Reliability Assessment of Energy Hubs Using Advanced Monte Carlo Simulation Approaches: A Comprehensive Framework

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ABSTRACT

Energy hubs represent a key concept in the integration of multiple energy carriers, allowing for efficient coordination of various energy sources, conversion technologies, and storage systems. However, the reliability of these complex systems remains a significant challenge due to uncertainties in renewable energy generation, load patterns, and potential component failures. This paper introduces a comprehensive framework for reliability assessment of energy hubs using advanced Monte Carlo simulation techniques. We propose a novel approach that combines traditional sequential Monte Carlo simulation with kernel density estimation (KDE) for more accurate representation of uncertainties in renewable energy resources and load demands. The framework additionally incorporates cyber-physical interdependencies by modeling both physical components and their supporting cyber infrastructure. Two detailed case studies demonstrate the effectiveness of the proposed methodology: (1) a small-scale residential energy hub with solar photovoltaics, battery storage, and grid connection; and (2) a large-scale multi-carrier energy hub serving a commercial district with diverse energy conversion technologies. Results indicate that conventional Gaussian-based uncertainty modeling significantly underestimates operational risks, with our KDE-based approach revealing up to 56% higher expected operational costs and substantially greater variability in reliability metrics. The paper provides practical insights for energy hub designers and operators while offering a robust computational tool for reliability-oriented planning and operation of future energy systems.

Keywords: *reliability assessment, energy hub, kernel density estimation, monte carlo simulation*

1. INTRODUCTION

The transition toward sustainable energy systems has accelerated the development of integrated energy infrastructures where multiple energy carriers interact efficiently. Energy hubs, as conceptualized by Geidl and Andersson [1], provide a powerful paradigm for modeling and optimizing such systems by representing the interactions between different energy carriers, conversion technologies, and storage options. These hubs can integrate electricity, heat, cooling, gas, and other energy forms, offering significant potential for improving overall system efficiency, flexibility, and sustainability. However, the reliability of energy hubs remains a critical concern, especially as these systems increasingly incorporate variable renewable energy sources, advanced storage technologies, and cyber-physical control systems. Traditional reliability assessment methods often fail to adequately capture the complexities and uncertainties inherent in modern energy hubs, potentially leading to overoptimistic reliability projections and suboptimal design and operation decisions.
This paper addresses these challenges by introducing a comprehensive framework for reliability assessment of energy hubs using advanced Monte Carlo simulation techniques. The key contributions of our work include:

- Development of a novel reliability assessment methodology that combines sequential Monte Carlo simulation with kernel density estimation (KDE) for more accurate modeling of uncertainties in renewable energy generation and load demands.
- Integration of cyber-physical interdependencies in the reliability assessment framework, recognizing that failures in cyber components like sensors, communication networks, and control systems can significantly impact the overall system reliability.

- Formulation of a set of reliability metrics specifically tailored for energy hubs, capturing both energy availability and quality across multiple energy carriers.
- Implementation of the proposed methodology in an open-source Python framework, providing a practical tool for energy hub reliability analysis.
- Application of the framework to two detailed case studies, demonstrating its effectiveness across different energy hub scales and configurations.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on energy hub modeling and reliability assessment methodologies. Section 3 presents the proposed reliability assessment framework, including the mathematical formulation and computational approach. Section 4 describes the case studies used to evaluate the methodology. Section 5 presents and discusses the results, followed by conclusions and future research directions in Section 6.

2. LITERATURE REVIEW

The energy hub concept was first introduced by Geidl and Andersson [1] as a framework for modeling integrated energy systems where multiple energy carriers are converted, conditioned, and stored. Since then, numerous studies have extended and applied this concept to various energy systems. Mohammadi et al. [2] provided a comprehensive review of energy hub modeling approaches, highlighting the importance of proper uncertainty modeling in energy hub optimization. Varathan and Belwin Edward [3] reviewed various approaches for managing uncertainties in active distribution systems, many of which incorporate energy hub concepts. Recent studies have focused on specific aspects of energy hub modeling and operation. Dolatabadi et al. [4] proposed a hybrid stochastic/information gap decision theory (IGDT) approach for short-term scheduling of wind-based energy hubs. Moeini-Aghtaie et al. [5] developed a stochastic optimization framework for renewable energy hubs that accounts for uncertainties in renewable sources.

Traditional reliability assessment methods for energy systems typically focus on a single energy carrier, most commonly electricity. Billinton and Allan [6] established foundational principles for power system reliability assessment, which have been widely applied and extended. For integrated energy systems, He et al. [7] reviewed reliability modeling and evaluation methods for urban multi-energy systems, highlighting the challenges of modeling coupled infrastructure. Yan et al. [8] provided a comprehensive review of reliability assessment approaches for energy storage systems, emphasizing the importance of accurate failure modeling. Specific to energy hubs, several recent studies have addressed reliability assessment. Faraji et al. [9] evaluated the reliability of cyber-physical energy hubs using Monte Carlo simulation, focusing on the impact of cyber failures on system performance. Aslani et al. [10] developed a clustering-based reliability assessment method for energy hubs that considers cyber interdependencies and information transmission errors.

