



Reliability Analysis of Multiple High Altitude Platform Systems Using Stochastic Modeling and Machine Learning Techniques

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Abstract

The advent of the Internet of Things (IoT) era has led to a growing demand for widespread connectivity and improved communication methods. Although there are many competent technologies working for the purpose of capacity enhancement and reliability of the communication system, such as Free Space Optics (FSO) and Radio Frequency (RF) technologies, there is still room and need for further improvement. High Altitude Platforms (HAP) have been identified as one of the promising avenues for boosting capacity due to their straightforward deployment, ability to operate smoothly, and their cost-efficient nature. The main idea remains to deploy multiple HAPs in a single network and operate over a region which enables fast, stable, and efficient, thereby bringing additional reliability and capacity where it is needed. In this article, a three-level hierarchical model is considered for estimating the reliability attributes via multiple HAP system for the considered 5G New Radio (NR) communication system. Stochastic modeling and reliability block diagram techniques are used to analyze performance metrics at each level of the hierarchical model, including the reliability function and mean time to failure. Particular attention is paid to the study of multiple HAP system reliability, for which various scenarios of its functioning are presented, such as repairable and non-repairable k -out-of- n models. An analytical study of the proposed k -out-of- n models is presented and validated using Discrete Event Simulation. The presented analysis of the findings obtained indicates a strong correlation between the simulation results and the analytical results. In addition, for the purpose of completeness, the accuracy of estimating reliability and time characteristics for various input data using significant parameters is achieved by using the well-known K -Nearest Neighbors (KNN) technique.

Keywords Multiple high altitude platform system · 5G(NR) · Reliability analysis · Hierarchical model · Reliability block diagram · Continuous time markov chain · Machine learning · K-nearest neighbors regression

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1 Introduction

The time of the fifth generation (5G) and beyond mobile communication networks has transitioned from a futuristic concept to a tangible reality, witnessed by its ongoing initial deployments across the world. It comes with high expectations, promising scenarios, and strict demands. For example, 5G New Radio (5G NR) has rigorous demands for high reliability and minimum delay, since billions of internet operated devices are working in real time over 5G networks. In addition to these two requirements, 5G networks are forecasted to encounter another challenge to face, which is the Internet of Things (IoT) networks. Nonetheless, attaining widespread connectivity and optimizing IoT operations impose significant obstacles, particularly in regions with uneven infrastructure and remote areas. The need to improve capacity will remain constant in the current and forthcoming generations of mobile communication networks.

In this context, a swift solution is essential for such scenarios, and the introduction of High Altitude Platforms (HAPs) has emerged as a viable option for pop-up networking. The concept revolves around deploying small cell base stations on HAPs, dispatched to hotspots for capacity enhancement as needed, thereby offering pop-up connectivity. Reliable connectivity improves user experience and alleviates the need for fixed infrastructure, thereby reducing the burden on mobile network operators. In addition to the capacity enhancement purposes, HAPs enable the expansion of broadband wireless telecommunication services in both rural and underserved areas, as well as in densely populated urban areas [1].

Furthermore, HAPs can help create smart cities by facilitating the integration of smart Internet-connected devices into our homes, public spaces, vehicles, and other areas. Therefore, HAPs save energy resources by covering a large area with a good level of Quality of Service (QoS) and the least delay. The ability to combine several HAPs (a system that consists of several HAPs) into a single network that enables fast, stable and efficient satellite-to-satellite communication over long distances by installing millions of ground relay stations. This integrated framework is referred to as a multiple-HAP system [2, 3].

Accordingly, the primary advantages of employing multiple HAPs in wireless networking can be outlined as follows:

- As the number of HAPs in the network increases, the workload of each HAP decreases proportionally. By incorporating more HAPs within a coverage area, each HAP can allocate greater resources to individual users, thereby meeting higher data rate demands. Consequently, the achievable user data rate can increase linearly [4].
- Users can benefit from seamless connectivity, as base stations deployed on multiple HAPs are mobile and equipped with user-tracking capabilities.
- Connectivity issues in pop-up scenarios can be effectively managed.

1.1 Related Work

Numerous studies have explored the provision of communication between stratospheric HAP and terrestrial terminals in the telecommunication industry. Below is a short review of the most important studies in this field. HAP is offered as an innovative answer for providing communication services to a diverse array of intelligent IoT devices [5–9]. The usage of IoT technologies in the context of smart cities poses significant challenges as researchers

seek to address the distinct requirements of broad networks, robustness, and low latency for a vast array of interconnected devices. Studies [3, 10–13] highlight the inadequacy of the existing infrastructure and design approaches in meeting the requirements of modern wireless systems and services, emphasizing the need for more robust and advanced wireless access architectures. In [11], recently the authors presented an adaptive offloading strategy based on the twin delayed deep deterministic policy gradient algorithm, which incorporates twin critics and prioritized experience replay to improve decision-making under dynamic conditions. The advantages of broadband access in developing countries are extensively explored in [14].

The books [15, 16] provide examples of how HAP nodes can be utilized either alone or in conjunction with other terrestrial network components. The articles [17, 18] discuss the integration of satellite systems and HAPs, paving the path for a hybrid communication system combining both terrestrial and satellite technologies. The study in [19] examines how the inter-HAP handoff procedure works when HAP employs stationary or adjustable directional antennas in the event of a HAP substitution for conservation or regular substitution of HAP with short endurance. In [20], the author developed a model to depict the geometry of antenna beam coverage in HAP, and the Monte Carlo method was subsequently employed to assess the likelihood of handoff during the swinging movement within the model of equal coverage area, achieved by computing the area of overlap.

In reliability theories, Machine Learning (ML) techniques are used to investigate various probabilistic and temporal properties of complex systems. Based on practically meaningful parameters, a variety of ML techniques, such as linear regression and K-nearest neighbors (KNN) regression, are utilized to derive reliability characteristics for arbitrary input data [21]. ML techniques are also helpful in situations where getting results through simulation or analysis is not possible [22]. In [22], the investigation revealed that the estimates obtained by using ML methods were more precise than those that were previously known.

In 5G (NR), the Base Stations (BSs) typically receive signals from a source, often satellites, which are weakened due to the substantial distance between them [23, 24]. Therefore, it becomes necessary to reduce the distance between the source and BSs to enhance the signal strength and improve the data transmission rate in 5G networks. To abbreviate (or diminish) this distance, a multiple HAP system can be utilized.

1.2 Comparison with the Existing Work

This section presents a performance comparison between the proposed approach and existing studies. Table 1 provides a summary of this comparative analysis.

As summarized in Table 1, several analytical models [25–28] have examined multi-HAP systems integrated with IoT-enabled devices over 5G (NR). Among these, only [27, 28] explicitly addressed the reliability analysis of HAPs. The study in [29] proposed combines Free Space Optics (FSO) and Radio Frequency (RF) technologies to establish multi-layer space–air–ground uplink networks, with HAPs serving as relay stations to enhance reliability. Additionally, Table 1 shows that only [26] concentrated on the reliability aspects of HAPs in the context of FSO communication.

This study addresses all aspects concerning repairable and non-repairable multiple HAP systems, including their associated adjacent failures. Consequently, it can be observed that

Table 1 Comparison of related works with the current one

References	Platform type	Ideology	Reliability	5G(NR)	ML
[25]	HAP	Describes various aspects of HAP, including their architectural design, techniques for allocating research resources, methods for modeling channels, and potential applications.	No	Yes	No
[26]	HAP	Explains the Free Space optics (FSO) communication technology, methods for transmitting data, and the results of experimental trials conducted for HAP.	Yes	No	No
[27]	Multiple satellite-aerial networks	Focuses on aspects of the routing layer and designs for multiple satellite-ground-aerial connections.	No	Yes	No
[28]	HAP	Focuses on addressing matters related to the scope and ability to accommodate data traffic by utilizing HAP	No	Yes	No
[3]	HAP	Emphasizes the possibilities of HAP, and explains how they possess capabilities to provide services in urban regions.	No	Yes	No
[30]	Satellite	Explains the recent developments in scientific, and satellite communications standards.	No	Yes	No
[31]	HAP	Focused on how HAP provide connectivity in the next communication systems.	No	No	No
This work	Multiple HAP system	Presents the hierarchical model of multiple HAPS network architecture over IoT and carries out its reliability analysis.	Yes	Yes	Yes

the proposed model is more accurate and closely aligned with achieving real-time simulation results based on the comparison in Table 1.

Furthermore, this work employs stochastic modeling as an innovative approach to evaluate the reliability of multiple HAP systems. Such models capture the inherent randomness and uncertainty due to diverse factors that affect the reliability of HAP.

1.3 Contribution

From the comprehensive literature survey, it is evident that the reliability of HAPs in the context of 5G network communication has been investigated in prior studies. Table 1 represents a comparison of the main lines of research on this topic, which include reliability analysis, the application of different platforms to solve the IoT communication problem, and the use of ML methods. However, there is no literature available in which a hierarchical model that includes both terrestrial and aircraft modules with multiple HAP system for providing broadband connection to IoT devices. This article aims to mitigate this gap.

Further, the salient features and contributions of this research work are given as follows:

- We consider a multiple HAP system architecture integrated with IoT devices over 5G (NR).
- *Hierarchical Reliability Model*: A hierarchical reliability model is considered for the

system architecture of multiple HAP system over IoT-enabled devices. It is further classified at three levels comprising complicated interoperations among IoT-enabled devices, multiple HAP system, and satellite. Hence, performing reliability analysis of the model at each level provides a comprehensive understanding and yields the most accurate approximations.

- *Reliability Analysis:* The reliability analysis at each level uses Reliability Block Diagrams (RBDs) and Continuous Time Markov Chains (CTMCs) to derive the performance measures such as Mean Time to Failure (MTTF) and reliability function.
- *The Application of k -out-of- n Model:* This manuscript makes a new contribution by using k -out-of- n model for reliability analysis at Level 2 for both repairable and non-repairable multiple HAP system.
- *Analytical and Simulation Results:* Closed-form expressions for the reliability function of k -out-of- n repairable and non-repairable multiple HAP system are obtained. Further, the obtained results are validated using Discrete Event Simulation.
- *Machine Learning Technique:* To obtain the precise and accurate results, well-known ML algorithm, KNN, is used. Its ability to process massive volumes of data significantly strengthens the study.

The rest of the paper is structured as follows. Section 2 describes the system architecture along with its reliability model. The hierarchical reliability model is discussed in Sect. 3. Section 4 represents the reliability investigation of k -out-of- n models for repairable and non-repairable multiple HAP system. Section 5 is devoted to numerical methods used for the reliability analysis, including analytical results, discrete event simulation, and ML, with further comparisons performed. The reliability analysis of the communication system depending on different topologies of multiple HAP system is presented in Sect. 6. Concluding remarks and a few future directions are given in Sect. 7.

