IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 12, No. 1, March 2023, pp. 357~366
ISSN: 2252-8938, DOI: 10.11591/ijai.v12.i1.pp357-366

Resource optimization-based network selection model for heterogeneous wireless networks

Nishatbanu Nayakwadi, Ruksar Fatima
Department of Computer Science and Engineering, Khaja Bandanawaz College of Engineering, Kalaburagi, India

Article Info

Article history:

Received Jan 4, 2022
Revised Aug 26, 2022
Accepted Sep 24, 2022

Keywords:

Handover execution
Heterogeneous wireless network
Machine learning
Network selection
Resource utilization

ABSTRACT

The internet of things (IoT) environment prerequisite seamless connectivity for meeting real-time application requirements; thus, required efficient resource management techniques. Heterogeneous wireless networks (HWNs) have been emphasized for providing seamless connectivity with high quality of service (QoS) performance to provision IoT applications. However, the existing resource allocation scheme suffers from interference and fails to provide a quality experience for low-priority users. As a result, induce bandwidth wastage and increase handover failure. In addressing the research issues this paper presented the resource-optimized network selection (RONS) method for HWNs. The RONS method employs better load balancing to reduce handover failure and maximizes resource utilization through dynamic slot optimization. The RONS method assures tradeoffs between high performance to high priority users and quality of experience (QoE) for low priority users. The experiment outcome shows the RONS achieves very good performance in terms of throughput, packet loss, and handover failures in comparison with existing resource selection methods.

Corresponding Author:

Nishatbanu Nayakwadi
Department of Computer Science and Engineering, Khaja Bandanawaz College of Engineering
9V22+WQR, opp. Kbn engg college, Khaja Colony, Kalaburagi, Karnataka 585104, India
Email: nishanthbanunayakwadi123456789 @rediffmail.com

1. INTRODUCTION

The world is connected with 25 billion embedded devices and 25 billion connected people generating 40 trillion gigabytes of data as of 2020 [1], [2]. In such an environment, wireless internet of things (IoT) plays a very important role in future smart applications. Nonetheless, connecting massive deployment of IoT device pose several research difficulties and challenges such as security, communication protocol, storage, and networking. Alongside, there are other challenges such as inter-operability, diversity, data and device management [3], [4]. In wireless Internet of Things environment, the radio resources are very limited; thus, resource management becomes an extremely challenging task, especially under a large density network where smart device content for resources. In such a network, the performance relies on how effectively the resource (orthogonal code, frequency, and time slots) are allocated in dynamic manner. Alongside, how connection fluctuation and traffic loads are handled to meet users' high quality of service (QoS) prerequisites. With growth of new IoT-based applications prerequisite high throughput, bandwidth, and spectral efficiency, and user context; thus, resource management becomes major issues [5], [6].

Heterogeneous wireless networks (HWNs) have been emphasized to address resource management problem with good effect across research communities and industries. In particular, resource allocation plays a very significant part in both network-level and user-perceived performances because of tradeoff associated with resource partitioning and sharing [1]. The resource sharing improves the efficiency of bandwidth usage;

however, induce interference among adjacent network. On the other side, the resource partitioning reduces resource utilization by eliminating interference with adjacent network. The future HWNs is expected coexist with multiple networks operating in non-overlapping frequency bands while other types of wireless access networks share the same spectrum band. As a result, both resource sharing and partitioning are expected to coexist in the future HWNs. Hence, for general HWNs as shown in Figure 1, it is critical to explore efficient resource allocation technique.

