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HYBRID OPTIMIZATION BASED ON SPECTRUM AWARE OPPORTUNISTIC ROUTING FOR COGNITIVE RADIO AD HOC NETWORKS

Abdullah Hashem. M.A., Kumar A.V. Senthil, Qasem Ahmed A.A., Mosleh M.A.S. **Hybrid Optimization Based on Spectrum Aware Opportunistic Routing for Cognitive Radio Ad Hoc Networks.**

Abstract. Opportunistic routing has increased the efficiency and reliability of Cognitive Radio Ad-Hoc Networks (CRAHN). Many researchers have developed opportunistic routing models, among them the Spectrum Map-empowered Opportunistic Routing (SMOR) model, which is considered a more efficient model in this field. However, there are certain limitations in SMOR, which require attention and resolution. The issue of delay and degradation of packet delivery ratio due to non-consideration of network bandwidth and throughput are addressed in this paper. In order to resolve these issues, a hybrid optimization algorithm comprising firefly optimization and grey wolf optimization algorithms are used in the basic SMOR routing model. Thus, developed Hybrid Firefly and Grey-Wolf Optimization-based SMOR (HFGWOSMOR) routing model improves the performance by high local as well as global search optimization. Initially, the relationship between the delay and throughput is analyzed and then the cooperative multipath communication is established. The proposed routing model also computes the energy values of the received signals within the bandwidth threshold and time; hence, the performance issues found in SMOR are resolved. To evaluate its efficiency, the proposed model is compared with SMOR and other existing opportunistic routing models, which show that the proposed HFGWOSMOR performs better than other models.

Keywords: Cognitive Radio Ad Hoc Networks, Opportunistic routing, Spectrum Map-empowered Opportunistic Routing, Firefly optimization, Grey-Wolf optimization, bandwidth threshold.

1. Introduction. Cognitive radio ad hoc network (CRAHN) is a type of distributed, self-organizing, self-Configuring wireless network in which the radios in the network can adapt their transmission and reception parameters in real-time, depending on the availability of the frequency spectrum.

The cognitive radio devices can sense the presence of other radio signals in specific bands, and dynamically adjust their transmission parameters to avoid interference with other devices, and, thus, maximizing the utilization of the available spectrum. This approach leads to a more efficient use of the radio spectrum, reducing the possibility of interference and increasing the capacity of the network. This type of Network uses cognitive radio technologies to allocate network resources dynamically such as frequency, bandwidth and power.

In CRAHN, nodes (CR-users) can sense the availability of the radio spectrum and adjust their transmission parameters accordingly to avoid interference with other users. This enables efficient utilization of the free available spectrum and improves network performance [1, 2].

CRAHNs can automatically search, monitor and use the available free spectrum to take care of the problem of the spectrum resource shortage and low utilization rate without affecting licensed users.

The cognitive radio rule has acquainted the thought with abuse spectrum holes (i.e., bands) which result from the demonstrated underutilization of the electromagnetic spectrum by present-day wireless communication and broadcasting advancements [3].

CRAHNs are often used in military, rural connectivity and emergency communication scenarios where the availability of spectrum is limited and rapidly dynamically reconfigure itself to maintain communication in the face of changing conditions [4].

The components of a Cognitive Radio Ad Hoc Network (CRAHN) are [4, 5, 6]:

– *Cognitive Radio Nodes*: The main component of the CRAHNs is the cognitive radio nodes (Secondary-User), which are equipped with the radio transceivers and the processing capabilities to monitor and adapt to the surrounding radio environment [6].

– *Spectrum Sensing:* Each node in CRAHNs infrastructure is equipped with a spectrum-sensing module to detect the presence of other users in the radio environment.

– *Decision Making:* Based on the information gathered through the sensing of spectrum, the nodes make decisions on which frequency band to use for communication, and how to allocate the available spectrum resources [7].

– *Spectrum Management*: The nodes in a CRAHN use their cognitive abilities to manage the available spectrum resources dynamically to avoid interference with other users and optimize the performance of the network.

– *Routing* the nodes in a CRAHN use routing protocols to dynamically establish and maintain communication links with other nodes in the network [8, 9].

– *Network Management*: CRAHNs use the network management techniques to monitor network performance and make adjustments to ensure optimal operation [10]. These components work together to enable dynamic, self-organizing, and efficient communication in a Cognitive Radio Ad Hoc Network [5, 6].

In cognitive radio, the secondary users (SUs) refer to a specific device that dynamically accesses and uses the underutilized portions of the radio spectrum that are licensed to primary users (PUs) such as government agencies or licensed commercial operators. The secondary user (US) operates on a non-interfering basis with the primary users and can vacate the spectrum when the primary user requests access [7, 8].

The primary users in a cognitive radio network are the licensed or authorized users who have been assigned the use of a particular frequency band by a regulatory authority, such as a government or standardization organization [8, 9].

