Probabilistic Risk Assessment for Multi-Network Integrated Energy Systems: Gap Analysis and Preliminary Results

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Abstract: This paper reports on ongoing research to advance probabilistic risk assessment (PRA) methods for integrated energy systems (IES). This research focuses on multi-network energy system configurations (i.e., those that couple multiple energy networks, such as electricity, natural gas, hydrogen, and heat) that integrate multiple generation sources, including nuclear, fossil fuel, and renewable energy sources. This paper summarizes the key findings of the literature review to assess the state of the art in IES risk analysis and identify key research gaps. To address those research gaps, the authors are developing a probabilistic simulation framework for multi-network IES risk analysis. This paper presents a probabilistic natural gas network simulation, which is one of the main modules of the IES risk analysis framework. A natural gas network model is developed based on physical governing equations (mass balance and the Weymouth formula) and operational constraints (pipeline pressure and flow rate). Uncertainty propagation is performed using Monte Carlo simulation, in which the variability of gas flow demands and random failure events at pipelines and compressor stations are accounted for. The gas supply is optimized, and the energy not supplied (ENS) is calculated. The gas network-level outcome is categorized into three consequences: (i) full delivery, where the gas flow demands are met; (ii) partial delivery, where the gas flow demands are partially met; and (iii) infeasibility, where the system fails, and the gas supply is disrupted. Ongoing work focuses on coupling the gas network simulation with an electric power network model and expanding the IES simulation to analyze IES reliability and risk associated with the connection of large-scale data centers.

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1. INTRODUCTION

Integrated energy systems (IES) have been studied and developed as a promising means to improve energy efficiency, reduce fossil fuel dependence, and enhance the reliability of energy supply. An IES couples multiple energy sources (e.g., nuclear, fossil fuels, and renewables) to produce diverse energy products, including electricity, heat, and hydrogen, through dynamic coordination among subsystems and components [1-3]. Integrating various energy technologies into an IES introduces operational and maintenance complexity; hence, understanding and assessing risks is essential for enabling a dependable IES. Compared to other technological systems more familiar to the PSAM community, IES introduces new challenges for risk analysis: highly dynamic feedback loops spanning a broad range of time scales, connectivity across spatial scales from individual facilities to regional multi-energy networks, and interdependencies arising from interconnected energy networks.

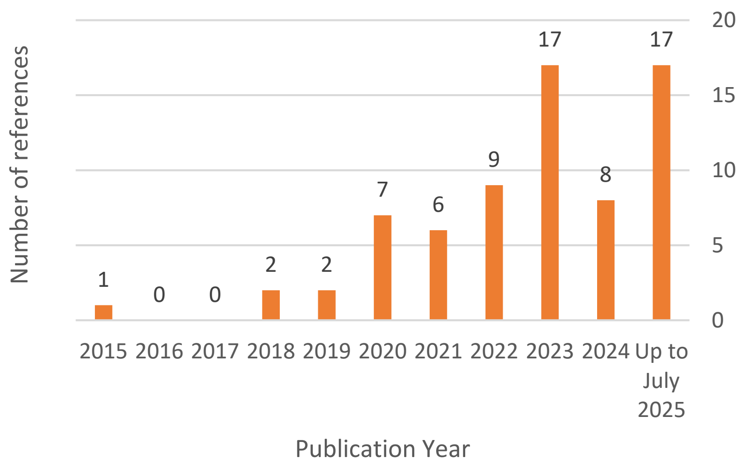
This paper reports on a research effort to advance probabilistic risk assessment (PRA) for IES. The scope of this study encompasses multi-network energy systems connected to multiple sources and loads. Smaller-scale IES configurations, such as individual multi-product energy facilities (e.g., a nuclear reactor producing electricity and hydrogen) or behind-the-meter co-location arrangements (e.g., a nuclear reactor co-located with a data center), are not the primary focus in this paper; however, the methodological framework developed in this research can be extended to explicitly incorporate such smaller-scale IES elements in future work.

