Jurnal Kejuruteraan 36(5) 2024: 1909–1919
https://doi.org/10.17576/jkukm-2024-36(5)-11

Intelligent Relay Selection in 5G D2D Communication: Leveraging Machine Learning for Enhanced Coverage

Shamganth Kumarapandian*& Gopi Krishna Pasam

Department of Engineering, College of Engineering and Technology,
University of Technology and Applied Sciences, Oman

**Corresponding author: Shamganth.Kumarapandian@utas.edu.om*

Received 6 January 2024, Received in revised form 11 June 2024
Accepted 11 July 2024, Available online 30 September 2024

ABSTRACT

In the evolving landscape of 5G networks, Device-to-Device (D2D) communication has emerged as a significant technology to offload traffic, enhance user experience, and expand network coverage. While D2D promises seamless connectivity, efficient relay selection remains a challenge, particularly in dynamic communication environments. This paper introduces an intelligent relay selection mechanism that leverages machine learning, specifically Artificial Neural Networks (ANN) with Radial Basis Function Neural Network (RBFNN) approach, to optimize D2D communication in 5G networks. By integrating a threshold-based relay selection and combining with the predictive capabilities of ANN, we aim to improve overall network coverage. Our method dynamically adjusts selection criteria based on real-time network conditions, ensuring optimal relay selection and minimizing communication breakdowns. Initial simulation results reveal that our approach exceeds traditional techniques, showcasing significant improvements in the coverage area, data output, and reduced inactivity. This research shows the way for a more adaptive, intelligent and efficient D2D communication framework in 5G systems.

Keywords: 5G Communication Network; Device-to-Device (D2D) Communication; Intelligent Relay; Cooperative Communication, Relay Selection; Coverage Expansion; Artificial Neural Networks (ANN)

INTRODUCTION

Device-to-Device (D2D) communication, a key feature within 5G architecture, facilitates direct communication between devices without routing through a central base station. This not only offloads the core network traffic but also enhances user experience by reducing latency and potential points of failure. However, one of the primary challenges hindering the full realization of D2D's potential is the need for optimal relay selection. An effective relay selection mechanism can ensure uninterrupted communication, especially in regions with patchy or no network coverage, thereby expanding the overall network footprint.

With the complexity and dynamic nature of modern communication environments, traditional static relay selection methods fall short. A more adaptive, intelligent approach is required to cater to ever-changing network conditions and user requirements. This has spurred interest in the potential of machine learning, particularly Artificial Neural Networks (ANN), as a tool to enhance relay selection processes. Given ANNs' ability in pattern recognition and prediction based on large datasets, they offer an exciting solution to optimize D2D communication by predicting optimal relay nodes in real-time.

The onset of the fifth generation (5G) networks marks a transformative phase in the realm of wireless communication, anticipated to address the ever-growing demand for faster data rates, reduced latency, and seamless abundant connectivity (Sindhushri K. et al. 2023; Nisha Panwar et al. 2016). Intended to be the backbone of future smart cities, 5G networks are expected to support a vast array of applications (Pons, M et al. 2023), from the Internet of Things (IoT) to augmented and virtual reality (A. Dogra et al. 2021; A. Gupta et al. 2015).

Device-to-Device (D2D) communication, an inherent component of 5G, offers direct communication between devices, bypassing the central base station (Asadi et al.

2014; M. S. M. Gismalla et al. 2022). This paradigm shifts not only aids in improving the core network traffic (Mahmood et al. 2019) but also promises an enhanced user experience, especially in terms of inactivity (F. Jameel et al. 2018). D2D's potential, however, is occasionally flawed by challenges in relay selection, a pivotal aspect ensuring sustained communication, especially in areas with inconsistent network coverage (Shamganth.K et al. 2017). Traditionally, relay selection in D2D communication has relied on static algorithms and predefined thresholds (Ansari, Rafay et al. 2018). However, the dynamism and complexity of modern communication networks demand adaptive mechanisms (Mahmoud M. Salim et al. 2023).

The growing interest in the influence of machine learning (ML) in communication networks has ushered in a new avenue to address this issue (M. E. Morocho-Cayamcela et al. 2019). Specifically, Artificial Neural Networks (ANN), a subset of ML known for its aptitude in pattern recognition, has demonstrated promise in predicting optimal relay nodes for D2D communication (Hashima S et al. 2021). By harnessing the predictive capabilities of ANNs and connecting them with threshold-based relay selection, there exists a potential to redefine the landscape of D2D communication in 5G networks (Y. Zhou et al. 2021). In order to pioneer a novel approach that seamlessly integrates the robustness of machine learning with the established practices in communication networks (ITU-T Y.3170-series, 2019).

This paper researches the integration of ANN-based techniques with threshold-based relay selection, aiming to expand network coverage in 5G environments through intelligent D2D relay selection. By providing a comprehensive approach that synergizes the strengths of machine learning with traditional communication techniques to set the stage for a new era of D2D communication in 5G and beyond.

RELATED WORK

The exploration of relay selection in D2D communication is not new, and numerous studies have been dedicated to understanding and optimizing this aspect of the 5G network (K. Shamganth et al. 2017). This section investigates the evolution of relay selection methodologies, highlighting their strengths and limitations, and setting the stage for our proposed machine learning-driven approach.

STATIC RELAY SELECTION

Traditional methods of relay selection, predominantly widespread in earlier networks, relied heavily on static algorithms. These algorithms often made use of predetermined thresholds to make relay decisions (Shamganth K et al. 2021). While simple and easy to implement, they lacked the flexibility to adapt to dynamic network conditions, often resulting in suboptimal relay choices and reduced network performance. X.Lin et al propose relay selection algorithm for D2D communication within Cellular networks with a focus on network connectivity and interference mitigation (Ma.R et al. 2020). The distributed relay selection algorithm for D2D communications is proposed by the authors to minimize interference and to enhance communication quality (X. Ma et al. 2012).