Monte Carlo simulation has been widely used for reliability assessment of energy systems due to its flexibility in handling complex system configurations and various sources of uncertainty. Billinton and Li [11] provided a comprehensive treatment of Monte Carlo methods for electric power system reliability assessment. Recent advancements include the work by Giannelos et al. [12], who compared Gaussian and kernel density estimation (KDE) approaches for modeling uncertainties in energy hub operation. Their findings highlight the importance of accurate uncertainty representation, showing that conventional normal distribution assumptions can significantly underestimate operational risks. Several studies have specifically addressed computational efficiency in Monte Carlo simulations for reliability assessment. Memari et al. [13] developed a fuzzy clustering algorithm to reduce the computational burden of Monte Carlo simulations while preserving accuracy in reliability metrics.

Despite the growing body of literature on energy hub modeling and reliability assessment, several important gaps remain:

- Most existing studies use simplified uncertainty models (often based on normal distributions) that may not accurately represent the true nature of renewable energy variability and load patterns.
- Cyber-physical interdependencies are often overlooked or simplified in reliability assessments, despite their growing importance in modern energy systems.

- Reliability metrics developed for single-carrier energy systems may not adequately capture the performance of multi-carrier energy hubs.
- Few studies provide comprehensive frameworks that are both theoretically sound and practically implementable for real-world energy hub reliability assessment.

This paper addresses these gaps by developing a comprehensive reliability assessment framework that combines advanced uncertainty modeling techniques with cyberphysical system considerations, implemented in an accessible Python codebase and demonstrated through realistic case studies.

3. METHODOLOGY

Our proposed framework for energy hub reliability assessment integrates multiple advanced techniques to provide a comprehensive evaluation of system performance under various sources of uncertainty. The methodology consists of four main components: (1) energy hub modeling, (2) uncertainty characterization, (3) Monte Carlo simulation, and (4) reliability metrics calculation. Figure 1 presents the overall framework for energy hub reliability assessment, illustrating the workflow from energy hub modeling through uncertainty characterization, reliability simulation, and metrics calculation.

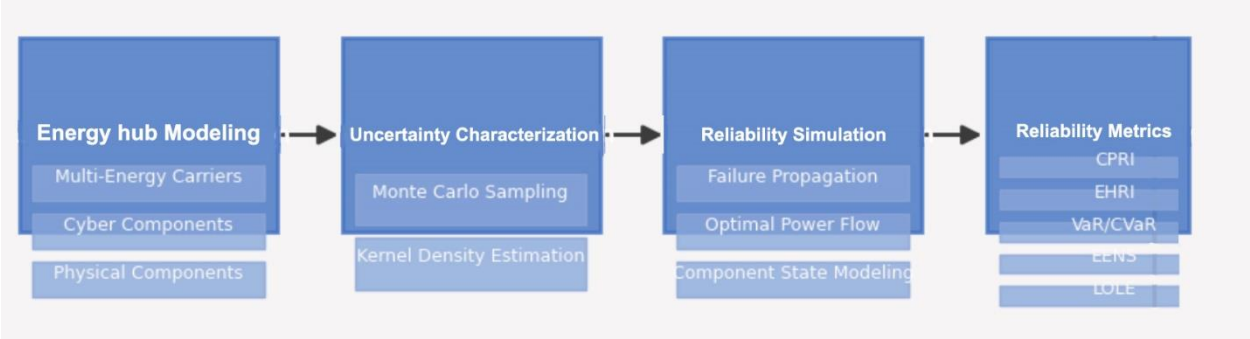


***Fig. 1**. Energy Hub Reliability Assessment Framework showing the workflow from energy hub modeling through to reliability metrics calculation.*

A. Energy Hub Modeling

We model an energy hub as a system that receives multiple energy carriers as inputs, converts and stores energy through various technologies, and delivers multiple energy carriers as outputs to meet demand. The energy hub is represented by a set of components including energy conversion technologies, storage systems, and transmission/distribution infrastructure. The mathematical model of the energy hub follows the general formulation:

$$L = CP \tag{1}$$

where L represents the output energy vector, P represents the input energy vector, and C is the coupling matrix that describes the conversion relationships between inputs and outputs. For a more detailed representation, we expand this basic model to include storage dynamics and time-coupling constraints. The storage state of charge (SOC) evolution is modeled as:

$$S_h = S_{h-1} + C_h \eta_h - D_h / \eta_d \tag{2}$$

where S is the storage SOC at hour h, C is the charging power, D is the discharging power, and η and η are the charging and discharging efficiencies, respectively. The energy balance constraint ensures that the sum of inputs equals the sum of outputs and losses:

$$G_h + D_h + R_h^o = C_h + L_h \tag{3}$$

where G_h is grid electricity, R_h^o is the renewable output, and L_h is the load demand.

