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RESEARCH ARTICLE

Assigning Optimal Multi-Objective Model in Cognitive Radio Networks

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Abstract

Radio cognitive technology is a promising solution for 5G communications, capable of addressing stringent spectrum requirements while offering cognitive capacity, reconfigurability, and adaptable transmission parameters. Its primary objectives include spectrum sensing, management, mobility, and sharing. In this study, a cellular telecommunications network is modeled using MATLAB, considering the roles of relays, communication paths, and network capacity. Traffic injection into data centers simulates the proposed strategy's performance. The best relay determination technique enhances data transmission rates, demonstrating that the proposed strategy reduces equipment and resource consumption by approximately 15% while optimizing network load balance. It identifies optimal paths, prioritizes packet transmission, and achieves up to 20% reduction in latency. Simulation results confirm the strategy's effectiveness in maximizing link utilization, improving load balancing, and enhancing network resource utilization. Additionally, the approach selects optimal routes based on user preferences while requiring fewer hardware resources, making it a practical and efficient solution for modern network challenges.

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Keywords: Cognitive Radio Network; Resource Management; Energy Consumption; Cooperative Relay; Wireless Communication; SWIFT Communication.

1. Introduction

A deficit in the available radio spectrum has been identified as a result of congestion caused by wireless devices and poor management of available frequencies. Forecasts suggest that the number of devices connected via wireless networks will exceed 50 billion by 2020, with a vast majority of them using the Internet. This sharp increase in wireless connectivity brings about a critical issue: the poor allocation of the scarce resource—radio spectrum—among users, which can lead to service disruptions such as denial of service (DoS) cases. Consequently, the scarcity of available radio spectrum in currently attractive frequency bands has become one of the most pressing issues to be addressed by future network research [1]. With the increasing demand for wireless services. The use of the radio-frequency spectrum is important, and as it is known, only part of the current radio spectrum is exploited while the rest of the frequency band is vacant or unutilized. Here we see the need to develop ways to manage these resources efficiently, especially with the high demand for radio frequencies. Therefore, new policies and solutions are being sought to ensure the optimal use of the available spectrum, because the pressure increases due to the expansion of wireless services [1].

To address these challenges, a novel solution referred to as intelligent radio cognition technology has been proposed. This technology is expected to enhance spectrum utilization by dynamically adjusting the allocation of available frequencies [2]. Cognitive radio technology is one of the most promising solutions to overcome the crisis of spectrum scarcity where spectrum can be shared between devices. This is particularly important for advancing next-generation communications, such as fifth generation, where spectrum-sharing technologies may become important for future networks. This technology can meet the stringent spectrum requirements of 5G networks, providing cognitive capability, reconfiguration, and adaptability to environmental features. Among its main objectives are spectrum sensing and management, mobility and participation. Spectrum sensing is vital to detect underutilized spectrum (spectrum gaps). The space-time frequency spectral cavity, which is temporarily unused by any primary or secondary users, varies with respect to space and time. By using the wireless spectrum opportunistically, cognitive radio technology is expected to alleviate the challenges posed by the scarcity and inefficiency of spectrum usage in wireless networks [2]. Cognitive radio has several advanced features, including agile sensing for early user detection and the simultaneous use of multiple spectrum bands. This technology helps in the transition from fixed spectrum management to dynamic spectrum management, leading to better use of frequency bands. In these networks, secondary users can use licensed domains when they are not occupied and evacuate them when the primary user is active to prevent interference [3]. Thus, radio-based NGNs allow dynamic frequency allocation and help ease spectrum restrictions. In addition, these networks offer the possibility of dynamic energy saving. Using a multi-objective mathematical model, this study also attempts to analyze and process energy saving consumption and spectrum utilization better, considering the above challenges [4]. Cognitive radio technology can solve these problems by enabling secondary users (SUs) to access the permissible spectrum as long as their interference with primary users (PUs) does not exceed the limit that primary users can afford [5]. The three main access strategies are spectrum sharing, accessing it when available, and not exploiting it is cognitively enhanced access. By increasing spectrum utilization, these strategies can help address the problem of current resource scarcity [6, 7]. To maximize the overall performance of the system and ensure quality of service (QoS) for communication users, efficient resource allocation needs to be improved. Different optimization strategies have been proposed for cognitive radio systems, and optimization with multiple objective constraints provides significant advantages over alternative methods [8, 9]. Multi-objective optimization models can make radio resource allocation more reliable and balanced. Multi-antenna technology is also increasingly used in cognitive wireless networks, where it can significantly affect system performance [10-12].

