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RESEARCH

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Distributed transmission and optimization of relay-assisted space-air-ground IoT systems

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Abstract

This paper investigates the integration of relay-assisted Internet of Things (IoT) systems, focusing on the use of multiple relays to enhance the system performance. The central metric of interest in this study is system outage probability, evaluated in terms of latency. Our research provides a comprehensive analysis of system outage probability, considering different relay selection criteria to optimize the system's transmission performance. Three relay selection strategies are employed to enhance the system transmission performance. Specifically, the first strategy, optimal relay selection, aims to identify the relay that minimizes the latency and maximizes the data transmission reliability. The second approach, partial relay selection, focuses on selecting a subset of relays strategically to balance the system resources and achieve the latency reduction. The third strategy, random relay selection, explores the potential of opportunistic relay selection without prior knowledge. Through a rigorous investigation, our paper evaluates the impact of these relay selection criteria on the performance of relay-assisted edge computing systems. By assessing the system outage probability in relation to latency, we provide valuable insights into the trade-offs and advantages associated with each selection strategy. Our findings contribute to the design and optimization of reliable and efficient edge computing systems, with implications for various applications, including the IoT and intelligent data processing.

Keywords: Space-air-ground networks, IoT networks, Distributed transmission, Relaying

1 Introduction

The trajectory of information technology development, particularly within Internet of Things (IoT) networks, has been marked by significant progress [1–4]. From the early days with limited coverage and low data rates leading to concerns about transmission outage probability, to the subsequent emergence of cellular IoT and low-power wide-area network (LPWAN) technologies that offered improved reliability and power efficiency, and finally, the advent of fifth-generation (5 G), which introduced high data rates, ultra-low latency, and minimized transmission outage probability, IoT networks have evolved significantly [5–8]. These advances have enabled a wide range of applications, with varying data rate requirements and stringent reliability demands, across industries, heralding a transformative era of real-time connectivity and operational efficiency while continually enhancing key performance metrics such as data rate and symbol error rate (SER) [2, 9–11].

Relaying is an effective technique employed in IoT networks to bolster wireless transmission performance [12–15]. It has a direct impact on key metrics such as outage probability, data rate, and SER. Relaying involves the use of intermediate devices or relay nodes to assist in the transmission of data between the source and destination [16–19]. By strategically positioning relays, it can extend communication range and mitigate the likelihood of transmission failures, thereby reducing outage probability [20–23]. Additionally, relaying can enhance data rates by amplifying signals and facilitating efficient data transmission over extended distances. However, the usage of relays may introduce latency, which could potentially affect data rates, and the quality of relay placement can influence SER either positively by improving signal quality or negatively if noise is introduced. Consequently, judicious relay deployment and signal amplification strategies are crucial to optimize the performance of wireless transmission in IoT networks.

Edge computing is another critical technique in IoT networks aimed at expediting computing tasks by decentralizing data processing and analysis closer to the data source or the network edge, effectively minimizing the system latency, energy consumption, and enhancing overall performance metrics [1]. By moving computation closer to IoT devices, edge computing reduces the round-trip time for data to travel to centralized cloud servers, significantly decreasing the system latency, and enhancing real-time processing capabilities. This approach, in turn, leads to a lower energy consumption as data transmission is minimized [24–27]. In further, it helps mitigate outage probability by ensuring that even if the central cloud server experiences downtime, essential computing tasks can continue at the edge. While edge computing often involves lightweight data processing, it can also optimize the data rate and SER by intelligently filtering, aggregating, or compressing data at the edge, reducing the volume of data transmitted and enhancing the accuracy of communication while conserving network resources. Consequently, edge computing plays a pivotal role in advancing the efficiency and reliability of IoT networks.

Motivated by the above literature review, this paper studies the integration of relay-assisted edge computing systems, with a specific emphasis on leveraging multiple relays to enhance the system performance. The central focal point of this investigation is the system outage probability, assessed within the context of latency. Our research undertakes a thorough and encompassing examination of the system outage probability, encompassing of three relay selection criteria. Specifically, the first strategy, known as the optimal relay selection, strives to pinpoint the relay that minimizes the latency and maximizes the data transmission reliability. In contrast, the second approach, referred to as partial relay selection, concentrates on a judicious selection of relays to harmonize system resources and achieve latency reduction. The third strategy, denoted as random relay selection, explores the potential of a serendipitous relay selection approach, devoid of prior knowledge. Through a comprehensive analysis, this paper scrutinizes the repercussions of these relay selection strategies on the performance of relay-assisted edge computing systems. By evaluating the system outage probability in the context of latency, it offers invaluable insights into the trade-offs and advantages inherent in each selection strategy, ultimately contributing to the refinement and optimization of dependable and efficient edge computing systems, with far-reaching implications across applications such as the IoT and real-time data processing.