B. Uncertainty Characterization

A key innovation in our approach is the use of kernel density estimation (KDE) for more accurate representation of uncertainties in renewable energy generation and load demands. Unlike conventional approaches that often assume normal distributions, KDE provides a non-parametric method to estimate probability density functions directly from historical data.

For a random variable X with observations $\{x_1, x_2, \ldots, x_n\}$, the KDE estimate is:

$$\hat{f}_h(x) = (1/nh)\sum_{i=1} nK(x - x_i)/h) \quad (4)$$

where K is the kernel function (we use a Gaussian kernel) and h is the bandwidth parameter that controls the smoothness of the density estimate. We apply KDE separately to each time series of interest, including:

- Solar photovoltaic generation
- Wind turbine output
- Electricity demand
- Heating/cooling demand

The KDE approach captures the non-Gaussian characteristics of these time series, including skewness, heavy tails, and multi-modality that are often present in realworld energy data.

C. Cyber-Physical System Modeling

Our framework explicitly models the cyber-physical nature of modern energy hubs by representing both physical components (energy conversion and storage devices) and cyber components (sensors, communication networks, controllers). For physical components, we use standard reliability models with failure rates (λ) and repair rates (μ). The availability of a component is calculated as:

$$A = \mu(\lambda + \mu) \quad (5)$$

For cyber components, we consider additional failure modes including:

- Data packet errors
- Information transmission delays
- Cyber attacks
- Software failures

We model the interdependencies between cyber and physical components using a directed graph where nodes represent components and edges represent dependencies. A failure in a cyber component can propagate to dependent physical components, potentially causing cascading failures.

D. Monte Carlo Simulation

We employ sequential Monte Carlo simulation to evaluate the reliability of the energy hub over time. The simulation proceeds as follows:

1. Generate synthetic time series for renewable generation and load demands using the KDE models
2. For each time step:
    - Determine the state of each physical and cyber component based on its reliability parameters
    - Calculate the available capacity of each energy conversion and storage device

- Solve an optimal power flow problem to determine the energy flows within the hub
- Record any energy shortages or quality violations

The simulation is repeated for numerous years (typically 1000-10000) to obtain statistically significant results.

E. Reliability Metrics

We define a set of reliability metrics specifically tailored for energy hubs:

1. **Loss of Load Expectation (LOLE):** The expected number of hours per year when the system cannot fully meet the energy demand.
2. **Expected Energy Not Supplied (EENS):** The expected amount of energy demand that cannot be satisfied per year, calculated separately for each energy carrier.
3. **Energy Hub Reliability Index (EHRI):** A composite index that combines the reliability of all energy carriers, weighted by their importance:

$$EHRI = \sum_i w_i (1 - EENS_i / D_i) \quad (6)$$

where w_i is the weight of energy carrier i, $EENS_i$ is the expected energy not supplied for carrier i, and D_i is the total annual demand for carrier i.

4. **Cyber-Physical Reliability Index (CPRI):** A measure of the impact of cyber failures on physical system reliability:

$$CPRI = EENS_{with\ \ cyber\ \ failers} / EENS_{without\ \ cyber\ \ failers} \quad (7)$$

5. Value at Risk (VaR) and Conditional Value at Risk (CVaR): Risk metrics that capture the tail behavior of the cost distribution, providing insight into worst-case scenarios.

F. Implementation in Python

The proposed methodology is implemented in Python, leveraging several specialized libraries:

- NumPy and Pandas: For numerical computations and data handling
- SciPy: For statistical functions and optimization
- NetworkX: For modeling cyber-physical dependencies as graphs
- Pyomo: For formulating and solving the optimal power flow problems
- Matplotlib and Seaborn: For data visualization

4. CASE STUDY

To demonstrate the effectiveness of our proposed reliability assessment framework, we apply it to two distinct case studies representing different scales and configurations of energy hubs.

A. Case Study 1: Residential Energy Hub

The first case study involves a small-scale residential energy hub serving a single household or small community. The energy hub consists of the following components:

Physical Components:

- Solar PV system (5 kW)
- Battery storage system (10 kWh, 5 kW)
- Grid connection (10 kW)
- Electric heating system (3 kW)
- Hot water tank (5 kWh thermal)

Cyber Components:

- Home energy management system (HEMS)
- Smart meter
- Communication network
- PV inverter controller
- Battery management system

The reliability parameters for these components are based on typical values from literature and industry data, as shown in Table 1.