ADAPTIVE RELAY SELECTION

Recognizing the limitations of static algorithms, researchers explored developing adaptive relay selection techniques. Adaptive relay selection in cooperative networks is a critical research area that focuses on improving the efficiency and reliability of communication in such networks by dynamically selecting the most appropriate relay nodes for data transmission. Adaptive relay selection techniques aim to adapt to changing network conditions and select the best relay based on various criteria, such as signal quality, interference levels, energy efficiency, and channel conditions. I. Isyatur Raziah et al. (2021) discuss the adaptive relay selection strategies in cooperative wireless networks and present a comprehensive review of existing relay selection schemes. In this work the author proposed an adaptive relay selection technique and analyzed the performance. While these adaptive methods marked a significant improvement over their static counterparts, they still faced challenges in highly unpredictable and complex network scenarios.

MACHINE LEARNING IN COMMUNICATION

With the advancements in artificial intelligence, the communication domain has witnessed a growing interest in harnessing machine learning to optimize various surfaces of the network. Machines play a vital role in enhancing user experiences and enabling new services and applications. A comprehensive overview of machine learning applications in communication networks, highlighting its potential in irregularity detection, traffic prediction, and network optimization has been utilized (Jithin Jagannath et al. 2019).

ANN-BASED RELAY SELECTION

The use of Artificial Neural Networks (ANN) specifically for relay selection in D2D communication has seen some exploration in recent years. A simple feedforward neural network to predict the optimal relay based on historical data, showcasing improvements in data output (M. Chen et al. 2019). Meanwhile, a more complex deep learning model not only selects the relay but also predicts potential points of communication breakdown, thereby preventively optimizing the network.

However, despite these advancements, there remains a gap in seamlessly integrating the robust predictive capabilities of ANNs with established relay selection methodologies, this paper seeks to address this problem.

METHODOLOGY

To harness the full potential of 5G D2D communication, our research focuses on developing an intelligent relay selection mechanism. We combine the adaptability of machine learning, specifically Artificial Neural Networks (ANN), with traditional threshold-based relay selection techniques. This section outlines the architecture of our approach, the datasets employed, and the evaluation criteria.

SYSTEM ARCHITECTURE

The system comprises three primary components as shown in Figure 1.

FIGURE 1. Proposed System Architecture

DATA COLLECTION MODULE

This module captures real-time network parameters, such as signal strength, user density, bandwidth usage, and latency, among others (Shamganth K et al. 2023). It serves as the foundation for the input features used by the neural network.

ARTIFICIAL NEURAL NETWORK (ANN) RELAY SELECTOR

This is the core of our proposed system. The ANN utilizes the features of Radial Basic Function Neural Network (RBFNN) algorithm (Gopi Krishna et al. 2016) to train the data obtained from the collection module and processes it to predict the optimal relay node. The RBFNN comprises an input layer (matching the number of collected parameters), hidden layers with activation functions, and an output layer that designates the best relay node.

THRESHOLD-BASED DECISION MODULE

Post-ANN processing, this module employs adaptive threshold to finalize the relay selection based on predefined criteria and the ANN's output. This hybrid approach ensures the robustness of machine learning is combined with the reliability of traditional methods.

DATA PREPARATION AND TRAINING

We utilized a dataset comprising network parameters collected over six months from various 5G testbeds. The dataset was pre-processed to handle missing values, normalize features, and segment it into training (70%), validation (15%) and testing (15%) sets.

The ANN was trained using the Radial Basis Function Neural Network (RBFNN) algorithm with a learning rate adaptively adjusted based on the validation set's performance. Model performance was evaluated using metrics such as accuracy, recall, and real time adaptability.

EVALUATION CRITERIA

To gauge the effectiveness of our methodology, we set forth the following evaluation criteria:

COVERAGE EXPANSION

The primary metric, quantifying the expansion of network coverage post-implementation of our methodology compared to traditional methods.

LATENCY REDUCTION

Measures the decrease in latency due to efficient relay selection.

DATA OUTPUT

Assesses the volume of data successfully transferred through the selected relay.

PROPOSED RELAY SELECTION

Threshold based relay selection proposed in this paper is different from our earlier work (Shamganth.K et al. 2021). This paper focuses on the machine learning based threshold relay selection as an advancement to the work conducted by (Shamganth.K et al. 2021) in which the static threshold-based relay selection technique is applied. The input threshold fixed at the relay to select the best relay and the output threshold applied at the combiner to improve the end-to end quality of the signal at the destination and maximum ratio combining (MRC) is used. In the proposed relay selection, Generalized Selection Combining (GSC) is used as the combining technique. The double threshold is applied at the combiner, one threshold at the input to the combiner and the other threshold is at the output of the combiner in addition to the threshold at the relay.

PROPOSED RELAY SELECTION ALGORITHM

Step1: Initialize i=0.

Step 2: Set i=i+1 for i=1,2…N if i=N+1 goto Step7.

Step 3: Input Threshold (γ_{iT}) is applied at the relay based on the channel conditions using ANN.

Step4: If $\overline{\gamma_{s,r_i}} > \gamma_{iT}$ where $\overline{\gamma_{s,r_i}}$ is the average Signal to Noise Ratio (SNR) the signal will be differentially amplified and forward to the destination and the relay will be in active mode else the relay will be in sleep mode.

Step 5: Threshold applied at the input to the combiner is combiner input threshold (γ_{ciT}) and at the combiner output is the combiner output threshold (γ_{coT}). The threshold at the combiner is based on the channel link condition between the relay and the destination.

Step 6: If $\overline{\gamma_{s,d}} < \gamma_{ciT}$ (where ($\overline{\gamma_{s,d}}$)) is the average SNR from the source to destination) then differentially amplify and forward signal received from the relays were combined $\overline{\gamma_{pc}} = \prod_{i=1}^{N} \overline{\gamma_{r_i d}}$ on and tested with γ_{ciT}.