The study looks at the impact of the proximity of devices to each other and how to allocate bandwidth to improve network efficiency. The results indicate that the priority in communication will be for devices that perform more important tasks, and this leads to more efficient use of bandwidth, which improves the overall performance of the network. The study also reveals the relationship between the distance between the device and the base station and its impact on network productivity, and the results confirm that the convergence of devices enhances the efficiency of operation, in addition to illustrating the role of (SWIFT) technology (intelligent adjustment of radio frequency) in improving network stability, which reduces interruptions and increases network reliability. It also addresses the impact of the size of the demand on the network such as response delay, network load, and data loss, and explains that choosing a navigation strategy helps reduce delays and improve load distribution on the network, which leads to better performance. It also reveals how choosing the best can increase the efficiency of the use of links and improve the performance of the network in general, when reducing the number of connections and improving their use. The network speed improves. Delays are reduced. The quality-of-service increases. In the end, the study provides an analysis of the relationship between operational productivity and distance between devices, which justifies the importance of choosing a mobility strategy to ensure stable and distinguished network performance.

2. Related Works

A number of publications pertaining to optimization strategies for spectrum allocation, both Single-Objective (SO) and Multi-Objective (MO), have been examined. In addition to impairing the performance of other objectives, single-objective optimization fails to achieve the trade-off between several competing goals. Researchers have defined multiple objectives as a Multi-Objective Optimization (MOO) problem in order to achieve balanced performance between these objectives. This section summarizes a few significant works in this field.

The Non-Sorting Genetic Algorithm (NSGA-II) was used in [13] to achieve maximum spectrum usage, minimal fairness, and maximum energy efficiency. The combined spectrum and power allocation in Cognitive Radio Networks (CRNs) was the primary goal of this work. In comparison to the NSGA-II and Multi-Objective Particle Swarm Optimization (MOPSO) algorithms, the Multi-Objective Differential Evolution (MODE) approach optimizes network capacity [14]. The Ant Colony Optimization (ACO) technique reduces the likelihood of false alarms, increases the detection rate, and improves spectrum utilization [15].

Throughput is increased, and proportional fairness is ensured with Xu's power and sub-channel allocation algorithm, which considers interference temperature thresholds and power constraints [16]. However, the unpredictability of channel information impacts the performance of this method. A robust optimization problem for optimizing energy efficiency under limited uncertainty in channel gain was later developed by the same authors [17]. In their study of robust beamforming in cognitive radio networks, Askari et al. were able to determine the highest achievable rate for secondary users [18]. Chen et al. improved system performance by investigating channel uncertainty errors using normalized distribution and adjusting the system model to ensure resilient transmit power [19]. All these optimizations are single-objective, and the results have notable drawbacks.

In the context of multi-objective optimization, Sun et al. developed a sticky bacterium method that strikes a balance between capacity maximization and interference reduction [20]. Similarly, Ranjan et al. employed greedy algorithms and the interference index to discover a combined optimization technique between interference and capacity [21]. By converting multiple objectives into a single objective using adaptive algorithms, system capacity is increased [22]. Utility functions, as used by Naseer et al., aim to minimize costs and allocate resources efficiently to maximize overall performance [23]. To find the best solution, Baias et al. used linear fractional programming to convert a problem involving the minimization of total power and signal-to-noise ratio into a convex problem [24]. These studies consider multi-objective optimization, but they do not account for system uncertainty. Nguyen et al. optimized the rate and total harvested energy under imperfect Channel State Information (CSI) using S-process theory and two convex function difference approaches [25]. Building on this, we will investigate multi-objective problems under channel uncertainty conditions using the Lagrange method and other techniques.

