Improved Random Forest Algorithm for Cognitive Radio Networks' Distributed Channel and Resource Allocation Performance

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Abstract. Modified Random Forest (MRF) machine learning algorithm aimed at improving the distributed channel allocation and resource allocation performance in cognitive radio networks (CRNs). The purpose of this research is to enhance the efficiency and effectiveness of CRNs by optimizing the allocation of channels and resources. The proposed MRF algorithm is developed by adapting and modifying the random forest technique to address the specific challenges of CRN allocation. Experimental evaluations demonstrate that the MRF algorithm achieves higher accuracy and efficiency compared to existing routing techniques and channel allocation algorithms like ACO and PSO. It exhibits a high packet delivery ratio, increased throughput, and reduced delay in channel selection, thus improving the overall performance of CRNs.The implications of this research are twofold. On a theoretical level, this study contributes to the field by extending the capabilities of the random forest algorithm and adapting it to the domain of CRNs. The modified algorithm demonstrates the potential of machine learning techniques in addressing allocation challenges in wireless communication systems. The findings emphasize the importance of advanced algorithms in improving the efficiency and effectiveness of channel and resource allocation processes.

Keywords: Random Forest, Routing, Throughput, Cognitive Radio Networks, Channel Allocation

1.Introduction

The increasing demand for wireless communication services, coupled with the limited availability of spectrum resources, has prompted the development of cognitive radio networks (CRNs). CRNs enable secondary users to opportunistically access underutilized licensed frequency bands, effectively sharing the spectrum with primary users. This dynamic spectrum access paradigm holds the promise of significantly improving spectrum utilization and accommodating the growing demand for wireless services. However, efficient allocation of channels and resources is crucial for the success of CRNs. Traditional approaches, such as fixed channel assignment or centralized allocation schemes, are ill-suited to the dynamic and decentralized nature of CRNs. These approaches often suffer from suboptimal performance, interference issues, and lack of adaptability to changing network conditions.

Machine learning techniques have shown great potential in optimizing various aspects of wireless communication systems, including channel allocation and resource allocation. Among them, the random forest algorithm has garnered attention for its ability to handle complex classification and regression tasks. By combining the predictions of multiple decision trees, random forest algorithms provide robust and accurate results.In the context of CRNs, previous research efforts have explored the application of machine learning algorithms, including random forest, for spectrum sensing, modulation classification, and spectrum prediction. However, relatively limited research has been conducted on the use of machine learning algorithms, specifically random forest, for improving the distributed channel allocation and resource allocation performance in CRNs.

By developing an optimized random forest algorithm for CRNs' allocation challenges, this research strives to contribute to the body of knowledge on cognitive radio networks and advance the understanding of machine learning techniques in the context of wireless communication systems. The outcomes of this research are expected to have practical implications by enabling more efficient and effective channel and resource allocation in CRNs, supporting various applications and services that rely on reliable and high-quality wireless communication.

The motivation behind this research is rooted in the challenges and opportunities presented by cognitive radio networks (CRNs). As the demand for wireless communication services continues to increase, efficient utilization of the limited spectrum resources becomes crucial. CRNs offer a promising solution by allowing secondary users to access underutilized licensed frequency bands. However, the distributed nature of CRNs and the dynamic allocation requirements pose significant challenges for efficient channel allocation and resource allocation.

2.Literature Review

Despite the growing interest in machine learning techniques for CRNs, limited research has been conducted on the use of random forest algorithms specifically for distributed channel and resource allocation. The existing literature primarily focuses on other aspects of CRNs, such as spectrum sensing and modulation classification. This research aims to bridge this gap by proposing an improved random forest algorithm tailored for CRNs' distributed channel and resource allocation.

Jiang et al. (2013) proposed a scheme for channel allocation and reallocation in cognitive radio networks. They utilized a multidimensional Markov chain and a multi-antenna interface connected to a single channel for channel allocation. The study analyzed the channel allocation behavior in server and non-server-based systems. The researchers developed an analytical model and defined performance metrics such as blocking probability, dropping probability, and throughput for secondary users. Simulation analysis demonstrated the improved performance of the cognitive radio system with the proposed scheme, specifically considering multiple antennas operating on a single channel (Jiang et al., 2013).

Jalali et al. (2015) introduced a dynamic channel access strategy for underlay cognitive radio networks using a Markov model. The researchers proposed a partial channel occupancy (PCO) mode that allows

secondary users to access a portion of the available bandwidth while coexisting with primary users. They developed a continuous-time Markov chain-based model to assess the performance of licensed and unlicensed networks. Additionally, a cost-against-gain analysis was conducted to evaluate the feasibility of the proposed technique in different traffic scenarios. The effectiveness of the scheme was validated through comprehensive simulation analysis (Jalali et al., 2015).