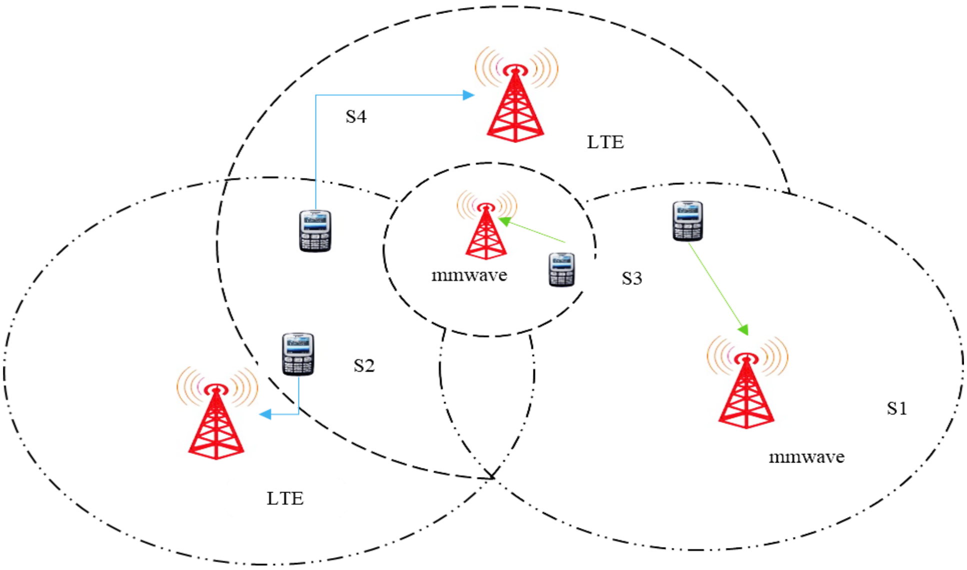

Figure 1. Architecture of heterogeneous wireless networks

This section conducts survey of some recent work designed for effective network resource selection mechanism for HWNs. A resource management technique has been modeled requiring accurate measurement; nonetheless, these model prerequisite manual optimization of parameter [7]. Recent, work have focused in meeting QoS parameter at network level [7]–[10] and [11]–[13] focused in meeting user preference requirement. However, this model consumes too much energy when try to improve success rate. Polese *et al.* [14] showed the importance of reutilizing system resource aiding energy efficiency [15] and resource utilization as well [16]. Recently, machine learning models have been used for automated decision making [17]. Yan *et al.* [17] presented a KNN-based handover execution model for 5G cellular network with good target discovery performance and showed benefit of using machine learning (ML) technique for decision making.

However, the model is designed considering homogeneous network and still lack of how to successfully employ ML methodologies into heterogeneous cellular network [18], [17]. According to Majid *et al.* [19], emphasized XGBoost based handover execution prediction model for reducing frequent measurement updated and enhance overall performance for next generation network. However, are not efficient when dataset exhibit imbalanced behavior. In Iborra *et al.* [20], showed existing model fails to address QoS and energy efficiency factor together. They modelled a supervised-based ML based method for selecting efficient network to meet application real-time prerequisite. Cao *et al.* explained to [21] addressed both frequent handover and load balancing issues together in large coverage network. They modelled a deep reinforcement algorithm namely deep Q-networks [22] for reducing signaling overhead and maximize throughput with minimal handover failures. The aimed at maximizing number of user in network with minimal handover failures considering mobility pattern of users considering largely populated network [23]. They presented a prediction mechanism to identify position of user based on previous states using online learning algorithm. A game-theory approach [24], [25] is modelled has NP-hard deterministic problem for obtaining optimal solution. Magoarou [26] focused on obtaining spatial location of user through unsupervised learning mechanism for practical handover and resource scheduling considering impact of small-scale fading. Tong *et al.* [27] used software defined network in HWNs for addressing mobility and user resource allocation issues. They modelled multipath-based communication design using three phase such as prediction user location using echo state network, network selection using fuzzy analytic hierarchical process, and finally handover execution using multipath transmission protocol [28]. Multiple attribute such as bit error rate, signal-to-noise-ratio, packet loss rate, moving speed, minimum delay, and maximum transmission rate are used for training neural network to carryout handover execution considering HWNs [28]. However, the resource selection is done through random manner and user priority requirement is not considered. Alongside, maximizing resource utilization with minimal handover failure through effective load balancing is not considered [29]–[33]. In addressing research challenges the following research methodology is presented.

2. METHOD

This work aimed at designing effective network resource selection method namely resource optimized network selection (RONS) method for HWNs. The RONS method is aimed at maximizing resource utilization maximization with minimal handover failure through effective load balancing for HWNs. The RONS method assure service priority and can mitigate the effect of interference for neighboring IoT device. Alongside, can assure high level of performance for high priority IoT device and provide decent performance to low priority IoT device. The significance of RONS is discussed.

2.1. Research significance

The importance of a resource-optimized network selection model is given: i) The RONS model is efficient in maximizing resource utilization with minimal handover failures in comparison with existing network resource selection models; ii) The RONS improves overall throughput of network with less packet loss considering different mobility model in comparison with existing network resource selection models; iii) The RONS improves overall throughput with less packet loss considering varied channel size, device size, and device speed in comparison with existing network resource selection models. The section present resource optimization-based network selection model for heterogeneous wireless network. The outcome achieved using RONS is discussed in section 3. The research contribution, enhancement achieved, and future work is discussed in section 4.

2.2. Resource optimization-based network selection model for heterogeneous wireless network

2.2.1. Analytical model

The RONS is aimed in maximizing resource utilization with minimal handover failure by assuring less interference with neighboring cells. The heterogeneous wireless network is composed of different network as shown in Figure 1, where different IoT device such as $\mathcal{P}$s (Higher priority) and $\mathcal{U}$s (Lower priority) with different service priority connects to different network for gaining services. Here both Ps and $\mathcal{U}$s IoT device can operate using same set of homogenous channels N. The parameter l defines the total number of $\mathcal{P}$s and identical bandwidth is given to both $\mathcal{P}$s and $\mathcal{U}$s. However, $\mathcal{P}$s can occupy only one channel at a time and can reclaim the channel on arrival to network from $\mathcal{U}$s. Using Poisson distribution, the arrival rate α_t and α_q of $\mathcal{P}$s and $\mathcal{U}$s are established, respectively. The service rate ω_t and ω_q of $\mathcal{P}$s and $\mathcal{U}$s follows negative exponential distribution, respectively. The network service provider (NSP) uses historical information of $\mathcal{U}$s for perfect sensing. Thus, the network service provider is accountable for allocating idle channel to $\mathcal{U}$s and perform classification of $\mathcal{U}$s and channel according to resource usage.

