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Original Research Article

Reliability assessment on natural gas pressure reduction stations using Monte Carlo simulation (MCS)

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Abstract

Gas pressure reduction stations play a key role in the timely and safe supply of natural gas (NG) to residential, commercial, and industrial customers. Accordingly, system reliability analysis should be performed to prevent potential failures and establish resilient operations. This research proposed a reliability assessment approach to natural gas pressure-reducing stations using historical data, statistical analysis, and Monte Carlo simulation (MCS). Historical data are employed to establish the probability distributions of the system and subsystems in gas stations. Then the Kolmogorov-Smirnov test is conducted to assess the goodness-of-fit for the developed distributions. Bayesian network (BN) is utilized to develop a system failure causality model. Finally, we performed MCS to precisely predict the failure rate and reliability of stations and all subsystems, such as the regulator, separator and dry gas filters, shut-off valves, and regulator. This research provided numerical findings on the reliability indicators of pressure reduction stations which can be used to improve system performance and, subsequently, the resilience of NG pipelines.

Keywords: Reliability assessment; Bayesian network (BN); Monte Carlo simulation (MCS); Pipeline.

1. Introduction

Natural gas (NG) is one of the most pivotal sources of fossil energy in the world, particularly for industrial purposes [1]. The pipeline transportation network is essential for the gas industry and even the entire process industry due to its high safety and efficiency [2]. The methods of transporting hazardous materials, especially NG [3]. However, the loss of containment of pipelines can have potential consequences for personnel, equipment, ecology, and the environment since the hazardous chemicals being transported are either flammable or toxic [4-5].

The maintenance of engineering facilities includes a wide range of repairs and services to enable the systems and equipment to perform their intended functions. This helps achieve the desired level of reliability and operational safety and improves the availability of the equipment, which will enhance the capability and productivity of the facilities [6]. The leakage of hazardous substances in process industries has long been a serious threat to workers and those who live near these industries; it has also caused substantial environmental damage [7].

Chemical process industries (CPIs) handle a variety of hazardous materials in quantities that might have the potential to have significant health, environmental, and financial impacts and, as such, are at risk of major accidents [8].

Due to their special operating conditions, these facilities have always been the site of catastrophic incidents throughout history. In the last decade, accidents have occurred in their process systems [9]; thus, the reliability assessment of gas pressure reduction station facilities is vital. Improving system reliability is one method for achieving a secure system [10].

Reliability engineering as a sub-discipline of system engineering includes the systematic application of engineering principles and techniques throughout a product lifecycle; therefore, reliability should be considered from concept plan to system/product wear out

[11]. Reliability assessment can be a valuable method for determining high-risk equipment and developing prevention strategies. Reliability assessment helps identify potential causes of system failure, thereby providing potential solutions to enhance safety by failure prevention [12].

Traditional reliability methods cannot correctly evaluate reliability in complex infrastructures that operate under variable conditions and consist of numerous components [13-14].Traditional reliability assessment methods are also conducted based on equipment failure data [15-19]; however, modern reliability engineering emphasizes model-based reliability evaluation [20-21].System reliability evaluation methods, such as logical modeling and system analysis, are traditionally used to estimate system reliability [22-24],and statistical calculations are used to calculate reliability indices [25-27]. However, traditional reliability methods cannot accurately evaluate reliability in complex infrastructures that operate under variable conditions and consist of many components [14, 27]. Due to these shortcomings, applying the traditional methods for analyzing complex engineering systems is difficult, which are characterized by a number of dependencies and uncertainties [28].

There are many approaches to stochastic modeling components of complex infrastructures such as NG pipeline networks, power grids, or rail systems. Stochastic simulation methods, for example, Monte Carlo-based methods [28-32], methods based on the Markov process [33-34], and other approaches [35-39], are widely used to model a complex system with uncertainty. Probabilistic dynamic modeling is applied to describe the interdependencies in critical infrastructures and the impacts of specific scenarios [40].

Researchers have proposed various methods for accurately estimating the probability of equipment failure and dealing with uncertainties, which can be summarized as follows: Wu et al. and Teixeira et al. (2008) proposed the use of Monte Carlo simulation (MCS) to accurately assess failure probability and deal with uncertainty [41-43].

