Reliability Engineering and System Safety 212 (2021) 107643

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Feasibility study of PRA for critical infrastructure risk analysis

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ARTICLE INFO

Keywords:
Probabilistic Risk Analysis
Critical infrastructure
Network models
Statistical learning theory

ABSTRACT

Probabilistic Risk Analysis (PRA) has been commonly used by NASA and the nuclear power industry to assess risk since the 1970s. However, PRA is not commonly used to assess risk in networked infrastructure systems such as water, sewer and power systems. Other methods which utilise network models of infrastructure such as random and targeted attack failure analysis, N-k analysis and statistical learning theory are instead used to analyse system performance when a disruption occurs. Such methods have the advantage of being simpler to implement than PRA. This paper explores the feasibility of a full PRA of infrastructure, that is one that analyses all possible scenarios as well as the associated likelihoods and consequences. Such analysis is resource intensive and quickly becomes complex for even small systems. Comparing the previously mentioned more commonly used methods to PRA provides insight into how current practises can be improved, bringing the results closer to those that would be presented from PRA. Although a full PRA of infrastructure systems may not be feasible, PRA should not be discarded. Instead, analysis of such systems should be carried out using the framework of PRA to include vital elements such as scenario likelihood analysis which are often overlooked.

1. Introduction

The use of Probabilistic Risk Analysis (PRA) as a tool for risk assessment was popularised in the 1970s with the assessment of the risk associated with nuclear power plants. The WASH 1400 report [1] which assessed accident risk of commercial nuclear power plants in the USA is referred to as the first modern PRA [2, 3]. Various terms such as Quantitative Risk Analysis (QRA) [4] and Probabilistic Safety Analysis (PSA) are also used to refer to the process of PRA, and for all three terms the word analysis is sometimes substituted with assessment.

There are two main elements of PRA: first, the severity of the consequences of all conceivable scenarios and second, the likelihood of each of these scenarios [5, 6]. The important factor is to estimate the likelihood of occurrence and not just the consequences, which is often lacking in assessments where methods of analysis other than PRA are used. In an engineering setting, PRA should fully assess the risks associated with a technological system. PRA then includes scenario identification of what can go wrong, what is the associated likelihood of each scenario occurring as well as the associated consequences [7].

When assessing infrastructure, network models or graphs can be used to represent the system. Such models are constructed of nodes and edges, where the nodes represent the important components of the system and the edges the connections between the components [8]. For example, in a network model of an electric power system the nodes represent components such as power stations, substations and poles, and the edges the transmission and distribution lines [9]. Edges can represent both physical connections, such as the transmission lines within an electric power system, but also non-physical connections, such as the sharing of information. Such models can then be used for a variety of methods to assess infrastructure risk and vulnerability, such as random and targeted attack failure analysis, *N-k* (including *N-1*) analysis and PRA (see [10-13] for examples).

Networks models can be used to represent only the structure or topology of a system or can be extended to couple with an engineering performance model which accounts for the physics of the flow of the commodity through the system (see, for example, [14, 15]). Dependencies or interdependencies between two or more systems can also be included within network models [16, 17]. Edges or connections between the different system's networks represent the dependencies between the systems, for example, the requirement of power from an electric power system to wells within a water system so that the wells can function [18].

For infrastructure systems such as power, communication and water systems, a full PRA is not a tool commonly used to assess the associated

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https://doi.org/10.1016/j.ress.2021.107643
Received 22 November 2019; Received in revised form 31 January 2021; Accepted 22 March 2021
Available online 25 March 2021
0951-8320/

risks. A full PRA is considered by the authors to be one that assesses all conceivable scenarios, including natural hazards and internal failures, as well as the associated likelihoods and consequences. Modern infrastructure systems are vast and complex, resulting in, if applied, an equally complex PRA. There are some examples within the literature of PRA of infrastructure systems, however, these focus on natural hazards and do not assess a range of scenarios or assess only a portion of the system such as only the high-voltage transmission portion of a power system rather than the entire system (see, for example, [13, 19, 20]).

Other methods of assessing the performance of infrastructure systems using network models have also been developed. Such methods include the use of cut sets, random and targeted attack failure analysis, and statistical learning theory [11, 12, 17, 21, 22]. Although such methods are less complex than PRA, there are elements of PRA which are not addressed in these. For example, most applications of network theory do not model the physics of flow within the system, and they do not estimate the likelihood of each possible future scenario. Similarly, cut-set methods likewise do not estimate scenario likelihoods. Most applications of statistical learning theory on the other hand are implicitly conditional estimates of system performance. That is, they estimate the conditional probability distribution (or a point estimate of it) given the occurrence of a hazard event.

In the present paper we explore a formulation of a full PRA for infrastructure systems before exploring the complexity of a full PRA using the water system of a virtual city for a chosen scenario as a basis for a more specific discussion. The formal formulation of a full PRA, along with the example, demonstrates how complex it can be to perform a PRA for modern critical infrastructure. More common methods of analysing critical infrastructure risk will be compared to PRA, highlighting which elements of PRA they encompass. This is followed by a discussion of how to improve current infrastructure risk assessment by including elements of PRA which are often not addressed in such assessments.

Section 2 gives an overview of PRA as a method and its uses for assessing critical infrastructure risk. This is followed by the formulation of a full PRA for an infrastructure system in Section 3. In Section 4, this formulation is applied to a virtual water system. Section 5 provides a comparison of other methods used in infrastructure risk analysis to PRA. A discussion of the difficulties associated with performing a full PRA for infrastructure systems is given in Section 6 before the conclusions of the paper are presented in Section 7.

2. Probabilistic risk analysis

Kaplan and Garrick [7] outlined a quantitative definition of risk which is now frequently used as a conceptual basis for PRA. They proposed that by answering three questions the risk associated with a system or event can be assessed quantitatively. These questions are:

1) What can happen/go wrong?
2) What is the likelihood that is will happen?
3) Given it does happen, what are the consequences?

The quantitative definition of risk, R, that results from answering these three questions is expressed as

$$R = \{\langle s_i,\ l_i,\ x_i \rangle\},\ i = 1,\ 2, \ldots, N \quad (1)$$

which defines risk as the set of triplets where each triplet contains a scenario of what can go wrong, s_i, the likelihood that the scenario will occur, l_i, and the consequence associated with the scenario, x_i [23]. The set contains *N* triplets which is the number of possible scenarios that are identified by the assessor.

The risk is often presented as a risk curve. As explained by Kaplan and Garrick [7] to generate the risk curve, the scenarios are arranged in increasing order of severity of damage, before calculating the cumulative likelihood of the scenarios. The consequences are then plotted against the cumulative likelihood, resulting in a staircase function with likelihood of exceedance on the y axis. Considering the staircase function as a discrete approximation of a continuous risk curve, a continuous risk curve can be approximated as the smoothed curve fitted to the staircase function. This is commonly referred to as the F-N or Frequency-Number curve. An example plot can be seen in Figure 1. This method was used to compare the risks associated with nuclear power plants with other man-made disasters by US Nuclear Regulatory Commission [1], where the risk curves were plotted on log-log scale [7]. Risk curves can be single hazard-specific or account for multiple hazards. An example of the former is the so-called PEER framework formula for the mean annual rate (or annual frequency) of events exceeding a specified threshold [24] (see also [25]). An example of the latter is the statistical model by Selva [26] for handling interaction between two different hazards in long-term multi-risk assessments.

