energies

MDPI

Article

# Stochastic Simulation of Flow Rate and Power Consumption Considering the Uncertainty of Pipeline Cracking Rate and Time-Dependent Topology of a Natural Gas Transmission Network

**Robertas Alzbutas * and Tomas Iešmantas**

Lithuanian Energy Institute, Breslaujos Str. 3-317, LT-44403 Kaunas, Lithuania; tomas.iesmantas@lei.lt
* Correspondence: robertas.alzbutas@lei.lt

**Abstract:** Various gas pipeline networks used for the transit of energy sources are some of the most important infrastructures. However, carrying gas from one point to another is not the only concern when planning the construction of a new network or expanding an already existing one. The reliability and environmental impact of the system are crucial when evaluating the network and risks posed by potential gas leaks, fires, explosions, etc. Even though everyone admits that reliability is a key aspect of any system, its constraints will still be most likely neglected in the assessment of the pipeline project. How much energy is wasted by pushing an additional amount of gas through the pipeline network, which will eventually gush out of the pipeline because of one crack or another? Moreover, if this additional power or fuel consumption and related environmental impact are significant, how could it be reduced? In this paper, an approach is introduced for the simulation and quantification of how much more power would be required if the pipelines are regarded as unreliable (i.e., by leaking, rupturing, or even exploding). By employing stochastic simulations and time-dependent topology (topology determined by the value of a variable representing time) of the pipeline network as a case study for the selected representative gas transmission network, the amount of additional power consumption in gas compressor stations due to uncertain cracking and the leaking rate was evaluated. Although the analysis of power consumption was performed for a hypothetical network, the estimates of the cracking rates, detection effectiveness, and leaking rates used were as close to the real cases as possible.

**Keywords:** stochastic simulation; natural gas; transmission network; pipeline cracking; time-dependent topology; power consumption; uncertainty and sensitivity



**Citation:** Alzbutas, R.; Iešmantas, T. Stochastic Simulation of Flow Rate and Power Consumption Considering the Uncertainty of Pipeline Cracking Rate and Time-Dependent Topology of a Natural Gas Transmission Network. *Energies* **2022**, *15*, 4549. https://doi.org/10.3390/en15134549

Academic Editors: Maciej Chaczykowski and Andrzej J. Osiadacz

Received: 2 April 2022
Accepted: 28 May 2022
Published: 22 June 2022



## 1. Introduction

Gas pipeline networks used for the transit of energy sources have been some of the most important infrastructures since their origin in 1890, when leak-proof pipeline couplings were invented [1]. However, carrying gas from one point to another is not the only concern when planning the construction of a new network or when expanding an already existing one. There are many questions, such as what size should the pipelines be, what kind and how many compressors are going to be needed, where should they be placed, what is the topology of the network needed, etc. This is far from a complete list of gas network planning questions that beg to be answered. One attempt to answer them is through mathematical optimization, which is usually formulated as a cost-benefit optimization issue. The literature on this issue is numerous and diverse, spanning from the outdated modeling of a simple single-sourced steady-state tree-like network [2] to a time-dependent simulation of a complex network with detailed models of compressors, valve stations, and valves without remote access, electric motors, etc. [3]. Reviews of the optimization issue and relevant modeling can be found in [4,5].

However, according to the author's knowledge, there are a few but not many papers focusing on the network reliability issue in optimization problems, whether it is cost minimization, consumed fuel minimization, or other similar tasks. There are still issues and a lack of clear answers for questions such as, how severe is the influence of the pipeline's cracks and leakages over compressors' power or fuel consumption, what will be the total costs if we choose one pipeline coating or isolation over another, how much power consumption in the network will be affected by failures, etc. Any complete research done to address the related issues, except for a brief mention of the importance of reliability, was found to be an example of strategic planning [6], optimal management [7], or optimal design [8]. An important contribution to this topic can be found in [9], where the authors provided an extensive review of the chronic leaks and their detection. In this paper, for the sake of demonstration, the effect of cracks and leakages on gas compressor power consumption is considered. There is no a priori knowledge about it, while, according to the current knowledge, no relevant research has been done. It was mainly noticed that there is an increasing concern over the economic and environmental side effects of the gases released into the atmosphere due to cracks in the whole body of the network. Somehow, the focus is just on the nature of the beast: cracks appear and grow unnoticed causing a flow of natural gas out of its body. Methane, which is one of the main constituents of natural gas, has a hand in the climate change process by being a more potent greenhouse gas than carbon dioxide. It has even been discussed that the leakage of natural gas would offset the carbon dioxide emissions reduction benefit of switching from coal to natural gas [10].

On the other hand, consumers suffer from skittled-away gases as well as natural gas pipeline leaks, costing consumers billions [11]. In the USA, it was estimated that consumers paid at least $20 billion in almost ten years' time for gas they never received [12]. That is because utilities are not quick enough to replace old pipeline systems that are generously pouring gas into the environment through multiple cracks and holes in the network.

Having these points in mind, other related questions can be raised: how much energy is wasted by pushing an additional amount of gas through the pipeline network that will eventually gush out of the system at one crack or another? Furthermore, if this additional power consumption is significant, how could it be reduced? The conclusions will be of great value in the network's complete optimization problem that was discussed before: complete optimization means that objective functions in optimization must consider the unreliability of the pipelines.

