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Outage Probability Analysis of Multi-hop Relay Aided IoT Networks

Fusheng Wei[1,*], Jiajia Huang[1], Jingming Zhao[1], and Huakun Que[1]

[1]Guangdong Power Grid Co., Ltd, Guangzhou, China.

Abstract

In this paper, we investigate an Internet of Things (IoT) network in severe fading environments, where the source sends some information to the destination. Due to the fading obstacle, the source cannot directly send the information to the destination. To tackle this issue, we consider the communication of IoT networks assisted by multi-hop relaying, where multiple relays can help assist the data transmission from the source to the destination. For the considered IoT networks assisted by multi-hop relaying, we evaluate the system performance by studying the transmission outage probability, where an analytical expression is derived to evaluate the IoT outage. We then evaluate the system performance by studying the transmission achievable data rate, where an analytical expression is provided to evaluate the IoT rate. Finally, we present some experimental results as well as the analytical results to verify the derived expressions for the IoT networks assisted by multi-hop relaying. In particular, the usage of multi-hop relaying can help extend the coverage area of IoT networks effectively.

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1. Introduction

The evolution of Information Technology (IT) has been marked by remarkable advancements and transformative shifts [1–4]. Beginning with the emergence of early computing systems in the mid-20th century, IT has progressed through successive waves of innovation, including the proliferation of personal computers in the 1980s, the advent of the internet and the World Wide Web in the 1990s, and the subsequent rise of mobile computing and cloud technology [5]. These developments have not only revolutionized communication, but also reshaped industries, economies, and societal interactions. The integration of machine learning, Internet of Things (IoT), and blockchain further exemplifies the ongoing evolution, with IT now playing a pivotal role in sectors ranging from healthcare and finance to manufacturing and entertainment [6–8]. As IT continues to rapidly evolve, its multidimensional impact underscores its status as a driving force behind contemporary socio-economic progress.

The research landscape surrounding IoT networks has burgeoned in response to the rapid proliferation of connected devices and their transformative impact on various domains [9–11]. Within this context, a substantial body of literature has emerged focusing on data transmission in IoT networks. Studies have delved into a spectrum of critical aspects, including communication protocols, routing strategies, energy efficiency, and security mechanisms tailored to the unique challenges posed by IoT's heterogeneous and resource-constrained environments [12–15]. The integration of wireless sensor networks, edge computing, and cloud platforms has engendered novel paradigms for data transmission and processing, catering to the escalating demands of real-time applications and massive data volumes generated by IoT devices. Research in this domain has not only strived to optimize the data transmission efficiency and reliability, but also grappled with issues of network scalability, latency reduction, and quality of service (QoS) assurance [16–18]. As IoT networks continue to expand their influence across sectors, the multifaceted research endeavors in data transmission underscore the

*Corresponding author: Weifusheng.eecs@hotmail.com.

critical role of innovation in ensuring the seamless, secure, and efficient functioning of IoT ecosystems.

The investigation of relaying techniques in communication systems has garnered substantial scholarly attention, with a particular focus on their impact on data transmission performance metrics such as outage probability and achievable data rate [19–22]. Through an array of research endeavors, scholars have probed various relaying methodologies, including amplify-and-forward (AF), decode-and-forward (DF), and cooperative relaying, among others [23–25]. These studies have critically assessed the efficacy of relaying strategies in mitigating fading-induced impairments and enhancing communication reliability. The exploration encompasses both theoretical analyses and empirical validations, wherein analytical models have been devised to quantify the outage probability, and expressions have been derived to evaluate the achievable data rate in relaying scenarios. These efforts collectively underpin the role of relaying techniques in improving communication quality and efficiency, to meet the escalating demands of diverse applications [26–29].

This paper studies the intricate realm of IoT networks, with a primary focus on augmenting their performance through the strategic incorporation of multi-hop DF relaying. These relays serve as a pivotal solution to counter the impediments imposed by signal attenuation, which can significantly impede the direct propagation of information from the source to the destination. To elucidate the implications of this approach, an analytical framework is meticulously formulated, offering a systematic avenue for the evaluation of both transmission outage probability and achievable transmission data rate within the context of IoT networks bolstered by multi-hop relaying. The precision and utility of the derived analytical expressions are underscored by their harmonization with empirical findings, collectively substantiating the discernible advantages conferred by multi-hop relaying. Notably, these empirical validations accentuate the capability of multi-hop relaying to effectively amplify the coverage of IoT networks, thereby enriching their operational efficiency and bolstering their capacity to cater to diverse application domains.