This research uses MCS and Bayesian network (BN) methods to deal with uncertainty and accurately estimate the probability of equipment failure in the gas pressure reduction station of the combined cycle power plant. By generating random numbers, the MCS method samples the density distribution of each system component, and by inserting these samples in the final model of the system, it simulates the output distribution. It can be used for any type of input and output distribution. This method provides a basic solution for mathematical and technical problems by using the probabilistic model of the system and the simulation of random variables. One of the most important features of this method is its high flexibility and lack of dependence on system dimensions [43-44]. Sawilowsky lists the characteristics of a high-quality Monte Carlo simulation as follows [45]:

- The number generator has certain characteristics
- The number generator produces values that pass randomness tests
- There are enough samples to ensure accurate results
- The proper sampling technique is used
- The algorithm used is valid for what is being modeled
- It simulates the phenomenon in question

In recent years, the use of BN in engineering applications has dramatically increased [46]. BN is a graphical qualitative model that visually represents interactions between variables and the relationship between them. Thus, it is a non-cyclic directed graph that includes nodes and arcs. Each node in the graph represents a random variable, and the branches (arcs) indicate the possible dependencies between the variables. Conditionals are often evaluated by certain statistical and probabilistic methods [46-47].

The reliability of gas pressure reduction is critical for a more efficient design of gas pipeline networks. To prevent the recurrence of accidents, the lack of comprehensive and accurate process safety laws, such as process safety management, and the lack of accurate reliability assessment of gas pressure reduction stations, highlighted the necessity of conducting this study due to the high probability of accidents and loss of life and property in these stations. Thus, this study performed a reliability assessment of a gas pressure reduction station using the BN and MCS.

2. Methodology

This study was conducted in 2021 to assess the reliability of a pressure reduction station. The overall framework of the research procedure is based on Figure 1:

Step 1: Studying the desired parts and station: It is necessary to get familiar with the system structure and performance. Safety specialists, occupational health engineers, operations engineers, maintenance engineers, and managers responsible for monitoring the system performance should be involved at this stage. Data tools such as flowcharts, block diagrams, fault trees, and status charts are very beneficial at this stage.

Step 2: Determining the structural model of the station using the BN: In this step, the relationship between the equipment was determined using the BN.

Step 3: Determining the time between failures of station equipment: The system and subsystem failure data were collected from 2018 to 2021 based on the reports of maintenance and instrumentation sectors.

Step 4: Determining the distribution function of equipment failure time based on modeling: The probability distribution function was determined using Easy Fit software and via trend and series correlation tests. The Kolmogorov-Smirnov test is applied to assess goodness-of-fit for the developed distributions.

Step 5: Defining the logic and structure of the system for simulation: When there is more than one part in the system, it is necessary to accurately define the logic and structure of the system. In this study, the system's structure is a series-parallel or series sequence.