The paper's structure is as follows. First, the proposed simulation approach is introduced. Second, the model of gas flows and model simulations of the defects or cracks, their growth, and an estimation of the cracking and leaking rate (leakage rate through those cracks) are presented. For this, a brief discussion is given about the Bayesian estimation of uncertain reliability characteristics, as they will be needed to simulate cracking as realistically as possible. Finally, concerning the case study, the power consumption of the compressors in the network, the dependence on the probability of detection (POD) of cracks, the initial number and other characteristics of cracks, etc., are explored.

## 2. Approach to Simulation

It was assumed that the network is composed of pipelines, compressors, and load or consumption points. Valve modeling was of no interest in this work. The topology of the network is not necessarily tree-like [2] and closed loops might be considered. Suppose that at each load point, the gas consumption follows some stochastic time series of flow rates. Time is measured in days and the point in time series is an average flow rate over one day. Such time discretization is required because the authors did not intend to model transient flow; instead, steady-state flow is assumed with all the physics that follows from this modeling assumption. Additionally, this enables the modeling of crack growth dynamics with more continuity, rather than abrupt jumps in case time would be measured in years.

It is assumed that a crack is a pseudo-consumption point (while the gas flow rate simulations will be presented in the following sections). Hence, at different time slices, a different number of gas consumption points will be active. This leads to the time-dependent topology (topology determined by the value of a variable representing time) of the network and a different number of equations and variables to solve for simulation. While the cracking process was modeled to be stochastic, the size of the system of equations was also stochastic; hence, it cannot be pre-programmed a priori.

In the following sections, the following questions are considered:

1. How can a network with a time-dependent topology be modeled?
2. How can the development of the cracking and leaking processes be modeled?
3. What is the model for the stochastic nature of cracking occurrences and how can it be reflected?

Summarily, the entire network modeling or high-level algorithm is based on the Monte Carlo simulation and can be divided into two major parts: one for crack-detection dynamics simulation and another for the simulation of gas and power consumption (see Figures 1 and 2, respectively).

**Cracking-detection dynamics simulation**

1. Generate time series of gas flow rates for each load or gas consumption point;
2. Repeat for each day ***t*** for entire simulation period:
   - 2.1. Predict number ***N*** of new cracks in the network using the data-based cracking rate estimates;
   - 2.2. Generate ***N*** initial crack depths;
   - 2.3. Generate ***N*** initial crack lengths;
   - 2.4. Generate ***N*** growth rates.
3. Repeat for each new $\boldsymbol{i}^{th}$ crack:
   - 3.1. Use POD curve to predict length ***L*** at which $\boldsymbol{i}^{th}$ crack is detected and then repaired;
   - 3.2. Grow that crack until the length ***L*** and terminate the grow process after [***L***/grow rate] days.

**Figure 1.** High-level algorithm for crack-detection dynamics in the network simulation.

**Gas flows and power consumption simulation**

1. Repeat for each day ***t***:
   - 1.1. Alter the adjacency matrix ***A*** by adding/destroying nodes, which represents new/repaired leakages;
   - 1.2. Estimate leak sizes for each new crack depending on its dimensions and consider it as a gas consumption point with nonzero gas flow rate;
   - 1.3. Automatically construct new system of nonlinear equations and solve them considering gas flows and pressures as steady state;
   - 1.4. Estimate power consumption in pipeline network.

**Figure 2.** High-level algorithm for gas flows and power consumption in the network simulation.

To obtain results as close to reality as possible, parameters validated and presented in various literature or treated as the representative or best estimate were used. Additionally, crack occurrence rates were taken from our study [13], where several different databases (like EGIG [14], UKOPA [15], NEB [16], and OPS [17]) were used to estimate rates as accurately as possible.

### *2.1. Time-Dependent Network Topology and Power Consumption*

As previously stated, due to the assumption of a crack or hole in the pipeline occurring at a random gas consumption points, the systems of equations (i.e., the number of equations and number of unknown variables) representing flows and pressures are time-dependent and stochastic. With each occurrence and repair of the cracks, the system of equations has to be altered to add or delete corresponding variables. The location and time of crack occurrence are random. This unforeseeable nature prohibits one from pre-programming a system of equations and reusing it at each time series point. At a random moment in time, the system of equations has to be changed. That is why an algorithm for the automatic construction of the system of equations and its solution is needed.

Next, flow simulation in a network is discussed. Each new topology of the network is handled by the same solution algorithm. The algorithm proposed for a formulation of co-tree flows [18] is adopted and basic ideas are briefly presented.

To represent the steady-state condition of the network, one must use the system of nonlinear equations expressed by the so-called potential equations (i.e., cut-set equations or the equations that reflect disconnection of the loop), the so-called flow equations (i.e., the circuit equations or continuity equations), and the so-called resistance equations (i.e., the equations that reflect pressure loss). Therefore, the system of these equations (in matrix format) is:

$$\begin{cases} K \cdot Q = 0, \text{ reflecting } n-1 \text{ equations of cut}-\text{sets;} \\ C \cdot P = 0, \text{ reflecting } p-n+1 \text{ so}-\text{called circuit equations;} \\ P(Q) = R(Q), \text{ reflecting } p \text{ so}-\text{called resistance equations;} \end{cases} \quad (1)$$

where $K$ is the cut-set matrix (minimal cut-set is a minimal set of links, which disconnects some nodes from the others); $Q$ is the flow rate vector; $C$ is the circuit matrix; $P$ is the pressure loss vector, which depends on $Q$; $R$ is the resistance coefficient, which depends on $Q$; $p$ is the number of pipe-links; and $n$ is the number of nodes.

