

Performance Analysis of Multi-Relay Assisted IoT Networks in Mixed Fading Environments

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Abstract

This study studies a multi-relay assisted Internet of Things (IoT) network within the context of mixed fading environments. Here, data transmission from the source to the destination is assisted through multiple decode-and-forward (DF) relays. In particular, this work revolves around mixed fading environments, characterized by the first-hop relaying links conforming to a uniform distribution while the second-hop relaying links exhibit Rayleigh fading. To enhance the overall efficacy of the network, we introduce two relay selection criteria. Specifically, the first criterion entails an optimal selection process hinging on the identification of the most proficient relay. This selection relies upon the channel parameters of dual-hop relaying links. In contrast, the second criterion adopts a sub-optimal selection approach by singling out the optimal relay solely based on the channel parameters of the second-hop relaying links. The performance evaluation of the two aforementioned relay selection criteria entails the derivation of analytical expressions governing the system outage probability. To validate the theoretical works presented in this research, we supplement our analysis with simulation results. Notably, our findings underscore the efficacy of augmenting network performance by augmenting the number of relays within the network topology, even in complicated mixed fading environments.

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Keywords: Multi-relay, IoT, outage probability, mixed fading

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1. Introduction

The evolution of Internet of Things (IoT) networks has been profoundly catalyzed by significant advancements in both mobile communication and edge computing [1–4]. The proliferation of mobile communication technologies, such as the fourth-generation (4G) and fifth-generation (5G), has provided the foundation for seamless connectivity and data exchange across diverse IoT devices [5–8]. These technologies offer higher bandwidth, lower latency, and increased capacity, allowing IoT devices to transmit and receive data more efficiently and reliably. Additionally, the rise of edge computing has revolutionized the way IoT networks function. By enabling data processing and analysis to occur closer to the data source, at the network's edge, edge computing reduces the strain on centralized cloud resources and minimizes latency [9–11]. This

paradigm shift not only accelerates real-time decision-making but also enhances privacy and security by processing sensitive data locally [12–14]. Consequently, the synergy between advanced mobile communication and edge computing has propelled the development of IoT networks, fostering innovation across industries by enabling smarter, more interconnected devices and systems [15–18].

To enhance the performance of IoT networks, relaying protocols have been proposed, which play a pivotal role in enhancing the efficiency and reliability of communication systems, particularly in scenarios where signal degradation and coverage limitations are prevalent [19–21]. Among the notable relaying protocols are decode-and-forward, amplify-and-forward, and denoise-and-forward [22–25]. The decode-and-forward protocol involves the intermediate relay decoding the received signal from the source and subsequently re-encoding it for transmission to the destination. This approach leverages error correction coding

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to mitigate errors and enhance overall reliability [26–28]. Amplify-and-forward, on the other hand, focuses on the relay amplifying the received signal before transmitting it to the destination. While it avoids the need for decoding, it is susceptible to noise and amplification distortion. Denoise-and-forward stands out by employing advanced signal processing techniques at the relay to suppress noise before transmitting to the destination. This protocol particularly excels in scenarios with high noise levels [29–31]. Each of these relaying protocols presents a distinct trade-off between complexity, performance, and practical implementation considerations, making their selection contingent on the specific communication environment and network requirements.

The integration of multiple relays into communication systems offers a host of advantages that significantly augment system performance and robustness [32–34]. One of the foremost benefits lies in the reduction of system outage probability and symbol error rate. By employing multiple relays, the network gains improved spatial diversity, effectively mitigating the adverse effects of fading and signal attenuation [35–37]. The increase in diversity order translates to enhanced reliability as the likelihood of simultaneous signal degradation across all relays diminishes, resulting in more consistent and reliable data transmission. The collaborative efforts of multiple relays in forwarding signals amplify the received signal strength at the destination, thereby bolstering the signal-to-noise ratio (SNR). This collective reinforcement, in turn, leads to reduced error rates and better overall communication quality [38–41]. In essence, the incorporation of multiple relays harnesses the inherent diversity within the communication environment, transforming it into a valuable asset that elevates the system performance and reinforces the seamless connectivity.