2 Multiple HAP System: Network Architecture

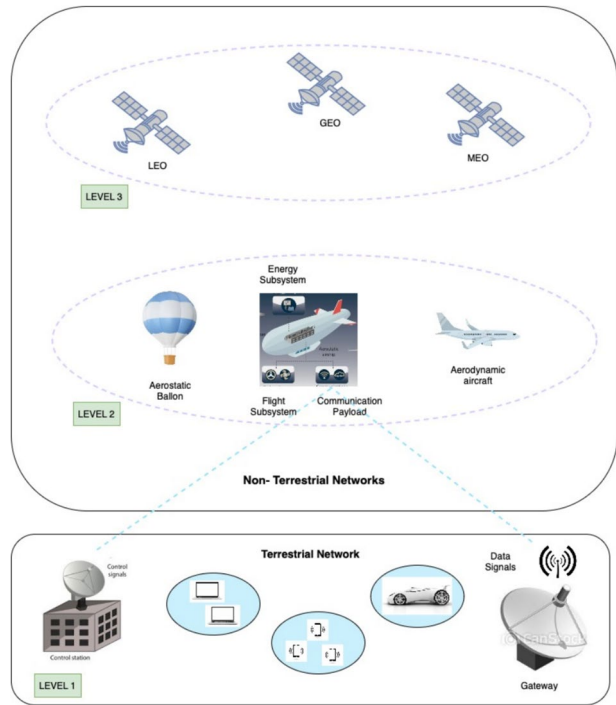
HAP is an aerial platform that functions at elevated altitudes, usually ranging from 17 to 22 kilometers above sea level. The multiple HAP system can be used in various architectural configurations. In the simplest configuration, this is a standalone platform whose coverage is restricted only by its capacity [3].

HAP has the potential to act as intermediary stations that gather data from IoT-enabled devices and transmit it to a Ground Station (GS) or data center. Additionally, HAP can establish communication links between IoT devices, which is beneficial when two IoT devices are located in separate remote areas without a direct communication link. In this case, multiple HAP system can function as relays to establish communication between them. In general form, the entire configuration of a multiple HAP system is shown in Fig. 1.

Based on the architecture discussed above, we proceed to introduce a reliability model that allows for the computation of the reliability analysis of IoT networks via a multiple-HAP system.

As seen in the figure, the proposed architecture is a hierarchical model consisting of three levels, namely GS at level 1, aerial network at level 2, and space network at level 3.

Fig. 1 Hierarchical model of multiple HAP system



- **Space Network:** A space network is defined as an arrangement of numerous components (satellites) that establish a connection between two points on the globe through various nodes. Satellite Network is commonly used for satellite communication. The main units of the space segment are the fuel part, telemetry controls, the satellite, and the transponder. Based on the architecture, HAP is connected to the satellite via Platform-Satellite links (PSLs). PSLs offer significant advantages to HAPs situated in regions with limited terrestrial infrastructure, such as remote or rural areas.
- **Aerial Network:** This part includes all the main network elements of multiple HAP system in the aerial domain. Each of these elements incorporates crucial onboard subsystems required for the efficient deployment of HAP and the smooth operation of the communication system. Interplatform Links (IPLs) facilitate the interconnection of multiple HAP system. In addition, IPL enables communication between adjacent HAPs without the need for any GS components.
- **Ground Network:** This level is closest to the IoT-enabled devices. It consists of the ground components of the HAP communication system such as Control Station, Communication Gateway, and Terrestrial Networks. After the establishment of connections between HAP and satellites, the GS is connected to Level 2 via Backhaul Link (BL). The BL serves to transmit data to a specific destination from where it can be distributed across the network. Backhauling is also utilized to route network data through a particular path, aiming to achieve faster delivery at lower costs.

2.1 Performance Measures

Within the scope of the reliability analysis task, the following performance metrics are taken into account:

- *Reliability*: Reliability is defined as the ability to perform a required function within a given time under specific circumstances. Let the system's lifetime be T , then $R(t) = P[T > t]$ gives the reliability function of the system at time t [32].
- *Mean Time to Failure*: MTTF is a reliability measure that denotes the expected time interval between a system's initial operation and the occurrence of its first failure.

These fundamental reliability indicators, which are significant for any technical system, make it possible to evaluate other characteristics. For example, the design life, that is the time during which the system will be reliable with a certain probability. Variance and standard deviation demonstrate the more accurate behavior of the system relative to MTTF, with the help of which confidence intervals can be obtained. Knowing these measures, one can reasonably plan preventive maintenance or repairs of the entire system to avoid unnecessary costs.

3 Reliability of a Multiple HAP System in Communication Networks

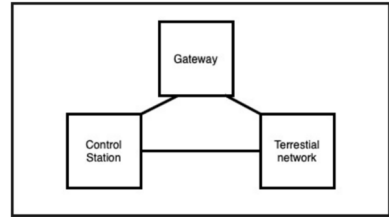
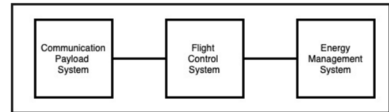
In this section, we present the proposed hierarchical model for reliability analysis of multiple HAP system in communication networks.

3.1 Reliability at Level 1: Ground Station

A GS serves as a vital component of the ground segment, functioning as the central communication hub linking Earth with satellites. It consists of Control Station (CS), Communication Gateway (CG), and Terrestrial Networks (TN). These three components of the GS are connected to HAP via the BL. The backhaul connects the central-level network to the individual link or public-level networks.

- *Control Station*: It facilitates communication between multiple HAP system units and different types of users. It is responsible for the human-machine interface and acts as an operator to minimize human errors.
- *Communication Gateway*: It connects the integrated HAP unit to the core network through the wired backhaul infrastructure. Dedicated backhaul antennas can be employed on the platform.
- *Terrestrial Networks*: It includes base stations, and different types of users using various IoT-enabled devices.

Consider the connection structure of GS's components. The CS and TN components are connected in series, and this series configuration is then connected in parallel with the CG. The RBD of the GS is shown in Fig. 2.

Fig. 2 RBD of ground station**Fig. 3** RBD of a HAP

Let $R_{CS}(t)$, $R_{CG}(t)$ and $R_{TN}(t)$ be the reliability function at time t of CS, CG and TN respectively. The failure rates of each component are supposed to follow an exponential distribution with corresponding parameters λ_{CS} , λ_{CG} , λ_{TN} . Then, the reliability of GS at time t , denoted by $R_{GS}(t)$, and is calculated as:

$$\begin{aligned}
 R_{GS}(t) &= [1 - [1 - (R_{CS}(t) \times R_{TN}(t))] \\
 &\quad \times [1 - R_{CG}(t)]] \\
 &= 1 - [1 - e^{-(\lambda_{CS} + \lambda_{TN})t}] \\
 &\quad \times [1 - e^{-\lambda_{CG}t}].
 \end{aligned} \tag{1}$$

3.2 Reliability at Level 2: Multiple HAP System

3.2.1 Reliability of a Single HAP

In this work, we suppose that all HAPs in the transmission range are equipped with identical GS. A HAP consists of several components such as Energy Management Subsystem (EMS), Communication Payload Subsystem (CPS), and Flight Control Subsystem (FCS). The functioning of these three components is interdependent, and therefore, they are in a series connection (see Fig. 3).

- **Flight Control Subsystem:** It provides handling, stability, and platform mobility control to guide the station toward the desired target direction. In general, it manages the interface between the platform and the ground CS.
- **Energy Management Subsystem:** It ensures production, consumption, and energy storage.
- **Communication Payload Subsystem:** It is responsible for managing communications among GS, HAPs, and satellites.

Assume that at time t , the reliabilities of FCS, EMS, CPS are denoted by $R_{FCS}(t)$, $R_{EMS}(t)$, and $R_{CPS}(t)$ respectively. Further, their failure rates are exponentially distributed with corresponding parameters λ_{FCS} , λ_{EMS} , and λ_{CPS} . Assuming components are

in UP states initially and failure of any component leads to the HAP failure. Then, the reliability function of HAP at time t , denoted by $R_{HAP}(t)$, is given by:

$$\begin{aligned} R_{HAP}(t) &= R_{FCS}(t) \times R_{EMS}(t) \times R_{CPS}(t), \\ &= e^{-(\lambda_{FCS} + \lambda_{EMS} + \lambda_{CPS})t}. \end{aligned} \quad (2)$$

3.2.2 Reliability of Multiple HAP System

In rural and suburban regions, the coverage performance of a wireless communication system takes precedence over capacity density. When dealing with areas of low user density, the primary focus is on maximizing coverage, which makes it more significant to consider HAPs as an alternative to terrestrial systems [28].

Currently, IoT has become the most common topic of interest in wireless research and academia. IoT-enabled devices are considered as low power minicomputers. Since, they are usually battery-powered, high-power consumption networks such as cellular networks or satellites are not ideal for them. A multiple HAP system provides a communication network at low power consumption. The general network architecture which integrates the Internet with IoT-enabled devices via a multiple HAP system is depicted in Fig. 4.

These multiple HAP systems are interconnected via various topologies for 5G (NR)[3]. Now, we analyze multiple HAP system reliability by using the following topologies:

- *Mesh topology*: Mesh topology is a type of network structure in which all nodes are interconnected, resulting in multiple alternative routes for data transmission, thereby providing redundancy in the network. For a small terrestrial infrastructure, mesh topology with platform interconnection via IPLs provides extended system coverage [33]. Mesh-

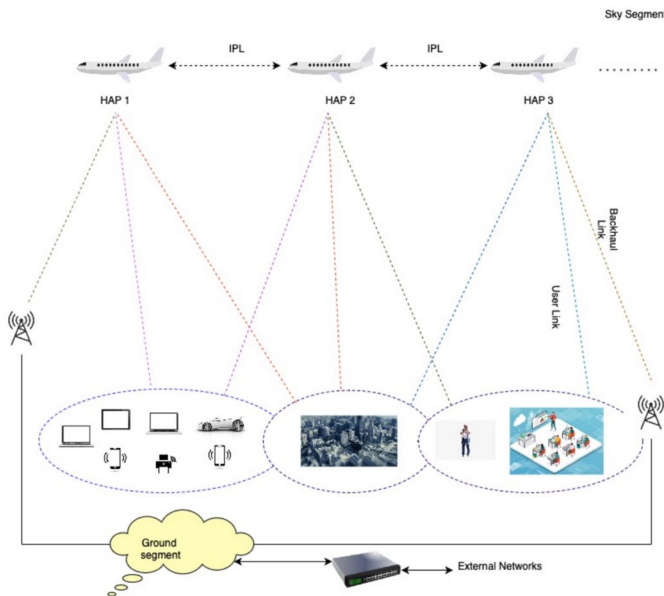
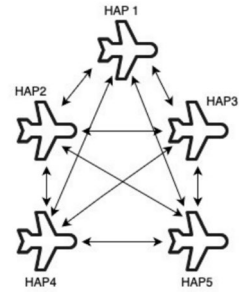
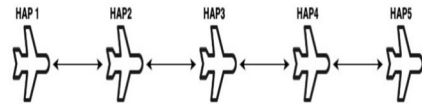