Then, by applying some matrix and graph theory-based analytical manipulations [18], the system can be solved with less demanding calculations as the following representation is derived:

$$\begin{cases} F(Q_T) = P(Q_T) + C_T P(Q_T) = 0; \\ \text{with } Q_T = C_T^t Q_{\tilde{T}} + S_{TD}; \end{cases} \quad (2)$$

where $C_T$ is the matrix obtained from the partition $C = \begin{bmatrix} I & 0 & C_D \\ 0 & I & C_T \end{bmatrix}$, $Q_{\tilde{T}}$ is the discharges for co-tree chords as obtained from the initial network graph, and along the tree branches, $S_{TD}$ is the discharge vector assuming that the co-tree chords are discarded.

In addition, the compressor performance equation is proposed as follows [19]:

$$\left(\frac{P_d}{P_s}\right)^m = K(A_c + B_c Q + C_c Q^2 + D_c Q^3) + 1, \quad (3)$$

where $K$ is the constant depending on the properties of the gas, $A_c = 6.35 \times 10^{-5}$, $B_c = -7.08 \times 10^{-5}$, $C_c = 2.54 \times 10^{-5}$, and $D_c = -2.92 \times 10^{-6}$ are compressor constants, and $Q$ is the output flow. Additionally, the power of the compressor needed to create discharge pressure $P_d$ is proposed as follows [20]:

$$Power = 4.0639 \frac{\gamma}{\gamma - 1} QT \frac{Z_s + Z_d}{2} \frac{1}{\eta} \left[ \left(\frac{P_d}{P_s}\right)^{\frac{\gamma-1}{\gamma}} - 1 \right], \quad (4)$$

where $Q$ is the inlet flow rate, $\gamma$ is the ratio of specific heats, $T$ is the inlet gas temperature, $Z_s$ and $Z_d$ are the compressibility of inlet and discharge gas, and $\eta$ is the compressor adiabatic efficiency.

All information that is needed to solve the equations is the adjacency (or connectivity) matrix $A$ of the corresponding graph, flow rate at gas consumption or load points, a physical parameter of the pipelines (like length, diameter), and working parameters of a compressor in the network.

Each time the crack or hole occurs or is repaired, i.e., each time a new gas consumption point is created or destroyed, the adjacency matrix $A$ must be automatically altered. Since other parameters like pipeline length and diameter stay unchanged, all that needs to occur is the enabling of random changes in the network topology to appropriately alter the adjacency matrix $A$.

Finally, from a computer implementation perspective, a procedure or the program without human interruption creates a system of equations as presented above and solves it by using adjacency matrix $A$ information as needed.

### *2.2. Stochastic Simulation of the Cracking and Leaking Features*

In general, two features need to be considered for the gas flow rate simulation, namely the occurrence of the crack and leak, i.e., cracking rate and leaking rate. To address the modeling of the first feature, a probabilistic model was used: as the cracks occur in the pipeline network, the initial sizes, and the growth rates were all assumed to be of random nature.

To simulate the occurrence of the crack the pipeline, incident databases were used and occurrence rates were estimated [13]. This allows a more realistic estimation of cracking and leaking rates. A more in-depth discussion of these estimates are presented in the following section.

To simulate the initial crack size (defect length) and the crack growth (corrosion) rate (see Figure 3), the information provided in the reference [21] was used. For demonstration purposes, the generating model is based on a lognormal distribution [22]. It should be noted that sensitivity to the type of distribution was not assessed in this work, as it aims to show the methodology at work rather than a benchmark-type analysis (this is set for future work).

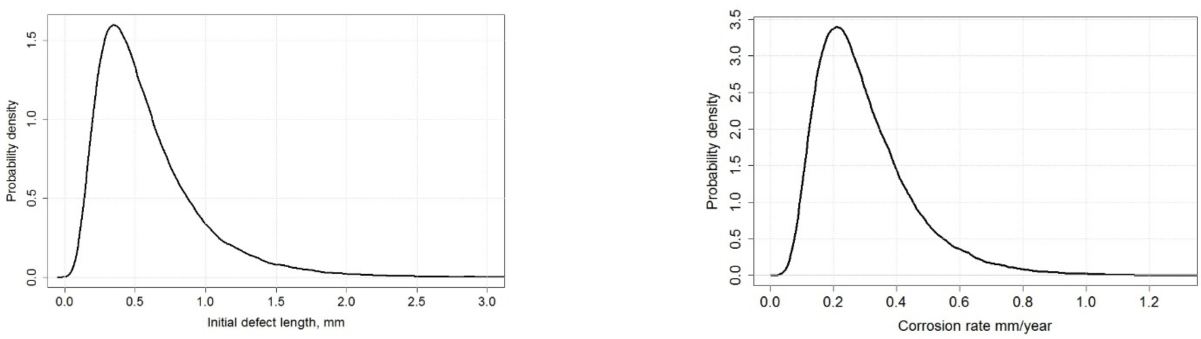


**Figure 3.** Initial crack length distributions and corrosion rate lognormal distribution parameters for length: location = −0.7, scale = 0.6; for rate: location = −1.33, scale = 0.5.