For completeness, Kaplan and Garrick [7] then introduce a final s_{N+1} scenario that acts as an “other” category, containing all possible scenarios that are not explicitly stated in the *N* scenarios that answer Question 1. This guides the assessor to consider the limitations of the assessment and give thought to events not listed as one of the *N* possible scenarios. Kaplan and Garrick [7] consider the “other” category of s_{N+1} as containing events that have not yet occurred. The fact that these events have not yet occurred in the assessed system, or any similar systems is a piece of knowledge that can be treated as evidence when applying Bayes’ theorem to assign a likelihood.

Once the list of possible scenarios is completed, the associated likelihood of each is then calculated. The likelihood of a scenario can be expressed in one of three ways [23]. The first is as a frequency. This applies to events that are recurrent and the rate of occurrence is known. The second method for expressing the likelihood is as a probability. This is used when the event is not recurrent and thus there is no frequency of occurrence. The probability instead expresses the degree of belief that the event will occur given the knowledge and information available at the time of the assessment. This interpretation of probability is often referred to as subjective or Bayesian probability [27-29]. The final way in which the likelihood can be expressed is as a probability distribution over a frequency. When the event is recurrent and the frequency of occurrence is unknown but there is some information and knowledge available to assess the frequency, then the likelihood is stated as a probability of the frequency.

When the likelihood is considered as a probability distribution over a frequency, which Garrick [23] suggests as the preferred representation, the triplet expressing the quantitative definition of risk instead can be expressed as

$$R = \{\langle s_i, p_i(\phi_i),\ x_i \rangle\} \quad (2)$$

where $p_i(\phi_i)$ is the probability density function that expresses the assessor’s state of knowledge of the frequency, ϕ_i. There is also uncertainty in the consequences associated with each scenario. The risk is being assessed for some time in the future and so the outcome cannot be known, which also results in uncertainty in the consequence of each scenario [7]. A joint distribution of the uncertainty in both the frequency and consequence can be used giving the quantitative definition of risk as

$$R = \{\langle s_i,\ p_i(\phi_i,\ x_i)\rangle\},\ i = 1,\ 2, \ldots, N. \quad (3)$$

The risk is now communicated as a series of risk curves. This allows the uncertainty in both the frequency and magnitude of the consequences to be explicitly displayed within the results. Each curve represents a chosen fractile of the probability distribution of the of the consequence or loss level shown on the horizontal axis [30].

In practise, tools such as event tress and fault trees are used to quantify the risk. As discussed in Section 1, a fault tree begins with a top event representing system failure which is then broken down into the preceding intermediate events that need to occur within the system so

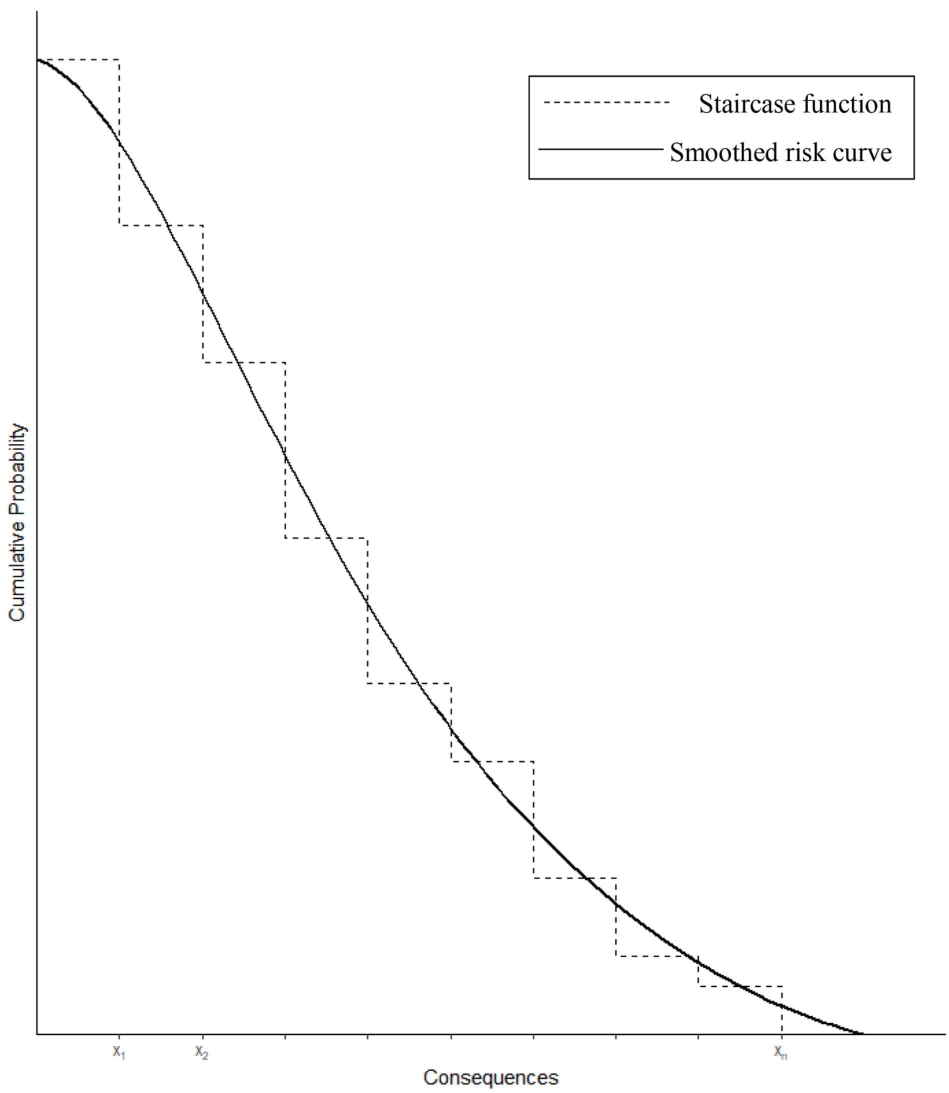

Figure 1. Risk curve resulting from plotting the consequences against the cumulative likelihood.

