Hybrid resource optimization strategy in heterogeneous wireless networks

Nagaraj Gadde[1], Rashmi Shivaswamy[2], Ramesh Babu Halasinanagenahalli Siddamallaih[3], Gowrishankar[4], Govindaih Thimma Raju[5], Subramani Suryakumar Prabhu Vijay[6]
[1]Department of Artificial Intelligence and Data Science, SJC Institute of Technology, Chickballapur, India
[2]Department of Computer Science and Engineering (Data Science), Dayananda Sagar College of Engineering, Bengaluru, India
[3]Department of Computer Science and Engineering, RNS Institute of Technology, Bangalore, India
[4]Department of Machine Learning (AI and ML), BMS College of Engineering, Bangalore, India
[5]Department of Information Science and Engineering, SJC Institute of Technology, Bangalore, India
[6]Software Engineer and Data Analyst, Navshya Technologies, Bengaluru, India

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ABSTRACT

The future generation of heterogeneous wireless networks (HWNs) will combine various radio access technologies for connecting various mobile subscribers (MS) based on the quality of service (QoS) and wireless network parameters, connecting MS to the best possible wireless network (WN) has been a trending research topic in HWNs. Existing resource optimization methods are designed to meet the QoS of network criteria and user preferences are neglected. Very limited work is done for resource optimization considering user preferences. However, these models are designed considering multi-mode terminals (MMTs) running a single service at a time under a low-density network; as a result, cannot be adopted to run multiple services simultaneously and; thus, fail to meet current users' service dynamics requirement. Further, fails to bring good tradeoffs between reducing interference and improving performance. In addressing the research problem this work introduced a hybrid resource optimization strategy (HROS) to reduce interference by establishing channel availability and enhancing resource utilization through game theory. The HROS proves the existence of nash equilibrium (NE) improves throughput by 16.32% and reduces collision by 26.16% over the existing resource optimization-based network selection (RONS) scheme.

Corresponding Author:

Nagaraj Gadde
Department of Artificial Intelligence and Data Science, SJC Institute of Technology
Chickballapur, Karnataka, India
Email: nagarajgadde11@gmail.com

1. INTRODUCTION

Heterogeneous-wireless networks (HWNs) have seen a recent rise in the research field and the wireless industries, and this growth is expected to continue [1]. Spectrum allocation (SA) has an important role in providing trade-offs among consumer quality-of-service and network management in common resource and non-shared environments. The use of shared resources can help to improve spectrum utilization in HWNs, but this comes at a price. However, cross-tier interruption should not be a problem in a non-shared environment; however, it strongly affects resource consumption. Wireless access points with various radio benchmarks have always been anticipated to co-exist and operate in non-overlapping frequencies in future HWNs. Because of this, spectrum allocation in HWNs is extremely difficult. The HWNs illustrate the importance of studying and analyzing various SA techniques to come up with an optimal heterogeneous-wireless-networks spectrum-allocation design [2].

In HWNs, the proposed research work examined a variety of recent allocation of resource models. Only a few studies [3] have attempted to address SA issues by considering static setup variations in constraint and objective function [4]. When we try to boost the intensity and heterogeneous nature of the network, the conventional hexagonal network suffers [5]. To capture the spatial information behavior of devices in HWNs, new studies are focusing on designing nonlinear geometry using point processes. The geometry-based model determines the interferences and meets the performance requirements of HWNs [6]. Performance of the network such as throughput, user-aware performance, and utility (such as rate of transmission, and signal-to-interference ratio) can be studied using the self-sovereign poisson-point-processes. Chattopadhyay *et al.* [7], the poison process yields good results when approximate interference is used. According to Deng and Haenggi [8], interference dissemination is modeled for general networks with non-poisson deployments, while in [9] the estimation of HWN interference is done. Kalamkar and Haenggi [9], this was extended to both single and multi-tier HWNs by considering signal interference with meta-distribution and reflects the idealistic model considering both long-term evolution and ultra-dense fifth-generation network deployments.