Bayhan and Alagöz (2014) presented a scheme for best fit channel selection in cognitive radio networks. They developed a Markov model-based scheme to theoretically analyze the best fit channel selection and introduced the concept of spectrum fragmentation. Performance evaluation of the proposed scheme compared to the longest ideal time-based channel selection scheme was crucial in terms of spectrum utilization. Simulation analysis demonstrated the good performance and significant results of the proposed scheme in practical scenarios, considering only a discrete state space (Bayhan & Alagöz, 2014).

Edeer et al. (2014) presented a multi-objective optimization approach for optimal link adaptation in OFDM-based cognitive radio systems. Their algorithm aimed to maximize system throughput while minimizing transmit power for both licensed and unlicensed users. The work considered imperfect sensing but did not account for the potential violation of interference constraints resulting from imperfect sensing (Edeer et al., 2014).

Mahdi et al. (2015) proposed an Adaptive Discrete Particle Swarm Optimization (ADPSO) algorithm using Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). Their study focused on the adaptation of transmission parameters in cognitive radio networks, aiming for high data rate and reduced power consumption. The researchers addressed two key issues: 1) reducing the convergence time when finding the optimal set of parameters and 2) overcoming the problem of local optima in PSO and GA. The ADPSO algorithm was introduced, and a multi-carrier system was used to evaluate its performance. Simulation results showed that the proposed algorithm achieved a fast convergence time and successfully addressed the problem of local optima (Mahdi et al., 2015).

3.Research Methodology

3.1Distributed Channel and Resource Allocation in CRNs

Distributed channel and resource allocation in CRNs present unique challenges due to the decentralized nature of decision making and the dynamic network conditions. Traditional approaches, such as fixed channel assignment or centralized allocation schemes, are not suitable for CRNs as they lack adaptability and scalability. Distributed algorithms based on game theory, optimization techniques, and reinforcement learning have been proposed to address the allocation challenges in CRNs. However, there is a need to explore the potential of machine learning algorithms, specifically random forest, in improving the distributed channel and resource allocation performance.

Input:

host_list, total number of host created in data center,

vm_list, total number of VMs to be created in host of the data center,

workload, CPU demand by cloud users in million instructions per seconds,

γ, discount factor,

L, specified episode for learning process.

Output: optimize the allocation of VMs.

Method:

1 init(*workload*) // read user workload and initialize data center components

2 createHost(host list) // create Hosts in Data Center with corresponding characteristics

3 createVM(vm_list)// create VMs in the data center with corresponding characteristics

4 createEnvironment() //set up state set S, action set A and initialize Q values and R values

5 **for each**$vm \in vm\_list$

6 **for each**$host \in host\_list$

7 $s_0 = \{e_t, h_t, u_t, v_t\}$ //assign Data center energy, Host, VM demand to initial state

8 **for each** time step $k = 0,1,2, \ldots, L$

9 $a_k = a \in max_a . Q_k(s_k, a')$ //execute policy for current utilization & energy and choose action (host) with maximum value

10 apply a_k, measure s_{k+1} // determine the value of the outcome action

11 reward r_{k+1} //calculate composite reward value for allocation with Fuzzy Logic

12 $Q_{k+1 (s_k, A_k)\neg r+}[\Upsilon max_a . Q_k(s_k, a+1)]$

Algorithm 1 Energy Efficient Resource Allocation Algorithm

The proposed algorithm is designed to be executed in a distributed manner, where each user or service makes its own channel allocation decision based on local information. The algorithm allows each user or service to have its own decision tree, which can be trained on the data available to the corresponding user or service. The algorithm also allows each user or service to select its own feature set, which can be used to improve the accuracy of the decision tree.It is a modified version of the random forest algorithm, which is designed for distributed channel allocation in cognitive radio networks.

3.2 Modified Random Forest (MRF)Algorithm

The objective is to leverage the strengths of random forest algorithms, such as their ability to handle high-dimensional data, deal with noisy or incomplete information, and provide robust predictions, to enhance the performance of CRNs in terms of spectrum utilization, interference mitigation, and overall system capacity.