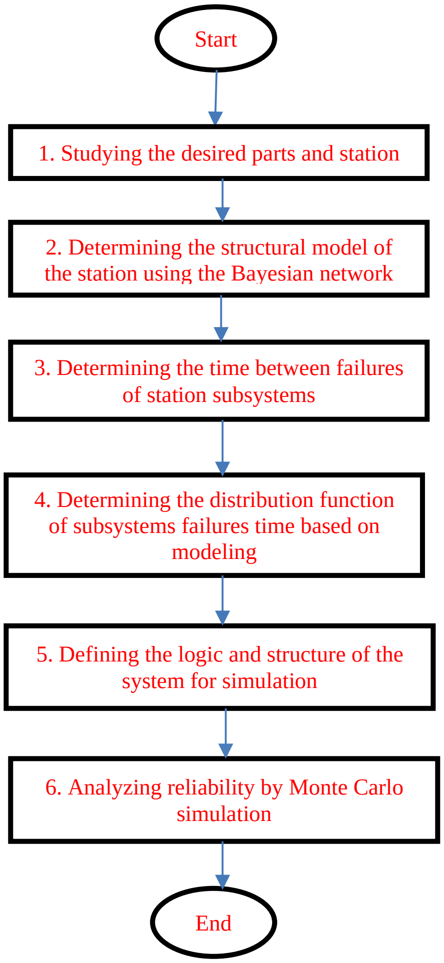

Figure 1. Framework of the research implementation method

Step 6: Analyzing reliability by MCS: The underlying basis for MCS is the ability to generate a sequence of independent random numbers with a given distribution and finite mean and variance. Many may not realize that a computer does not generate a random number but generates a pseudorandom number using a software-specific algorithm. If a user starts a stream of random numbers at a specific point in the algorithm and later on starts another stream of random numbers from the same point, both streams of numbers will be exactly the same. This starting point is called the seed and should be reported in all simulation reports. Moreover, random varieties from any statistical distribution arise from a uniform distribution and are then transformed into the needed distribution [48].

MCS is a probabilistic numerical technique used to estimate the outcome of a given, uncertain (stochastic) process. This means it is a method for simulating events that cannot be modeled implicitly. This is usually the case when we have a random variable in our processes. MCS is a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The underlying concept is to use randomness to solve problems that might be deterministic in principle. MCS methods are often used in physical and mathematical problems and are most useful when it is difficult or impossible to use other approaches. These methods are mainly used in three problem classes: optimization, numerical integration and generating draws from a probability distribution. Monte Carlo methods vary but tend to follow a particular pattern:

- Defining a domain of possible inputs
- Generating inputs randomly from a probability distribution over the domain
- Performing a deterministic computation on the inputs
- Aggregating the results [49-51]

3. Results

Step 1. Studying desired parts and station: The main components of the station include the separator filter, dry gas filter, heater and pressure reduction section (regulators, shut-off, safety valve) (Figure 2).

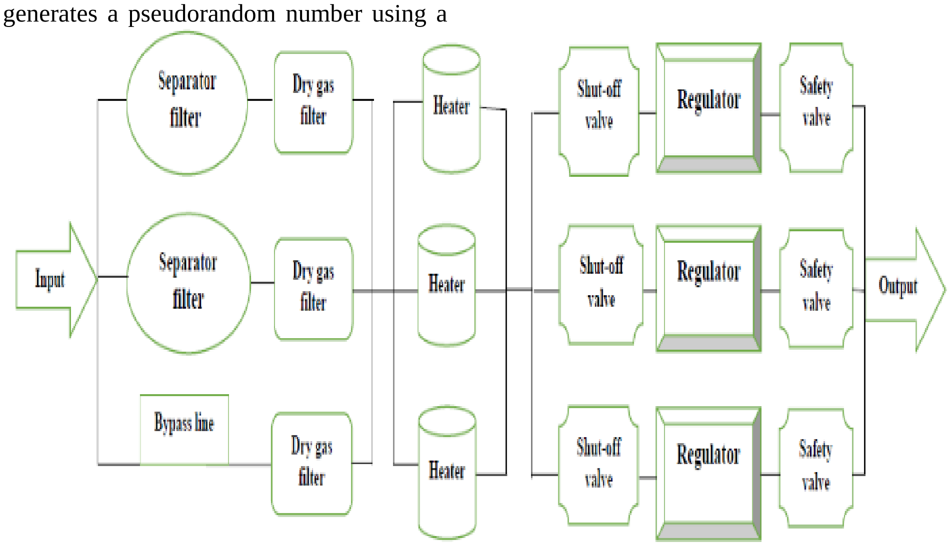

Figure 2. The main components of the pressure reduction station

Step 2: Determining the structural model of the station using the BN: Figure 3 displays the development of a structural model for the gas pressure reduction station based on BN.

Step 3: Determining the time between failures of station equipment: The system and subsystem failure data were collected from 2018 to 2021 based on the reports of maintenance and instrumentation sectors.

Step 4: Determining the probability distribution function of equipment failure time based on modeling: In all sections, no trend or correlation was observed in the data; therefore, the renewable process method was chosen as the best method to model these reliability subsystems. Also, according to these results, the distribution function of the station part failures was determined using the statistical analysis of real data and the most effective modeling method was identified Kolmogorov-Smirnov test (Table 1).

