by analyzing uncertainty and using age-dependent estimates of gas combustion probabilities instead of constant ones.

The presented model for hazard evaluation of natural gas pipeline accident and introduced probabilistic uncertainty analysis enables to get the point and interval estimates of the gas combustion consequences in the case of pipeline failure and thermal radiation from a sustained fire.

Applying uncertainty analysis the tolerance limits and distribution function of thermal radiation intensity are given as the outcome and demonstrates how widely model results are distributed due to identified ten uncertain parameters and variation of possible conditions. The values in uncertainty interval expressed as tolerance interval (347, 179480) of heat flux quite well fits to the Gamma

distribution and the largest part of them is concentrated in the beginning of this interval. Therefore, the larger consequences are less probable in spite of symmetric variation of uncertain parameters.

In order to decrease the uncertainty interval and to get more precise mean or other point estimates of the result the calculated sensitivity measures enabled to identify the most significant parameters of the model. The outcome of probabilistic sensitivity analysis confirmed that considered variation of distance from the hazard center has the greatest influence on the uncertainty of heat flux caused by gas pipeline combustion. In addition, the analysis showed that the importance of uncertainty of effective hole diameter of gas pipeline can be emphasized as well.

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