- Introduce modifications to the traditional Random Forest algorithm to improve its performance in distributed channel and resource allocation.
- Employ cross-validation or a separate validation dataset to estimate generalization capability.
- Incorporate additional decision rules or splitting criteria specifically tailored for CRNs.
- Explore techniques like adaptive feature selection, enhanced handling of imbalanced classes, or domain-specific constraints.
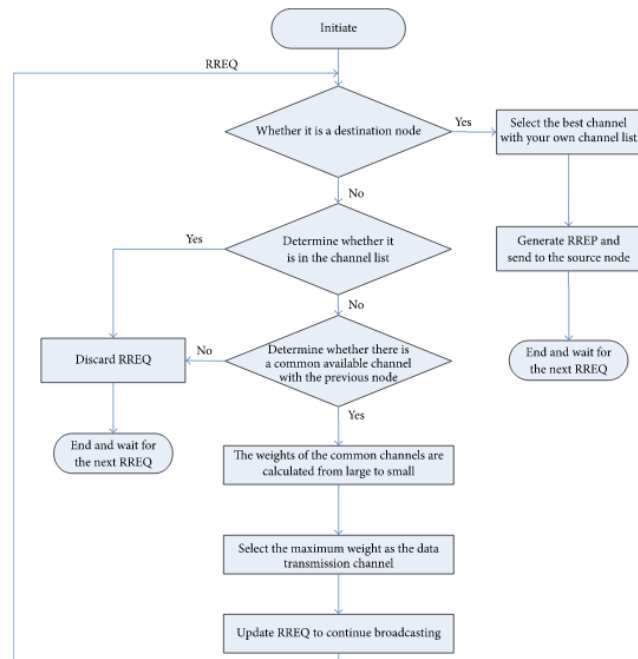
Fig.1: Neighbor node processing RREQ control packet.

4.Results and Discussion

4.1 Simulation Setup

In this section, our strategies are implemented and conduct extensive simulation experiments using NS-2 for efficient allocation of channel and resource utilization in cognitive radio networks. The cognitive nodes are randomly distributed in the rectangular plane region. There are nine data channels and a common control channel in the network, and the channel states of different channels are independent and random.

Table 1: Simulation Set up

Parameter	Value
Simulator	NS - 2.3.5
Channel type	Wireless channel
Protocols	MRF-AODV,ACO, and PSO
Simulation duration	120 second
Packet size	1024 bits
Traffic rate	128 bytes
Mobility Models	Random Waypoint
MAC Layer Protocol	802.11
Traffic Models	CBR
Network size	1000 nodes
Topology	2000 m x 2000m
Initial Energy	100J

In this section, the following important parameters are analyzed and represented in Table 2

- Packet Delivery Ratio
- End -to-End Delay
- Throughput

Table 2: Comparison of Simulation Results

No. of Nodes	Packet Delivery Ratio			Throughput			End -to-End Delay		
	MRF-AODV	ACO	PSO	MRF-AODV	ACO	PSO	MRF-AODV	ACO	PSO
100	3.9	3.1	3.0	4.1	3.6	3.8	1.9	2.3	2.1
250	4.7	4.1	4.1	4.9	4.5	4.3	2.6	3.0	2.8
500	5.9	5.1	4.8	6.1	5.3	4.6	3.1	3.8	3.9
750	8.0	6.7	6.2	7.6	6.2	6.1	3.8	4.3	4.3
1000	9.4	8.2	7.7	9.2	7.9	8.1	4.6	6.2	5.9

4.2 Packet Delivery Ratio

Packet Delivery Ratio (PDR) is a metric used to measure the percentage of data packets that are successfully delivered from the source to the destination in a communication network. PDR is an important performance metric in evaluating the quality of service (QoS) of a network, particularly in wireless networks where there may be limited resources and potential for interference and signal degradation.

To calculate PDR, the number of packets successfully delivered is divided by the total number of packets sent:

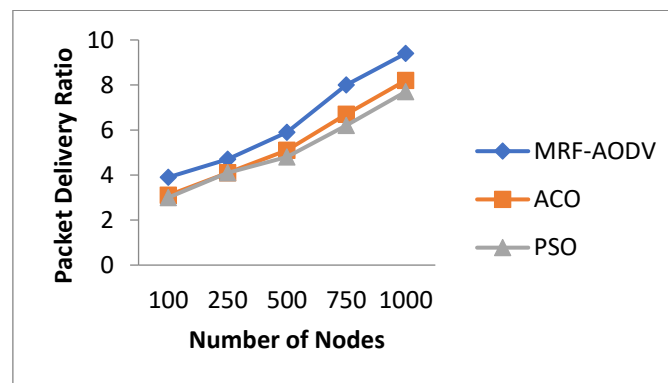PDR = (Number of Packets Delivered / Total Number of Packets Sent) * 100

Fig. 3: PDR Vs Number of nodes

4.3 Throughput

Throughput is a metric used to measure the amount of data that is successfully transmitted over a communication network in a given period of time. It is typically measured in bits per second (bps), or its multiples such as kilobits per second (Kbps), megabits per second (Mbps), or gigabits per second (Gbps).