Furthermore, there is one more issue: how long does the crack grow until it is detected? This question is discussed in the case study, where different POD curves are used to reflect the influence of various inspection effectiveness and their influence on power consumption.

As for the leaking rate, because a steady-state assumption in calculating the flow was considered, the leaking process was assumed to be similar. For the case study, the leaking flows into the atmosphere and the pressure in the pipeline at the leak point is much higher; one has a sonic flow through the orifice with the rate equal to [23]:

$$Q = A_{cr} P \sqrt{\frac{M}{ZRT} k \left( \frac{2}{k+1} \right)^{\frac{k+1}{k-1}}}, \quad (5)$$

where $A_{cr}$ is the area of the crack, $P$ is the pressure at the crack point, $M$ is the molecular mass of natural gas, $Z$ is the compressibility factor of gas, $R$ is the specific gas constant, and $k$ is the ratio of specific heats. The values used are $M = 19.5$ kg/kmol, $R = 9.314$ Pa $\cdot$ m$^3$/(mol $\cdot$ $K$), $Z$ = 0.9, and $k$ = 1.27.

Hence, using the cracking rate and leaking rate, the simulated gas flow rate was then further used at a gas consumption point and added to the network topology as a separate node with the appropriate alteration of the adjacency matrix $A$.

### 2.3. Consideration of the Uncertain Number of Cracks

The question of how many new cracks occur during a given period time is difficult to answer due to the two-fold uncertainty issue: the cracking process is stochastic and uncertain; hence, statistical estimation techniques must be applied. On the other hand, to perform statistical inference, sample data have to be collected. However, the unfortunate nature of the issue is that cracks of a certain size cannot be detected with complete certainty, i.e., with the detection probability being equal to 1.

To account for the uncertainty due to the stochastic nature of cracking, the Bayesian inference techniques were used and estimates were obtained using joint analysis of data collected from various pipeline incident databases like EGIG [14], UKOPA [15], NEB [16], and OPS [17]. Estimates of the authors' previous research [13] are used and only the basic issues tackled in the estimation process are presented below.

Each database has its own data collection or registration criteria, which itself might change over time (e.g., OPS database incident criteria were changed three times since the 1970s). Thus, one has to have a model to take those different criteria into account. For this, a criteria-dependent Poisson (CDP) model was devised to consider data collected under different criteria [13]. Another problem was to join information from different databases for one analysis and not to lose information about the between-database uncertainty, i.e., to include the variability of crack occurrence rates caused by the varying environment conditions, maintenance conditions, etc. For this, the hierarchical Bayesian method proved to be of great use in this issue [24]. Thus, the dynamics of the cracking rate were estimated by using the hierarchical CDP model. The resulting trend and the uncertainty bounds are presented in Figure 4.

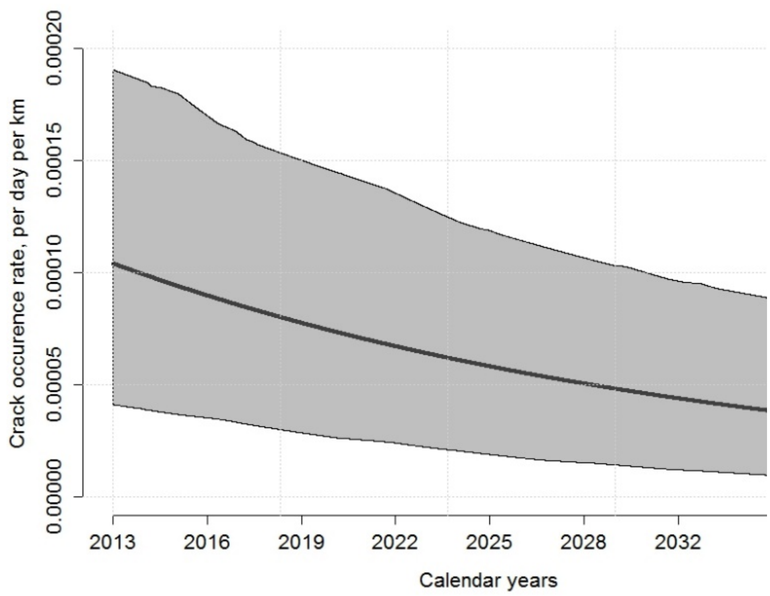


**Figure 4.** Cracking rate dynamics as obtained by Bayesian inference and CDP model.

The resulting average rate of crack occurrence and related 95% uncertainty bounds are presented in Figure 4; however, the more realistic best estimates are even higher as some cracks could be not detected at all for a while. This means that the presented curve, in this case, is an underestimation of the real cracking rate in the pipeline network. To evaluate how much this affects the overall leaked gas amount and consumption of power, the sensitivity analysis can be performed by slightly varying the cracking rate.

## 3. Case Study and Results

The case study and calculations are based on the proposed approach performed for a hypothetical pipeline network. However, it was intended to have a topology as flexible and representative of the real world as possible. Moreover, the results and calculations were more focused on the demonstration of qualitative investigations rather than quantitative ones, i.e., the authors intend to obtain insights on how large the effect of network leakages is because of stochastic cracking on the consumption of power in compressor stations.