3. Methods and Materials

This paper explains the Wireless Cognitive Radio Network (WCRN) as shown in Figure 1. The network consists of three main components: a battery-operated relay node (R), a destination node (D), and a source node (S), all of which are equipped with antennas. The system model primarily focuses on energy and signal-related issues, emphasizing how the restricted delay constraint can impact communication performance.

Under this model, limited delay transmission means that decoding incoming signals occurs on a block-by-block basis, which may require more time than the block time allocated for their transmission. This challenge increases the probability of imposing strain on the available time and energy resources within the system. The network operates in half-duplex mode, meaning the total transmission time (T) is divided into two equal periods. In the first phase, the source node (S) transmits data to both the destination (D) and the relay node (R). At this stage, the relay node not only demodulates the signal but also performs Energy Harvesting (EH), in which the relay node captures a portion of the energy from the received signal. In the second phase, the relay node (R), using the harvested energy from the EH process, forwards the signal to the destination node (D). The destination node then applies the Maximal Ratio Combining (MRC) technique to combine the signals received directly from both the source and relay nodes, enhancing the overall signal quality. The links between the nodes are modeled using Rayleigh fading channels: h_{sd}, h_{sr} and h_{rd} , which represent the fading effects independently and randomly on the S-D, S-R, and R-D links. This fading model simulates the practical scenario of signal attenuation that occurs through wireless channels, which the system must address to effectively serve its intended purpose.

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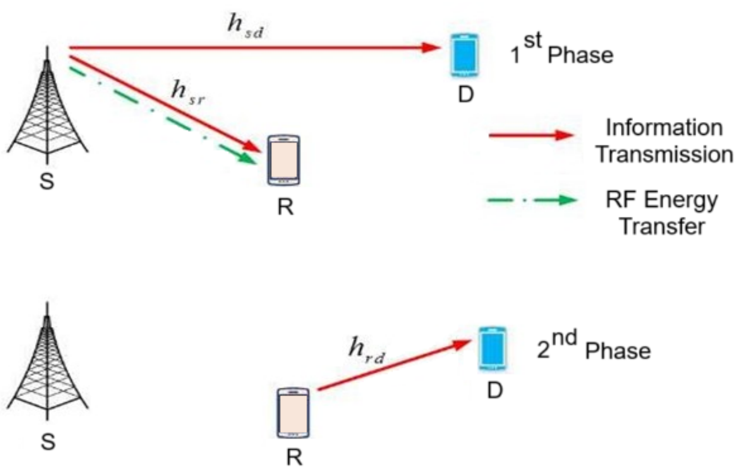

Fig. 1. The proposed system model.

3.1. Direct Transfer

The signal received for the direct S-D connection at the destination (D) during the first phase is given by the following equation [26]:

$$Y_{sd} = 1/\sqrt{d^a}\ \sqrt{p_s h_{sd}} s + z_d \tag{1}$$

where P_s is the source power transmission, α indicates losses, d is the distance from S to D, and s is the normalized information signal at the source node (S), with $E[|s|^2]1$, which equals $E(0)$ for the expected operation. The average zero-mean Gaussian white noise (AWGN) at D, with variance σ_a^2, is represented by the variable (z_d).
In light of equation (1), the Signal-to-Noise Ratio (SNR) at the destination for direct transmission, ρ_{dl}, is defined as:

$$\rho_{dl} = P_s|h_{sd}|^2 / d^a\sigma^2 d \tag{2}$$

3.2. Cooperative Relay Transfer

In the first phase, the communication process begins with the signal being transmitted from the source node (S) to the relay node (R). The signal received by the relay node can be mathematically characterized using the following equation, as outlined in references [26]:

$$Y_{sr} = 1/\sqrt{d^a{}_1} * \sqrt{P_s}\, h_{sr} S + Z_r \tag{3}$$

where d_1 denotes the S-R distance and z_r is the relay node's AWGN. The PSR protocol at R uses the received signal in two sections: β or energy harvesting, and β-1 for information amplification and retransmission. The power division rate (β) is denoted by $0 \leq \beta \leq 1$. The total energy is expressed as:

$$Q = \xi\beta Ps|h_{sr}|^2 T / 2d_1^a \tag{4}$$

which $0 \leq \xi \leq 1$ is the energy conversion efficiency.
The received information signal in the relay, after PS and down conversion, is given by

$$Y_{sr} = 1/\sqrt{\ } d_1^a \sqrt{(1 - \beta)} P_s h_{sr} S + \sqrt{(1 - \beta)} Z_r + Z_{cr} \tag{5}$$

where Z_{cr} is the sampled AWGN from the baseband signal's conversion from the RF band. The relay then delivers the received signal to the destination node after amplifying it in the second phase. The SNR for the S-R link is represented as [26]:

$$\rho_{sr} = (1 - \beta)P_s|h_{sr}|^2 / d_1^a\sigma^2{}_R \tag{6}$$

The following equation represents the signal received at the destination node [26]:

$$y_{nl} = 1/\sqrt{d_1^a}\ \sqrt{P_r} h_{rd} x + z_d + z_{dc} \tag{7}$$

In this equation, P_r represents the transmission power of the relay using battery energy, d_2 is the R-D distance, and xxx is the transmission signal from R with $\mathcal{E}[|x|^2] = 1$, The AWGNs at the destination and the converted baseband signal are represented by z_d and z_{dc} respectively. Changes occur at the destination node.
If the relay node is battery-operated, then its transmission power P_r, is determined using the following equation, derived from equation (4), and is given by [26]:

$$P_r = \xi[Q] / T/2 = \xi\beta Ps / d_1^a \tag{8}$$

assuming $\mathcal{E}[|h_{sr}|^2] = 1$. The variance $\sigma_R^2 = (1 - \beta)\sigma_r^2 + \sigma^2{}_{cr}$. Equation (7) can be substituted into equation (8) to obtain the SNR for the R-D link, ρ_{rd} [26]:

$$\rho_{rd} = \xi\beta Ps|h_{rd}|^2 / d^a{}_1 d^a{}_2 \sigma^2{}_D \qquad \text{where } \sigma^2{}_D = \sigma\ d^2 + \sigma\ cd^2 \tag{9}$$

The flowchart of the proposed method is shown in Figure 2.

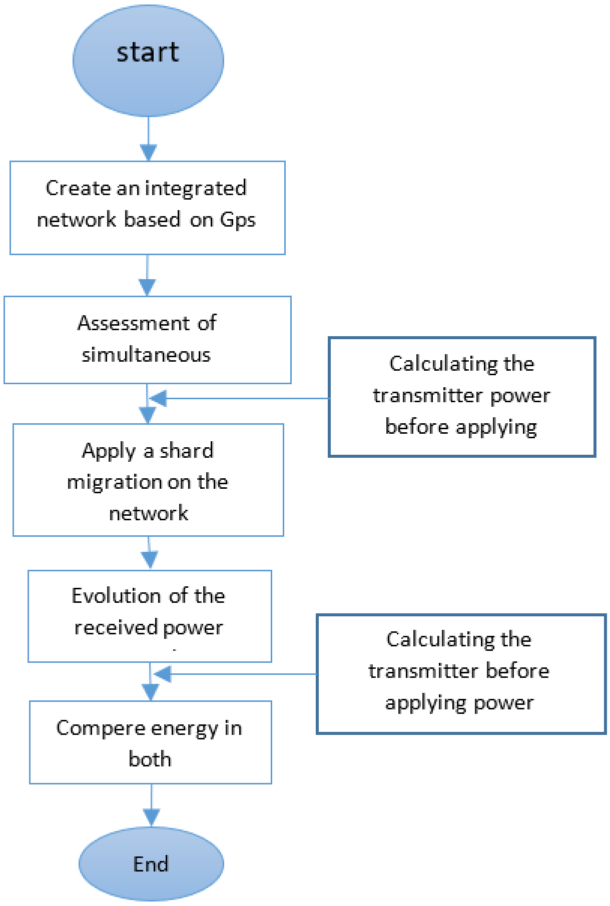

Fig. 2. The flowchart for the proposed method.