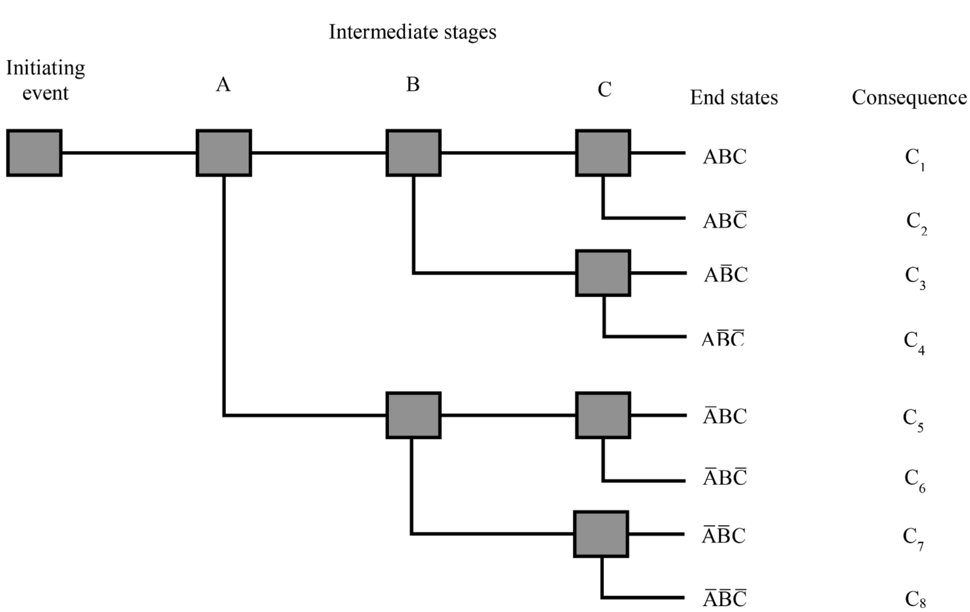

Figure 2. Example of an event tree

that the end state is reached [6]. They typically include "AND" and "OR" gates, with other, less common, gates also used when needed. From a fault tree, the minimum cut sets related to the end state can be found. A minimal cut set in the context of fault tree analysis provides the combination of the minimum number of events that need to occur such that the associated top event will be reached.

An event tree begins with an initiating event, such as a hurricane, and follows a path through the intermediate stages of the system to reach the end state, resulting in the associated consequence. Each branch in the event tree has an associated probability that the intermediate event will occur [6]. A simple example of an event tree is shown in Figure 2 where each intermediate event either occurs or does not.

The likelihood of an end state can be found by multiplying the frequency of the initiating event with the string of conditional probabilities of all intermediate events that result in that end state. For example, the likelihood of reaching the end state with consequence C_3 is

$$\phi(ES_{C_3}) = \phi(IE)\ \phi(AIE)\ \phi\left(\overline{B}|A\ IE\right)\ \phi\left(C\middle|\overline{B}\ A\ IE\right) \tag{4}$$

where $\phi(IE)$ is the frequency of the initiating event, $\phi(X|Y)$ is the frequency of the intermediate state X conditional on Y, and ES_{C_3} is the end state with consequence C_3. The expected consequence of the initiating event can be found by summing over the products of the likelihood and associated consequences of each end state. Once the expected consequence for each initiating event is calculated and ranked in order severity, the risk curve can be produced.

When the frequency of the initiating event and the intermediate states are unknown, the likelihood is interpreted as probability of frequency. The severity of the consequences is also unknown and also are given as a probability. This instead results in a family of risk curves as previously discussed.

State enumeration and Monte Carlo simulation are common methods to analyse combinations of component failures during a risk assessment. Both methods enable the user to select the number of component states to be analysed. For simple assessments, the components are considered as only functional or failed. For more complex analysis, the component states can specify the level of functionality for components that can be partially functional. Some refer to the two methods separately [5, 31] while others use state enumeration as a blanket term which encompasses system state selection methods, which are referred to as Monte Carlo simulation and contingency enumeration [32].

State enumeration (or contingency enumeration) is used in practise when either the system being analysed or the set of system states to be assessed are relatively small in size. A predetermined list of system states are used to analyse the system [33]. The probability of the system being in these specified states is calculated before assessing the consequences and risk associated with each state. A similar process is followed when using Monte Carlo simulation, but rather than a predetermined list of system states, system states are sampled based on the joint probability distribution of the component states [32], after which the consequences and risk associated with each state is calculated. When analysing a relatively large system or evaluating a high order of contingencies, Monte Carlo simulation is the preferred method [32].

2.1. PRA of critical infrastructure

Although PRA is not commonly used to assess critical infrastructure risk, there are some examples of partial or limited PRA within the literature, mainly with a focus on the effects of natural hazards. Such examples include Lamb and Garside [13] who perform a PRA of Britain's railway network for the limited scenario of bridge scour due to flooding. The complexity of PRA is illustrated in [13] where, to limit the computational expense, the risk is assessed for a subset of edges rather than the entire network. The number of possible edge failure combinations is also limited. Scherb and Garrè [20] and Cavalieri et al. [34] both explore the inclusion of the engineering performance model of an electric power system within a PRA. Cavalieri and Franchin [34] compare several network models of an electric power system given a seismic event. Both topological and flow-based (engineering performance) networks are constructed, the results of which are compared, and suggestions are made for which situations the more complex flow-based model such be used and when a simpler topological network is sufficient. Scherb and Garrè [20] present a framework for the inclusion of the engineering performance model of an electric power system of a PRA when hurricane scenarios are assessed. The results show that the internal cascading disruptions have a greater influence on the overall system performance than the characteristics of the hurricane, highlighting the need to account for the flow of power within the system.

Other examples of partial or approximate PRAs within the literature have demonstrated how to account for both the direct and indirect effects of natural hazards on infrastructure systems. Argyroudis et al. [35] consider both the direct damage of an earthquake to a road network and the indirect damage due to building collapse. Poljanšek et al. [36] demonstrates an example of a PRA for the dependent gas and electric power systems of Europe when seismic hazards occur. Here, the electric power system relies on the gas system at gas-fired power stations. Thus, modelling these dependencies allows for both the direct and indirect effects of an earthquake on the system to be considered. Argyroudis et al. [37] presents a method for multi-level stress testing to assess the risk of non-nuclear infrastructure. The method allows for both independent and interdependent infrastructure to be assessed for both single and multiple hazards occurring simultaneously, with a focus on natural hazards.

The SYNER-G research project, which focused on the vulnerability and risk of seismic hazards to buildings, lifelines and infrastructure in Europe uses an Object-Oriented (OO) model used in such assessments [38]. Cavalieri et al. [39] present the general method developed by the SYNER-G project the in context of a transportation and electric power system. The generation of each system model is explained, and the assessment of seismic disruptions to the two systems separately is demonstrated. Franchin and Cavalieri [19] and Cavalieri et al. [40] both demonstrate the use of the OO model to account for interactions between infrastructure systems and the effects of seismic hazards in terms of social losses. Cavalieri and Franchin [40] investigate social losses in terms of fatalities, casualties and displaced population due to seismic events. To assess the level of population displaced the direct effects of the earthquake on building structure is considered, as well as disruptions to the power, water and transportation services that service the building to establish if a building is habitable. Franchin and Cavalieri [19] include the recovery of buildings to habitable conditions to investigate the resilience of civil infrastructure to earthquakes by modelling the time taken until housing is restored after an earthquake. Different recovery strategies to restore housing are investigated, including the effects that the uncertainties in the magnitude of the hazard, weather conditions and damage level to buildings have on recovery efforts.