They have the primary rights to use the spectrum bands and are usually traditional users, such as government agencies, television and the radio broadcast stations, or mobile networks. They have priority over the secondary users in accessing the radio spectrum and can use it without interference [10].

The main aim of CR-AHNs is to increase the utilization of available spectrum by detecting and avoiding busy frequency bands, and exploiting unused ones. The nodes in CR-AHNs can also cooperate and share information with each other to make more efficient decisions about spectrum utilization. This technology results in increased network performance, efficiency and capacity, energy consumption, provides better quality of service to users, and improved overall performance [11]. On the other hand, the key idea behind CRAHNs is to allow wireless devices to sense and adapt to changes in the radio environment, such as the presence of other devices, interference, or changes in channel conditions.

In order to handle these difficulties, the opportunistic routing (OR) strategy has been connected in CRAHNs with a specific end goal to uncover the effect of the spectrum availability on the stability of the routing. Considering the predominance of the broadcast feature and the exceptionally decent variety of wireless mediums, the OR strategy has been earlier proposed in the amazingly opportunistic routing protocol (ExOR) [6, 7, 12]. Instead of firstly deciding the following hop SU and after that sending the packet to the following hop SU, a SU with the OR strategy broadcasts the packet keeping in mind the end goal to get the outcomes that all neighbors of the SU have the chance to get the packet and help with forwarding the data packets.

Contrasted with the traditional routing methodologies, the OR strategy brings the high throughput gains. Additionally, it is likewise hard to keep up the routing table for a SU because of the embodiment of dynamic spectrum access [13]. Consequently, the pre-decided end-to-end routing cannot be fitting for the CRAHN situation. Because of the way that the OR strategy does not require the earlier foundation of the routes, the OR strategy is more suitable to be utilized in the CRAHN situation with dynamic changes of channel availability because of the dynamic behavior of PUs [9, 14].

On analysis, the SMOR routing model [10] has been found to be the most efficient OR strategy for CRAHNs. Previously some improved models of OR have been proposed [11 – 16]. However, due to the limitations of performance due to network bandwidth and throughput in SMOR, leads this paper to develop an HFGWO-SMOR routing model, which utilized hybrid Firefly, and grey-wolf optimization algorithms to improve the delay-throughput relationship analysis and improve the cooperative multipath communication.

The main challenges and issues in CRAHNs. Besides the basic challenges and issues such as (Spectrum Sensing, Spectrum Management and Allocation, Interference Management, Routing and Network Protocols, Security and Privacy), there are some of the principal issues are:

– Minimize the energy consumption of the network while ensuring the reliable data transmission; it takes into account the dynamic spectrum availability and channel conditions to make routing decisions.

– The interaction between primary users and secondary users that while achieving an optimal network performance.

– Optimization of spectrum sensing and routing in cognitive radio ad hoc networks; routing decisions to maximize network throughput while avoiding interference to primary users.

– Quality-of-service (QoS)-aware opportunistic routing in multi-channel cognitive radio ad hoc networks.

The main Contributions of this paper are:

– Deep study of the Cognitive Radio Ad Hoc Network;

– This work had made significant contributions to the understanding and development of cognitive radio systems;

– Analysis of the existing studying of the delay, and degradation of packet delivery ratio due to non-consideration of network bandwidth and throughput problems;

– Proposing a new modeled based on the “hybrid optimization model” to solve the above problems.

Structure of this research paper. The rest of the article is organized as Section 2, which presents a review of related research works. Section 3 presents the proposed system model and Section 4 explains the proposed hybrid optimization model and utilization of it in the OR strategy. Section 5 evaluates the performance of the proposed model while Section 6 makes a conclusion about this routing model.

2. Related Work. There are several research papers, which focus on the CRAHNs, these papers, serve as a starting point for understanding and exploring the field of hybrid optimization-based spectrum-aware opportunistic routing in cognitive radio ad hoc networks.

As stated above, the interest in the CRAHN routing models has been very high recently. Many existing efforts focus on developing OR strategy with channel assignment and maximizing network throughput. In [17], a new route metric called multichannel expected any path transmission time is proposed, which exploits the channel assorted variety and resource of multiple applicant forwarders for the opportunistic routing. In light of the new metric, a distributed algorithm named channel-aware opportunistic routing is also displayed.

In study [18], an online opportunistic routing algorithm is proposed by utilizing multi-specialist support learning; introduces the concept of opportunistic spectrum access in cognitive radio networks and proposes an optimization-based approach for selecting the best available spectrum bands for communication. The proposed routing plan together addresses the connection and relay determination in light of transmission achievement probabilities. This advanced learning system effectively investigates openings in part recognizable and non-stationary conditions of CRAHNs.

