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Probabilistic gas transmission network simulator and application to the EU gas transmission system

Keywords

gas network, energy security, reliability, Monte Carlo

Abstract

The paper describes the methodology approach and the results obtained by the probabilistic gas network simulator ProGasNet software tool. The ProGasNet has been applied to a number of test cases, all based on real gas transmission networks of the EU countries. Various types of analysis have been performed: reliability, vulnerability, security of supply and various types of results have been reported: supply reliability estimates, time-dependent storage discharge effect, quantitative effects of new infrastructure, security of supply under different disruption scenarios. The ProGasNet model provides an indication of the worst networks nodes in terms of security of supply and provides their numerical ranking. The model is very powerful to compare and evaluate different supply options, new network development plans and analyse potential crisis situations.

1. Introduction

A number of energy supply disruptions due to economic, political or technical reasons highlight the need to study energy infrastructure networks from the security of supply point of view. After the major supply disruption in January 2009 due to the Russia-Ukraine dispute, the European Commission reacted by issuing Regulation 994/2010 on security of gas supply [6] which requires the EU Member States to fulfil a number of requirements, including risk assessment, preventive action plan and emergency action plan, installation of cross border reverse flow capabilities, and supply and infrastructure standards, including the N-1 criterion.

Gas transmission network is a part of critical infrastructure that has been recently addressed by various initiatives from research institutions and governments worldwide. The European Commission has taken the initiative to organize a network consisting of research and technology organizations within the European Union with interests and capabilities in critical infrastructure protection [11]. Interdependencies between critical infrastructures make the analysis complicated and challenging, but the topic is attracted by a growing number of researchers [14], [18]-[19]. For energy infrastructures the most interesting interdependence is between gas and electricity networks, a benchmark study presented in [3].

From the computational point of view, the analysis of large infrastructure networks is very demanding. In this paper we will look at the gas network from the reliability analysis point of view which is then extended to perform vulnerability assessment as well. A detailed review of the state of the art in the field of network reliability analysis is reported in [1], in which computational complexity, exact algorithms, analytic bounds and Monte Carlo (MC) methods are presented. Reliability analysis of a natural gas compression station and surrounding gas pipeline networks is presented in [16]. A non-simulation-based reliability analysis method is proposed and demonstrated on stochastic networks in [9] and [12]. Interdependence effects in complex networked systems were studied in [7], while [20] and [17] focused on identification of top contributors to power networks.

The application case of paper [13] refers to the interface between the power grid and the gas transmission systems. Two hazard types are considered: random hazards and hurricane hazards. Three edge-based attack strategies are proposed to measure the roles of the different edges on the cascading propagation in [21].

This is far from a complete list of references in the field, but it illustrates the diversity and complexity of the approaches proposed and problems to be solved.

The paper describes the work performed by using ProGasNet software tool to specific test case based on real gas transmission network of the EU countries. Various types of analysis have been performed: reliability, vulnerability, security of supply and various types of results have been reported: supply reliability estimates, security of supply under different disruption scenarios.

2. Methodology

The paper presents development process of the ProGasNet software tool to address European gas transmission network reliability, risk, security of supply issues. A number of studies have been conducted so far however all faced many limitations and various simplifications [15]. The recent JRC report [10] presents testing results of two approaches implemented for relatively simple benchmark network systems: Monte-Carlo (MC) reliability simulation and fault tree (FT) analysis. The results of test cases indicate potential of both methods for network reliability analysis and the need for further research. The current paper presents further development of the MC approach and provides a number of country wide or regional analysis examples.

