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OPTIMIZING MULTICHANNEL PATH SCHEDULING IN COGNITIVE RADIO AD HOC NETWORKS USING DIFFERENTIAL EVOLUTION

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Abstract. One important area of study in cognitive radio ad hoc networks is multi-channel path scheduling. Cognitive radio networks have trouble communicating and using the spectrum effectively because of weather and dispersion. Optimizing multichannel path scheduling enhances network performance and reliability in a cognitive radio ad hoc net. The Optimizing Multichannel Path Scheduling (OMPS) model methodically tackles various scheduling problems. For the OMPS model, this domain is new. It effectively resolves multichannel path scheduling. The computer method used in the study is called Differential Evolution. During optimization, several factors are carefully considered, including Channel Fade Margin, Cross-Correlation and Coherence Time, Spectral Efficiency, Interference Level, Power Consumption, Retransmission Rate, Access Probability, and Propagation Delay. To increase the scheduling efficiency of the DE algorithm, many steps are meticulously planned: initialization, mutation, crossover, fitness evaluation, selection for iteration evolution, and termination. Latency, Packet Delivery Ratio (PDR), Spectrum Utilization, Interference Level, Energy Efficiency, and Established Path Success Rate are all assessed by the OMPS model. These indicators assess the effectiveness and dependability of the network. OMPS performs better in crucial simulations than the existing model. The demonstration demonstrates decreased latency for real-time applications, greater packet delivery ratios (PDRs), improved spectrum efficiency, channel interference, energy efficiency, and connection formation odds, as well as increased throughput that enhances network resource utilization. To do this, a variety of multichannel path scheduling situations are simulated

Key words: Collision, Moving Objects. Global Positioning System, Machine Learning, Binary Classification, Gann Angle Degree, Trajectory Interception Detection, Unmanned Aerial Vehicles, Zero-Shot Learning.

1. Introduction.

The burgeoning demand for wireless communication has amplified the requirement for efficient radio spectrum utilization, highlighting the essentiality of Cognitive Radio Ad hoc Networks (CRAHNs) [1]. This article sets out to explore, evaluate, and address the intricacies of the pressing challenge of multichannel path scheduling within these networks.

CRAHNs, known for their adaptive potential, empower secondary users (SUs) to intelligently identify and leverage vacant spectrum bands. While this is a notable breakthrough in network utilization, the task of optimizing multichannel path scheduling remains a significant challenge, directly impacting the efficacy of data transmission across the network [2]. The motivation behind this work arises from the need to address this challenge, ensuring the capability of CRAHNs is maximized.

The problem statement of this research revolves around the efficient management and optimization of multichannel path scheduling in CRAHNs. The primary objective is to introduce an advanced model that improves network performance by ensuring optimal path selection for data transmission, considering multiple fitness parameters.

To meet these objectives, we introduce the OMPS model, utilizing an evolutionary computation approach known as Differential Evolution (DE). Further, to validate the proposed model's effectiveness, an exhaustive comparison is carried out with the Path Discovery for end-to-end Data Transmission (PDDT) in Cognitive Radio Ad-Hoc Networks using Genetic Algorithms (GA) model. The comparison is based on a thorough simulation study examining key performance metrics including Throughput, Packet Delivery Ratio (PDR), Latency, Spectrum Utilization, Interference Level, Energy Efficiency, and Success Rate of Established Paths.

This paper demonstrates the superiority of the OMPS model, leading to significant enhancements in network performance metrics. By achieving these results, we believe this research contributes substantially to the

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growing body of knowledge in the field of CRAHNs, also paving the way for future studies to further optimize network performance.

2. Related Work. This synthesis of research reviews provides a thorough exploration into the domain of cognitive radio (CR) technology, with a specific focus on the development and evaluation of various protocols, methodologies, and techniques that contribute towards effective management and exploitation of spectrum frequency bands.

"Efficient Management and Exploitation of Spectrum Frequency Bands" by Yaseer et al. [3] offers an evaluation of different CR Medium Access Control (MAC) protocols, notably putting forward the PECR-MAC protocol as the most efficient one. However, the research could be improved by considering the effects of interference and mobility on the performance of CR networks, which is absent in this paper.

In their work, "Mobile Cognitive Radio Ad Hoc Networks (CRAHNs) Using a Cluster-Based Distributed Medium Access Control (CDMAC) Protocol", Wu et al. [4] develop mobile CRAHNs that group nodes based on significance, with cluster heads chosen dynamically. By selecting control and data channels based on the stability and success probability of idle Primary User (PU) channels, they successfully reduce MAC contention delay.

"Dynamic MAC Frame Design and Optimal Resource Allocation for Multi-Channel CRAHN" by Yoo et al. [5] introduces a dynamic resource allocation model formulated as a multi-objective constrained optimization problem. Using the Particle Swarm Optimization (PSO) technique, they demonstrate how this approach can effectively maximize the utility function while ensuring fairness among secondary users (SUs).

In "Fuzzy-Based Optimization Framework for the 802.11 (DCF) MAC Protocol in CRAHNs", Joshi et al. [6] provide a novel perspective by suggesting a fuzzy-based optimization framework. By altering the contention window and packet length of the IEEE 802.11 DCF MAC protocol, their work shows a substantial increase in throughput and significant reduction in delay. "Group MAC (GMAC) Protocol for Multichannel Ad Hoc Cognitive Radio Networks" by Kadam et al. [7] is a ground-breaking study that introduced the GMAC protocol designed for networks with several node groups. Although it shows efficient distribution of traffic from secondary nodes, it comes with the caveat of significant bandwidth consumption when not in use by primary users.

Nagul [8] in "Path-Finding Method for End-to-End Data Transmission in CRAHNs" (PDDT) presents an innovative path-finding methodology for multi-channel broadcasting, factoring in Quality of Service (QoS) metrics. The results indicate substantial improvements in channel allocation.

Salih et al.'s [9] "Dynamic Channel Estimation-Aware Routing Protocol for Mobile Cognitive Radio Networks" offers an advanced routing protocol that balances minimizing PU interference and routing delay while improving throughput.

Dinesh et al. [10] propose the "Salp Swarm Optimization Algorithm (SSOA) and Round Robin (RR) Algorithm for Spectrum Sensing and Scheduling". The work proves the superiority of this approach over conventional methods through performance metrics like throughput, settling time, and base station bands.

Zhong et al. [11] in "Obstacle Aware Opportunistic Data Transmission Technique (OODT) in CRAHNs" present a pioneering method for selecting forwarding candidates and avoiding obstacles, demonstrating its effectiveness in comparison to other approaches.

Suganthi and Meenakshi's [12] "Round Robin Priority (RRP) Scheduling Method for Cognitive Radio Network" proposes a queuing mechanism that mitigates the issue of non-real-time secondary user starvation in CR Networks.

Finally, Padmanadh et al.'s [13] "The Importance of Routing Techniques in Cognitive Sensor Networks (CSNs)" highlights the significance of efficient routing techniques in CSNs to address packet losses and node connectivity due to spectrum scarcity.

In conclusion, each piece of research contributes unique insights and advancements in the field of cognitive radio networks, indicating the potential of CR technology and underscoring the importance of ongoing investigation and optimization for practical application.

The table 2.1 represents a checklist detailing specific aspects of the research papers reviewed. The columns represent various features expected to be covered by the articles reviewed under this section.

3. Proposed Method and Materials. This section comprehensively details unique approach to multi-channel path scheduling optimization, based on the integration of evolutionary computation and the Differential

Table 2.1: A checklist detailing specific aspects of the research papers reviewed.

Author(s)	**Multi-channel Paths**	**End-to-End Data Transmission**	**Optimized Scheduling**	**Spectrum Utilization**	**QoS Parameters**	**Mobility Impact**
[3]	×	✓	×	×	×	✓
[4]	✓	✓	✓	×	×	✓
[5]	✓	×	✓	×	×	×
[7]	✓	×	✓	✓	×	×
[8]	✓	✓	✓	✓	✓	×
[10]	✓	×	✓	✓	×	×
[11]	×	✓	✓	×	×	×
[12]	×	×	✓	✓	✓	×

Evolution (DE) algorithm. This section intended to offer a clear, concise, and comprehensive explanation of our methodology that shown in figure 3.1.