In study [19], the randomization structure is summed up, which is initially proposed for the information line changing to a SNR – based interference model in multi-hop wireless networks. Further, circulated power assignment and correlation calculation are produced, which accomplishes about 100% throughput. In study [20], a Bayesian decision rule-based algorithm to take care of the throughput maximization problem ideally with steady time multifaceted nature is proposed. To organize PU transmissions, the throughput maximization problem is re-detailed by adding a constraint on the PU throughput.

In study [21], the throughput execution of the network is portrayed by utilizing a lining theoretic investigation, and throughput is additionally boosted by means of the use of the Lagrangian duality hypothesis. In study [22], by applying the convex optimization method, the shut-shape articulation for the ideal time portions is acquired to boost the sum throughput. To beat this problem, another execution metric known as the common throughput is proposed, which considers the additional constraint that all users ought to be designated with an equivalent rate paying little respect to their distances to the H-AP.

In study [11], presents a hybrid optimization algorithm for opportunistic routing in cognitive radio ad hoc networks. This algorithm uses the hybrid artificial bee colony optimization to achieve a trade-off between exploration and exploitation in the route selection process, considering spectrum availability and energy efficiency. The authors propose a routing protocol that takes into account the variation in channel conditions and utilizes a particle swarm optimization algorithm to select the best routes based on spectrum availability and link quality.

In study [10] the authors developed the SMOR model, the Spectrum-Map-Empowered Opportunistic Routing (SMOR) model focuses on leveraging spectrum mapping techniques to enhance opportunistic routing in the cognitive radio ad hoc networks (CRAHNs). The model is designed to address the challenges posed by dynamic spectrum availability in CRAHNs; which was developed separately for both regular CRAHNs as SMOR-1 algorithm and large scale as regular CRAHNs as SMOR-2 algorithm. By incorporating spectrum mapping and opportunistic routing, the SMORT model likely aims to improve spectrum utilization, enhance overall network performance, and mitigate the effects of varying spectrum availability in CRAHNs.

SMOR-1 Algorithm (for regular CRAHNs): The SMOR-1 algorithm, specifically tailored for regular CRAHNs, aims to optimize opportunistic routing by utilizing a spectrum map. The spectrum map provides information about the availability and quality of different spectrum bands in the network. Based on this information, the SMOR-1 algorithm selects the most suitable spectrum band and path for data transmission, considering factors such as channel conditions and interference [10, 11, 26].

SMOR-2 Algorithm (for large-scale CRAHNs): The SMOR-2 algorithm, developed for large-scale CRAHNs, extends the concepts of the SMOR-1 to address the scalability issues inherent in larger networks. It aims to efficiently utilization of spectrum resources while considering the challenges of topology dynamics and resource limitations in large-scale CRAHNs. The SMOR-2 algorithm may incorporate additional optimizations or techniques to handle the increased complexity and scale of the network [10].

In Stochastic geometry analysis for regular CRAHNs, the mathematical analysis for transmission delay of multi-hop communications is examined via Markov chain modelling and queuing network theory, and the SMOR-1 algorithm is proposed to exploit opportunistic selections for cooperative relay regarding link transmission qualities. For large-scale CRAHNs, the corresponding delay of opportunistic links is derived via stochastic geometry and queuing network analysis, and the SMOR-2 algorithm is proposed to fulfill geographic opportunistic routing, exhibiting cooperative diversity in such large-scale networks [10, 26].

3. System Model. Due to the challenges that face the decentralized infrastructure of Cognitive radio ad hoc network, and due to the fact that CRAHN has no infrastructure backbone, we considered the system to involve with a finite of (M= 10) Primary users (PUs), every PU has its own licensed spectrum to communication in specific spectrum band $X' \subseteq X$ where X is estimated area of 500m x500 m.

PUs share an unused channel with Secondary Users (SUs) which are specified with (N=100) SUs when PU is in the off state, SU is able to find a PU spectrum hole to establish connection and communication with a single transmitter Tx and K receivers Rx over the time interval [*t0, T*].

Let n denote the number of the transmitting and receiving pairs for SU and Tn= {1,2,..,n} denotes the set of SU where the pairs of transmitting and receiving of SU i (SU i for i∈N) are changeable based on the PU activities; that means, the licensed spectrum of PU i should be busy during transmitting and receiving of PU i, otherwise the opportunistic Spectrum will be available for SU i. Figure 1 shows the system model utilized in this paper [25 – 31].

This system model proposes a hybrid optimization-based routing protocol for cognitive radio ad hoc networks. It combines genetic algorithms and particle swarm optimization to optimize the routing path selection while considering spectrum availability.