Motivated by the above literature review, this work investigates a multi-relay assisted IoT network within the context of mixed fading environments. In this setting, data transmission from the source to destination is assisted by multiple decode-and-forward relays. In particular, our investigation centers on mixed fading environments, characterized by the first-hop relaying links adhering to a uniform distribution, while the second-hop relaying links are subject to Rayleigh fading. To enhance the overall efficiency of the network, we introduce two relay selection criteria. Specifically, the first criterion involves an optimal selection process pivoting on the identification of the most proficient relay, relying on the channel parameters of dual-hop relaying links. In contrast, the second criterion adopts a sub-optimal selection approach, singling out the optimal relay based solely on the channel parameters of the second-hop relaying links. Evaluating the performance of these relay selection

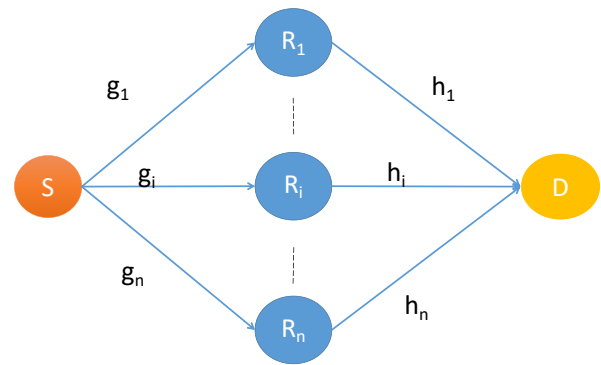


Figure 1. System model of multi-relay assisted IoT Networks in mixed fading environments.

criteria necessitates deriving analytical expressions governing the system overall outage probability. To validate the theoretical foundations presented in this research, we complement our analysis with simulation results, notably underscoring the efficacy of improving network performance by increasing the number of relays within the network topology, even in complicated mixed fading environments.

2. System Model of Multi-relay assisted IoT network structure

Fig. 1 shows the system model of multi-relay assisted IoT networks in mixed fading environments, where S is the transmit node, D is the receive node. Between S and D , there are n decode-and-forward (DF) relays denoted by $\{R_i | i \in [1, n]\}$, where n is the total number of relays. Through establishing multiple relay nodes, the network topology with redundant paths can be formed. When a node fails or the signal quality decreases, other nodes can take over signal transmission to ensure continuity of communication, reduce the risk of signal interruption, and improve communication reliability.

Let x_S be the transmitted signal, and then the received signal at the i -th relay node can be expressed as

$$y_{R_i} = g_i * \sqrt{P} * x_S + n_R, \quad (1)$$

where $n_R \sim CN(0, \sigma^2)$ is the white noise, P is the transmit power at the source, and g_i is the wireless channel from S to R_i where its probability density function (PDF) is expressed as

$$f_{|g_i|^2}(u) = \begin{cases} \frac{1}{\theta_b - \theta_a}, & \text{If } u \in [\theta_a, \theta_b] \\ 0, & \text{Otherwise} \end{cases} \quad (2)$$

From y_{R_i} , the relay R_i can decode the transmitted signal, and then send the decoded signal to the destination D . Accordingly, the received signal at D is,

$$y_D = h_i * \sqrt{P} * x_S + n_D, \quad (3)$$

where $n_D \sim CN(0, \sigma^2)$ is the white noise, h_i is the wireless channel from R_i to D and its probability density function (PDF) is expressed as

$$f_{|h_i|^2}(v) = \begin{cases} \frac{1}{\alpha} e^{-\frac{v}{\alpha}}, & \text{If } v > 0 \\ 0, & \text{Otherwise} \end{cases} \quad (4)$$

