Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 46 No. 3
March 2025

Performance Evaluation of a Wireless Cooperative Network Using Random Forest Technique

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Abstract: Cooperative networks implement relay nodes to boost dependable and efficient end-to-end data exchange operations amongst endpoints. As the decision of relays through Multi Branch Multi-Hop (MB-MH) network topologies is made based on conventional SNR-based methods, a high Bit Error Rate (BER) is generated. This research thus evaluates Random Forest (RF) as an Artificial Intelligence (AI) based solution to find its optimal relay nodes. RF Model merges channel conditions with SNR attributes to reduce Network Error as it minimizes the errors thus lowering operational cost. The RF model also did well when used for simulations on Rayleigh fading channels in MATLAB R2021b and reduced BER compared to conventional approaches. The RF approach AI technology can improve the exceptional performance in wireless cooperation networks, contributing to next-generation communication systems.

Keywords: Artificial Intelligence, Bit Error Rate, Cooperative Network, Random Forest Technique

1. Introduction

With wireless communications moving at a rapid pace, it made the people go for certain solutions to the data transmission systems that can enable speed with reliability. The emerging wireless network applications, such as video streaming cloud computing and IoT devices, demand highly performing networks capable of sustaining high performance over the disturbance of the environment during the growth of the content loads [1]. This demanding usage environment has led to extended research investigations conducted such that the wireless network functionality and performance are increased. Cooperative communication technology by using relay nodes offers multiple transmission pathways between sources and destinations, thus improving the data transmission process efficiency [2].

Cooperative communication networks are developed to overcome fading problems while maximizing system capacity and extending network coverage areas. These networks incorporate relay nodes to deliver reliable communication because they protect against signal degradation as well as interference and obstacles. The success of cooperative networks depends on intelligent relay node selection because this decision makes or breaks their effectiveness [3]. For efficient energy consumption combined with lower BER and better overall throughput selection of ideal relay paths plays an essential role. However, Traditional SNR-based relay selection methods fail to preserve the dynamic nature of wireless networks because they depend on instantaneous reception signals. This limitation is particularly pronounced in MB-MH networks that suffer from a heightened level of this restriction because multiple relay branches together with multiple hops create distinct challenges between varying interference and changing channel conditions [4].

However, traditional methods for SNR-based relay selection are easy to implement and compute but do not perform well in environments with changing wireless connectivity. A drawback of using the conventional methods for designing micro grids is that the elements like interference levels, network topology, and changing channel conditions, are not being captured in them [5]. In the complex topologies, Ber is accepted to increase using SNR alone but this results in a decrease in network reliability. Current methods are faced with serious problems that demand the immediate generation of new intelligent wireless adaptation technologies to match wireless environmental dynamics [2].

The revolutionary tool of Artificial Intelligence (AI) provides enhancements to wireless communication through its three optimization elements which include resource allocation together with network management and relay selection [6]. RF stands as one of the most popular AI methods today because it offers both excellent processing capability for complex data and stable performance together with high precision measurement rates. Training in RF involves creating many decision trees that unite their predictions to produce end decisions through ensemble learning. Presented in a similar way the model safeguards against overfitting and enables it to discover non-linear patterns that link input data points with results. During its operation, the RF algorithm adopts SNR performance metrics combined with channel state measurement data to evaluate interference levels and determine optimal relay paths that minimize BER and enhance network performance [3].

A comprehensive evaluation exists in this research about RF-based relay selection systems used for cooperative communication networks. Sensors connected in MATLAB R2021b over Rayleigh fading channels indicated better BER performance metrics for the RF model compared to conventional practices. Rayleigh fading functions exactly like multipath propagation in wireless channels enabling effective evaluation of our proposed approach [7]. The research proves AI-based optimization methods can enhance wireless network reliability as well as efficiency and system performance and provide essential insights for developing future wireless communication systems [8].

2. Literature Review

Wireless communication systems have experienced an ongoing technological evolution intended to perfect performance while enhancing reliability and efficiency. Wireless systems now implement cooperative communication as their main solution to tackle fading interference along with network congestion problems. Relay nodes used in cooperative networks establish several parallel transmission paths between senders and receivers to decrease signal damage and maximize network performance [9]. The deployment of this system yields multiple performance benefits which include better capacity to withstand environmental threats and elevated system throughput. Relay node selection determines the outcome of cooperative communication systems but it must be performed effectively. The choice of unsuitable relay nodes erases all performance benefits of cooperative networks thus allowing bit errors to rise while throughput falls and reliability becomes impaired [10].