Real-time safety applications in the future will require high-speed and reliable communication in the vehicular network. According to recent research [10], a sub-channel allocation of resources method was presented to improve the effectiveness of the vehicle network's energy usage and meet quality-of-service (QoS) and reliability requirements in the architecture of allocation of resources meetings. The standard wireless and vehicular ad-hoc networks are modeled using cognitive behavior [11]. High mobility was shown to have a significant impact on the accuracy of channel estimation in this study. A resource provisioning method must consider imperfections of the channel-state information (CSI) to ensure the reliability of the vehicle network. CSI-based allocation of resources methods for vehicle-to-device communication was considered in [12]. All fast and slow disintegrating characteristics were considered by [13] in their model of resource allocation. Chen *et al.* [14], a kernel-based machine-learning model was developed to predict the spots of devices using CSI [15] in sub-6 gigahertz bands. Nayak *et al.* [16] showed using CSI for positioning systems will not incur additional costs. When it comes to optimizing resource allocation in a game theory (GT) [14], [17] the resource allocation methods for WSNs presented in [18] outperformed machine-learning models [19].

A high level of access equity and high-performing efficiency cannot be achieved with the existing GT-based allocation of resources models [20], [21]. High-efficiency allocation of resources is the focus of this research work by modeling a hybrid resource optimization strategy (HROS). With the help of CSI and the use of both contention-less and contention-based allocation of resources, the HROS scheme is extremely efficient in decreasing interference and maintaining a high level of performance. Because of its high throughput and low collision rate, HROS can allocate resources fairly and efficiently to newly joined multi-mode transmissions. The significance of this research work is as follows. The proposed model develops a novel channel-state estimation model using reinforcement learning employing the markov state model. Developed a HROS to reduce collision and improve overall network throughput. The HROS is very efficient considering highly dynamic mobility models i.e., low-high density and speed. The HROS employs dynamics service of transmission simultaneously (i.e., both real-time and non-real-time traffic) more efficiently in comparison with existing models.

The paper is organized as follows. Section 2 discusses various existing models of resource optimization in HWNS. Section 3 discusses the working of the proposed resource optimization strategy for HWNs. Section 4 discusses the performance outcome of the proposed HROS over existing methods. The last section concludes the research work with future enhancement.

2. RELATED WORK

This section studies various resource optimization strategies for modern wireless networks like 5th generation and 6th generation heterogenous wireless networks. Kamruzzaman *et al.* [22], have explained the importance of heterogeneous cellular networks (HCNs). The main role of the HCNs is to provide the best quality of service for the 5th-generation network. Further, it allows the devices to communicate with the other devices directly without connecting them to the base stations. In this model, they have addressed the problem of mode selection for the devices. For this, they have first analyzed the three most important factors required for the connection of the device to the device, cell density, signal-to-interference noise ratio, and outage probability. Further, they have proposed an algorithm based on a distance-based method to reduce the interference which provides better QoS for the device-to-device (D2D) communication.

Hamid *et al.* [23], addressed the communication of the device to the device that is it does not require a base station for the transmission of the data from one device to another. Further, they have addressed the problem of co-channel interference in the D2D devices. The problem of co-channel interference in the D2D devices reduces the QoS during the transmission of the data from one device to another device. Due to this problem, they have modeled using a coloring-based algorithm. They have used the weights of the required spectrum resources and using this they have enabled the transfer of data among the D2D users which reduces the resources and provides better QoS by further utilizing the single cellular resources of the D2D users. This algorithm is simple and doesn't require more computations, hence, it provides good power control. Zhang *et al.* [24], discussed the non-orthogonal multiple-access satellite network. In this network the base station constantly communicates with the backhaul link of the satellite. Also, the spectrum resources are shared by using the user equipment. First, they have obtained a utility function that has all the user ratings, and the cross-tier interference produced by the base station is used to design a model. From the utility function, can solve the optimization problem of the model by increasing the utility function according to the backhaul ratings of the satellite which will solve the problem of the user equipment and QoS. The optimization problem cannot be satisfied very easily and requires much attention due to which various factors must be checked.