The paper is organized as follows. Section 2 summarizes findings from a literature review on the state of the art and research gaps in IES risk analysis. Section 3 presents progress on a probabilistic IES simulation framework, focusing on gas network modeling as one of the main modules of IES, combined with uncertainty quantification and energy supply optimization. Section 4 provides conclusions and recommends future work.

2. SUMMARY OF LITERATURE REVIEW

This section summarizes the literature review on IES risk assessments. The literature search is conducted using ScienceDirect (www.sciencedirect.com) and Web of Science (Webofscience.com). The search results are further screened to identify the references that satisfy both criteria: (i) conducting a risk assessment for IES and (ii) characterizing risk at the entire IES level, either quantitatively or semi-quantitatively. The review focuses on publications from 2015 to July 2025. As a result of the literature screening, 69 references are included for detailed review (Figure 1). This figure clearly shows that IES risk assessment research has attracted increasing attention since 2020.

Figure 1: Number of IES Risk Assessment References by Publication Year



The literature review identified three key research gaps, as summarized below:

- Literature mostly assumes that the IES component failure rate is constant, independent of loading history and start/stop cycles. This assumption may not provide a reasonable approximation when the failure rate of a component varies significantly over time due to stressors that can initiate and accelerate component degradation, such as dynamic loading history, start/stop cycles, and thermal ramping.

- Transient analysis, which examines the dynamic behavior of network variables following sudden changes in system conditions, is limited to natural gas, heating, and cooling networks [4-7], while most studies assume electrical networks reach their steady state in a negligibly short interval. This assumption is grounded in the idea that the electrical network stability is always guaranteed; however, it requires further investigation, especially when IES are connected to rapidly fluctuating energy sources (e.g., renewables) and loads (e.g., data centers), or when the electrical network operates in isolated mode, isolated from the inertia of the main grid.

- The dependency among uncertain input parameters is modeled using a stationary correlation matrix [8-12]. Using a stationary correlation matrix, however, is inadequate for capturing structural breaks in the copula structure induced by a rapid shift in the underlying dependence (e.g., triggered by component failures or market policy shocks). An example of a structural break is the failure of a gas pipeline in winter, which can lead to increased gas load shedding, resulting in higher demand on the electrical network and a significant change in the regime of dependency between gas and electrical loads.

The goal of this research is to develop an IES risk assessment framework that is capable of addressing the research gaps identified above. The current effort focuses on building a baseline computational platform that will be gradually expanded as additional methods and modules are integrated. Section 3 describes the current status of the computational platform development.

3. PROBABILISTIC SIMULATION FOR INTEGRATED ENERGY SYSTEMS

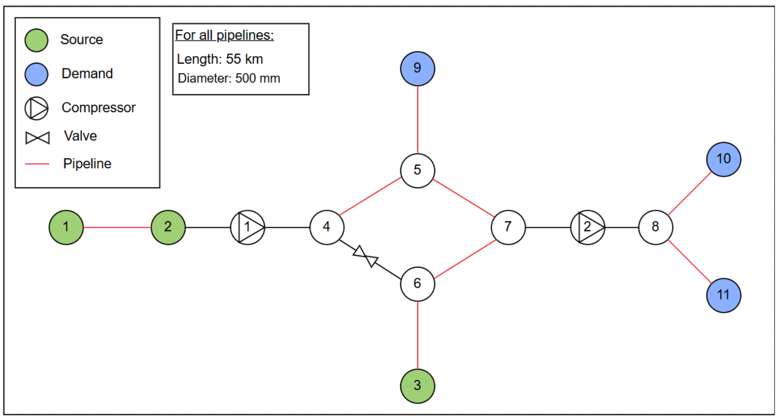
To develop a systematic risk model for IES leveraging PRA techniques, two broad modeling pathways are available: (i) probabilistic graphical methods, such as event trees, fault trees, and Bayesian networks; or (ii) probabilistic simulation, which solves physical governing equations for system behavior under uncertainty. This research adopts the second pathway for two reasons. First, continuous state variables (e.g., gas flow rate, energy not supplied) are more important than logical events (e.g., success or failure) for characterizing IES risk scenarios. Second, addressing the research gaps identified in Section 2 requires dynamic risk assessment, which is more naturally supported by probabilistic simulation than by static PRA. Meanwhile, probabilistic graphical methods are incorporated as a complementary aid in visualizing and interpreting risk information.