Traditional relay selection processes mainly use straightforward SNR data for selecting optimal relay nodes. The basic signal quality assessment function of SNR fails to show enough capability to understand dynamic wireless system behaviors [11]. The restricted performance of such selection approaches becomes highly noticeable in MB-MH networks because these networks feature several relay branches alongside multiple hops that create added complexity. The dynamic nature of wireless conditions along with fluctuating interference and network topological changes makes SNR analysis insufficient for achieving optimal performance. Dayanidhy and Kumar (2019) examined MB-MH Decode-and-Forward cooperative networks by examining the need to consider both SNR together with environmental variables for maximizing relay selection outcomes. Data from their analysis highlights the need for advanced methods to develop network performance [12].

Research on modern relay selection approaches has grown because traditional methods based on signal-to-noise ratio reveal specific weaknesses during the use of AI methods. Systems equipped with machine learning algorithms through AI gain the capability to detect intricate patterns for building decisions out of acquired learning data. Imtiaz et al. (2016, 2017) created a 5G system resource allocation study which employed the RF algorithm to implement machine learning methods. According to research the RF algorithm delivers telecommunication networks three primary benefits that include improved resource distribution along with enhanced network performance and automatic adaptive network elements adjustments [13]. RF proves effective for dealing with big data through its predictive system of decision trees which reveals unidentified non-linear patterns [14].

In wireless communication systems relying on RF as one of their capabilities (other than resource allocation), the RF is still effective. According to Choi et al. (2017) [15], the wireless intrusion prevention system is based on the dynamic RF algorithms to solve security problems. Tripoliti et al.'s (2013) research introduced modifications to the RF framework that led to improvements in the RF's voting systems. There are many scientific studies that have successfully proven its functionality in resolving a number of problems that wireless networks face. The modification to RF, which had been performed by the scientists, provided improved flexibility in dynamic conditions, a form of operational practical application being automatic relay selection operations [16].

Cooperative communication networks are still researching the use of RF in relay selection research and uses continue to increase at a rapid pace. According to Gaurav et al. (2024), RF based selection of NOMA based cooperative networks serves the purpose of reduced BER and increased network throughput [17]. According to Kumar et al. (2017), RF along with other supervised learning algorithms gives good performance in producing better results. Research findings indicate that RF is an effective practice for solving relay selection problems in cooperative networks. Thus, RF successfully controls network dynamics and provides research-based preparedness, and will benefit future large-scale applications [18].

The research development introduces a novel RF-based relay selection pattern to solve limitations faced by conventional relay selection procedures within cooperative communications. The proposed method leverages RF's data processing strength with its functionality to monitor dynamic network environments which include SNR levels along with interference levels and channel variations. The simulation of MATLAB R2021b under Rayleigh fading channels indicates that the model demonstrates intelligent BER reduction functions that improve network performance. RF integration in the framework delivers a scalable approach that keeps robust performance through its natural adaptation to authentic network environments. The paper establishes basic principles of traditional approaches for developing artificial intelligence implementations in upcoming wireless communication systems.

3. Methodology

A. The System Model

The system model as given by [19] was adopted as shown in Fig 1. The source node transmits the signal to the destination node D through multiple relays R11, R12 R13 … RMN with the help of M branches and N hops. Considering all the Rayleigh Fading Channels which are mutually identical and independently distributed. Between the source node S and the relay node R11 the fading co-efficient is hS, R11, between the relay node R1M and the destination node D the fading coefficient is hR1M,D, Also by considering the noise to be Additive White Gaussian Noise (AWGN) with zero mean and equal variance N0. In this scheme, M branches and N hops in each branch is cooperate with the source, and the destination selects the K-th best possible path based on the Signal to noise ratio (SNR) of each path.