2.2.2. Standard resource selection method

In standard resource allocation model, the $\mathcal{U}$s are divided into m service classes with different priority where k_m defines the size of $\mathcal{U}$s of class $(m = 1,2)$. The resources are allocated in random manner employing continuous time Markov model. The Markov states is defined as $T(j, k_1, k_2)$, where j, k_1 and k_2 signifies the number of resources engaged by $\mathcal{P}$s, higher priority type-1 $\mathcal{U}$s ($\mathcal{U}$s-1) and lower priority type-2 $\mathcal{U}$s ($\mathcal{U}$s-2), respectively. The parameter N defines the total channel available, D_y defines the total channel that is occupied at any given instance of time, and O^{idle} defines the total idle channel at any given instance of time. The D_y is computed as shown in (1).

$$D_y = (j + k_1 + k_2) \tag{1}$$

The O^{idle} is computed as shown in (2).

$$O^{idle} = N - D_y \tag{2}$$

In accordance to arrival or departure $\mathcal{P}$s and $\mathcal{U}$s from network, the Markov state $T(j, k_1, k_2)$ is changed to new state $T'(j, k_1, k_2)$. The probability vector δ considering steady state is computed through linear equation $\delta R = 0$ with constraint $\delta e = 1$ utilizing [34], where e defines column vector with all 1s and R defines the state transition matrix.

2.2.3. Proposed resource selection method

The major drawback of standard resource allocation model is that the low-prioritized $\mathcal{U}$s-2 will attain deficient service in comparison with other high prioritized $\mathcal{U}$s-1 or $\mathcal{P}$s. However, the proposed resource selection addresses the QoE issues of $\mathcal{U}$s-2 and maintain high performance of high prioritized IoT device. This is done by giving more channels to $\mathcal{U}$s-2 with minimum resource starvation time through improved channel allocation (reservation and aggregation) design; here the channels are clustered and utilized for $\mathcal{U}$s-2. Alongside, the improved resource selection model can improve performance of $\mathcal{U}$s-1, by giving connection right after being dropped; here the $\mathcal{U}$s is classified into different classes according to its priority requirement. The modified states of channel reservation mechanism is defined as $A(j, k_1', k_1, k_n, k_o)$, where j signifies channel occupied by high priority IoT devices $\mathcal{P}$s, k_1', k_1, k_n and k_o defines the number of returned-type-1 ($\mathcal{U}$s-$S1$), urgent data $\mathcal{U}$s who resumed connection immediately after being dropped, the total $\mathcal{U}$s-1, real-time information $\mathcal{U}$s, the number of $\mathcal{U}$s-2, non-real-time information $\mathcal{U}$s who aggregate n and o channels, respectively. The parameter n defines maximum amount of aggregation channels and o defines minimum amount of aggregation channels. Accordingly, the total $\mathcal{U}$s-2 are measured through following equation.

$$k_2 = (k_n + k_o) \tag{3}$$

The IoT device $\mathcal{P}$ is given higher priority and will occupy the channel N_{sq} that are designated (i.e., allocated) to $\mathcal{P}$s. After that, the $\mathcal{P}$s will look out for unallocated channel in random manner. Let consider that $\mathcal{U}$s-$S1$ only has capability for utilizing N_1'channels. Conversely, $\mathcal{U}$s-1 can use these channels, if $\mathcal{U}$s-$S1$ doesn't present. The parameter N_2' defines the total channels that is only reserved for $\mathcal{U}$s-2. Therefore, the total accessible channels for $\mathcal{U}$s-1 is measured as shown in (4).

$$N_1 = \left(N - N_{sq} - N_2'\right) \tag{4}$$

and the total accessible channels for $\mathcal{U}$s-2 is measured as shown in (5).

$$N_2 = \left(N - N_{sq} - N_1'\right) \tag{5}$$

The parameter N_y defines the total channel that is occupied at any given instance of time and is measured asashown in (6).

$$N_y = [j + k_1' + nk_n + ok_o] \tag{6}$$

and N^{idle} defines the total channel that is occupied at any given instance of time and is measured as shown in (7).

$$N^{idle} = \left(N - N_y\right) \tag{7}$$

In accordance to arrival or departure $\mathcal{P}$s and $\mathcal{U}$s from network, the Markov state$A(j, k_1', k_1, k_n, k_o)$ is transformed to new state$A'(j, k_1', k_1, k_n, k_o)$. The probability vector δ considering steady state is computed through linear equation $\delta Q = 0$ with constraint $\delta e = 1$ utilizing [34], where e defines column vector with all 1s and Q defines the state transition matrix.