In this section, the development of a probabilistic simulation for a gas network, one of the core modules of the IES computational platform, is presented. Section 3.1 introduces the illustrative gas network used as a case study. Section 3.2 describes the gas network model. Section 3.3 presents the probabilistic gas network simulation using the Monte Carlo method. Section 3.4 describes a scenario-based gas network simulation, in which the Monte Carlo-based probabilistic simulation is complemented by event tree analysis.

3.1. Gas Network Case Study

As an illustrative natural gas network, GasLib-11 [13] is used. GasLib is a collection of technical descriptions of gas networks based on real-world network data. The GasLib-11 network contains three source nodes and three demand nodes. The network also includes two compressors and one valve. The GasLib description provides boundaries for the pressures and flow rates within each pipeline and node, which is implemented into the model, as described in Section 3.2.

Figure 2: Diagram of GasLib-11 Natural Gas Network



3.2. Gas Network Model

Constraint equations are derived using the following methods: node mass balance, Weymouth method [14], and compressor ratios.

The node mass balance equations express the conservation of flow rates at each node.

$$\text{Node 1: } S_1 - Q_{1,2} = 0, \tag{1}$$

$$\text{Node 2: } S_2 + Q_{1,2} - Q_{4,5} - VQ_{4,6} = 0, \tag{2}$$

$$\text{Node 3: } S_3 - Q_{3,6} = 0, \tag{3}$$

$$\text{Node 5: } Q_{4,5} - Q_{5,7} - Q_{5,9} = 0, \tag{4}$$

$$\text{Node 6 : } Q_{3,6} + VQ_{4,6} - Q_{6,7} = 0, \tag{5}$$

$$\text{Node 7: } Q_{5,7} + Q_{6,7} - Q_{8,10} - Q_{8,11} = 0, \tag{6}$$

where $Q_{x,y}$ represents the flow rate from node x to node y ($\mathrm{m}^3/\mathrm{day}$), while S_x denotes the source flow rate at node x ($\mathrm{m}^3/\mathrm{day}$). It must be noted that the flow rate from node 5 to node 9 would be equivalent to the demand flow rate at node 9 and so forth. To incorporate the valve between node 4 and node 6, a variable, V, is added in Equation (5) to control the flow rate between these nodes. This variable takes the value of either 1 or 0, depending on the success or failure of the valve.

To determine the flow rate in each pipeline, Weymouth's Equation is used, given the pipe pressures and diameters. The general form of this equation is given in equation (7). One equation should be formulated for each pipeline, resulting in 8 total equations.

$$Q_{i,j}^2 = K_{i,j}\left(P_u^2 - P_d^2\right) \tag{7}$$

$$K_{i,j} = \frac{(435\eta)^2 D_{i,j}^{5.333}}{G \cdot T \cdot L_{i,j} \cdot Z} \cdot \left(\frac{T_b}{P_b}\right)^2 \tag{8}$$

where:

- P_u: Upstream pressure (kPa)
- P_d: Downstream pressure (kPa)
- η: Pipeline efficiency factor
- $D_{i,j}$: Internal diameter of pipeline between nodes i and j (mm)
- G: Gas specific gravity relative to air
- T: Gas temperature (K)
- $L_{i,j}$: Pipeline length between nodes i and j (km)
- Z: Gas compressibility factor
- T_b: Base temperature (K)
- P_b: Base pressure (kPa)

The compressor equations are formulated as shown in Equation (9).

$$P_y = CP_x, \tag{9}$$

where P_y is the output pressure (kPa), P_x is the input pressure (kPa), and C is the compressor ratio.