### *3.1. Gas Pipeline Network*

Initially, we assumed the network topology as in Figure 5, including one gas compressor (which could be treated as a compressor station), with each line (a segment of the pipeline) of equal length (100 km) and equal diameter (1000 mm). Since calculations are theoretical, a simple network topology with a few lines was considered, which is complex enough for this paper and demonstration purposes.

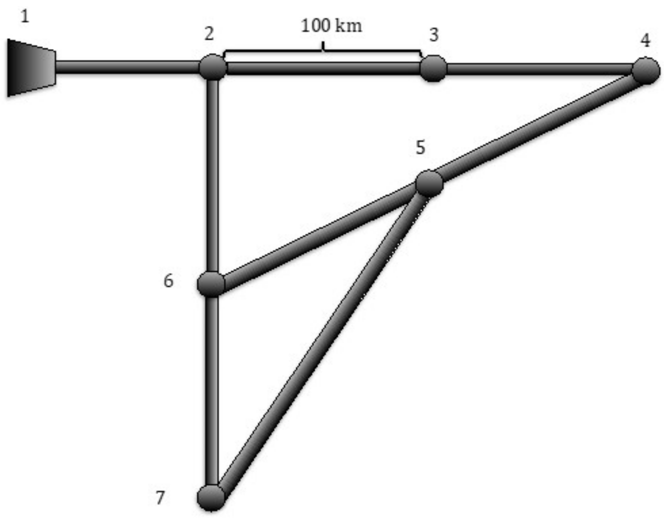


**Figure 5.** Pipeline network used for calculations.

Then, the adjacency (or connectivity) matrix $A$ for 7 nodes in the case study is as follows:

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{pmatrix}. \quad (6)$$

The adjacency matrix $A$ is the only information necessary to automatically create a set of equations for network flow. When a crack appears in one of the lines, additional rows and columns are added to the adjacency matrix $A$ and this new matrix is then used to automatically generate the set of the equations presented in the proposed approach. Such automation is very handy since, to establish valid estimates, multiple iterations need to be handled, and it would not be possible in practice to alter the code by hand.

Next, it was assumed that there was a possible gas consumption at each point. For the demonstration purpose, the consumption time series are generated from the lognormal distribution: each point has its unique time series. Nonetheless, this allows an estimation of the gas low rate in the network and power consumption at the compressor. An example of a gas flow rate time series at a point is presented in Figure 6.

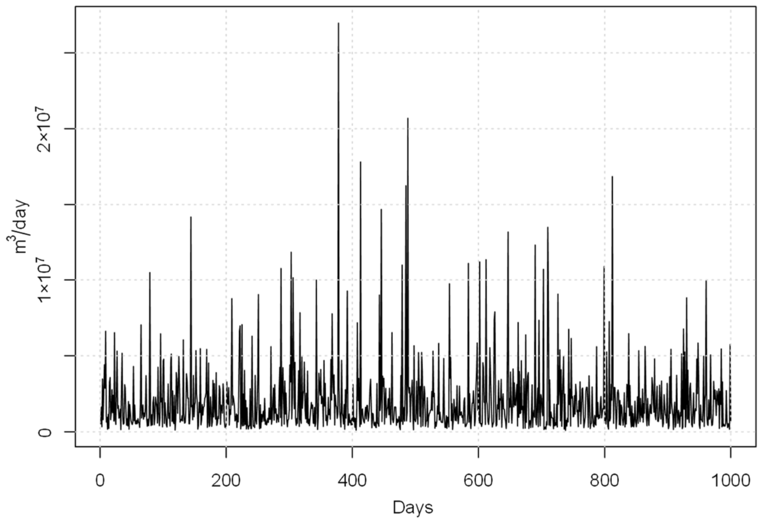


**Figure 6.** Gas flow rate time series at one of the gas consumption points.

The average gas flow rates at gas consumption points are representative of the average in a real network. However, for simplicity, seasonality in the gas consumption process is not included.

### *3.2. Simulation Results*

At first, simulations were run as if the network was perfectly reliable without any cracks occurring in its entire body. The distribution of average power consumption per day is visualized in Figure 7.

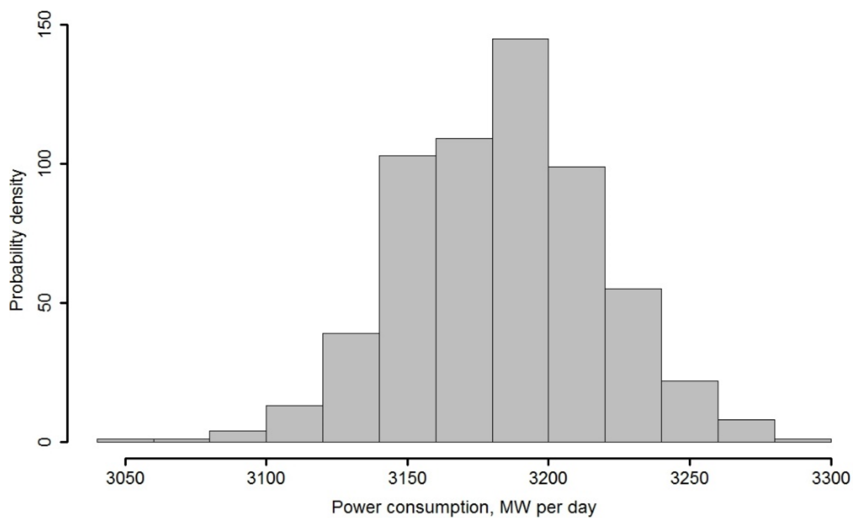


**Figure 7.** Power consumption distribution for a perfectly reliable network over 25 years.

The simulation results for the perfect network serve as a baseline for comparison with cases when the occurrence of a crack or hole in the pipeline has a nonzero probability.