The efficiency of cognitive radio networks is increased using a novel scheduling technique called OMPS (Optimizing Multichannel Path Scheduling in Cognitive Radio Ad Hoc Networks using Differential Evolution). OMPS uses the Differential Evolution technique to optimize a variety of complicated network properties, such as Channel Fade Margin, Cross-Correlation, and Coherence Time. An experimental comparison reveals that in terms of throughput, latency, packet delivery ratio, and energy efficiency, OMPS performs better than the PDDT model. This demonstrates how the OMPS is a reliable way to ensure effective networking since it is well suited to managing the dynamic and flexible communications requirements of cognitive radio networks.

3.1. The Features.

Channel Fade Margin. Channel Fade Margin is essentially the measure of a signal's strength surplus that can prevent the signal from dropping below an acceptable level due to fading. Fading refers to the variations in the signal's strength over time, space, or frequency due to factors such as multi-path propagation, shadowing, and Doppler shift. A higher fade margin indicates that the signal is more resilient to these factors.

The fade margin is usually expressed in decibels (dB) and is calculated using the following formula:

$$CFM = PR - PS \tag{3.1}$$

where:

- $CFM$is the Channel Fade Margin,
- PR is the received power (usually in dBm or dBW), and
- PS is the minimum signal strength necessary for the receiver to correctly decode the signal (also in dBm or dBW).

It's important to note that PS is typically defined by the system requirements or the characteristics of the receiver. For instance, in a digital communication system, PS could be the minimum signal strength required to achieve a certain bit error rate(BER).

Channel Cross-Correlation. Channel Cross-Correlation is used in multichannel path scheduling in cognitive radio networks. It gauges the evolution of the similarity between two channels.

High cross-correlation indicates that the conditions of the channels change simultaneously. Low cross-correlation indicates that conditions change independently for each channel. By comprehending channel cross-correlation and scheduling multichannel, cognitive radios can maximize the use of the spectrum.

Mathematically, the cross-correlation between two channels can be assessed using the Pearson Correlation Coefficient, which is defined as:

$$xy = Cov(X, Y)/(x * y) \tag{3.2}$$

where:

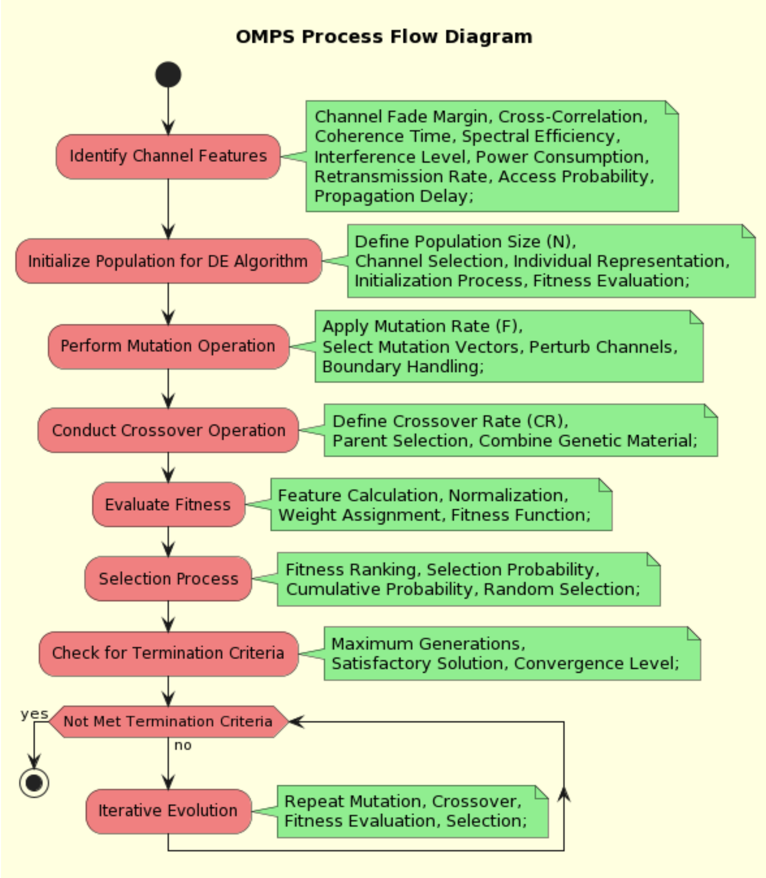


Fig. 3.1: The process flow representation of OMPS

- xy is the Pearson Correlation Coefficient,
- $Cov(X, Y)$ is the covariance between channels X and Y,
- x and y are the standard deviations of channels X and Y, respectively.

The covariance, $Cov(X, Y)$, measures the joint variability of channels X and Y, and can be calculated as:

$$Cov(X, Y) = [(x_i - x) * (y_i - y)]/n, \tag{3.3}$$

where:

- x_i and y_i are the individual samples of channels X and Y, respectively,
- x and y are the mean values of channels X and Y, respectively,
- n is the number of samples.

The standard deviation of a channel, x for instance, measures the dispersion of the channel's values and can be calculated as:

$$x = sqrt[(x_i - x)^2/n] \tag{3.4}$$

Between$-1$and $+1$is the range of the "Pearson Correlation Coefficient"xy. A score of $+1$ denotes a complete positive correlation, which means that circumstances on both channels change in the same manner. The state of the channels changes in the opposite direction when the value of the correlation is exactly negative, or-1. If the correlation is zero, then the channel conditions vary independently.

Channel Coherence Time. Channel coherence time is an essential metric in understanding how quickly the conditions of a wireless channel change. It is particularly important in environments with high mobility, where the relative speed between the transmitter and receiver can cause the channel's properties to change quickly.

The coherence time (Tc) is typically defined as the inverse of the maximum Doppler shift (fD). The maximum Doppler shift occurs due to the relative motion between the transmitter and receiver, and it can be calculated using the formula:

$$(fD) = (v/) \tag{3.5}$$

where v is the relative velocity between the transmitter and receiver, and is the wavelength of the carrier signal.

Hence, the coherence time (Tc) can be expressed as:

$$Tc = 1/fD \tag{3.6}$$

However, in many cases, the 0.423 rule or the 0.5 rule is applied to get a more practical estimate of the coherence time, which can be expressed as:

$$Tc = 0.423/fDorTc = 0.5/fD \tag{3.7}$$

This mathematical model provides an estimate of the duration over which the wireless channel's characteristics remain relatively constant, which is particularly important for scheduling decisions in cognitive radio networks.

Channel Spectral Efficiency. The rate of information that can be transmitted over a given bandwidth. Spectral efficiency $SE$is usually expressed as $SE = birate/bandwdith$.

The information rate that can be transferred over a specified bandwidth in a particular communication system is represented by channel spectral efficiency, which is often expressed in "bits per second per hertz (bps/Hz)". It gauges how efficiently the spectrum resources are being utilised. In other words, spectral efficiency measures how much data, at a certain signal-to-noise ratio, can be delivered over a given bandwidth.

The Shannon-Hartley Theorem provides a mathematical model for the calculation of the maximum possible spectral efficiency, expressed as:

$$C = B * log2(1 + SNR) \tag{3.8}$$

where:

- C is the channel capacity (the maximum achievable data rate) in bits per second,
- B is the bandwidth of the channel in hertz (Hz),
- $log2()$ denotes the base-2 logarithm, and
- SNR is the Signal-to-Noise Ratio.

To calculate the spectral efficiency (), we divide the channel capacity by the bandwidth:

$$= C/B = log2(1 + SNR)bps/Hz \tag{3.9}$$

This model assumes an additive white Gaussian noise (AWGN) channel. It defines the upper limit of the spectral efficiency achievable in such a channel. .

Channel Interference Level . The level of interference a channel experiences from neighboring channels. This can be calculated by summing the power of interfering signals and comparing it to the power of the desired signal.

Channel Interference Level quantifies the level of undesired signals that can affect the performance of a wireless communication channel. Interference can originate from various sources such as co-channel interference (CCI), adjacent channel interference (ACI), or even intermodulation products within a network. High interference levels can degrade the communication quality by reducing the Signal-to-Noise Ratio (SNR), increasing bit error rates (BER), and even causing a total loss of communication in extreme cases.

One simple mathematical model to quantify interference is by calculating the Interference-to-Noise Ratio (INR), which is the ratio of interference power to the noise power. It is given by:

$$INR = P_i/N \tag{3.10}$$

where:

- INR is the Interference-to-Noise Ratio,
- P_i is the total received interference power (usually in dBm or dBW), and
- N is the noise power (usually in dBm or dBW).