2.2.4. Resource utilization

The standard resource utilization method V is measured through ratio among average engaged slots with respect to total slots of corresponding network as described in (8).

$$V = \sum_{t \in T} \frac{D_y}{N} \delta_t. \tag{8}$$

where D_y total engaged slots and N represent total slots available considering steady state probabilityδ_t. The modified resource utilization method V' is measured as shown in (9).

$$V' = \sum_{t \in T} \frac{N_y}{N} \delta_a. \tag{9}$$

where N_y defines total amount of occupied slot at any given instance of times with steady state probability δ_a considering presence of obstacle in line of sight [35], [36].

2.2.5. Load balancing

If the complete network is busy, the new user $\mathcal{U}$ joining the network will be blocked from accessing the resource. The congestion probability of aforementioned case is computed as:

$$Q_c = \frac{\text{Total } \mathcal{U} \text{ congestion rate}}{\text{total IoT device arrival rate}} = \frac{\alpha_t \delta}{(l-j)\alpha_q + \alpha_t}. \tag{10}$$

The standard resource allocation method congestion probability Q_{c1} and Q_{c2} of $\mathcal{U}_1$ and$\mathcal{U}_2$, respectively is measured by (11) and (12). The modified resource allocation model congestion probability Q_{c1} and Q_{c2} of $\mathcal{U}_1$ and$\mathcal{U}_2$, respectively is measured by (13)-(15).

$$Q_{c1} = \sum_{j=0, t\in T}^{N} \sum_{j_1=0, j_2=0; O^{idle}=0}^{N} \frac{\alpha_t \delta_t}{(l-j)\alpha_q + \alpha_t}. \tag{11}$$

$$Q_{c2} = \sum_{j=0, t\in T}^{N} \sum_{j_1=0, O^{idle}=0}^{N-(j+j_2)} \frac{\alpha_t \delta_t}{(l-j)\alpha_q + \alpha_t}. \tag{12}$$

$$Q'_{cS1} = \sum_{j=0, a\in A; k'_1=N'_1}^{N} \frac{\alpha_t \delta_a}{(l-j)\alpha_q + \alpha_t}. \tag{13}$$

$$Q'_{cS1} = \sum_{j=0, a\in A}^{N} \sum_{\substack{k_1=0, k'_1+k_1=N_1; \\ j+k'_1+k_1 \geq N-N_2}}^{N_1} \frac{\alpha_t \delta_a}{(l-j)\alpha_q + \alpha_t} \tag{14}$$

$$Q'_{cS2} = \sum_{j=0, a\in A}^{N} \sum_{\substack{k_1=0, k_o=N_2, k_n; \\ k'_1+k_1+k_n=N_2, k_n=0}}^{N_1} \frac{\alpha_t \delta_a}{(l-j)\alpha_q + \alpha_t} \tag{15}$$

2.2.6. Handover probability

The handover probability: the handover probability of prioritized user $\mathcal{P}$ arrives at respective frequency slot occupied by $\mathcal{U}$ while idle slots are accessible, $\mathcal{U}$ will be handoff to idle channel for carrying out communication. The handover probability of aforementioned scenarios is computed using (16).

$$Q_i = \frac{\text{Total } \mathcal{U} \text{ transition rate}}{\text{Total user association rate}} = \frac{\frac{f(k)}{N-j}(l-j)\alpha_t \delta}{f(Q_c)\left((l-j)\alpha_q + \alpha_t\right)}. \tag{16}$$

where parameter $f(k)$ relies on the size of $\mathcal{U}$ at the state and $f(Q_c)$ relies on the size of $\mathcal{U}$ in congestion probability; thus, there values are dynamic in nature with respect to $\mathcal{U}$. The standard resource allocation scheme handover probability Q_{i1} and Q_{i2} of $\mathcal{U}_1$ and $\mathcal{U}_2$, respectively is computed using (17) and (18).

$$Q_{i1} = \sum_{j=0, t\in T}^{N} \sum_{k_1=1, O^{idle}>0}^{N-(j+k_2+1)} \frac{\frac{k_1}{N-j}(l-j)\alpha_q \delta_t}{(1-Q_{c1})\left((l-j)\alpha_q + \alpha_t\right)} \tag{17}$$

$$Q_{i2} = \sum_{j=0, t\in T}^{N} \sum_{k_2=1, O^{idle}>0}^{N-(j+k_1+1)} \frac{\frac{k_1+k_2}{N-j}(l-j)\alpha_q \delta_t}{(1-Q_{c2})\left((l-j)\alpha_q + \alpha_t\right)} \tag{18}$$

The modified resource allocation scheme handover probability Q_{i1} and Q_{i2} of $\mathcal{U}_1$ and $\mathcal{U}_2$, respectively is computed using (19) to (21).