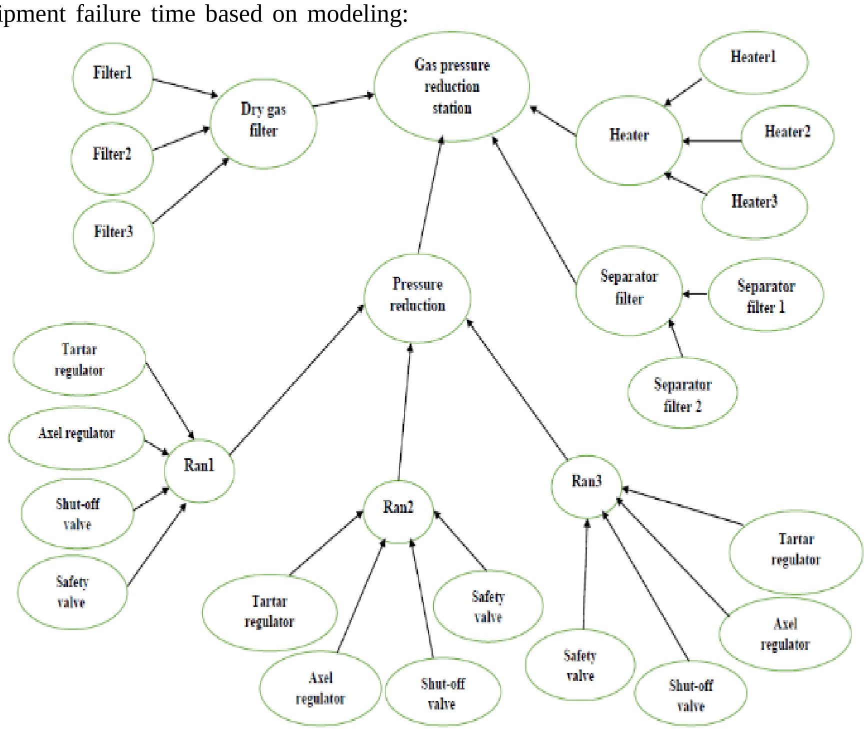

Figure 3. Development of a structural model for the gas pressure reduction station based on BN

Table 1. Results of the probability distribution function of equipment failure time based on modeling

Part	Function type	K-S value
Separator filter 1	Lognormal (3P)	0.14108
Separator filter 2	Gamma (3P)	0.14868
Dry gas filter 1	Lognormal (3P)	0.2071
Dry gas filter 2	Lognormal (3P)	0.23258
Dry gas filter 3	Lognormal (3P)	0.23258
Heater 1	Exponential(2P)	0.1147
Heater 2	Lognormal (3P)	0.1522
Heater 3	Lognormal	0.1976
Tartar regulator ran 1	Lognormal (3P)	0.1379
Axel regulator ran 1	Lognormal	0.1288
Shut-off valve ran 1	Normal	0.1846
Safety valve ran 1	Lognormal (3P)	0.2569
Tartar regulator ran 2	Lognormal (3P)	0.4508
Axel regulator ran 2	Lognormal	0.1241
Shut-off valve ran 2	Normal	0.1281
Safety valve ran 2	Lognormal (3P)	0.1695
Tartar regulator ran 3	Lognormal (3P)	0.1956
Axel regulator ran 3	Lognormal	0.1116
Shut-off valve ran 3	Normal	0.1583
Safety valve ran 3	Lognormal (3P)	0.1554

Step 5: Defining the logic and structure of the system for simulation: In this study, the structure of the system is in series-parallel or series sequence. Therefore, the station's reliability is calculated based on the following formulas.

$$R_{pi} = 1 - \prod_{j=1}^{k} F_{ij} \qquad (1)$$

R_{pi}: Reliability under parallel system

F_{ij} : Probability of failure under ij system

$$R_{sp} = \prod_{i=1}^{m} \left[1 - \prod_{j=1}^{k} F_{ij} \right] \qquad (2)$$

R_{sp}: Reliability of a series-parallel or series-sequence network

Step 6: Analyzing reliability by MCS: The iteration number may be any simulation's most important performance parameter. This parameter greatly affects the accuracy of the program output and its execution time. Thus, station reliability was calculated using 100-7000 repetitions with the step iteration of 100 units. The results of these calculations for the separator filter 1 are presented in Figure 4.