In a more practical scenario, when you consider both the desired signal and the interference, a common measure is the Signal-to-Interference-plus-Noise Ratio ($SINR$), which can be expressed as:

$$SINR = P_s/(P_i + N) \tag{3.11}$$

where:

- $SINR$ is the Signal-to-Interference-plus-Noise Ratio,
- P_s is the received signal power (usually in dBm or dBW),
- P_i is the total received interference power (usually in dBm or dBW), and
- N is the noise power (usually in dBm or dBW).

The $SINR$ effectively quantifies the quality of the desired signal in the presence of both interference and noise.

In the context of optimizing multichannel path scheduling in cognitive radio networks, the interference level is a critical factor. Channels with high interference levels could degrade the performance of the cognitive radio network, hence they are less preferred for data transmission. The differential evolution optimization process can consider the interference level as one of the critical features to optimize multichannel path scheduling, thereby improving the overall performance and reliability of the cognitive radio network.

Channel Power Consumption. The power required for transmitting data over the channel. This can be modeled as the product of the current drawn and the voltage used. Channel Power Consumption refers to the amount of power required to transmit data over a specific channel in a cognitive radio network. It is a crucial consideration, particularly in energy-constrained environments where optimizing power consumption is essential for prolonging the network's battery life and reducing operational costs.

The mathematical model for calculating Channel Power Consumption depends on several factors, including the transmitter's characteristics, modulation scheme, coding rate, and transmit power. One simplified model for power consumption is:

$$P = V * I \tag{3.12}$$

- P represents the power consumption in watts (W),
- V denotes the voltage used for transmission in volts (V) and
- I represents the current drawn during transmission in amperes (A).

In practice, the actual power consumption might vary depending on the hardware implementation, circuit efficiency, and other factors. Advanced models can incorporate additional parameters like amplifier efficiency, digital signal processing power, and signal coding complexity to provide a more accurate estimation of power consumption.

In the optimization of multichannel path scheduling, considering Channel Power Consumption is essential. Lower power consumption channels are generally preferred as they enable energy-efficient communication and help to conserve the network's resources. By including Channel Power Consumption as a feature in the differential evolution optimization process, the multichannel path scheduling can be optimized to select channels that minimize power consumption while meeting the communication requirements of the cognitive radio network.

Channel Retransmission Rate. The rate at which packets need to be retransmitted due to errors. This can be represented as the ratio of the number of retransmitted packets to the total number of transmitted packets. Channel Retransmission Rate refers to the rate at which packets need to be retransmitted due to errors in a specific channel. It quantifies the efficiency and reliability of data transmission over the channel. A high retransmission rate indicates a higher number of packet retransmissions, which can lead to increased latency, reduced throughput, and inefficient channel utilization.

Mathematically, the Channel Retransmission Rate (R_r) can be calculated by dividing the number of retransmitted packets (N_r) by the total number of transmitted packets (N_t):

$$R_r = N_r/N_t \tag{3.13}$$

The number of retransmitted packets (N_r) can be counted at the receiver, and the total number of transmitted packets (N_t)represents the total packets sent over the channel.

Optimizing the Channel Retransmission Rate is crucial for improving the overall performance of cognitive radio networks. By minimizing the retransmission rate, it is possible to enhance throughput, reduce latency, and improve the utilization of available spectrum resources. In the context of the proposed approach using differential evolution optimization, the Channel Retransmission Rate can be considered as one of the features to optimize multichannel path scheduling. Channels with lower retransmission rates can be prioritized, resulting in more reliable and efficient data transmission in the cognitive radio network.

Channel Access Probability. The likelihood that a secondary user will successfully access the channel without conflicting with the primary user. This could be modeled probabilistically based on the activity patterns of the primary user. Mathematically modeling the Channel Access Probability depends on various factors and can be quite complex due to the dynamic nature of channel availability. The specific model employed will depend on the characteristics of the cognitive radio network and the access protocols used. Here, we'll provide a simplified representation.

One possible approach to estimating the Channel Access Probability is through empirical observations and measurements. By monitoring the channel activity over time, the probability of a channel being idle (i.e., not in use by the primary user) can be determined. This probability of channel idleness can be considered as an approximation of the Channel Access Probability for the secondary user.

The mathematical model for the Channel Access Probability ($Pacc$) can be expressed as:

$$Pacc = TimeChannelisIdle/TotalTime \tag{3.14}$$

where:

- $Pacc$ is the Channel Access Probability,
- Time Channel is Idle represents the accumulated duration that the channel is observed to be idle, and
- Total Time refers to the total observation time.

In the context of "Optimizing Multichannel Path Scheduling in Cognitive Radio Networks: An Evolutionary Computation Approach Using Differential Evolution," the Channel Access Probability plays a crucial role in the decision-making process for channel selection. Higher Channel Access Probability implies a higher chance for the secondary user to successfully access the channel without causing interference to the primary user. By incorporating the Channel Access Probability as a feature in the differential evolution optimization process, the multichannel path scheduling can be optimized to select channels with higher access probabilities, resulting in improved channel utilization and enhanced performance in the cognitive radio network.

Channel Propagation Delay. The time taken for a signal to travel from the sender to the receiver. The usual formula for calculating this is to divide the distance between the sender and receiver by the speed of light, with modifications made for the transmission medium. It is mathematically possible to determine the Channel Propagation Delay (D) by using the formula

$$D = Distance(d)/Speedoflight(c) \tag{3.15}$$

where:

- D represents the Channel Propagation Delay,
- $Distance(d)$ is the physical distance between the transmitter and receiver, and
- $Speedoflight(c)$ is the speed at which electromagnetic signals travel through the medium (approximately 299,792 kilometers per second or 186,282 miles per second in a vacuum).

The time it takes for a signal to travel from the transmitter to the receiver, including any lags brought on by the transmission medium, is taken into account by the channel propagation delay.

The proposal takes the Channel Propagation Delay into account as a key factor when attempting to optimize multichannel path scheduling. In general, it is preferred to use channels with lower propagation delays because they reduce the network's overall latency. The multichannel path scheduling can be optimized to choose channels with shorter propagation delays by incorporating Channel Propagation Delay as a feature in the differential evolution optimization process. This improves communication efficiency and lowers latency in the cognitive radio network.

In order to optimize the multichannel path scheduling process in cognitive radio networks, this section investigates the use of the Differential Evolution (DE) algorithm. This section examines the DE algorithm, its fundamental ideas, and the associated mathematical models that support its efficiency in dealing with the difficulties of multichannel path scheduling. A detailed explanation of the DE algorithm's design for multichannel path scheduling optimization follows:

(1) Initialization: Initializing a population of people is the first step in the DE algorithm. In this scenario, every person stands in for a series of data transmission channels. There are numerous such sequences in the population. Following is a description of the initialization algorithm's steps:

- **Population Size:** Determines the desired population size, denoted as N, which represents the number of individuals (channel sequences) in the population. This value is typically predefined based on the problem size and available computational resources.
- **Channel Selection:** Randomly selects N channel sequences from the available set of channels. Each channel sequence represents a potential solution for multichannel path scheduling.
- **Individual Representation:** Each individual (channel sequence) in the population is represented as a vector or string of discrete channel indices. For example, if there are M channels available, each channel sequence would consist of M elements, where each element corresponds to the index of the selected channel for a specific position in the sequence.
- **Initialization:** Randomly assigns channel indices to the elements of each individual's vector. The selection of channel indices can be uniformly distributed or follow a specific probability distribution based on prior knowledge or constraints.
- **Fitness Evaluation:** Evaluate the fitness or objective function value of each individual in the population. The fitness function should reflect the performance metrics relevant to multichannel path scheduling, such as throughput, reliability, energy efficiency, or any other desired criteria. This step provides an initial assessment of the quality of each channel sequence.
- **Population Creation:** Create the initial population by repeating steps 3-5 for N individuals, resulting in a population of N channel sequences.

The mathematical modeling for the initialization step in DE is relatively straightforward and involves random assignment of channel indices to the elements of each individual's vector. It can be represented as:

$$Individual(i) = [c_1, c_2, ..., c_M] \tag{3.16}$$

where $Individual(i)$ represents thei^{th} individual in the population, $c_1, c_2, ..., c_M$ are the randomly assigned channel indices for each position in the sequence, and M is the total number of channels available.