2 System and computing models

2.1 System model

Figure 1 shows the system model of an edge computing system from source node S to destination node D, assisted by N decode-and-forward (DF) relays denoted as $\{R_n|1 \leq n \leq N\}$. In this system model, data are transmitted from the source node S to the destination node D via a set of N relay nodes, each labeled as R_n. These relay nodes serve as intermediaries to facilitate the data transmission. The data transmission process includes various parameters such as transmission latency, computation latency, task size, CPU-cycle frequencies, the required CPU cycles for computation, wireless bandwidth, transmit power, additive white Gaussian noise (AWGN), and wireless channel parameters.

The task processing latency for each relay R_n, denoted as T_n, is the sum of the transmission latency (T_n^{trans}) and computation latency (T_n^{comp}). Transmission latency is influenced by wireless parameters like channel conditions, bandwidth, and transmit power, while computation latency is determined by CPU-cycle frequencies and the complexity of the computation tasks. The task size, denoted as L, represents the amount of data to be processed. The processing latency must meet a predefined threshold, denoted as Y_{th}, for successful operation. If the processing latency exceeds this threshold, it leads to an outage scenario.

The outage probability (OP) is defined as the probability of the processing latency exceeding the threshold Y_{th}. This probability is affected by various factors, including the transmission parameters and the wireless channel characteristics, which follow specific distributions such as Rayleigh fading. The system model considers the use of multiple relay nodes to enhance the data transmission and computation, optimizing performance while ensuring that the processing latency remains within acceptable limits.

2.2 Communication and computing process

The task processing latency through relay R_n is written as

$$T_n = T_n^{\text{trans}} + T_n^{\text{comp}}, \tag{1}$$

$$= \frac{L}{W\log_2\left(1+\frac{P|h_{1n}|^2}{\sigma^2}\right)} + \frac{L}{W\log_2\left(1+\frac{P|h_{2n}|^2}{\sigma^2}\right)} + \frac{L\kappa}{f_c}, \tag{2}$$

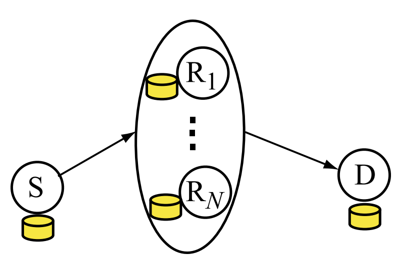

Fig. 1 System model of relay-assisted edge computing systems

where L is the task size, f_c is the CPU-cycle frequencies of D, and κ indicates the required CPU cycles to compute each bit. Moreover, W is the wireless bandwidth, P is the transmit power, σ^2 denotes variance of the additive white Gaussian noise (AWGN), $h_{1n} \sim \mathcal{CN}(0, \alpha)$ is the wireless channel parameter from S to relay R_n, and $h_{2n} \sim \mathcal{CN}(0, \beta)$ is the wireless channel parameter from relay R_n to D. In practice, the processing latency needs to be within a threshold Y_{th}, given by

$$T_n = \frac{L}{W \underbrace{\log_2\left(1 + \frac{P|h_{1n}|^2}{\sigma^2}\right)}_{A_n}} + \frac{L}{W \underbrace{\log_2\left(1 + \frac{P|h_{2n}|^2}{\sigma^2}\right)}_{B_n}} + \frac{L\kappa}{f_c} < Y_{th}. \tag{3}$$

Once the processing latency exceeds a given threshold Y_{th}, the system should be in outage, and the outage probability (OP) is

$$\mathrm{P_{out,n}} = \Pr\left[\frac{L}{WA_n} + \frac{L}{WB_n} + \frac{L\kappa}{f_c} \geq Y_{th}\right], \tag{4}$$

$$= 1 - \Pr\left[\frac{L}{WA_n} + \frac{L}{WB_n} + \frac{L\kappa}{f_c} < Y_{th}\right], \tag{5}$$

$$= 1 - \Pr\left[\frac{1}{A_n} + \frac{1}{B_n} < \frac{W\left(Y_{th} - \frac{L\kappa}{f_c}\right)}{L}\right]. \tag{6}$$