Tools developed for PRA are also used for stand-alone analysis of infrastructure systems, especially when investigating the possibility of a specific scenario occurring that affects the system. One example is fault trees, which are used to estimate a 'top event' probability by modelling the occurrence of that event based on if other events have occurred in the system or not. Both Lindhe et al. [41] and ten Veldhuis et al. [42] analyse water systems using fault trees. Lindhe and Rosén [41] assess the risk of the system in terms of the quantity and quality of the water reaching the consumers while ten Veldhuis and Clemens [42] focus on quantifying the probability of flooding, highlighting areas of the water system that can be improved. The use of fault trees allowed both to investigate the probability of failure within the respective water systems, however, both methods could be extended to provide a PRA of the respective systems. Lindhe and Rosén [41] could be extended to a full PRA by including the likelihood of scenarios which resulted in the basic events present in the fault trees. ten Veldhuis and Clemens [42] did not include the severity of the consequences associated with a flood, which, if included, would extend the analysis to present a PRA of the water system.

While these examples give some idea of what a PRA for an infrastructure system may look like they are limited. They generally either truncate the set of scenarios considered (e.g., limiting to seismic events) or they truncate the portion of the system being addressed (e.g., electric power transmission system only, excluding the distribution system). What would a full PRA for infrastructure be?

3. Infrastructure PRA formulation

In the most basic understanding, an infrastructure is a system of components that are, in the simplest realisation, either functioning or not. Once an initiating event has occurred within an infrastructure, the intermediate stages can then be thought of as the state change of components from the functional state to the non-functional state. Each component changes state depending on the initiating event and the preceding intermediate stages of the infrastructure. The end state will then be the combination of all components that have changed from the functioning to the non-functioning state, and the associated consequence of the component failure combination can be assessed.

To put this in context of the risk triplet, start with the consequence of a scenario s_i. The consequence is dependent upon the end state of the system, which can be expressed as $x_i(c_i)$ where $c_i = (c_i^1,\ c_i^2,\ \ldots, c_i^N)$ is a vector of the component states for the n components within the system. Each c_i^j is binary expressing the state of the component j as functional (0) or non-functional (1), though this could be extended to multi-state components. The scenario, s_i, that results in consequence c_i is the occurrence of the initiating event, intermediate states and the end state of the system that results in consequence c_i. The event tree example shown in Figure 2 shows eight possible scenarios. The likelihood of scenario s_i is the joint likelihood of the initiating event occurring and the end state reached by the system. This can be expressed as $l_i = l(IE_i)l(c_i)$.

The main difficultly in performing PRA for infrastructure systems is the sheer size of the system. The number of components that are potentially affected when an initiating event occurs is vast in a large system such as an electrical power system. For example, the Pacific Gas and Electricity (PG&E) company in California provides electric power to 5.4 million customers over with over 120,000 circuit miles of power lines over an area of 70,000 square miles [43]. The number of components in such a system is likely in at least the millions, although a full enumeration has not been carried out for a system such as this.

For cases when the system being assessed is small, there may exist a workable number of minimal cut sets that can be used, reducing the complexity of the analysis. However, finding these minimal cut sets can also be challenging depending on the number and/or functionality of the components included within the system model. For larger systems, there may also exist a workable number of minimal cut sets, but even finding the minimal cut sets can have a large computational burden.

Now that a formulation of PRA for infrastructure systems has been explored, this can be applied to an infrastructure system to investigate the feasibility of performing PRA for infrastructure systems.

4. Infrastructure PRA example

To aid in the discussion of the feasibility of PRA for infrastructure, an example of applying the formulation expressed in the previous section to an infrastructure system is first completed. The PRA formulation will be applied to the virtual water system of Micropolis [44].

4.1. Micropolis water system

Micropolis is a virtual city developed by Brumbelow and Torres [44] to aid infrastructure research. The aim of developing Micropolis was to provide open access data for infrastructure systems of a city without the need of data from real infrastructure systems. For our purposes, the water system of Micropolis will be used to illustrate how the PRA formulation from the previous section can be applied to an infrastructure system.

The water system of Micropolis has been modelled as if it has developed and expanded over a number of years. The "oldest" parts of the system are constructed as if it was built in 1910, with expansions and rehabilitations completed in 1950 and 1980. This results in an array of pipe materials and diameters. The primary input to the water system is from a surface reservoir, with the older source well now used as a backup water supply. A water tank is also present in the system and is located in the centre of the city. The end users of the system are both residential and commercial buildings which have different demand patterns throughout a 24-hour period. The water system available from Brumbelow and Torres [44] is modelled using EPANet [45]. The water distribution network of Micropolis can be seen in Figure 3.

4.2. PRA of Micropolis water system

To illustrate the PRA formulation provided in Section 3, an earthquake scenario was chosen to show the process involved in analysing one scenario within the PRA. This is a limited PRA in that it is analysing *only* a seismic hazard scenario. A full PRA would include all possible initiating events. However, as will be clear below, this one type of initiating event is sufficient to illustrate the main point.

4.2.1. Simulation of earthquake scenario

To demonstrate the application of PRA, we used a single earthquake intensity scenario. To simulate an earthquake affecting the water distribution network of Micropolis the mean and standard deviation values for Peak Ground Velocity (PGV) were chosen to represent the PGV of an earthquake of magnitude 6 on the Modified Morcalli Intensity (MMI) scale [46]. Therefore, a normal distribution with mean of 5 and standard deviation of 1 was used to sample the PGV. The same PGV was then applied to all pipes in Micropolis given the small size of the city.

The probability of each pipe breaking given the PGV was then calculated. We used a model from ASCE [47] in which the probability of a pipe breaking depends on the length and the material of each pipe. First the failure rate per 1000ft is estimated for each pipe material, using the equation:

$$RR_{1000} = 0.0187 * K * PGV, \tag{5}$$

where K is adjustment factor depending on pipe material [47]. We are assessing the disruption to only the main pipes within the network, for which there are only three different types of materials in Micropolis. Table 1 shows the possible materials and the adjustment factor for each.

The failure rate per 1000ft is then adjusted for the length of each pipe, resulting in the failure rate for each pipe, RR. Given a Poisson distribution of the failure rate, the probability of at least one break in each pipe is

$$P(failure) = 1 - e^{-RR}. \tag{6}$$

Monte Carlo simulation was then used to find the state, failed or not, of each of the 651 main pipes within the network for 100,000 iterations. It is worth noting that the number of iterations to run was chosen arbitrarily for this example. For the purpose of presenting the example 100,000 iterations is relatively high number but is computationally inexpensive. When carrying out an actual PRA the number of iterations should be chosen based on convergence.