The fitness evaluation step, mentioned in step 5, involves the calculation of the fitness value for each individual. The specific mathematical model for the fitness function would depend on the performance metrics and objectives considered in the multichannel path scheduling problem. The fitness value can be expressed as:

$$Fitness(i) = f(c_1, c_2, ..., c_M) \tag{3.17}$$

where Fitness(i) represents the fitness value of the i^{th} individual, and $f(c_1, c_2, ..., c_M)$ is the mathematical function that evaluates the performance of the channel sequence $c_1, c_2, ..., c_M$ according to the specified metrics.

By initializing the population using random channel assignments and evaluating the fitness of each individual, the DEalgorithm sets the groundwork for subsequent evolutionary steps, aiming to find optimal channel sequences for multichannel path scheduling in cognitive radio networks.

(2) Mutation: DE performs mutation to generate new candidate solutions. In the context of multichannel path scheduling, the mutation operation perturbs the existing sequences of channels to create new sequences. This introduces exploration in the search space by considering alternative channel sequences. The algorithm steps can be described as follows:

i. Mutation Rate: Determine the mutation rate, denoted as F, which controls the extent of perturbation or variation introduced to the channel sequences. The mutation rate should be predefined based on problem characteristics and empirical knowledge.

ii Mutation Vector: For each individual in the population, select three distinct individuals, a.b and c,that are different from each other and the current individual being mutated.

iii. Mutation Operation: For each element (channel) in the current individual's channel sequence:

- Generate a random number r for each element.
- If r is less than or equal to the mutation rate F or if the current element is the last element in the sequence, perform mutation by applying the following equation: $new_element = a + F * (b - c)$, where $new_{element}$represents the mutated value for the current element, and $a.bandc$, are the corresponding elements from the three distinct individuals.

iv. Boundary Handling: If the mutated element exceeds the available channel indices or falls below the minimum channel index, handle the boundary conditions appropriately. This can be done by wrapping around the channel indices or limiting the values within the valid range.

v. Create Mutated Individuals: Repeat the mutation operation for each element in the current individual's sequence to obtain a mutated channel sequence.

vi. Fitness Evaluation: Evaluate the fitness or objective function value of the mutated individuals. Calculate the fitness value based on the performance metrics relevant to multichannel path scheduling, such as throughput, reliability, energy efficiency, or any other desired criteria.

vii. Population Update: Replace the current individual with its mutated counterpart if the mutated individual has higher fitness. Otherwise, keep the current individual in the population.

viii. Repeat: Repeat steps 2-7 for each individual in the population to perform mutation on the entire population.

The mathematical modeling for mutation in DE involves the perturbation of channel sequences using the mutation rate F and the difference between selected individuals $a.bandc$,. The specific mathematical model for mutation can be represented as:

$$Mutation(i, j) = a(i, j) + F * (b(i, j) - c(i, j)) \tag{3.18}$$

where Mutation(i,j) represents the mutated value of the j^{th}element in the i^{th} individual's channel sequence, $a(i, j), b(i, j), andc(i, j)$ are the corresponding elements from the three distinct individuals used for mutation, and F is the mutation rate.

By applying the mutation operation to the population of channel sequences, the DE algorithm introduces variation and explores different possibilities for multichannel path scheduling in cognitive radio networks.

(3) Crossover: DE employs crossover to combine information from different individuals. In multichannel path scheduling, crossover can be used to exchange and combine sequences of channels between individuals, producing offspring with different combinations of channels. This promotes the exploration of potentially better scheduling configurations.

The algorithm steps for crossover can be described as follows:

i. Crossover Rate: Determine the crossover rate, denoted as CR, which controls the probability of performing the crossover operation. The crossover rate should be predefined based on problem characteristics and empirical knowledge.

ii. Parent Selection: For each individual in the population, select three distinct individuals, $x, y, andz$ that are different from each other and the current individual being crossed over.

iii. Crossover Operation: For each element (channel) in the current individual's channel sequence:

- Generate a random number r for each element.
- If r is less than or equal to the crossover rate CR or if the current element is the last element in the sequence, perform crossover by combining genetic material from the selected individuals as follows:
- Select a random index, k, from 1 to the length of the channel sequence.
- Create an offspring by copying the element from the parent individual if the random number r is less than or equal to the crossover rate CR, or copying the element from the current individual otherwise.
- Increment the index k in a cyclic manner and continue the process until all elements have been processed.

iv. Fitness Evaluation: Evaluate the fitness or objective function value of the offspring created through crossover.

Calculate the fitness value based on the performance metrics relevant to multichannel path scheduling, such as throughput, reliability, energy efficiency, or any other desired criteria.

v. Population Update: Replace the current individual with the offspring if the offspring has higher fitness. Otherwise, keep the current individual in the population.

vi. Repeat: Repeat steps 2-5 for each individual in the population to perform crossover on the entire population.

The mathematical modeling for crossover in DE involves the recombination of genetic material from selected individuals based on the crossover rate CR and a random index k. The specific mathematical model for crossover can be represented as:

$$Crossover(i,j) = offspring(i,j) \tag{3.19}$$

where $Crossover(i,j)$ represents the crossover value of the j^{th} element in the i^{th} individual's channel sequence, and $ffspring(i,j)$ represents the value of the corresponding element in the offspring created through crossover.

By applying the crossover operation to the population of channel sequences, the DE algorithm combines genetic material from selected individuals, promoting diversity and exploration in the search for optimal multichannel path scheduling solutions in cognitive radio networks.

(4) Fitness Evaluation: Each individual in the population, i.e., each sequence of channels, is evaluated based on specific performance metrics relevant to multichannel path scheduling. These metrics could include throughput, reliability, energy efficiency, or any other criteria that define the quality of the channel sequence. The algorithm steps for fitness evaluation can be described as follows:

i. Feature Calculation: Calculate the values of the features used for optimizing multichannel path scheduling. These features could include channel capacity, signal-to-noise ratio (SNR), channel utilization, latency, link stability, PU activity, channel compliance probability, channel desertion probability, channel realization probability, channel inference probability, channel bandwidth probability, and channel idle timespan. Calculate these features based on the characteristics and measurements of the channels and network environment.

ii. Normalization: Normalize the feature values to bring them into a common range or scale. This step is necessary when the features have different units or scales. Normalization ensures that each feature contributes proportionally to the overall fitness evaluation, preventing dominance by features with larger numerical values.

iii. Weight Assignment: Assign weights to the normalized feature values. These weights reflect the relative importance or priority of each feature in the fitness evaluation. The weights can be predefined based on domain knowledge or determined through experimentation and analysis.

iv. Fitness Function: Combine the normalized and weighted feature values using a fitness function. The fitness function aggregates the individual feature values into a single fitness value for each individual. The specific form of the fitness function depends on the problem requirements and objectives. It can be a weighted sum, a weighted average, or a more complex mathematical expression that captures the desired trade-offs among the features.

v. Fitness Evaluation: Evaluate the fitness of each individual by applying the fitness function to their corresponding feature values. Assign the resulting fitness value to each individual, representing their performance or quality in terms of the multichannel path scheduling objectives.

The mathematical modeling for fitness evaluation depends on the specific form of the fitness function and the weighted combination of the normalized feature values. It can be represented as:

$$Fitness(i) = w_1 * f_1 + w_2 * f_2 + ... + w_n * f_n \tag{3.20}$$

where $Fitness(i)$ represents the fitness value of the i^{th} individual, $w_1, w_2, ..., w_n$ are the weights assigned to the normalized feature values $f_1, f_2, ..., f_n$, respectively. The fitness function aggregates the feature values with their corresponding weights to determine the overall fitness value for each individual.

By performing fitness evaluation, the DE algorithm assesses the quality of each individual in the population based on the specified features and performance metrics. This enables the selection of individuals with higher fitness for the subsequent evolutionary steps, facilitating the optimization of multichannel path scheduling in cognitive radio networks.