A total of 500 simulations (runs) were used, each time taking a random sample from the posterior distributions of pipeline cracking rates (see Figure 4). Each such sample contained around 12,000 points as the simulation ran for 25 years. Finally, the simulations resulted in an average power consumption point. Since each simulation out of those 500 ran under different cracking rates (as sampled from posterior distributions), a random sample of average power consumption was obtained. The distribution of the average power consumption in the imperfect sample and its comparison with the consumption in the perfect (ideal) network is presented in Figure 8.

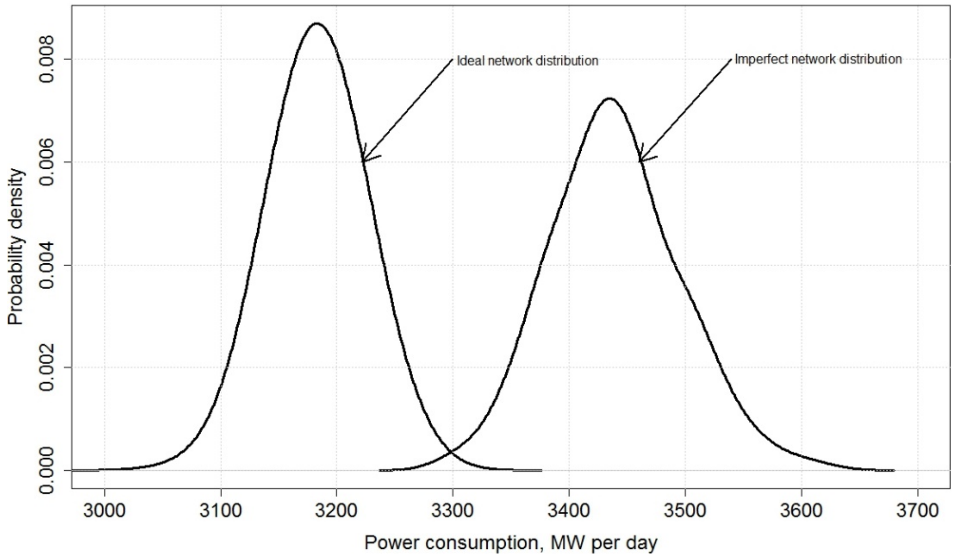


**Figure 8.** Distributions of average power consumption in different networks over 25 years.

These results demonstrate how significant the influence of leakages through cracked pipelines is (possibly due to degradation or human-induced damages). The difference between the expected values of the compressor station power's consumption for ideal and imperfect network cases is approximately 8%. This difference would possibly result in the same percentage increase in daily costs. Over a year or several years, this would result in the loss of a large amount of money or the loss of other resources, which would result in an increase in gas prices for consumers. Thus, even from this point of view, one can see the necessity to include reliability considerations in overall gas network planning and complete optimization.

In such a way, the simulation-based evidence that the influence of reliability parameters on overall network performance can be significant was established. Next, since the cracking rate as presented in Section 2.3 could be an underestimation of the real rate (due to a fraction of leakages or cracks not observed by various inspection techniques), a sensitivity analysis for the cracking rate (observable variation range [0.2, 0.7] events per day per 1000 km) was performed. Additionally, it was taken into consideration that we might not know the true ability to detect the cracks in the pipelines; hence, we used three different POD curves for variation of detection effectiveness.

Just for demonstration purposes, it was assumed that the probability of detection follows a flexible gamma distribution with scale parameters equal to 0.007 and shape parameters PD equal to 20, 30, and 40. Corresponding POD curves are presented in Figure 9.

Results from the sensitivity analysis are presented in Figure 10. As can be seen from these results, the average power consumption increases almost linearly concerning the cracking rate. This implies that the true difference between the average power consumption of a compressor station in the ideal network and the imperfect network will differ by more than 8%, as estimated in the above analysis (see Figure 8). That is because the true cracking (failure) rate might be slightly higher than that estimated in studies without POD consideration [13].

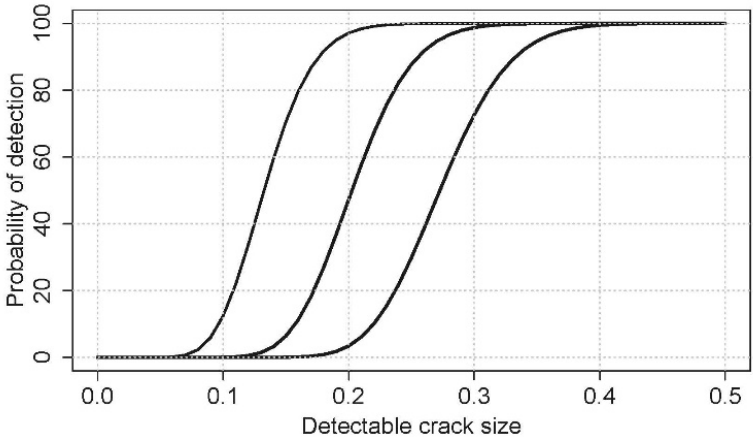


**Figure 9.** POD curves represent inspection effectiveness concerning the crack size. Curves with shape parameters PD equal 20, 30, and 40 are shown from left to right, respectively.