From the above equations, we can write the end-to-end received signal-to-noise ratio (SNR) with the i -th relay as,

$$\text{SNR}_{e2e,i} = \frac{P}{\sigma^2} \min(|h_i|^2, |g_i|^2). \quad (5)$$

3. System optimization and performance analysis

3.1. Relay selection

To enhance the network performance, we can choose one best relay among n ones to assist the data transmission from S to D . When the channel state information (CSI) of dual-hop relaying links is available, we can perform the relay selection according to the following criterion,

$$n^* = \arg \max_{1 \leq i \leq n} \min(|g_i|^2, |h_i|^2). \quad (6)$$

Note that this relay selection process based on dual-hop relaying links involves a strategic approach to optimize the network performance, which aims to identify the most suitable relay for the data transmission by evaluating both fading conditions of the relay channels and ensuing signal quality. The selected relay, denoted as R_{n^*} , is determined by the relay index i that maximizes the minimum value between the squared magnitudes of the corresponding dual-hop relaying links g_i and h_i . By employing this selection criterion, the system seeks to strike a balance between the various relay options, considering both the quality of the individual relaying links and their collective impact on the data transmission reliability. This criterion ensures an optimal relay choice that capitalizes on the available resources and the network overall resilience against fading effects.

When only the CSI of the second-hop relaying links is available, we can perform the relay selection according to the following criterion,

$$n^* = \arg \max_{1 \leq i \leq n} |h_i|^2. \quad (7)$$

Note that the above partial selection criterion, rooted in the second-hop relaying links, offers a pragmatic strategy for optimizing the relay selection within the network. In this criterion, the selected relay R_{n^*} focuses exclusively on the squared magnitude of the second-hop relaying links h_i across the available relay

options indexed from 1 to n . By selecting the relay index i that maximizes this criterion, the system selects the relay with the strongest second-hop relaying link, thereby enhancing the signal quality during the second-hop data transmission. This criterion is particularly beneficial in scenarios where the second-hop relaying links are more indicative of improved transmission conditions, enabling a sub-optimal yet efficient relay choice. Through this criterion, the network can efficiently capitalize on the favorable aspects of second-hop relaying links to bolster the overall communication reliability.

3.2. Outage probability analysis

The outage probability of the data transmission from S to D associated with the i -th relay can be described as,

$$P_{out,i} = \Pr(\text{SNR}_{e2e,i} < Y_{th}), \quad (8)$$

where Y_{th} is the threshold of targeted SNR. We firstly derive the analytical expression of outage probability when there is only one relay. Specifically, from the expression of $\text{SNR}_{e2e,i}$, we can re-write $P_{out,i}$ as

$$P_{out,i} = \Pr\left(\min(|g_i|^2, |h_i|^2) < \frac{Y_{th}\sigma^2}{P}\right), \quad (9)$$

$$= 1 - \Pr\left(\min(|g_i|^2, |h_i|^2) > \frac{Y_{th}\sigma^2}{P}\right). \quad (10)$$

According to the distribution of $|g_i|^2$ and $|h_i|^2$, $P_{out,i}$ can be derived as

$$P_{out,i} = 1 - \left(1 - \Pr\left(|g_i|^2 < \frac{Y_{th}\sigma^2}{P}\right)\right) \left(1 - \Pr\left(|h_i|^2 < \frac{Y_{th}\sigma^2}{P}\right)\right), \quad (11)$$

$$= 1 - \left(1 - \int_{\theta_a}^{\frac{Y_{th}\sigma^2}{P}} \frac{1}{\theta_b - \theta_a} du\right) \left(1 - \int_0^{\frac{Y_{th}\sigma^2}{P}} \frac{1}{\alpha} e^{-\frac{v}{\alpha}} dv\right), \quad (12)$$

$$= 1 - \left(1 - \frac{\frac{Y_{th}\sigma^2}{P} - \theta_a}{\theta_b - \theta_a}\right) e^{-\frac{Y_{th}\sigma^2}{P\alpha}}, \quad (13)$$

where $\theta_a < \frac{Y_{th}\sigma^2}{P} < \theta_b$.