(5) Selection: The selection process determines which individuals are selected to survive and pass their genetic information to the next generation. In DE, the selection is typically based on the fitness value assigned to each individual. Individuals with higher fitness, indicating better scheduling performance, have a higher chance of being selected. The algorithm steps for selection can be described as follows:

i. Fitness Ranking: Rank the individuals in the population based on their fitness values. The ranking can be performed in ascending or descending order, depending on whether the goal is to minimize or maximize the fitness value.

ii. Selection Probability Calculation: Calculate the selection probability for each individual. The selection probability is proportional to the individual's fitness value. A higher fitness value corresponds to a higher probability of selection.

iii. Cumulative Probability Calculation: Calculate the cumulative probability for each individual by summing up the selection probabilities from the first individual to that specific individual. This cumulative probability determines the selection range for each individual.

iv. Random Selection: Generate a random number between 0 and 1 for each selection. This random number determines which individual is selected within the selection range.

v. Selection Process: Iterate through the random numbers generated in step 4. For each random number, identify the corresponding individual in the population by finding the first individual whose cumulative probability is greater than or equal to the random number. Select that individual to be part of the next generation.

vi. Repeat: Repeat steps 4-5 until the desired number of individuals for the next generation is selected.

The mathematical modeling for selection involves the calculation of selection probabilities and the use of random numbers for the selection process. The specific mathematical model for selection probability calculation and random selection can be represented as follows:

$$SelectionProbability(i) = Fitness(i)/(Fitness(j)) \tag{3.21}$$

where $SelectionProbability(i)$ represents the selection probability of the i^{th} individual, $Fitness(i)$ is the fitness value of thei^{th} individual, and the summation is taken over all individuals in the population.

To perform random selection, generate a random number r between 0 and 1. Then, for each random number generated, find the first individual i in the population such that the cumulative probability Cumulative $Probability(i)$ is greater than or equal to r. Select the individual i for the next generation.

By applying the selection process, the DE algorithm ensures that individuals with higher fitness values have a higher chance of being selected, increasing the likelihood of passing their genetic information to the next generation. This promotes the evolution of the population towards better multichannel path scheduling solutions in cognitive radio networks.

(6) Iterative Evolution: The mutation, crossover, fitness evaluation, and selection steps are iteratively repeated for multiple generations. This process allows the DE algorithm to explore the search space, gradually improving the quality of the channel sequences over time.

(7) Termination: The DE algorithm terminates based on predefined stopping criteria. This could be a maximum number of generations reached, the attainment of a satisfactory solution, or a certain level of convergence.

By iteratively applying mutation, crossover, fitness evaluation, and selection, the DE algorithm evolves the population of channel sequences, aiming to find the optimal configuration for multichannel path scheduling. The ultimate goal is to maximize performance metrics and optimize the use of available channels in cognitive radio networks.

4. Experimental study. To assess the performance of the proposed "Optimizing Multichannel Path Scheduling (OMPS) in Cognitive Radio Ad hoc Networks" and the existing "Path Discovery for end-to-end Data Transmission (PDDT) [8] in Cognitive Radio Ad-Hoc Networks", a simulation model can be created with the parameters from Table 4.1 and Table 4.2.

Table 4.1: Simulation parameters and Fitness parameters used in Experimental study

Parameter	OMPS with DE	PDDT with GA
Number of Iterations	10 Iterations	10 Iterations
Number of Channels	10 to 50	10 to 50
Number of Primary Users	10 to 50	10 to 50
Number of Secondary Users	10 to 50	10 to 50
Channel Conditions	Rayleigh or Rician Fading	Rayleigh or Rician Fading
PU Activity Patterns	Random processes	Random processes

Table 4.2: Fitness parameters and the threshold values

Fitness Parameter	Threshold	
Channel Fade Margin	10 dB	X
Channel Cross-Correlation	0.5	X
Channel Coherence Time	100 ms	X
Channel Spectral Efficiency	2 bits/s/Hz	X
Channel Interference Level	-100 dBm	X
Channel Power Consumption	0.5 W	X
Channel Retransmission Rate	0.1	X
Channel Access Probability	0.8	X
Channel Propagation Delay	50 ms	X
Lapsed white space ratio	X	0.1
Desired white space	X	0.9
Residual white space ratio	X	0.8
Recurring diffusions ratio	X	0.2
Primary user's interference ratio	X	0.05
Usage realization ratio	X	0.8
Realization count	X	8
Channel fading ratio	X	0.2

4.1. Performance Analysis. This section meticulously evaluates the efficacy of the proposed Optimizing Multichannel Path Scheduling (OMPS) model, employing the Differential Evolution computational approach. Performance metrics used to assess the effectiveness and efficiency of the proposed OMPS and contemporary model PDDT are:

(1) Throughput: This is the total amount of data that can be transmitted through the network over a certain period of time. Higher throughput is generally better, as it indicates that the network can handle more data. Performance metrics are used to assess the effectiveness and efficiency of the network models. This is typically calculated as the total size of successfully delivered packets divided by the total time it takes to deliver them. It is measured in bits per second (bps) or Megabits per second (Mbps):

$$Throughput = Totaldata(bits)/Totaltime(s) \tag{4.1}$$

(2) Latency: This measures the time it takes for a packet of data to travel from the source to the destination. Lower latency is typically better, especially for real-time or interactive applications. It's typically the total time taken for a packet to travel from source to destination including all types of delays (transmission, propagation, queueing, processing delays etc.). It is measured in seconds (s) or milliseconds(ms):

$$Latency = Time_{received} - Time_{sent} \tag{4.2}$$

(3) Packet Delivery Ratio (PDR): This is the ratio of packets that are successfully delivered to their destination to those that are generated by the source. A higher PDR indicates a more reliable network. It's the number of packets successfully delivered divided by the total number of packets sent, multiplied by 100 to get a percentage:

$$\text{PDR (\%)} = \left(\frac{\text{Number of packets delivered}}{\text{Total number of packets sent}}\right) \times 100 \tag{4.3}$$

(4) Spectrum Utilization: These measures how efficiently the available spectrum is being used. In the context of CRAHNs, this might be calculated as the proportion of time that the SUs is able to use the channels, or the proportion of the spectrum that is being used by the SUs. It's the bandwidth used divided by the total bandwidth available, multiplied by 100 to get a percentage:

$$\text{Spectrum Utilization (\%)} = \left(\frac{\text{Bandwidth used}}{\text{Total available bandwidth}}\right) \times 100 \tag{4.4}$$

(5) Interference Level: This measures the degree of interference experienced by the SUs from the PUs. Lower interference is generally better, as it reduces the chance of communication errors and increases the likelihood that the SUs will be able to use the channels. It's typically measured as the power of the interfering signal compared to the power of the desired signal. It is measured in decibels dB:

$$\text{Interference Level (dB)} = 10 \cdot \log_{10}\left(\frac{\text{Power of Interference}}{\text{Power of Desired Signal}}\right) \tag{4.5}$$

(6) Energy Efficiency: These measures how much data can be transmitted per unit of energy consumed. This is particularly important in wireless networks, where devices may be battery-powered and energy conservation is a concern. It's the ratio of the data rate (bits per second) to the power consumed (in watts). It's expressed in bits per Joule

$$\text{Energy Efficiency (bits/J)} = \frac{\text{Data Rate (bits/s)}}{\text{Power (W)}} \tag{4.6}$$

(7) Success rate of established paths: It measures the ratio of successfully established paths to total attempted path establishments. It's the number of successful path establishments divided by the total number of path establishment attempts, multiplied by 100 to get a percentage:

$$\text{Success rate of established paths (\%)} = \left(\frac{\text{Number of successful paths}}{\text{Total number of path attempts}}\right) \cdot 100 \tag{4.7}$$

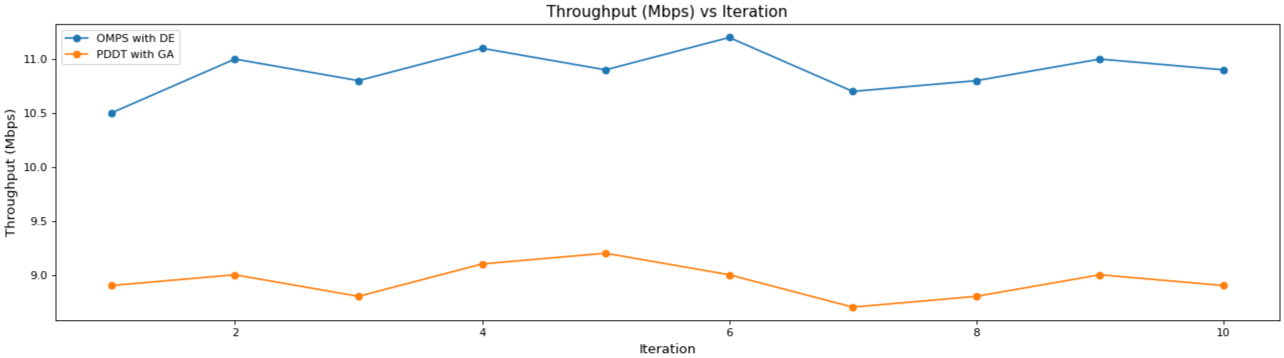
Each of these metrics could be calculated based on the simulation results, and used to compare the performance of the OMPS and PDDT algorithms. For example, you might compare the average throughput, latency, and PDR for each algorithm over multiple simulation runs, under various network conditions. This could provide a comprehensive view of the relative strengths and weaknesses of each algorithm.