$$Q'_{iS1} = \sum_{\substack{j=N_{sq}, z\in Z; k'_1=N'_1 \\ N_y<N, k_n>0; \\ N_y<N, k_n=k_o=0; \\ N_y<N, K_0=0}}^{N} \frac{\frac{k'_1}{N-j}(l-j)\alpha_q \delta_a}{(1-Q'_{cS1})\left((l-j)\alpha_q + \alpha_t\right)} \tag{19}$$

$$Q'_{i1} = \sum_{\substack{j=N_{sq} \\ z\in Z}}^{N} \sum_{\substack{k_1=1 \\ N_y<N, k_o=0; \\ N_y=N, k_n=0; \\ N_y<N, k_n=k_o=0}}^{N} \frac{\frac{k'_1+k_1}{N-j}(l-j)\alpha_q \delta_a}{(1-Q'_{c1})\left((l-j)\alpha_q + \alpha_t\right)}. \tag{20}$$

$$Q'_{iS2} = \sum_{\substack{j=N_{sq},a\in A \\ N_y=N,k_2\neq 0,k_n>0 \\ N_y<N,k_o=0,k_n\neq 0; \\ N_y<N,,k_n=0,k_0\neq 0; \\ N_y<N,k_n\neq 0,k_o\neq 0}}^{N} \frac{\frac{k'_1+k_1+k_2}{N-j}(l-j)\alpha_q\delta_a}{(1-Q'_{c2})\left((l-j)\alpha_q+\alpha_t\right)} \quad (21)$$

Once the IoT device is handoff to the new network; A channel is assigned to corresponding IoT device that maximize resource utilization through modified resource allocation design. The RONS model achieve better handover execution performance with improved resource utilization which is experimentally shown in next section.

3. RESULT AND DISCUSSION

This section method namely existing system-resource selection (ES-RS) method [17], [27]. The SIMITS simulator [37], [38] is used for studying the model considering dynamic mobility model [35], [36]. The throughput, packet loss, and handover failure are performance metrics used for studying the model through simulation study. The IoT device are varied from 25, 50, and 100 and are mobile in nature which is varied from 3, 5 and 7 cycle per frame, channel size is varied from 4, 6, and 8 and simulation study is conducted and result obtained are graphically shown considering aforementioned performance metric. studies the performance of RONS with existing resource and resource selection.

3.1. Throughput performance

The Figure 2 shows throughput performance achieved using RONS and ES-RS methodologies under varied size of IoT device and keeping the speed and channel constant at 3 cycle per frame and 8, respectively. An average throughput enhancement of 23.58% is achieved using RONS in comparison with ES-RS under varied IoT device size (25, 50, and 100). The Figure 3 shows throughput performance achieved using RONS and ES-RS methodologies under varied mobility speed and keeping the channel and IoT device size constant at 3 cycle per frame and 8, respectively. An average throughput enhancement of 30.47% is achieved using RONS in comparison with ES-RS under varied mobility speed (3, 5, and 7). The Figure 4 shows throughput performance achieved using RONS and ES-RS methodologies under varied channel size (4, 6, and 8) and keeping the speed and IoT device size constant at 3 cycle per frame and 50, respectively. An average throughput enhancement of 30.83% is achieved using RONS in comparison with ES-RS under varied channel size. Overall result achieved shows that the RONS utilize resource more efficiently by increasing the throughput achieved in comparison with ES-RS under varied scenarios such as varying IoT device size, varying speed, and varying channel size.