Since there are more unknowns than governing equations, the system has multiple solutions. The desired solution is the one that maximizes the total gas supply. This problem is solved through optimization, where the optimizer adjusts flow rates in pipes, pressures at nodes, and demand allocations at three delivery points to maximize total gas delivered while satisfying mass balance and pressure-flow constraints, as formulated in Equation (10). The optimization is conducted in Python using the SciPy package [15].

$$\max_{\mathbf{x}}\left(Q_{5,9} + Q_{8,10} + Q_{8,11}\right) \text{ subject to } \mathbf{x} \in \mathcal{X}, \tag{10}$$

where $\mathbf{x}$ is a vector of the adjusted parameters (flow rates, pressures, and demand allocations), while $\mathcal{X}$ represents the feasible set for $\mathbf{x}$.

3.3. Probabilistic Simulation Using the Monte Carlo Method

Uncertainty in the gas network model inputs is propagated by Monte Carlo simulation. Table 1 lists the uncertain input parameters and their probability distributions. The failure probabilities for the discrete random variables representing component status are provided in Table 2.

Table 1: Uncertain Input Variables

Variable	Probability Distribution
Source flow rates	Uniform distributions $S_1 \sim U(5E4, 7.5E5)$, $S_2 \sim U(1E5, 5E5)$, $S_3 \sim U(0, 5E5)$
Demand flow rates	Normal distributions $\mu_9 = 6E5, \sigma_9 = 1.5E5$, $\mu_{10} = 1.6E5, \sigma_{10} = 4E4$, $\mu_{11} = 2.8E5, \sigma_{11} = 7E4$
Pipeline failure	Discrete random variable (See Table 2)
Valve failure	Discrete random variable (See Table 2)
Compressor failure	Discrete random variable (See Table 2)

Table 2: Failure Probabilities for Components

Component	Failure Probability
Pipelines	0.002
Valve	0.01
Compressors	0.02

Two risk outputs are computed from the Monte Carlo outputs. The first is the probability distribution over gas network outcomes, grouped into three categories: (i) full delivery, where gas demand at all three load nodes is fully met; (ii) partial delivery, where demand is partially unmet due to load shedding caused by operational constraints; and (iii) infeasibility, where no feasible solution exists that satisfies all constraints, indicating total gas network failure. The second risk output is energy not supplied (ENS), defined in Equation (10) as the daily volume of gas demand that could not be fulfilled.

$$ENS_{\text{Gas}} = \sum_k \left(Q_k^{demand} - Q_k^{actual}\right) \tag{10}$$

where Q_k^{demand} is the gas demand at load node k (m^3/day), and Q_k^{actual} is the actual gas supplied at load node k (m^3/day). Under full delivery, $ENS_{\text{Gas}} = 0$; under partial delivery, $0 < ENS_{\text{Gas}} < \sum_k Q_k^{demand}$; under the infeasibility scenarios, $ENS_{\text{Gas}} = \sum_k Q_k^{demand}$.

To determine a sufficient sample size, a convergence study is performed. The sample size is varied from 500 to 100,000 to assess the convergence of the partial delivery and infeasibility probabilities, as well as the expected ENS (Figure 3). Based on these results, a sample size of 100,000 is selected.

Figure 3: Convergence Study for Selecting a Sufficient Sample Size.