4. Results and Discussion

This work focuses on optimal relay selection to enhance cognitive radio networks, particularly in the context of SWIFT communication in modern cellular telecommunication technologies. Relay selection is a critical aspect in implementing the relay concept, especially when multiple devices need to communicate within a single environment characterized by limited spectrum. The study begins by analyzing the First Message Exchange (FME) phase between devices in a network.

During this step, every gadget must start a link with its nearby gadgets. This way of linking is key, as it helps gadgets pick possible relays based on their job flow importance. The levels of job flow show the exact data needs and the priority in choosing relay gadgets. The aim is on the use of SWIFT talks in modern cell phones, the idea of relay picking is key to sending good data and keeping network steady, especially in situations where lots of devices talk and share resources in a changing, tight-band environment.

Start of the study. Examining the initial phase of communication between devices in the network during this phase, each device has to connect to its neighboring devices. A process as important as it allows the devices to recognize and choose potential relays according to the different levels of mission flow. Different data requirements and priorities that may be there for specific devices and that finally affect relay selection require all devices. The selection is not random but adaptive and intelligent. The criteria used by devices in the choice of relays are based on the available spectrum, SNR, energy efficiency, and network traffic load.

This adaptive relay selection process allows the system to increase data throughput, lower latency, and remove potential bottlenecks in the rush hour. Figure 3 provides a picture of this communication method and shows how it determines and interacts with devices to pick the right relay to receive a message. It also illustrates how neigh boring devices are identified and child relay nodes are then eliminated to optimize network operation under different conditions.

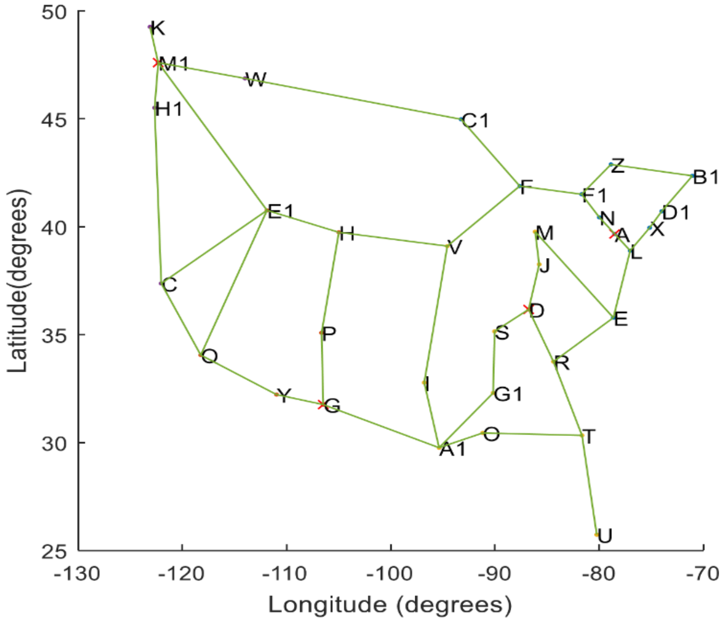

Fig. 3. SWIFT communication system model in cellular networks.

The study begins on how devices communicate within the network in the initial stage of communication. At this stage, each device tries to establish links with devices near it. This process is considered basic and simple as it allows devices to identify other devices that can act as an intermediary for data transfer based on different task flow levels.

This adaptive and smart choice ensures that the choice of relays in the network is not random, but depends on several factors to ensure the best performance, the devices decide which relay is the most appropriate based on several things such as signal quality, frequency availability, power consumption, and congestion in the network, so the goal of the smart choice is to improve data flow, reduce delays, and avoid bottlenecks, especially when there is great pressure on the network An illustration of how devices communicate with each other appears when choosing the best way to send data is shown in Figure 4. This figure also illustrates the evaluation of SWIFT communication links in relation to relay selection, emphasizing the critical role of this process in optimizing network performance.