Tang *et al.* [25], modeled resource allocation, which reduces the latency time and random packet loss using an algorithm. In this algorithm, first, they have developed an algorithm for controlling congestion which uses a backlog queue model based on the congestion window. After this, they have assumed two boundaries for the model which delimits the oscillations of the queue model to reduce the random packet loss and congestion. This model can detect and adjust the congestion window during a tradeoff. Wei *et al.* [26], addressed the problem of multipath slot optimization in the HWNs. Here a congestion and packet-scheduling which is based on the round-trip propagation time and bottleneck-bandwidth is designed. Based on the communication rates of the sub-flow in the HWNs, an out-of-order delivery model has been designed which will help the application to complete the tradeoff in a given time. Nagarajan and Mohamad [27], have described how the 5G network can provide a better spectral and energy efficiency model with the least latency in each environment. In this model, they have proposed an algorithm, the sequential best throughput seek algorithm, which will be used for the computation of the interference threshold for the optimum resource blocks and cellular-user-equipment in the D2D pairs. To reduce the transmission power, this model has proposed an optimized genetic algorithm that will handle interference among cellular users. This model increases the QoS and reduces the energy consumption [28]. However, poor resource utilization is exhibited due to the adoption of a random resource allocation design. In overcoming research issues in the next section, a novel HROS is designed.

3. PROPOSED METHOD

This section presents a HROS for newly joined mobile terminals in heterogeneous wireless networks. Here we present a model for channel state estimation using reinforcement learning through continuous time markov chain. Then, it presents a contention-less-based resource optimization strategy and proves the existence of nash equilibrium. Similarly, the present contention-based resource optimization strategy proves the existence of nash Equilibrium. Finally, HROS combines both contention-less-based resource optimization strategy and contention-based resource optimization strategy for providing fair and high-efficiency resource optimization strategy for newly joined MMTs without affecting existing/primary MMTs.

3.1. Channel state estimation

Every time a user switches to a new heterogeneous wireless network, their device competes with other devices for access to available channels, which can lead to significant levels of interference among nearby devices that are also sharing the same channel. For this reason, it is critical to keep track of channel conditions. The following equation can be used to calculate the mean channel availabilityω_c of channel c at any given moment using (1).

$$\omega_c = (1 - \delta_c) + \delta_c \alpha_{I,c} = 1 - \delta_c \alpha_{B,c.} \tag{1}$$

In (1), δ_c is used to represent the mean-fraction region traveled by an existing mobile-terminal node on the given channel c. Furthermore, δ_c is expressed using the (2).

$$\delta_c = {4T^2}\Big/{A_{l,i}^2} \tag{2}$$

Where $\alpha_{I,c}$ specifies the stable probabilities of the primary multimode mobile terminals that are actively communicating in channel c, whereas $\alpha_{B,c}$ specifies the stable probabilities of the primary multimode mobile terminals that are not communicating in channel c, i.e., they are inactive. The state $M_{N,c}$ indicates if a multimode mobile terminal has departed from the covering region of the primary multimode mobile terminals; hence, the parameter $K_{N,c}$is an exponential distribution of $\mu_{N,c}$. The above statement is given using the following (3).

$$\mu_{N,c} = \mu_{b,c} + \frac{s'}{f(A_{l,c} - T_c)} \alpha_{b,c} \tag{3}$$

Then, considering a balanced scenario where we have:

$$\alpha_{X,c}\mu_{X,c} = \alpha_{N,c}\mu_{N,c} \tag{4}$$

in (4), the $\alpha_{X,c}$ can be expressed using the given (5):

$$\alpha_{X,c} = \omega_c \tag{5}$$

similar to the $\alpha_{X,c}$, $\alpha_{N,c}$ can be expressed using the given (6):

$$\alpha_{N,c} = 1 - \omega_c \tag{6}$$

from (5) and (6) we can obtain the transition rate $\mu_{X,c}$ which is described using the (7).