2. System Model of multi-hop relaying IoT networks

Fig. 1 shows the system model of the considered multi-hop relaying aided IoT system, where one source needs to transmit its message to the destination with the help of K DF relays. Specifically, let $\{\mathrm{R}_k \mid k = 1, 2, \ldots, K\}$ denote the set of K DF relays. Moreover, the K relays in multi-hop channels process only the signal from the immediately preceding relays. The total system bandwidth is set to unit, and is equally allocated to the source as well as relays to avoid interference. Subsequently, we shall elucidate the comprehensive system model of the multi-hop relaying network.

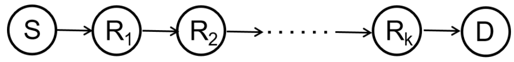

Figure 1. System of multi-hop relaying IoT networks.

In the multi-hop relaying IoT system, the source needs to transmit its message to the destination with the help of K relays. Due to the error propagation among multi-hop DF relays, the system performance is limited by the weakest link. Therefore, the equivalent received signal-to-noise ratio (SNR) at the destination node can be given by

$$\mathrm{SNR}_D = \frac{P \cdot \min\{|h_1|^2, |h_2|^2, \ldots, |h_{K+1}|^2\}}{\sigma^2}, \tag{1}$$

where P is the transmit power at the source and relays, $h_k \in \mathcal{CN}(0, \alpha)$ is the channel parameter of the k-th hop, and σ^2 is power of AWGN. According to the Shannon theorem, the transmission data rate can be given by

$$R = \frac{1}{K+1} \log_2 (1 + \mathrm{SNR}_D). \tag{2}$$

In the following sections, we will evaluate the system performance in terms of outage probability and achievable rate.

3. Outage Probability of multi-hop relaying IoT networks

Within the context of the examined multi-hop relaying system, the system outage is manifest when the transmission data rate R falls below a prescribed threshold denoted as R_{th}. Accordingly, the probability of system outage can be formulated as,

$$P_{\mathrm{out}} = \Pr[R < R_{\mathrm{th}}]. \tag{3}$$

In the ensuing discussion, we shall ascertain a mathematically explicit expression for the outage probability pertaining to the analyzed multi-hop relaying IoT system. More precisely, we shall recast equation (3) as,

$$P_{\text{out}} = \Pr\left[R < \frac{1}{K+1}\log_2(1+\text{SNR}_D) < R_{\text{th}}\right], \quad (4)$$
$$= \Pr\left[\text{SNR}_D < 2^{(K+1)R_{\text{th}}} - 1\right], \quad (5)$$
$$= \Pr\left[\min\{|h_1|^2, \ldots, |h_{K+1}|^2\} < \frac{\sigma^2}{P}\left(2^{(K+1)R_{\text{th}}} - 1\right)\right]. \quad (6)$$

From this equation, we can further write P_{out} as,

$$P_{\text{out}} = 1 - \Pr\left[\min\{|h_1|^2, \ldots, |h_{K+1}|^2\} \geq \frac{\sigma^2}{P}\left(2^{(K+1)R_{\text{th}}} - 1\right)\right], \quad (7)$$
$$= 1 - \left(\Pr\left[|h_k|^2 \geq \frac{\sigma^2}{P}\left(2^{(K+1)R_{\text{th}}} - 1\right)\right]\right)^{K+1}. \quad (8)$$

After some manipulations, we can further have,

$$P_{\text{out}} = 1 - \left(1 - \Pr\left[|h_k|^2 < \frac{\sigma^2}{P}\left(2^{(K+1)R_{\text{th}}} - 1\right)\right]\right)^{K+1}, \quad (9)$$
$$= 1 - \left(1 - \left(1 - \exp\left(\frac{\sigma^2}{P}\frac{1 - \exp(\ln 2R_{\text{th}}(K+1))}{\alpha}\right)\right)\right)^{K+1}, \quad (10)$$
$$= 1 - \exp\left(\frac{\sigma^2(K+1)\left(1 - \exp(\ln 2R_{\text{th}}(K+1))\right)}{\alpha P}\right), \quad (11)$$

where we use the probability density function of $|h_k|^2$, which follows the exponential distribution with $\mathbb{E}[|h_k|^2] = \alpha$. From the above equation consisting of elementary functions only, we can readily evaluate the outage probability for the considered multi-hop relaying IoT system.