From the above analytical outage probability of the system with only one relay, we proceed to derive the analytical outage probability with multiple relays. For criterion I performed in (6), the system outage probability can be expressed as,

$$P_{I,out} = \Pr\left(\text{SNR}_{e2e,n^*} < Y_{th}\right), \quad (14)$$

$$= \Pr\left(\min(|g_{n^*}|^2, |h_{n^*}|^2) < \frac{Y_{th}\sigma^2}{P}\right). \quad (15)$$

Due to the independence between the dual-hop relaying links, we can further write $P_{I,out}$ as

$$P_{I,out} = 1 - \left(1 - \Pr \left(|g_{n^*}|^2 < \frac{Y_{th}\sigma^2}{P} \right) \right) \times \left(1 - \Pr \left(|h_{n^*}|^2 < \frac{Y_{th}\sigma^2}{P} \right) \right). \quad (16)$$

As $n^* = \arg \max_{1 \leq i \leq n} \min(|g_i|^2, |h_i|^2)$, we can write the analytical form of P_{out} from the theory of order statistics as

$$P_{I,out} = \left(1 - \left(1 - \frac{Y_{th}\sigma^2}{\theta_b - \theta_a} \right) e^{-\frac{Y_{th}\sigma^2}{P\alpha}} \right)^n. \quad (17)$$

On the other hand, when we use criterion II in (7) to choose the best relay to assist the data transmission, we should firstly analyze the distribution of $|h_{n^*}|^2$ before deriving the analytical expression for the system outage probability. In particular, the distribution of $|h_{n^*}|^2$ can be derived as

$$F_{|h_{n^*}|^2}(v) = \Pr(|h_{n^*}|^2 < v), \quad (18)$$

$$= \Pr(|h_1|^2 < v) \cdot \Pr(|h_2|^2 < v) \cdots \Pr(|h_n|^2 < v), \quad (19)$$

$$= \sum_{i=0}^n (-1)^i \binom{n}{i} e^{-\frac{iv}{\alpha}}, \quad (20)$$

where $n^* = \arg \max_{1 \leq i \leq n} (|h_i|^2)$ is applied. From the above distribution of $|h_{n^*}|^2$, we can readily derive the analytical expression of outage probability for criterion II as,

$$P_{out,II} = 1 - \left(1 - \frac{Y_{th}\sigma^2}{\theta_b - \theta_a} \right) \left(1 - \sum_{i=0}^n (-1)^i \binom{n}{i} e^{-\frac{iY_{th}\sigma^2}{P\alpha}} \right). \quad (21)$$

4. Experimental results and discussions

In this section, we present the simulation results to validate the analytical findings. Specifically, we will analyze the impact of network parameters such as P , Y_{th} , α , and n in the following experiments to verify the analytical results. The experiments in this section are divided into two parts, whereas the first part focuses on the IoT with a single relay, while the second part examines the IoT with multiple relays. The parameters θ_a and θ_b are set to 0 and 100, respectively, and σ^2 is set to 3.

4.1. Outage probability of the system with $n = 1$.

This part demonstrates the impact of network parameters on the system performance, when there is only