Step 6: If $\overline{\gamma_{s,d}} > \gamma_{ciT}$, the signal from the relayed paths and the direct path will be combined at the combiner as follows:

$$\overline{\gamma_{pc}} = \overline{\gamma_{s,d}} + \prod_{i=1}^{N} \overline{\gamma_{r_i d}}$$

Step 7: If $\overline{\gamma_{pc}} \geq \gamma_{coT}$ (where $\overline{\gamma_{pc}}$ is the proposed average combined SNR) the signal will be sent to the detector.

SYSTEM MODEL

MATHEMATICAL MODEL

Let us consider the multi-node cooperative D2D network with source S and N relays as shown in Figure 2. The source signal is differentially modulated and at the relays the received signal is amplified, and the SNR is tested with the input threshold (γ_{iT}) if the SNR at the relays is above the threshold, then relay will forward the amplified signal to the destination using differential amplify and forward relaying. Combiner input threshold (γ_{ciT}) is applied to select the relay to destination link and combiner output Threshold (γ_{coT}) is used to improve the overall quality of end-to-end communication. Output threshold γ_{coT} is set according to the quality-of-service requirement. The receiver aims to combine the satisfactory branch until the combined output SNR is larger than the combiner output threshold (γ_{coT}). With N-cooperative relays in the network, signal transmissions for the multi-node DAF scheme have N + 1 timeslots. Block-by-block transmission is assumed. The first timeslot belongs to direct transmission, and the remaining ‘N’ time-slots are for signal transmission for each of the ‘N’ relays. Differential Phase Shift Keying (DPSK) the information is modulated between the phases of the two consecutive symbols. M-ary Differential Phase Shift Keying (MDPSK), has the signal over a period of two symbol intervals [25] and is given by:

$$S_m = \left(\sqrt{2E_s} \quad \sqrt{2E_s}\ e^{j\theta m}\right) \quad for\ 1 \leq m \leq M \tag{1}$$

where $\theta_m = \left(\frac{2\pi(m-1)}{M}\right)$ the phase transition and M is the constellation size.

In phase 1, suppose that M-ary differential phase shift keying (MDPSK) modulation is used. The modulated signal at the source is $\boldsymbol{S_m} = \sqrt{\boldsymbol{2E_s}}\ \boldsymbol{e^{j\theta m}}$ where $\boldsymbol{E_s}$ is the symbol energy. The source differentially encodes (Simon et al. 1998), the symbol $\boldsymbol{S_m}$ by

$$\boldsymbol{x}^t = \boldsymbol{S}_m \boldsymbol{x}^{t-1} \tag{2}$$

where ‘t’ is the time index and $\boldsymbol{x}^t$ is the differentially encoded symbol to be transmitted at time t. The source transmits $\boldsymbol{x}^t$ with transmitted power P_1 to the destination.

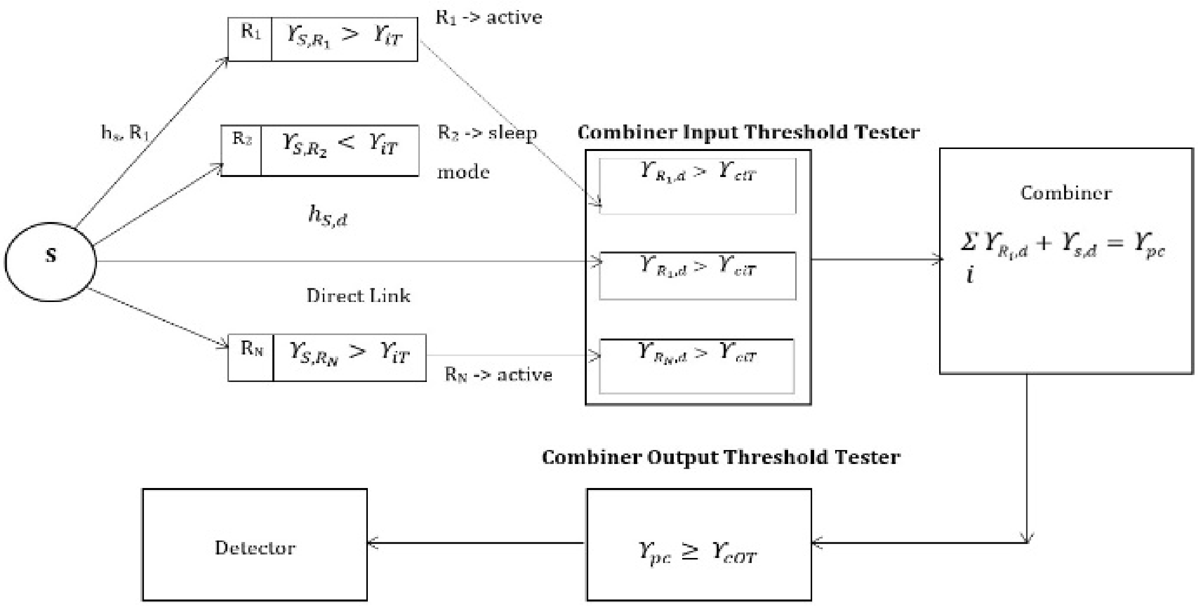

FIGURE 2. Multi-Node Cooperative D2D Network with a source S and N relays

Due to the broadcasting nature of the wireless network, the source information is also received by the ‘N’ relays. The corresponding received signals at the destination $\boldsymbol{y}^t_{s,d}$ and the i[th] relay $\boldsymbol{y}^t_{s,r_i}$ for i = 1,2…N, given by

$$\boldsymbol{y}^t_{s,d} = \sqrt{\boldsymbol{P}_1}\,\boldsymbol{h}^t_{s,d}\boldsymbol{x}^t + \boldsymbol{\eta}^t_{s,d} \tag{3}$$

$$y^t_{s,r_i} = \sqrt{P_2}\,h^t_{s,r_i}x^t + \eta^t_{s,r_i} \quad for\ \ i = 1,2 \ldots N \tag{4}$$