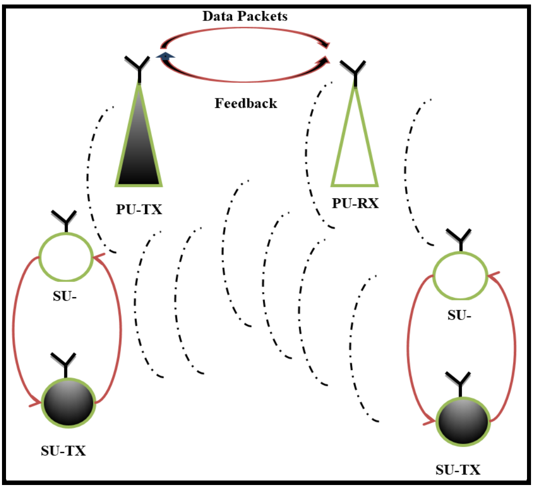

Fig. 1. System Model

The following Table 1 illustrates the main parameters in the system model, the energy of transmission in PU i is denoted by p_i^P, as well as the transmission energy in SU i is denoted by p_i^s, while it is supposed that the pairs of SU i transmitter/receiver are inside the communication range of each other.

Table 1. Simulation Parameter

No.	Simulation Parameters	
	Parameter	Parameter Value
1	Simulation Area Size	500m x500 m.
2	Simulation time	120s
3	Number of CR-Nodes (SUs)	100
4	Number of PU-Nodes	10
5	Size of frames to be scheduled	64 to 196 kb
6	Variable transmission time ranges	10–50 µs
7	Number of channels utilized to schedule the frame transmission	35
8	Size bandwidth available per channel	2 MB/s
9	Distance between the Nodes	Random
10	Node Energy Capacity	250mAH

4. Hybrid Firefly and Gray-Wolf optimization based on SMOR Model. This proposed routing model follows the processes in SMOR; the existing SMOR model has been shown to improve and enhance the network throughput, reduce the delay and the packet loss, then, enhance the network resilience to channel variations and node failures. However, it also required careful design and optimization of the spectrum sensing, channel selection, and opportunistic routing algorithms, as well as the handoff criteria and the routing metrics.

Overall, the SMOR model is a promising approach to improve the performance and efficiency of cognitive radio ad hoc networks as explained in the previous relative work section in this paper; therefore, the proposed new approach is developed to enhance the performance, efficient opportunistic routing in CRAHN via hybrid firefly and Gray-Wolf optimization approach.

Based on these strategies, the proposed HFGWO-SMOR model has developed. The relationship between the delay and throughput is optimized using the hybrid algorithms.

The behavior of the fireflies and the Gray wolves are merged to develop this model. First, the basic concept of these two optimization models has been discussed in [25]. The flashing behaviors of fireflies are utilized to develop firefly-inspired algorithms.

Firefly Approach (FA) and Gray Wolf Optimization Approach are a metaheuristic optimization algorithm.

4.1. Firefly Approach (FA). Xin-She Yang defined the Firefly Algorithm, which is an optimization algorithm that is based on the flashing characteristics of fireflies. It was proposed by the author in 2008 as a novel optimization technique to solve complex optimization problems. The algorithm is inspired by the properties of fireflies, which use their flashing behavior to attract mates and communicate with each other [33].

The algorithm then simulates the flashing characteristics of the fireflies, where the intensity of their flashes represents the quality of the solution they represent. On the other hand, the algorithm models the behavior of fireflies, which communicate with each other through bioluminescence. The brightness of a firefly's light is proportional to its attractiveness to other fireflies, and fireflies tend to move toward the brightest light they can see [23, 24].

Firefly Approach; this algorithm uses a set of parameters, such as the light absorption coefficient and the step size, to control the movement of the fireflies. On the other hand, the firefly’s movements are also influenced by the distance between the fireflies, with closer fireflies having a stronger attraction.

The Firefly algorithm has been shown to be effective in solving a wide range of optimization problems, including function optimization, parameter estimation, and machine learning. It is also known for its simplicity and fast convergence rate.

The proposed hybrid algorithm is developed by hybridizing both of these behaviors. For a maximization problem, it obtains the highest possible value of the fireflies function, the brightness and flashing can be proportional to the value of the possible objective function. In maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x) \propto f(x)$. However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies.

Thus, it will vary with the distance rij between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption [23 – 26]:

$$\beta_{i,j} = \beta_0 e^{-\gamma r_{ij}^2}, \tag{1}$$

where β_0 is the attractiveness at r=0.and γ is the light exhaust coefficient. The distance between two transmitters of i and receiver j is arrived using deff. The movement of transmitter i as its being powered by the brighter receiver j is calculated as follows:

$$\Delta x_i = \beta_0 e^{-\gamma r_{ij}^2} \left(x_j^t - x_i^t \right) + \alpha \varepsilon_i, \quad (2)$$

where the γ second term is due to the attraction. The third term ∝ is a randomization vector drawn from a Gaussian disposal.