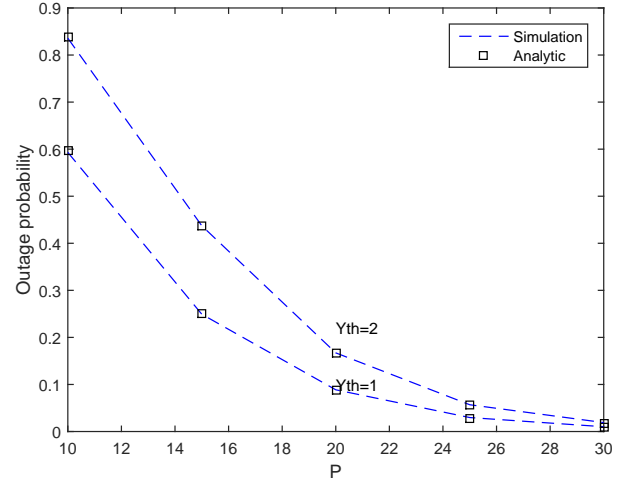


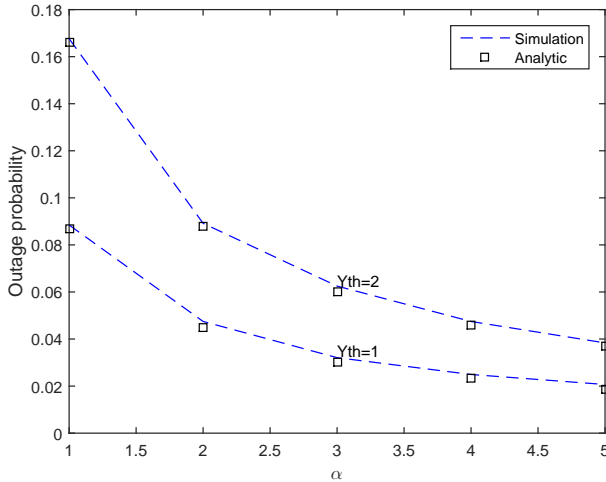
Figure 2. System outage probability with $n = 1$ versus P and Y_{th} .

one relay with $n = 1$. In the first experiment, we set $\alpha = 1$, $P \in [10, 15, 20, 25, 30]$, and $Y_{th} \in [1.0, 2.0]$. The experimental results are shown in Fig. 2 and Table 1. As depicted in Fig. 2 and Table 1, one can observe that the simulation and analytical results exhibit similar values for various values of Y_{th} and P . For instance, when $Y_{th} = 1.0$ and $P = 10\text{dB}$, the simulation result is 0.5959, whereas the analytical result is 0.5971, yielding a difference of only 0.0012. Similarly, for $Y_{th} = 2.0$ and $P = 30\text{dB}$, the simulation result is 0.0190, whereas the analytical result is 0.0186, yielding a difference of only 0.0004. Based on these findings, it can be concluded that the simulation results validate the analytical results, indicating the accuracy of the derived analytical outage probability. Moreover, there are two curves in Fig. 2 corresponding to two distinct values of Y_{th} , namely $Y_{th} = 1.0$ and $Y_{th} = 2.0$. The curve associated with $Y_{th} = 2.0$ lies above the curve with $Y_{th} = 1.0$, as a smaller threshold indicates an increased delay tolerance, thereby enhancing the system performance. In further, the results for both curves demonstrate that as P increases, the system outage probability decreases. This outcome signifies that a higher value of P can enhance the transmission capability for the considered system.

In the second experiment, we set $P = 20\text{dB}$, $\alpha \in [1, 2, 3, 4, 5]$, and $Y_{th} \in [1.0, 2.0]$. In Table 2 and Fig. 3, we present the experimental results for the system with respect to Y_{th} and α . As shown in Table 2 and Fig. 3, one can find that the simulation and analytical results yield similar values for different values of Y_{th} and α . For instance, when $Y_{th} = 1.0$ and $\alpha = 1$, the simulation result is 0.0885, while the analytical result is 0.0869, resulting in a difference of only 0.0016. Similarly, when $Y_{th} = 2.0$ and $\alpha = 5$, the simulation result is 0.0384,

Table 1. Numerical outage probability with $n = 1$ versus P and Y_{th} .