For each iteration, any failed pipes were assumed to be leaking 200 gallons per minute (gpm) and the simulation of the water system was run for 72 hours. In order to simulate a pipe leaking a demand of 200gpm was assigned to the end junction of the pipe. In the case where the pipe ended at a valve rather than a junction, the demand was assigned to the junction at the start of the pipe as a demand cannot be assigned to valves within EPANet. Although this is a somewhat simple

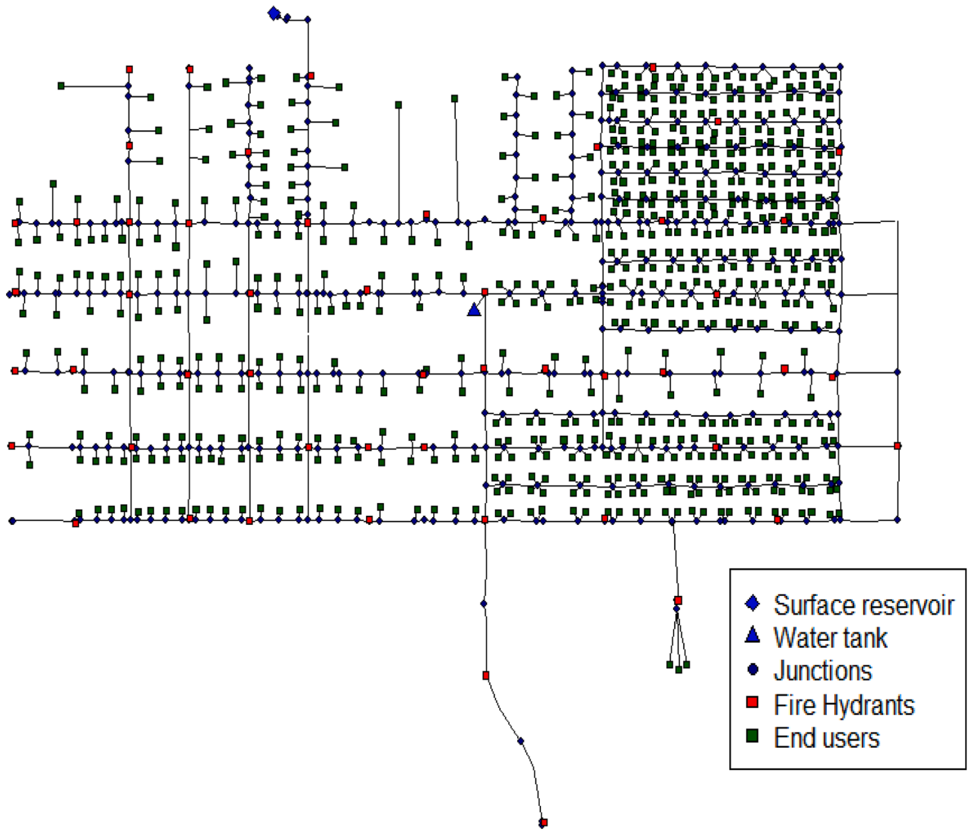

Figure 3. Distribution network of Micropolis water system.

Table 1
Pipe material adjustment factor, K, used to calculate failure rate of water pipes.

Material	Adjustment factor (*K*)
Ductile iron	0.5
Cast iron	1.0
Asbestos cement	1.0

method of simulating pipe leakage within EPANet, there exists no easily replicable method of simulating pipe leaks within a demand-driven hydraulic model like EPANet within the literature at this time [48-50]. For each simulated set of failed pipes, we then ran EPANet for a 72-hour run.

The consequences to the water system were measured as the number of terminal nodes that experienced insufficient pressure. Terminal nodes here refers to the system's end users, both residential and commercial buildings, as well as fire hydrants. There are 737 terminal nodes in the Micropolis water system network. For fire hydrant nodes, a failure was recorded when the pressure was below 20 psi as this is used as the standard in several U.S. states for baseline pressure needed for adequate fire-fighting [51]. For residential and commercial a failure was recorded when the pressure fell below 30 psi. Ghorbanian et al. [52] summarises current pressure standards for several countries, which range from 14 psi to 50 psi. 30 psi was chosen as a benchmark for buildings as this was roughly the median of the different countries pressure standards. It is worth noting that when the EPANet simulation of Micropolis is ran under normal conditions, only one pipe has a pressure below 20psi at 17 psi. The results of this Monte Carlo simulation can be seen in Figure 4. The 100,000 Monte Carlo iterations were ran in parallel, on a Xeon E5-2640 v3 CPU with 256GB RAM, taking several hours to run all 100, 000 iterations. Although this is relatively quick, this is only one scenario assessment on a system is a small, relatively simple system and thus for more complex systems and more iterations (if needed) the run time would increase greatly.

Figure 4 shows the frequency of terminal nodes which experienced insufficient pressure during the 72-hour EPANet simulation. It is worth noting that the frequencies are plotted on a log scale. For roughly two thirds of the 100,000 iterations (64,027) no pipes were affected by the earthquake and so there were no terminal nodes which experienced insufficient pressure. When pipe failures did occur due to the simulated earthquake, the majority of the simulations (24,004 of 35,973) resulted in 4 terminal nodes experiencing insufficient pressure. It is worth noting that there is a jump in the number of terminal nodes that experience insufficient pressure from 21 to 693, where no iterations resulted between 22 and 692 terminal nodes inclusively with significant loss of pressure during the simulation. This suggests there is a subset of pipe failures that have a relatively low effect on the water system and a subset of pipe failures that have a high impact on the water system.

A quick exploration of the iterations where 2 pipe failures occurred (as this resulted in either a small or large number of terminal nodes with insufficient pressure) indicates that the location of the two failed pipes may contribute to if a small or high proportion of terminal nodes have insufficient pressure. Although it is not within the scope of this illustrative example, a further exploration into the connectivity of the network for *N-2* failures, especially that of terminal nodes and source nodes, to see which combinations of two pipe failures result in small and large number of terminal nodes with insufficient pressure could provide great insight to the operators of the system.

4.2.2. PRA of earthquake scenario

The results of the Monte Carlo simulation of the effects of a magnitude 6 earthquake can also be presented as an FN curve, as shown in Figure 5. The figure shows on the y-axis the cumulative frequency of exceeding a give number of terminal nodes with insufficient pressure due to an earthquake of magnitude 6 on the MMI scale, where the