The algorithm uses the following phases:

1. Initialization: Generate an initial population of fireflies with random positions and intensities.
2. Fitness Evaluation: Evaluate the fitness of each firefly based on the problem's objective function.
3. Attraction: Move each firefly towards the brightest firefly (i.e., the one with the highest intensity) in its vicinity, where the degree of attraction is based on the distance between the fireflies and their intensities.
4. Randomization: Introduce random movement to each firefly to prevent premature convergence and to explore new areas of the search space.
5. Updating: Update the positions and intensities of the fireflies based on their movements and fitness values.
6. Termination: The algorithm stops when a certain stopping criterion is met, such as a maximum number of iterations, or when the desired accuracy is achieved.

Definition: *Light intensity:* The light intensity of each firefly is calculated as follows:

$$I\_i = f\left(x\_i\right), \quad (3)$$

where I_i is the light intensity of firefly i and f(x_i) is the fitness value of firefly i.

Attraction: Each firefly is attracted to other fireflies based on their light intensity and distance. The attraction of firefly i towards firefly j is calculated as follows:

$$r\_ij = \left\| x\_j - x\_i \right\|, \quad (4)$$

$$beta = beta\_0 * exp(-gamma * r\_ij^{\wedge 2}), \quad (5)$$

$$x\_i = x\_i + alpha * \left(x\_j - x\_i\right) + beta * epsilon\_i, \quad (6)$$

where r_ij is the Euclidean distance between fireflies i and j, beta_0 is the initial attractiveness, gamma is the light absorption coefficient, alpha is the step size, and epsilon_i is a random vector with values drawn from a Gaussian distribution [27 – 32].

4.2. Gray Wolf Optimization Approach. In 2014, in studies [31, 34] the authors proposed the Gray Wolf Optimization (GWO) algorithm, inspired by the social hierarchy and hunting behavior of gray wolves in the wild.

It simulates the hunting behavior of wolves, the algorithm starts with an initial population of wolf packs where the range of each pack is from 5 to 12 wolves, each pack consisting of alpha, beta, and delta wolves. In the GWO algorithm, a population of wolves is used to search for the optimal solution to a problem. The alpha wolf is responsible for leading the hunting, while the beta and delta wolves assist the alpha wolf in the hunting process [33, 34].

The GWO algorithm optimizes a function by updating the positions of wolves, which represent the best solutions found so far. The algorithm is based on the social behavior of gray wolves, where each wolf has a specific role in the pack and works together to achieve a common goal.

Definition: The algorithm iteratively searches for the optimal solution by simulating the hunting behavior of the wolf packs. During each iteration, the alpha wolf updates its position based on its hunting experience, while the beta and delta wolves adjust their positions based on the alpha wolf's position. The alpha wolf represents the best solution found so far, the beta wolf represents the second-best solution, and the delta wolf represents the third-best solution [35].

At each iteration, the positions of the wolves are updated using the following equation [32, 33]:

$$x'ij = xij + a*(2*r1-1)*|A*xalpha - xij|, \quad (7)$$

where $x'ij$ is the updated position of the i-th wolf in the j-th dimension, xij is the current position of the i-th wolf in the j-th dimension, a is a coefficient that decreases linearly from 2 to 0 as the number of iterations increases, $r1$ is a random number between 0 and 1, and $A*xalpha$ is the position of the alpha wolf.

The Gray Wolf Optimization algorithm steps:

1. *Initialization:* The algorithm starts with an initial population of n search wolves (where CR user searches for free Spectrum holes) that are randomly distributed in the search space.

2. *Fitness evaluation*: The fitness of each search wolf (get a Spectrum-hole that belongs to PUs) is evaluated by applying the objective function of the optimization problem to its corresponding search space. The search wolf is ranked according to their fitness values, with the best (i.e., lowest) fitness values having the highest rank.

3. *Pack updating (alpha, beta, and delta) wolves*: The algorithm identifies the three best wolves in the population. The position of these wolves is then updated based on the positions of the other wolves in the population. The three search agents with the highest ranks are designated as the alpha, beta, and delta wolves, respectively.

4. *Solution update:* The algorithm updates the positions of the candidate solutions, and checks if the new solutions improve the overall fitness of the pack.

Definition: The algorithm continues to update the positions of the wolves until a stopping criterion is met, such as reaching a maximum number of iterations or a satisfactory solution [35].

Updating the position of the alpha wolf:

$$D\_alpha = |C1 * X\_alpha - X\_i|, \tag{8}$$

$$X1 = X\_alpha - A1 * D\_alpha. \tag{9}$$

Updating the position of the beta wolf:

$$D\_beta = |C2 * X\_beta - X\_i|, \tag{10}$$

$$X2 = X\_beta - A2 * D\_beta. \tag{11}$$

Updating the position of the delta wolf:

$$D\_delta = |C3 * X\_delta - X\_i|, \tag{12}$$

$$X3 = X\_delta - A3 * D\_delta. \tag{13}$$

Updating the position of the other wolves:

$$X\_i = (X1 + X2 + X3) / 3, \tag{14}$$

where X_i is the position of the i-th wolf, X_alpha, X_beta, and X_delta are the positions of the alpha, beta, and delta wolves, respectively, C1, C2, and

C3 are random vectors between 0 and 1, A1, A2, and A3 are constants that control the step size of the update.