4. Achievable Rate of multi-hop relaying IoT networks

In this section, we study the achievable rate for the multi-hop relaying IoT networks. The achievable rate can be given by

$$R_a = \mathbb{E}\{R\}, \quad (12)$$
$$= \mathbb{E}\left\{\frac{1}{K+1}\log_2\left(1 + \frac{P\cdot\min\{|h_1|^2, |h_2|^2, \ldots, |h_{K+1}|^2\}}{\sigma^2}\right)\right\}. \quad (13)$$

As $|h_k|^2$ follows the exponential distribution with $\mathbb{E}[|h_k|^2] = \alpha$, we can have that the random variable $\min\{|h_1|^2, |h_2|^2, \ldots, |h_{K+1}|^2\}$ follows the exponential distribution with a mean of $\frac{\alpha}{K+1}$. Therefore, we can rewrite (12) as

$$R_a = \int_0^\infty \frac{1}{\alpha}\log_2\left(1 + \frac{P}{\sigma^2}x\right)\exp\left(-\frac{(K+1)x}{\alpha}\right)\mathrm{d}x, \quad (14)$$
$$= \frac{1}{\alpha\ln 2}\int_0^\infty \ln\left(1 + \frac{P}{\sigma^2}x\right)\exp\left(-\frac{(K+1)x}{\alpha}\right)\mathrm{d}x, \quad (15)$$
$$= -\frac{1}{(K+1)\ln 2}\cdot\exp\left(\frac{\sigma^2(K+1)}{\alpha P}\right)\cdot\text{Ei}\left(-\frac{\sigma^2(K+1)}{\alpha P}\right), \quad (16)$$

where Ei(·) is one-argument exponential integral function [?]. From the above equation consisting of elementary functions only, we can readily evaluate the achievable data rate for the considered multi-hop relaying IoT system.

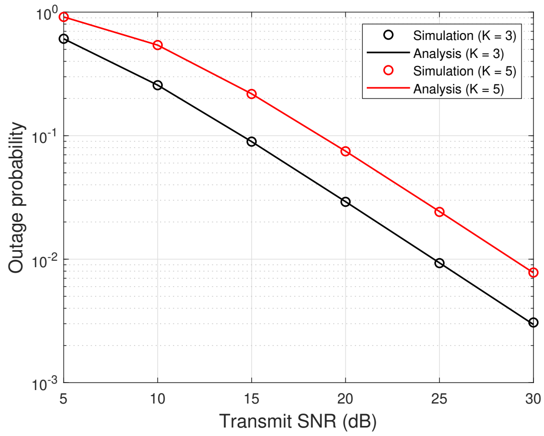

Figure 2. Outage probability of multi-hop relaying IoT networks versus the transmit SNR.

5. Simulations and Discussions

In this part, we perform some simulations on multi-hop relaying to verify the proposed studies in this work. If not specified, the number of hops is assumed to be $K = 5$. Moreover, uniform values are adopted for the transmit power at both the source and relays, both set at $P = 1$ W. The average channel gain, represented by α, is uniformly set to 1, ensuring a standardized reference for the channel conditions. Additionally, the predetermined transmission data rate threshold R_{th}, is established at 0.2bps/Hz, serving as a pivotal parameter within the simulation framework. This meticulous configuration of simulation parameters facilitates a comprehensive analysis of the system performance and characteristics, leading to insightful conclusions regarding the outage probability and achievable transmission data rate.

Fig. 2 and Table 1 show the system outage probability of the multi-hop relaying IoT networks versus the transmit SNR and hop number K over Rayleigh

Table 1 Numerical outage probability of multi-hop relaying IoT networks versus the transmit SNR.

SNR/dB	5	10	15	20	25	30
Simulation (K=3)	0.6087	0.2561	0.0894	0.0291	0.0092	0.0031
Analysis (K=3)	0.6083	0.2565	0.0894	0.0292	0.0093	0.0029
Simulation (K=5)	0.9146	0.5413	0.2174	0.0746	0.0241	0.0077
Analysis (K=5)	0.9147	0.5408	0.2182	0.0748	0.0243	0.0077

