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Towards resilient pipeline infrastructure: lessons learned from failure analysis

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Received: 8 July 2024 / Accepted: 14 October 2024
Published online: 02 November 2024

Abstract
Understanding the mechanisms of pipeline failures is crucial for identifying vulnerabilities in gas transmission pipelines and planning strategies to enhance the reliability and resilience of energy supply chains. Existing studies and the American Society of Mechanical Engineers' (ASME) Code for Pressure Piping primarily focus on corrosion, recommending inspections every 10 years to prevent incidents due to this time-dependent threat. However, these guidelines do not provide comprehensive regulation on the likelihood of incidents due to other causes, especially non-time-dependent events (i.e. do not provide any indication of the inspection frequency or the most likely time for an incident to occur). This study adopts an innovative approach adopting machine learning, particularly artificial neural networks (ANNs), to analyse historical pipeline failure data from 1970 to 2023. By analysing records from the US Pipeline & Hazardous Materials Safety Administration, the model captures the complexity of various degradation phenomena, predicting failure years and hazard frequencies beyond corrosion. This innovative approach allows adopting more informed preventive measures and response strategies, offering deep insights into incident causes, consequences, and patterns. The results provide practical insights for maintenance planning, offering an estimation of periods when a pipeline may be more susceptible to incidents based on various factors. However, since all models inherently present uncertainties, both in the data and the modelling process, these estimates should be interpreted as probabilistic assessments. This study provides operators with a strategic framework to prescriptively address potential vulnerabilities, thereby promoting sustained operational integrity and minimising the occurrence of unexpected events throughout the service life of pipelines. By expanding the scope of risk assessment beyond corrosion, this study significantly advances the field of pipeline safety and reliability, setting a new standard for comprehensive incident prevention.

Article Highlights

- This study proposes a machine learning (ANNs) model to estimate the year of incidents in pipelines, considering multi-cause-and-effect relationships.
- 12,182 pipeline incidents from 1970 to 2023 in the United States are analysed, considering both time-dependent and non-time-dependent hazards.
- The results offer probabilistic insights for a deeper understanding of pipeline failure dynamics, promoting risk mitigation.

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Keywords Gas pipelines · Historical failures · Artificial neural networks (ANNs) · Service life · Maintenance

1 Introduction

Pipelines are recognised as the most cost-effective and reliable solution for energy transportation, playing a critical role in gas conveyance, especially within modern societies and in response to the escalating global demand for natural gas resources [1–3]. Even though being characterized by a relatively low probability of operational failures in comparison with alternative transportation methods [4–7], pipelines are complex systems carrying hazardous materials, subjected to several deterioration mechanisms, often operated by human beings, making them prone to catastrophic incidents [8]. While the occurrence of fatalities due to the pipeline leaks is relatively low in absolute numbers, the consequences of such incidents pose serious threats to human safety, the environment, and economic stability [9, 10].

The failure of pipelines is a complex phenomenon, and during their operational age, pipelines are exposed to a multitude of degradation agents and mechanisms [11, 12]. This cumulative aging process has the potential to compromise the structural integrity of the pipelines, ultimately reducing their durability and service life. The degradation factors can be categorized in: (i) physical, as type of material, pipeline section or joints, welding failures, nominal diameter, type of coating, wall thickness, among others; (ii) operational, which involve parameters such as pressure, flow velocity, and related operational variables; and (iii) environmental factors include temperature, humidity, traffic loads, soil type, natural hazards, and climate change [13–17].

When evaluating the hazards affecting risk analysis, it is possible to categorize them into two types: firstly, time-dependent hazards encompass factors such as internal and external corrosion, which tend to evolve progressively over time; secondly, time-independent hazards, such as natural disasters, equipment failure and damage caused by third parties [18]. Some corrosion models are often employed in a time-independent context, focusing on corrosion rates as functions of environmental factors (e.g., temperature, humidity) without explicitly accounting for the progression of corrosion over time. Nevertheless, in this study the corrosion is analysed as a time-dependent failure mechanism, based on the understanding that, over extended periods, cumulative corrosion effects, such as material degradation, thinning, or pitting, gradually worsen and lead to eventual failure. While some models treat corrosion rates as constant or instantaneous, the physical manifestation of corrosion progresses over time, making it a time-dependent process when assessing long-term structural integrity [18]. Moreover, industry practice supports time-dependent models in predictive maintenance and failure prediction, especially when periodic monitoring of corrosion is feasible [19]. For instance, an explosion occurred on July 2nd, 2011, along a natural gas pipeline in China that had been in service for nearly a decade. This incident, attributed to stress corrosion cracking—a time-dependent hazard—resulted in damage to approximately 100 square meters of forest and inflicted severe burns on a villager [20]. On the contrary, incidents originating from time-independent hazards, like third party activity (e.g., digging, piling, ground works) and ground movement (e.g., dike breakage, erosion, floods, landslides, mining, riverbed erosion, riverbank erosion), pose a significant risk of severe consequences. Significantly, holes and ruptures in European onshore gas pipelines were primarily caused by external interference, also referred as third-party interference [21].

A comprehensive interpretation of the complex interaction among these factors and their combined contribution to risk analysis is imperative for a more profound insight into the probability of failure of pipelines [17]. Considering that pipelines currently deliver approximately 93% of the global natural gas supply and operate in over 60 countries, prioritizing the maintenance of gas transportation infrastructures becomes paramount. Besides risk analysis, the implementation of effective risk control measures is equally relevant [22–25].

The United States represent 65% of the total pipeline length in the world, where ~ 515,000 km corresponds to the natural gas transmission pipelines in operation [26–28]. Approximately 25% of total energy consumption in the United States is primarily carried through the vast gas pipeline infrastructures [29].

In 1970, the United States introduced its initial pipeline incident regulation [30]. These led to the creation of databases derived from 12,182 incidents, recorded by the Pipeline & Hazardous Materials Safety Administration (PHMSA) from 1970 to 2023, which offer a unique opportunity for a comprehensive continental-scale analysis of the factors contributing to gas pipeline failures in the United States (U.S.). Our study encompasses the primary causes of incidents, operational factors, and their consequences, all grounded in the dataset available (12,182 incidents). The data used in this study, including incident reports, are publicly available through the Pipeline & Hazardous Materials Safety Administration (PHMSA) database. Readers can access the PHMSA database by visiting https://www.phmsa.dot.gov/ and searching for relevant datasets under the "Data and Statistics" section.

The lack of full analyses of historical failure data, including assessments of aging effects on material properties and examinations of the interplay between critical degradation factors, underscores the critical need for the development of models capable of describing and identifying multi-cause-and-effect relationships among degradation factors and pipeline failure incidents. To address this need, a machine-learning approach is proposed, specifically artificial neural networks (ANNs), to develop a prediction model that estimates the year of a pipeline failure based on relevant explanatory variables. While this methodology offers a data-driven approach to understanding potential failure risks, the predictions should be viewed as probabilistic assessments rather than precise forecasts due to inherent uncertainties in the data and modelling process. The study introduces a new perspective by exploring causal effects among different factors and the incident year, seeking to unravel the dynamics leading to pipeline failures. The proposed model intends to identify risks associated with predictable, time-dependent, or systematic causes of failure. Adopting a "lessons learned" perspective, recommendations and interventions are proposed to mitigate the occurrence of such incidents. The model's potential applications include prioritising inspection schedules, optimising maintenance interventions, and conducting risk assessments based on historical failure data. These uses align with the broader goal of enhancing pipeline safety and reliability, even though the model is not intended to predict every failure mechanism, particularly those driven by random external factors.

2 Literature review: understanding pipeline incidents

Over the past two decades, various studies have been conducted to analyse the risk and consequences of incidents in transmission and distribution pipelines, adopting the database of failure incidents available from the PHMSA within the U.S. Department of Transportation (DOT).

Bersani et al. [31] used 128 accident records from the United States' Department of Transportation, spanning 1971 to 1996, employing artificial neural networks (ANNs) for their analysis. The features used included the average population density within a 1 km^2 area surrounding the pipeline, land use patterns, road crossings, river crossings, and railway intersections. The aim of this study was to present a methodology that could identify pipeline segments potentially at risk of failure due to third-party activities.

A study performed by Siler-Evans et al. [32] explores the trends, causes, and repercussions of natural gas and hazardous liquid pipeline accidents in the United States, drawing from PHMSA data spanning 1968 to 2009 and encompassing around 40,000 incidents. The study underscores that while the number of distribution pipeline incidents has remained relatively steady since 1970, occurrences that are more recent tend to exhibit a lower incidence of fatalities and injuries.

Wang and Duncan [33] examined the likelihood of leaks and failures within natural gas transmission pipelines in the United States by analysing PHMSA data from 2002 to 2009. Their study investigated the causes and consequences of these incidents, identifying corrosion, external forces, and construction/material defects as primary contributors to pipeline failures. Particularly noteworthy was the prominence of construction and material defects, accounting for 75.8% and 83.6% of significant incidents in larger and smaller transmission pipelines, respectively.

Zakikhani et al. [34] proposed failure prediction models for external corrosion in underground gas transmission pipelines, considering both conventional and geo-environmental variables, considering the failure incidents reported in gas transmission pipelines in the United States, in a 20-year period from 1996 to 2016. The aim was to anticipate the critical timing of external corrosion-related pipeline failures by utilizing multiple linear regression analysis to construct a prediction model. This predictive approach aimed to offer valuable insights for strategically scheduling maintenance activities.

Rodriguez [35] performed a comprehensive statistical analysis of the incidents reported between January 2010 and January 2021, involving hazardous liquid and natural gas pipelines in the United States. This study specifically assesses the underlying mechanisms contributing to corrosion-induced degradation of pipeline components. It further evaluates the ramifications of hazardous substance releases, affecting both operator-owned properties and the surrounding environment.