These equations of GWO are applied to each candidate solution (wolf) in the population in each iteration of the algorithm, and the process continues until a stopping criterion is met (e.g., a maximum number of iterations or a desired level of convergence).

The steps of the HFGWO Approach:

1. Initialize values of Firefly Approach **(**FA) parameters: population, maximum iterations, attraction coefficient, etc.…
2. Initialize Gray Wolf Optimization (GWO) parameters: population (primary-users), search agents (CR-User).
3. Generate initial fireflies.
4. Evaluate fitness and update light intensity.
5. Find the brightest firefly.
6. Update information.
7. Feed FA results to GWO.
8. GWO initializes search agents and solutions.
9. Evaluate fitness.
10. Compare with other agents to determine the best search agent.
11. Verify the result of FA.
12. Return the best grey-wolf firefly agent.

Based on this concept of HFGWO, the SMOR routing model is modified and improved. The proposed model initializes the nodes as fireflies and selects the best firefly using FA while it is cross-checked using GWO to verify the best selection. This concept is presented in the following algorithm.

Algorithm 1. HFGWO-SMOR

```
Initialize network parameters (Number of PUs, SUs, Data Rate, etc...)
Partition traffic into batches of packets
For each time slot
    Source Collect link information
    Prioritize forwarding nodes
    Select data packets for each path via HFGWO
    Initialize FA & GWO parameters: (population, maximum iterations, an
        attraction coefficient and algorithm parameters).
    Find the brightest of fireflies with a high attraction coefficient
    Change attractive level and distance
    Select the best Firefly node
    Feed FA result to GWO
    Verify the node information using GWO
    Initialize the best three solutions, the first best solution as χα, the second
        best solution as χβ, and the third best solution as χδ, respectively.
```

```
While (k < maximum number of iterations or a desired level of
    convergence)
    For i= 1:n
      Update the current position of the search agent based on the
        desired level of convergence
    End for
Evaluate the fitness.
Update the coefficient vector
If there is a better solution, then update the best agents, xα, xβ and xδ.
k=k+1;
Return the best forwarding node
Update the parameters
Send test data
If ACK is not received
Initiate path-checking process
For each relay node
    Check the packet transmission information
Update lists
Return packet data
End While
Transmit data
End For
```

5. Performance Evaluation. The proposed HFGWO-SMOR routing model is evaluated using MATLAB. The routing performance of this model is compared with that of SMOR [10], HABC-SOR [11], HB-SOR [12] and HFSA-SOR [13]. The simulation environment is set as in [10 – 16] and the comparisons are simulated in concepts of end-to-end delay (EED), Bit Error Rate (BER), throughput and packet delivery ratio. MATLAB simulators provide a framework for modeling the various network components and their interactions.

5.1. Delay. Simulating delays in cognitive radio ad hoc networks involves modeling the various factors that contribute to delays in the network. Delays in the network can be caused by factors such as propagation delay, queuing delay, processing delay, and transmission delay. Delay simulation in cognitive radio ad hoc networks can be represented mathematically using a queuing model; queuing models provide a framework for modeling the arrival and service processes in a network, and can be used to estimate the queuing delay and other performance metrics [29].

One commonly used queuing model for delay simulation in cognitive radio networks is the M/G/1 queuing model. In this model, packets arrive according to a Poisson process with rate λ. The queuing delay for each packet can then be calculated as:

$$D = (\rho/(\mu-\lambda)) * (1/2 + (V/2\mu)^2), \quad (15)$$

where $\rho = \lambda/\mu$ is the traffic intensity, and V is the coefficient of variation of the service time distribution. This equation assumes that the service time distribution is memoryless, which is a reasonable assumption for many communication protocols in cognitive radio networks.

$$\textit{Total delay} = \textit{Propagation delay} + \textit{Queuing delay} + \textit{Processing delay} + \textit{Transmission delay}. \quad (16)$$

Propagation delay: Propagation delay is the time it takes for a signal to be traveled from the transmitter to the receiver, and is dependent on the distance between the nodes and the propagation speed of the medium. Mathematically, propagation delay can be expressed as:

$$\textit{Propagation delay} = \textit{distance between nodes} / \textit{propagation speed of the medium}. \quad (17)$$

Queuing delay: Queuing delay is the time it takes for packets to wait in a buffer before they can be transmitted, and is dependent on the network congestion and the size of the buffer:

$$\textit{Queuing delay} = \textit{packet size} / \textit{available bandwidth}. \quad (18)$$

Processing delay: Processing delay is the time it takes for the node to process a packet before forwarding it, and is dependent on the processing power of the node [30 – 37]. Mathematically, processing delay can be expressed as:

$$\textit{Processing delay} = \textit{packet size} / \textit{processing power of the node}. \quad (19)$$

Transmission delay: Transmission delay is the time it takes for the packet to be transmitted over the wireless medium, and is dependent on the bandwidth of the channel and the size of the packet. Mathematically, transmission delay can be expressed as:

$$\textit{Transmission delay} = \textit{packet size} / \textit{available bandwidth}. \quad (20)$$

5.2. Throughput: The throughput of a cognitive radio ad hoc network is affected by various factors such as the number of nodes in the network, the data rate of the channel, the propagation delay, the processing delay, and the queuing delay [28, 29].