$$\mu_{X,c} = \frac{\omega_c}{1-\omega_c}\mu_{N,c} = \frac{\delta_c \alpha_{b,c}}{1-\delta_c \alpha_{b,c}}\left(\mu_{b,c} + \frac{s' \cdot \alpha_{b,c}}{f(A_{l,c} - T_c)}\right) \tag{7}$$

Hence, $K_{X,c} \sim Exp(\mu_{X,c})$. The possible channel availability β of channel c is defined as the average period during which channel c is available for communication by the sensing device. The communication of the sensor device is evaluated using the (8).

$$\beta_c = \varphi_c \cdot K'_{X,c} = \frac{\varphi_c}{\mu_{X,c}} \tag{8}$$

Where $\varphi_c \in (0,1)$ denotes the primary multi-mode mobile-terminals interference threshold. By increasing the value of φ, we can increase the channel accessibility at the expense of increased disturbance with major multi-mode mobile terminals. These multi-mode mobile terminals are presumed to have temporal and spatial distribution information about major multi-mode mobile terminals. Heterogeneous wireless networks provide the major multi-mode mobile terminals with a number of channels. Assuming that the new multi-mode mobile terminals can gain realistic channel accessibility, that is, $\beta_j, j \in \mathcal{A}$ as a result of their mobile nature, they will be able to access channels. Furthermore, there are some models like game theory that will allow the newly-joined multi-mode mobile terminals to utilize the channel in a distributed way and maximize its expected utility function without interfering with major existing multi-mode mobile terminals. A nash equilibrium in HROS, which includes both contention less and contention and resource allocation, is shown to exist in the following sections of this work.

3.2. Contentionless-based resource optimization strategy

The channel is assigned randomly to multi-mode mobile terminals with randomized timeout periods in a contention-less-based allocation of resources algorithm. Once the timeout period has expired and a slot has become available, the channel is made available to multi-mode mobile terminals. As time slots expire, certain multi-mode mobile terminals can use the available slots, while others must sit idle and await the end of the timeout period before creating idle channels. The channel access function in a contention less-based allocation of resources method is described using (9).

$$s(o) = {}^{1}/_{o} \tag{9}$$

The utility function of the channel access function in a contention-less-based allocation of resources method is given using (10).

$$V^{j}_{k\{rnd\}} = \frac{\beta_j}{o_j}. \tag{10}$$

Where $f_{rnd}(o)$ is equal to 1. Contention-less-based allocation of resources schemes can attain perfect NE by making the following assumptions. A congested vector $\boldsymbol{o} = (o_1, o_2, o_3, \dots, o_D)$ that results in a NE-set (o) should satisfy the restriction specified in (11) for a contention-less based allocation of resources method.

$$\begin{cases} o_j = \left\lceil \frac{\beta_j O - \sum_{a\neq j, a\in D}\beta_a}{\sum_{a\in D}\beta_a} \right\rceil + X_0 \;\; j = 1,2,3,\dots,D \\ \sum_{j=1}^{D} o_j = O \end{cases} \tag{11}$$

where $X_0 \in \{0,1,2,3,\dots, \lceil \beta_j |O| + \beta_j(|\mathcal{D}| - 1)/\sum_{a\in D}\beta_a \rceil - \lceil \beta_j |O| - \sum_{a\neq j, a\in D}\beta_a/\sum_{a\in D}\beta_a \rceil - 1\}$.

3.3. Contention-based resource optimization strategy

This section discusses the working of a contention-based resource optimization strategy. The contention-based model reduces the probability of channel collision with decent resource utilization. The model adopts a probabilistic-based computation model. In a manner like the contention-less-based allocation of resources method, the following expression can be used to determine the bandwidth rate of each multi-mode mobile-terminal in the contention-based allocation of resources method.

$$pl(\mathcal{P}) = \mathcal{P}(1 - \mathcal{P})^{o-1} \tag{12}$$

In (12) $\mathcal{P}$ represents the probability of the channel c. To increase the bandwidth, we make $pl'(\mathcal{P})$ as 0, then, $\mathcal{P} = \frac{1}{o}$, and using this the contention-based allocation of the resource method is obtained. The contention-based allocation of the resource is given using (13).