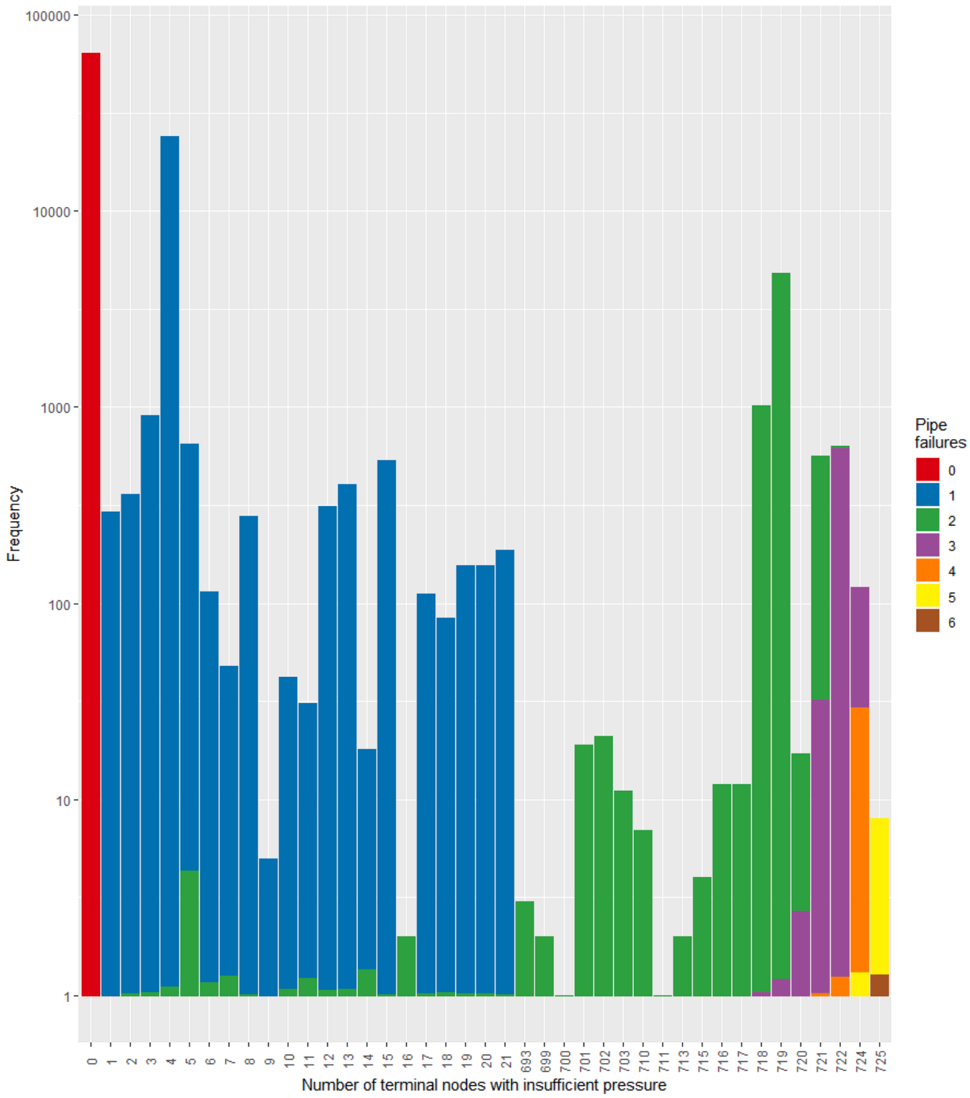

Figure 4. Results of the Monte Carlo simulation of 100,000 iterations showing the frequency of the number of terminal nodes had insufficient pressure on a log scale. The fill represents the number of pipes which failed due to the earthquake.

frequency is plotted on a log scale. The large horizontal section of the curve in the centre shows that no iterations resulted in between 22 and 692 terminal nodes having insufficient pressure.

To complete the conditional PRA of a scenario where an earthquake of magnitude 6 effects the Micropolis water system, the likelihood of this scenario occurring also needs to be calculated. However, as this is an illustration of how one would carry out PRA of infrastructure systems, and Micropolis is a virtual city, determining the likelihood of an earthquake of the given magnitude effecting the system is not particularly meaningful.

To provide a full PRA of the water system of Micropolis, other scenarios must also be evaluated. These could include events such as a water tower leak, failure of components, such as pumps, improper treatment of water and so on. Earthquakes of different magnitudes would also be included, and other non-seismic initiating events would need to be included. The likelihood and consequences of all scenarios would need to be assessed, as well as thinking about scenarios which have not yet occurred. Even with only one scenario and a small-scale system, it is clear that the computational burden and information required is large.

4.2.3. *Complexity of infrastructure PRA*

Even for a relatively small water system such as Micropolis the number of components within the systems is large. For the analysis of the magnitude 6 earthquake presented in Section 4.2.1 assumptions have been made which simplify the scenario to one which can be assessed, and the run times of the simulations are reasonable. For all scenario assessments within PRA, assumptions are made, and these can often, although not intentionally, lead to results that can be misleading. There is a trade-off between the comprehensiveness of the analysis and the time available to perform the analysis as well as the level of information currently available.

Scenarios also need to be included which look at combinations of single scenarios which have the potential to occur at the same time. For example, if an earthquake does occur it could not only result in pipe breaks (as analysed above) but could also result in damage within the water treatment centre which results in a fire. There is also the possibility of the earthquake causing disruption to another infrastructure which the water system is dependent upon, for example the electricity power system. This could result in other components such as the pumps not functioning correctly and increasing the severity of the consequences.

PRA of an infrastructure is time consuming and requires large quantities of data. This can become expensive for infrastructure owners and managers. Depending on the procedures, many utilities do not keep the relevant data or do have the information available, but it would need