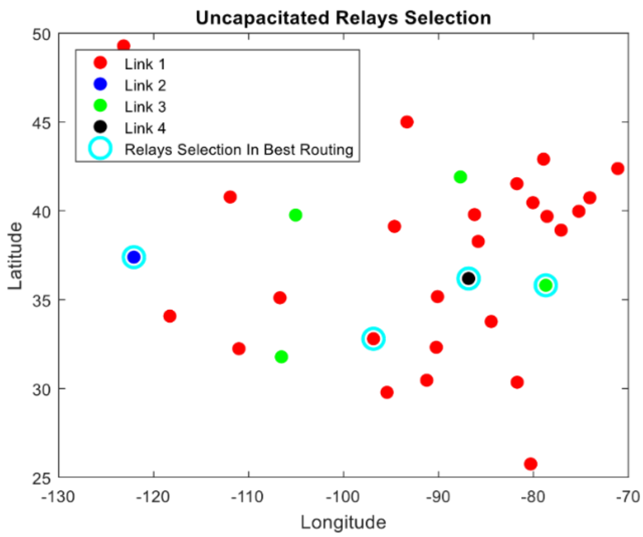

Fig. 4. Evaluation of SWIFT communication links based on the role of relays.

Additionally, the proposed study investigates the influence of device proximity and bandwidth allocation on network efficiency. Prioritizing devices with higher task levels and those closer in proximity results in more efficient use of available bandwidth, thereby improving overall network performance. This is demonstrated in Figure 5, where the total data transfer delay with and without optimal relay usage is compared, highlighting the significant role of relay selection in reducing latency.

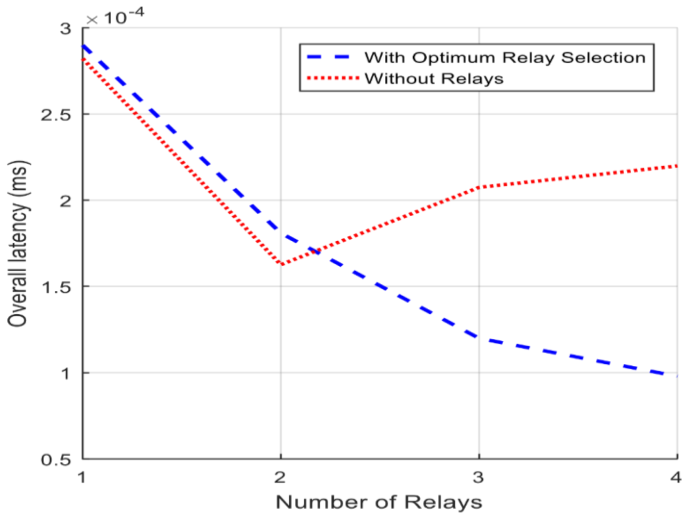

Fig. 5. Evaluation of SWIFT communication links based on the role of relays.

Figure 6 demonstrates how relay selection influences data transport latency. It also highlights how efficient relay prioritization reduces latency for devices with higher task levels and closer proximity, by comparing the total data transfer delays with and without optimal relay utilization.

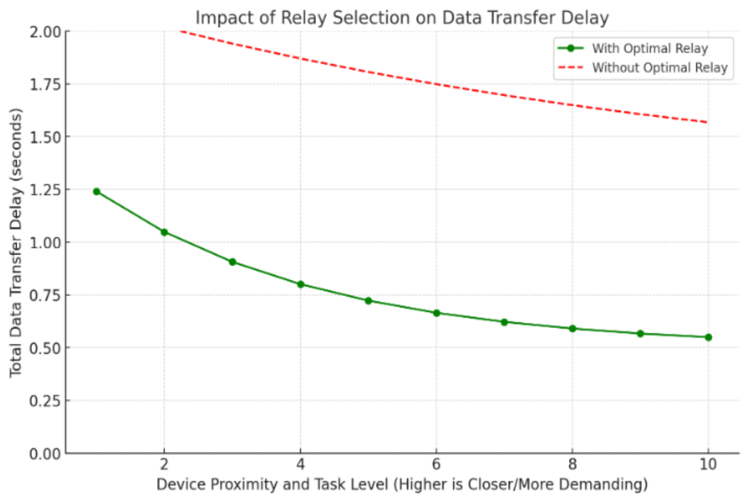

Fig. 6. Impact of relay selection on data transfer delay.