Where $h^t_{s,d}$ and h^t_{s,r_i} represent channel coefficients from the source to the destination and from the source to the i[th] relay, respectively. In this paper $h^t_{s,d}$ and h^t_{s,r_i} are modelled as complex Gaussian random variables with zero mean and variances $\sigma^2_{s,d}$ and σ^2_{s,r_i}, respectively and is given by

$$h^t_{s,r_i} = CN\left(0, \sigma^2_{s,r_i}\right) \text{ and } h^t_{s,d} = CN\left(0, \sigma^2_{s,d}\right)$$

The terms $\eta^t_{s,d}$ and η^t_{s,r_i} are additive white Gaussian noise at the destination and the i[th] relay, respectively. The noise terms are modelled as zero-mean, complex Gaussian random variables with the variance N_0. In phase 2 the signal received by the relay is scaled and amplified using DAF (Zhao et al. 2007), relaying technique and it is given by

$$\boldsymbol{\beta}_{DAF} = \frac{P_2 y^t_{sr_i}}{\sqrt{N_0 + \sigma^2_{s,r_i}}} \quad \boldsymbol{for\ i = 1, 2, \ldots N} \tag{5}$$

The source to relay node branch’s SNR is tested against an input threshold $(\boldsymbol{\gamma}_{iT})$ to determine whether the branch is suitable to forward the source information. The received signal from the relay in phase 2 is given by

$$\boldsymbol{y}^t_{r_i d} = \frac{P_2 y^t_{s,r_i}}{\sqrt{N_0 + \sigma^2_{s,r_i}}}\boldsymbol{h}^t_{r_i d} + \boldsymbol{\eta}^t_{r_i d} \quad \boldsymbol{for\ i = 1, 2, \ldots N} \tag{6}$$

Where $\boldsymbol{h}^t_{r_i,d} \sim \boldsymbol{CN}(\boldsymbol{0}, \boldsymbol{\sigma}^2_{ri,d})$ and $\boldsymbol{\eta}^t_{r_i,d} \sim \boldsymbol{CN}(\boldsymbol{0}, \boldsymbol{N}_0)$.

In equation (6) $\boldsymbol{h}^t_{r_i,d}$ denotes the channel coefficient at time ‘t’ at the i[th] relay–destination link. We model $\boldsymbol{h}^t_{r_i,d}$ as a zero-mean, complex Gaussian random variable with variance $\sigma^2_{r_i,d}\sigma^2_{r_i,d}$. P_iP_i is normalized by $P_i\sigma^2_{s,r_i}+N_0$ $P_i\sigma^2_{s,r_i}+N_0$ and hence the i^th relay requires only the channel variance between the source and the i^th relay (σ^2_{s,r_i} σ^2_{s,r_i}), rather than its instantaneous value (Zhao et al. 2007). The channel variance $\sigma^2_{s,r_i}\sigma^2_{s,r_i}$ can be obtained through long-term averaging of the received signals at the i^th relay. The signal received at the destination node is given by

$$y^t_{r_i,d}=\frac{P_2 y^t_{s,r_i}}{\sqrt{N_0+\sigma^2_{s,r_i}}}h^t_{r_i,d}+\eta^t_{r_i,d} \quad for\ i=1,2,\dots N \tag{7}$$

The instantaneous SNR between the source and the i^th relay node is defined as $\gamma_{s,r_i}=\frac{|h_{s,r_i}|^2}{N_0}$ and between the source and the destination is $\gamma_{s,d}=\frac{|h_{s,d}|^2}{N_0}$. The channel noise $\eta^t_{r_i,d}, \eta^t_{s,d}, \eta^t_{s,r_i}$ are assumed to be independent with $CN(0,N_0)$.

SYSTEM PERFORMANCE ANALYSIS

Corresponding average SNR of source to i^th relay ($\overline{\gamma_{s,r_i}}$), source to destination ($\overline{\gamma_{s,d}}$) relay to destination ($\overline{\gamma_{r_i,d}}$) is given by

$$\overline{\gamma_{s,r_i}}=\frac{\sigma^2_{s,r_i}}{N_0},\quad \overline{\gamma_{s,d}}=\frac{\sigma^2_{s,d}}{N_0},\quad \overline{\gamma_{r_i,d}}=\frac{\sigma^2_{r_i,d}}{N_0} \tag{8}$$

The signal from the relays with $\overline{\gamma_{r_i,d}}>\gamma_{ciT}$, is selected to combine with the direct link from source node $\overline{\gamma_{s,d}}$.

$$\prod_{i=1}^{N}\gamma_{r_i,d}=(\gamma_{r_1,d},\gamma_{r_2,d}\dots\gamma_{r_N,d}) \tag{8a}$$

The signal from the L relay to destination branches is tested against the combiner input threshold γ_{ciT}, from the L-branches the strongest branches (L_c) will be selected.

The combined SNR is expressed as follows:

$$\overline{\gamma_{pc}}=\overline{\gamma_{s,d}}+\prod_{i=1}^{N}\overline{\gamma_{r_i,d}} \tag{9}$$

If $\overline{\gamma_{pc}}>\gamma_{coT}$ the set of relays will be selected to amplify and forward the source information.