We can further write $\mathrm{P}_{out,n}$ as,

$$\mathrm{P_{out,n}} = 1 - \Pr\left[\frac{A_n + B_n}{A_n B_n} < \frac{W\left(Y_{th} - \frac{L\kappa}{f_c}\right)}{L}\right], \tag{7}$$

$$= 1 - \Pr\left[\frac{A_n B_n}{A_n + B_n} > \frac{L}{W\left(Y_{th} - \frac{L\kappa}{f_c}\right)}\right], \tag{8}$$

where $\frac{A_n B_n}{A_n + B_n} \leq \min(A_n, B_n)$ is applied, and therefore, the lower bound on the outage probability is

$$\mathrm{P}^{LB}_{\mathrm{out,n}} = 1 - \Pr\left[\min(A_n, B_n) > \frac{L}{W(Y_{th} - \frac{L\kappa}{f_c})}\right], \tag{9}$$

$$= 1 - \Pr\left[\min(|h_{1n}|^2, |h_{2n}|^2) > \underbrace{\frac{\sigma^2}{P}\left(2^{\frac{L}{W(Y_{th} - \frac{L\kappa}{f_c})}} - 1\right)}_{C}\right]. \tag{10}$$

As Rayleigh fading environments are considered, the channel gain follows the distribution as

$$|h_{1n}|^2 \sim \exp\left(\frac{1}{\alpha}\right), \tag{11}$$

$$|h_{2n}|^2 \sim \exp\left(\frac{1}{\beta}\right). \tag{12}$$

The CDFs of $|h_{1n}|^2$ and $|h_{2n}|^2$ are

$$F_{|h_{1n}|^2}(x) = 1 - e^{-\frac{x}{\alpha}}, \tag{13}$$

$$F_{|h_{2n}|^2}(y) = 1 - e^{-\frac{y}{\beta}}. \tag{14}$$

When $x \to 0$ and $y \to 0$, we can obtain the asymptotic expression of (13) and (14) as

$$F_{|h_{1n}|^2}(x) \simeq \frac{x}{\alpha}, \tag{15}$$

$$F_{|h_{2n}|^2}(y) \simeq \frac{y}{\beta}. \tag{16}$$

3 Performance analysis

3.1 Outage analysis for optimal relay selection strategy

Optimal relay selection in a network with N relays is a technique used to maximize the data transmission performance by systematically choosing the relay that provides the best channel conditions based on specific criteria such as signal-to-noise ratio or path loss. This selection process reduces the likelihood of transmission failures, enhancing reliability and signal quality. Optimal relay selection can be dynamic or static, adaptable to changing channel conditions, and its complexity varies with the number of relays and measurement requirements. It is a powerful strategy when the performance is critical, as it minimizes the outage probabilities by selecting the most advantageous relay, given by

$$n^* = \underset{1\le n\le N}{\operatorname{argmax}} \min(|h_{1n}|^2, |h_{2n}|^2). \tag{17}$$

According to (9) and (17), the analytical solution of the outage probability is

$$\mathrm{P}_{\mathrm{out,n^*}}^{LB} = 1 - \Pr\left[\min(|h_{1n^*}|^2, |h_{2n^*}|^2) > C\right], \tag{18}$$

$$= 1 - \Pr\left[\max_{1\le n\le N} \min(|h_{1n}|^2, |h_{2n}|^2) > C\right]. \tag{19}$$

We can further write $\mathrm{P}_{\mathrm{out,n^*}}^{LB}$ as,

$$\mathrm{P}_{\mathrm{out,n^*}}^{LB} = \Pr\left[\max_{1\le n\le N} \min(|h_{1n}|^2, |h_{2n}|^2) \le C\right], \tag{20}$$

$$= \Pr\{\min(|h_{11}|^2, |h_{21}|^2 \leq C\} \cdots \Pr\{\min(|h_{1N}|^2, |h_{2N}|^2 \leq C\}. \tag{21}$$

In further, $\mathrm{P}^{LB}_{\mathrm{out,n^*}}$ is derived as,

$$\mathrm{P}^{LB}_{\mathrm{out,n^*}} = \left[1 - \Pr(|h_{11}|^2 > C)\Pr(|h_{21}|^2 > C)\right] \cdots \left[1 - \Pr(|h_{1N}|^2 > C)\Pr(|h_{2N}|^2 > C)\right], \tag{22}$$

$$= \left[1 - (1 - F_{|h_{1n}|^2}(C))(1 - F_{|h_{2n}|^2}(C))\right]^N, \tag{23}$$

$$= \left[1 - e^{-\frac{C}{\alpha}} e^{-\frac{C}{\beta}})\right]^N. \tag{24}$$

According to (15) and (16), we can obtain the asymptotic solution as

$$\mathrm{P}^{LB}_{\mathrm{out,n^*}} \simeq \left[1 - \left(1 - \frac{C}{\alpha}\right)\left(1 - \frac{C}{\beta}\right)\right]^N. \tag{25}$$