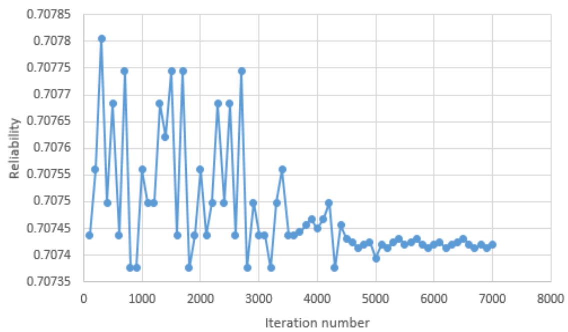

Figure 4. Effect of iteration number on the simulated reliability of separator filter 1

Based on Figure 4, by increasing the program iteration number, the calculated reliability values neared the range of between 0.70735 and 0.7078. After 5000 repetition cycles and more, the reliability value simulated by the software remains almost fixed. Therefore, to run the main simulation, 5000 was chosen as the iteration number for the program. In the following, this process was carried out for all the subsystems and the number of iterations was determined for simulating the subsystems. The simulation steps algorithm is shown in Fig 5. Easy Fit software generated random numbers based on the probability distribution function. Finally, the reliability assessment of each part was conducted based on formula 1 (Table 2) and the Station reliability was carried out based on formula 2.

The structure of the station parts is parallel; therefore, the reliability of the parts station was calculated based on formula 1. So, the reliability of the separator, dry gas filter, heater, and pressure reduction ran is 0.951, 0.9972, 0.9992, and 0.9831, respectively. The reliability of the station is calculated based on formula 2. Therefore, the reliability of the station is 0.93.

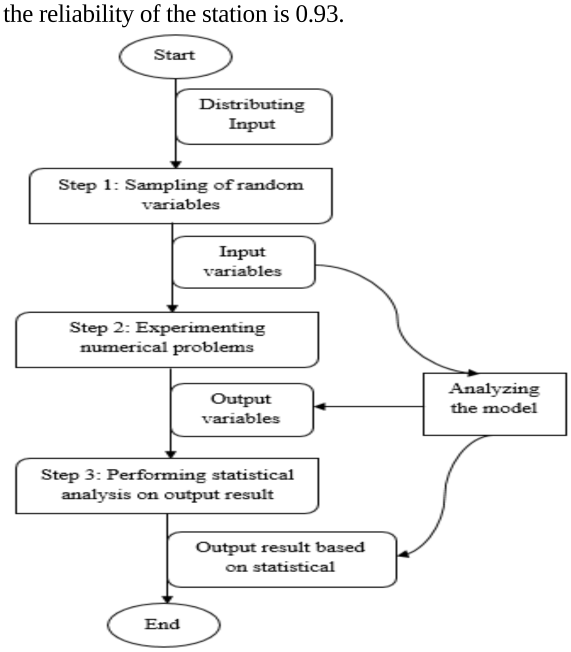

Figure 5. The MCS algorithm used to determine the reliability of the gas pressure reduction station

4. Discussion

Gas pressure reduction stations play a key role in the timely and safe supply of NG to residential, commercial, and industrial customers. Accordingly, system reliability analysis should be performed to prevent potential failures and establish resilient operations. This research proposed a reliability assessment approach to natural gas pressure-reducing stations using historical data, statistical analysis, and MCS. Historical data are employed to establish the probability distributions of systems and subsystems in gas stations, and then the Kolmogorov-Smirnov test is conducted to assess goodness-of-fit for the developed distributions. BN is utilized to develop a system failure causality model. Finally, we performed MCS to precisely predict the failure rate and reliability of stations and all subsystems, such as the regulator, separator and dry gas filters, shut-off valves, and regulator. This research provided numerical findings regarding reliability indicators on pressure reduction stations which can be used to improve system performance and, subsequently, the resilience of natural gas pipelines. Herein, BN and MCS were adopted to draw the system's structural model and evaluate the station's reliability, respectively.