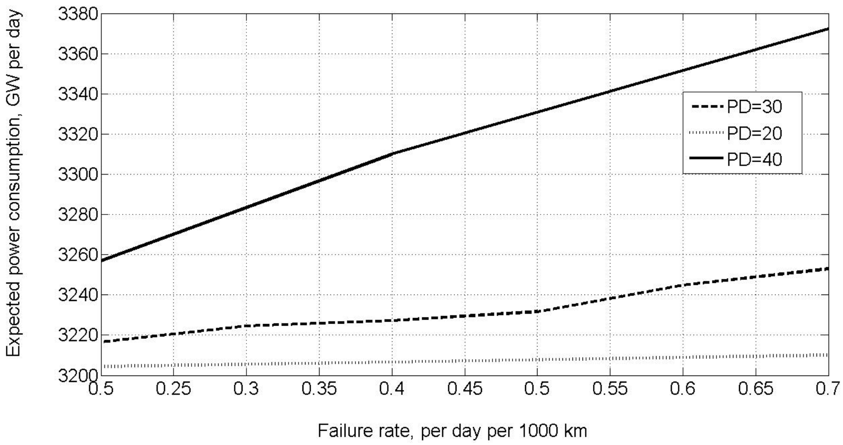


**Figure 10.** Power consumption dependence on cracking rate and detection effectiveness.

Furthermore, the difference by which average power consumption increases (by increasing cracking rate) depends on the effectiveness of crack or leakage detection.

## 4. Conclusions

In this research, the possibility to include the reliability characteristics of the gas pipeline network in power consumption estimation at the compressor station was explored. The main guidelines were drawn on how to perform such an inclusion and how to implement it by applying the proposed stochastic simulation approach.

Even though assumptions and simplifications were made along the way, such as steady-state flow instead of transient flow, as much realistic information and dynamic features as currently available were included: crack growth parameters and age-dependent cracking rate. Additionally, average gas consumption rates were taken to be representative of the real network. A validated orifice gas consumption model was used as well. Therefore, one can be confident that the approach and results may be taken as a good practice.

The main conclusions of this work are that costs due to compressor station work and power consumption may be significant if one includes network reliability characteristics as compared to the case of an ideal (in terms of reliability) network. Power consumption and the cost of running compressors are tightly related to the level of network reliability. In the long run, roughly 8% will be added to the network operating cost due to the leaking pipelines.

We also conclude that detection level, i.e., its effectiveness, has a significant impact on the average power consumption. The better the inspection, the more leakages will be traced down and resolved, leading to reduced power consumption. However, since the maintenance strategies cannot be improved indefinitely, eventually the aging effect or degradation process will "outperform" the maintenance and the leaking rate might start to increase. This challenge—the improvement of maintenance and balancing of the degradation process—is out of the scope of this paper and cannot be taken into account at this stage due to a lack of a general maintenance model.

In addition, there is another dimension to the problem of significant gas leaks from the pipelines: the environmental aspect. A total of 8% of the power consumption increase means that a significant amount of gas is wasted in the atmosphere while it increases the amount of greenhouse gas.

Even though inferences were made about the cracking process's influence on the overall power consumption in compressor stations, it is not the only aspect of network unreliability or risk that will eventually lead to additional spending. In this work, risk due to gas fires or explosions (e.g., [24]) was not considered. The main focus was on the aspect of power consumption due to the additional load only caused by wasting gas in the atmosphere.

Future work might focus on the benchmark type of analysis. In this paper, more focus was given to the illustration of the methodology. In future work, there could be a plan to incorporate various inputs from the industry and the data provided by the gas network operators.