Fig. 4 Multiple HAP system with IoT devices

Fig. 5 Fully meshed HAPs network topology ($N = 5$)**Fig. 6** Bus HAPs network topology ($N = 5$)

based HAPs networks are particularly well-suited for expanding the availability of high-speed Internet connectivity in remote and isolated locations. Also, mesh-based HAPs networks have extended range and are resistant to critical environmental conditions with minimal hardware. A fully meshed HAPs topology (for $N = 5$) is shown in Fig. 5. Assume that N represents the initial number of HAPs operating in the network area. Each of the N HAPs is connected to the remaining $(N - 1)$ HAPs in the mesh topology. Then, there must be a total of $\binom{N}{2}$ unique connections among these N communicating HAPs within a transmission range. The probability of a failure-free connection of two different HAPs is equal to $R_{HAP}^2(t)$. In the case of mesh topology of multiple HAP system, let $R_{mnet}(t)$ be the network's reliability at time t . Thus, from [34], we have,

$$R_{mnet}(t) = \left[1 - [1 - R_{HAP}^2(t)]^{\binom{N}{2}} \right]. \quad (3)$$

- *Bus topology*: Bus topology refers to a network structure in which all devices are connected to a single communication line, commonly referred to as a “bus”. Every device connected to the network can communicate with any other device on the network via the bus. Bus topology can be used to connect HAPs when the communication in the coverage area of one HAP is unstable. In such cases, IoT-enabled devices can reconnect to neighboring HAPs. As an example, the case of $N = 5$ HAPs in bus topology is presented in Fig. 6. Let N represent the initial number of HAPs operating in the network area. The functioning of all these HAPs is dependent on each other and are connected in a bus topology. In the case of a bus topology in multiple HAP system, let $R_{bnet}(t)$ be the network's reliability at time t , which is given by the following expression,

$$R_{bnet}(t) = (R_{HAP}(t))^N. \quad (4)$$

Now, let $R_{HAPS}(t)$ denote the reliability of a multiple HAP system at time t . Thus, we have,

$$R_{HAPS}(t) = \begin{cases} R_{mnet}(t), & \text{in mesh} \\ R_{bnet}(t), & \text{in bus.} \end{cases} \quad (5)$$

3.3 Reliability at Level 3: Satellite Network

A satellite can establish communication with a multiple HAP system simultaneously. In addition, HAPs can communicate with other HAPs through the satellite. This arrangement expands the coverage area and improves communication for users. Star topology ensures a reliable and efficient approach to connecting the satellite to HAPs, providing centralized control, improved coverage and connectivity, as well as redundancy capabilities. In case of a failure or other technical problems with one HAP, the remaining HAPs can continue to communicate with each other via satellite. This guarantees uninterrupted network operation. Fig. 7 demonstrates the connection of the satellite and the HAPs in a star topology when HAPs are connected in bus network topology.

Let the reliability of the satellite network with a multiple HAP system be given by $R_{snet}(t)$ at time t . Suppose that the failure rate of a single satellite follows an exponential distribution with parameter λ_{SAT} . Therefore, $R_{snet}(t)$ is given by the following expression,

$$R_{snet}(t) = R_{SAT}(t) \times R_{HAPS}(t), \quad (6)$$

where $R_{SAT}(t)$ is the reliability of a single satellite at time t .

3.4 General Expression for System Reliability

The paper aims to examine the reliability of the communication system through IoT-enabled devices, which depends on its reliable hardware and software. Suppose that the communication system for IoT-enabled devices consists of one GS, a network with N HAPs, and one satellite. Then, the system reliability depends on active HAPs in the group that are within the transmission range of GS. The GS is connected in series with all HAPs. Hence, the system is reliable if at least one HAP is active among all HAPs and the GS is also operational. RBD of such a system is shown in Fig. 8.

Thus, by combining the results from Sects. 3.1 and 3.2, the reliability of the communication system under consideration can be obtained. The communication system reliability at time t is denoted by $R_{SYS}(t)$, and the following equation holds,

Fig. 7 Satellite–HAP network: star topology

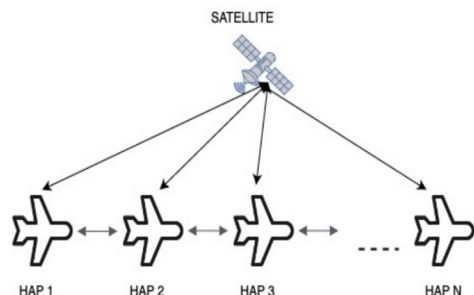
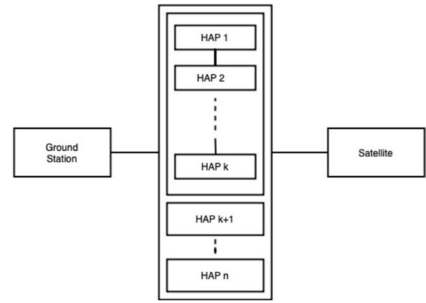


Fig. 8 RBD of the communication system

$$R_{SYS}(t) = R_{GS}(t) \times R_{HAPS}(t) \times R_{SAT}(t) \quad (7)$$

4 Reliability Analysis of Complex Multiple HAP Configurations Based on the k -out-of- n Model

The architecture of HAP networks can exhibit significantly greater complexity than the simplified models discussed in Sect. 3.2.2. For the reliability analysis of a multiple HAP system, we employ k -out-of- n models. This modeling approach enables system designers to enhance network robustness, ensuring continued operation even if a subset of HAPs fails or becomes unavailable. In the proposed framework, the parameter n denotes the total number of HAPs in the network, while k specifies the threshold number of HAP failures that the system can tolerate before overall network performance is compromised.

4.1 Non-Repairable HAPs network

A non-repairable k -out-of- n model represents a reliability framework in which the system remains operational only if at least k out of n components function correctly, with no provisions for repairing failed components. In the context of HAP networks, this implies that the system operates autonomously, and the failure of any k HAPs results in the complete failure of the network.

4.1.1 Network Failure Depends on the Number of Failed HAPs

Suppose that HAP network failure depends only on the number of failed HAPs.

Let the probability $P(t)$ be the probability that exactly i out of n HAPs in the network operates at time t . Then $P(t)$ can be expressed as:

$$P(t) = \binom{n}{i} (1 - R_{HAP}(t))^{n-i} (R_{HAP}(t))^i.$$

Hence, the mathematical representation of the probability that HAP network operates without failure for a given time duration t , which is commonly referred to as the reliability function and denoted by $R_{HAPS}(t)$, can be formulated as follows [35]:

$$R_{HAPS}(t) = \sum_{i \geq k}^n \binom{n}{i} (1 - R_{HAP}(t))^{n-i} \times (R_{HAP}(t))^i. \quad (8)$$

Also, the corresponding MTTF (m) is given by

$$m = \int_0^{\infty} R_{HAPS}(t) dt. \quad (9)$$

For example, for the 2-out-of-5 model, which corresponds to a network of 5 HAPs that works until its 3 HAPs operate, Eq. (8) is rewritten as:

$$R_{HAPS}(t) = \sum_{i \geq 2}^5 \binom{5}{i} (1 - R_{HAP}(t))^{5-i} \times (R_{HAP}(t))^i. \quad (10)$$

Suppose that the lifetime of an HAP has an exponential distribution with parameter α , thus its reliability function is given by $R_{HAP}(t) = e^{-\alpha t}$, and the mean lifetime $a = \alpha^{-1}$. In this case, $R_{HAPS}(t)$ takes the form,

$$R_{HAPS}(t) = \sum_{i \geq 2}^5 \binom{5}{i} (1 - e^{-\alpha t})^{5-i} (e^{-\alpha t})^i.$$

4.1.2 Network Failure Depends on the Number of Adjacent Failed HAPs

Generally, HAPs are not only expensive but also have limited capacity with respect to payload weight and available energy [36]. The failure of two adjacent HAPs can result in serious consequences for IoT services relying on their connectivity, such as communication disruption, reduced coverage, data loss and delay or service disruption [3]. Obviously, there is an overlap of IoT coverage areas between two neighboring HAPs. If one HAP fails, neighboring HAPs can take over the workload of the failed one. However, if an adjacent platform fails along with an already failed HAP, this results in a complete loss of connectivity for devices over a large area, causing full operational disruption. So, the deployment of HAP systems must be well-planned.

Thus, consider a non-repairable k -out-of- n model the failure of which depends on the location of the failed HAPs. Here, k determines the number of adjacent failed HAPs. Suppose that if any 2 adjacent HAPs fail, then the system becomes inoperative. Let k mean the number of failed HAPs. If $i < \lfloor \frac{(n+1)}{2} \rfloor$ (where, the symbol $\lfloor \cdot \rfloor$ denotes the floor function, i.e., the greatest integer less than or equal to the value inside), then the network operates as long as there is at least one operational HAP between every two failed HAPs. By the rules of combinatorics [37] the number M_i , of ways to arrange n HAPs including i failed HAPs and $n - i$ functioning HAPs such that no 2 failed ones are adjacent to each other is equal to

$$\begin{aligned}
 M_i &= \binom{(i+1) + (n-2i+1) - 1}{n-2i+1} \\
 &= \binom{n-i+1}{i}.
 \end{aligned} \tag{11}$$

Then, the multiple HAP system reliability is given by,

$$\begin{aligned}
 R_{HAPs}(t) &= \sum_{i=0}^{\lfloor (n+1)/2 \rfloor} M_i (1 - R_{HAP}(t))^i \\
 &\quad \times (R_{HAP}(t))^{(n-i)}.
 \end{aligned} \tag{12}$$

As an example, consider the 2-out-of-5 model, which corresponds to a network of 5 HAPs that remains operational unless 2 adjacent HAPs fail. That leads to the following result,

$$\begin{aligned}
 R_{HAPs}(t) &= \sum_{i=0}^3 \binom{6-i}{i} (1 - R_{HAP}(t))^i \\
 &\quad \times (R_{HAP}(t))^{(5-i)}.
 \end{aligned} \tag{13}$$

If a HAP's lifetime has an exponential distribution with parameter α , from equation (13) we have,

$$\begin{aligned}
 R_{HAPs}(t) &= \sum_{i=0}^3 \binom{6-i}{i} (1 - e^{-\alpha t})^i \\
 &\quad \times (e^{-\alpha t})^{(5-i)}.
 \end{aligned}$$

4.2 Repairable HAP Network

In a repairable k -out-of- n model, the system relies on k out of n components for proper operation, and if any of these components fail, they can be repaired to ensure the system functions as intended.

4.2.1 Network Failure Depends on the Number of Failed HAPs

Consider a repairable k -out-of- n multiple HAP system model. Suppose that the failure and repair rates of a HAP are exponentially distributed with parameters α and β , respectively. Corresponding averages will be denoted as $a = \alpha^{-1}$ and $b = \beta^{-1}$.

Consider the CTMC

$$\begin{aligned}
 X(t) &:= \{i \mid \text{system has } i \text{ number of} \\
 &\quad \text{failed HAPs at time } t\}, i \in E,
 \end{aligned}$$

where E represents the state space for the random process $\{X(t) : t \geq 0\}$ and is given by $E = \{0, 1, 2, \dots, k\}$.

Further, it is assumed that initially, all HAPs are in UP states, i.e., $i = 0$ and state k is the absorbing state. Also, we assume that not more than one HAP can fail at any time instant t . Let there be only one repair device. We are interested in calculating the reliability function. The state transition diagram of the CTMC $\{X(t) : t \geq 0\}$ is presented in Fig. 9. Further, the failure rate of i -th HAP is $\lambda_i = (n - i)\alpha$, when the system is in the state i .