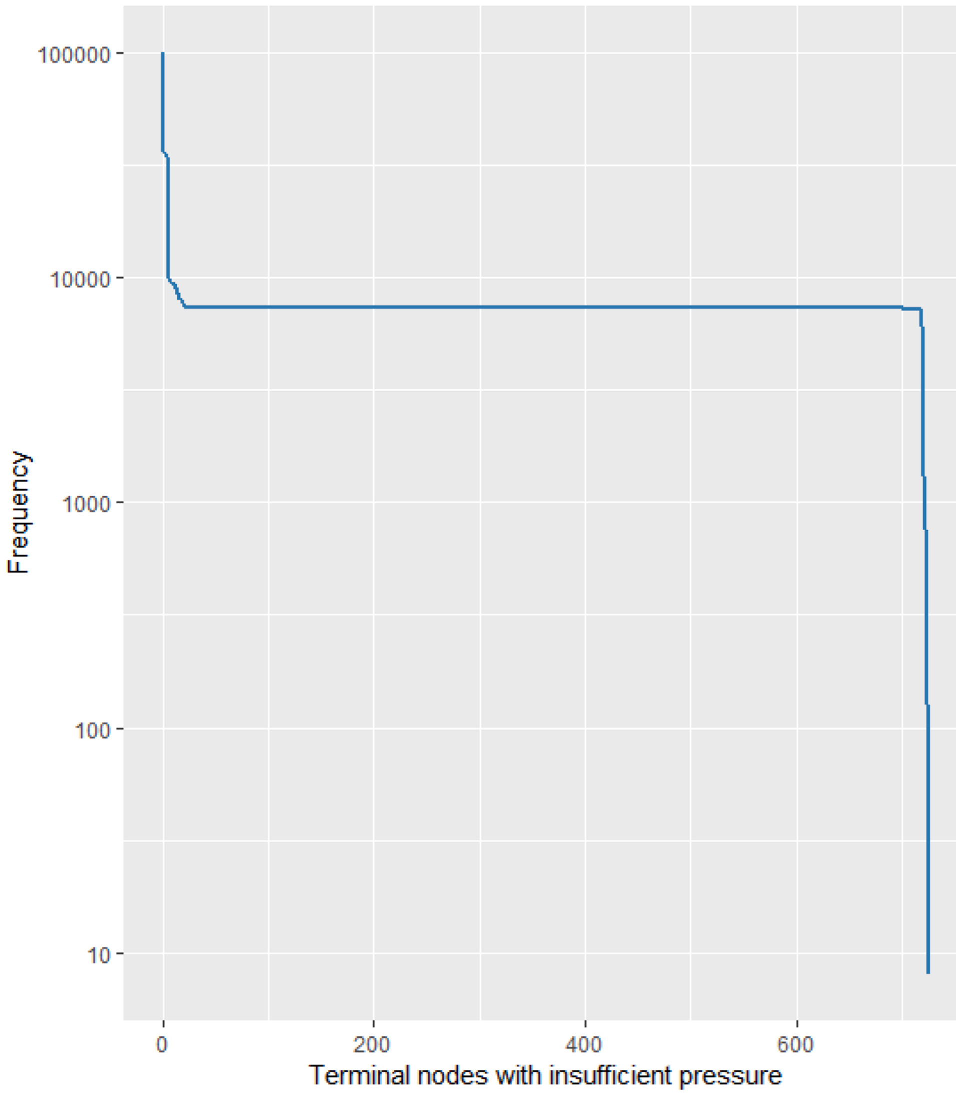

Figure 5. Cumulative frequency of terminal nodes with insufficient pressure due to an earthquake of magnitude 6 on the MMI scale, with a log scale on the y-axis.

to be processed before being useful to the assessor. This again needs resources to be allocated that may not be available within the company's budget. Instead, expert knowledge would be relied upon.

5. Comparison of infrastructure risk analysis methods

Although PRA is used within the nuclear power industry, other methods using network models have been developed which are more prevalent in other infrastructure sectors. This section aims to give a brief review of some of these methods and discuss which elements of PRA are covered and what would need to be included to better approximate PRA results. The methods chosen to compare with PRA are those which contain elements that can be related to PRA. Table 2 shows a summary of the non-PRA methods discussed and which elements and techniques of PRA these methods contain.

Random or targeted attack failure analysis can be performed to assess the effect of a subset of components within the infrastructure being non-functional. This is modelled by removing nodes and/or edges from the network model of the infrastructure. For random failure analysis, the initial node or edge removals are chosen randomly [11, 53]. This simulates failures due to the random failing of components due to age etc. For targeted attack failure analysis, the removals are chosen due to some characteristic, such as type of nodes, nodal degree (the number of edges a node has), or spatial position [12, 54-56]. Removals due to node/edge characteristics simulates intentional attack events, where the intention is to cause the greatest disruption possible when targeting a low percentage of nodes/edges within the system. When spatial position is considered, the analysis represents spatial hazards

Table 2
Comparison of non-PRA methods to PRA

Non-PRA method	Main elements of PRA: Possible scenario	Likelihood assessment	Consequence assessment	Related PRA technique
Random failure analysis	Subset of scenarios	No	Yes	Monte Carlo simulation
Targeted attack failure analysis	Subset of scenarios	No	Yes	State enumeration
Cut set analysis	Subset of scenarios	No	Yes	Fault tree analysis
N-k analysis (including *N-1*)	Subset of scenarios	No	Yes	State enumeration
Statistical learning theory	Usually one specific scenario	No	Yes	Consequence estimation

such as fire or earthquakes.

Both random and targeted attack failure analysis allow for different system states to be investigated but again the probability of these states occurring due to initiating events is not considered. Random failure analysis is comparable with Monte Carlo simulation to find system states to investigate, however the probability of each node/edge failing is implicitly assumed to be equal within the system. Targeted attack failure analysis is more in line with state enumeration, where the system states to be assessed are pre-determined. The use of cut set analysis aims to identify critical components of the infrastructure system. In terms of graph theory, a cut set is a set of nodes (or edges) that if removed, will disconnect a specified pair of nodes within the network [57]. Cut set analysis is widely used within transportation networks, where the removal of a link leads to the redistribution of the traffic using diversions [22]. This increases both the distance travelled, as well as the volume of traffic on alternative routes. Rather than removing edges, the capacity of edges can be reduced, assessing, for example, the closure a lane on a road [58]. In this scenario, the cut set analysis can be used to see which link removals are critical in terms of these factors. The use of cut set analysis identifies important components in terms of connectivity within the network.

N-1 analysis, and the extension to *N-k* analysis allows the consequences of system states to be assessed and easily compared. *N-1* analysis is common in the electricity sector of the USA due to regulations enforcing that generation and transmission systems should be able to function with the loss of one element, such as transformers or generators [59]. This has been extended to cases of *N-k* analysis where *k* components become non-functional simultaneously, or in a close time frame [10, 60, 61]. This analysis allows the assessor to see which components, or combination of components are the most critical if non-functional and can provide direction on how to harden the system to ensure if these critical components are not functional that the system still performs as needed/expected.

In terms of PRA analysis, *N-k* analysis allows the consequences of system states to be assessed and easily compared. It contains elements of state (or contingency) enumeration, where the predetermined list of system states to assess is all possible combinations where *k* of the main components are non-functional. However, the likelihood of each component failure in the *N-1* analysis, or combination of component failures in *N-k* analysis is not considered. Components or combination of components which have large consequences when non-functional may be given focus when ideally, if the likelihood of failure was included, other components or combination of components which are more likely to fail should be given more attention. Hardening such components may lead to a better decrease in the overall risk of system.

Statistical learning theory is a method of assessing critical infrastructure with a focus on natural hazard disruptions. It involves using present knowledge to develop statistical models to estimate the impacts that natural events, such as hurricanes, have on critical infrastructure. The explanatory variables cover both aspects of the critical infrastructure system, the surrounding environment and characteristics of the natural hazard [21]. For example, Han et al. [62] developed a model to estimate the number of customers without power after a hurricane event in the Gulf Coast region. The model did not use a network of the power system, but instead a grid was superimposed over the assessed space and the number of customers, transformers, poles switches and miles of overhead lines for each grid was known. The model also used variables that characterise the hurricane and the area of each grid including land use, soil type and precipitation. The model was developed and trained on past hurricane events and the corresponding data.

Statistical learning theory methods of assessing infrastructure express the consequences of a given scenario. Therefore, they could be used to assess natural hazard scenarios within PRA, given that sufficient relevant data is available. The probability of the intermediate and end states are used within the model to arrive at the resulting consequences; however, the model does not explicitly state these. The method has been developed to be used when there is an indication that an event is occurring and thus does not explore the probability of the initiating event (such as a hurricane).