The proposed study also investigates the impact of device distance on network throughput, particularly in terms of the operational capacity and packet throughput of the network. Figure 7 the distance between the device and the base station and the network throughput, where the closer the device is to the base station, the faster the data transfer speed.

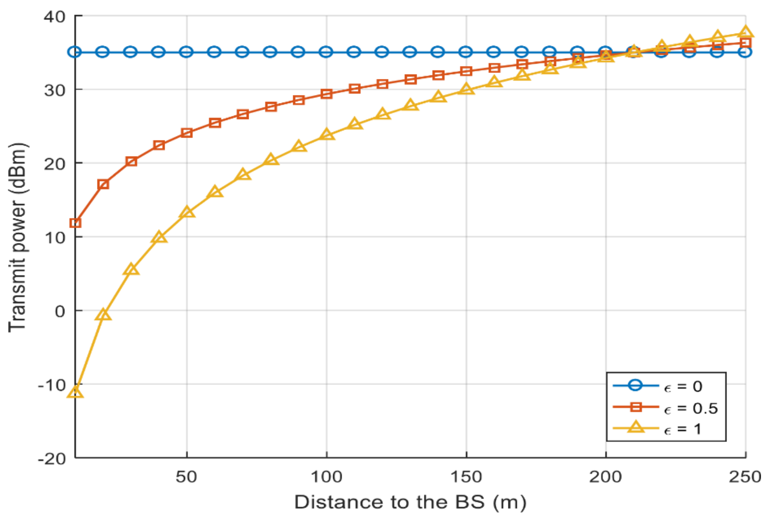

Fig. 7. Comparing the distance of the devices to the base station and the effect on the throughput of sending packets.

The association between device distance and network productivity is represented in Figure 8, where this figure illustrates how network performance decreases as the distance from the base station increases to demonstrate the importance of proximity to maximize operational capacity.

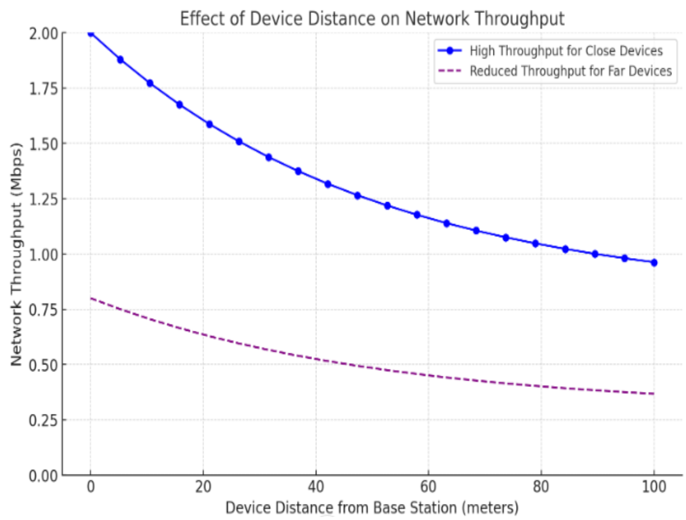

Fig. 8. The effect of device distance on network throughput.

Moreover, the study investigates the impact of SWIFT resource utilization and device mobility on enhancing network stability. Increased utilization of SWIFT resources, combined with device mobility, contributes to improved network stability and reduced communication interruptions. Figure 9 provides a visual representation of this analysis, highlighting the role of resource utilization and device mobility in maintaining stable network performance.