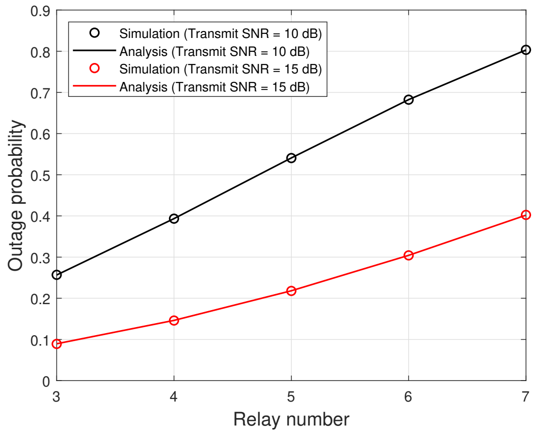

Figure 3. Outage probability of multi-hop relaying IoT networks versus the number of hops.

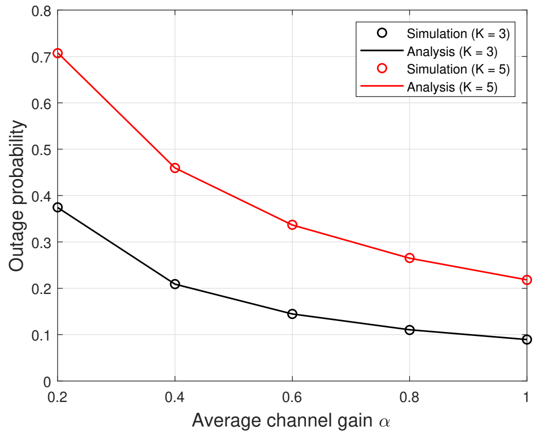

Figure 4. Outage probability of multi-hop relaying IoT networks versus the average channel gain α.

fadign channels [30–32], where the transmit SNR exhibits a range from 5 dB to 30 dB, and the number of relays is selected from the set $K \in 3, 5$. As illustrated in Fig. 2 and Table 1, as anticipated, the system outage performance demonstrates enhancement with an augmented transmit SNR, signifying that an increased transmit SNR can lead to higher transmission rates. For example, the outage probability with $K = 3$ and SNR=15dB is about 0.089, while that with $K = 3$ and SNR=30dB is about 0.0031. The outage probability with $K = 5$ and SNR=15dB is about 0.22, while that with $K = 3$ and SNR=30dB is about 0.0077. Moreover, as the number of hops K increases, the outage performance gets worse, because more relays will be affected by a server error propagation. In further, it is noteworthy that across various combinations of K and transmit SNR values, all the analytical curves closely align with the simulation results, thereby substantiating the precision and reliability of the formulated expression for the system outage probability.

Fig. 3 and Table 2 illustrate the outage probability of the considered multi-hop relaying IoT system versus the hop number K across a spectrum of transmit SNR values. It is evident that the system outage probability exhibits a notable degradation as the value of K increases, as discerned from Fig. 3 and the information presented in Table 2. In particular, the system outage probability with $K = 3$ and SNR=10dB is about 0.25, while that with $K = 7$ and SNR=10dB is about 0.89. The system outage probability with $K = 5$ and SNR=10dB is about 0.54, while that with $K = 7$ and SNR=10dB is about 0.22. This is because that the system performance is limited by the weakest relaying link, and hence increasing the number of hops will worsen the weakest relaying link. Moreover, it is evident that an elevated transmit SNR is associated with an improved system outage probability. Additionally, it is noteworthy that the analytical curves closely align with the corresponding simulation results, affirming the validity and accuracy of the derived analytical expression for the outage probability.

Fig. 4 and Table 3 depict the system outage probability under different average channel gain α and hop number K, where the average channel gain α ranges from 0.2 to 1 and the hop number $K \in \{3, 5\}$.

Table 2 Numerical outage probability of multi-hop relaying IoT networks versus the number of hops.

Hop number K	3	4	5	6	7
Simulation Transmit SNR = 10dB	0.2569	0.3933	0.5405	0.6823	0.8034
Analysis Transmit SNR =10dB	0.2565	0.3934	0.5408	0.6825	0.8031
Simulation Transmit SNR = 15dB	0.0891	0.1458	0.2178	0.3041	0.4024
Analysis Transmit SNR = 15 dB	0.0894	0.1462	0.2182	0.3042	0.4018

Table 3 Numerical outage probability of multi-hop relaying IoT networks versus the average channel gain α.