We introduce time-dependent state probabilities for the above-mentioned system as follows:

$$\pi_j(t) = P\{X(t) = j\}, \quad j \in E.$$

Consider that the reliability function of this system is denoted by $R(t)$ and is given by,

$$R_{HAPs}(t) = 1 - \pi_k(t). \quad (14)$$

For the above-mentioned system, the Kolmogorov differential equations for $(k + 1)$ -state Markov process are given by [38]:

$$\begin{aligned} \frac{d}{dt} \pi_0(t) &= -\lambda_0 \pi_0(t) + \beta \pi_1(t), \\ \frac{d}{dt} \pi_i(t) &= -(\lambda_i + \beta) \pi_i(t) + \lambda_{i-1} \pi_{i-1}(t) \\ &\quad + \beta \pi_{i+1}(t), \quad i = \overline{1, k-2} \\ \frac{d}{dt} \pi_{k-1}(t) &= -(\lambda_{k-1} + \beta) \pi_{k-1}(t) \\ &\quad + \lambda_{k-2} \pi_{k-2}(t), \\ \frac{d}{dt} \pi_k(t) &= \lambda_{k-1} \pi_{k-1}(t). \end{aligned} \quad (15)$$

Further, taking the Laplace Transform (LT) $\tilde{\pi}_i(s)$ of the system of equations (15) with the initial conditions $\pi_0(0) = 1$, $\pi_i(0) = 0$, $i = \overline{1, k}$ and replacing the final equation with the normalization condition $\sum_{i=0}^k \pi_i(t) = 1$, we obtain,

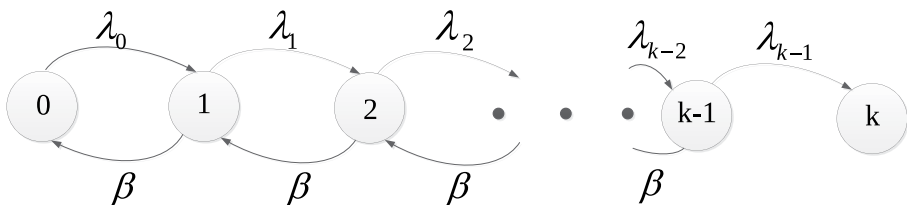


Fig. 9 Transition graph of repairable k -out-of- n model with absorption

$$\begin{aligned}
(s + \lambda_0)\tilde{\pi}_0(s) - \beta\tilde{\pi}_1(s) &= 1, \\
(s + \lambda_0 + \beta)\tilde{\pi}_i(s) - \lambda_{i-1}\tilde{\pi}_{i-1}(s) \\
&\quad - \beta\tilde{\pi}_{i+1}(s) = 0, \quad i = \overline{1, k-2}, \\
(s + \lambda_{k-1} + \beta)\tilde{\pi}_{k-1}(s) - \lambda_{k-2}\tilde{\pi}_{k-2}(s) &= 0, \\
s \cdot \sum_{i=0}^k \tilde{\pi}_i(s) &= 1,
\end{aligned}$$

which gives us

$$\begin{aligned}
\tilde{\pi}_0(s) &= \frac{1 + \beta\tilde{\pi}_1(s)}{s + \lambda_0}, \\
\tilde{\pi}_i(s) &= \frac{\lambda_{i-1}\tilde{\pi}_{i-1}(s) + \beta\tilde{\pi}_{i+1}(s)}{(s + \lambda_0 + \beta)}, \quad i = \overline{1, k-2}, \\
\tilde{\pi}_{k-1}(s) &= \frac{\lambda_{k-2}\tilde{\pi}_{k-2}(s)}{s + \lambda_{k-1} + \beta}.
\end{aligned}$$

Further, with the help of recursive substitution, the LT of the reliability function defined in Eq. (14) is used, and its LT is obtained as follows,

$$\tilde{R}_{HAPs}(s) = \frac{1}{s} - \tilde{\pi}_k(s). \quad (16)$$

When we consider a particular case of a repairable 2-out-of-5 model. Then its reliability function has the following form,

$$\tilde{R}_{HAPs}(s) = \frac{s + 9\alpha + \beta}{s^2 + s(9\alpha + \beta) + 20\alpha^2},$$

using inverse LT it gives,

$$\begin{aligned}
R_{HAPs}(t) &= (2\Delta)^{-1} e^{-\frac{1}{2}(9\alpha + \beta + \Delta)t} \left[-9\alpha - \beta \right. \\
&\quad \left. + \Delta + e^{\Delta t}(9\alpha + \beta + \Delta) \right], \quad (17)
\end{aligned}$$

where $\Delta = \sqrt{\alpha^2 + 18\alpha\beta + \beta^2}$.

4.2.2 Network Failure Depends on the Number of Adjacent Failed HAPs

Similar to Sect. 4.1.2, consider the case of adjacent failures, but with the possibility of recovery of the failed HAPs. This case has a more complicated process for arbitrary k , so let us consider the results of calculating the reliability function using the 2-out-of-5 model as an example:

In this case, for the already defined stochastic process $\{X(t) : t \geq 0\}$ in Sect. 4.2.1, the state space becomes $E = \{0, 1, 2, 3, -2\}$, where -2 represents the failure of two adjacent HAPs, which leads to system failure. The state transition diagram of the CTMC $\{X(t) : t \geq 0\}$ is presented in Fig. 10.

For the process to pass from state 0 to state 1, one HAP among multiple HAP system must fail. Further, the failure of a HAP is considered to follow an exponential distribution, the corresponding rate of failure is considered as α . Also, the repair of a HAP is considered to follow an exponential distribution with the rate β . There is a possibility of the following two events occurring: either the failed HAP will recover with rate β , or the non-adjacent HAP will fail. A new failure can occur only in the adjacent of those who have already failed.

Case i): In general, the failure of any HAP in state i occurs with an equal probability $\frac{1}{M_i}$. There are $i + 1$ possible cases of state i that may change into state $i + 1$, so there are M_{i+1} possible cases of state $i + 1$. Therefore, the total number of ways for transitions from i to $i + 1$ equals to $(i + 1)M_{i+1}$. Then we get the transition rate from state i to state $i + 1$, $\frac{(i + 1)M_{i+1}}{M_i}\alpha$.

Case ii): The transition from state i to state $-(i + 1)$ will be carried out with the rate $\left((n - i) - \frac{(i + 1)M_{i+1}}{M_i}\right)\alpha$.

According to these arguments, the rates of the transition from state 1 to state 2 as well as from state 1 to state -2 are given by the following equations:

From case i), transition of state 1 to 2
and 2 to 3 :

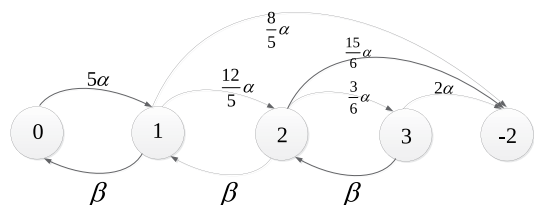
$$\frac{2M_2}{M_1}\alpha = \frac{12}{5}\alpha \quad \text{and} \quad \frac{3M_3}{M_2}\alpha = \frac{3}{6}\alpha.$$

Similarly, we have

from case ii), state 1 to -2 and 2 to -2 :

$$\left(4 - \frac{2M_2}{M_1}\right)\alpha = \frac{8}{5}\alpha \quad \text{and} \\ \left(3 - \frac{3M_3}{M_2}\right)\alpha = \frac{15}{6}\alpha.$$

Fig. 10 Transition graph of repairable 2-out-of-5 model with dependent failures



The transition from state 3 to state -2 occurs because the fourth failed HAP will be located next to the already failed one. Therefore, the HAP failure rate, given that three out of five HAPs have already failed, is equal to 2α .

Since -2 is an absorbing state, repair from a system failure state -2 is not considered.

For the above-mentioned system, the system of Kolmogorov differential equations for the considered Markov process takes the following form:

$$\begin{aligned}
 \frac{d}{dt}\pi_0(t) &= -5\alpha\pi_0(t) + \beta\pi_1(t), \\
 \frac{d}{dt}\pi_1(t) &= -(4\alpha + \beta)\pi_1(t) + 5\alpha\pi_0(t) \\
 &\quad + \beta\pi_2(t), \\
 \frac{d}{dt}\pi_2(t) &= -(3\alpha + \beta)\pi_2(t) + \frac{12}{5}\alpha\pi_1(t) \\
 &\quad + \beta\pi_3(t), \\
 \frac{d}{dt}\pi_3(t) &= -(2\alpha + \beta)\pi_3(t) + \frac{3}{6}\alpha\pi_2(t), \\
 \frac{d}{dt}\pi_{-2}(t) &= \frac{8}{5}\alpha\pi_1(t) + \frac{15}{6}\alpha\pi_2(t) \\
 &\quad + 2\alpha\pi_3(t).
 \end{aligned} \tag{18}$$

Taking $\text{LT } \tilde{\pi}_i(s)$ in the system of Eq. (18) with the initial conditions $\pi_0(0) = 1, \pi_i(0) = 0, i \in E$ and replacing the final equation to the normalization condition $\sum_{i \in E} \pi_i(t) = 1$, we obtain

$$\begin{aligned}
 (s + \lambda_0)\tilde{\pi}_0(s) - \beta\tilde{\pi}_1(s) &= 1, \\
 (s + 4\alpha + \beta)\tilde{\pi}_1(s) - 5\alpha\tilde{\pi}_0(s) \\
 - \beta\tilde{\pi}_2(s) &= 0, \\
 (s + 3\alpha + \beta)\tilde{\pi}_2(s) - \frac{12}{5}\alpha\tilde{\pi}_1(s) \\
 - \beta\tilde{\pi}_3(s) &= 0, \\
 (s + 2\alpha + \beta)\tilde{\pi}_3(s) - \frac{3}{6}\alpha\tilde{\pi}_2(s) &= 0, \\
 s \cdot \sum_{i \in E} \tilde{\pi}_i(s) &= 1,
 \end{aligned}$$

from where we get,

$$\begin{aligned}
\tilde{\pi}_0(s) &= \frac{1 + \beta\tilde{\pi}_1(s)}{s + \lambda_0}, \\
\tilde{\pi}_1(s) &= \frac{5\alpha\tilde{\pi}_0(s) + \beta\tilde{\pi}_2(s)}{s + 4\alpha + \beta}, \\
\tilde{\pi}_2(s) &= \frac{\frac{12}{5}\alpha\tilde{\pi}_1(s) + \beta\tilde{\pi}_3(s)}{s + 3\alpha + \beta}, \\
\tilde{\pi}_3(s) &= \frac{\frac{3}{6}\alpha\tilde{\pi}_2(s)}{s + 2\alpha + \beta}, \\
s \cdot \sum_{i \in E} \tilde{\pi}_i(s) &= 1
\end{aligned}$$

and the reliability function is calculated as per the Eq. (16).

5 Numerical Illustration

This section presents the results of a comparison of analytical and simulation methods to assess the reliability of HAP network, including discrete event modeling and machine learning methods.

5.1 Simulation Algorithm

Discrete event simulation is one of the widely used methods for modeling stochastic systems. It allows modeling the system behavior through changes in its states over random durations. In this paper, the Python programming language is chosen for modeling the system under study. To set up the simulation of a k -out-of- n system, we use the following parameters:

- system parameters, n and k ($k < n$), given as integer values;
- lifetime distribution A with corresponding mean and variance according to an absolute continuous distribution function;
- repair time distribution B with corresponding mean and variance according to an absolute continuous distribution function;
- total simulation time T , which should be as large as possible to enhance the accuracy of results obtained.