$$f_{SMAC}(o) = \frac{1}{o}\left(1 - \frac{1}{o}\right)^{o-1} \tag{13}$$

For the contention-based allocation of the resource method $f_{SMAC}(o) = (1 - 1/o)^{o-1}$ should be in between the $f''_{SMAC}(o) > 0$ and $f'_{SMAC}(o) < 0$. If the o goes to an infinite state, then the total bandwidth of the contention-based allocation of the resource method changes to (14).

$$\lim_{o\to\infty} fS_{MAC}(o) = \frac{1}{\mathcal{F}} \tag{14}$$

The utility function for the contention-based allocation of the resource method for the multi-mode mobile-terminal is given using (15).

$$V^{j}_{k\{SMAC\}} = \beta_j \frac{1}{o_j}\left(1 - \frac{1}{o_j}\right)^{o_j-1} \tag{15}$$

It is very difficult to extract a perfect nash equilibrium using a contention-based allocation of resources method, unlike a contention-less-based resource allocation strategy. Assume we're playing a game of resource access where the multi-mode mobile terminals are O-sized and the channels are D-sized, and each multi-mode mobile terminal sequentially selects an available channel. Before channel access, one multi-mode mobile terminal selects the best solution (BS). Hence, in each iteration of multi-mode mobile terminals, there is an optimal answer. Perfect nash equilibrium with adaptive allocation of resources may only be achieved in this manner if the following conditions are met. The following condition must be met if the recently joined multi-mode mobile terminals have two BS, namely BS_1 and BS_2. By agreeing to empty resources when no multi-mode mobile terminals pick them, and then agreeing to already-chosen resources when BS_2 agrees, BS_1 is excellent. When at least one multi-mode mobile terminal selects a resource, the resource with the most realistic number of resources is preferred. In the next section, high-efficiency resource allocation proposes a plan to promote equitable and efficient distribution of available resources.

3.4. Hybrid resource optimization strategy

This high-efficiency allocation of resources method incorporates both the contention-less-based and contention-based resource allocation methods to attain perfect nash equilibrium (NE) in distributed systems with equal resource allocation efficiency. Furthermore, Algorithm 1 explains how the high-efficiency allocation of resources strategy works. Each multi-mode mobile terminal in algorithm 1 randomly selects a time to back off, and then the timeout time begins. During the time-out time, the multi-mode mobile terminal selects a communication channel based on the best solution it has already found with that channel. To establish their solution, multi-mode mobile-terminal broadcast their solution to other multi-mode mobile-terminal. It has been proven through simulations that the given model achieves better network performance and fair allocation of resources than the usual allocation of resources scheme.

Algorithm 1. Resource optimization strategy
```
1. Obtain available resource/channel 𝒟 through sensing operation
2. Update and arrange available channel [β_1, β_2, β_3, …, β_D] in decreasing order for respective time u_t.
3. Every MMT that looks for communication opportunity chooses a random back-off time u_c from (0, u_c↑) and the back-off time is initialized.
4. While present time ≤ (u_t + u_c↑) do
5.      if the backoff time of MMT j finishes then
6.           if contentionless-based resource allocation scheme then
7.                   Select the BS with a free channel
8.           End if
9.           if contention-based resource allocation scheme then
10.                  Select the resource with higher BS.
11.          End if
12.    The selected channel id is broadcasted
13.    End if
14. End while
15. Every MMT optimizes its radio according to the ideal channel and initializes communication utilizing desired resource allocation schemes
16. Return
```