More recently, Xiao et al. [28] employed domain knowledge and pertinent studies to identify six key features—pipe diameter, thickness, thickness-to-diameter ratio, strength, pressure, and location class—when modelling steel gas transmission pipelines failures. This was achieved by leveraging PHMSA failure data spanning from 1970 to the present.

These studies analysed the root causes of gas pipeline leaks and failures with different perspectives, using only part of the available database to address a specific subject. Most of those studies analyse the different defect types individually, mainly focusing on corrosion-induced failures [36, 37], to predict the probability of distinct failure modes [13, 38]. The majority of the contemporary research continues to rely on probabilistic models for predicting the behaviour of failures in gas pipelines [39–43]. However, machine learning-based approaches are increasingly recognized as a prominent option for anticipating unexpected failures in these pipelines, especially given the complex and broad nature of such failure occurrences [44–46]. Existing artificial intelligence models are usually developed for predicting mechanical, corrosion, and third-party failures [47].

Currently, the deterioration of gas pipelines operating for the last 60 years has been significantly investigated from mechanical point of view [48]. Nevertheless, the estimation of the pipelines' service life regarding their operating conditions has been neglected. In this paper, an innovative approach is used, employing the available sample from 1970 until 2023, to enable a more comprehensive analysis of the different degradation mechanisms contributing to the deterioration of gas pipelines. Artificial neural networks (ANNs) are used to analyse the historical pipeline failure data to ascertain past hazard frequencies and to predict the year of failure of gas pipelines, considering a multitude of factors. The model intends to express the inherent complexity of the degradation phenomena of gas pipelines, by navigating the multi-dimensional non-linear correlation among the relevant degradation factors responsible for the occurrence of incidents.

3 Materials and methods

Natural gas represents approximately 33% of all primary energy in the US and is predominantly utilized for electricity generation and heating purposes. Texas is the largest natural gas-consuming state (15.2%), followed by California (6.8%), Louisiana (5.9%), Pennsylvania (5.7%) and Florida (5.0%) [49]. This study analyses 12,182 incidents identified from 1970 until 2023, present in the database of failure incidents available from the PHMSA within the DOT. Figure 13, in Appendix, presents the first page of the incident report for gas distribution systems of PHMSA. In this study, nine quantitative variables and eight qualitative variables are analysed. Table 1 presents the statistical description of the numerical variables under analysis. The qualitative variables analysed in this study are the: (i) cause; (ii) leak part; (iii) ignition; (iv) explosion; (v) location; (vi) material; (vii) previous notification; (viii) previous mark. Each categorical variable has several mutually exclusive classes, which will be described in detail in the next sections.

In the context of this study, an artificial neural networks (ANNs) model is proposed to identify when the pipeline is going to failure by considering various relevant explanatory variables. By adopting the "year of the incident" as the dependent variable, the ANNs model can capture and predict the temporal dynamics inherent in the degradation processes and failure events of gas pipelines, contributing to a more comprehensive understanding of the factors influencing their integrity over time.

ANNs have proven to be effective tools to address complex problems across different scientific domains, including for modelling the condition of pipelines [13, 50]. ANNs present a relevant adaptive capacity and can learn and predict the behaviour of a given phenomenon directly from data, which enables the solution of difficult problems that pose analytical challenges [51].

While there are other modelling techniques—often referred to as "white-box" methods—that provide more straightforward interpretations of feature importance and the outputs of the model, the choice of ANNs was driven by several key factors. The ANN's ability to model complex, non-linear relationships was crucial to model this specific dataset, which

Table 1 Descriptive statistics of the numerical variables under analysis

	N	Minimum	Maximum	Mean	Standard deviation	Confidence interval (95%)
Incident year	12,182	1970	2023	1980.99	12.55	0.22
Incident pressure	11,939	0	164,917	275.89	1571.19	27.90
Maximum pressure	11,941	0	60,000	393.75	928.83	16.49
Installation year	12,182	1855	2022	1958.87	21.50	0.38
Nominal maximum diameter (NMD)	11,711	0	8625	182.50	448.88	7.97
Wall thickness	10,955	0	950	93.15	116.25	2.06
Fatalities	12,182	0	8	0.03	0.26	0.00
Injuries	12,182	0	59	0.24	1.26	0.02
Property	12,182	0	$1,586,502 068.00	$204,592.35	$14,662,956.15	$260,381.62

exhibited characteristics that might not be adequately captured by simpler models. ANNs offer a high degree of flexibility and present an adequate performance modelling scenarios where the underlying relationships between features are intricate and not easily disentangled.

The ANNs present advanced capabilities in learning from complex patterns within the data, which is particularly critical for the purpose of this study. In this sense, the predictive model developed in this study, using the ANNs, can estimate the year of failure for pipelines, including those not represented in the original dataset (i.e. ANNs can generalize from the training data to make accurate predictions on new, unseen data—such as predicting the failure year of pipelines not included in the initial dataset).

ANNs simulate biological neural systems, acquiring knowledge based on a learning process through data analysis [52, 53]. The neuron is the foundational component of ANNs, receiving inputs via synapses, process them through synaptic weights, execute a non-linear operation, and generate an output [54]. Typically, a neuron's output connects to multiple synapses, establishing connection with other neurons in the network. The most common type of ANNs is the multilayer perceptron (MLP) with an input layer, one or more hidden layers, and an output layer, as described in Eq. (1) [55, 56]. MLPs are fully connected feed-forward networks, indicating that every neuron in a layer is connected to all neurons in the subsequent layer, allowing information to flow unidirectional from input to output (Fig. 1). Additionally, an extra bias input $\left(b_i\right)$ is incorporated to enhance the network's performance to help minimize the cost function [57], as shown in Eq. (1).

$$\begin{aligned} u_i &= \sum_{j=1}^{n} (w_{ij}x_j) \\ y_i &= \varphi\left(u_i + b_i\right) \end{aligned} \tag{1}$$

where y_i represents the activation function φ of the output unit, b_i is the bias and x_j refers to the activations of the input units, n is the number of neurons in the prior layer, u_i the global input for the i^{th} neuron of the layer, w_{ij} is the synaptic weights between the i^{th} input neuron and the j^{th} output neuron. Each hidden unit is a function of the weighted sum of the inputs [55, 56].

Two distinct types of activation functions (φ) were used: the widely employed hyperbolic tangent function (Eq. 2), working as the activation function in the hidden layers of neural network [58]; and the identity function (Eq. 3) was used since the network output requires a real (or floating-point) number.

$$\tanh(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}}, u \in \mathbb{R} \tag{2}$$

$$y_i = f(x) = x, \forall x \tag{3}$$

The backpropagation algorithm (BPA) was used for training the ANN. BPA works toward minimizing the cost function within the weight and biases space by using the gradient descent optimization algorithm to find the local minimum, enabling a swift reduction of the cost function. The batch normalisation algorithm is used to obtain a regular distribution of activation values during training [59].

The Sum of Squared Errors (SSE) cost function was applied for both training and cross-validation. Therefore, the final ANNs model selected corresponds to the best overall result based on the largest coefficient of determination (R^2) value and the lowest mean squared error (MSE) value—Eqs. (4) and (5).

$$SSE = \sum\nolimits_{i=1}^{P} (y_i - \hat{y}_i)^2 \tag{4}$$

$$\begin{aligned} R^2 &= 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2}, \\ \bar{y} &= \frac{1}{P} \sum_{p=1}^{P} y_p \end{aligned} \tag{5}$$

where for each pattern i, y_i the observed values, $\overline{y}_i$ the average of the observed values, $\hat{y}_i$ the values predicted by the model [54].