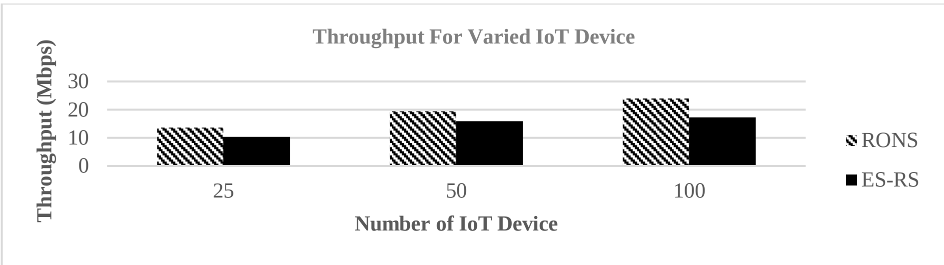

Figure 2. Throughput performance for varied IoT device

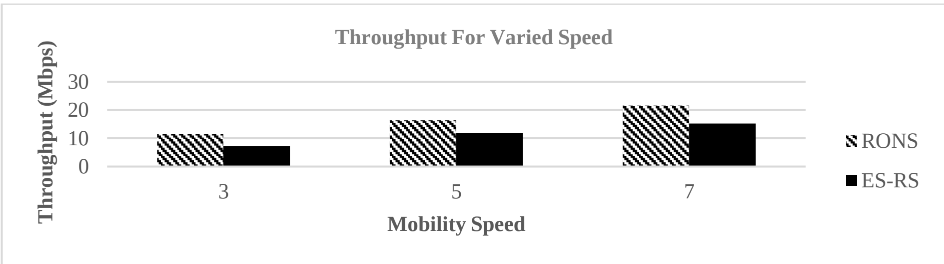

Figure 3. Throughput performance for varied speed

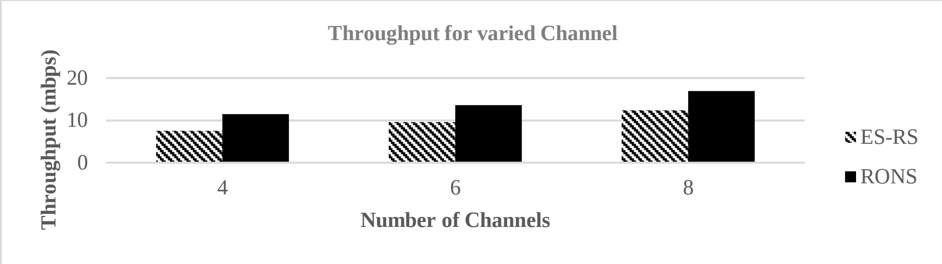

Figure 4. Throughput performance for varied channel size

3.2. Packet loss

The Figure 5 shows packet loss performance achieved using RONS and ES-RS methodologies under varied size of IoT device and keeping the speed and channel constant at 3 cycle per frame and 8, respectively. An average packet loss reduction of 40.34% is achieved using RONS in comparison with ES-RS under varied IoT device size (25, 50, and 100). The Figure 6 shows packet loss performance achieved using RONS and ES-RS methodologies under varied mobility speed and keeping the channel and IoT device size constant at 3 cycle per frame and 8, respectively. An average packet loss reduction of 24.5% is achieved using RONS in comparison with ES-RS under varied mobility speed (3, 5, and 7). The Figure 7 shows packet loss performance achieved using RONS and ES-RS methodologies under varied channel size (4, 6, and 8) and keeping the speed and IoT device size constant at 3 cycle per frame and 50, respectively. An average packet loss reduction of 74.1% is achieved using RONS in comparison with ES-RS under varied channel size. Overall result achieved shows that the RONS aid in reducing resource wastages efficiently by reducing packet loss in comparison with ES-RS under varied scenarios such as varying IoT device size, varying speed, and varying channel size.

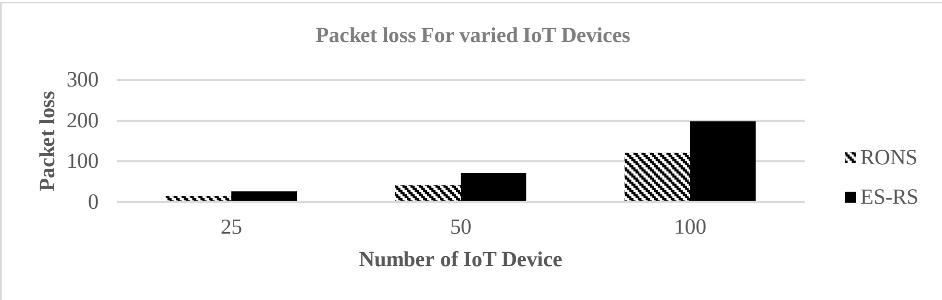

Figure 5. Packet loss performance for varied IoT device

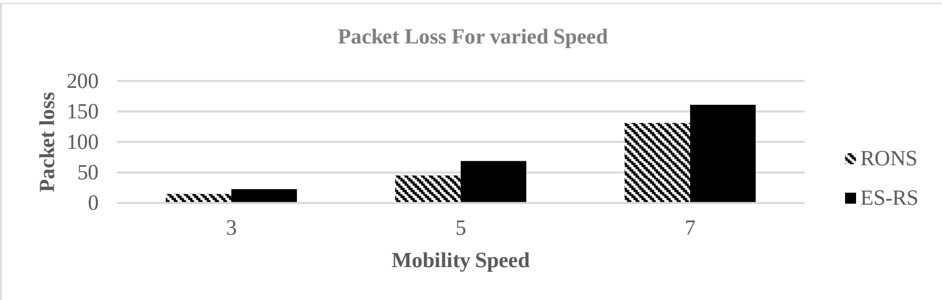

Figure 6. Packet loss performance for varied speed

3.3. Handover failure

The Figure 8 shows handover failure performance achieved using RONS and ES-RS methodologies under varied size of IoT device and keeping the speed and channel constant at 3 cycle per frame and 8, respectively. An average handover failure reduction of 32.33% is achieved using RONS in comparison with

ES-RS under varied IoT device size (25, 50, and 100). The Figure 9 shows handover failure performance achieved using RONS and ES-RS methodologies under varied mobility speed and keeping the channel and IoT device size constant at 3 cycle per frame and 8, respectively. An average handover failure reduction of 34.66% is achieved using RONS in comparison with ES-RS under varied mobility speed (3, 5, and 7). The Figure 10 shows handover failure performance achieved using RONS and ES-RS methodologies under varied channel size (4, 6, and 8) and keeping the speed and IoT device size constant at 3 cycle per frame and 50, respectively. An average handover failure reduction of 30.09% is achieved using RONS in comparison with ES-RS under varied channel size. Overall result achieved shows that the RONS aid in reducing network overhead by minimizing handover failure in comparison with ES-RS under varied scenarios such as varying IoT device size, varying speed, and varying channel size.