4.1.1. Comparative Study. This section explores experimental results, which are illustrated in a series of data tables and graphs for each metric, demonstrate how the OMPS model compares to the Path Discovery for end-to-end Data Transmission (PDDT) model. Our findings show that the OMPS model significantly outperforms the PDDT model in all the performance metrics considered, signifying its effective utilization and superior performance.

Throughput (Mbps). Figure 4.1 presents the comparison of the throughput, measured in Megabits per second (Mbps), between two models - Optimizing Multichannel Path Scheduling (OMPS) and Path Discovery for end-to-end Data Transmission (PDDT) - over ten iterations of a simulation study.

In each iteration, the throughput of both the models is calculated and tabulated. The throughput value indicates the rate at which data is successfully transmitted over the network. A higher throughput value is desirable as it indicates a higher data transfer rate.

Throughput performance of OMPS consistently outperforms that of PDDT from the first to the tenth iteration. From a low of 10.5 Mbps in the first iteration to a high of 11.2 Mbps in the sixth, OMPS's throughput



Iteration	OMPS with DE	PDDT with GA
1.0	10.5	8.9
2.0	11.0	9.0
3.0	10.8	8.8
4.0	11.1	9.1
5.0	10.9	9.2
6.0	11.2	9.0
7.0	10.7	8.7
8.0	10.8	8.8
9.0	11.0	9.0
10.0	10.9	8.9

Fig. 4.1: The comparison of the throughput, measured in Megabits per second (Mbps) vs iteration of the OMPS, PDDT

varies. The throughput for PDDT, on the other hand, varies from a low of 8.7 Mbps (in the seventh iteration) to a high of 9.2 Mbps (in the fifth iteration).

This suggests that the OMPS model is more effective at using the network resources in this simulation study to achieve a higher data transfer rate, making it a better option for applications where high throughput is essential.

Packet Delivery Ratio (PDR) (%). Figure 4.2 compares the Packet Delivery Ratio (PDR) performance, expressed in percentage (%), of the Path Discovery for End-to-End Data Transmission (PDDT) model and the Optimizing Multichannel Path Scheduling (OMPS) model over ten simulation iterations.

The percentage of packets that are successfully delivered to their destinations in relation to the total number of packets sent is known as the packet delivery ratio. As a lower rate of packet loss occurs during transmission, a higher PDR denotes a communication protocol that is more dependable and effective.

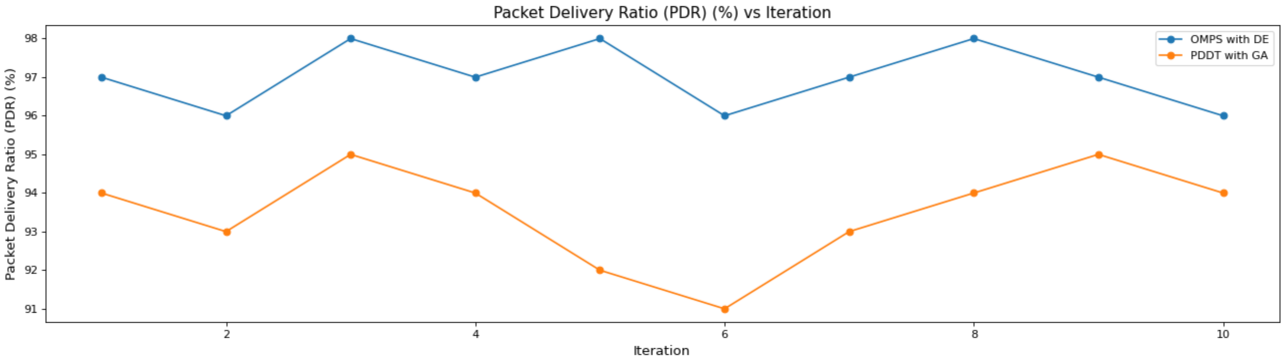
The results indicate that the OMPS model consistently outperforms the PDDT model in terms of PDR across all ten iterations. The PDR of the OMPS model ranges from 96% to 98%, suggesting that it successfully delivers nearly all of the sent packets. In contrast, the PDR for the PDDT model ranges from 91% to 95%, indicating a higher rate of packet loss compared to OMPS.

Therefore, according to these simulation results, the OMPS model provides a more reliable and efficient data transmission process than the PDDT model.

Latency (ms). Figure 4.3 provides a comparison of the Latency performance, measured in milliseconds (ms), of two models: Optimizing Multichannel Path Scheduling (OMPS) and Path Discovery for end to end Data Transmission (PDDT) over ten iterations of a simulation study.

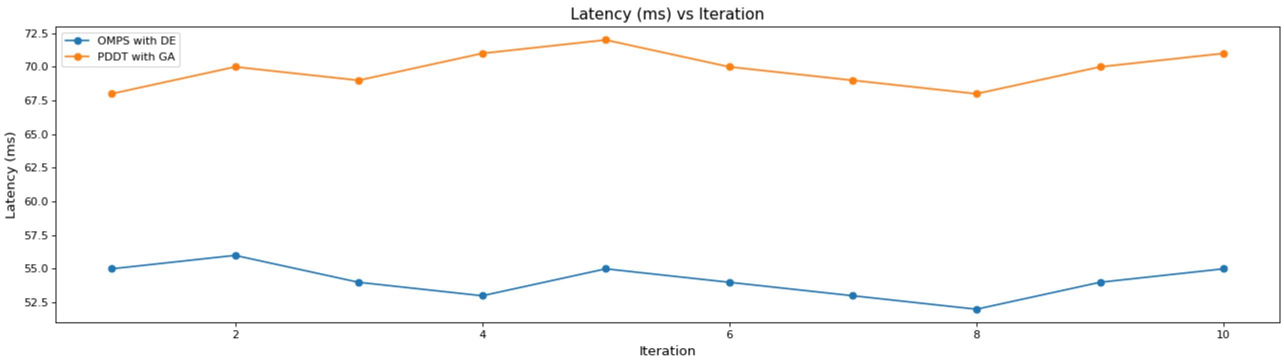
Latency, in this context, refers to the total time taken for a packet of data to travel from the source to the destination in a network. Lower latency is preferred as it signifies a faster transmission time, leading to real-time or near-real-time communication.

Looking at the results, we can observe that the OMPS model consistently demonstrates lower latency values as compared to the PDDT model in all ten iterations. Latency for OMPS ranges between 52 ms (in the eighth



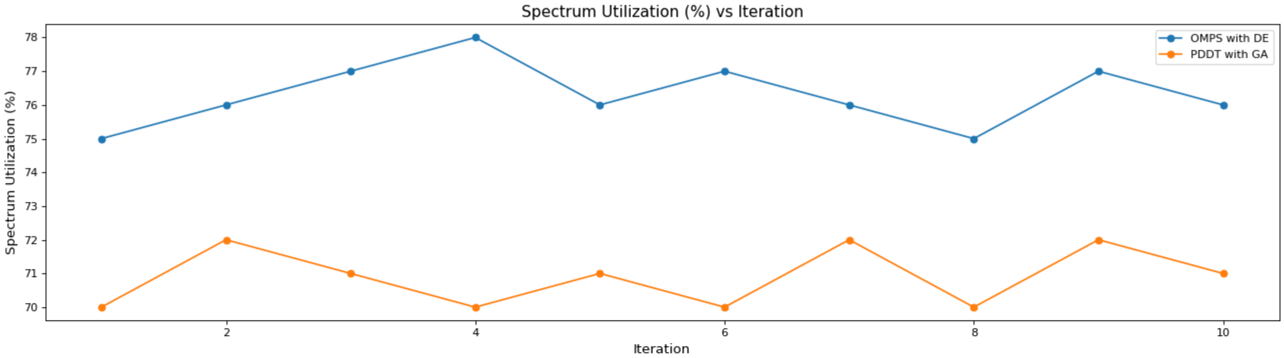
Iteration	OMPS with DE	PDDT with GA
1	97	94
2	96	93
3	98	95
4	97	94
5	98	92
6	96	91
7	97	93
8	98	94
9	97	95
10	96	94