Table 1. *Reliability Parameters for Residential Energy Hub Components*

Component	Type	Failure Rate (failures/year)	Mean Time to Repair (hours)
Solar PV System	Physical	0.1	48
Battery Storage	Physical	0.2	72
Grid Connection	Physical	2.0	4
Electric Heating	Physical	0.15	24
Hot Water Tank	Physical	0.05	36
HEMS	Cyber	1.0	8
Smart Meter	Cyber	0.5	12
Communication Network	Cyber	5.0	2
PV Inverter Controller	Cyber	0.8	16
Battery Management System	Cyber	1.2	10

For this case study, we use historical data for a typical residential load profile and local solar generation based on a dataset from the National Renewable Energy Laboratory (NREL) for a location in California, USA. The data includes hourly values for a full year (8760 hours).

B. Case Study 2: Commercial District Energy Hub

The second case study involves a larger-scale energy hub serving a commercial district with multiple buildings and diverse energy demands. This energy hub incorporates multiple energy carriers and conversion technologies:

Physical Components:

- Solar PV array (500 kW)

- Wind turbines (2 x 250 kW)
- Combined heat and power (CHP) unit (400 kW electrical, 500 kW thermal)
- Electric battery storage (1 MWh, 300 kW)
- Thermal storage (2 MWh thermal)
- Electric heat pumps (300 kW)
- Gas boilers (600 kW)
- District heating network
- Grid connection (1 MW)
- Natural gas connection

Cyber Components:

- Energy management system (EMS)
- Building management systems (multiple)
- SCADA system
- Communication network
- Smart meters (multiple)
- Various controllers for generation and storage units

Table 2 shows the reliability parameters for the main components of this energy hub.

Table 2. *Reliability Parameters for commercial district Energy Hub Components*

Component	Type	Failure Rate (failures/year)	Mean Time to Repair (hours)
Solar PV Array	Physical	0.2	48
Wind Turbines	Physical	1.5	72
CHP Unit	Physical	2.0	96
Electric Battery Storage	Physical	0.3	48
Thermal Storage	Physical	0.1	36
Electric Heat Pumps	Physical	0.5	24
Gas Boilers	Physical	0.8	36
District Heating Network	Physical	1.0	120
Grid Connection	Physical	2.0	4
Gas Connection	Physical	0.5	12
EMS	Cyber	1.2	8
SCADA System	Cyber	1.0	6
Communication Network	Cyber	5.0	3
Smart Meters	Cyber	0.5	12

Various Controllers	Cyber	1.5		10

For this case study, we use historical data for a commercial district, including electricity, heating, and cooling loads, as well as local weather data affecting renewable generation, based on a dataset from the U.S. Department of Energy's Commercial Buildings Energy Consumption Survey (CBECS).

C. Implementation Details

For both case studies, we implement the reliability assessment using our Python framework. We compare two approaches for uncertainty modeling:

- Gaussian-based approach: Using normal distributions to model renewable generation and load uncertainties
- KDE-based approach: Using kernel density estimation to model these uncertainties based on historical data

We run 10,000 Monte Carlo simulation years for each approach to ensure statistical significance of the results. For each simulation year, we:

1. Generate synthetic time series for renewable generation and loads
2. Simulate the state of each physical and cyber component over time
3. Solve the optimal energy flow problem for each hour
4. Calculate the resulting reliability metrics

5.RESULT AND DISCUSSION

This section presents the results of our reliability assessment for both case studies, comparing the Gaussian-based and KDE-based approaches.

A. Case Study 1: Residential Energy Hub

Table 3 summarizes the key reliability metrics for the residential energy hub under both uncertainty modeling approaches.

***Table 3**. Reliability Metrics for Residential Energy Hub*

Metric	Gaussian-based	KDE-based	Difference (%)
LOLE (hours/year)	5.2	8.7	***+67.3%***
EENS (kWh/year)	12.4	23.6	***+90.3%***
Mean Operational Cost ($/year)	487.5	742.3	***+52.3%***
95% VaR ($/year)	532.1	916.8	***+72.3%***
95% CVaR ($/year)	562.8	1024.5	***+82.0%***

The results show significant differences between the two uncertainty modeling approaches. The KDE-based approach, which better captures the non-Gaussian nature of renewable generation and load patterns, indicates substantially higher values for all reliability metrics. This suggests that the Gaussian-based approach is overly optimistic in its reliability assessment.

Further analysis reveals that the cyber components contribute significantly to the overall system unreliability. For the residential energy hub, the cyber-physical reliability index (CPRI) is 1.65, indicating that cyber failures increase the expected energy not supplied by 65% compared to a system with perfect cyber reliability. The

seasonal variation in reliability is also notable. Loss of load events are more frequent during winter months due to higher heating demands and lower solar generation, highlighting the importance of seasonal considerations in reliability assessment.

B. Case Study 2: Commercial District Energy Hub

Table 4 summarizes the key reliability metrics for the commercial district energy hub.