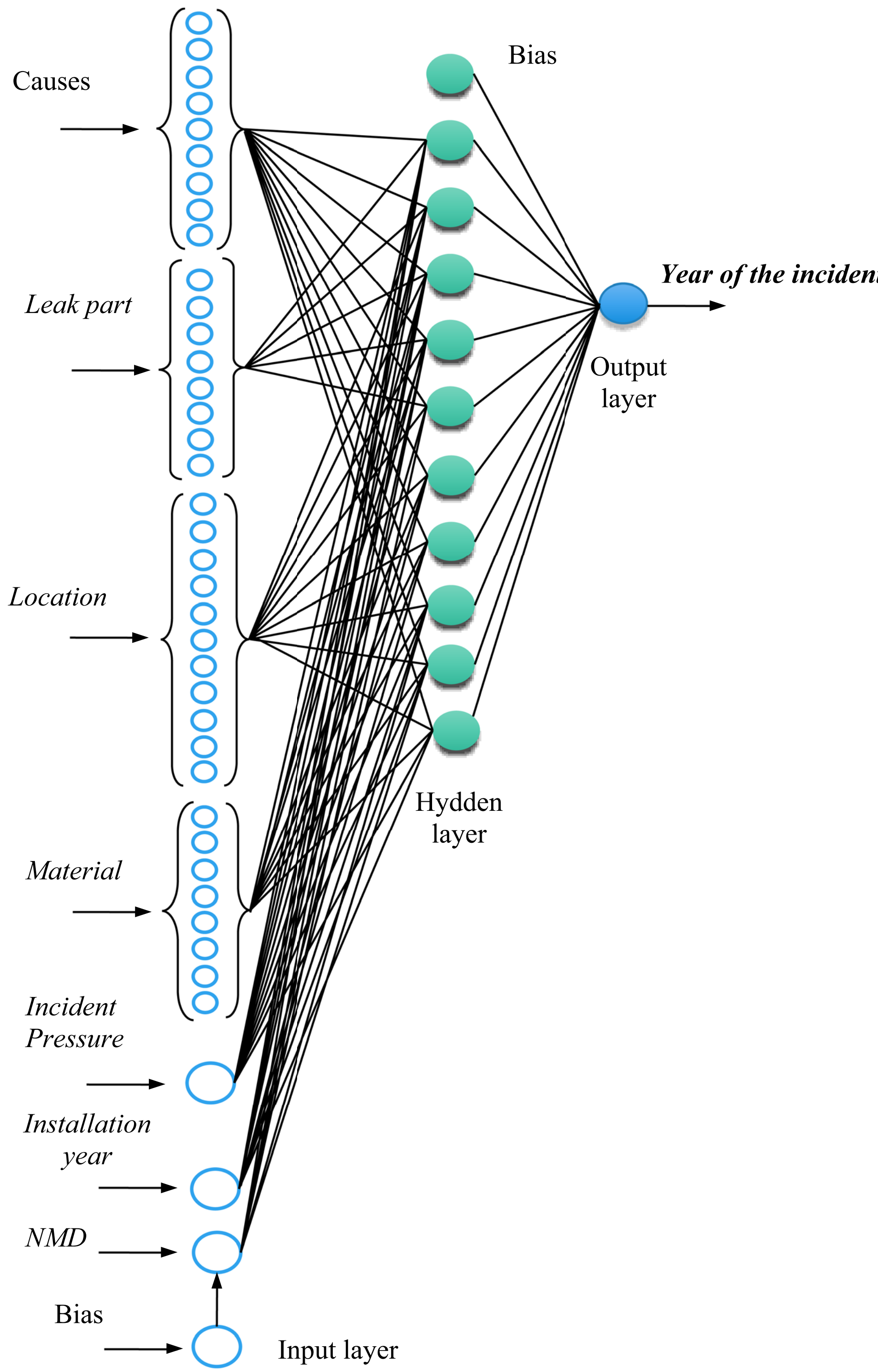


Fig. 1 Multilayer perceptron model created to predict the age of incident of gas pipelines [entries represented in a simplified way]

The ANNs model is created using the SPSS software [60]. The selection of the appropriate Multilayer Perceptron (MLP) to predict the year of an incident of a gas pipeline according to the relevant explanatory variables involves a trial-and-error process encompassing the analysis of different network architectures. Several architectures are tested, including the variation of the input layer and the number of hidden layers. MLPs with one and two intermediate layers were considered, i.e. N–H-1 architectures, where N is the number of cells in the input layer and H is the number of cells in the intermediate layer. A neural network with one hidden layer was chosen as the optimal architecture. Ten runs were performed for each architecture, with the global set of patterns randomly divided into three groups—training

(60%), cross-validation (15%), and test (25%—across all runs). Figure 1 presents the neural network developed for the prediction of the year of incidents in pipelines and the coefficients of the ANNs are presented in Table 2 in appendix.

To avoid creating very complex and uninterpretable models containing redundant information from certain features, a Feature Selection process was implemented in the models [61, 62]. A forward stepwise selection of the input variables is carried out, including in the model the variables with greater explanatory power, considering the principle of parsimony [62]. In the model, equal weighting is assigned to all variables within the input, and the feature selection process is performed automatically. By systematically assessing the impact of each input variable on the model's predictive performance, feature selection allows determining the relevance of each variable for the explanation of the variability of the output variable (in this case, the year of the incident) within the artificial neural network model.

The adoption of automatic feature selection and equal weight initialization in the ANNs model ensures an unbiased starting point for the learning process. ANNs, through backpropagation, iteratively adjust weights based on the error gradient, meaning that the final learned weights and feature importance emerge as a result of the training process, largely independent of the initial values. While different initialization schemes—such as randomized or structured—could introduce variability in the learning process, the decision to start with equal weights aims to avoid predisposing the model toward any particular feature at the outset. Nevertheless, feature importance in ANNs can vary depending on both the initialization method and the training process itself.

Figure 2 presents the relative importance of input variables in the ANN model developed, which intends to predict the year of incident of gas pipelines. Seven variables are included in the model, by order of relevance (Fig. 2): (i) the cause of the incident; (ii) the year of installation; (iii) the leak part; (iv) the nominal maximum diameter (NMD); (v) the location of the pipeline; (vi) the pipelines' material; (vii) and the pressure at the time of the incident.

The proposed ANNs model presents a sum of the square errors (SSE) of 29 for the training set, with a relative error of 0.19, and an SSE of 12 for the test sample, with a relative error of 0.21. A Pearson correlation coefficient (r) of 0.9 and a coefficient of determination (R^2) of 0.8 are obtained for the model, demonstrating the model's efficiency to predict the year of the gas pipelines incidents based on the variables included in the model.

4 Results and discussion

4.1 Hidden risks: unveiling root causes of pipeline failures

The cause of the incident should be analysed in detail since it is considered by the ANNs' model as the most important feature to predict the year of the incident (as shown in Fig. 2). Figure 3 presents the frequency of different causes of incidents in gas pipelines in United States (between 1970 and 2023). The causes are categorised into nine groups: construction defects or material failure; corrosion; damage by outside forces; equipment failure; excavation damage; incorrect operation; natural forces; pipe, weld, or joint failures; and other causes, or when the detailed cause is unknown or not reported.

Incidents caused by outside forces are predominant in the sample analysed (around 67%). Most of these incidents are caused by motorized vehicles or equipment not engaged in excavations, by nearby industrial, man-made, or other fire/explosion as primary cause of incident, by electrical arcing from other equipment or facility, by boats and fishery

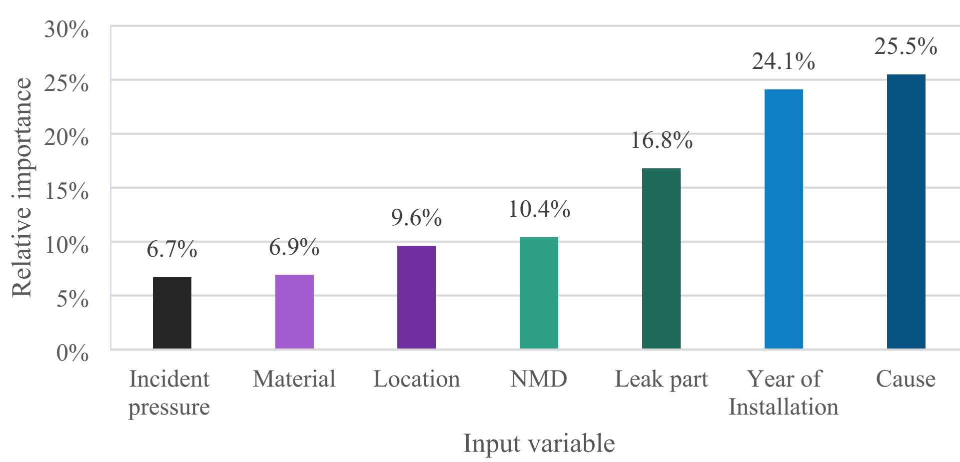


Fig. 2 Relative importance of the features included in the ANNs model

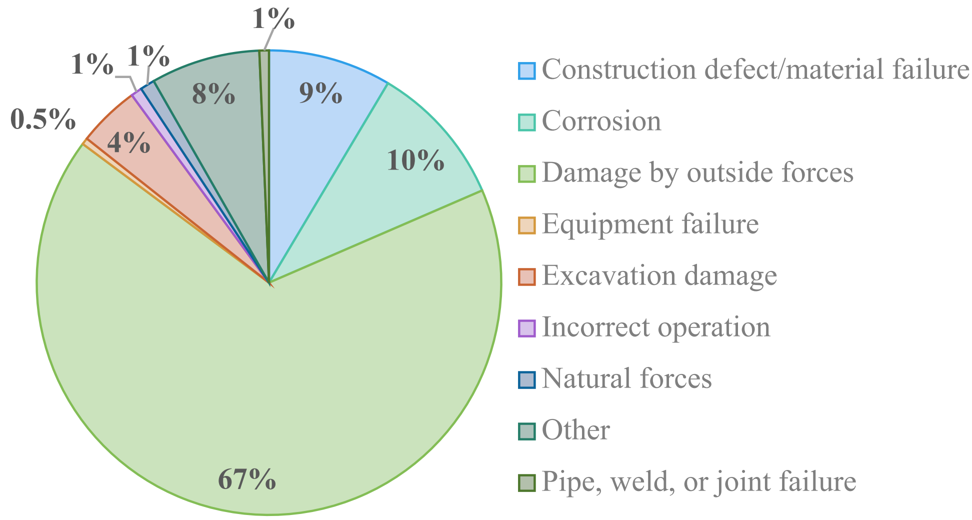


Fig. 3 Distribution of frequency of main causes of incidents (between 1970 and 2023)

anchors, or by vandalism. These events are complex and almost impossible to predict when and where they will occur, and how they will affect the pipelines' integrity, since depend on several factors that are beyond the control of the pipeline operators.

Corrosion is the second more common cause of incidents, followed by construction defects or material failures. Both causes are related with inadequate design or material defects (e.g. incorrect material specification) or construction deficiencies [63].

In an overall perspective, the frequency of incidents has decreased over time, in the sample under analysis, which can be explained by the evolution of the state of knowledge, safety protocols and quality regarding the materials used and the growing use of in-line inspection [64, 65]. 79% of the incidents due to material failure occur in the 1970s, which can be explained by the electric resistance welded pipes used [66]. An observable correlation emerges between the incident year and installation year, attributed to advancements in design, improvements in steelmaking and line-pipe manufacturing, the adoption of more durable materials, and enhanced corrosion protection. Aligned with PHMSA's findings, an analysis of European onshore gas pipeline data from 2010 to 2019, encompassing around 140,000 cumulative km—the second-largest natural gas pipeline incident dataset after PHMSA's—indicates a decrease in failure frequencies attributed to various causes over the years. This decline is also attributable to technological progress, particularly in welding techniques, improved inspection methodologies, the integration of in-line inspections for condition monitoring, and the implementation of enhanced strategies for damage prevention and detection [21]. The incidents reported by PHMSA attributed to excavation operation, incorrect operation, and natural forces have increased progressively. This rise can be primarily attributed to the expansion of pipeline infrastructure, intensified urban development and increased population density near pipelines, as well as the escalating frequency of extreme weather events resulting from climate change [67].