ProGasNet uses a distance-based approach of a stochastic network commodity flow model. Priority based commodity supply pattern is based on distances from the source node, so nodes closer to the source are served first. This supply pattern is typical in gas transmission pipeline networks. In each Monte-Carlo simulation step, firstly component failures, especially pipeline failures, are sampled according to an empirical probabilistic law taken, for example, from a failure database. In order to estimate the maximum of transmitted flow from source nodes to sink nodes under reliability and capacity constraints given by the stochastically imperfect elements, which can randomly fail with known failure probabilities, we apply the maximum flow algorithm with multiple sources and multiple sinks. Moreover, in order to identify critical gas supply nodes, which are, under supply crisis conditions, normally geographically far from gas source nodes, we estimate the distance from the virtual source to sink nodes. We use a Dijkstra's algorithm for calculating the distance matrix. Then, we compute a permutation matrix of the graph isomorphism problem according to the distance from the gas source. In this way we transfer the original model to the distance-based approach by a dynamic reordering of nodes and lines of the network graph model [4]. This graph isomorphism task is performed by linear algebra operations [2]. Consequently, we are able to compute the flow matrix of the Maximum flow algorithm. To finish the simulation step, the computed flow matrix is transformed back into the original problem by an inversion linear algebra operation.

Finally, Monte-Carlo simulations are used for estimating that the probability of less than demanded volume of the commodity (for example, gas) is available in selected network nodes. These simulated results are also used for the vulnerability (critical component) analysis. A combination of detected failures leading to the most dominant loss of the available gas is presented and analysed in depth by statistical methods.

3. Test case study

3.1. Definition of the study case

The *Figure 1* illustrates the graph topology of the test gas transmission network model used in the case study. The test case is based on a real country gas transmission network and realistic supply/demand data, however due to confidentiality issues its geographical topology is not disclosed. The network contains the following elements: pipelines, LNG terminal and compressor station. This test case lacks only one type of gas infrastructure element – storage. Modeling of storages will be considered in the near future as well as time dependent Monte-Carlo simulations, necessary for exploring the full potential and importance of storage in gas networks.

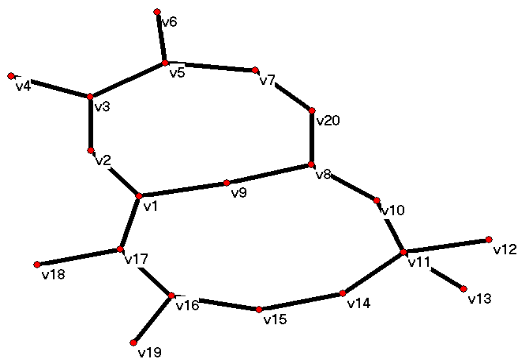

Figure 1. Virtual topology of the gas transmission network – test case No.2

The Node 1 indicates a virtual supply source. All numbers are considered to have million (mln) cubic meters per day dimension. It means that the actual supply nodes are three: 2, 9 and 17. In order to simplify the figure, the virtual sink node 21 with connections is not visualized.

Tables below provide a test gas network data: capacities (*Table 1*) and lengths of the edges between nodes (*Table 2*) and demands at consuming nodes (*Table 3*). It means that maximum theoretical gas supply to the network is 68.9 mln m3 per day. Node 10 represents a compressor station and no gas consumption is assumed at that node. In the reliability model it is assumed that the annual probability of failure of the compressor station is 0.01. When there is a failure of this compressor station node, the import capacity of Node 9 is reduced from 5.2 to 2.7 mln m3/day and import capacity of Node 20 is reduced from 12 to 9.8 mln m3/day. Technical flow capacity between the remaining connected nodes is more than the daily maximum consumption, so no internal bottlenecks exist in the benchmark system.

Table 1. Test network sink nodes

Node	Capacity, million m^3/day
2	51.2
9	5.2
17	12.5

In this test case model, it is assumed that the virtual nodes with the connected lines are perfectly reliable, i.e. there are no failures of source and sink nodes, except source node 17, which represents a LNG terminal. It is assumed that source Node 17 fails with known annual probability of 0.02. In a case of failure, the incoming gas at Node 17 is reduced from nominal value 12.5 mln m^3 per day to zero in the model. It is also expected that all lines are bidirectional, except the line between nodes 7 and 20. In this line it is expected that the flow can run only from node 7 to node 20. This direction flow constrain is modeled by the capacity matrix using the relation $C(20, 7)=0$ and also by the length matrix $L(20, 7)=inf$, as the network element is not accessible for the reverse flow.