4. RESULT AND ANALYSIS

Here the performance achieved using the proposed HROS and existing resource optimization-based network selection (RONS) [28] is evaluated. Experiments are conducted using an ns3-based simulator namely, simits simulator [28]. Here the multi-mode terminal uses different kinds of service classes such as real-time polling service (RTPS), non-real-time polling service (NRTPS), and best effort (BE) service and moves through a geographical area composed of heterogeneous networks formed using universal mobile telecommunications system (UMTS), worldwide interoperability for microwave access (WiMAX), long-term evolution (LTE), and wireless local area network (WLAN). The MMT exhibits dynamic mobility that moves through high-density environments with low speed such as cities and less-density environments with high speed such as expressways and highways. The ieee 802.11 standard medium access control (MAC), rayleigh channel with addictive white gaussian noise is used. The log-normal path loss model with multipath fading is considered with bandwidth set to 3-27 Mbps for experiment analysis. The users move in the network with randomness following uniform distribution. All the subscribers including new and handoff users, follow Poisson distribution. The traffic generated in the network majorly is non-real-time service with 40%, real-time with 30%, and best-efforts with 30%. The throughput and collision are the performance metrics used for validating the HROS and RONS scheme.

4.1. Throughput performance

The throughput experienced using HROS and RONS is studied by considering different case studies. A total of three different case studies such as varying density, slots, and speed is considered for the simulation study. In case 1, throughput is measured by varying the MMT size with a fixed speed of 5 m/s. Here the MMT size varies from 50, 100, and 200, and the throughput outcome achieved using the HROS scheme and RONS scheme is graphically shown in Figure 1. An average throughput enhancement of 19.52% is achieved using the HROS scheme in comparison with the RONS scheme for varied multi-mode mobile terminal density. In case 2, throughput is measured by varying MMT speed with fixed MTTs size of 100. Here the MMT speed varies from 3, 6, and 9 m/s and throughput outcome achieved using the HROS scheme and RONS scheme is graphically shown in Figure 2. An average throughput enhancement of 13.12% is achieved using the HROS scheme in comparison with the RONS scheme for varied multi-mode mobile terminal speeds. An average throughput enhancement of 16.32% is achieved using the HROS scheme in comparison with the RONS scheme for varied time slot sizes. The RONS model uses channel state information for resource allocation optimization by minimizing co-channel interference and tries to maximize the resource utility; however, the model failed to ensure a higher throughput with fairness; thus, resulting in higher collision and degraded throughout especially for higher node density considering different scenario as shown in Figures 1 and 2. On the other side, the HROS leverages both contention and contention-less resource allocation design to assure higher resource utilization with minimal interference aiding in improved throughput considering different scenarios as shown in Figures 1 and 2.