By using appropriate values for these parameters and applying the following equation, one can simulate the throughput of the network and analyze the performance of the network under different scenarios.

The throughput in HFGWO-SMOR Model is modeled mathematically using the following equation:

$$Throughput = total\ number\ of\ bits\ received\ /\ total\ time, \tag{21}$$

where the total number of bits received is the number of bits received by all the nodes in the network during a given period of time, and the total time is the time taken for all the bits to be received. The total number of bits received can be calculated as:

$$Total\ number\ of\ bits\ received = number\ of\ nodes * data\ rate * time, \tag{22}$$

where the number of nodes is the number of nodes in the network, data rate is the data rate of the channel, and time is the period of time for which the data rate is measured. The total time can be calculated as:

$$Total\ time = transmission\ time + propagation\ delay + processing\ delay + queuing\ delay. \tag{23}$$

By the way, Table 1 shows the main parameters to simulate the delays and throughput in our system model, in order to model delays in the network; one can configure the simulator to include parameters such as the distance between nodes, the buffer size, the processing power of the nodes, and the bandwidth of the channel. By adjusting these parameters, one can simulate different network scenarios and measure the resulting delays.

It is also important to consider the impact of interference in the network, as cognitive radio networks rely on the ability to detect and avoid interference. Simulating interference was done by introducing competing signals in the network, or by modeling the spectrum sensing capabilities of the nodes.

We obtained the total delay in a cognitive radio ad hoc network in our research. The resulting delay value is used to evaluate the performance of the network and to compare different network configurations and scenarios, the Figure 2 shows the EED vs. lambda comparison of SMOR, HABC-SOR, HB-SOR, HFSA-SOR and the proposed HFGWO-SMOR.

HFGWO-SMOR shows a remarkable improvement in the packet delay aspect, which leads to minimizing the delay in all levels of the offered load with an average of 4%, HFGWO-SMOR model reduced delay than other models because of the improved optimal selection of the routing paths.

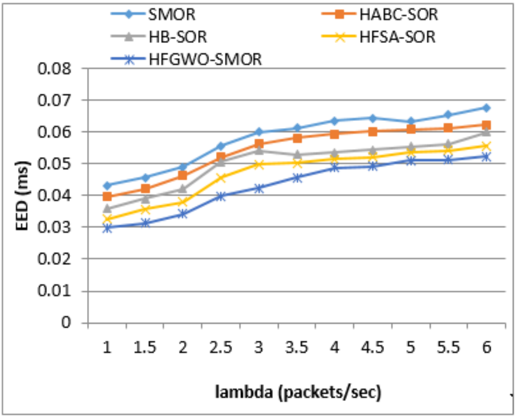

Fig. 2. End-to-end delay

Figure 3 shows the BER vs. lambda comparison of SMOR, HABC-SOR, HB-SOR, HFSA-SOR and the proposed HFGWO-SMOR. HFGWO-SMOR shows a lower error rate with a 4% decrease on average while other models have comparatively higher BER. This is because the path selection is highly reliable in the proposed model.

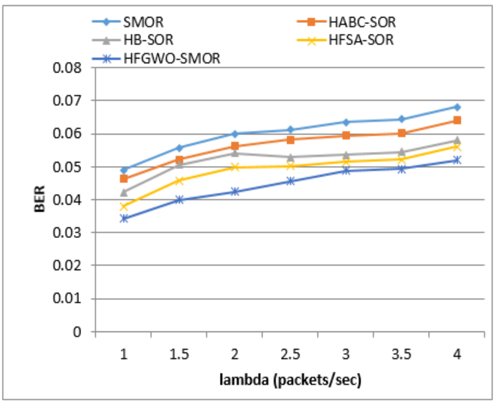

Fig. 3. BER comparison

Figure 4 shows the Throughput vs. lambda comparison of SMOR, HABC-SOR, HB-SOR, HFSA-SOR and the proposed HFGWO-SMOR. HFGWO-SMOR provides a higher throughput rate with a 3% increase on average due to a significant selection of optimal paths while other models have comparatively less throughput.