During the modeling, reliability measures of the system are calculated. Therefore, the specific parameters to be recorded during simulation should be determined by the overall objectives of the task. Moreover, changing input parameters can provide some results in the sensitivity analysis of the system.

While introducing some additional notation to describe the k -out-of- n model simulation procedure, we first consider the simulation algorithm for the non-repairable k -out-of- n model.

- **Step 1.** Determine parameters to set up the model as described above.

- **Step 2.** The initial system state is 0, that is, all the HAPs are in “UP” state. Determine a vector of HAP’s lifetime according to its distribution A , $X = \{A_1, A_2, \dots, A_n\}$. The first failure occurs in time $\min(A_i)$, $i = \overline{1, n}$, which is the current simulation time t . All the values from X are shifted by this time $\min(A_i)$, after which this value is removed from X .
- **Step 3.** The next state of the system is 1. The failure of the second HAP occurs in time $\min(A_i)$, $i = \overline{1, n-1}$, and the current simulation time t is incremented by the time of the second failure. If the system failure depends on the location of its failed HAPs, then
 - **Step 3.1.** Check if the second failure is adjacent to the previous one. If yes, and the total number of failed adjacent HAPs is k , the system fails.
 - **Step 3.2.** If no, or the number of failed adjacent HAPs is less than k , the system continues to operate. Thus, all values in X are shifted by the current lifetime, and the failure time is removed from X .
 - **Step 3.3.** The system is in state j . Repeat Step 3.1 and Step 3.2, calculating a new failure time $\min(A_i)$, $i = \overline{1, n-j}$, shifting X and removing this time from X after adding it to the current simulation time t .

If the system failure doesn’t depend on the location of its failed HAPs, then calculate a new failure time and update the current simulation time t and vector X according to **Step 3.3** without checking the location of the failed HAP, while the total number of failed HAPs is less than k .

- **Step 4.** The system fails if its k (adjacent or any) HAPs fail. The system returns to state 0, repeating the simulation cycle until $t < T$.
- **Step 5.** If $t \geq T$, calculate the reliability scores $R(t)$ and MTTF.

Thus, during the simulation, the time until the first system failure is collected as statistical data. From this data, the reliability function and MTTF are calculated.

The simulation algorithm of the repairable k -out-of- n model is similar to the one proposed above, with the additional possibility of repairing failed HAPs. After a failure occurs, a recovery time B is generated according to its distribution. If it is less than the next failure time, then a repair occurs. The repair time is added to the current simulation time t . Then all the values from X are shifted to time B , after that a new failure time A_i is generated and added to the vector X . If the time to the next failure is less than the repair completion time, then a failure occurs. The further procedure is repeated according to the steps above, changing the system’s states relative to lifetimes and repair times..

5.1.1 Comparison of Analytical and Simulation Results

This section presents the feasibility of the proposed dependability model through numerical experimentation. We derive the closed form outcomes for the reliability of the multiple HAP system. However, our primary objective in this manuscript is not the precise parameterization of the model; rather, it is to establish a methodology for analytically deriving the network’s dependability attributes. The parameter values utilized to derive the results are $\alpha = 1, 0.5, 0.1$.

The graphical representation of the reliability function is shown in Figs. 11a, 11b, 12a and 12b. The corresponding values of MTTF are presented in Table 2.

When comparing the results of calculated reliability function of the HAPs network, where the failure is determined by either the number of failed HAPs or their specific locations, a notable influence of the latter scenario on the network's reliability becomes apparent. For each mean HAP's lifetime, the MTTF of the HAP network is ≈ 1.8 times higher when system failure depends solely on the number of failures. It is important to emphasize that the second scenario aligns more closely with the real-world problem discussed in this paper.

Note that the ability to repair failed HAPs increases the reliability of the network if the relative recovery rate (the ratio of the mean lifetime to the mean repair time) is $\frac{a}{b} = a\beta > 10$ as shown in Fig. 12a.

By comparing the obtained results of reliability of 2-out-of-5 models with and without consideration of the locations of failed HAPs, it is apparent that the former exhibits higher system reliability. This disparity can be attributed to the fact that while the failure of two adjacent HAPs directly results in system failure, the failure of three HAPs located farther apart does not lead to a simultaneous failure of multiple HAPs.

Fig. 11 Reliability function of the 2-out-of-5 non-repairable system: **(a)** with non-adjacent failures, **(b)** with adjacent failures

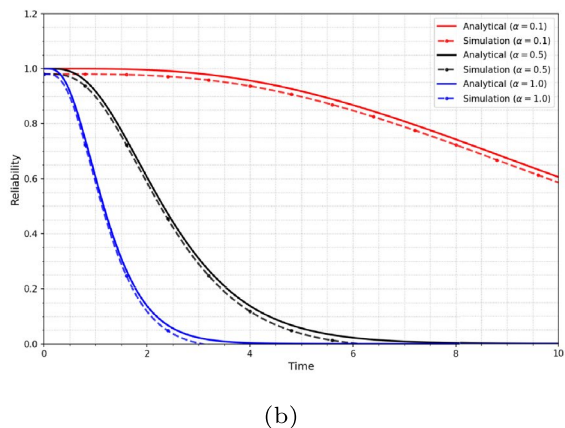
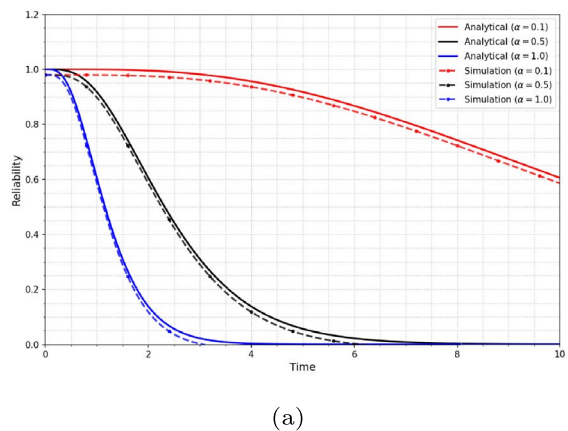
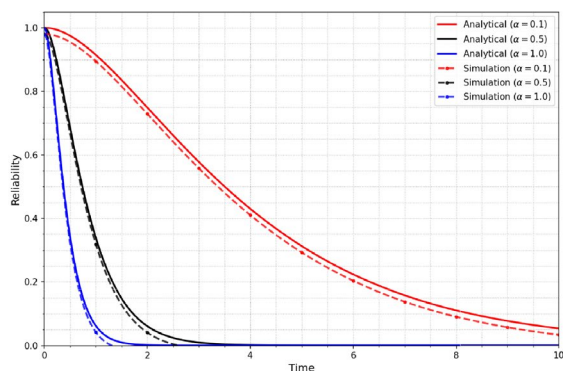
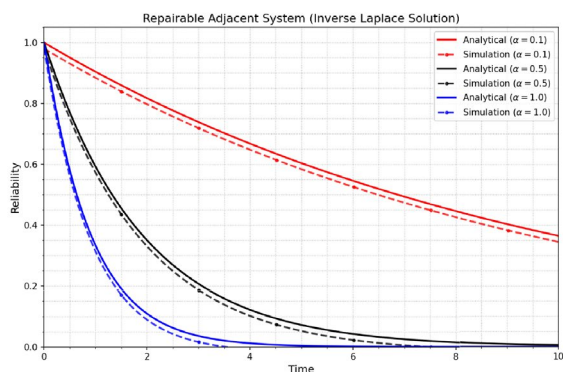


Fig. 12 Reliability function of the 2-out-of-5 repairable System: **(a)** with non-adjacent failures, **(b)** with adjacent failures



(a)



(b)

Table 2 MTTF of multiple HAPs system in 2-out-of-5 model with repair and dependent failures

	$\alpha = 1,$	$a = 0.5,$	$\alpha = 0.1,$	$a = 10$
Non-repairable model	1.2833	2.56667	12.8334	
Non-repairable model with dependent failures	0.7	1.4	7	
Repairable model	0.95	2.9	54.5	
Repairable model with dependent failures	1.728485	5.86121	128.742	

Various potential configurations of HAP network were taken into account, considering the nuances of its operation. It is important to note that all units of measurement utilized in the examples are arbitrary and do not correspond to actual data. Additionally, specific failure and restoration scenarios for HAPs were not taken into consideration.

Due to the computational complexity and time required for analytical reliability analysis, researchers often turn to simulation methods to obtain system reliability estimates. This is particularly relevant when dealing with complex networks involving numerous HAPs, where the initial parameters can vary significantly. In our study, simulation methods, includ-

ing machine learning techniques, are employed to efficiently and accurately estimate the reliability of multiple HAP system networks with diverse and complex configurations.

To validate the accuracy of the simulation model, we conducted experiments using the data from the previous section and compared the results with the numerical examples mentioned earlier. Suppose that $k = 2$, $n = 5$, and assume that both HAP life and repair time follow an exponential distribution for both the numerical and simulation methods. The following parameters are chosen for such an experiment: $\alpha = 1, 0.5, 0.1$, mean lifetime $a = 1, 2, 10$, $\beta = 10$, $b = 0.1$, if the repair is possible. For both cases, variance is equal to 1. In the simulation modeling, the total simulation time should be as long as possible to achieve high accuracy relative to the numerical results, so we set $T = 10^6$. The results of evaluating the reliability function are presented in Figs. 11a, 11b, 12a and 12b.

The simulation is repeated 30 times using the same set of parameters, yielding 30 observations of the performance metric. To evaluate the reliability of the simulation outcomes, a t-test is applied. Since the t-distribution accounts for uncertainty in the sample standard deviation, it is particularly appropriate for relatively small sample sizes. The sample mean and standard deviation of the 30 observations are then computed, and confidence intervals (CIs) are constructed to assess the accuracy of the results. For a 95% confidence level, the CI is given by

$$CI = \bar{X} \pm \frac{s}{\sqrt{k}} t_{\alpha/2, k-1},$$

where $\bar{X}$ is the sample mean, s is the sample standard deviation, k is the number of replications, and $t_{\alpha/2, k-1}$ denotes the tabulated t -value at significance level $\alpha/2$ with $k - 1$ degrees of freedom.

The results of the experiments in Figs. 11a, 11b, 12a and 12b closely match those obtained using the analytical approach in this section. A graphical comparison of the figures illustrates the high degree of convergence and accuracy of the reliability function curves.

Further, we compare the results of MTTF assessment (see Table 3). The results in Table 3 closely align with those obtained above (see Table 2) and show the high accuracy of the simulation-based assessment.

To study the accuracy of results obtained, consider absolute Δ and relative ε errors,

$$\Delta = |MTTF_{th} - MTTF|, \quad \varepsilon = \frac{\Delta}{MTTF_{th}},$$

where $MTTF_{th}$ denotes the values given from the analytical approach, and MTTF is the simulation estimates (see Table 4).