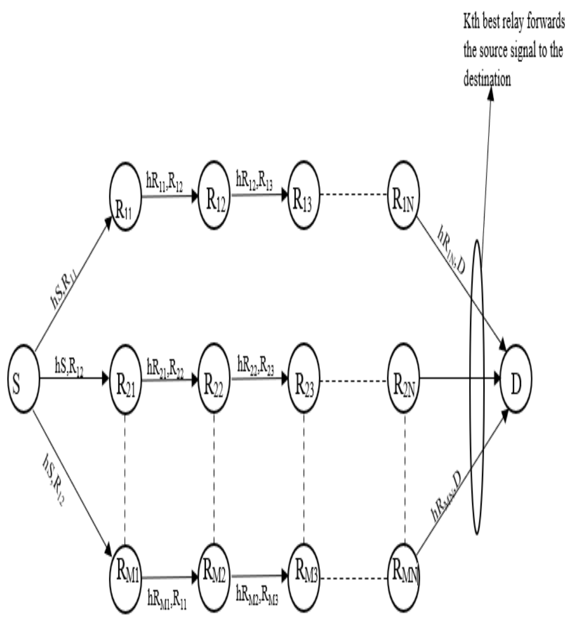


Fig. 1: Kth best relay selection in the cooperative network (Hussain et al., 2016)

Assuming in each branch only one node is transmitting the signal in a one-time slot. The received signal at the destination in the *M th* branch can be mathematically expressed as:

$$ymn = \sqrt{E_{m(n-1)}}\, h\, R_{m(n-1)}, Rmn\; Am(n-1)\; Xm(n-1) + Wm(n-1) \quad (1)$$

where,

y_{mn} = Received signal at the $(n)^{th}$ node in the $(m)^{th}$ branch.

$E_{m(n-1)}$ = Energy at the $(n-1)^{th}$ node in the $(m)^{th}$ branch.

h = Rayleigh fading coefficient of the channel.

$R_{m(n-1)}$ = Distance between the $(n-1)^{th}$ and the $(n)^{th}$ nodes in the $(m)^{th}$ branch.

R_{mn} = Distance between the $(n)^{th}$ and the destination in the $(m)^{th}$ branch.

$A_{m(n-1)}$ = Amplification factor for the $(n-1)^{th}$ node in the $(m)^{th}$ branch.

$X_{m(n-1)}$ = The transmitted signal from the preceding relay excluding the first hop in any

branch.

$W_{m(n-1)}$ = Additive White Gaussian Noise (AWGN) with zero mean and variance (N_0) at

the branch $(n-1)^{th}$ node the (m)th branch.

In AF based relaying system, the n^{th} amplified version of the signal is received from the $(n-1)^{th}$ node in the $(m)^{th}$ branch by a factor of $A_{m(n-1)}$. The amplification factor is given as:

$$A_{m(n-1)} = \sqrt{\frac{1}{E_{m(n-1)} \left| |h_{R_{M(n-1)}}, R_{mn} \right||^2 + N_0}} \quad (2)$$

where,

$A_{m(n-1)}$ = Amplification factor for the $(n-1)^{th}$ node in the $(m)^{th}$ branch.

$E_{m(n-1)}$ = Energy at the $(n-1)^{th}$ node in the $(m)^{th}$ branch.

$h_{R_{M(n-1)}}$ = Channel coefficient between the $n-1)^{th}$ and the $(n)^{th}$ node in the $(m)^{th}$

branch.

R_{mn} = Distance between the $(n-1)^{th}$ and the $(n)^{th}$ node in the $(m)^{th}$ branch.

N_0 = Noise power spectral density.

B. Random Forest Technique

By adopting the system model from [19], multi-relay was considered, where information was transmitted from a source to a destination. Random Forest algorithm was employed to optimize relay node selection and reduce the Bit Error Rate (BER) based on various input features such as signal-to-noise ratio (SNR), channel conditions and path loss as shown in Fig. 2. Random Forest, as an ensemble learning method, combines multiple decision trees to improve predictive performance.