$$\simeq \left(\frac{C}{\alpha} + \frac{C}{\beta}\right)^N. \tag{26}$$

3.2 Outage analysis for partial relay selection strategy

Partial relay selection in relaying networks with N relays is a strategy that strikes a balance between the performance optimization and implementation simplicity. Instead of selecting a single relay as in the case of optimal relay selection, partial relay selection involves choosing a subset of the available relays for each transmission. The selection can be based on criteria like signal strength, channel quality, or distance, with the aim of improving reliability without the computational complexity associated with optimal selection. By utilizing only a subset of relays, partial relay selection can enhance the diversity and reduce outage probability, making it a practical compromise when the number of relays is large or when real-time decision-making requirements are stringent. This approach simplifies implementation while still offering improved performance compared to random relay selection, given by

$$n^* = \underset{1 \leq n \leq N}{\operatorname{argmax}} |h_{1n}|^2. \tag{27}$$

According to (9) and (27), the analytical solution of the outage probability is

$$\mathrm{P}^{LB}_{\mathrm{out,n^*}} = 1 - \Pr\left[\min(|h_{1n^*}|^2, |h_{2n}|^2) > C\right], \tag{28}$$

$$= 1 - \Pr\left(|h_{1n^*}|^2 > C\right)\Pr\left(|h_{2n}|^2 > C\right). \tag{29}$$

We can further write $\mathrm{P}^{LB}_{\mathrm{out,n^*}}$ as,

$$\mathrm{P}^{LB}_{\mathrm{out,n^*}} = 1 - \Pr\left(\max_{1 \leq n \leq N} |h_{1n}|^2 > C\right)\Pr\left(|h_{2n}|^2 > C\right), \tag{30}$$

$$= 1 - \left[1 - \Pr\left(\max_{1\le n\le N} |h_{1n}|^2 \le C\right)\right]\left[1 - \Pr\left(|h_{2n}|^2 \le C\right)\right]. \tag{31}$$

In further, $\mathrm{P}^{LB}_{\mathrm{out,n}^*}$ is derived as,

$$\mathrm{P}^{LB}_{\mathrm{out,n}^*} = 1 - \left[1 - \Pr\left(|h_{11}|^2 \le C, ..., |h_{1N}|^2 \le C\right)\right]\left[1 - \Pr\left(|h_{2n}|^2 \le C\right)\right], \tag{32}$$

$$= 1 - \left[1 - \Pr\left(|h_{11}|^2 \le C\right) \cdots \Pr\left(|h_{1N}|^2 \le C\right)\right]\left[1 - \Pr\left(|h_{2n}|^2 \le C\right)\right]. \tag{33}$$

$\mathrm{P_{out,n}}$ can be further derived as,

$$\mathrm{P}^{LB}_{\mathrm{out,n}^*} = 1 - \left[1 - \left(F_{|h_{1n}|^2}(C)\right)^N\right]\left[1 - F_{|h_{2n}|^2(C)}\right], \tag{34}$$

$$= 1 - \left[1 - \left(1 - e^{-\frac{C}{\alpha}}\right)^N\right]e^{-\frac{C}{\beta}}. \tag{35}$$

According to (15) and (16), we can obtain the asymptotic solution as

$$\mathrm{P}^{LB}_{\mathrm{out,n}^*} \simeq 1 - \left[1 - \left(\frac{C}{\alpha}\right)^N\right]\left[1 - \frac{C}{\beta}\right], \tag{36}$$

$$\simeq \left(\frac{C}{\alpha}\right)^N \frac{C}{\beta}, \tag{37}$$

$$= \frac{C^{N+1}}{\alpha^N \beta}. \tag{38}$$

3.3 Outage analysis for random relay selection strategy

Random relay selection in relaying networks with N relays is a straightforward but less sophisticated approach where relays are chosen without considering their channel conditions or specific criteria. In this strategy, the selection of a relay is entirely based on chance, which can be achieved using methods like lottery or a random number generator. While simple to implement, random relay selection lacks the ability to optimize the performance by considering channel quality, leading to less predictable and generally lower overall system performance, as it cannot adapt to changing channel conditions. It is often used in scenarios where computational resources and decision-making complexity are limited and where the performance trade-off is acceptable, making it a cost-effective choice in relatively stable communication environments.