α	0.2	0.4	0.6	0.8	1
Simulation (K=3)	0.3746	0.2091	0.1446	0.1100	0.0894
Analysis (K=3)	0.3741	0.2089	0.1446	0.1105	0.0894
Simulation (K=5)	0.7071	0.4595	0.3369	0.2654	0.2181
Analysis (K=5)	0.7079	0.4595	0.3365	0.2648	0.2182

As depicted in the graphical representation and the tabulated data, it is evident that the analytical results closely converge with the simulated outcomes, thus affirming the accuracy of the analytical model. For instance, when $K = 3$ and $\alpha = 1$, the simulated system outage probability is approximately 0.0894, while the associated analytical value is also about 0.0894. The simulated system outage probability with $K = 5$ and $\alpha = 1$ is about 0.2181, while the associated analytical value is also about 0.2182, where the difference can be almost ignored. In addition, the system outage probability improves with a larger α, as a larger average channel gain can lead to a larger transmission rate. Addition to that, with less number of hops, the system outage probability improves.

Illustrated in Fig. 5 and Table 4, the simulated and analytical results delineate the relationship between the achievable data rate, transmit SNR, and the number of hops, operating within Rayleigh fading channels. The investigation encompasses the transmit SNR from 5dB to 30dB, with the hop number $K \in \{3, 5\}$. Notably, the graphical insight aligns with expectations, demonstrating that heightened transmit SNR yields augmented data rate performance, signifying the pivotal role of higher SNR in enhancing transmission

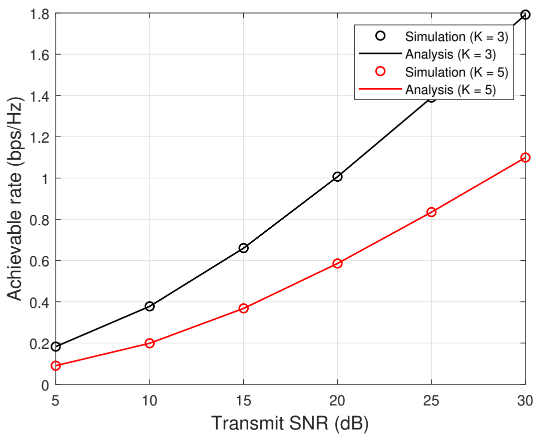

Figure 5. Achievable rate of multi-hop relaying IoT networks versus the transmit SNR.

Table 4 Numerical achievable rate of multi-hop relaying IoT networks versus the transmit SNR.

SNR/dB	5	10	15	20	25	30
Simulation (K=3)	0.1828	0.3780	0.6605	1.0066	1.3901	1.7920
Analysis (K=3)	0.1827	0.3779	0.6601	1.0065	1.3900	1.7918
Simulation (K=5)	0.0904	0.1990	0.3682	0.5858	0.8348	1.0995
Analysis (K=5)	0.0904	0.1990	0.3680	0.5860	0.8347	1.0993

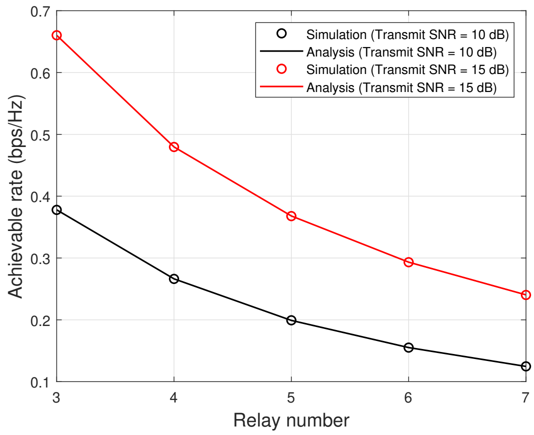

Figure 6. Achievable rate of multi-hop relaying IoT networks versus the number of hops.

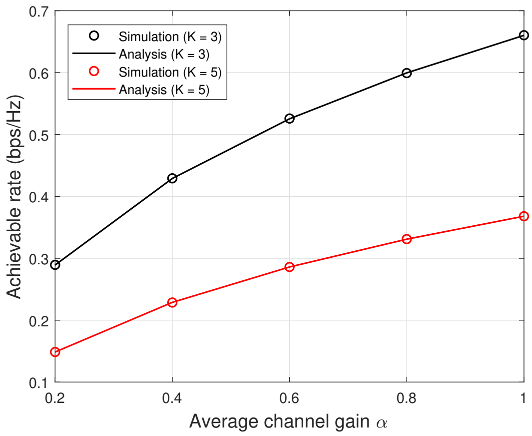

Figure 7. Achievable rate of multi-hop relaying IoT networks versus the average channel gain.