Fig. 4.2: The comparison between the Packet Delivery Ratio (PDR) performance, expressed in percentage (%), vs Iteration OMPS and PDDT



Iteration	OMPS with DE	PDDT with GA
1	55	68
2	56	70
3	54	69
4	53	71
5	55	72
6	54	70
7	53	69
8	52	68
9	54	70
10	55	71

Fig. 4.3: The comparison of the Latency performance, measured in milliseconds (ms), vs Iteration of the OMPS and PDDT



Iteration	OMPS with DE	PDDT with GA
1	75	70
2	76	72
3	77	71
4	78	70
5	76	71
6	77	70
7	76	72
8	75	70
9	77	72
10	76	71

Fig. 4.4: The comparison of the Spectrum Utilization performance, expressed in percentage (%) vs Iteration of the OMPS, PDDT

iteration) and 56 ms (in the second iteration). In contrast, the latency for the PDDT model is notably higher, ranging between 68 ms (in the first and eighth iterations) and 72 ms (in the fifth iteration).

According to these simulation results, the OMPS model provides faster data transmission, hence might be more suitable for applications requiring real-time or near-real-time communication such as video conferencing or online gaming.

Spectrum Utilization (%). Figure 4.4 showcases a comparison of the Spectrum Utilization performance, expressed in percentage (%), of the Optimizing Multichannel Path Scheduling (OMPS) model and the Path Discovery for end to end Data Transmission (PDDT) model over ten iterations of a simulation study.

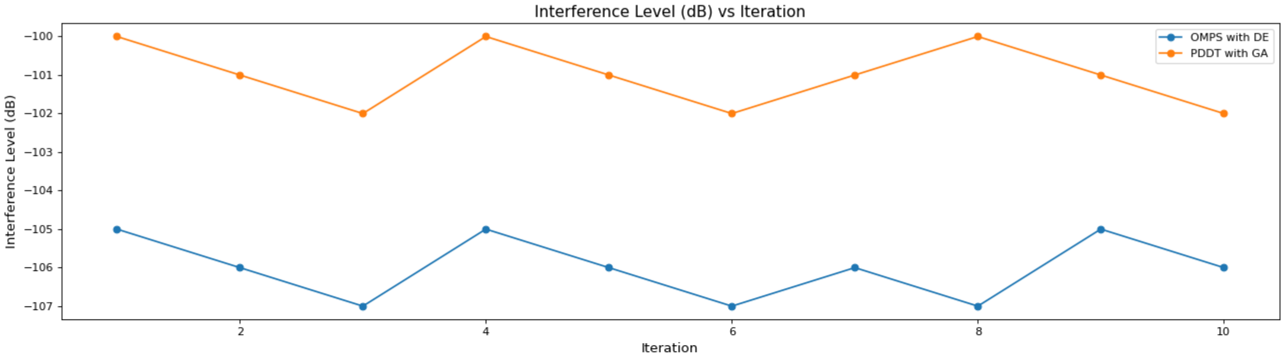
Spectrum Utilization is a measure of how effectively the available frequency spectrum is being used by a communication protocol. Higher values indicate that a greater portion of the available spectrum is being used, which usually suggests more efficient utilization. In each of the ten iterations, the OMPS model demonstrates a higher percentage of spectrum utilization compared to the PDDT model. The spectrum utilization by OMPS ranges from 75% to 78%, indicating that it effectively uses a substantial portion of the available spectrum. In contrast, the spectrum utilization by PDDT is slightly lower, ranging from 70% to 72%.

These results imply that, in these simulation conditions, the OMPS model is more efficient in utilizing the available frequency spectrum than the PDDT model. This could potentially result in higher throughput and better overall network performance.

Interference Level (dB). Figure 4.5 provides a comparison between the Interference Level, measured in decibels (dB), of the Optimizing Multichannel Path Scheduling (OMPS) model and the Path Discovery for end-to-end Data Transmission (PDDT) model over ten iterations of a simulation.

Interference Level quantifies the degree to which a signal transmission might be affected or disturbed by other sources or signals, with lower values being more desirable as they indicate less interference. It's important to note that in the context of wireless communication, interference levels are often expressed as negative dB values. The smaller the numerical value (or the more negative), the lower the interference level.

In this scenario, the OMPS model consistently demonstrates lower (more negative) interference levels as



Iteration	OMPS with DE	PDDT with GA
1	-105	-100
2	-106	-101
3	-107	-102
4	-105	-100
5	-106	-101
6	-107	-102
7	-106	-101
8	-107	-100
9	-105	-101
10	-106	-102

Fig. 4.5: The comparison between the interference level, measured in decibels (dB) vs iteration of the OMPS, PDDT

compared to the PDDT model across all ten iterations. The interference level for OMPS ranges between -105 dB and -107 dB, indicating less signal disruption and a cleaner transmission path. On the other hand, the interference level for the PDDT model ranges between -100 dB and -102 dB, indicating a relatively higher level of signal interference.

Based on these simulation results, the OMPS model offers better performance in terms of mitigating signal interference compared to the PDDT model.

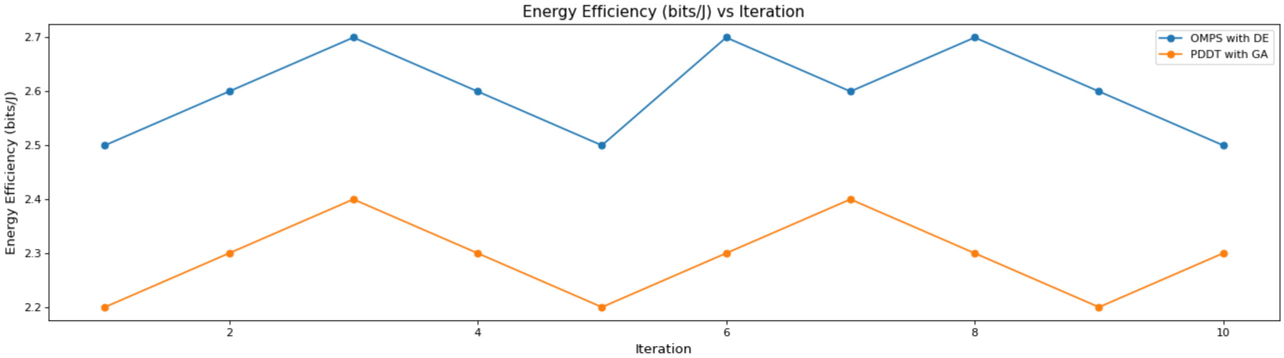
Energy Efficiency (bits/J). Figure 4.6 compares the Energy Efficiency of two models, the Optimizing Multichannel Path Scheduling (OMPS) and the Path Discovery for end-to-end Data Transmission (PDDT), across ten iterations of a simulation study. Energy Efficiency is measured in bits per joule (bits/J), indicating the number of bits successfully transmitted per unit of energy consumed. Higher values suggest better energy efficiency, which is desirable for conserving resources, especially in power-limited environments such as wireless sensor networks or mobile devices.

From the figure 4.6, it can be observed that the OMPS model consistently delivers higher energy efficiency values across all iterations, ranging between 2.5 and 2.7 bits/J. This indicates that OMPS can transmit more data for the same amount of energy consumed, making it more energy-efficient. In contrast, the PDDT model demonstrates slightly lower energy efficiency across all iterations, ranging between 2.2 and 2.4 bits/J.

Based on these simulation results, it appears that OMPS outperforms PDDT in terms of energy efficiency.