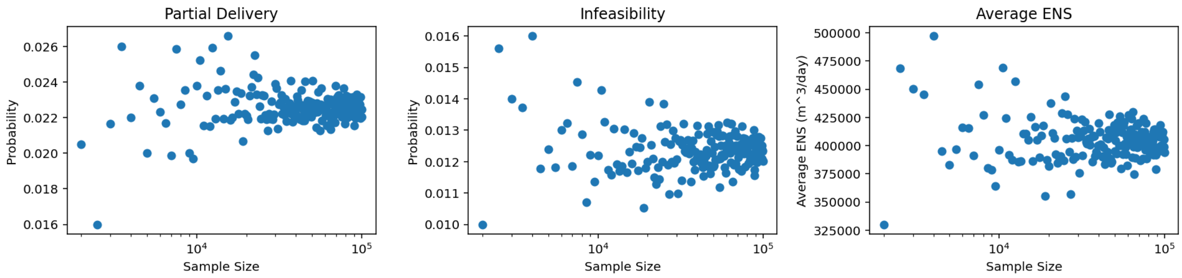


Table 3 presents the estimates of the partial delivery and infeasibility probabilities along with their 95% confidence intervals. The histogram of ENS is shown in Figure 5, which shows a bi-modal distribution with peaks at 0 and 2.5E7 m^3/day. The left peak at 0 m^3/day represents the partial delivery samples, while the right peak contains infeasibility scenarios. This point is illustrated in Figure 5, which provides individual ENS histograms for partial-delivery and infeasibility scenarios, respectively.

Table 3: Partial Delivery and Infeasibility Probabilities from Monte Carlo Simulation

	Point Estimate	95% Confidence Intervals
Partial Delivery	0.03123	(0.03019, 0.03227)
Infeasibility	0.01210	(0.01093, 0.01327)

Figure 4: Total ENS Histogram for Infeasibility and Partial Delivery Scenarios

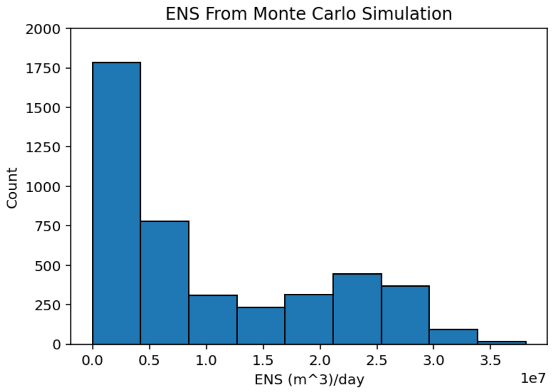
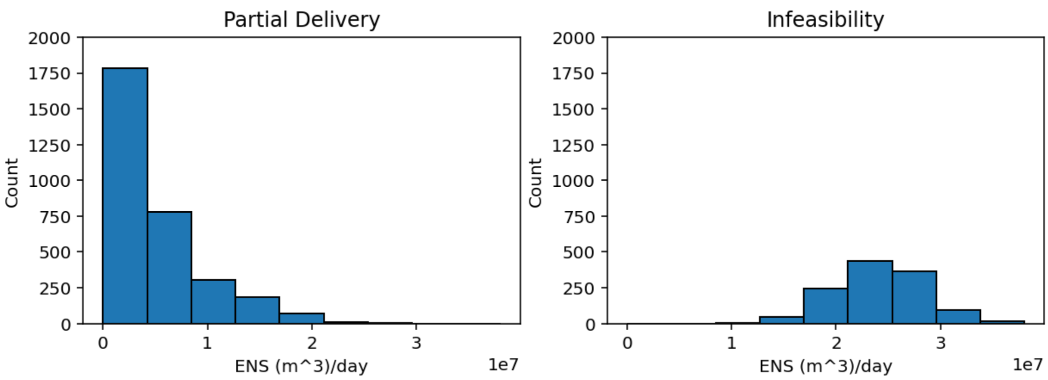


Figure 5: Decomposed ENS Histograms of Infeasibility and Partial Delivery Scenarios