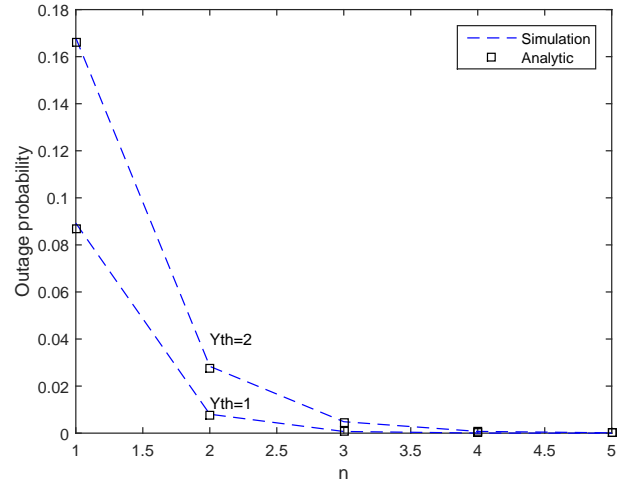
Methods	Y_{th}	P/dB				
		10	15	20	25	30
Simulation	1.0	0.5959	0.2528	0.0901	0.0298	0.0101
	2.0	0.8365	0.4368	0.1675	0.0564	0.0190
Analysis	1.0	0.5971	0.2498	0.0869	0.0283	0.0090
	2.0	0.8377	0.4372	0.1662	0.0559	0.00186

**Figure 3.** System outage probability with $n = 1$ versus α and Y_{th} .

while the analytical result is 0.0371, resulting in a difference of only 0.0013. Based on these findings, it can be concluded that the simulation results verify the accuracy of the analytical results, thus validating the effectiveness of the system analysis. Moreover, two curves in Fig. 3 representing different values of Y_{th} are plotted, namely $Y_{th} = 1.0$ and $Y_{th} = 2.0$. The curve corresponding to $Y_{th} = 2.0$ is located above the curve associated with $Y_{th} = 1.0$ due to a smaller latency threshold leading to an improved system performance. Additionally, the results for both curves reveal that the system outage probability decreases as α increases. This outcome indicates that a higher value of α can enhance the wireless transmission quality for the considered system.

4.2. Outage probability of the system with $n > 1$.

In this part, we perform the simulations in terms of the system outage probability with multiple relays, where $n \in [1, 2, 3, 4, 5]$ and relay selection criterion I or II is employed. When criterion I is used, the associated experimental results are shown in Fig. 4 and Table 3. As demonstrated in Fig. 4 and Table 3, one can see that the simulation and analytical results exhibit similar values for various values of Y_{th} and n . For example, when $Y_{th} =$

**Figure 4.** System outage probability versus relay number n and Y_{th} for criterion I.

1.0 and $n = 1$, the simulation result is 0.0876, while the analytical result is 0.0869, yielding a difference of only 0.0007. Similarly, when $Y_{th} = 2.0$ and $n = 5$, the simulation result is 0.0001, while the analytical result is 0.0001, which is the same as each other. These findings lead to the conclusion that the simulation results validate the accuracy of the analytical results, thereby confirming the effectiveness of the system analysis on the outage probability. Moreover, the two curves in Fig. 4 are plotted representing different values of Y_{th} , namely $Y_{th} = 1.0$ and $Y_{th} = 2.0$. The curve associated with $Y_{th} = 2$ is positioned above the curve corresponding to $Y_{th} = 1.0$ due to the a lower threshold. Additionally, the results for both curves reveal that the system outage probability decreases as n increases. This outcome suggests that a higher value of n can help enhance the transmission quality effectively for criterion I.

For criterion II with multiple relays, the experimental results are shown in Fig. 5 and Table 4. As shown in Fig. 5 and Table 4, one can obtain that the simulation results and analytical results demonstrate similar values for different values of Y_{th} and n . For instance, when $Y_{th} = 1.0$ and $n = 1$, the simulation result is 0.0885, while the analytical result is 0.0869, resulting in a difference of

Table 2. Numerical outage probability with $n = 1$ versus α and Y_{th} .

Methods	Y_{th}	α				
		1	2	3	4	5
Simulation	1.0	0.0885	0.0475	0.0321	0.0249	0.0207
	2.0	0.1676	0.0892	0.0625	0.0475	0.0384
Analysis	1.0	0.0869	0.0449	0.0304	0.0231	0.0187
	2.0	0.1662	0.0877	0.0599	0.0457	0.0371

Table 3. Numerical outage probability versus relay number n and Y_{th} for criterion I.