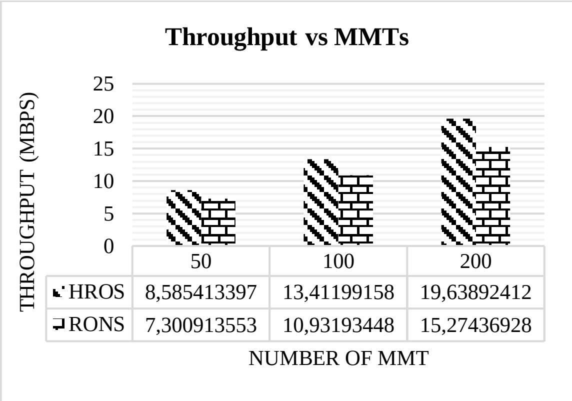

Figure 1. Throughput vs MMTs

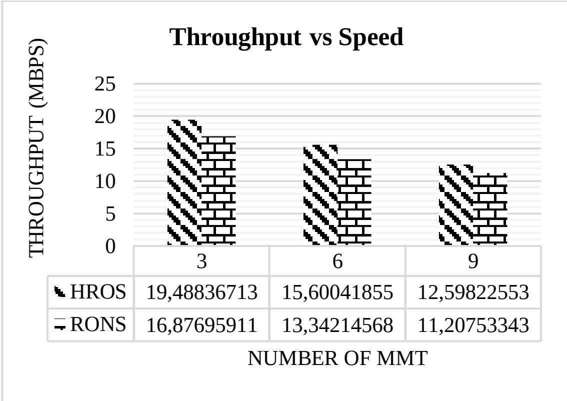

Figure 2. Throughput vs speed

4.2. Collision performance

Here collision performance of the HROS scheme and RONS scheme is evaluated by varying network density, speed, and slot size. In case 1, collision is measured by varying the MMT size with a fixed speed of 5 m/s. Here the MMT size is varied from 50, 100, and 200, and collision outcome achieved using the HROS scheme and RONS scheme is graphically shown in Figure 3. An average collision reduction of 24.5% is achieved using the HROS scheme in comparison with the RONS scheme for varied multi-mode mobile terminal density. In case 2, collision is measured by varying MMT speed with fixed MTTs size of 100. Here the MMTs speed is varied from 3, 6, and 9 and the collision outcome achieved using the HROS scheme and RONS scheme is graphically shown in Figure 4. An average collision reduction of 28.27% is achieved using the HROS scheme in comparison with the RONS scheme for varied multi-mode mobile terminal speeds. An average collision reduction of 26.16% is achieved using the HROS scheme in comparison with the RONS scheme for varied time slot sizes. The RONS model uses channel state information for resource allocation optimization by minimizing co-channel interference and tries to maximize the resource utility; however, the model failed to ensure a higher throughput with fairness; thus, resulting in higher collision and degraded throughout especially for higher node density considering different scenario as shown in Figures 3 and 4. On the other side, the HROS leverages both contention and contention-less resource allocation design to assure higher resource utilization with minimal interference aiding in a significant reduction of collision considering different scenarios as shown in Figures 3 and 4.

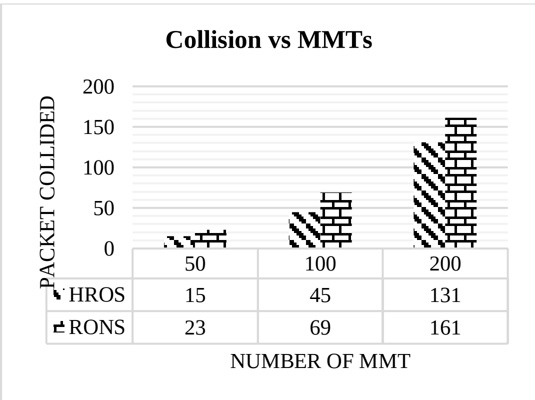

Figure 3. Collision vs MMTs

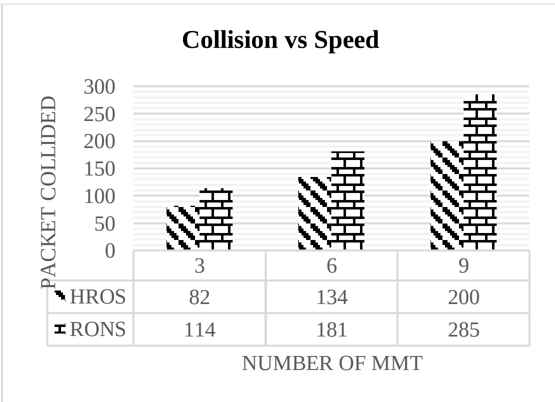

Figure 4. Collision vs speed

5. CONCLUSION

This paper first studied various methods. Here we presented a HROS for heterogeneous networks. The HROS scheme uses channel state information through a continuous chain Markov chain model for establishing channel availability for different instances of time. The HROS employs both contention-less-based and contention-based resource allocation schemes for providing high throughput and minimal collision. Game theory is applied to obtain optimal resource allocation for newly joined users without affecting the current ongoing communication of existing MMTs. Here to provide fair resource allocation back-off window is selected randomly. The experiment is conducted to validate HROS over the RONS scheme. The HROS scheme achieves much higher throughput with less number collisions in comparison with RONS considering varied network density, speed, and time slot size. Thus, the HROS scheme is robust and can allocate resources to MMTs fairly and efficiently. Significant result enhancement especially for varied time slots is due to the adoption of a hybrid resource allocation design; the adoption of such design aided in addressing the trade-offs problem of interference (minimization) and resource allocation (maximization). Then, the markov state model for obtaining channel state information and optimizing the resource allocation dynamically according to states i.e., whether a new user joins or leaves the current network or not. Then, access fairness is assured through the existence of the nash equilibrium game. Future work would further consider developing an efficient resource provisioning algorithm considering channel state information of users to utilize HWN resources more efficiently and evaluate performance under more dynamic mobility environment.