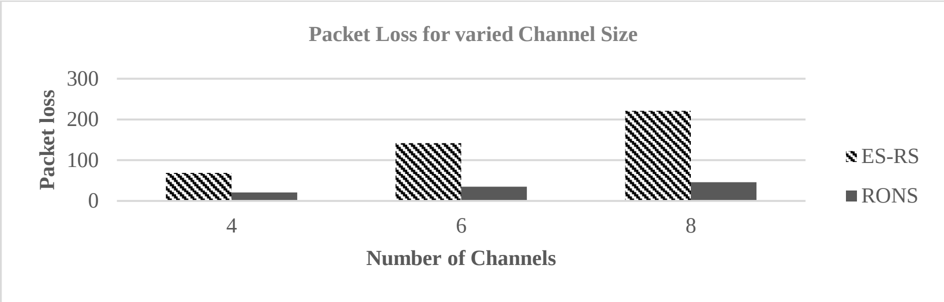

Figure 7. Packet loss performance for varied channel size

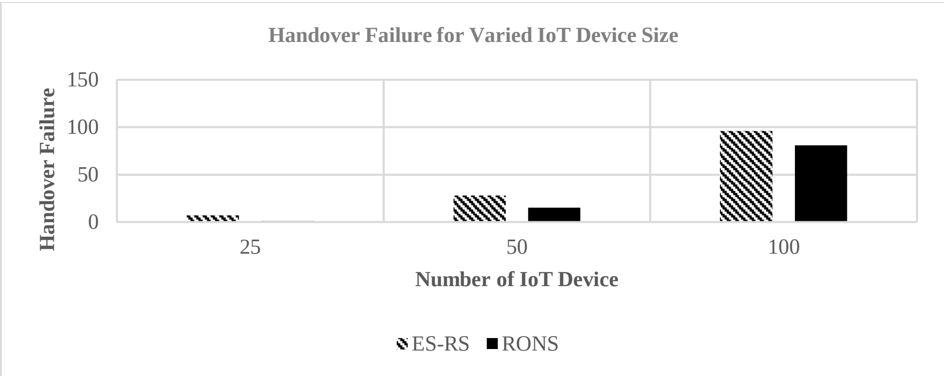

Figure 8. Handover failure performance for varied IoT device

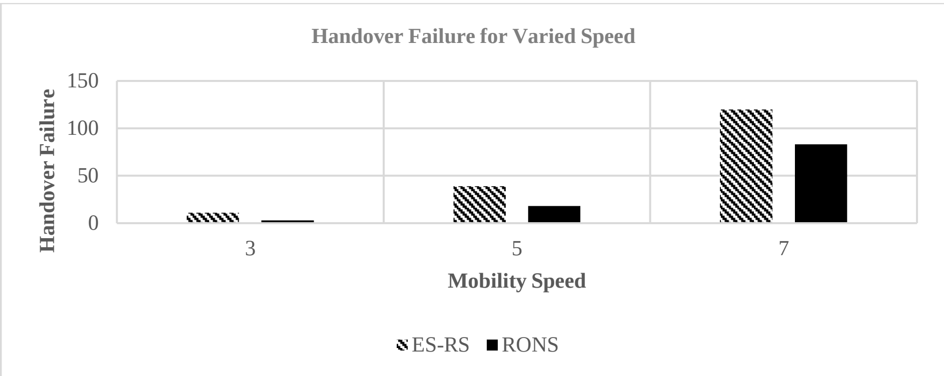

Figure 9. Handover failure performance for varied speed

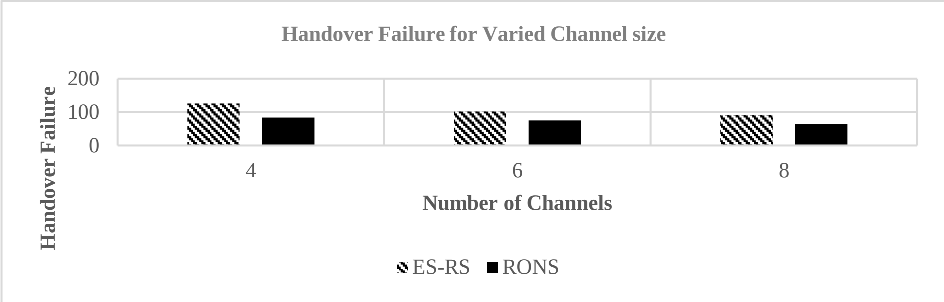

Figure 10. Handover failure performance for varied channel size

4. CONCLUSION

Here we studied challenges involved in performing resource selection optimization in heterogeneous wireless communication environment. Existing model induce resource wastage and fails to assure quality of experience for low priority user. However, this work presented an effective resource selection model namely RONS, which assures high level performance to prioritized user and optimal level resource is allocated to low priority user without degradation of quality of experience. Further, the proposed model assures effective load balancing model to reduce handoff failure and utilize resource more efficiently. No prior work has modeled such kind of resource allocation model. Experiment is conducted considering diverse network scenarios that resemble the real-time environment. The outcome achieved show the proposed RONS achieves much better throughput with less packet loss and handover failures in comparison with existing resource selection model, ES-RS. Future work would study the model under more diverse mobility condition and also study the impact of blocking resource by high priority user with respect to performance experienced by low prioritized users.

REFERENCES

[1] M. Peng, C. Wang, J. Li, H. Xiang, and V. Lau, "Recent advances in underlay heterogeneous networks: Interference control, resource allocation, and self-organization," *IEEE Communications Surveys and Tutorials*, vol. 17, no. 2, pp. 700–729, 2015, doi: 10.1109/COMST.2015.2416772.

[2] F. Hussain, *Internet of Things: Building Blocks and Business Models*. 2017.

[3] B. Debasis and S. Jaydip, "Internet of things: Applications and challenges in technology and standardization," *Wireless Personal Communications*, vol. 58, no. 1, pp. 49–69, 2011.

[4] U. S. Shanthamallu, A. Spanias, C. Tepedelenlioglu, and M. Stanley, "A brief survey of machine learning methods and their sensor and IoT applications," in *2017 8th International Conference on Information, Intelligence, Systems and Applications, IISA 2017*, 2018, vol. 2018-Janua, pp. 1–8, doi: 10.1109/IISA.2017.8316459.