The analysis of failure data from PHMSA provides valuable knowledge about the service life of pipeline infrastructures. The pipelines' service life can be defined as the period of time during which they can operate safely and reliably without major failures or repairs [37, 68].

In this study, the estimated service life of gas pipelines is given by the difference between the year of the incident and the installation year, i.e. the period of time since installation until the failure or incident that compromised the operation of the pipeline or, in a simpler way, the age of the pipeline on the incident. The pipelines' service life depends on several variables, such as the design and manufacturing conditions, inspection and maintenance circumstances, as well as the environmental and operational conditions that they are exposed to. Figure 4 illustrates the estimated service live of gas pipelines based on incident causes.

4.2 Assessing the influence of pipelines' components on incidents

In the ANNs model created in this study, the 'leak part' is identified as the third most influential variable to explain the temporal aspect of gas pipeline incidents (Fig. 2). The distribution system comprises different types of lines, namely [29]: supply main, which runs between the interconnection with the transmission system and the feeder

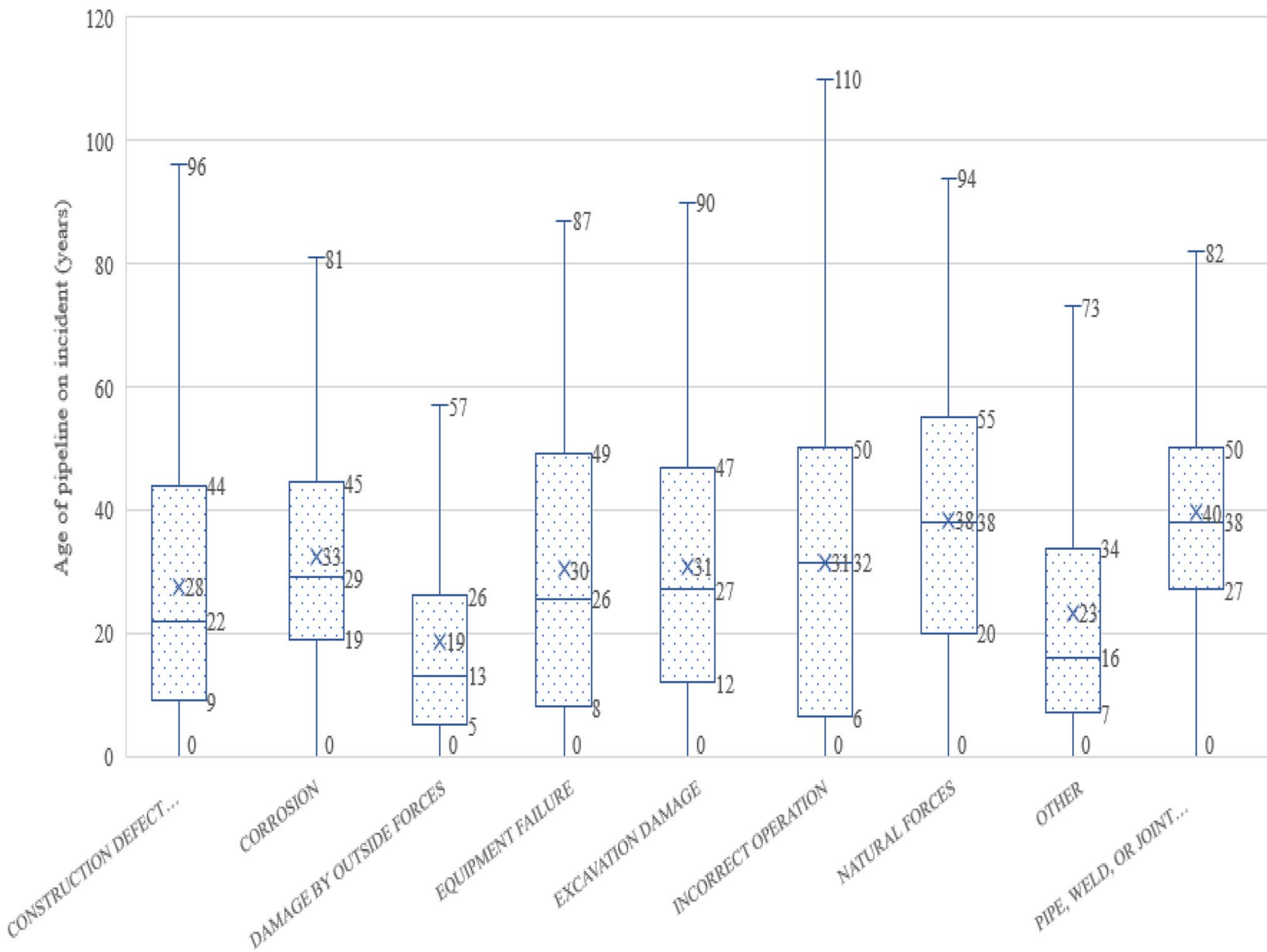


Fig. 4 Estimated service life of gas pipelines according to the cause of the incident

mains, with typical pressures ranging from 150 to 400 psi; feeder main, which connects the supply main to the distribution main, being connected to supply mains at a regulator station that reduces the pressure of the line to ranges between 26 and 60 psi; distribution main, which bends throughout the service territory transporting gas to areas of mass consumption, with typical pressures ranging from 1 to 25 psi; and service line, which connects a home or business with the distribution main that may be running underneath the cities' streets, with typical pressures between ¼ to 1 psi (this pressure can be higher for larger customers).

Figure 5 presents the estimated service life of gas pipelines according to the leak part. The results show that the service riser presents the higher estimated service life, which can be explained by the adoption of prefabricated risers, having their own buoyancy systems to support them, which brings more safety to pipeline installation [69]. The main lines and the district regulator present high estimated service lives, with maximum values of 95 and 87, respectively. These segments of the pipeline network are usually designed and constructed with careful consideration of industry standards and regulations, since incidents involving large-diameter and high-pressure pipelines can be catastrophic for society and environment [33]. Moreover, these segments are usually located in less populated or remote areas and buried at a higher depth, being less exposed to external threats or third-party activities, which is the main cause of incidents, thus reducing the likelihood of incidents that could impact their service life. Numerous corporations and design standards recognize the critical role played by maintaining an adequate depth of cover in mitigating susceptibility to external interference [21].

The meter set and the pressuring limit present lower estimated service lives, since withstands a variety of loads at the same time. The service line is the segment with the lowest service life, which can be explained by the proximity to populated areas and by the pipes' lower nominal diameter and thickness [33].

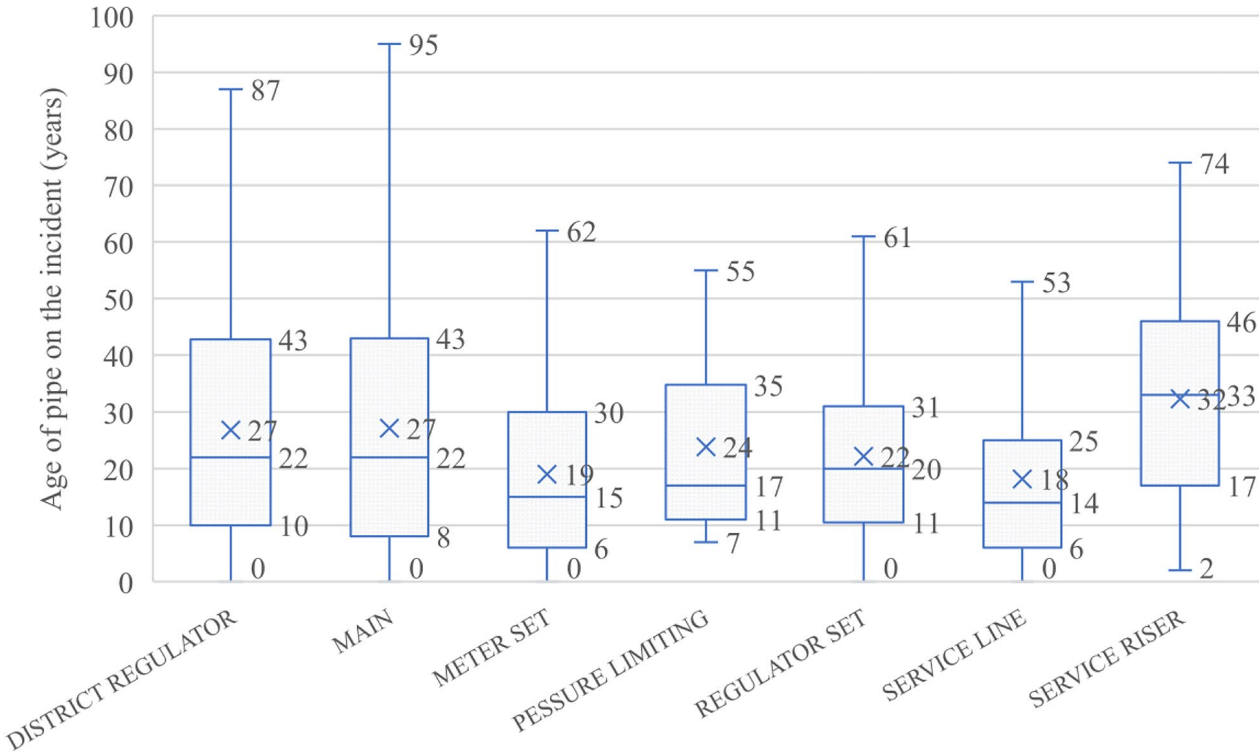
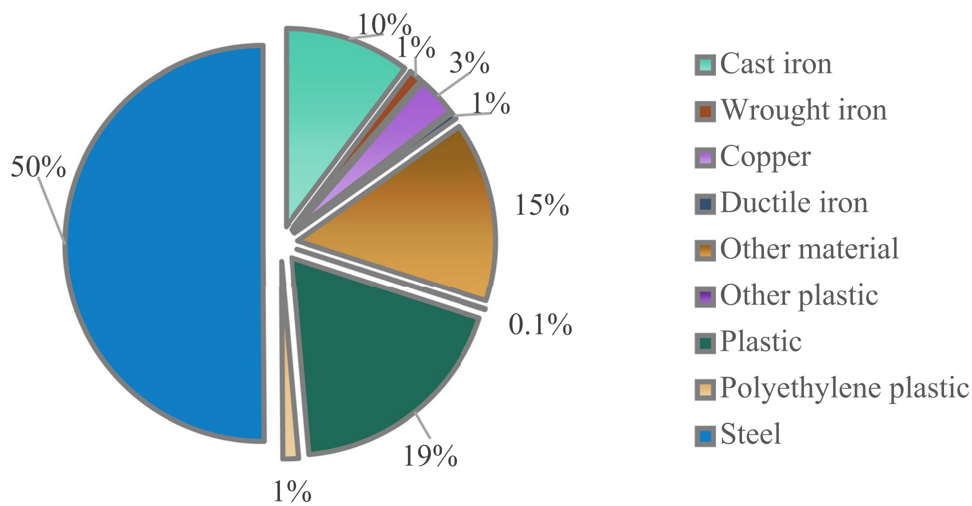