efficiency. For example, the achievable data rate with $K = 3$ and SNR=5dB is about 0.18bps/Hz, while that with $K = 3$ and SNR=30dB is about 1.79bps/Hz. The achievable data rate with $K = 5$ and SNR=5dB is about 0.09bps/Hz, while that with $K = 5$ and SNR=30dB is about 1.1bps/Hz. Moreover, an adverse correlation surfaces between the increased hop number K and achievable data rate, attributable to exacerbated error propagation within the relaying network. Noteworthy is the congruence observed between the analytical and simulated results across diverse K and SNR scenarios, affirming the accuracy of the derived data rate expression through validation against simulations.

Fig. 6 and Table 5 delineate the achievable data rate within a multi-hop relaying concerning variation in the hop number K, while considering diverse transmit SNR levels. Notably, the graphical and numerical results evince a diminishing trend in the achievable data rate as K increases. For example, the achievable data rate with $K = 3$ and SNR=10dB is about 0.38bps/Hz, while that with $K = 7$ and SNR=10dB is about 0.12bps/Hz. The achievable data rate with $K = 3$ and SNR=15dB is about 0.66bps/Hz, while that with $K = 7$ and SNR=10dB is about 0.24bps/Hz. This trend stems from the system performance being dictated by the weakest relay link, which is exacerbated with an augmented count of hops. Additionally, heightened transmit SNR engenders elevated the achievable data rate, accentuating the role of enhanced SNR in augmenting communication efficiency. In further, all analysis curves fit well with the simulation ones, which validates the derived expression of the achievable rate.

Fig. 7 and Table 6 depict the system achievable data rate under different average channel gains α and hop number K, where the average channel gain α varies from 0.2 to 1 and the hop number $K \in \{3, 5\}$. As depicted in the provided figure and table, it is evident that the analytical findings exhibit a strong concurrence with the simulation results, thereby serving to validate the robustness and accuracy of the analytical model. For example, the simulated achievable data rate with $K = 3$ and $\alpha = 0.2$ is about 0.2893bps/Hz, while the associated analytical value is about 0.2891bps/Hz. The simulated achievable data rate with $K = 5$ and $\alpha = 0.2$ is about 0.1486bps/Hz, while the associated analytical value is about 0.1485bps/Hz. In addition, the

Table 5 Numerical achievable rate of multi-hop relaying IoT networks versus the the number of hops.

Hop number K	3	4	5	6	7
Simulation Transmit SNR = 10 db	0.3778	0.2661	0.1992	0.1550	0.1247
Analysis Transmit SNR = 10 db	0.3779	0.2662	0.1990	0.1551	0.1246
Simulation Transmit SNR = 15 db	0.6603	0.4795	0.3677	0.2931	0.2402
Analysis Transmit SNR = 15 db	0.6601	0.4796	0.3680	0.2932	0.2403

Table 6 Numerical achievable rate of multi-hop relaying IoT networks versus the average channel gain.

α	0.2	0.4	0.6	0.8	1
Simulation (K=3)	0.2893	0.4292	0.5258	0.5992	0.6604
Analysis (K=3)	0.2891	0.4289	0.5253	0.5995	0.6601
Simulation (K=5)	0.1486	0.2285	0.2859	0.3310	0.3679
Analysis (K=5)	0.1485	0.2287	0.2859	0.3308	0.3680

achievable data rate increases with a larger α, as a larger average channel gain can lead to a larger transmission rate. Addition to that, with less number of hops, the achievable rate is enhanced.

6. Conclusion

In conclusion, this study delved into the intricacies of IoT networks, focusing on the challenges posed by signal fading hindrances in direct source-to-destination communication. Through the application of multi-hop relaying, an effective solution was pursued. The investigation encompassed an evaluation of system performance through the analysis of transmission outage probability, resulting in the derivation of an analytical expression to quantify IoT outage. In addition, this paper studied the achievable data rate, substantiated by an analytical expression quantifying the IoT data rate. The veracity of the derived analytical expressions was affirmed through a combination of simulated findings and analytical results. Notably, the strategic integration of multi-hop relaying emerged as a potent strategy for augmenting the coverage footprint of IoT networks, thereby bolstering their operational reach and viability.

6.1. Copyright

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