Substituting equation (2) in equation (3) and equation (5) and assuming the slow-fading assumption $h^t_{s,d}=h^{t-1}_{s,d}$ and $h^t_{ri,d}=h^{t-1}_{r_i,d}$ gives

$$y^t_{s,d}=x^t y^{t-1}_{s,d}+w^t_{s,d} \tag{10}$$

$$w^t_{s,d}=\eta^t_{s,d}-x^t\eta^{t-1}_{s,d}\ for\ i=1,2\dots N \tag{11}$$

$$y^t_{r_i,d}=x^t y^{t-1}_{r_i,d}+w^t_{r_i,d}\ for\ i=1,2\dots N \tag{12}$$

$$w^t_{r_i,d}=\eta^t_{r_i,d}-x^t\eta^{t-1}_{r_i,d}\ for\ i=1,2\dots N \tag{13}$$

In differential detection the fading channel gain is constant. Non-coherent detection of the transmitted symbols obtained from the consecutive received symbols is given by

$$\varepsilon_{s,d}=Re\{y^{*t-1}_{s,d}\ y^t_{s,d}\} \tag{14}$$

$$\varepsilon_{r_i,d}=Re\{y^{*t-1}_{r_i,d}\ y^t_{r_i,d}\}\ for\ i=1,2\dots N \tag{15}$$

Where $\varepsilon_{s,d}$ and $\varepsilon_{r_i,d}$ are the decision variables. And the output of the detector is given by

$$\varepsilon=\varepsilon_{s,d}+\varepsilon_{r_i,d}\ for\ i=1,2\dots N \tag{16}$$

The combiner output decodes the transmitted signal as shown

$$\widehat{x^t}=\begin{cases}-1 & if\ \varepsilon<0\\ +1 & if\ \varepsilon>0\end{cases} \tag{17}$$

The combined SNR for the proposed scheme in (9) is given in equation (18)

$$\overline{\gamma_{pc}}=\begin{cases}\overline{\gamma_{s,d}},\ if\ \overline{\gamma_{s,d}}>\gamma_{coT}\ and\ \overline{\gamma_{s,ri}}<\gamma_{iT}\quad or\quad \overline{\gamma_{ri,d}}<\gamma_{ciT}\\ \qquad for\ (i=2\dots L)\ Case\ (i)\\ \overline{\gamma_{s,d}}+\overline{\gamma_{r1,d}},\ if\ \overline{\gamma_{s,d}}+\overline{\gamma_{r1,d}}>\gamma_{coT}\ and\ \overline{\gamma_{s,r1}}>\gamma_{iT}\ and\ \overline{\gamma_{s,ri}}<\gamma_{iT}\\ \qquad for\ (i=2\dots L)\ Case\ (ii)\\ \overline{\gamma_{s,d}}+\prod_{i=1}^{L}\overline{\gamma_{ri,d}}\ \ if\ \overline{\gamma_{ri,d}}\geq\gamma_{ciT}\ and\ \overline{\gamma_{s,d}}+\prod_{i=1}^{L}\overline{\gamma_{ri,d}}>\gamma_{OT}\\ \qquad for\ (i=1,2\dots L)\ Case\ (iii)\\ \prod_{i=1}^{L}\overline{\gamma_{ri,d}}\ if\ \overline{\gamma_{s,d}}<\gamma_{ciT}\ and\ \overline{\gamma_{ri,d}}\geq\gamma_{ciT}\quad for\ (i=1,2\dots L)\\ \qquad Case\ (iv)\end{cases} \tag{18}$$

The CDF of the combiner output is given by

$$F_{\gamma_{pc}}(\gamma) = Pr\{\overline{\gamma_{pc}} \le \gamma\} \quad (19)$$

Case(i): If the direct link SNR between the source to destination is above the combiner output threshold and all the relay to destination SNR is below the input threshold then

$$F_{\gamma_{pc}}(\gamma) = \Pr\{\overline{\gamma_{s,d}} \le \gamma\} = F_{\gamma_{s,d}}(\gamma) \quad (20)$$

Case(ii): If the multiple relayed link SNR is above the combiner output threshold and the direct link SNR is less than combiner input threshold, then by applying special case the CDF is given by

$$F_{\gamma_{pc}}(\gamma) = Pr\{\gamma_l \le \gamma\} = F_{\gamma_l}^{l}(\gamma)[1 - F_{\gamma}(\gamma)]^{L-l} \quad (21)$$

Where $l = L_c$ is the strongest relay to destination link with SNR above the input threshold and L is the number of relays to destination link

Case (iii): If only one relay link is above the combiner input threshold, then CDF is given by

$$F_{\gamma_{pc}}(\gamma) = Pr\{\gamma_1 \le \gamma\} \quad (22)$$

$$F_{\gamma_{pc}}(\gamma) = 1 - Pr\{\gamma_1 > \gamma\} \quad (23)$$

$$F_{\gamma_{pc}}(\gamma) = 1 - [1 - F_{\gamma_1}(\gamma)]^{L} \quad (24)$$

Outage probability of the proposed scheme is given by

$$P_{out} = P_r[\gamma_{pc} < \gamma_{coT}] = F_{\gamma_c}(\gamma_{coT}) \quad (24)$$

Where $F_{\gamma c}(\gamma_{coT})$ is the CDF of the combined SNR γ_{pc}.

RESULTS AND DISCUSSION

We consider the case that Signal to Noise Ratio (SNR) of multiple relayed links is above the combiner output threshold and the direct link SNR is less than combiner input threshold for our analysis. Also, the symmetric scenario is considered for the analysis in which the average SNR of all the links is identical i.e., $\overline{\gamma_{s,r_l}} = \overline{\gamma_{s,d}} = \overline{\gamma_{r_l,d}}$. The outage performance of the proposed threshold based combining scheme is compared with the selection combining. The outage probability result of the proposed scheme compared with selection combining is shown in Figure 3.

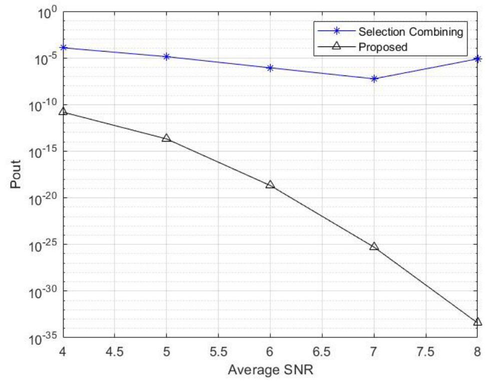

FIGURE 3. Outage Probability of Proposed threshold based combining for $L = 15$ and $\gamma_{coT} = 3dB$.