Fig. 5 Estimated service life of gas pipelines according to the leak part

4.3 The influence of design characteristics: nominal diameter

In fact, the pipelines nominal diameter is considered as the fourth more relevant variable to explain the year of the incident (as shown in Fig. 2). The relevance of the nominal diameter and the pipelines' wall thickness influences, to some extent, the part of the pipeline where the leakage or failure occurs, as observed in the analysis of Fig. 6. Smaller pipelines (i.e. with lower diameter and wall thickness), as the one used in service lines, are more vulnerable to the action of external forces such as third-party activities, and even to excavation and earth movements' actions, or natural hazards [17]. Moreover, larger pipelines with higher pressures are more carefully maintained [70].

Fig. 6 Distribution of frequency of incidents (between 1970 and 2023) according to the materials used in the pipelines



4.4 The impact of pipelines' materials on the occurrence of incidents

In addition to the nominal diameter and pipelines' thickness, the material adopted for gas pipelines also influences their service life. According to the PHMSA [29], around 98% of natural gas distribution pipelines in the U.S. were made of plastic or steel at the end of 2022, and only 1% is iron pipe. Figure 6 presents the frequency of accidents according to the materials used and Fig. 7 shows a two-dimensional analysis of the estimated service life of gas pipelines according to the leak part and the material applied.

Cast iron and unprotected steel pipelines are considered as posing extremely high risks and have been substantial reduced since the 1990s, being replaced by protected steel and plastic [71]. Despite initiatives, such as the Pipeline Safety, Regulatory Certainty, and Job Creation Act of 2011, aimed at removing cast and wrought iron pipes, a considerable number of these pipelines continue to supply natural gas to homes and businesses today (US Department of Transportation, 2017).

The materials used in gas pipelines varied considerably over the last 30 years, but since 2017, plastic and related elastic materials have been used for distribution and steel for transmission lines [38]. This justifies the predominance of incidents in plastic pipelines and the lower estimated service life obtained (Fig. 7).

4.5 The relevance of pipelines' location to the occurrence of incidents

The location of the pipeline is also considered a relevant variable to explain the behaviour of the year of the incident (Fig. 2). Figure 8 presents the estimated service life of gas pipelines according to the location of the pipeline.

The variable "location of the pipeline" has eleven classes: (i) above ground (e.g. facility piping; overhead crossing); (ii) below road (paved); (iii) below road (unpaved); (iv) below walkway; (v) open ditch; (vi) other location; (vii) transition area (e.g. soil/air interference, wall sleeve); (viii) underground; (ix) under pavement; (x) under water; and (xi) within building.

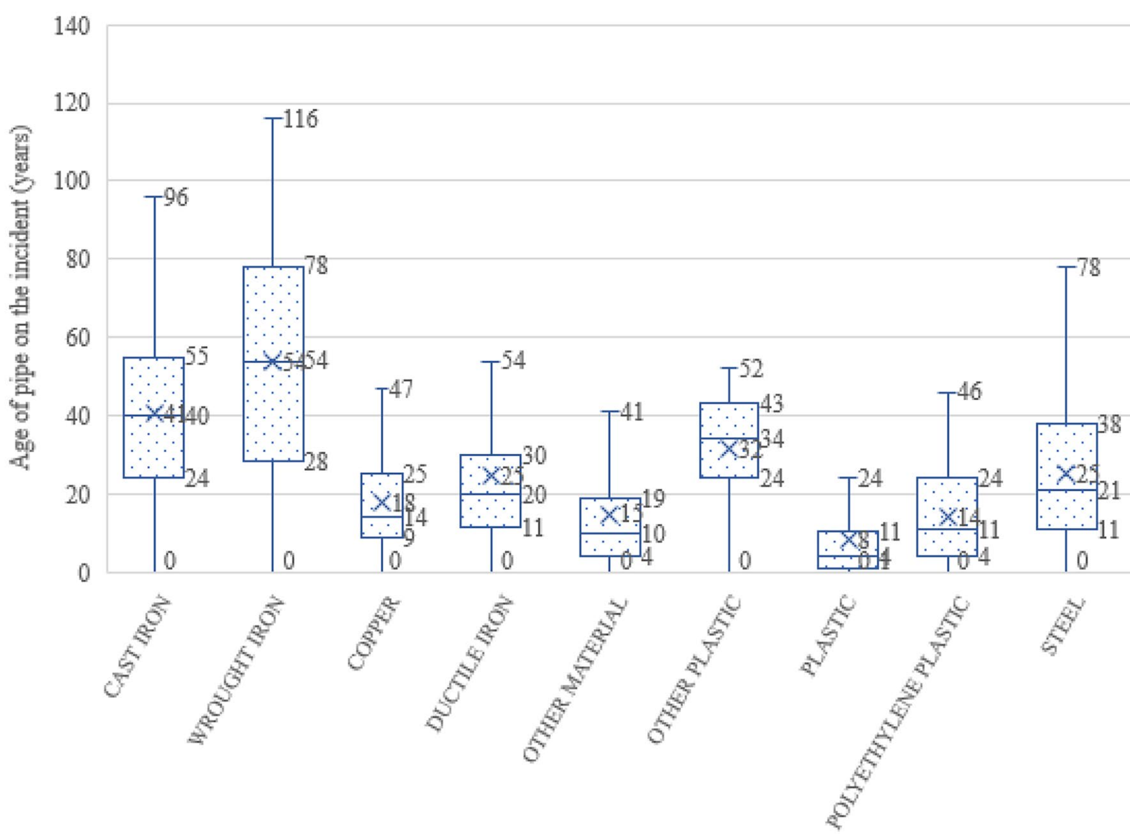


Fig. 7 Estimated service life of gas pipelines according to the pipelines' materials

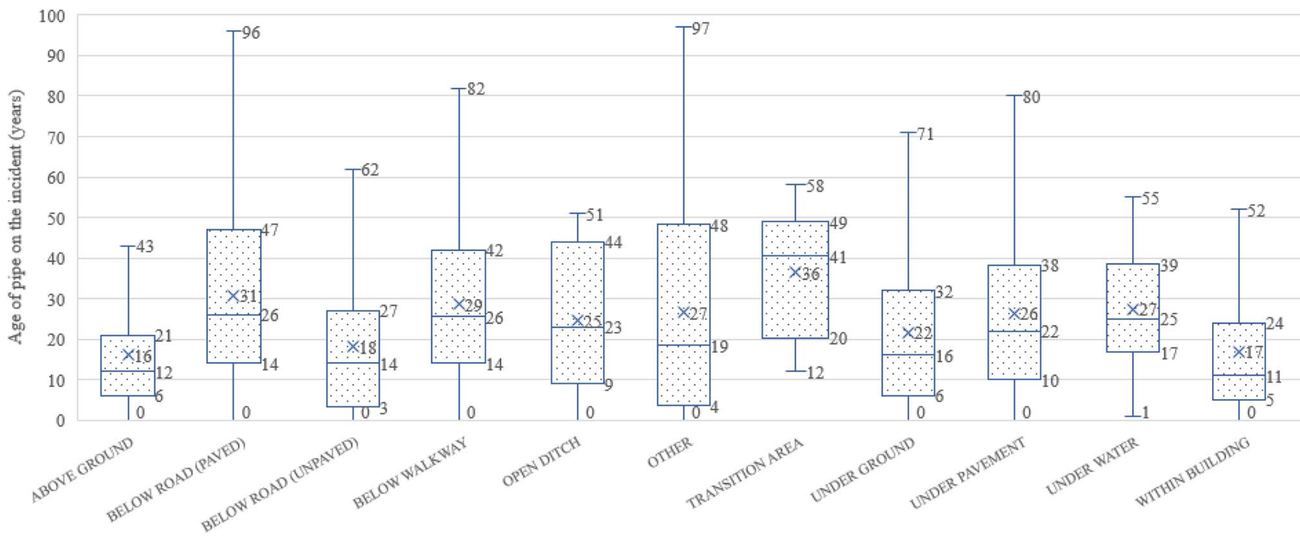


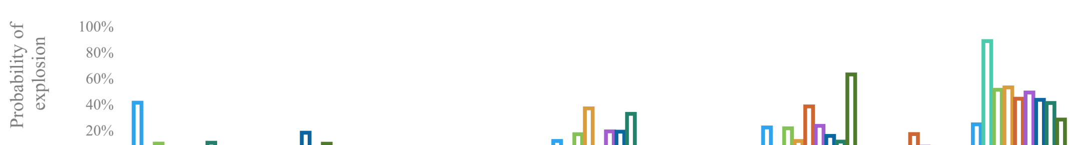
Fig. 8 Estimated service life of gas pipelines according to the location of the pipeline

4.6 Lessons learned from failure events and their consequences

The failure of gas pipelines is always an undesirable incident that entails severe consequences, which can manifest as economic losses, environmental impacts, and, in the most severe scenarios, human injuries or casualties [72]. Even small leakages can have catastrophic consequences and affect a large number of people [73]. A historical example is the 1937 incident at Consolidated High School in Texas, where an undetected gas leak caused a devastating explosion, resulting in the complete destruction of the building and the tragic loss of 309 lives, including 294 students [74]. The analysis of the consequences of gas pipelines incidents is crucial to ensure a cost-effective and secure long-term operation of pipeline networks [75, 76].