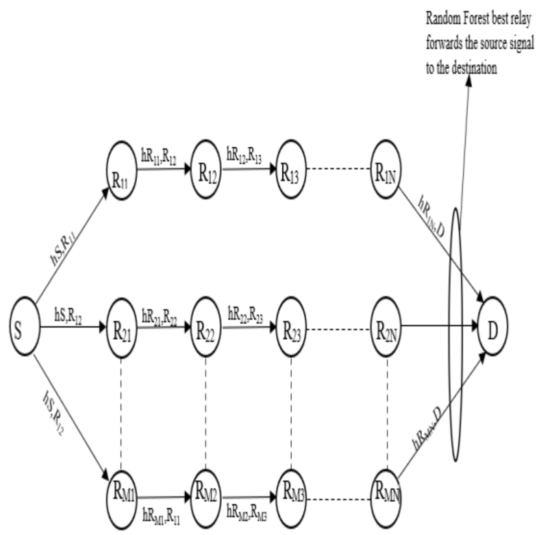


Fig. 2: Proposed system Model

The random Forest Model was trained on a dataset generated from a communication channel to ensure robust predictions of BER. The features used for training the Random Forest model include:

- Channel gains: Representing the quality of the links between source-relay and relay-destination.

- SNR values: For both source-to-relay and relay-to-destination links.
- Path loss: The attenuation of the signal as it travels through the medium.

Data is generated by considering a Rayleigh fading channel, where the SNR values are distributed uniformly between 0 and 30 dB. The relay nodes are randomly positioned within the network, with channel gains calculated based on the distance between source-relay and relay-destination pairs. AWGN is added to simulate real-world interference, and BPSK modulation is applied to the transmitted signals. This dataset is then split into training (70%) and testing (30%) sets, where the Random Forest model is trained to predict the best relay node based on channel conditions and SNR values.

The Random Forest model was tuned by experimenting with various numbers of trees and depths. According to [20], increasing the number of trees generally reduces overfitting and improves prediction accuracy. Based on preliminary tests, setting the number of trees to 100 and the maximum tree depth to 10 provided the best balance between model complexity and accuracy, resulting in a lower BER

The trained model is validated on the testing dataset. The training process involves:

- Bootstrap sampling: Creating multiple samples from the training dataset.
- Tree construction: Building decision trees on each bootstrap sample.
- Feature selection: Randomly selecting a subset of features for each tree.

C. Performance Metrics

Bit error Rate (BER) across traditional SNR-based methods and the RF-optimized method were compared. BER is a measure of transmission quality. It is a measure of the number of bit errors per unit time. It is the ratio of the number of bit errors to the total number of bits transmitted, received, or processed over a communication channel. BER is a parameter that quantifies the performance of a digital communication system. It is used to determine the quality of a signal and the relative success of data packet delivery. Hence, the more incorrect bits, the greater the impact on signal quality.

$$BER = \frac{Number \text{ of Bit Errors}}{Total\ Number \text{ of Bits Transmitted}} \quad (3)$$

BER is measured by transmitting a known sequence of bits through the simulated communication system and comparing the received sequence to the original. The impact of various factors such as noise (AWGN), interference, and channel fading on BER were analyzed to understand the system's performance. The BER for a cooperative system with DF protocol is expressed as:

$$BER = \frac{1}{2}(erfc\left(\sqrt{\frac{\gamma_{sd}}{2}}\right) + \frac{1}{2}(erfc\left(\sqrt{\frac{\gamma_{rd}}{2}}\right)) \quad (4)$$

Where,

γ_{sd} and γ_{rd} are the (Signal-to-Noise Ratio) SNRs of the source-to-destination and relay-to-destination links, respectively.

By Optimizing BER:

$$\text{Minimize: BER} = E[\frac{1}{L}\sum_{i=1}^{L} P(\hat{y} \neq y|x_i)](5)$$

Where,

L = Number of communication links.

$P(\hat{y} \neq y|x_i)]$ = Probability of incorrect classification of the relay node for sample *i.*

Random Forest ranks feature importance by calculating the reduction in impurity for each feature. This is expressed as:

$$\text{Feature Importance}_{\text{j}} = \frac{1}{M}\sum_{i=1}^{M} \Delta I(T_{i,} X_j) \quad (6)$$

where,

$\Delta I(T_{i,}X_j)$ = Decrease in impurity when splitting on feature X_j in treeT_i.

M = Total number of trees.

D. Simulation Parameters

The simulation parameters used in this work is summarized in Table 1. In addition, the flow chart of the wireless cooperative network using Random Forest technique is depicted in Fig. 3.