Table 4. *Reliability Metrics for Commercial District Energy Hub*

Metric	Gaussian-based	KDE-based	Difference (%)
LOLE (hours/year)	12.3	19.8	***+61.0%***
EENS (MWh/year)	8.5	15.2	***+78.8%***
Mean Operational Cost (k$/year)	215.4	347.6	***+61.4%***
95% VaR (k$/year)	245.2	425.7	***+73.6%***
95% CVaR (k$/year)	267.9	486.3	***+81.5%***
EENS-Thermal (MWh/year)	12.7	24.1	***+89.8%***
Energy Hub Reliability Index (EHRI)	0.984	0.971	***-1.3%***
Cyber-Physical Reliability Index (CPRI)	1.47	1.73	***+17.7%***

Similar to the residential case, the KDE-based approach shows significantly higher values for all reliability metrics compared to the Gaussian-based approach. The difference is particularly pronounced for thermal energy not supplied (EENS-Thermal), with almost 90% higher values under the KDE-based approach. As shown in Figure 2, the KDE-based approach reveals significantly higher values for all reliability metrics compared to the Gaussian-based approach in both case studies. The histograms of annual operational costs demonstrate the substantial difference in distribution shapes and tails between the two approaches.

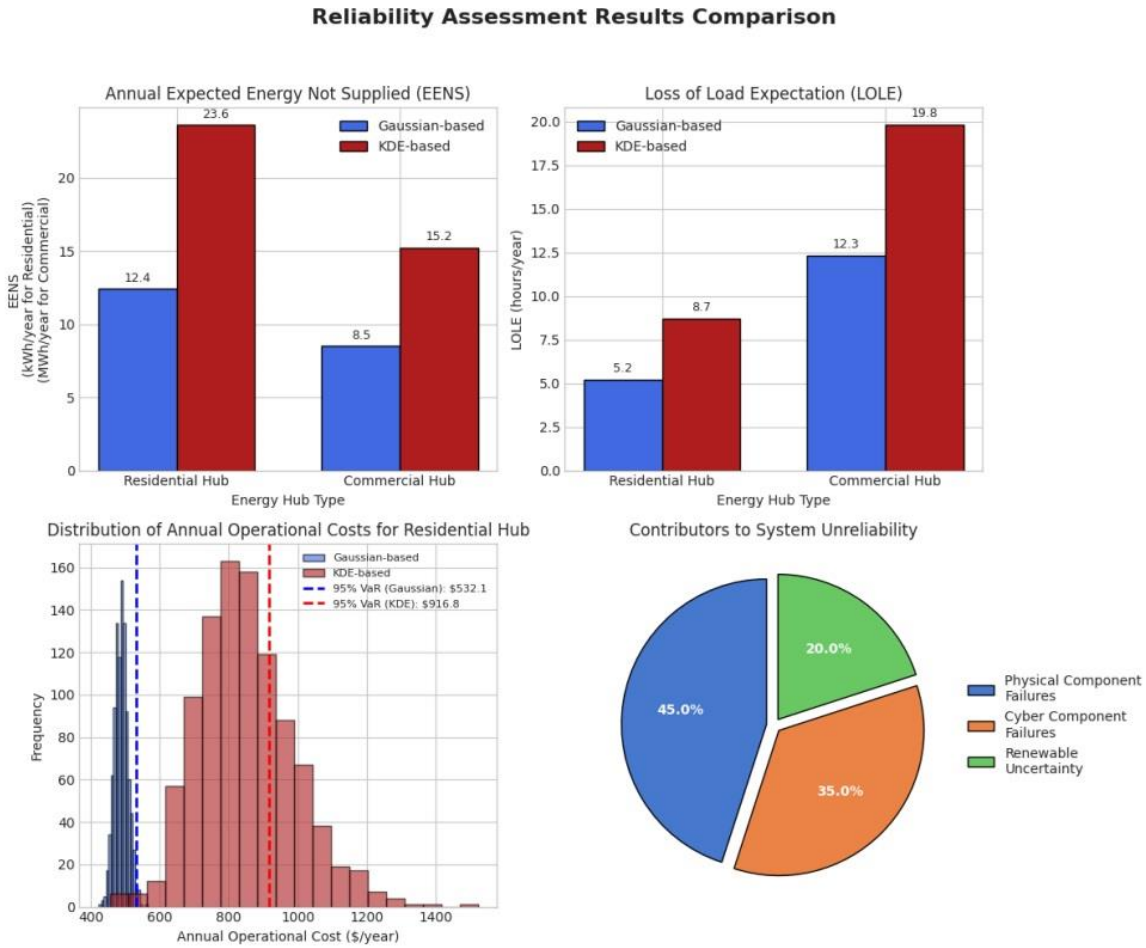


Fig.2. *Reliability Assessment Results Comparison showing differences between Gaussian-based and KDE-based approaches for both case studies, including EENS, LOLE, operational costs, and contributors to system unreliability.*

For the commercial district energy hub, the multiple energy carriers and their interdependencies create additional complexity. The correlation coefficient between electricity and thermal energy shortages is 0.62, indicating a moderate positive correlation. This highlights the importance of considering multiple energy carriers in reliability assessment, as failures in one system can propagate to others.