Today, the current level of safety of the gas pipeline industry results, in a large extent, from the lessons learned over the years from historical data [77]. The causes of these incidents were unknown beforehand, and there were no indications that the incident could occur, which would have allowed for its prevention. Figure 9 shows the probability of explosion of a gas pipeline according to the type of material and the cause of the incident.

In this study, 12,182 failure events are analysed and a total of 6506 ignitions were reported (53.4%) and 1807 explosions occurred (15% of the reported incidents resulted in explosions), which reveals a odds ratio of 28% of an ignition result in an explosion. Figure 10 presents the consequences of the incidents, revealing that the most significant consequences occur in cases where there is ignition followed by an explosion.



	CAST IRON	CAST/WROUGHT IRON	COPPER	DUCTILE IRON	OTHER MATERIAL	OTHER PLASTIC	PLASTIC	POLYETHYLENE PLASTIC	STEEL
CONSTRUCTION DEFECT/MATERIAL FAILURE	40%	0%	2%	1%	11%	0%	21%	1%	23%
CORROSION	3%	2%	5%	1%	2%	0%	0%	0%	87%
DAMAGE BY OUTSIDE FORCES	9%	1%	3%	1%	16%	0%	20%	0%	50%
EQUIPMENT FAILURE	0%	2%	0%	0%	36%	0%	11%	0%	52%
EXCAVATION DAMAGE	0%	2%	0%	0%	1%	0%	37%	16%	43%
INCORRECT OPERATION	0%	2%	1%	1%	18%	1%	22%	6%	48%
NATURAL FORCES	0%	17%	3%	0%	18%	2%	15%	3%	42%
OTHER	9%	2%	5%	1%	32%	0%	10%	2%	40%
PIPE, WELD, OR JOINT FAILURE	0%	9%	0%	0%	2%	0%	62%	0%	27%

Fig. 9 Probability of explosion according to the type of material and the cause of the incident

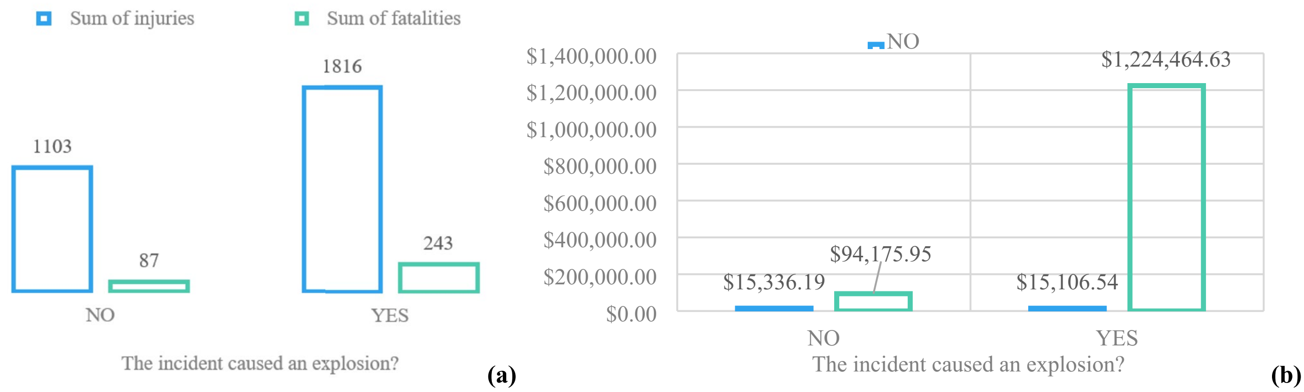


Fig. 10 Consequences of the incidents: **a** human injuries and fatalities; **b** property damage

A higher incidence of explosion is observed for steel pipelines, in particular due to corrosion. The progression of corrosion in aged steel pipelines reduces the materials' strength and increases the likelihood of leakage and failures [78]. Corrosion manifests independently of wall thickness; however, it has been observed that thinner corroded pipeline walls accelerate the pipeline's failure [21]. In the sample analysed, only 10% of the incidents occur due to corrosion (Fig. 3) and in only 2% of the incidents the maximum operating pressure was exceed, which reveals that despite this, when these incidents occur, they have serious consequences. In fact, most operators are focused on controlling the operating pressure in order to avoid incidents, but in the sample analysed, in 98% of the incidents, the explosion occurred in cases where there was no pressure overload, i.e., the incident occurred for operating pressures under the maximum pressure allowed.

5 Final remarks

The results reveal a causal relationship between the cause of the incident and the pipelines' service life. Causes related to natural degradation processes—such as pipe, weld, or joint failure, corrosion, equipment failure, or construction defects—typically progress slowly over time, leading to longer estimated service lives. While these natural processes act gradually, they differ fundamentally from external causes like accidents or mishandling, which occur abruptly and are inherently driven by human interference. The service life of gas pipelines is compromised when incidents result from third-party actions (e.g. damage by outside forces, other causes, or vandalism). While incidents from natural degradation processes are often modelled by degradation curves and predicted in the designed service life assumed by industry standards, third-party activities introduce an element of unpredictability, being difficult to preventively mitigate the impact of these actions. Consequently, the service life of gas pipelines tends to experience a visible reduction in such instances as shown in Fig. 5, with an average service life of 19 years for damage by outside forces. Comparing incidents driven by human factor is difficult due to their distinct nature and impact on pipeline integrity. However, pipelines above ground, inside the buildings and below unpaved roads present lower estimated service lives, highlighting the importance of their location context.

In United States, pipelines are designed in accordance with the standard by the American Society of Mechanical Engineers [19], assuming a service life of 50 years, with a conservative safety factor. Similarly, European onshore gas pipelines support this notion, as it has been established that pipelines constructed within the last 50 years show no correlation between the frequency of corrosion-related failures and their age or construction year class [21]. Gas pipelines, when adequately maintained are designed to last several decades, but on some occasions, gas pipelines may need to be replaced after only a few years.

Data from the Ukraine gas-transportation system (GTS) reveal that 58% of Ukrainian gas pipelines present a service life between 15 and 50 years, but 5.8 thousand km of pipelines completed their service live in 33 years [79]. The US federal regulations on gas pipelines consider that pipelines with more than 25 years are potentially at risk depending on the pipeline's coating and corrosion condition, steel quality, toughness and welding [80].

The average estimated service life obtained in this study (according to the sample used) is 23 years, which is consistent with the referred literature values. However, when accounting for construction defects/material failures, equipment failures, corrosion, and pipe/weld/joint failures, the service life extends to 33 years. This estimation presents

Average age of pipe on the incident (years)	District regulator	Main	Meter set	Pressure limiting and regulating facility	Regulator set	Service	Service line	Service riser	Overall
Cast iron		43				23			41
Wrought iron	33	68	19		15	35			55
Copper		30			33	15		43	18
Ductile iron		34				21		8	25
Other material	30	32	13	11	20	12	34	27	17
Other plastic		24					42		32
Plastic		8			18	7		23	8
Polyethylene plastic		14	14				15		14
Steel	25	28	27	27	25	23	47	38	26
Overall	**27**	**27**	**19**	**24**	**22**	**18**	**31**	**32**	**23**

Fig. 11 Heat map of the average estimated service life according to the material applied and the leak part

a higher standard deviation and can vary widely depending on the different variables analysed in this study, due to the complexity of the multitude of the pipeline conditions and their significant effect on the degradation rate. In this sense, a more detailed analysis is needed to comprehend the causal effects between the different variables to develop more accurate predictive models and implementing targeted strategies to enhance the resilience and durability of gas pipelines under varying circumstances.

Figure 11 presents a heat map to evaluate the impact of the material applied in different parts on the pipelines' service life. This information is crucial for future decisions related to the design of pipelines. The results obtained based on historical data on incidents reveal that pipelines in wrought iron applied in main lines present a higher estimated service life (68 years) when compared with other materials, in particular in comparison with plastic, which presents the lower estimated service life (8 years). Copper seems to be the most suitable material to be applied in service risers, while ductile iron presents the worst results (a service life of 8 years). For service lines, steel presents the higher estimated service life (47 years) while polyethylene plastic presents the worst results (15 years).