According to (9), we can obtain the analytical solution of the outage probability as

$$\mathrm{P}^{LB}_{\mathrm{out,n}} = 1 - \Pr\left[\min(|h_{1n}|^2, |h_{2n}|^2) > C\right], \tag{39}$$

$$= 1 - \Pr\left(|h_{1n}|^2 > C\right)\Pr\left(|h_{2n}|^2 > C\right). \tag{40}$$

We can further write $\mathrm{P}_{\mathrm{out,n}}^{LB}$ as,

$$\mathrm{P}_{\mathrm{out,n}}^{LB} = 1 - \left[1 - \Pr\left(|h_{1n}|^2 \le C\right)\right]\left[1 - \Pr\left(|h_{2n}|^2 \le C\right)\right], \tag{41}$$

$$= 1 - \left[1 - F_{|h_{1n}|^2}(C)\right]\left[1 - F_{|h_{2n}|^2}(C)\right], \tag{42}$$

$$= 1 - e^{-\frac{C}{\alpha}} e^{-\frac{C}{\beta}}. \tag{43}$$

According to (15) and (16), we can obtain the asymptotic solution as

$$\mathrm{P}_{\mathrm{out,n}}^{LB} \simeq 1 - \left(1 - \frac{C}{\alpha}\right)\left(1 - \frac{C}{\beta}\right), \tag{44}$$

$$= \frac{C}{\alpha} + \frac{C}{\beta}. \tag{45}$$

Note that the trade-off among optimal relay selection, partial relay selection, and random relay selection in cooperative communication systems revolves around balancing outage probability performance and implementation complexity. Optimal relay selection, while offering the best outage probability performance, is complex and computationally intensive, making it suitable for scenarios where performance is paramount. Partial relay selection strikes a balance between the performance and complexity, involving less computation but still requiring some decision-making. In contrast, random relay selection is the simplest to implement but provides the least favorable performance due to its lack of channel quality consideration. The choice of relay selection depends on the specific system requirements, available resources, and the trade-offs that best align with the application's objectives.

4 Simulation results and discussions

In this part, we provide some numerical results to illustrate the impact of network parameters on the system performance for three relay selection strategies. If not specified, we set the number of relays to five. In addition, we set $P = 2$W, $W = 5$MHz, $\alpha = 0.5$, $\beta = 1$, and $\sigma^2 = 1 \times 10^{-2}$. Moreover, the task size L is set to 3Mbits, computational capability f_c is 1GHz, $\kappa = 2$, and the latency threshold $Y_{th} = 0.18$s.

Figure 2 and Table 1 present the outage probability versus P for three strategies, where P varies within the range of 1W to 5W. Observing Fig. 2 and Table 1, we find that the asymptotic results of three strategies become convergent to the analytical ones as P increases. This convergence is attributed to the fact that the increasing P aligns the asymptotic solution more closely with the analytical solution, which thereby verifies the derivation of the analytical and asymptotic expressions of the OP. Moreover, it becomes evident that the OP of the three relay selection strategies experiences a decline as P

Table 1 Numerical outage probability versus *P* for three strategies

Method	Solution	*P* (W)				
		1	2	3	4	5
Optimal	Analytical	0.0011	0.0001	0	0	0
	Asymptotic	0.0017	0.0001	0	0	0
Partial	Analytical	0.0946	0.0484	0.0325	0.0245	0.0196
	Asymptotic	0.0994	0.0496	0.0331	0.0248	0.0198
Random	Analytical	0.2573	0.1382	0.0944	0.0717	0.0578
	Asymptotic	0.2778	0.1438	0.0970	0.0731	0.0587

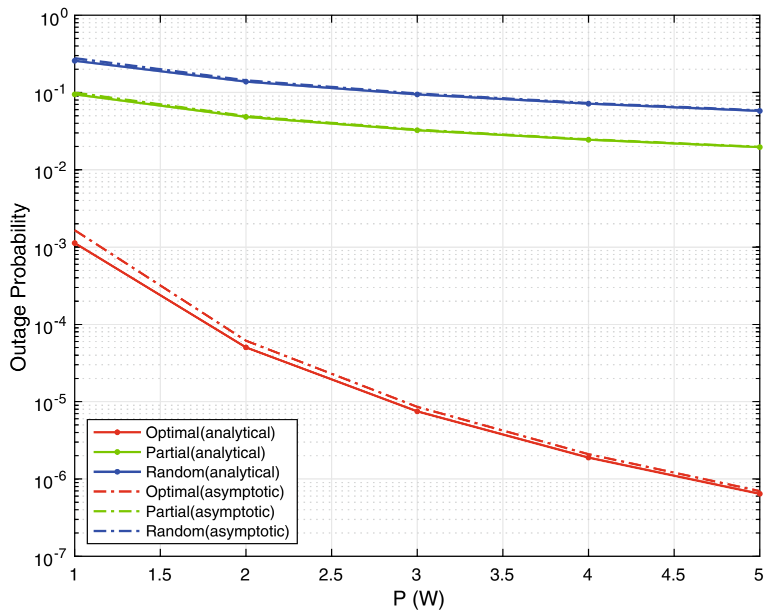

Fig. 2 Outage probability versus *P* for three strategies

increases. This is because that the increasing P results in a high transmit signal-to-noise ratio (SNR), subsequently reducing the transmit latency and consequentially reducing the OP. In further, it is noteworthy that the OP of the optimal strategy exhibits a superiority over that of the other strategies. Specifically, when $P = 5$W, the OP of the optimal method reaches 0, which is 100% lower than that of the other methods. This disparity accentuates the effectiveness and superiority of the optimal strategy.