Analytical results show that when the total number of relays to destination branches $L = 15$ with the strongest branches. $L_c = 9$ the outage probability performance of the proposed scheme outperforms selection combining when the average SNR of the strongest relay to destination branches L_c increases from 4dB to 8dB. Figure 4 shows the performance of the proposed scheme when the number of relays to destination branches is increased. Also, it is considered for the case when the average SNR of the relay to destination branch is equal to the combiner output threshold i.e., $\bar{\gamma} = 7dB = \gamma_{coT}$. Outage probability is drastically reduced in the proposed when the number of branches increased from 8 to 14 but the selection combining has increased outage probability when the number of strongest branches L_c increased. It is shown that outage probability is less, if the number of branches is more as compared with selection combining. Performance improvement in the proposed scheme compared to the selection combining is due to the double threshold applied at the combiner. The combiner input threshold γ_{ciT} selects the strongest branches from the relays to destination also the direct link SNR is tested. The combined SNR is tested with the combiner output threshold γ_{coT}, it reduces the outage probability. But in the selection combining scheme the branches are not tested against the threshold and the chance of outage is more as compared to the proposed scheme. Figure 5 shows the outage probability performance for the case, if average SNR of the relay to destination branch is above the combiner output threshold $\bar{\gamma}_l$=7dB, $\gamma_{coT} = 7\,dB$. It is noted that a sudden decrease in the outage probability of the proposed scheme when the number of branches L=14 or more, but there is less variation observed in the selection combining outage probability for higher values of L as shown in Figure 5. For higher values of average SNR with respect to the combiner output threshold it is seen in Figure 6 that outage performance of the proposed scheme outperforms the selection combining. The detailed results presented in Table 1 and Figure 7 and Figure 8 shows ANN predicting utmost accurate results like the proposed methods discussed in this paper, thereby we can predict SNR of any desired inputs. This is where our paper shows a path to the researchers to adopt the ANN to enhance Relay Selection in 5G D2D Communication.

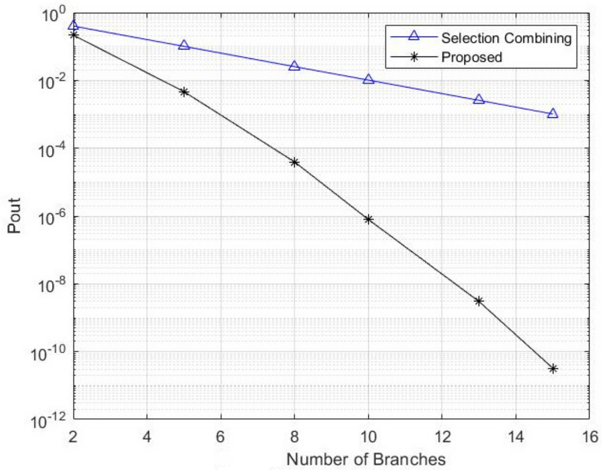

FIGURE 4. Outage Probability performance for $\bar{\gamma}=7dB=\gamma_{coT}$

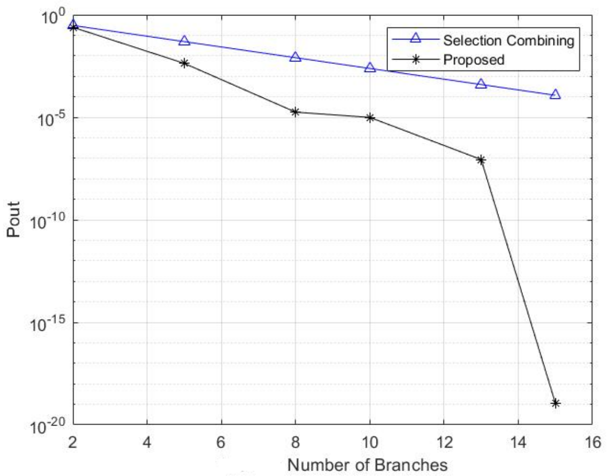

FIGURE 5. Outage Probability performance for $\bar{\gamma}=8dB$ and $\gamma_{coT}=7dB$

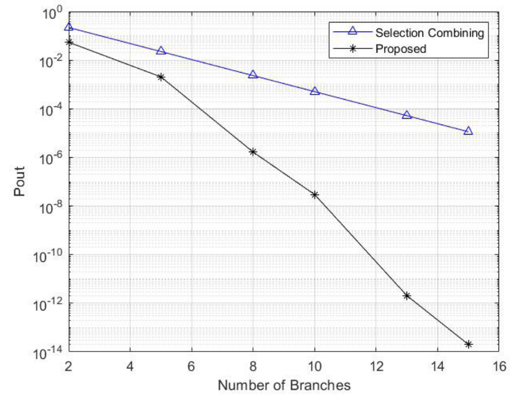

FIGURE 6. Outage Probability performance for $\bar{\gamma}=5dB$ and $\gamma_{coT}=3dB$