The statistics from the US natural gas transmission pipeline incidents from 1986 to 1996 shows that the incident frequency was 1.6×10^{-4} per kilometer-year, see a discussion of the US PHMSA Pipeline Safety Program in [13]. According to the EGIG reliability report [5], the average failure frequency of a European gas transmission pipeline is 3.5×10^{-4} per kilometer-year. In our case study, let us assume that 10% of the reported failures cause the total failure of the pipeline elements. This assumption is based on EGIG estimation of pipeline ruptures proportion to leaks and other incidents. Consequently, we set pipeline the failure probability as $p_f = 3.5 \times 10^{-5}$ per kilometer-year in our numerical experiments.

Table 2. Test network length matrix: list of non-zero elements

Branches (from, to)	Length, km
(2,3)	288
(3,4)	65
(3,5)	414
(5,6)	61
(5,7)	117
(8,9)	276
(8,10)	66
(10,11)	168
(11,12)	65
(11,13)	35
(11,14)	140
(14,15)	34
(15,16)	8
(16,17)	20
(17,18)	33
(16,19)	83
(7,20)	0.5
(8,20)	27

Table 3. Test network demand nodes

Nodes	Demand, million m^3/day
4	36.5
6	2.7
8	1
9	2
11	1
12	0.5
13	0.5
14	1
15	0.5
16	1
18	4
19	8
20	0.5
Total demand	59.2

3.2. Disruption case studies

The reliability model takes into account internal component failures: pipelines, compressor stations and LNG terminals. However, external import supply by pipeline is not probabilistically modeled because of a number of reasons:

- Lack of upstream pipeline system model;
- Difficult to estimate numerically possible political/social origin of the disruption (e.g. Libyan war or Russian-Ukraine gas dispute).

Therefore, a conservative approach is taken and complete disruption scenarios are assumed and modeled. This approach enables to determine the most critical system elements under particular difficult supply circumstances. In order to model the test network reaction to gas supply disruptions, the two following scenarios are assumed:

- Scenario A: No external disruption, i.e. all three input nodes are supplied as contracted and only internal system failures are modeled.
- Scenario B: No supply at Node 2.

In these scenarios, we assume that the network components (pipelines, compressor station and LNG terminal) might fail, according to the above discussed probabilistic data. The Monte-Carlo simulations were run 1 million times for each scenario (30 minutes of CPU time) and a steady state of supply/demand was studied for both. The network component failures were modelled on an annual basis.

The reliability gas network simulation software tool, which is currently under development, is able to produce a cumulative distribution function of a sum of supply over all nodes, a list of statistical properties of supply at selected nodes, a list of node demands and, finally, a list of probabilities for various levels of demand at selected nodes. All measures of the presented case-study are considered to have million cubic meters per day dimension.

The model can be used not only for evaluating the current situation of security of supply, but also for testing effects of new network components, for example pipelines, in order to test various development strategies of the transmission network.

3.3. Simulation results: Scenario A

In Scenario A, no limitations on gas input are assumed and only internal failures of the network components are possible. It means that source nodes (2 and 9) are fully reliable suppliers, while supply from the LNG node 17 can fail with annual probability 0.02.

Figure 2 presents a cumulative distribution function of a sum of supply over all nodes. The sum of supply varies between 2 mln m3/day and the maximum demand 59.2 mln m3/day. In order to highlights the tail area of the distribution, the horizontal axis of the figure is cropped.