Table 3 MTTF of the multiple HAP system in 2-out-of-5 configuration with repair and dependent failures

	$\alpha = 1$,	$a = 0.5$,	$a = 0.1$,	$a = 10$
Non-repairable model	1.2824	2.5657	12.8384	
Non-repairable model with dependent failures	0.6996	1.4002	6.9948	
Repairable model	0.9494	2.8984	54.4287	
Repairable model with dependent failures	1.7285	5.8796	128.6859	

Table 4 Δ and ε of MTTF of the multiple HAP system in 2-out-of-5 configuration with repair and dependent failures

Errors	$\alpha = 1, \quad a = 1$		$\alpha = 0.5, \quad a = 2$		$\alpha = 0.1, \quad a = 10$	
	Δ	ε	Δ	ε	Δ	ε
Non-repairable model	0.0009	0.0007	0.001	0.0004	0.005	0.0004
Non-repairable model with dependent failures	0.0004	0.0006	0.0002	0.0001	0.0052	0.0007
Repairable model	0.0006	0.0006	0.0016	0.0006	0.0713	0.0013
Repairable model with dependent failures	$1.5 \cdot 10^{-5}$	$8.7 \cdot 10^{-6}$	0.0184	0.0031	0.0561	0.0004

The calculation results confirm the high accuracy of MTTF estimates and validate the constructed simulation model. The maximum absolute error $\max(\Delta) \approx 0.07$ is observed when $a = 10$, and the maximum relative error, $\max(\varepsilon) \approx 0.003$, is obtained when $a = 2$. Therefore, the proposed simulation model effectively describes all the considered models with dependent failures and the possibility of recovery, and it can be employed for more complex scenarios involving varied life and repair time distributions of components.

5.1.2 When the Life and Repair Time Distributions of HAPs Follows Gamma Distribution

The simulation model enables exploration of the reliability of networks where the life and repair times of HAPs in a multiple HAP system follow non-exponential distributions. This is a significant task because the “memoryless” property of the exponential distribution provides a suitable description of the system’s reliability in a stationary mode, independent of time. By extending the simulation model to accommodate non-exponential distributions, we can represent the real-world behavior of complex systems and their reliability over time more accurately.

The Gamma distribution is indeed widely used in reliability theory, and it is suitable for modeling various types of lifetimes and repair times. The Gamma distribution was chosen because its varying shape parameter allows it to effectively model a wide range of non-Markovian behaviors, including those with a dependency on past events. In the case of the non-repairable k -out-of- n model, where the lifetime of HAPs follows a Gamma distribution, and the repairable k -out-of- n model. The repair time of HAPs follows a Gamma distribution while the lifetime follows an exponential distribution. We can analyze the behavior of the model as the coefficient of variation v (CoV) changes. CoV is the ratio of the standard deviation to the mean, and it characterizes the dispersion of the distribution and the degree of variability relative to the mean. By exploring the model’s behavior under varying CoV, we can gain insights into how the variability impacts the reliability of the system. This analysis can provide valuable information for optimizing the design and maintenance of such systems in real-world applications.

Consider, as before, the 2-out-of-5 model for the multiple HAP system, for which

- Non-repairable case: lifetime distribution of one HAP follows Gamma distribution, with mean $a = 10$, and corresponding CoV values $v = 5, 1, 0.5, 0.1$.
- Repairable case: lifetime distribution of one HAP follows an exponential distribution with mean $a = 10$, while the repair time follows a Gamma distribution with mean $b = 1$

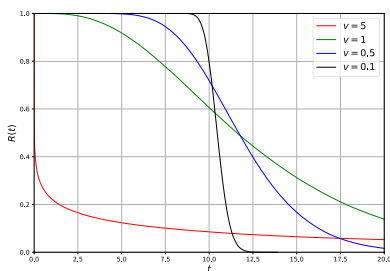
and CoV values $v = 10, 5, 1, 0.5, 0.1$.

The results of the experiments, as depicted in Fig. 13, reveal the significant influence of the CoV (v) on the reliability function of 2-out-of-5 model. In the case of the non-repairable model, an increase in CoV leads to a decrease in reliability, and the curve exhibits a rapid decline towards zero. As v is constrained to be less than or equal to 1, (i.e.), $v \leq 1$, the system's behavior becomes ambiguous. Notably, at the smallest value of $v = 0.1$, the reliability function remains close to 1 up to $t \approx a \approx 10$, after which it decreases rapidly to zero. Furthermore, for $v = 0.5$ and $v = 1$, the reliability function descends more rapidly from 1, yet the decline towards zero occurs at a slower rate as t increases.

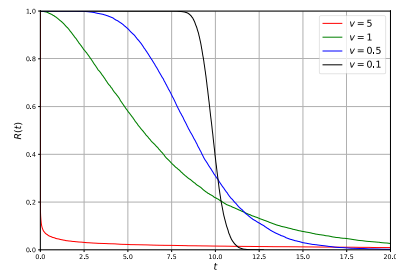
In the case of the repairable model, CoV of the repair time has a distinct impact on the reliability function of the 2-out-of-5 model. Notably, as $v \leq 1$, this influence is not prominent, as the reliability function curves remain quite close to each other. However, when $v > 1$, the reliability function exhibits higher values across the considered interval of t .

The calculated MTTF values using the simulation models are presented in Table 5. These results indicate that CoV for both life and repair time have a notable impact on MTTF.

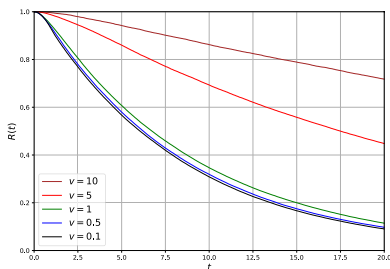
Therefore, it is evident that, when studying the reliability of a multiple HAP system network, understanding not only its mean life and repair time, but also the corresponding CoV is essential. This parameter is derived solely from statistical data and does not exist



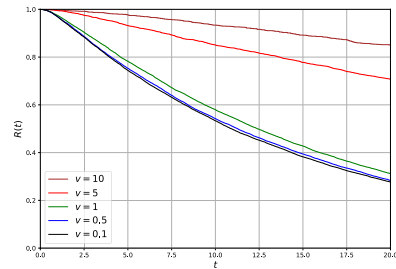
a) $A \sim \Gamma$ in case of non-repairable 2-out-of-5 model



b) $A \sim \Gamma$ in case of non-repairable 2-out-of-5 model with dependent failures



c) $A \sim \text{Exp}$, $B \sim \Gamma$ in case of repairable 2-out-of-5 model



d) $A \sim \text{Exp}$, $B \sim \Gamma$ in case of repairable 2-out-of-5 model with dependent failures

Fig. 13 Reliability of the HAPs network in a 2-out-of-5 configuration with non-exponential life and repair time distribution

Table 5 MTTF of multiple HAP system network in 2-out-of-5 configuration with non-exponential life and repair time distribution

	$v = 10$	$v = 5$	$v = 1$	$v = 0.5$	$v = 0.1$
Non-repairable model	–	4.2820	12.8489	12.0155	10.4791
Non-repairable model with dependent failures	–	0.7179	7.0538	8.8285	9.8331
Repairable model	56.8717	24.43474	9.4991	8.8018	8.5384
Repairable model with dependent failures	136.2756	54.9212	17.4164	15.9889	15.5457

as a technical characteristic. Moreover, by making certain assumptions concerning CoV, a probabilistic analysis of the reliability of the HAP network becomes attainable.

Given the convenience of analyzing the reliability of a multiple HAP system network by varying its initial parameters (k, n), as well as the mean values (a, b) and CoV v , an approach based on the utilization of well-known machine learning methods is proposed for use [21].

5.2 Application of Machine Learning Methods

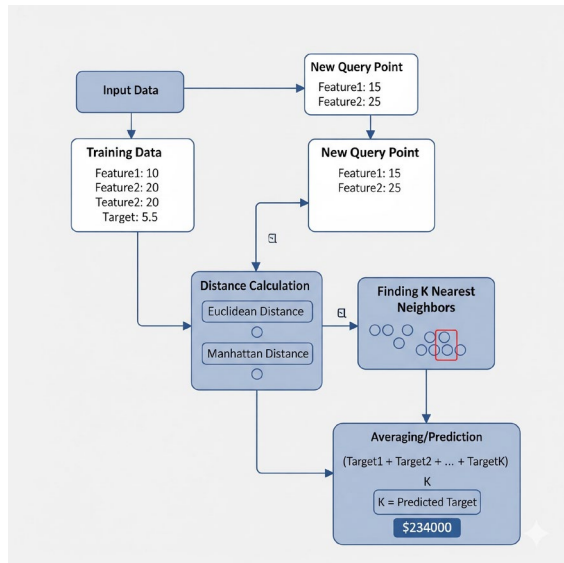
One of the main advantages of using machine learning as a research method is the ability to obtain results quickly after training the model. This becomes particularly important in the context of complex system modeling and design, such as with the HAP networks. The speed and efficiency of obtaining results through machine learning techniques significantly expedite the analysis, design, and optimization of complex systems, allowing for more rapid decision-making and improvements.

The use of K-Nearest Neighbors (KNN) regression for predicting the reliability characteristics of a multiple HAP system network based on the k -out-of- n configuration, as outlined in paper [21], is a compelling approach. The architecture of KNN regression is shown in Fig. 14. The KNN algorithm is renowned for its simplicity and low error rate. Its fundamental principle lies in considering the majority of the k nearest samples to a query point q_i in a given space, and classifying the query point q_i based on the distance in that space. A trained dataset with well-defined classification labels is required initially for this method to be applied effectively [39].

In this study the application of KNN for the prediction of reliability characteristics for multiple HAP system networks using the k -out-of- n configuration involves utilizing the Python programming language and the scikit-learn library. This demonstrates a practical implementation of machine learning techniques to address complex system reliability problems.

5.2.1 Data Collection

To evaluate the reliability $R(t)$ of the multiple HAP system network based on the input data presented in Table 6, several considerations need to be taken into account. The number of HAPs in the network ranges between 4 and 10, and the parameter k is selected within the interval from 2 to $\frac{n}{2}$ rounded up, irrespective of whether the network failure occurs due to

Fig. 14 Architecture of KNN regression**Table 6** Variables and their range

Type	Variable	Symbol	Range
Input	Total number of HAPs	n	$4 - 10$
	Needed number of failed HAPs for network failure	k	$2 - \frac{n}{2}$
	Network uptime with a given level t of reliability		> 0
	<i>For non-repairable model</i>		
	Mean lifetime of one HAP	a	$1 - 10$
	Coefficient of variation	v_a	$0.1 - 1$
	<i>For repairable model</i>		
Output	Mean lifetime of one HAP	a	$1 - 10$
	Mean repair time	b	$0.1a$
	Coefficient of variation	v_b	$1 - 10$
	Reliability	$R(t)$	$0.5 - 1$

adjacent HAPs or only their number. It is important to ensure continuous communication between IoT enabled devices throughout the coverage area of one HAP, even in the event of failures. Consequently, if more than half of the HAPs in a multiple HAP system network fail, the connection may become unstable.

The parameters of average life time a and repair time b of HAPs are determined based on the potential for repair and its absence. Furthermore, assuming that the lifetime is longer than the repair time for repaired multiple HAP systems, as HAPs rarely fail, ensures high performance of the entire communication network system. Consequently, the average repair time b is set to 10% of the average lifetime of one HAP a . The values of CoV, v_a and v_b for life and repair respectively are chosen to maximize the reliability of the system. It is important to note that values $v_b < 1$ are not considered, as in such cases the resulting reliability is

very close to the reliability when $v_b = 1$. Finally, for $R(t)$, it is assumed that the probability of HAPs network operability being ≥ 0.5 is sufficient for ensuring a high level of QoS.