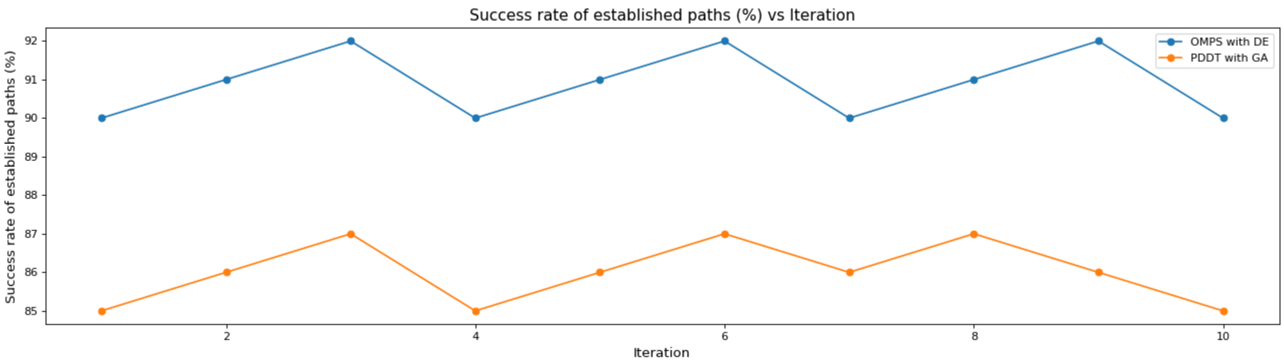
Success rate of established paths (%). Figure 4.7 shows a comparison of the Success Rate of Established Paths for two models, the Optimizing Multichannel Path Scheduling (OMPS) and the Path Discovery for end-to-end Data Transmission (PDDT), over ten iterations of a simulation study. The success rate is expressed in percentage (%), representing the proportion of successful paths established compared to the total attempts. A higher percentage signifies a better success rate, indicating the model's capability to successfully establish a data transmission path between the source and destination.

Throughout all ten iterations, the OMPS model consistently shows a higher success rate ranging between 90% and 92%. This suggests that the OMPS model can establish a successful path most of the time, making



Iteration	OMPS with DE	PDDT with GA
1.0	2.5	2.2
2.0	2.6	2.3
3.0	2.7	2.4
4.0	2.6	2.3
5.0	2.5	2.2
6.0	2.7	2.3
7.0	2.6	2.4
8.0	2.7	2.3
9.0	2.6	2.2
10.0	2.5	2.3

Fig. 4.6: The energy efficiency (bits/J) vs iteration of the proposed OMPS compared PDDT



Iteration	OMPS with DE	PDDT with GA
1	90	85
2	91	86
3	92	87
4	90	85
5	91	86
6	92	87
7	90	86
8	91	87
9	92	86
10	90	85

Fig. 4.7: The comparison of the success rate of established paths (%), vs iteration of the OMPS, PDDT

it more reliable and efficient for data transmission.

On the other hand, the PDDT model consistently shows a slightly lower success rate for established paths, ranging between 85% and 87%.

Based on these simulation results, the OMPS model appears to outperform the PDDT model in terms of the success rate of path establishment. Nonetheless, these are simulation results, and real-world performance might differ depending on network conditions and configurations. To fully evaluate and compare the performance of the two models, other metrics such as throughput, latency, energy efficiency, and interference level should also be considered.

5. Conclusion. Under the OPMS model, the DE algorithm optimizes multichannel radio path scheduling under cognitive radio networks. This promotes the dependability and efficiency of these networks. Channel Fade Margin, Cross-Correlation, Coherence Time, Spectral Efficiency, Interference Level, Power Consumption, and Retransmission Rate are all considered by the model. The networks' coverage is greatly enhanced by these characteristics. Because it incorporates Initialization, Mutation, Crossover (Exchange), Fitness Evaluation, Selection, and Iterative Evolution, the DE method is solid. It tackles the innate complexity and dynamism of cognitive radio networks. When it comes to these parameters, OPMS consistently beats the Path Discovery for End-to-End Data Transmission (PDDT) model in matches between humans and computers. Outperforming all other networks in terms of resource use, it provides superior reliability, acceptable latency, and faster data speeds. OPMS is very useful in cognitive radio ad hoc networks with complex dynamics. Given that it can adapt to different channel conditions and user requirements, its adaptability makes it a good option for these networks. It is possible to use the excellent results obtained by using OPMS in this study as a model for further research and development, suggesting that it will be used to more robust practical applications in the future. This advancement in cognitive radio technology is important. It proposes an OPMS model that can manage the complexity of scheduling three or more multichannel paths by overcoming a number of obstacles.

REFERENCES

[1] A. J. Onumanyi, A. M. Abu-Mahfouz, and G. P. Hancke, "Low Power Wide Area Network, Cognitive Radio and the Internet of Things: Potentials for Integration," *Sensors*, vol. 20, no. 23, pp. 6837, Nov. 2020, doi: 10.3390/s20236837.

[2] T. M. Chiwewe, C. F. Mbuya, and G. P. Hancke, "Using Cognitive Radio for Interference-Resistant Industrial Wireless Sensor Networks: An Overview," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, pp. 1466–1481, Dec. 2015, doi: 10.1109/TII.2015.2491267.

[3] M. Yaseer, H. Ur, A. Usman, and M. Tayyab, "Analysis of Efficient Cognitive Radio MAC Protocol for Ad Hoc Networks," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 2, 2019, doi: 10.14569/IJACSA.2019.0100219.

[4] C.-M. Wu, M.-S. Wu, Y.-J. Yang, and C.-Y. Sie, "Cluster-Based Distributed MAC Protocol for Multichannel Cognitive Radio Ad Hoc Networks," *IEEE Access*, vol. 7, pp. 65781–65796, 2019, doi: 10.1109/ACCESS.2019.2917906.

[5] S.-J. Yoo, H. Khan, and K.-S. Kwak, "Dynamic MAC Frame Configuration and PSO-Based Optimal Resource Allocation in Multi-Channel Cognitive Radio Ad-Hoc Networks," *Wireless Personal Communications*, vol. 109, no. 1, pp. 595–620, Nov. 2019, doi: 10.1007/s11277-019-06581-x.

[6] N. Joshi, A. Kumar, D. Minenkov, D. Kaplun, and S. C. Sharma, "Optimized MAC Protocol Using Fuzzy-Based Framework for Cognitive Radio AdHoc Networks," *IEEE Access*, vol. 11, pp. 27506–27518, 2023. [Online]. Available: https://doi.org/10.1109/ACCESS.2023.3256890

[7] S. Kadam, D. Prabhu, N. Rathi, P. Chaki, and G. S. Kasbekar, "Exploiting Group Structure in MAC Protocol Design for Multichannel Ad Hoc Cognitive Radio Networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 1, pp. 893–907, Jan. 2019. [Online]. Available: https://doi.org/10.1109/TVT.2018.2883392

[8] S. Nagul, "PDDT: Path Discovery for End to End Data Transmission in Cognitive Radio Ad-Hoc Networks," in *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)*, Bangalore, India, 2020, pp. 1–6. [Online]. Available: https://doi.org/10.1109/CONECCT50063.2020.9198420

[9] Q. M. Salih et al., "Dynamic Channel Estimation-Aware Routing Protocol in Mobile Cognitive Radio Networks for Smart IIoT Applications," *Digital Communications and Networks*, vol. 9, no. 2, pp. 367–382, Apr. 2023. [Online]. Available: https://doi.org/10.1016/j.dcan.2023.01.019

[10] G. Dinesh, P. Venkatakrishnan, and K. Meena Alias Jeyanthi, "Dispersed Spectrum Sensing and Scheduling in Cognitive Radio Network Based on SSOA-RR," *International Journal of Communication Systems*, e4588, Aug. 20, 2020. [Online]. Available: https://doi.org/10.1002/dac.4588

[11] X. Zhong, L. Li, Y. Zhang, B. Zhang, W. Zhang, and T. Yang, "OODT: Obstacle Aware Opportunistic Data Transmission for Cognitive Radio Ad Hoc Networks," *IEEE Transactions on Communications*, vol. 68, no. 6, pp. 3654–3666, Jun. 2020. [Online]. Available: https://doi.org/10.1109/TCOMM.2020.2979976

[12] N. Suganthi and S. Meenakshi, “An Efficient Scheduling Algorithm Using Queuing System to Minimize Starvation of Non-Real-Time Secondary Users in Cognitive Radio Network,” *Cluster Computing*, vol. 25, no. 1, pp. 1–11, Feb. 2022. [Online]. Available: https://doi.org/10.1007/s10586-017-1595-8

[13] G. B. V. Padmanadh, P. V. Krishna Raja, and J. V. R. Murthy, “A survey on opportunistic routing and channel assignment scheme in cognitive radio ad hoc networks,” *Journal of Science and Technology*, vol. 6, no. 4, pp. 258–273, Jul.-Aug. 2021. [Online]. Available: https://doi.org/10.46243/jst.2021.v6.i04.pp258-273

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