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BIOGRAPHIES OF AUTHORS

Nagaraj Gadde is a Professor in the Department of Artificial Intelligence and Data Science, SJC Institute of Technology, Chickaballpur, Affiliated to Vishveswaraya Techonological University, Belagavi, India. He Completed BE in Computer Science and Engineering, M.Tech and Ph.D in Computer Science and Engineering. His area of interest includes wireless networks. He has more than 23 years of academic experience, he authored research publications in reputed International journals and conference with good no of citations in Scopus Indexed journals. He can be contacted at email: nagarajgadde11@gmail.com.

Rashmi Shivaswamy is an Incharge Head in Department of Computer Science and Engineering (Data Science) at Dayananda Sagar College of Engineering, Bengaluru. Her main research interests includes Cloud Computing, Blockchain Technology, IoT, Machine Learning and Cyber security. She has earned Ph.D. in Computer Science and Engineering from VTU, Belgaum for her work in the area of Cloud Computing, in Jan 2019. She is an IEEE Senior member and has worked as a Managing Committee Member of Computer Society of India, Bangalore chapter for the year 2019-2020. She has published 2 Indian Patents and 20+ referred publications. She can be contacted at email: rashmineha.s@gmail.com.

Ramesh Babu Halasinanagenahalli Siddamallaih is a professor in the Department of Computer Science and Engineering, RNS Institute of Technology, Bangalore, Affliated to Vishveswaraya Technological University, Belagavi, India. He completed BE, MS and Ph.D. in Computer Science and Engineering. Having an Academic and Research Experience of 27 years, he authored research publications in reputed International journals and conference with good no. of citations in Scopus and Google scholar. His research interest includes wireless networks, wireless sensor networks, and internet of things. He guided 5 Ph.D. research scholars and currently guiding research scholars leading to Ph.D. He can be contacted at email: rameshbabu.hs@gmail.com.

Gowrishankar is a senior professor and heading the machine learning (AI and ML) Department at BMS College of Engineering, Bangalore. He served as Head of the Department of CS and E and IS and E of BMSCE. He is actively associating in Research collaborative Sabbatical program with University of Albama, Huntsilve (UAH), USA and he is a visiting professor for UAH. Having an Academic and Research Experience of 24 years, he authored more than 80 research publications in reputed International journals and conference with 150 citations in Scopus and Google scholar. His research interest includes performance evaluation, wireless network and deep learning. He guided 6 Ph.D. research scholars and currently guiding 8 research scholars leading to Ph.D. He is Chief Co-ordinator of data center, BMSCE since March 2009. Data Center comprises of many state of the art software and hardware repositories. Under his leadership, department of computer Science and Engineering, has NBA accredited under teir-1 format. He can be contacted at email: gowrishankar@bmsce.ac.in.

Govindaih Thimma Raju is a professor in the Department of Information Science and Engineering, SJC Institute of Technology, Chickballapura, Affliated to Vishveswaraya Technological University, Belagavi, India. He completed BE, M. Tech and Ph.D in Computer Science and Engineering. Having an Academic and Research Experience of 30 years, he authored research publications in reputed International journals and conference with good no. of citations in Scopus and Google scholar. His area of research knowledge discovery in databases, clustering and prefetching techniques, pattern recognition, web mining and its applications, image processing, semantic web, information retrieval techniques, AI and machine learning. He guided 20 Ph.D research scholars and currently guiding research scholars leading to Ph.D. He can be contacted at email: gtraju1990@yahoo.com.

Subramani Suryakumar Prabhu Vijay received is the research analyst and senior software developer at navshya technologies. Areas of interest includes wireless sensor networks, internet-of-things, cloud computing, network security, wireless communication network, image processing, image forensic. He has assisited in technical content writeup and software development various academics and industrial projects. Attented as as a guest lecturer and trainer in various workshops. He can be contacted at email: navshyatechnologies@gmail.com.