Table 4 includes probabilistic results of Scenario A. The table includes the list of nodes with non-zero demands and probabilities that the node supply X will be zero, expressed by the symbol P(X=0), or less than 50%, 80% or 100% of the node demand. The symbol "Total" is a nick-name of a total sum of gas consumption in the network. Probability that the whole network demand (59.2 mln m3/day) will not be successfully covered is 0.074, see *Table 4*. Node "Total", column P(X<D). Probability of supplying of less than 80% of total demand, i.e. the probability that supply is less than 59.2×0.8=47.36 mln m3/day is 0.013, see the line "Total", column "P(X<0.8D)", *Table 4*.

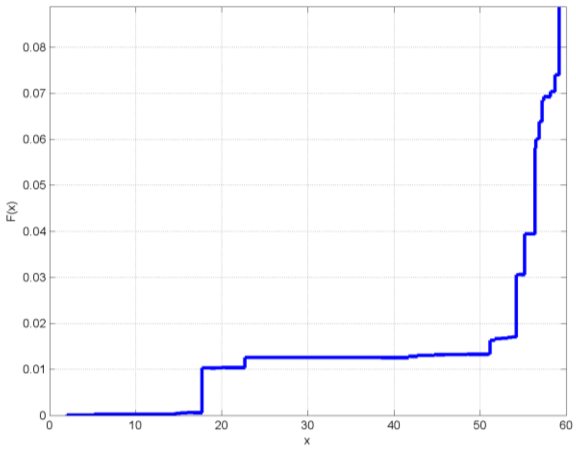

Figure 1. Results of Scenario A: Cropped cumulative distribution function of a sum of supply in all nodes

Several results of *Table 4* can be easily verified analytically. For example, in case of Node 4, there exists only one path from source Node 2 through Node 3 with the total distance 288+65 km = 353 km, according to *Table 2*. So, in this special case, the probability of zero supply at Node 4 is 353×3.5×10-5 ~ 0.0124, which is consistent with the Monte-Carlo approximation ~ 0.013. Moreover, as the model considers that the line between nodes 7 and 20 is unidirectional, the same verification can be done for Node 6, as in this special case there is only one path from source Node 2 to Node 6 with the total distance of 763 km. So, the probability of zero supply at Node 6 is 763×3.5×10-5 ~ 0.0267, which satisfactorily agrees with the presented Monte-Carlo approximation ~0.027. Of course, these direct analytical computations can be easily done only for special cases, for example networks with series-parallel structure [1]. In contrary, the here presented Monte-Carlo simulation approach is a robust tool, which naturally covers reliability and capacity constraints of complex stochastic networks.

According to *Table 4,* Nodes 12 and 13 would be also seen as the "most weakest nodes" of the network as the probability of having no gas during a year is estimated by the Monte Carlo simulations to be the largest in the network: P(X=0) is approximately 0.04 for those two nodes. Of course, all reported "no gas at a node" probabilities are relatively small, as Scenario A represents a 'business as usual' case, i.e. without any external disruption.

Table 4. Results of Scenario A: List of nodes (Node) with non-zero demands (D) and probabilities that the node supply will be zero or less than 50% or 100% of the node demand.

Node	D	P(X=0)	P(X<0.5D)	P(X<D)
4	36.5	0.013	0.013	0.013
6	2.7	0.027	0.027	0.027
8	1	0.00028	0.00028	0.00058
9	2	0	0	0
11	1	0.0087	0.0087	0.0087
12	0.5	0.039	0.039	0.039
13	0.5	0.038	0.038	0.038
14	1	0.00095	0.00097	0.00097
15	0.5	0.00093	0.00093	0.00093
16	1	0.00092	0.00092	0.00092
18	4	0.0021	0.0021	0.0021
19	8	0.0039	0.0043	0.065
20	0.5	0.00059	0.00059	0.00059
Total	59.2	0	0.013	0.074