Figure 3 and Table 2 illustrate the impact of W on the outage probability for three strategies, where W changes from 3MHz to 7MHz. We can find from the figure and Table that the OP of the asymptotic result gradually converges to that of the analytical result when W increases, which verifies the effectiveness of the derived analytical and asymptotic expressions for all strategies. Moreover, it is observed that the OP associated with the three relay selection strategies exhibits a decreasing trend as W increases. The reason is that the increasing W results in a high transmit SNR, thereby reducing the OP. In further, the result in the figure shows that the performance of the optimal strategy is better than those of the other strategies. Specifically, when $W = 7$MHz, the OP of the

Table 2 Numerical impact of *W* on the outage probability of the three strategies

Method	Solution	*W* (MHz)				
		3	4	5	6	7
Optimal	Analytical	0.0487	0.0009	0.0001	0	0
	Asymptotic	0.1176	0.0013	0.0001	0	0
Partial	Analytical	0.2405	0.0900	0.0484	0.0311	0.0223
	Asymptotic	0.2935	0.0944	0.0496	0.0316	0.0226
Random	Analytical	0.5465	0.2462	0.1382	0.0906	0.0655
	Asymptotic	0.6517	0.2649	0.1438	0.0929	0.0667

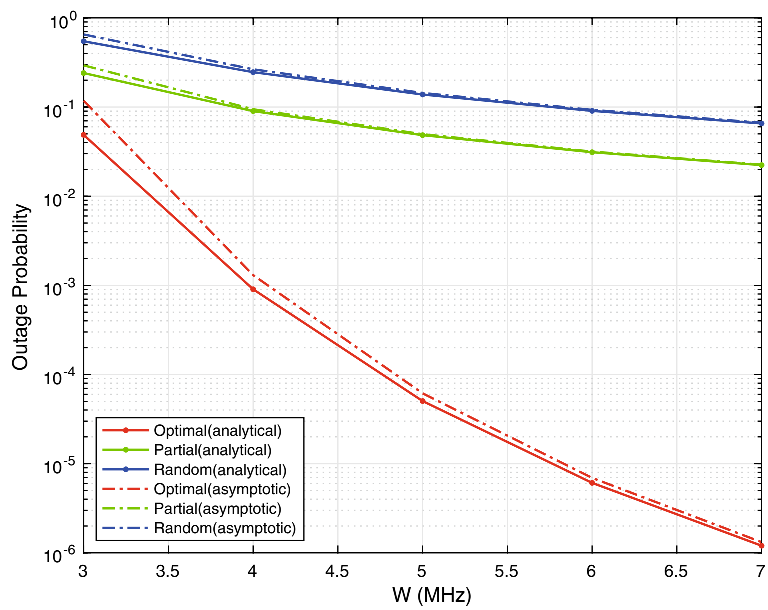

Fig. 3 Impact of *W* on the outage probability of the three strategies

optimal method reaches 0, which is 100% lower than that of the other methods. This verifies the superiority of the optimal strategy.

Figure 4 and Table 3 depict the influence of Y_{th} on the outage probability for three strategies, where Y_{th} varies from 0.1s to 0.5s. Observing from the figure and table, we can find that the asymptotic result gradually converges to that of the analytical one in the high Y_{th} region. This convergence substantiates the effectiveness of the derived analytical and asymptotic solutions. Moreover, it is evident that the OP of the three relay selection strategies decreases as Y_{th} increases, which is attributed to the fact that a larger value of Y_{th} signifies a greater permissible latency within the system, consequently leading to a lower OP. In further, the OP of the optimal strategy is always lower than that of the other strategies. Specifically, when $Y_{th} = 0.5$s, the OP of the optimal method reaches 0, which is 100% lower than that of the other methods. This attests the superiority of the optimal strategy.