In the evaluation of the reliability using the KNN algorithm, these input parameters are utilized to train the model, which can subsequently be used to predict the reliability $R(t)$ of the multiple-HAP system network under various circumstances and configurations.

To train and validate machine learning models for predicting the reliability $R(t)$ of a multiple HAP system using the k -out-of- n models, four different datasets are generated based on the operating scenarios outlined above, with the help of the simulation model described in Section 5.1 and using the parameters defined in Table 6.

For the non-repairable model, datasets are generated with HAPs' lifetimes following Gamma distribution. In the case of the repairable model, datasets include HAPs' lifetimes and repair times following exponential and Gamma distributions, respectively.

After collecting the datasets, they are divided into a training set with a ratio of 80% and a test set with a ratio of 20%. This division allows training ML models on a subset of the data and subsequently evaluating their performance on a separate subset to ensure their generalization capability. This approach ensures that the machine learning models are trained and tested on diverse datasets that represent different operating scenarios, thereby enabling comprehensive validation and assessment of reliability prediction capabilities of the models under varying conditions.

5.2.2 Preparing for Training

At the training preparation stage, it is necessary to determine the hyperparameters of the KNN method. In our experiments, the following initial parameters were used:

- the number of neighbors is set to 5,
- the weight function is uniform,
- k -fold cross-validation with $n_splits = 10$ and mean squared error as scoring,

The accuracy of predicted results in regression models is typically assessed using standard metrics such as mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2):

$$MSE = \frac{1}{N} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2,$$

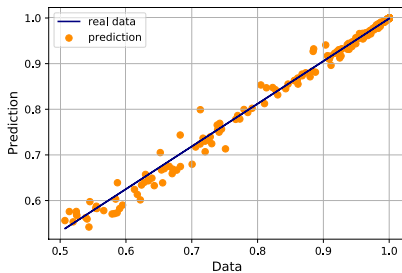
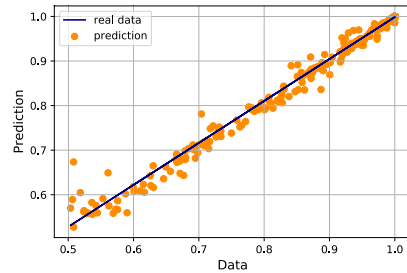
$$MAE = \frac{1}{N} \sum_{i=1}^n |Y_i - \hat{Y}_i|,$$

$$MAPE = \frac{100}{N} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right|,$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^N (y_i - \bar{Y}_i)^2},$$

Table 7 Accuracy of predicting $R(t)$ for non-repairable models

	Simple case		With adjacent failures	
	Training	Testing	Training	Testing
MSE	0.00013	0.00027	0.00014	0.00027
MAE	0.00324	0.00528	0.00376	0.00588
MAPE	0.00492	0.00794	0.00568	0.00877
R^2	0.99115	0.98306	0.99173	0.98426

a) Estimation of $R(t)$ in simple modelb) Estimation of $R(t)$ in model with adjacent failures**Fig. 15** Scatter plots for the test set for non-repairable k -out-of- n models

where Y_i represents the actual value, $\hat{Y}_i$ is the predicted value, and $\bar{Y}_i$ signifies the mean actual value. A more accurate prediction is indicated when MAE, MSE, and MAPE are closer to 0, while R^2 falls within the range of 0 to 1 and should approach a value closer to 1.

5.2.3 Results of Training and Testing with KNN

The application of the ML technique to assess the reliability of k -out-of- n models is demonstrated using the results from training and testing non-repairable models. Table 7 presents the accuracy outcomes for predicting $R(t)$ in both basic scenarios and situations involving dependent failures. Notably, in all cases, the KNN method achieved the lowest prediction errors.

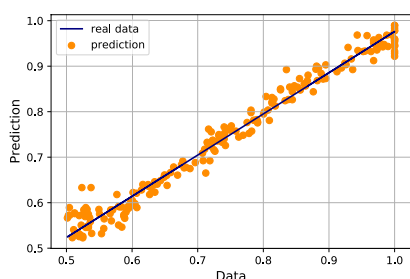
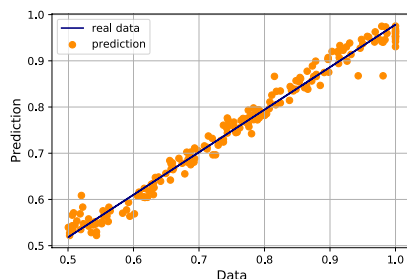
MSE values fall within acceptable ranges, indicating reasonable accuracy. MAE scores measure the relative magnitude of prediction errors, while MAPE shows the average percentage deviation of predicted data from actual values. The R^2 metric quantifies the proportion of variance in the data explained by the model. Together, these results confirm that KNN demonstrates strong predictive performance, evidenced by low MAE, MSE, and MAPE scores alongside high R^2 , reflecting a strong correlation between inputs and outputs.

The prediction results for the test set are visually presented in scatter plots (refer to Fig. 15). Notably, each of these figures is based on a set of 500 randomly selected samples, even though the test sample comprises about 3000 instances. The graphs reveal some degree of deviation in the predicted data from the true values. Despite this, the assessment of $R(t)$ for both models yields satisfactory results.

Now, let's examine the accuracy results for the training and testing of repairable models. Table 8 displays the accuracy estimates for $R(t)$ prediction. Notably, MAE, MSE, and

Table 8 Accuracy of predicting $R(t)$ for repairable models

	Simple case		With adjacent failures	
	Training	Testing	Training	Testing
MSE	0.00037	0.00071	0.00029	0.00051
MAE	0.01333	0.01927	0.01174	0.01652
MAPE	0.01880	0.02717	0.01639	0.02293
	0.98456	0.97003	0.98737	0.97826

a) Estimation of $R(t)$ in Simple Modelb) Estimation of $R(t)$ in Model with Adjacent Failures**Fig. 16** Scatter plots for the test set for repairable k -out-of- n models

MAPE scores are observed to be quite small, while R^2 remains close to 1. These results indicate a high level of accuracy in the predicted data relative to the original values.

Similarly, we can visualize the test results through scatter plots (refer to Fig. 16). These graphs provide visual confirmation of the high accuracy achieved in predicting the reliability of repairable k -out-of- n models using the KNN method.

Therefore, once trained, the model can rapidly and accurately predict the reliability of multiple HAP systems based on k -out-of- n configurations. In the following subsection, we apply the trained ML models to calculate the reliability of a 4-out-of-9 model and compare the results with those obtained from simulation.

5.2.4 Comparison of Simulation Results and Predictions Using Trained KNN

In this subsection, the final validation of reliability predictions using KNN is presented by comparing the results with those obtained from simulation modeling. Let's consider a multiple HAP system consisting of 9 HAPs, where failure occurs if any 4 adjacent HAPs fail, and no repair occurs after a failure, representing a non-repairable 4-out-of-9 model. Assume that the mean lifetime of one HAP is $a = 1$ and its CoV is $v_a = 0.1$ or $v_a = 1$. The comparison of the reliability assessment by KNN with the simulation results is demonstrated graphically in Fig. 17.

Both examples demonstrate the high accuracy achieved in predicting system reliability using the trained KNN model. It is important to note that these reliability estimates were obtained from relatively small sets of initial datasets, which required a significant amount of time. In comparison, simulation modeling took even longer because the total simulation time was determined to be $T = 10^6$ to achieve the best convergence.

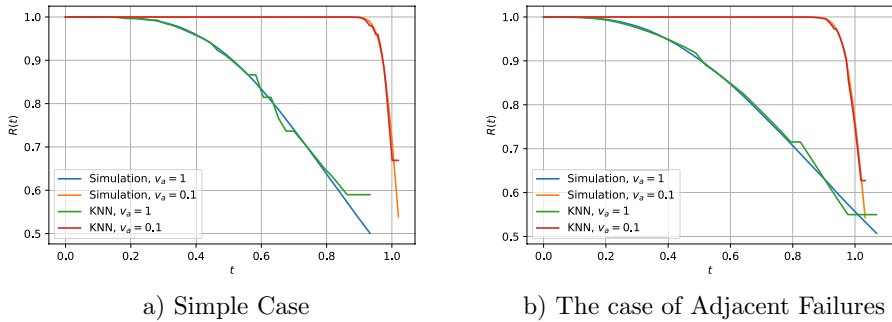


Fig. 17 Comparison of simulation and prediction of KNN for non-repairable 4-out-of-9 models

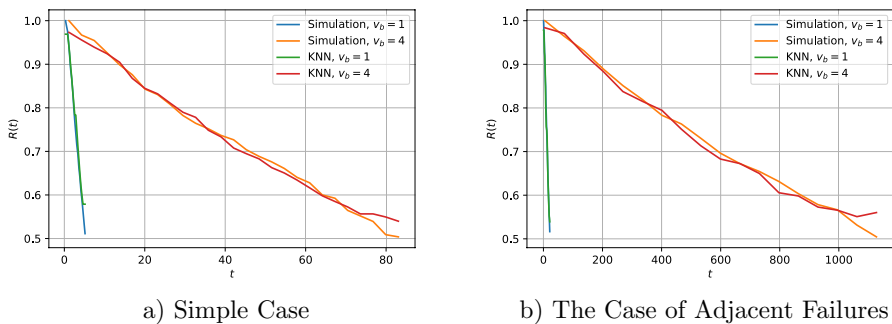


Fig. 18 Comparison of Simulation and Prediction of KNN for Repairable 4-out-of-9 Models

Similarly, let's consider a repairable 4-out-of-9 model, in which the mean HAP's lifetime is $a = 4$, and its mean repair time is $b = 0.4$, with corresponding CoV values of $v_b = 1$ and $v_b = 4$ (see Fig. 18). As with the previous examples, the trained KNN model again demonstrates high accuracy in predicting system reliability compared to simulation results.

6 Reliability Analysis of Communication System based on Different Multiple HAP System Topology

In this section, we examine the reliability of a communication system for IoT-enabled devices based on various multiple HAP system topologies. We present a numerical analysis of the results obtained in the previous sections. Specifically, we focus on equation (7), where $R_{HAPS}(t)$ can be calculated for different multiple HAP system topologies, including k -out-of- n configurations based on both repairable and non-repairable models with dependent failures. To assess the reliability of multiple HAP system as k -out-of- n models, we utilized the results predicted by the trained KNN model.