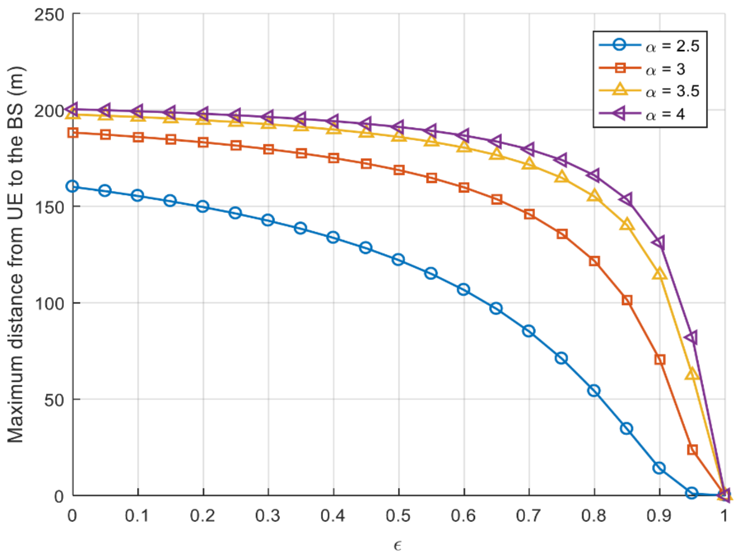

Fig. 9. Investigating the impact of using SWIFT resources according to the movement of devices.

Additionally, the performance of traffic engineering and load balancing within the network were analyzed, emphasizing the critical role of optimal relay selection in improving these aspects. Figure 10 demonstrates the performance of traffic engineering as influenced by relay selection, underscoring the importance of efficient relay prioritization in achieving load balancing and optimizing overall network performance.

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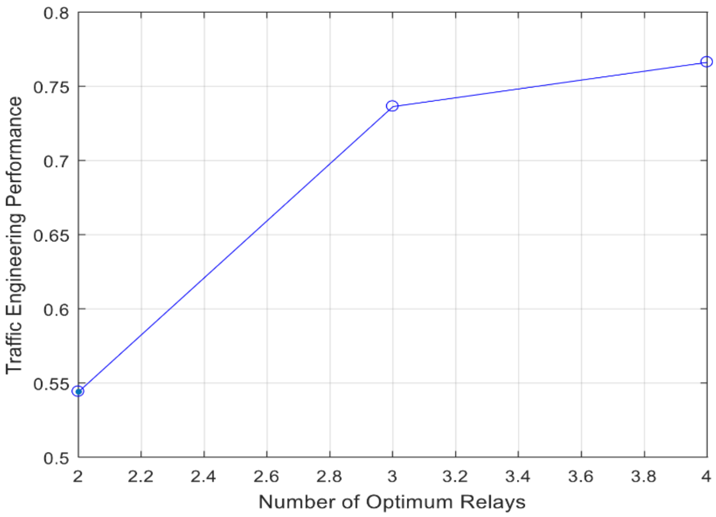

Fig. 10. Performance of traffic engineering on the network based on the performance of relays.

5. Conclusion

From the proposed study findings, we suggest that improving cognitive radio networks further depends on eliminating sub-optimal relay selection. Effective relay selection techniques dramatically affect network performance, especially when relays are used in highly variable traffic scenarios. These had broad effects on resource allocation and balancing the load throughout the system and reducing latency. The main aim of this paper was to find the best relays while decreasing the use of equipment and network resources so that the best route for data transmission could be determined simultaneously, ensuring optimal load distribution across the network. The second aim was to improve data performance by adapting packet transmission to current network traffic conditions.

These findings emphasized the factors that should motivate designers and deployers of cognitive radio systems to include relay selection algorithms. The results of the simulations conducted in this work demonstrated that it significantly outperformed existing methods in many very important aspects, such as link utilization, distribution of load across network links, latency, and resource efficiency. Also, the proposed study optimized routing by using the least hardware and network resources while keeping user preferences in consideration. This might improve the communication process, thus further increasing the effectiveness of cognitive radio networks in fulfilling modern demands for wireless communications.

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