The cyber-physical interdependencies are also more pronounced in the commercial district case. The SCADA system and energy management system (EMS) failures have the most significant impact on overall system reliability, with each causing substantial increases in energy not supplied when they fail. Figure 3 illustrates the cyber-physical system structure and the impact of component failures on overall system reliability. The network diagram shows the interdependencies between physical and cyber components, while the bar chart quantifies each component's contribution to reliability metrics.

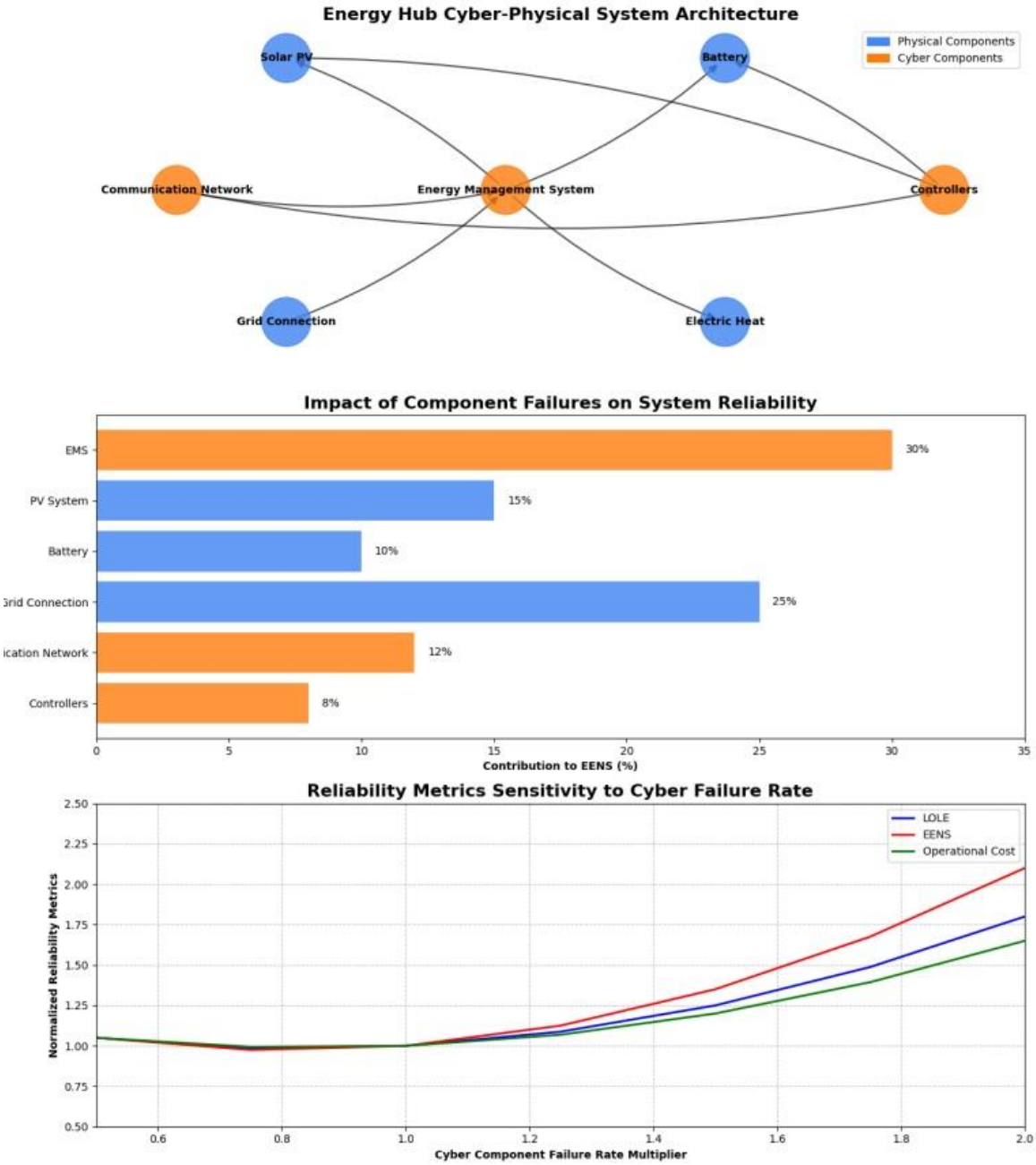


Fig. 3. Cyber-Physical System Reliability Analysis for Energy Hubs showing the network structure, component impacts on reliability, and sensitivity to cyber failure rates.