3.4. Simulation results: Scenario B

In Scenario B, it is assumed that there is no input flow from Node 2. In this case, the upper limit of available gas is 17.7 mln m3/d. That implies that the whole network demand (59.23 mln m3/d) cannot be covered, even without component failures. Of course, the theoretical upper limit 17.7 mln m3/d can be decreased by network failures, see for example *Figure 3*, which presents a cropped cumulative distribution function of a sum of supply over all nodes. According to Table 5, the probability of having no gas is 1 for nodes 4 and 6, as there is no gas from the source Node 2 and because the link between node 7 and 20 is unidirectional, so there is no path from remaining gas sources to these two nodes. Moreover, the probability of having no gas at Node 12 and Node 13 is estimated by the Monte Carlo simulations as 0.97, as these two nodes have the largest distance from the sources. Table 5 shows how the network deals with supply insufficiency of Scenario B under the given reliability constrains of the network: Let us remind that the 'no gas' event probability of the LNG terminal (Node 17) is 0.02. The probability of having no gas is close to 0.02 for nodes 11, 14-16, 18-20, because the supply of these nodes depends mainly on the source node 17 (LNG terminal).

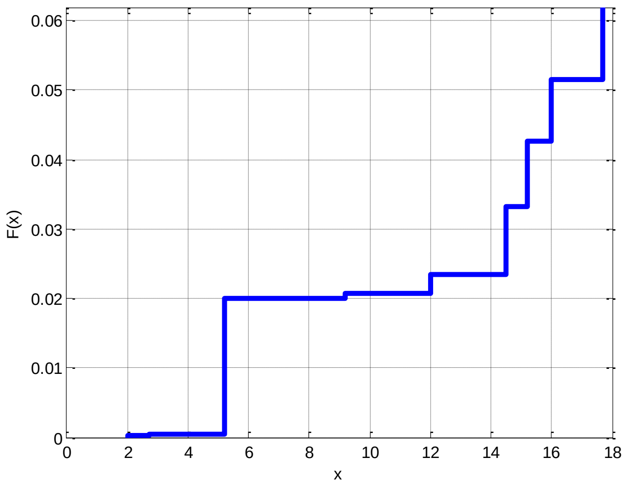

Figure 3. Results of Scenario B: Cropped cumulative distribution function of a sum of supply over all nodes

Table 5. Results of Scenario B: List of nodes (Node) with non-zero demands (D) and probabilities that the node supply will be zero or less than 50% or 100% of the node demand

Node	D	P(X=0)	P(X<0.5D)	P(X<D)
4	36.5	1	1	1
6	2.7	1	1	1
8	1	0.0098	0.0098	0.02
9	2	0	0	0
11	1	0.028	0.028	0.028
12	0.5	0.97	1	1
13	0.5	0.97	0.97	0.97
14	1	0.022	0.022	0.022
15	0.5	0.021	0.021	0.021
16	1	0.021	0.021	0.021
18	4	0.021	0.021	0.021
19	8	0.024	0.024	1
20	0.5	0.021	0.021	0.021
Total	59.2	0	1	1

3. Vulnerability analysis

Vulnerability analysis can be considered in a number of perspectives [8]. The Monte Carlo model used for reliability analysis can be successfully employed for vulnerability analysis, however certain analysis patterns change. From global vulnerability analysis perspective, we can run the model not with randomly failing network components, but by enforcing failures of the components or increasing consumption demand in deterministic manner. The results of such an analysis are outside the scope of this paper, but such a study can be performed with little programming efforts. From critical component analysis perspective, the largest negative consequences are determined under failures of each component or their groups. Having already performed reliability analysis and as a bunch of simulations and their results are available, we have developed a software tool to extract the most critical components in terms of the largest negative consequences.

Firstly, we sorted the sum of supply from all Monte-Carlo simulations over all nodes by the ascending order. The results of the first 80 000 values include both the theoretical minimum supply 2 mln m3/d and also the maximum theoretical supply 59.2 mln m3/d, so it is not necessary to analyse a larger set of simulations.