**Author Contributions:** Conceptualization, R.A.; Data curation, T.I.; Formal analysis, R.A.; Investigation, T.I.; Methodology, T.I.; Project administration, R.A.; Resources, R.A.; Software, T.I.; Supervision, R.A.; Validation, R.A.; Visualization, T.I.; Writing—original draft, T.I.; Writing—review & editing, R.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Mokhatab, S.; Poe, W.A.; Speight, J.G. *Handbook of Natural Gas Transmission and Processing*; Gulf Professional Publishing: Burlington, MA, USA, 2006; ISBN 9780750677769.
2. Wong, P.J.; Larson, R.E. Optimization of Tree-Structured Natural-Gas Transmission Networks. *J. Math. Anal. Appl.* **1968**, *24*, 613–626. [CrossRef]
3. Schmidt, M.; Steinbach, M.C.; Willert, B.M. High detail stationary optimization models for gas networks. *Optim. Eng.* **2015**, *16*, 131–164. [CrossRef]
4. Carter, R.G. *Pipeline Optimization: Dynamic Programming after 30 Years*; Pipeline Simulation Interest Group: Denver, CO, USA, 1998.
5. Rios-Mercado, R.Z.; Sanchez, C.B. Optimization problems in natural gas transportation systems: A state-of-the-art review. *Appl. Energy* **2015**, *147*, 536–555. [CrossRef]
6. Kabirian, A.; Hemmati, M.R. A strategic planning model for natural gas transmission networks. *Energy Policy* **2007**, *35*, 5656–5670. [CrossRef]
7. Grudz, V.; Grudz, Y.; Zapukhliak, V.; Chudyk, I.; Poberezhny, L.; Slobodyan, N.; Bodnar, V. Optimal Gas Transport Management Taking into Account Reliability Factor. *Manag. Syst. Prod. Eng.* **2020**, *28*, 202–208. [CrossRef]
8. Wang, B.; Yuan, M.; Zhang, H.; Zhao, W.J.; Liang, Y. An MILP model for optimal design of multi-period natural gas transmission network. *Chem. Eng. Res. Des.* **2018**, *129*, 122–131. [CrossRef]
9. Behari, N.; Sheriff, M.Z.; Rahman, M.A.; Nounou, M.; Hassan, I.; Nounou, H. Chronic leak detection for single and multiphase flow: A critical review on onshore and offshore subsea and arctic conditions. *J. Nat. Gas Sci. Eng.* **2020**, *81*, 103460. [CrossRef]
10. Lenox, C.; Kaplan, P.O. Role of natural gas in meeting an electric sector emissions reduction strategy and effects on greenhouse gas emissions. *Energy Econ.* **2016**, *60*, 460–468. [CrossRef] [PubMed]
11. America Pays for Gas Leaks: Natural Gas Pipeline Leaks Cost Consumers Billions. A Report Prepared for Sen. Edward J. Markey. U.S. Congressional Research Digital Collection. Released: 1 August 2013. Available online: https://www.markey.senate.gov/imo/media/doc/documents/markey_lost_gas_report.pdf (accessed on 14 May 2022).

12. Ailworth, E. Gas Leaks Cost Consumers $1.5 b, Study Says. The Boston Globe. Globe Staff, 1 August 2013. Available online: https://www.bostonglobe.com/business/2013/07/31/gas-leaks-costing-mass-consumers/5nIv3FsJaZRwscJ48jGMsI/story.html (accessed on 14 May 2022).
13. Iešmantas, T.; Alzbutas, R. Bayesian reliability of gas network under varying incident registration criteria. *Qual. Reliab. Eng. Int.* **2016**, *32*, 1903–1912. [CrossRef]
14. EGIG-Report. Gas Pipeline Incidents: 11th Report of the EGIG (Period 1970 to 2019). European Gas Pipeline Incident Data Group (EGIG). 2020. Available online: https://www.egig.eu/reports/$60/$61 (accessed on 14 May 2022).
15. UKOPA-Report. Pipeline Product Loss Incidents and Faults Report (1962 to 2019). United Kingdom Onshore Pipeline Operators' Association, Pipeline Maintenance Centre. 2021. Available online: https://www.egig.eu/reports (accessed on 14 May 2022).
16. NEB-Report. *Focus on Safety and Environment: A Comparative Analysis of Pipeline Performance, 2000–2009*; National Energy Board (NEB): Calgary, AB, Canada, 2011. Available online: https://publications.gc.ca/collections/collection_2012/one-neb/NE2-2-2009-eng.pdf (accessed on 14 May 2022).
17. U.S. Department of Transportation. Pipeline and Hazardous Materials Safety Administration. OPS-Database, All Reported Incident 20-Year Trend. Office of Pipeline Safety (OPS). Available online: https://www.phmsa.dot.gov/data-and-statistics/pipeline/pipeline-incident-20-year-trends (accessed on 14 May 2022).
18. Rahal, H. A co-tree flows formulation for steady state in water distribution networks. *Adv. Eng. Softw.* **1995**, *22*, 169–178. [CrossRef]
19. Woldeyohannes, A.D.; Majid, M.A. Simulation model for natural gas transmission pipeline network system. *Simul. Model. Pract. Theory* **2011**, *19*, 196–212. [CrossRef]
20. Menon, E.S. *Gas Pipeline Hydraulics*, 1st ed.; CRC Press: New York, NY, USA, 2005.
21. Heerings, J.; Trimborn, N.; Den Herder, A. Inspection effectiveness and its effect on the integrity of pipe work. In Proceedings of the 2004 SEM X International Congress on Experimental and Applied Mechanics, Los Angeles, CA, USA, 4–10 June 2004.
22. Lecchi, M. Evaluation of predictive assessment reliability on corroded transmission pipelines. *J. Nat. Gas Sci. Eng.* **2011**, *3*, 633–641. [CrossRef]
23. Yuhu, D.; Huilin, G.; Jing'en, Z.; Yaorong, F. Mathematical modeling of gas release through holes in pipelines. *Chem. Eng. J.* **2003**, *92*, 237–241. [CrossRef]
24. Alzbutas, R.; Iešmantas, T.; Povilaitis, M.; Vitkutė, J. Risk and uncertainty analysis of gas pipeline failure and gas combustion consequence. *Stoch. Environ. Res. Risk Assess.* **2014**, *28*, 1431–1446. [CrossRef]