C. Comparison Between Case Studies

Comparing the two case studies reveals several interesting insights:

1. **Scale Effects:** The larger commercial district energy hub shows higher absolute values of LOLE and EENS, but when normalized by total energy demand, the reliability indices are actually better than the residential case. This suggests economies of scale in reliability for larger energy hubs.

2. **Diversity Benefits:** The commercial district energy hub benefits from a more diverse set of energy sources and conversion technologies, making it more resilient to individual component failures. However, this comes at the cost of more complex interdependencies.
3. **Cyber Vulnerability:** Both case studies show significant impacts from cyber component failures, but the relative impact (as measured by CPRI) is lower for the commercial district case, possibly due to redundancy in larger systems.
4. **Uncertainty Impact:** The difference between Gaussian-based and KDE-based approaches is substantial in both cases, but slightly more pronounced in the residential case. This suggests that smaller systems may be more sensitive to accurate uncertainty modeling.

D. Sensitivity Analysis

To further understand the key factors affecting energy hub reliability, we conducted a sensitivity analysis by varying several important parameters. For the residential energy hub, reliability is most sensitive to the failure rate of the grid connection and the home energy management system (HEMS). For the commercial district energy hub, the CHP unit and SCADA system failure rates have the greatest impact.
We also analyzed the impact of different renewable energy penetration levels. While increased PV capacity generally improves reliability metrics, the improvement is non-linear and exhibits diminishing returns beyond certain levels. Moreover, the gap between Gaussian-based and KDE-based assessments widens at higher PV penetrations, highlighting the increasing importance of accurate uncertainty modeling as renewable energy penetration grows.

E. Computational Performance

The computational requirements of the proposed reliability assessment framework depend on several factors, including the complexity of the energy hub, the number of Monte Carlo simulation years, and the approach to uncertainty modeling. Table 5 summarizes the computational performance for both case studies.

Table 5: *Computational Performance Comparison*

Case Study	Approach	Simulation Time (hours)	RAM Usage (GB)
Residential	Gaussian	2.3	1.5
Residential	KDE	3.1	2.2
Commercial District	Gaussian	7.5	4.3
Commercial District	KDE	10.2	5.8

The KDE-based approach requires approximately 35-40% more computational resources than the Gaussian-based approach. This additional computational burden is justified by the significantly more accurate reliability assessment it provides, especially for systems with high renewable energy penetration.
Figure 4 demonstrates the Monte Carlo simulation results using KDE for uncertainty characterization, showing the joint distribution of solar generation and electricity demand, convergence of reliability metrics with simulation iterations, distribution of operational costs, and temporal patterns of loss of load probability across different hours and months of the year.