Winkler et al. [63] and Ouyang and Duenas-Osorio [9] have both used a hurricane model, developed using statistical learning theory, and a network model to assess electric power systems. The hurricane model is used to assign failure likelihood to components of the power network, which are used to choose which nodes, and edges fail. The performance of the electric power system is assessed after the disruptions have affected the network flow model. This combination of the two methods provides the likelihood of the first intermediate state of the system to be found. However, the likelihood of all proceeding intermediate and end states are assumed to be one, given the event occurs. In reality, this may not be the case. The probability of the scenario occurring, in these examples the hurricane, is also still not assessed.

6. Discussion

Although PRA gained popularity with the development of nuclear power system for assessing the risks associated with the systems in the 1970s, it is not commonly used to assess networked infrastructure such as water, power, and sewer systems. The two main reasons are resource and data availability. It takes considerable time and input from many people, both internal and external, to develop a full PRA for a given infrastructure system. This imposes high cost on an infrastructure management organisation. The complexity and size of the system means identifying those who have the knowledge needed to assess a certain area or subsystem of the infrastructure can be difficult. Collection of relevant data for the assessment can also be difficult. It can be expensive and time consuming to collate, although this is becoming easier with technological advancements. Knowing which information is needed is also challenging and may be a process of trial and error. Such impediments can deter organisations from investing in data collection. Therefore, many organisations do not have the data and experts needed to identify all states, assign probabilities to them and estimate their consequences.

Infrastructure systems are also becoming more complex as technology advances, particularly through more widespread adaption of automation and SCADA systems. These make the system more difficult to understand and model, which can also lead to an increase in the events that have not yet occurred, which are more complex to assess. As new technologies are developed and used, the more limited the assessors' knowledge of the system becomes and thus more uncertainty that is present in the analysis.

PRA also becomes even more complex when incorporating infrastructure interdependencies within the analysis. The interdependencies between the different systems are especially noticeable when large natural hazards such as earthquakes and hurricanes occur. These large-scale scenarios have the potential to affect several systems at once, leading to larger consequences than when only one system is affected. However, many infrastructure systems are privately owned and for safety and security reasons it is not common to willing share information with other systems. This makes assigning a likelihood of failure difficult when an event in a different infrastructure system that we have limited knowledge of is the initiating event of a scenario.

Although there are difficulties associated with PRA of infrastructure, meaning a full PRAis not always feasible, this does not mean that PRA in the context of infrastructure should be discounted or ignored. Instead, assessments of infrastructure should be carried out with PRA in mind and should strive to cover the three main elements of PRA. The aim of a full PRA is to assess all possible risks to the system. Currently the likelihood of initiating events is not covered in many non-PRA methods. Thus, combining non-PRA approaches within the framework of a PRA could lead to a more thorough risk analysis of infrastructure systems. Adding an assessment of scenario likelihood, either before an analysis using non-PRA methods could be carried out to identify which scenarios are more likely, and thus should be investigated, or to highlight which combinations of component failures are not possible which can then be excluded from the consequence analysis. Both would contribute to reducing the computational expense of consequence assessment. The likelihood assessment could also be done after the consequence assessment, to highlight scenarios which may need a more thorough analysis, if they are more likely to occur, as well as highlighting scenarios to investigate if it is possible to implement measures to reduce the likelihood of occurrence, or to mitigate the consequences if such scenarios do occur.

Although it may not be feasible to assess the risk of all possible scenarios, using the PRA framework as a guidance when performing non-PRA methods could help guide the assessors to critically evaluate the scenarios which have and have not been assessed during non-PRA methods. Performing analysis for a combination of defined system states as well as randomly selected system states (i.e., a combination of state enumeration and Monte Carlo type simulations) using non-PRA methods could enable the assessors to analysis both scenarios that are likely, as well as scenarios which may not have been overlooked in the in the pre-defined system states to analysis but are important to include.

Non-PRA methods can also be used to support the PRA. There could be results seen in the PRA which warrant further analysis. For example, the results in Section 4 show that for the event of an earthquake which leads to two pipe failures within the system, there is a subset of combinations of 2 pipe breaks which results in a small number of end users with insufficient pressure (21 or less) and a subset of combinations of 2 pipe breaks which results in a large number of end users with insufficient pressure (693 or more). This could be explored using N-2 analysis to see which combinations of 2 pipe failures results in a small consequence whereas others result in larger consequences. Exploring the topology of the system could also be of use, to investigate if these larger consequences are due to how some combinations of 2 pipe breaks results in large parts of the system being disconnected from the source nodes. This could aid the water network operators in implementing methods such as additional water tanks in areas which could reduce the consequences of multiple pipe breaks or highlight pipes where regular inspections and/or maintenance or upgrades would reduce the likelihood of failure thus reducing the likelihood of large consequences given an earthquake scenario.

7. Conclusion

The use of PRA to assess the risk associated with an infrastructure system provides, in theory, a comprehensive assessment. The results show not only the consequences related to each possible scenario but also the associated likelihood. However, in practise performing a PRA for a full infrastructure system is very complex and expensive. This makes it unlikely to be fully implemented in practise.

The example using the Micropolis water distribution system demonstrates that even the analysis of a single scenario for a small, synthetic system is complex. Micropolis is a virtual city, where there is complete information available about the water distribution system. However, for real infrastructure systems such detailed information may not be available or easily accessible by the assessor. Even with access to the complete water distribution system data of Micropolis the assessment is complex. To reduce the complexity and allow for timely scenario assessments, assumptions must be made and the level of detail at which to model the system is decided, both of which can influence the results. For the example presented in Section 4, only damage to main pipes was included in the model. This could be extended by also including damage to other component types such as the water tower and pumps but would add to the computational burden of the analysis. Such trade-offs and assumptions are common not just for PRA, but for all methods of risk analysis. However, due to the number of different scenarios assessed during PRA, this can be more time consuming than for other analysis methods.

Due to the intricacy of performing PRA for infrastructure systems, other methods such as random or targeted failure analysis or *N-k* analysis are more common when assessing such systems. These methods are less complex than PRA which is why they are preferred in practice. However, they tend to encompass an assessment of the system for only a handful of given events or scenarios and not all possible scenarios. They also often do not consider the likelihoods of different damage scenarios. Different methods are favoured for different types of scenarios, which does not allow for an easy comparison of the results. However, the results for PRA are presented in such a way that allows for comparison of all possible scenarios.

Although practically implementing PRA within an infrastructure setting is not feasible, some elements of PRA that are not yet covered by other methods should be included into the analysis of infrastructure systems. The likelihoods associated with both the occurrence of a scenario and the resulting consequences need to be present within infrastructure assessments. Methods more common in infrastructure analysis tend not to include this aspect. Framing infrastructure risk analysis within the three main elements of PRA; that is scenario identification, likelihood assessment and consequence assessment, can help to improve the assessment of critical infrastructure.

CRediT authorship contribution statement

Caroline A. Johnson: Writing – original draft, Writing – review & editing, Software, Visualization, Data curtion. **Roger Flage:** Supervision, Writing – review & editing. **Seth D. Guikema:** Conceptualization, Supervision, Methodology, Resources, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ress.2021.107643.

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