3.4. Scenario-based IES Simulation Using Event Tree Concept

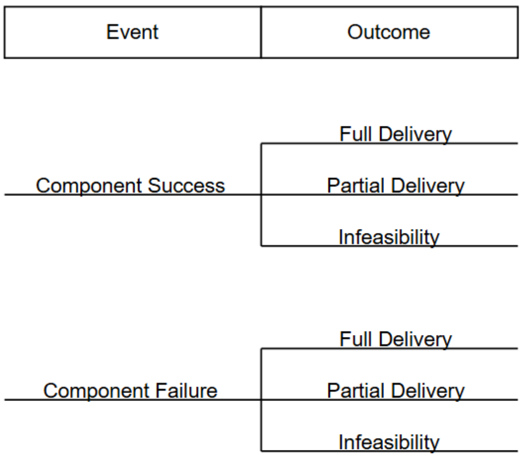
Most of the existing IES risk assessment studies reviewed in Section 2 rely on probabilistic simulations, similar to the Monte Carlo approach in Section 3.3. While these approaches can produce accurate results, pooling different types of uncertain inputs, such as continuous state variables and discrete component availability into a single sampling process can obscure the interpretability of the results. One solution to this challenge is to combine probabilistic simulation with scenario-based PRA methods, such as event tree analysis.

For demonstration, the valve between nodes 4 and 6 is selected as the key component to construct scenarios in an event tree (Figure 6). Here, there are two event sequences to analyze: the valve works properly (represented by a set V) and the valve fails (represented by a set $\bar{V}$). Using the law of total probability, the total probability of outcome s, $s \in \{\text{Full Delivery}, \text{Partial Delivery}, \text{Infeasibility}\}$, can be computed by Equation (11).

$$\Pr(s) = \Pr(s \mid V)\Pr(V) + \Pr(s \mid \bar{V})\Pr(\bar{V}) \tag{11}$$

To compute this equation, $\Pr(V)$ and $\Pr(\bar{V}) = 1 - \Pr(V)$ are already available in Table 2. $\Pr(s \mid V)$ and $\Pr(s \mid \bar{V})$ are estimated from two separate sets of Monte Carlo simulations. Specifically, half of the samples (50,000 samples) are run given the component has failed, and the other half (remaining 50,000 samples) are run given the component succeeded. All other random variables are sampled as described in Section 3.3.

Figure 6: Event Tree Analysis



The partial delivery and infeasibility probabilities obtained from the event tree analysis are presented in Table 4. These results are in good agreement with the full Monte Carlo simulation outputs (Table 3), verifying that the scenario-based approach can also be used to perform probabilistic IES simulations.

Table 4: Partial Delivery and Infeasibility Probabilities from Event Tree Analysis

	Point Estimate	95% Confidence Intervals
Partial Delivery	0.03182	(0.03012, 0.03352)
Infeasibility	0.01253	(0.01170, 0.01336)

4. CONCLUSION

This paper presents progress toward a probabilistic simulation framework for multi-network IES risk analysis. A literature review identified key research gaps in existing IES risk assessment studies (Section 2), which motivated the development of a probabilistic IES simulation framework. The gas network module, reported in this paper, simulates physical governing equations and operational constraints, propagates uncertainty using Monte Carlo simulation, and computes two risk metrics, i.e., probabilities and energy not supplied, across three network-level outcomes: full delivery, partial delivery, and infeasibility. The scenario-based extension using event tree analysis demonstrates that stratified sampling produces results consistent with full Monte Carlo simulation while enhancing interpretability of the results by separating the uncertainty for continuous state variables and discrete random variables representing component availability.

Ongoing work is extending the computational framework in two directions. The gas network simulation is coupled with an electric power network model to advance the multi-network IES simulation platform. In parallel, an energy consumption prediction model for hyperscale data centers is being developed to support risk assessment of large-scale data center loads connected to IES. Results from these efforts will be reported in subsequent publication.

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