The results showed that the reliability of the separator, dry gas filter, heater, and pressure reduction ran 0.951, 0.9972, 0.9992, and 0.9831, respectively. So, the reliability of the station is 0.93.

Based on the results, the trend tests were almost linear in all the sectors and subsystems. Moreover, the data did not have a trend and had a stationary distribution. The serial correlation test indicated a lack of correlation between the data. Therefore, the renewal process was selected as the best method for modeling the reliability of subsystems, which was consistent with the results of the studies by Heydari et al. [52]and Hosseini et al. [53].

Table 2. The reliability assessment of each station subsystem

Part	Subsystem	Failure Rate (per hour)	Reliability
Separato r filter	Separator filter 1	0.000039 92	0.70744
	Separator filter 2	0.000021 1416	0.8325
Dry gas filter	Dry gas filter 1	0.000012 3287	0.8986
	Dry gas filter 2	0.000020 0913	0.8342
	Dry gas filter 3	0.000020 0913	0.8342
Heater	Heater 1	0.000028 3105	0.7823
	Heater 2	0.000004 6575	0.9604
	Heater 3	0.000011 5068	0.9051

Part	Subsystem	Failure Rate (per hour)	Reliability
Pressure reduction ran 1	Tartar regulator	0.0000030137	0.9742
	Axel regulator	0.0000200456	0.8405
	Shut-off valve	0.000003105	0.9734
	Safety valve	0.0000070045	0.9411
Pressure reduction ran 2	Tartar regulator	0.0000030137	0.9742
	Axel regulator	0.0000283562	0.7820
	Shut-off valve	0.0000025571	0.9781
	Safety valve	0.0000025571	0.9781
Pressure reduction ran 3	Tartar regulator	0.0000030137	0.9742
	Axel regulator	0.0000166666	0.8654
	Shut-off valve	0.0000070045	0.9411
	Safety valve	0.0000070045	0.9411

Based on the results, the probability distribution of station subsystems has different functions. This finding was in line with Heydari et al. [52] and Hosseini et al. [53]. The pressure reduction and separator filter parts were among the most critical parts of the station. Zarei et al. found that the failure of the pressure reduction sectors was the worst risk scenario at pressure reduction stations [3], which was consistent with the results of this research so that the failure of filtration system and regulators could increase gas pressure in station pipelines and cause accidents such as explosions if the shut-off valves do not operate properly.

The results revealed the pressure reduction part had a low level of reliability at the station, which was 0.9831. This was considered the critical part of the station, and to improve its reliability of which, an extra component was proposed so that the extra component could perform the task assigned to the main component when it failed to operate.

Although this study performed the reliability evaluation based on a simulation, some limitations should be taken into account. Future studies are advised to use the Monte Carlo-Markov chain (MCMC) simulation method. Given that in such systems, some components in different stages of their life cycle have variable failure rates with time, by using these methods, the effects of temporal changes on the failure rate (which are among the time-constant characteristics of complex systems with long lifetimes) can be calculated with great accuracy. Based on the results, it is also suggested that a suitable program be developed for station equipment maintenance.

5. Conclusion

In this study, BN and MCS were adopted to draw the system's structural model and evaluate the station's reliability. The results indicated that the equipment of the pressure reduction and separator filter parts required more attention to improve the system. Therefore, the reliability of the pressure reduction station could be improved using the redundancy method and regular maintenance program, which are among the most crucial methods for improving reliability.

6. Conflict of interest

The authors declare that, the present study did not have any conflict of interest.

7. Acknowledgment

This study was taken from a Ph.D. dissertation on occupational health and was approved by the Tehran University of Medical Sciences with ethical code no. IR.TUMS.SPH.REC.1400.151. We would like to express our gratitude to the National Iranian Gas Company (North Khorasan Province) for providing financial support and the Department of Occupational Health Engineering of Tehran University of Medical Sciences for their assistance in this study.

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