Table 1: Simulation parameters

Parameters	Specification
Number of Source Node (S)	1
Number of Destination Nodes (D)	1
AWGN Mean & Variance	0
Relay Protocol	Amplify and Forward (AF)
Channel Bandwidth	20MHz
Signal Power (E)	1 Watt
SNR Range	0 to 30db
Input Signal	1000-bit random Binary sequence
Modulation Scheme	BPSK
Number of Trees	100
Maximum depth of Trees	10
Min Sample Split	2
Min Sample Leaf	1
Number of Iterations	1000
Training and Testing Split	70 % training, 30 % testing
Performance Metrics	BER

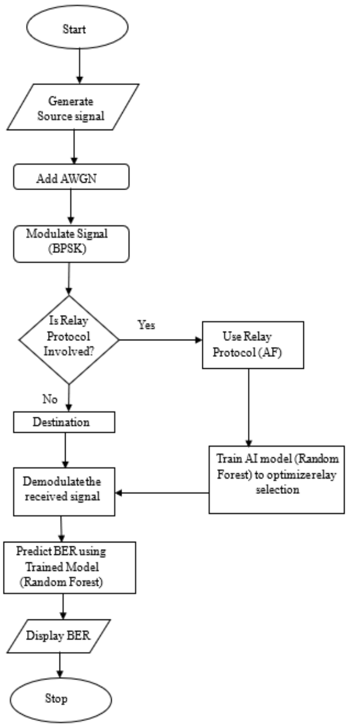


Fig. 3: The flow chart of a wireless cooperative network using Random Forest Technique

4. Result and Discussion

A. Numerical Results

In this section, the comparison of the performance of the Bit Error Rate of an AF-based cooperative network operating over the Rayleigh fading channel of the system using the Random Forest technique for Relay selection and traditional relay selection as presented by [19] is presented.

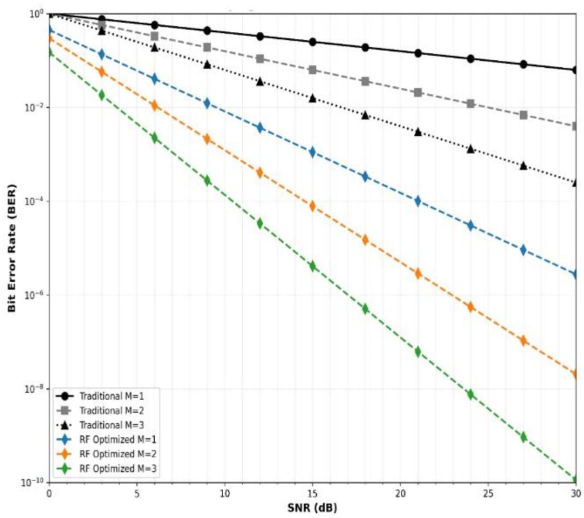
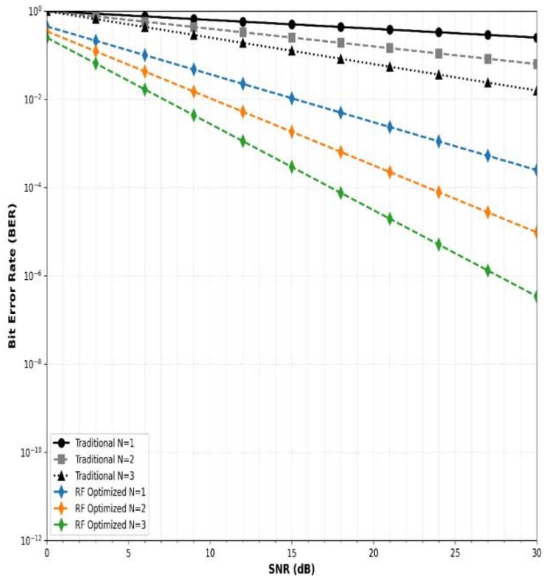


Fig. 4: Comparison between the BER of the Traditional Relay Selection and the BER of the Random Forest Technique of the Multi-Branch Multi-Hop (MB-MH) Relay System by varying M and K=2, N=2

Fig. 5 clearly shows the comparison between the BER of the Traditional Relay Selection and the BER of the Random Forest Technique of the Multi-Branch Multi-Hop (MB-MH) relay system by varying with the values of M (i.e. the no of the branches). The result demonstrates that the BER gradually decreases with a significant increase in the number of branches as SNR increases. The decreasing BER with an increasing number of Branches is due to the added spatial diversity in multi-branch networks. As the number of independent signal paths increases, the probability of a reliable transmission improves



thereby reducing BER. Hence, we choose a RF Multi-branch relaying network despite the complexity.