Figure 5 and Table 4 illustrate the impact of f_c on the outage probability for three strategies, where f_c varies from 0.2GHz to 1GHz. From this figure and table, we can find that the asymptotic solution is close to the analytical one, which validates

Table 3 Numerical influence of Y_{th} on the outage probability of the three strategies

Method	Solution	Y_{th} (s)				
		0.1	**0.2**	**0.3**	**0.4**	**0.5**
Optimal	Analytical	0.1801	0	0	0	0
	Asymptotic	0.5804	0	0	0	0
Partial	Analytical	0.3749	0.0370	0.0155	0.0093	0.0066
	Asymptotic	0.6363	0.0377	0.0156	0.0094	0.0066
Random	Analytical	0.7097	0.1068	0.0456	0.0277	0.0196
	Asymptotic	0.8969	0.1101	0.0462	0.0279	0.0197

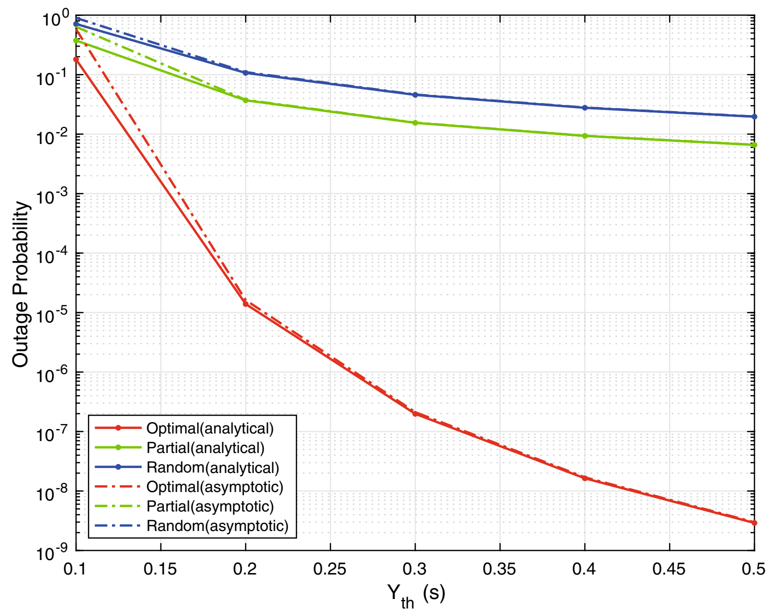

Fig. 4 Influence of Y_{th} on the outage probability of the three strategies

the effectiveness of the derived analytical and asymptotic expressions of the outage probability for three strategies. Moreover, we find that the OP of the three relay selection strategies decreases with the increasing f_c. This is because that a larger f_c results in a lower computational latency, thereby reducing the OP. In further, the optimal strategy is always superior to the other strategies. Specifically, when $f_c = 1$ GHz, the optimal method is 98.96% superior to the other methods. This attests the superiority of the optimal strategy.

Figure 6 and Table 5 depict the impact of L on the outage probability for three strategies, where L varies from 1Mbits to 5Mbits. As observed from this figure and table, we can find that the asymptotic result becomes convergent to the exact one in the low region of L, which validates the effectiveness of the derived analytical and asymptotic expressions of the outage probability for all strategies. Moreover, we find that the OP of the three relay selection strategies increases with the increasing L. This is because that a larger L results in a higher computational latency, thereby increasing the OP. In further, the performance of the optimal strategy is always better than those of the other

Table 4 Numerical impact of f_c on the outage probability of the three strategies

Method	Solution	f_c (GHz)				
		0.2	**0.4**	**0.6**	**0.8**	**1**
Optimal	Analytical	0.332e-3	0.0973e-3	0.0671e-3	0.056e-3	0.0504e-3
	Asymptotic	0.4462e-3	0.1223e-3	0.0829e-3	0.0687e-3	0.0615e-3
Partial	Analytical	0.0723	0.0556	0.0514	0.0495	0.0484
	Asymptotic	0.0751	0.0572	0.0527	0.0507	0.0496
Random	Analytical	0.2015	0.1576	0.1463	0.1412	0.1382
	Asymptotic	0.2137	0.1650	0.1526	0.1470	0.1438