Methods	Y_{th}	n				
		1	2	3	4	5
Simulation	1.0	0.0876	0.0076	0.0007	0.0001	0.0000
	2.0	0.1680	0.0275	0.0049	0.0008	0.0001
Analysis	1.0	0.0869	0.0076	0.0007	0.0001	0.0000
	2.0	0.1662	0.0276	0.0046	0.0008	0.0001

only 0.0016. Similarly, when $Y_{th} = 2.0$ and $n = 5$, the simulation result is 0.0044, while the analytical result is 0.00019, resulting in a difference of only 0.0025. These observations lead to the conclusion that the simulation results validate the accuracy of the analytical results, thereby confirming the effectiveness of the system analysis on the outage probability. Moreover, the two curves in Fig. 4 are plotted representing different values of Y_{th} , namely $Y_{th} = 1.0$ and $Y_{th} = 2.0$. In particular, the curve associated with $Y_{th} = 2.0$ is positioned above the curve corresponding to $Y_{th} = 1.0$ due to a lower threshold enhancing the system performance. In further, the results for both curves reveal that the system outage probability decreases as n increases. This outcome suggests that a higher value of n can help enhance the transmission quality effectively for criterion II.

5. Conclusions

In conclusion, this paper has extensively investigated multi-relay assisted IoT networks in mixed fading environments. Through the use of DF relays, data transmission has been facilitated from source to destination. The study’s focal point was on mixed fading environments, particularly those characterized by distinct fading behaviors in the first-hop and second-hop relaying links. The introduction of two relay selection criteria has been pivotal in enhancing the overall network efficiency. The optimal selection criterion, which centers around identifying the most proficient relay based on dual-hop relaying links, and the sub-optimal selection criterion, which chooses the optimal relay based on the second-hop relaying link characteristics, have been provided. The evaluation of these criteria’s performance involved the derivation of analytical expressions governing the system outage probability. The validity of the

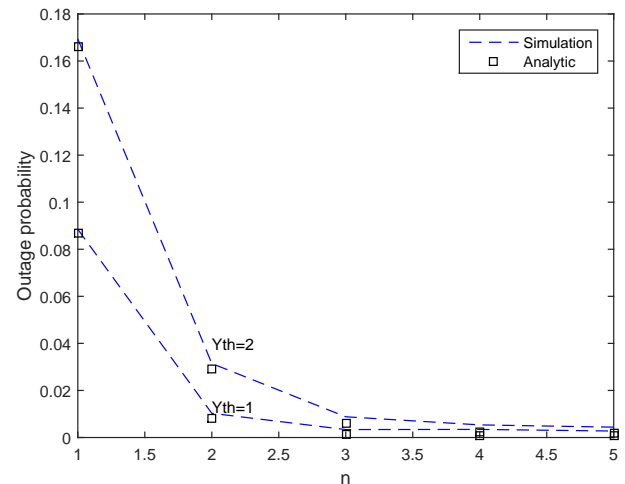


Figure 5. System outage probability versus relay number n and Y_{th} for criterion II.

theoretical framework has been demonstrated through comprehensive simulation results. Notably, the research findings underscore the positive impact of increasing the number of relays in the network topology on enhancing network performance, even in complicated mixed fading environments.

5.1. Copyright

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Table 4. Numerical outage probability versus relay number n and Y_{th} for criterion II.

Methods	Y_{th}	n				
		1	2	3	4	5
Simulation	1.0	0.0885	0.00.0103	0.0034	0.0034	0.0027
	2.0	0.1674	0.0295	0.0081	0.0049	0.0044
Analysis	1.0	0.0869	0.0083	0.0015	0.0010	0.0010
	2.0	0.1662	0.0289	0.0063	0.0025	0.0019

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