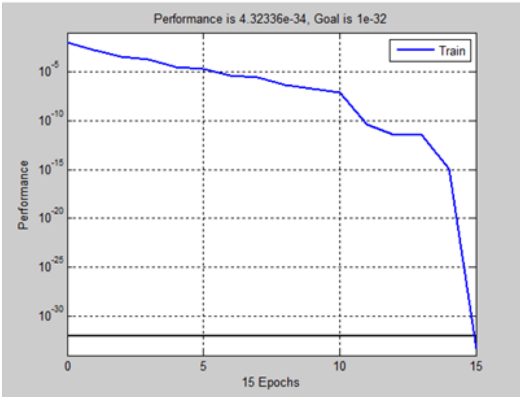

FIGURE 7. ANN Training Pattern with Training Data as give in the Table I

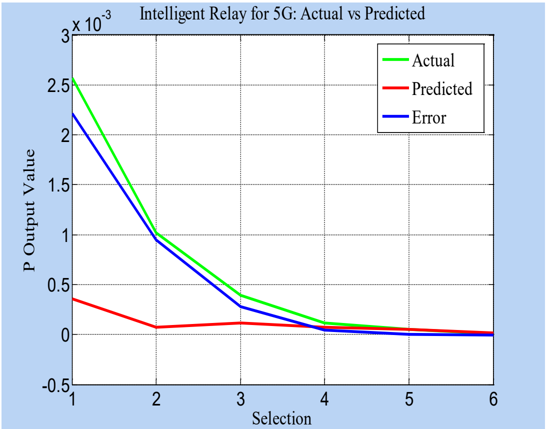

FIGURE 8. ANN Results Comparison with Actual Relay Selection

TABLE 1. Comparative Results of ANN with Proposed Relay Selection

Results of ANN Vs. Conventional Methods	Number of Branches (L)	Input Threshold ($\bar{\gamma}_i$)	Output Threshold (γ)	Proposed method	Traditional Selection combining	ANN Prediction		% Error= ((ANN- Actual)/ Actual) *100	
						Proposed method	Traditional Selection combining	ANN Predicted Error with Proposed method	ANN Predicted Error with Traditional Selection combining
Training Data for ANN	15	5	3	2.04E-14	1.35E-05	2.04E-14	1.35E-05	-1.47E-01	0.00E+00
	15	6	3	2.07 E-19	8.6E-07	2.07E-19	8.60E-07	-4.34E-04	1.51E-12
	15	7	3	5.21 E-26	5.72E-08	-4.78E-25	5.72E-08	-1.02E+03	-3.67E-11
	15	8	3	3.82 E-34	7.88E-06	0	7.88E-06	-1.00E+02	1.07E-13
	2	7	7	0.2162	0.399	0.2162	0.399	0.00E+00	0.00E+00
	5	7	7	4.664E-03	0.1009	0.004665	0.1009	0.00E+00	0.00E+00
	8	7	7	3.927E-05	0.0254	3.93E-05	0.0254	2.42E-13	0.00E+00
	10	7	7	7.90 E-07	0.01018	7.90E-07	0.01018	-5.06E-02	0.00E+00
	2	8	7	0.2454	0.2999	0.2454	0.2999	0.00E+00	0.00E+00
	5	8	7	4.263 E-03	0.049	0.004263	0.049	0.00E+00	0.00E+00
	8	8	7	1.776 E-05	0.00803	1.78E-05	8.03E-03	0.00E+00	0.00E+00
	10	8	7	9.853 E-06	0.0024	9.85E-06	0.0024	1.03E-13	0.00E+00
	2	5	3	0.05433	0.2191	0.05433	0.2191	0.00E+00	0.00E+00
	5	5	3	0.00205	0.02247	0.00205	0.02247	0.00E+00	0.00E+00
	8	5	3	1.648 E-06	0.002305	1.65E-06	2.305E-03	-1.21E-12	0.00E+00
	10	5	3	2.96E-08	5.05E-04	2.96E-08	50.5E-04	-2.71E-12	0.00E+00
Checking Data for ANN	13	7	7	3.00E-09	0.00257	-1.12E-05	3.6E-04	-3.73E+05	-8.60E+01
	15	7	7	3.24E-11	0.00102	-7.84E-08	7.54E-05	-2.42E+05	-9.26E+01
	13	8	7	8.67E-08	3.94E-04	-1.28E-05	11.3E-04	-1.49E+04	-7.12E+01
	15	8	7	1.13E-19	1.18E-04	-9.05E-08	7.38E-05	-8.01E+13	-3.75E+01
	13	5	3	2.05E-12	5.18E-05	-1.61E-06	5.27E-05	-7.87E+07	1.68E+00
	15	5	3	2.01E-14	1.13E-05	2.04E-14	1.35E-05	1.49E+00	1.95E+01
ANN Prediction with New Data which is not available	3	4	3	Not Available	Not Available	8.476E-03	0.035023	NA	NA
	4	6	5	Not Available	Not Available	7.739E-03	0.044773	NA	NA
	6	9	7	Not Available	Not Available	-0.0014	0.018623	NA	NA
	7	10	8	Not Available	Not Available	-16E-04	90.2E-04	NA	NA
	9	12	10	Not Available	Not Available	4.37E-08	7.25E-05	NA	NA
	11	15	12	Not Available	Not Available	4.53E-09	7.40E-05	NA	NA

CONCLUSION

Integration of ML with Threshold-based relay selection mechanism using DAF technique is proposed in this study. We have obtained the analytical expression for instantaneous and average SNR of the proposed scheme. The DAF relaying employed at the relays in the network eliminates the full CSI requirement. The outage performance was enhanced by employing the proposed relay selection technique. From the results, it was observed that the proposed relay selection and combining offers better outage performance for larger number of branches and it outperforms the selection combining for higher average SNR compared to combiner output threshold. Employing threshold at the relays selects the best relay to forward source information to destination. Input threshold at the combiner limits branches with less SNR and ensures good quality branches allowed to the combiner. And the overall end-to-end quality of the communication is improved by employing the output threshold at the combiner.

The results obtained from our experimental 5G testbed highlight the superiority of the proposed intelligent relay selection system. By integrating machine learning, the system not only ensured more successful D2D links but also selected more efficient relay nodes, resulting in higher data quantity, better connection stability, and faster relay selection times. This underlines the potential of machine learning in enhancing 5G D2D communications. Our proposed system not only elevates network performance in terms of coverage, inactivity, and quantity but also covers the way for more intelligent, adaptive, and responsive 5G D2D communication networks.