Consider the reliability of the communication system in which HAPs have the following input parameters,

- mean failure times of system HAPs defined in Section 3 and expressed in years are

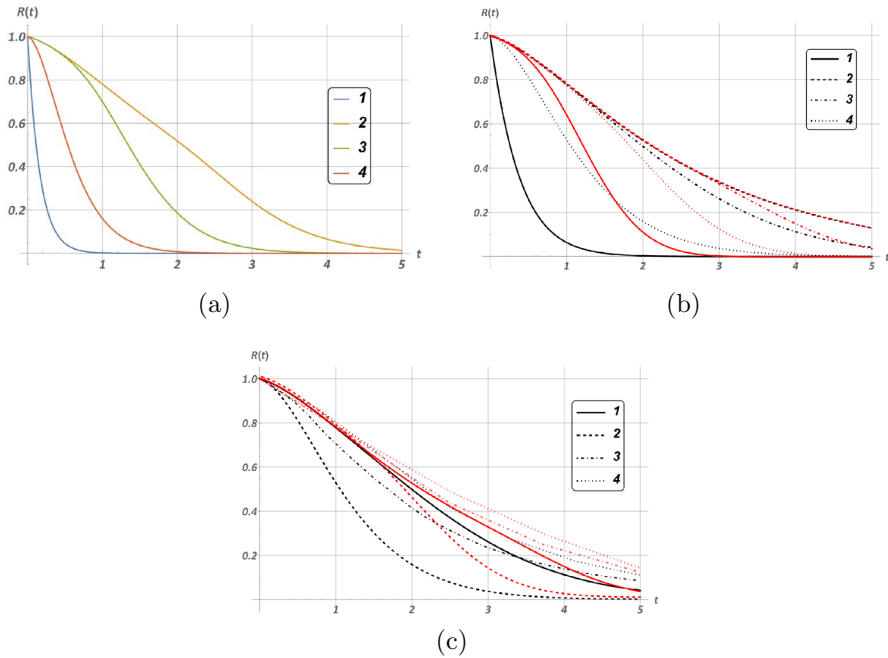


Fig. 19 $R_{SYS}(t)$ (a) Case 1, (b) Case 2 and (c) Case 3

$$\lambda_{CS}^{-1} = 3, \lambda_{CG}^{-1} = 3, \lambda_{TN}^{-1} = 3, \lambda_{FCS}^{-1} = 5, \lambda_{EMS}^{-1} = 5, \lambda_{CPS}^{-1} = 5, \lambda_{SAT}^{-1} = 10;$$

- number of HAPs is $n = 10$, its mean lifetime is $a = 4$ years while its coefficient of variation suppose to be $v_a = 1, 0.5$;
- the minimum number of HAPs at which the system will fail is $k = 4$;
- if repair is available, then its meantime is $b = 0.4$ year while its coefficient of variation takes values $v_b = 1, 3$.

Next, we compare different cases of representing the topology of multiple HAP system within the framework of communication system reliability for IoT-enabled devices.

Case 1. The reliability of one HAP in a multiple HAP system, $R_{HAP}(t)$ is calculated using its components, as described in Sect. 3.2.1 and using Eq. (2). Therefore, its reliability depends on the reliability of its components: FCS, EMS, and CPS. We assume that repair is not available after a HAP failure, and the multiple HAP system has the following topologies:

1. Bus topology Eq. (4);
2. Mesh topology Eq. (3);
3. Non-repairable 4-out-of-10 model Eq. (8);
4. Non-repairable 4-out-of-10 model with adjacent failures Eq. (12).

The results of calculating the reliability function are presented graphically in Fig. 19a. The legend defines the multiple HAP system topology number corresponding to each color of the reliability function $R_{SYS}(t)$ curve. The results indicate that the highest communication reliability is achieved when the multiple HAP system has a mesh topology, while the least

reliable connection is provided by the bus topology. When using 4-out-of-10 configurations, the case where the system failure depends only on the failed HAPs, but not on their location, is preferable, as it results in higher communication reliability compared to other configurations. Additionally, in this case, it is noted that for $t < 1$, the curve of topology 3 is very close to that of topology 2.

It is also noteworthy that, given the initial parameters, the communication system for IoT-enabled devices operates without failure with a probability of more than 80% in less than one year in the case of topology 1, where $R_{SYS}(1) \approx 0.8$. If topology 3 is used, then the system operation time with the same probability is approximately equal to 0.8 years ($R_{SYS}(0.8) \approx 0.8$), which corresponds to roughly 10 months. In the case of topologies 1 and 4, the highly reliable operation time of the system is less than 6 months.

Case 2. The reliability of one HAP in a multiple HAP system $R_{HAP}(t)$ is calculated using the exponential and Gamma distributions with fixed mean lifetime and CoV. For bus and mesh topologies, the reliability functions of one HAP are given by:

$$R_{HAP}(t) = \begin{cases} e^{-t/a}, & \text{if exponentially distributed,} \\ \int_0^\infty \frac{x^{v_a^2-1} e^{-x}}{\Gamma(v_a)} dx, & \text{if follows Gamma distribution} \end{cases}$$

In the case of applying 4-out-of-10 configurations, the results of the trained KNN model are used. Suppose that the multiple HAP system has the same topologies as in Case 1. The graphical results are presented in Fig. 19(b), where black color corresponds to $v_a = 1$, and red color is used for $v_a = 0.5$.

Fig. 19(b) depicts the behavior of the reliability function curves concerning different topologies of a multiple HAP system, which is similar to Case 1. The highest reliability of the communication system is achieved using the mesh topology. On the other hand, Fig. 19(b) demonstrates the influence of the CoV of the lifetime of one HAP on the reliability of the communication system. When considering topologies 1, 3, and 4, a smaller value of v_a for one HAP leads to an increase in the reliability of the entire system. The corresponding curves lie higher compared to the case of $v_a = 1$ with a similar topology. The greatest difference between reliability curves is observed for topologies 1 and 4 at different CoV values. In the case of topology 3, the curves of $R_{SYS}(t)$ are close to each other.

It is interesting to note that in the case of topology 2, the influence of the CoV on the reliability of the communication system is not observed, since the curves corresponding to $v_a = 1$ and $v_a = 0.5$ merge over the entire interval of t . This fact indicates the presence of insensitivity of the reliability function, $R_{SYS}(t)$, to the value of the CoV of the lifetime of one HAP.

Case 3. The reliability of one HAP in multiple HAP system $R_{HAP}(t)$, is calculated using its life and repair time distributions. A multiple HAP system with 4-out-of-10 configurations and available repair is considered. For the reliability prediction of multiple HAP system, the results of the trained KNN model are used. The numbering of the considered configurations of multiple HAP system is designated as follows,

1. Non-repairable 4-out-of-10 model;

2. Non-repairable 4-out-of-10 model with adjacent failures;
3. Repairable 4-out-of-10 model;
4. Repairable 4-out-of-10 model with adjacent failures.

The reliability function of the communication system for IoT-enabled devices is presented in Fig. 19(c). The colors in the figure determine the values of the CoV of life and repair time:

- black color corresponds to the exponential distribution of life and repair time ($A \sim Exp$, $B \sim Exp$, $v_a = v_b = 1$)
- red color is used for $v_a = 0.5$ ($A \sim \Gamma$) in non-repairable models and $v_b = 3$ in repairable ones ($A \sim Exp$, $v_a = 1$, $B \sim \Gamma$).

Here, the solid and dashed curves for topologies 1 and 2 (both black and red) replicate some results from Case 2. They are included to illustrate the impact enabling repair on the reliability of the entire system.

First, we examine the reliability of the communication system within the multiple HAP system, where failure occurs due to the failure of any 4 HAPs (curves 1 and 3). If $A \sim Exp$ and $B \sim Exp$ (black curves), the recovery of failed HAPs in the multiple HAP system does not increase overall communication system reliability. At $t = 1$, the reliability $R_{SYS}(t)$ in the case of the non-repairable 4-out-of-10 model (topology 1) is about 10% higher than in the repairable model (topology 3). If the CoV of either the lifetime v_a or repair time v_b differs from 1 (red curves), then the reliability $R_{SYS}(t)$ increases compared to the case of $v_a = v_b = 1$. In this case, the curves of $R_{SYS}(t)$ are relatively close to each other for $t < 3$. For $t > 3$, a repairable multiple HAP system supports a more reliable communication system compared to the non-repairable model.

The comparison of topologies 2 and 4 reveals the following results. Multiple HAP system configurations with dependent failures and available repair (topology 4) significantly increase the reliability of the communication system compared to the model without repair (topology 2). The dotted curve lies above the dashed curve for both the black and red curves. The influence of the CoV of the life and repair time of HAP is consistent with that observed in topologies 1 and 3.

It should be noted that for $t \leq 1$, the probability of the communication system's operability is approximately the same for all topologies, except for non-repairable models with $v_a = 1$. The group of corresponding curves lies very close to each other, and as $t = 1$, the system's reliability is quite high, with $R_{SYS}(1) = 0.8$. Among all the topologies considered in this example, the repairable 4-out-of-10 configuration with adjacent failures for the multiple HAP system results in the highest reliability of the communication system for IoT-enabled devices. Additionally, this configuration provides the most reliable operation of the entire system compared to all the multiple-HAP topologies examined in Cases 1, 2, and 3.

7 Conclusion, Discussion and Future Work

This paper proposes a hierarchical architecture design for IoT integrated with a multiple HAP system. In order to capture the relationship between HAPs in the multiple HAPs network system and get accurate analytical results, the hierarchical model is further classi-

fied at each level using CTMCs and RBDs. Some features of the functioning of multiple HAP system are considered through both repairable and non-repairable k -out-of- n models, including the case where the failure of adjacent HAPs leads to the failure of the entire system. Performance metrics are obtained analytically and verified by simulation. The results show that reliability and MTTF are maximized when repairable k -out-of- n models with adjacent failures are used. To enable quick and accurate calculation of reliability functions for multiple-HAP systems under k -out-of- n models, the KNN method was applied. The accuracy scores are given and compared using MSE, MAE, MAPE, and R^2 metrics. The reliability analysis of the communication network over IoT-enabled devices for various configurations of multiple HAP system is performed. Among all the topologies, the repairable k -out-of- n model with adjacent failures for multiple HAP system under mesh topology demonstrates the highest reliability for IoT-enabled devices.

This study evaluates the performance of the system and provides useful insights for managers in making informed decisions and designing effective maintenance strategies of multiple HAP system. These strategies aim to enhance system reliability, improve control, and ensure better overall performance. A major concern addressed in the study is the imperfect recovery process, where some issues are not successfully resolved, leading to longer system downtimes. To address this, it is important for system designers and engineers to plan maintainability through appropriate recovery mechanisms. Furthermore, sensitivity analysis supports real-time system improvements by guiding adjustments to key parameters under different conditions, ultimately improving reliability and increasing the MTTF.

In the future, we plan to use unsupervised ML techniques, such as Artificial Neural Networks, Convolution Neural Networks, Support Vector Machines to achieve improved reliability predictions. We also intend to incorporate stochastic geometry or correlated failure processes for a more realistic approach by using explicit spatial distributions and inter-HAP dependencies. We also plan to work on latency and spectrum usage by integrating semi-Markov analysis, RBDs and CTMCs.

Author Contributions Anupam Gautam: Conceptualisation of Model, Model Analysis, Investigation, Research Methodology, Visualisation, Writing-Original draft, Writing-Review and editing. Nika Ivanova: Model Analysis, Investigation, Project administration, Writing-Review and editing. Ishu Jain: Conceptualisation of Model, Model Analysis, Investigation, Research Methodology, Visualisation, Writing-Original draft, Writing-Review and editing. S. Dharmaraja: Project administration, Supervision, Resources, Writing- review and editing.

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Data Availability No datasets were generated or analysed during the current study.

Code Availability Not applicable.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval Not applicable.

Consent for Publication The authors affirm that the research article with figures provided are informed consent for publication.

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