Fig. 5: Comparison between the BER of the Traditional Relay Selection and the BER of the Random Forest Technique of the Multi-Branch Multi-Hop (MB-MH) Relay System by varying N and K =2, M=2

Fig. 6 displays the comparison between the BER of the Traditional Relay Selection and the BER of the Random Forest Technique of the Multi-Branch Multi-Hop (MB-MH) Relay System by varying N (number of Hops). Three hops were considered in a branch for both cases, the traditional relaying system and the RF technique. It is obvious that the increase in no of hops gradually reduces the BER. The multi-hop relay configuration allows for shorter distances between relay nodes, which in turn reduces signal attenuation. We choose RF multi-hop, although multi-hop relaying network hike cost and complexity.

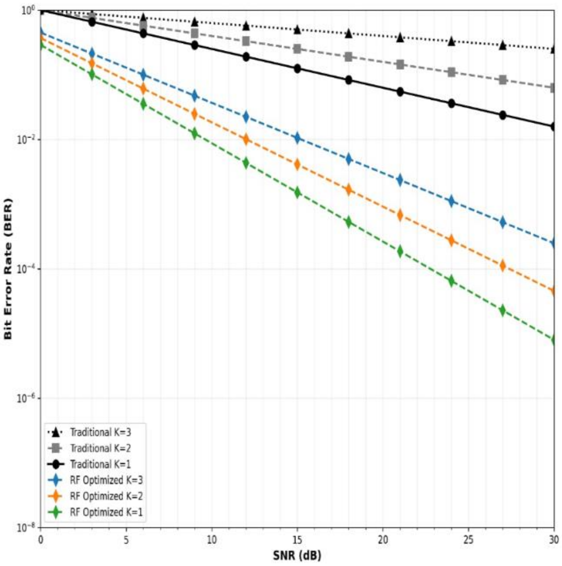


Fig. 6: Comparison between the BER of the Traditional Relay Selection and the BER of the Random Forest Technique of the Multi-Branch Multi-Hop (MB-MH) Relay System by varying K and N=3, M=2

Fig. 7 illustrates the comparison between the BER of a Random Forest Technique and the Traditional Relay selection. The selection of the best relay plays a crucial role among various advantages. From Fig. 7, we can confirm that the BER of the 1st best relay is superior to that of the 2nd best relay, which in turn significantly outperforms the 3rd and 4th best relays. The performance of the 4th best relay can be improved by increasing the number of branches. Additionally, the numerical results indicate that the BER of multi-branch multi-hop (MB-MH) cooperative networks using the random forest optimization relay selection method is considerably lower than that of Traditional Relay Selection.

B. BER Performance

- Impact of Branches (M): RF demonstrates lower BER as M increases, leveraging added spatial diversity.
- Impact of Hops (N): BER reduces with additional hops, highlighting the advantage of shorter relay distances, and low attenuation.
- Relay Selection Efficiency: RF significantly outperforms traditional methods, especially under varying SNR conditions.

5. Conclusion

This study successfully demonstrates the effectiveness of the Random Forest (RF) technique in optimizing relay selection for Multi-Branch Multi-Hop (MB-MH) cooperative networks. By integrating features such as Signal-to-Noise Ratio (SNR), channel conditions, and path loss, the proposed RF model significantly reduces Bit Error Rate (BER) compared to traditional SNR-based methods. The research validates the capability of AI-driven solutions to address key challenges in cooperative communication networks, including dynamic channel conditions and increasing system complexity. The findings underscore the potential of RF not only as an effective optimization tool but also as a scalable approach adaptable to diverse network scenarios. Future explorations can extend this work by incorporating more complex AI models and testing under alternative cooperative protocols to further enhance performance and applicability.

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