We are able to zoom into each simulation and extract which component failures have caused it and what are the consequences (how much gas is available in the network).

The minimal theoretical sum of supply over all nodes is 2 mln m3/d which is equal to supply of Node 9, as it is a source node and also a sink node, so no failures are expected in this node at our case study. This minimal theoretical sum of supply was also observed using Monte-Carlo simulations.

Then, the detailed analyses of Monte-Carlo results showed that this dominant failure is caused by simultaneous failures of pipelines between nodes 2 and 3 and also between nodes 8 and 9 together with a failure of source Node 17, see Table 6.

Table 6 includes detailed results of vulnerability analysis for selected supply levels. For the each supply level, the total available gas supply, failure sequence, and its likelihood expressed by the frequency are presented. Failure of Node 10 represents a compressor station failure, which simultaneously affects two source nodes: Node 9 and Node 20. Let us also remind, when there is a failure of this compressor station node, the import capacity of Node 9 is reduced by 2.5 (from 5.2 to 2.7) mln m3/d and import capacity of Node 20 is reduced by 2.2 (from 12 to 9.8) mln m3/d.

Failure of Node 17 represents a total LNG total failure, which affects only node 17. Let us recap, in a case of Node 17 failure, the incoming gas at Node 17 is reduced from nominal value 12.5 mln m3/d to zero in the model.

According to Table 6, the supply level 4 implies a reduction of the available supply to 17.7 mln m3/d. Detailed analyses of Monte-Carlo results showed that this supply level is caused by a single pipeline failure between nodes 2 and 3. So, in fact, this network supply level has the same supply level consequence as the Scenario B analyzed before.

The vulnerability analysis showed that the analyzed network includes a variety of failure combinations, which can reduce the total supply from 59.2 mln m3/d to approximately 50 mln m3/d, see *Figure 4*. The software tool ProGasNet, which is under development, is able to analyze all these cases. However, in this paper we analyzed only a small set of cases in order to demonstrate the potential of the software vulnerability tool.

Table 6. Detailed results of vulnerability analysis for selected supply levels

Supply level, mcm/d	Failure sequence	Estimated frequency
2	Pipelines:(2,3), (8,9) Nodes:17	5.00E-06
2.7	Pipelines:(2,3) Nodes:10, 17	2.00E-06
5.2	Pipelines:(2,3) Nodes:17 (99.1% of cases)	2.32E-04
	Pipelines:(3,4),(3,5) Nodes:17 (0.9% cases)	
17.7	Pipelines:(2,3) Nodes: -	1.02E-02

4. Concluding remarks

The paper describes the methodology approach and the results obtained by the probabilistic gas network simulator ProGasNet software tool. The ProGasNet has been applied to real gas transmission networks of several EU countries however geographical information cannot be disclosed. Various types of analysis have been performed: reliability, vulnerability, security of supply and various types of results have been reported: supply reliability estimates, security of supply under different disruption scenarios.

The ProGasNet model provides an indication of the worst networks nodes in terms of security of supply and provides their numerical ranking. It is recommended to use the results of the model in a qualitative (comparative) way rather than interpret numerical values directly. The model is very powerful to compare and evaluate different supply options, new network development plans and analyse potential crisis situations.

The model has a number of advantages and limitations that must be considered by interpreting the results. The model at this stage cannot model adequately consequences of failures of compressor stations. Currently, it is assumed that pipeline capacity is reduced by 20% in the nearest section, however this assumption needs to be validated by physical flow computations. Failures of two nearby compressor stations would have severe effect on the network capacity, but this event is not considered in the current version of the probabilistic model. Futher work is needed to overcome these limitations.

Acknowledgements

The authors thank to M. Masera and R. Bolado-Lavin of European Commission, Joint Research Centre, Institute for Energy and Transport for valuable discussions and suggestions.

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