Throughput is influenced by a number of factors, including the bandwidth of the network, the

number of users, the distance between the sender and the receiver, and the amount of interference or noise to the channel. To calculate the throughput, the amount of data successfully transmitted is divided by the time taken to transmit that data:

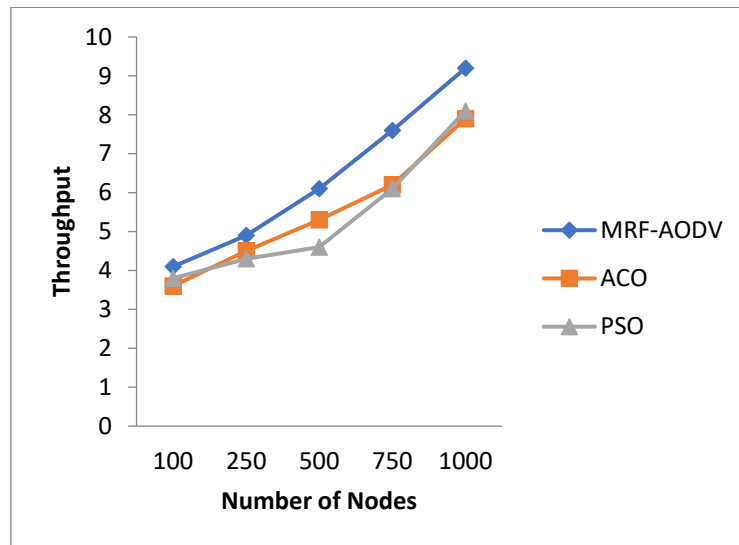$$\text{Throughput} = \text{Amount of Data Transmitted} / \text{Time Taken to Transmit}$$

Fig. 4: Throughput vs Number of Nodes

4.4 End -to-End Delay

End-to-end delay is a metric used to measure the time it takes for a data packet to travel from the source to the destination in a communication network. It is typically measured in milliseconds (ms), and includes the time taken for packet processing and queuing, transmission delay, propagation delay, and any other delays in the network
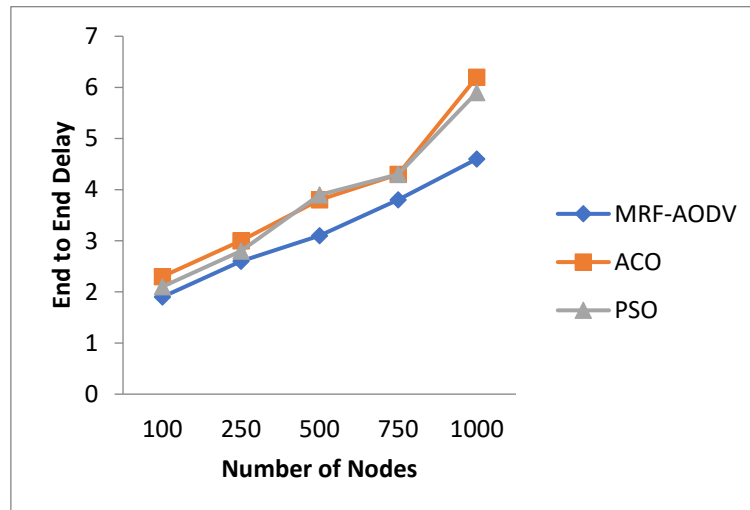

Fig. 5: End -to-End Delay vs Number of Nodes

5.Conclusion

In order to optimize the performance of cognitive radio networks, the AODV algorithm is improved in this paper based on random forest approach. In comparison with current routing protocols and channel allocation algorithms like ACO and PSO for improving the efficiency of the channel allocation, the proposed routing protocol MRF-AODV achieves high packet delivery ratio, throughput, and minimal

delay for selecting channel. This proves the proposed technique, achieves better accuracy, and improves the performance of the cognitive radio networks in terms of spectrum sensing and energy consumption. The modifications made to the Random Forest algorithm in the MRF algorithm are based on assumptions and design choices. These modifications may not fully capture all the complexities and nuances of distributed channel and resource allocation in CRNs. Alternative modifications or variations of the algorithm may yield different results and performance.

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