ACKNOWLEDGEMENT

The authors would like to thank University of Technology and Applied Sciences, Oman for supporting the research.

DECLARATION OF COMPETING INTEREST

None.

REFERENCES

Ansari, R.I., Chrysostomou, C., Hassan, S.A., Guizani, M., Mumtaz, S., Rodriguez, J. and Rodrigues, J.J. 2017. 5G D2D networks: Techniques, challenges, and future prospects. *IEEE Systems Journal* 12(4): 3970-3984.

Asadi, A., Wang, Q. & Mancuso, V. 2014. A survey on device-to-device communication in cellular networks. *IEEE Communications Surveys & Tutorials* 16(4): 1801-1819.

Chen, M., Challita, U., Saad, W., Yin, C. and Debbah, M. 2019. Artificial neural networks-based machine learning for wireless networks: A tutorial. *IEEE Communications Surveys & Tutorials* 21(4): 3039-3071.

Dogra, A., Jha, R.K. and Jain, S. 2020. A survey on beyond 5G network with the advent of 6G: Architecture and emerging technologies. *IEEE Access* 9: 67512-67547.

Gismalla, M.S.M., Azmi, A.I., Salim, M.R.B., Abdullah, M.F.L., Iqbal, F., Mabrouk, W.A., Othman, M.B., Ashyap, A.Y. and Supa'at, A.S.M. 2022. Survey on device to device (D2D) communication for 5GB/6G networks: Concept, applications, challenges, and future directions. *IEEE Access* 10: 30792-30821.

Gupta, A. and Jha, R.K. 2015. A survey of 5G network: Architecture and emerging technologies. *IEEE Access* 3: 1206-1232.

Hashima, S., ElHalawany, B.M., Hatano, K., Wu, K. and Mohamed, E.M. 2021. Leveraging machine-learning for D2D communications in 5G/beyond 5G networks. *Electronics* 10(2): 169.

ITU-T Y.3170-series, 2019 – Machine learning in future networks including IMT-2020: Use cases, ITU-T Y-series Recommendations – Supplement 55, vol.10.

Jagannath, J., Polosky, N., Jagannath, A., Restuccia, F. and Melodia, T. 2019. Machine learning for wireless communications in the Internet of Things: A comprehensive survey. *Ad Hoc Networks* 93: 101913.

Jameel, F., Hamid, Z., Jabeen, F., Zeadally, S. and Javed, M.A. 2018. A survey of device-to-device communications: Research issues and challenges. *IEEE Communications Surveys & Tutorials* 20(3): 2133-2168.

Ma, R., Li, B. and Liu, G. 2020. Relay-involved device-to-device communications in LTE networks. In *Encyclopedia of Wireless Networks* (pp. 1199-1208). Cham: Springer International Publishing.

Ma, X., Yin, R., Yu, G. and Zhang, Z. 2012, September. A distributed relay selection method for relay assisted device-to-device communication system. In 2012 IEEE 23rd International Symposium on Personal, Indoor and Mobile Radio Communications-(PIMRC) (pp. 1020-1024). IEEE.

Morocho-Cayamcela, M.E., Lee, H. and Lim, W. 2019. Machine learning for 5G/B5G mobile and wireless communications: Potential, limitations, and future directions. IEEE Access 7: 137184-137206.

Panwar, N., Sharma, S. and Singh, A.K. 2016. A survey on 5G: The next generation of mobile communication. *Physical Communication* 18: 64-84.

Pasam, G.K. and Manohar, T.G. 2016. Multi-objective decision based available transfer capability in deregulated power system using heuristic approaches. *Journal of The Institution of Engineers (India): Series B* 97: 385-393.

Pons, M., Valenzuela, E., Rodríguez, B., Nolazco-Flores, J.A. and Del-Valle-Soto, C. 2023. Utilization of 5G technologies in IoT applications: Current limitations by interference and network optimization difficulties—A review. *Sensors* 23(8): 3876.

Raziah, I., Yunida, Y., Away, Y., Muharar, R. and Nasaruddin, N. 2021. Adaptive relay selection based on channel gain and link distance for cooperative out-band device-to-device networks. *Heliyon* 7(7).

Salim, M.M., Elsayed, H.A. and Abdalzaher, M.S. 2023. A survey on essential challenges in relay-aided D2D communication for next-generation cellular networks. *Journal of Network and Computer Applications* 216: 103657.

Shamganth, K. and Ahmed, Q.Z. 2021, January. Performance analysis of double-threshold based multi-relay selection with differential modulation for cooperative D2D network. In 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 1343-1346). IEEE.

Shamganth, K. and Sibley, M.J. 2017, August. A survey on relay selection in cooperative device-to-device (D2D) communication for 5G cellular networks. In 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS) (pp. 42-46). IEEE.

Shamganth, K., Ahmed, Q.Z. and Khan, F.A. 2023. Double threshold based optimal device selection scheme for D2D or Sidelink network. *ICT Express* 9(1): 22-28.

Siddiqui, M.U.A., Qamar, F., Ahmed, F., Nguyen, Q.N. and Hassan, R. 2021. Interference management in 5G and beyond network: Requirements, challenges and future directions. *IEEE Access* 9: 68932-68965.

Simon, M.K. and Alouini, M.S., 1998. A unified approach to the probability of error for noncoherent and differentially coherent modulations over generalized fading channels. *IEEE Transactions on Communications* 46(12): 1625-1638.

Sindhushree, K. and Naik, D.C. 2023, July. Advancements and Challenges in 5G Networks. In 2023 International Conference on Smart Systems for applications in Electrical Sciences (ICSSES) (pp. 1-6). IEEE.

Zhao, Q. and Li, H. 2007. Differential modulation for cooperative wireless systems. *IEEE Transactions on Signal Processing* 55(5): 2273-2283.