In fact, while plastic pipelines are widely accepted as a safe and cost-effective alternative to steel or other materials, the National Transportation Safety Board (NTSB) [81] has identified instances of brittle-like cracking in plastic piping involved in several pipeline accidents. The NTSB's special investigation suggests that the strength rating procedure for plastic pipelines adopted in the United States may have overestimated their resilience and resistance to brittle-like cracking, particularly in pipes manufactured and used for gas service from the 1960s through the early 1980s. Consequently, a significant portion of this piping may be prone to premature brittle-like failures under stress intensification, posing a potential public safety hazard [81]. The sample analysed revealed a high incidence of explosions in plastic pipelines, especially due to pipe, weld or joint failures, or due to excavation damage.

Figure 12 shows the heat map portraying the causal effects between the leak part, the pipelines' material and the location of the incident. This heat map allows identifying critical points, which must be operated and maintained with higher caution. Critical points are identified for pressure limiting and regulating facilities under ground. Moreover, pipelines in open ditch with incorrect operation present an estimated service life of 8 years, while pipelines above ground with construction defects show a service life of 10 years, which is clearly not enough, and measures must be taken to ensure that the service life of the pipelines is increased in these particular conditions. In the sample analysed, pipelines above ground, inside the buildings and below unpaved roads present lower estimated service lives, being particularly susceptible to construction defects and damage by outside forces.

Pipelines are manufactured assuming strict control rules, ensuring recognised quality and safety control limits. Nevertheless, during its service life, a pipeline will contain defects that require a fitness-for-purpose assessment to determine the need for intervention and the necessary measures to avoid incidents [82].

The approach proposed, and the results obtained, enables discussing the significance of incident causation on pipelines' service life, and some recommendations can be drawn for possible measures to mitigate and avoid the risk of failure of gas pipelines.

	Average age of pipe on the incident (years)	Above ground	Below road (paved)	Below road (unpaved)	Below walkway	Open ditch	Transition area	Under ground	Under pavement	Under water	Within building	Overall
Leak part	District regulator/ metering station	23						47				27
	Main	24	34	20	29	28	34	24	32	29	28	27
	Meter set	18						46			22	19
	Pressure limiting and regulating facility	27						7			15	23
	Regulator set	22					52					22
	Service	13	23	14	28		30	18	20	21	20	18
	Service line	27				18		31	36		45	31
	Service riser	32					32	35				32
Cause	Construction defect/material failure	10	37	21	33	38		21	25	42	26	27
	Corrosion	27	32	29	40			33	30	28	37	32
	Damage by outside forces	15	28	17	24	13	33	17	20	19	15	19
	Equipment failure	21						38		20		30
	Excavation damage	42				36	50	30	34	40	36	31
	Incorrect operation	28				8	39	34			31	31
	Natural forces	28					38	46	51	48	42	38
	Other	17	34	22	24	21		25	28	33	17	23
	Pipe, weld, or joint failure	43					17	39				40
	Overall	**16**	**31**	**18**	**29**	**25**	**36**	**22**	**26**	**27**	**17**	**22**

Fig. 12 Heat map of the average estimated service life according to the leak part, the pipelines' material and the location of the incident

The historical data analysed reveals a difficult to anticipate the incidents; in 79% of the incidents, the pipeline was not marked and in 82% of the incidents, the pipeline was not notified. A serious problem is thus identified, since most incidents occur through phenomena that cannot be modelled (such as the action of third parties) and there is a lack of fit-to-purpose procedures for assessing the state of degradation of pipelines over time.

This study identifies two critical concerns, which are pipelines crossing populated areas, where small leaks can have catastrophic consequences, and the incidents caused by external interference, which is the most common cause of incidents. Both need immediate attention once detected and require sophisticated tools for pipelines' condition assessment.

Intentional or accidental third-party actions are the most common causes of incidents but are still the least studied factor in pipeline hazard assessment [83]. The incident rates by third party activities can be reduced by enhancing the design of pipelines through the adoption of a safety factor, by increasing the depth of pipelines' cover and adopting a wider pipe wall thickness and employing modern coatings like polyethylene or epoxy coatings.

An analysis of European onshore gas reveals corrosion incidents (26.5%) and external forces (27.2%) occurring nearly equally. Subsequently, construction material/defects (15.7%) were equally prevalent as natural forces, specifically ground movement (15.7%). Contrary to the situation in the U.S., improvements related to excavation damage have been reported. This shift may be attributed to stricter enforcement of land use planning regulations and the adoption of one-call systems regulating external parties' excavation activities. Many European countries have now made it a legal requirement to report such activities, prompting companies to implement measures such as supervision or marking of pipelines in proximity to excavation sites [21].

Moreover, the results emphasise the critical importance of situational awareness within the pipelines' industry, defined as the capacity to comprehend the contextual surroundings of pipelines, in order to predict potential hazards and put into practice informed measures to ensure the pipelines' safety. Reporting near-miss incidents emerges as a crucial tool for learning and prevention. The mitigation of accidents hinges significantly upon addressing human factors, notably through the implementation of robust feedback mechanisms derived from incidents' historical data. Enhancing human performance involves a multilayered approach, encompassing the reinforcement of management, crew, and company-wide proficiency, as well as adherence to established policies, standards and procedures. Through continual improvement initiatives focusing on human error reduction and the reinforcement of skills and knowledge, a sustainable framework for accident prevention can be cultivated within the industry.

Currently, the existing models to predict the residual service life of pipelines and risk assessment models are focused on specific degradation mechanisms. Corrosion is the most studied phenomenon, due to its relevance, since steel pipelines, when they fail due to corrosion phenomena, have a high probability of triggering an explosion, as shown in the results of this study. However, the current conventional corrosion assessment codes are conservative, proposing unnecessary repairs and premature replacement of pipelines, which entails high and unnecessary costs [84]. In this sense, the results of this study reveal the need for comprehensive risk assessment strategies, maintenance protocols (with effective emergency response), and adherence to industry standards (considering the operators' policy, practices, and organizational culture) to increase the resilience of gas pipelines, particularly when confronted with the unpredictable nature of third-party activities.

This study transforms encapsulated data into self-contained case reports into an accessible knowledge framework.

The model proposed and the results obtained are expected to help pipeline operators to assess and predict the condition of existing gas pipelines and consequently prioritise their inspections and maintenance needs. The heat maps allow proactively identify and address potential failure points, implementing proactive maintenance procedures at the right time (considering the estimated service life of pipelines according to their characteristics), in order to increase the performance and reliability of pipelines.

Future maintenance decisions should not be based on these results alone. Instead, they should be informed by a holistic approach that includes the model outputs but also expert judgment, historical performance data, and established safety margins. By integrating these components, the industry can ensure that maintenance strategies are more robust and well-rounded. This study intends to foster a more comprehensive and cautious approach to pipeline maintenance, enhancing overall safety and reliability. By leveraging this knowledge to implement proactive maintenance procedures, organizations can minimize risks, optimize operations, and maintain a competitive edge in their respective industries.

This study thus provides relevant information to enhance the effective management of existing pipelines, which is critical for ensuring their long-term safety, reliability, and efficiency. The predictive model proposed can provide probabilistic information to aid in periodic inspections for early detection of corrosion, fatigue, or damage.

This model is the initial step in developing a risk-based maintenance approach that assists in prioritising maintenance for pipeline segments more susceptible to failure, based on factors such as age, material, environment, and operational history.

This approach optimizes resource allocation by focusing maintenance efforts on higher-risk areas rather than applying a uniform strategy. Integrating data from multiple sources can provide a more comprehensive view of pipeline conditions. Using predictive analytics driven by machine learning models, such as ANNs, can anticipate potential failure points and recommend preventive interventions before critical failures occur.

Acknowledgements The authors acknowledge the funding from the European Economic Area (EEA) Grants and Norwegian Financial Mechanisms for the support of the "PIPELIFE" bilateral initiative (FBR_OC2_71). The authors also acknowledge the support of the Portuguese Foundation for Science and Technology (FCT) and research unit CERIS (UIDB/04625/2020). Ana Silva and Jónatas Valença acknowledges FCT for the funding the individual project CEECIND/01337/2017 and CEECIND/04463/2017, respectively.

Author contributions A.S and M.P.M. wrote the main manuscript and define the methodology. L.E., C.F. and J.V. help in data analysis and discussion of the results, as well as revised the manuscript. All authors reviewed the manuscript.

Data availability Data is provided within the manuscript and more information will be provided once requested.

Declarations

Competing interests The authors declare no competing interests.

Appendix

See Table 2 and Fig. 13.