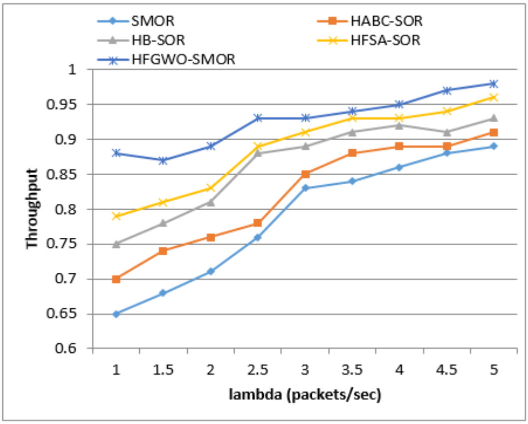

Fig. 4. Throughput comparison

Figure 5 shows the Packet delivery ratio vs. no. of nodes comparison of SMOR, HABC-SOR, HB-SOR, HFSA-SOR and the proposed HFGWO-SMOR.

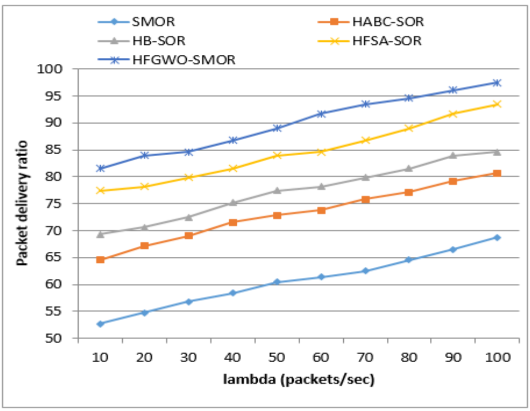

Fig. 5. Packet delivery ratio

HFGWO – SMOR provides a higher packet delivery ratio, which is almost 22% higher than the SMOR model and significantly higher than other models. From the performance evaluation results, it was found that the proposed HFGWO-SMOR model has better performance than other models in providing efficient opportunistic routing.

6. Conclusions. This paper aimed at developing an improved opportunistic routing model that can resolve the limitations of the SMOR model. This has been achieved by the HFGWO-based SMOR routing model that further improves the opportunistic routing behavior. The proposed HFGWO-SMOR model follows the process of SMOR with additional improvement achieved in the optimal selection routing paths. The experimental results also prove that the proposed model has reduced delay, less error rate, improved throughput and improved packet delivery ratio. This model provides more efficient opportunistic routing performance than the other models compared including SMOR, which is evident from the evaluation results. In the future, the feasibility of improving this model by adding viable concepts of path loss, node failures, and power consumption will be examined.

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ОППОРТУНИСТИЧЕСКАЯ МАРШРУТИЗАЦИЯ НА ОСНОВЕ ГИБРИДНОЙ ОПТИМИЗАЦИИ С УЧЕТОМ СПЕКТРА ДЛЯ САМООРГАНИЗУЮЩИХСЯ СЕТЕЙ КОГНИТИВНОЙ РАДИОСВЯЗИ

Абдулла Х.М., Кумар А., Касем Ахмед А.А., Саид Мослех М.А. **Оппортунистическая маршрутизация на основе гибридной оптимизации с учетом спектра для самоорганизующихся сетей когнитивной радиосвязи.**

Аннотация. Оппортунистическая маршрутизация повысила эффективность и надежность в самоорганизующихся сетях когнитивной радиосвязи (CRAHN). Многие исследователи разработали модели оппортунистической маршрутизации, в том числе модель оппортунистической маршрутизации на базе карты спектра (SMOR), которая считается более эффективной моделью в этой области. Однако в SMOR существуют определенные ограничения, которые требуют внимания и устранения. В данной статье рассматривается проблема задержки и ухудшения коэффициента доставки пакетов из-за неучета пропускной способности сети. Чтобы решить эти проблемы, в базовой модели маршрутизации SMOR используется гибридный алгоритм оптимизации, состоящий из алгоритмов оптимизации Firefly и Grey Wolf. Разработанная таким образом гибридная модель маршрутизации SMOR на основе оптимизации Firefly и Grey-Wolf (HFGWOSMOR) повышает производительность за счет высокой локальной и глобальной поисковой оптимизации. Первоначально анализируется взаимосвязь между задержкой и пропускной способностью, а затем устанавливается совместная многолучевая связь. Предлагаемая модель маршрутизации также вычисляет значения энергии принимаемых сигналов в пределах порога полосы пропускания и периода времени, и, следовательно, проблемы с производительностью, обнаруженные в SMOR, решаются. Чтобы оценить её эффективность, предложенная модель сравнивается со SMOR и другими существующими моделями оппортунистической маршрутизации, которые показывают, что предлагаемая модель HFGWOSMOR работает лучше, чем другие модели.

Ключевые слова: самоорганизующиеся сети когнитивной радиосвязи, оппортунистическая маршрутизация, оппортунистическая маршрутизация на базе карты спектра, оптимизация Firefly, оптимизация Grey-Wolf, порог пропускной способности.

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