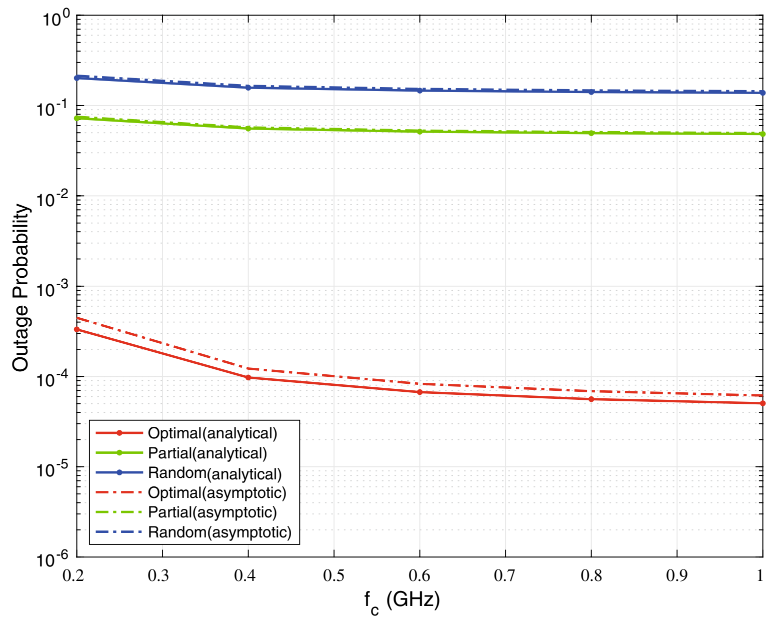

Fig. 5 Impact of f_c on the outage probability of the three strategies

Table 5 Data for Fig. 6

Method	Solution	L (Mbits)				
		1	**2**	**3**	**4**	**5**
Optimal	Analytical	0	0	0.0001	0.0026	0.0662
	Asymptotic	0	0	0.0001	0.0041	0.1701
Partial	Analytical	0.0059	0.0190	0.0484	0.1140	0.2640
	Asymptotic	0.0059	0.0192	0.0496	0.1214	0.3365
Random	Analytical	0.0175	0.0559	0.1382	0.3037	0.5810
	Asymptotic	0.0176	0.0568	0.1438	0.3328	0.7017

strategies. Specifically, when $L = 1$Mbits, the OP of the optimal method reaches 0, which is 100% better than that of the other methods. This validates the superiority of the optimal strategy.

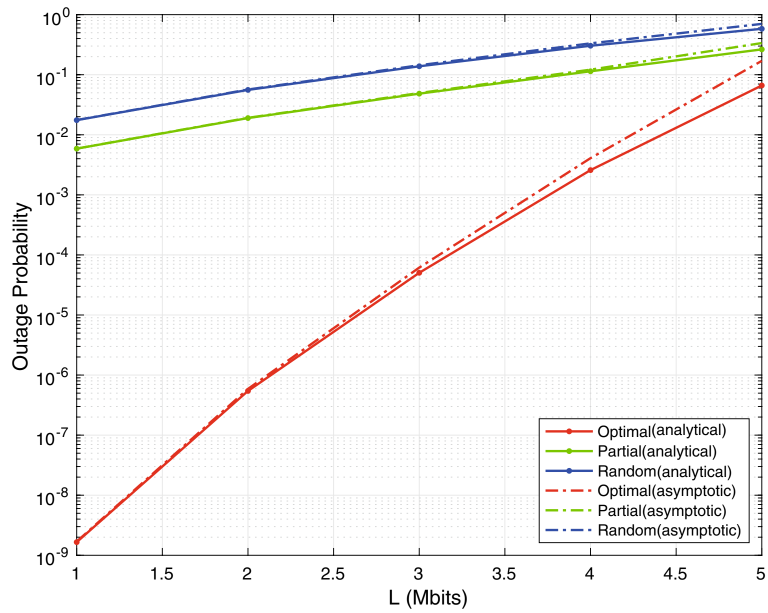

Fig. 6 The impact of *L* on the outage probability for three strategies

5 Conclusions

In conclusion, the investigation into relay-assisted edge computing systems was completed in this work. The use of multiple relays was found to be helpful in enhancing the system performance, particularly in reducing the system outage probability and latency. The comprehensive analysis of system outage probability, involving various relay selection criteria, was undertaken to optimize the system transmission performance. The three relay selection strategies, including optimal relay selection, partial relay selection, and random relay selection, were employed, revealing their respective impacts on enhancing the system transmission. The results demonstrated that optimal relay selection excelled in minimizing the latency and maximizing the data transmission reliability. In contrast, partial relay selection strategically balanced resources and reduced latency, while random relay selection explored opportunistic relay selection without prior knowledge. These findings have contributed to the design and optimization of reliable and efficient edge computing systems, with broad implications for applications, including the IoT and real-time data processing.

Abbreviations

IoT	Internet of Things
LPWAN	Low-power wide-area network
SER	Symbol error rate
DF	Decode-and-forward
AWGN	Additive white Gaussian noise
OP	Outage probability
SNR	Signal-to-noise ratio

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Author contributions
YS was responsible for designing the proposed approach, performing the simulations, and the writing in the manuscript.

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Availability of data and materials
The data for this study can be acquired by emailing the authors.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
All authors of this paper agree to publish the work in this paper.

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The authors declare that they have no competing interests.

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