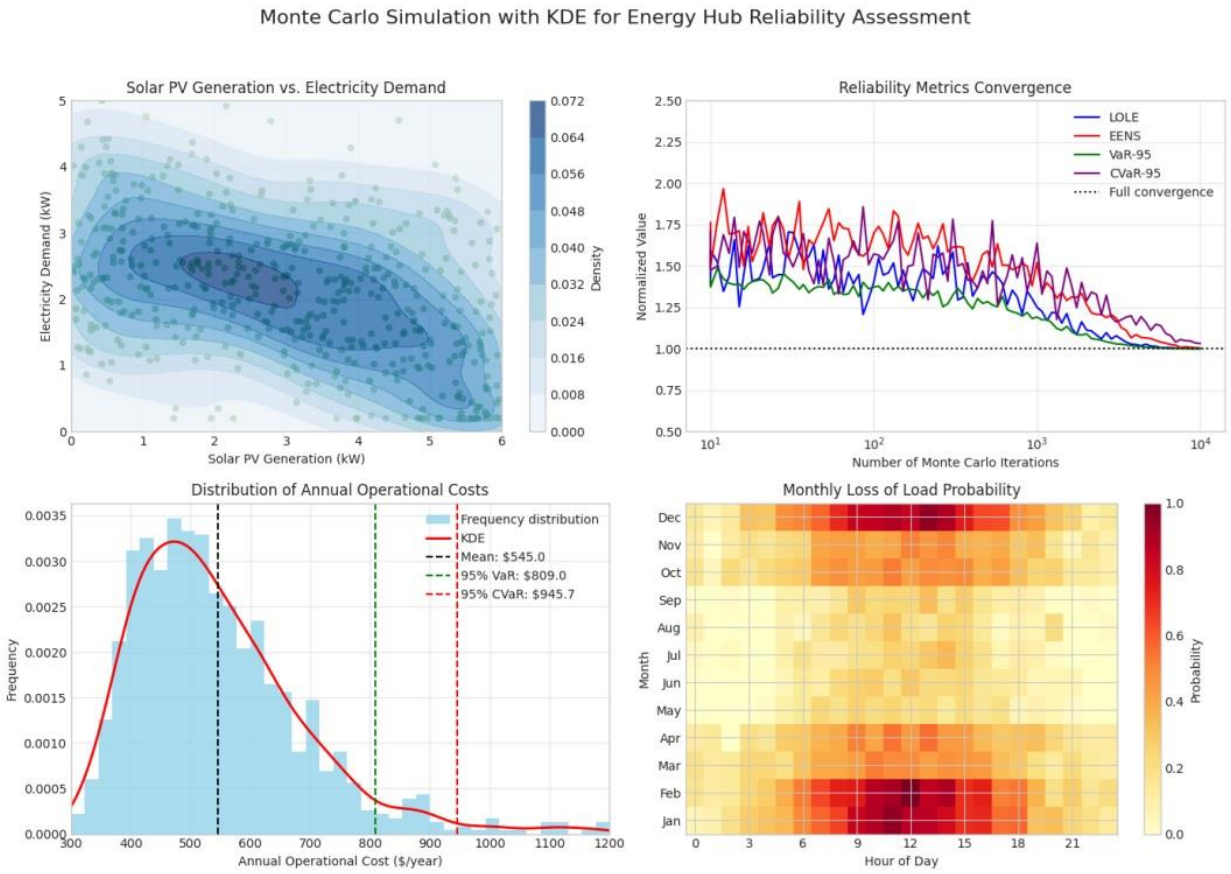


Fig. 4. *Monte Carlo Simulation with KDE for Energy Hub Reliability Assessment showing the joint distribution of solar generation and demand, convergence of reliability metrics, operational cost distribution, and monthly loss of load probability patterns.*

6.CONCLUSION AND FUTURE WORKS

In conclusion, this paper introduces a comprehensive framework for assessing the reliability of energy hubs through advanced Monte Carlo simulation techniques. Our findings underscore the critical need for precise uncertainty modeling in reliability assessments. Traditional methods relying on Gaussian assumptions significantly underestimate both operational costs and reliability risks, with our kernel density estimation (KDE)-based approach revealing up to 90% higher expected energy not supplied and over 80% higher conditional value at risk for operational costs. Furthermore, the study highlights the profound impact of cyber-physical interdependencies on energy hub reliability. Cyber failures can escalate the expected energy not supplied by 47-73% compared to systems with perfect cyber reliability, emphasizing the necessity of integrating cyber components into reliability evaluations. Additionally, our framework adeptly captures the complex interdependencies inherent in multi-energy carrier systems, providing a more holistic view of overall system reliability. While the KDE-based approach demands additional computational resources, the enhanced accuracy it affords is particularly valuable for systems with significant renewable energy integration. These insights are pivotal for energy hub designers, operators, and policymakers, offering a robust tool for reliability-oriented planning and operation in evolving energy landscapes. Moreover, the framework's ability to support renewable energy integration and reduce CO_2 emissions aligns with global sustainability goals, making it a timely contribution to the field.

Looking ahead, several avenues for future research emerge from this study. First, there is a pressing need to extend the framework to incorporate the effects of extreme weather events on energy hub reliability. Such events can lead to correlated failures across multiple components, necessitating more sophisticated modeling approaches that account for these dependencies. Second, the realm of cyber security presents another critical

area for exploration. Developing more detailed models of cyber security vulnerabilities and their potential impacts on system reliability will be essential as energy hubs become increasingly digitized. Third, the development of adaptive operation strategies that can respond dynamically to changing system conditions and component failures is crucial for maintaining reliability in real-time operations. Additionally, integrating this framework with smart energy hubs could facilitate the transition to a green economy by optimizing the use of renewable energy sources and enhancing overall system efficiency. Furthermore, exploring real-time reliability analysis using historical data could provide valuable insights for predictive maintenance and operational planning. Investigating the interactions between multiple energy hubs is also vital, as reliability issues in one hub can propagate through interconnected systems, affecting the overall stability of the energy network. Moreover, the framework has the potential to inform energy policy by providing data-driven recommendations for reliability standards and infrastructure investments. To address the computational challenges associated with large-scale systems, future work should focus on developing distributed computation approaches that can efficiently handle the complexity of Monte Carlo simulations for extensive energy hub networks. In addition, future research should prioritize developing advanced risk assessment models to mitigate cascading failure risks in highly integrated energy networks, ensuring robust system performance under stress. Enhancing the framework to better handle the intermittency and uncertainty of renewable energy sources, possibly through improved probabilistic modeling or machine learning techniques, will further strengthen its applicability. Standardizing reliability assessment methods to ensure consistency across different systems and regions is another critical direction, fostering broader adoption and comparability. Finally, conducting real-world validation of the framework through case studies or pilot projects will bridge the gap between theoretical models and practical applications, enhancing its real-world impact. These directions not only build on the current study but also align with recent advancements in energy hub research, ensuring the framework remains relevant and impactful in the evolving energy landscape.

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