Table 2 Coefficients for the ANNs' model proposed

		Hidden layer										Output
		H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (1:8)	H (1:9)	H (1:10)	Incident year
Input layer	(Bias)	0.500	0.241	− 0.110	0.500	0.164	− 0.253	0.054	0.599	− 0.268	0.217	
	[Cause = CONSTRUCTION DEFECT/MATERIAL FAILURE]	0.155	0.283	− 0.090	− 0.384	− 0.293	0.376	− 0.504	0.643	0.512	0.447	
	[Cause = CORROSION]	0.067	− 0.551	0.360	− 0.118	− 0.445	0.452	− 0.545	0.054	− 0.397	0.593	
	[Cause = DAMAGE BY OUTSIDE FORCES]	− 0.187	− 0.482	0.461	− 0.073	− 1.032	0.427	− 0.236	0.286	− 0.468	0.478	
	[Cause = EQUIPMENT FAILURE]	− 0.500	− 0.075	− 0.515	0.220	0.016	0.237	0.353	0.436	0.175	0.248	
	[Cause = EXCAVATION DAMAGE]	0.108	0.155	0.576	− 0.062	0.921	− 0.732	0.100	− 0.011	− 0.079	− 0.465	
	[Cause = INCORRECT OPERATION]	0.010	− 0.152	− 0.099	− 0.119	0.050	− 0.378	− 0.311	− 0.114	− 0.430	− 0.679	
	[Cause = NATURAL FORCES]	0.287	0.079	− 0.404	0.288	0.535	− 0.494	0.033	− 0.161	0.008	0.353	
	[Cause = OTHER]	0.585	− 0.153	0.150	− 0.074	− 0.770	0.523	0.045	0.036	− 0.038	− 0.070	
	[Cause = PIPE. WELD. OR JOINT FAILURE]	− 0.630	0.075	− 0.270	0.170	0.120	− 0.195	0.177	0.249	− 0.462	− 0.257	
	[Leak = MAIN]	− 0.156	0.305	0.285	− 0.226	0.124	− 0.128	− 0.444	0.313	− 0.164	0.238	
	[Leak = METER SET]	− 0.260	− 0.138	0.203	0.235	− 0.233	− 0.764	0.388	− 0.316	− 0.379	− 0.132	
	[Leak = NO DATA]	0.463	− 0.498	0.286	− 0.145	0.017	0.227	0.365	0.441	0.472	0.240	
	[Leak = OTHER]	0.108	− 0.412	0.266	0.258	− 0.321	0.443	0.153	− 0.144	− 0.254	0.507	
	[Leak = OUTSIDE METER/REGULATOR SET]	− 0.141	0.105	− 0.492	− 0.411	− 0.415	0.212	− 0.150	− 0.307	0.206	0.110	
	[Leak = PRESSURE LIMITING AND REGULATING FACILITY]	− 0.278	− 0.280	− 0.414	0.467	− 0.032	− 0.153	− 0.108	− 0.584	0.173	0.014	
	[Leak = SERVICE]	− 0.105	− 0.251	0.663	− 0.238	0.082	0.169	− 0.209	− 0.157	− 0.264	0.612	
	[Leak = SERVICE LINE]	0.102	0.043	− 0.163	0.334	0.104	− 0.315	− 0.029	0.491	− 0.412	− 0.118	
	[Location = ABOVE GROUND]	− 0.427	− 0.456	0.186	0.279	− 0.228	− 0.190	− 0.234	0.212	0.299	− 0.523	
	[Location = BELOW ROAD (PAVED)]	− 0.383	− 0.488	− 0.116	0.441	− 0.590	0.244	0.487	0.411	0.035	0.145	

Table 2 (continued)

		Hidden layer										Output
		H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (1:8)	H (1:9)	H (1:10)	Incident year
	[Location = BELOW ROAD (UNPAVED)]	0.033	− 0.556	− 0.033	− 0.078	− 0.327	− 0.066	− 0.478	− 0.317	0.376	0.103	
	[Location = BELOW WALK-WAY]	− 0.068	0.315	0.249	0.292	0.004	0.492	0.379	− 0.271	0.338	− 0.120	
	[Location = NO DATA]	0.195	0.418	− 0.210	− 0.275	− 0.444	− 0.423	0.519	0.127	− 0.186	− 0.034	
	[Location = OPEN DITCH]	0.147	0.341	− 0.154	0.149	0.199	− 0.024	− 0.292	0.042	0.089	0.247	
Input layer	[Location = OTHER]	− 0.296	0.026	− 0.459	0.340	0.359	− 0.017	0.178	− 0.018	− 0.327	− 0.391	
	[Location = TRANSITION AREA]	0.289	0.007	0.164	0.319	− 0.314	0.074	− 0.223	0.039	− 0.303	0.360	
	[Location = UNDER GROUND]	− 0.041	− 0.195	0.163	− 0.356	− 0.049	− 0.103	0.217	− 0.027	− 0.527	− 0.397	
	[Location = UNDER PAVE-MENT]	− 0.019	0.309	0.301	0.095	0.238	− 0.339	0.155	0.372	0.076	0.279	
	[Location = UNDER WATER]	− 0.459	− 0.032	− 0.109	− 0.284	− 0.274	− 0.430	− 0.377	0.489	0.306	0.256	
	[Location = WITHIN BUILD-ING]	− 0.175	0.460	0.137	− 0.220	0.419	0.424	− 0.089	0.216	− 0.196	− 0.269	
	[Material = CAST IRON]	− 0.117	− 0.177	0.077	− 0.146	− 0.399	0.093	0.295	− 0.148	0.387	0.138	
	[Material = CAST/ WROUGHT IRON]	− 0.343	0.466	− 0.086	− 0.120	− 0.129	− 0.562	− 0.210	0.086	0.339	− 0.064	
	[Material = COPPER]	− 0.341	0.331	0.364	0.164	0.019	− 0.035	− 0.329	0.257	0.306	− 0.082	
	[Material = DUCTILE IRON]	0.341	0.095	0.316	− 0.494	0.129	− 0.500	0.052	− 0.131	0.113	0.042	
	[Material = OTHER MATE-RIAL]	− 0.177	− 0.019	0.051	0.243	− 0.592	0.428	0.263	0.025	0.169	− 0.155	
	[Material = OTHER PLASTIC]	− 0.483	− 0.065	− 0.099	− 0.379	− 0.331	0.047	0.309	− 0.324	− 0.126	− 0.539	
	[Material = PLASTIC]	− 0.141	− 0.181	0.138	0.223	− 0.482	− 0.036	− 0.510	− 0.198	0.021	0.199	
	[Material = POLYETHYLENE PLASTIC]	− 0.271	0.244	0.013	0.199	0.149	− 0.466	0.021	0.857	− 0.511	0.846	
	[Material = STEEL]	0.419	0.408	− 0.189	0.455	− 0.165	0.238	− 0.103	− 0.018	− 0.159	− 0.098	

Table 2 (continued)

	Hidden layer										Output
	H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (1:8)	H (1:9)	H (1:10)	Incident year
Incident pressure	0.421	− 0.289	0.172	0.446	− 0.985	0.327	− 0.625	− 0.628	− 0.449	0.096	
Installation year	− 0.113	0.442	0.463	− 1.019	0.618	− 0.258	0.681	− 0.782	− 0.097	0.313	
NMD	0.585	0.091	1.137	− 0.009	− 0.071	0.021	0.180	− 0.259	− 0.199	− 0.048	

		Incident year
Hidden layer	(Bias)	0.269
	H (1:1)	− 0.649
	H (1:2)	0.075
	H (1:3)	− 0.845
	H (1:4)	0.783
	H (1:5)	0.976
	H (1:6)	− 1.144
	H (1:7)	0.473
	H (1:8)	− 0.982
	H (1:9)	− 0.454
	H (1:10)	− 0.766

NOTICE: This report is required by 49 CFR Part 191. Failure to report can result in a civil penalty as provided in 49 USC 60122.	OMB NO: 2137-0635 EXPIRATION DATE: 4/30/2022

U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration	**INCIDENT REPORT – GAS DISTRIBUTION SYSTEM**	Report Date REPORT_RECEIVED_DATE No. REPORT_NUMBER SUPPLEMENTAL_NUMBER (DOT Use Only)

A federal agency may not conduct or sponsor, and a person is not required to respond to, nor shall a person be subject to a penalty for failure to comply with a collection of information subject to the requirements of the Paperwork Reduction Act unless that collection of information displays a current valid OMB Control Number. The OMB Control Number for this information collection is 2137-0635. Public reporting for this collection of information is estimated to be approximately 12 hours per response, including the time for reviewing instructions, gathering the data needed, and completing and reviewing the collection of information. All responses to this collection of information are mandatory. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to: Information Collection Clearance Officer, PHMSA, Office of Pipeline Safety (PHP-30) 1200 New Jersey Avenue, SE, Washington, D.C. 20590.

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Important: *Please read the separate instructions for completing this form before you begin. They clarify the information requested and provide specific examples. If you do not have a copy of the instructions, you can obtain one from the PHMSA Pipeline Safety Community Web Page at http://www.phmsa.dot.gov/pipeline/library/forms.*

PART A – KEY REPORT INFORMATION Report Type: *(select all that apply)* ☐ Original ☐ Supplemental ☐ Final REPORT_TYPE

A1. Operator's OPS-issued Operator Identification Number (OPID): /__/__/__/__/__/ OPERATOR_ID

A2. Name of Operator: _____*auto-populated based on OPID*_____ NAME

A3. Address of Operator:

A3a. _____ *auto-populated based on OPID* _____ OPERATOR_STREET_ADDRESS
(Street Address)

A3b. _____ *auto-populated based on OPID* _____ OPERATOR_CITY_NAME
(City)

A3c. State: *auto-populated based on OPID* /__/__/ OPERATOR_STATE_ABBREVIATION

A3d. Zip Code: *auto-populated based on OPID* /__/__/__/__/__/- /__/__/__/__/ OPERATOR_POSTAL_CODE

A4. Earliest local time *(24-hr clock)* and date an incident reporting criteria was met:
LOCAL_DATETIME
/__/__/__/__/ /__/__/ /__/__/ /__/__/
Hour Month Day Year

TIME_ZONE
A4a. Time Zone for local time (select only one) ○ Alaska ○ Eastern ○ Central ○ Hawaii-Aleutian ○ Mountain ○ Pacific.

A4b. Daylight Saving in effect? ○ Yes ○ No DAYLIGHT_SAVINGS_IND

A5. Location of Incident:

A5a. _____ LOCATION_STREET_ADDRESS _____ (Street Address or location description)

A5b. _____ LOCATION_CITY_NAME _____ (City)

A5c. _____ LOCATION_COUNTY_NAME _____ (County or Parish)

A5d. State: /__/__/ LOCATION_STATE_ABBREVIATION

A5e. Zip Code: /__/__/__/__/__/- /__/__/__/__/ LOCATION_POSTAL_CODE

A5f. Latitude: /__/__/. /__/__/__/__/__/__/ LOCATION_LATITUDE

Longitude: - /__/__/__/. /__/__/__/__/__/__/ LOCATION_LONGITUDE

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Fig. 13 First page of the incident report for gas distribution systems from U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration

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