[5] Y. Li, Z. Gao, L. Huang, X. Du, and M. Guizani, "Resource management for future mobile networks: Architecture and technologies," *Computer Networks*, vol. 129, pp. 392–398, Dec. 2017, doi: 10.1016/j.comnet.2017.04.007.

[6] X. Li, J. Fang, W. Cheng, H. Duan, Z. Chen, and H. Li, "Intelligent power control for spectrum sharing in cognitive radios: A deep reinforcement learning approach," *IEEE Access*, vol. 6, pp. 25463–25473, 2018, doi: 10.1109/ACCESS.2018.2831240.

[7] M. Ozturk, M. Akram, S. Hussain, and M. A. Imran, "Novel QoS-Aware proactive spectrum access techniques for cognitive radio using machine learning," *IEEE Access*, vol. 7, pp. 70811–70827, 2019, doi: 10.1109/ACCESS.2019.2918380.

[8] A. Zhu, S. Guo, B. Liu, M. Ma, J. Yao, and X. Su, "Adaptive multiservice heterogeneous network selection scheme in mobile edge computing," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 6862–6875, 2019, doi: 10.1109/JIOT.2019.2912155.

[9] Q. Liu, T. Han, and N. Ansari, "Energy-Efficient on-demand resource provisioning in cloud radio access networks," *IEEE Transactions on Green Communications and Networking*, vol. 3, no. 4, pp. 1142–1151, 2019, doi: 10.1109/TGCN.2019.2926287.

[10] A. Roy, V. Borkar, P. Chaporkar, and A. Karandikar, "Low complexity online radio access technology selection algorithm in LTE-WiFi HetNet," *IEEE Transactions on Mobile Computing*, vol. 19, no. 2, pp. 376–389, 2020, doi: 10.1109/TMC.2019.2892983.

[11] J. Ali *et al.*, "Network selection in heterogeneous access networks simultaneously satisfying user profile and QoS," *International Journal of Communication Systems*, vol. 31, no. 13, 2018, doi: 10.1002/dac.3730.

[12] J. Chen, Y. Wang, Y. Li, and E. Wang, "QoE-Aware intelligent vertical handoff scheme over heterogeneous wireless access networks," *IEEE Access*, vol. 6, pp. 38285–38293, 2018, doi: 10.1109/ACCESS.2018.2853730.

[13] G. Liang and H. Yu, "Network selection algorithm for heterogeneous wireless networks based on service characteristics and user preferences," *Eurasip Journal on Wireless Communications and Networking*, vol. 2018, no. 1, 2018, doi: 10.1186/s13638-018-1264-5.

[14] M. Polese, R. Jana, V. Kounev, K. Zhang, S. Deb, and M. Zorzi, "Exploiting spatial correlation for improved prediction in 5g cellular networks," 2019.

[15] R. Li *et al.*, "Intelligent 5G: When cellular networks meet artificial intelligence," *IEEE Wireless Communications*, vol. 24, no. 5, pp. 175–183, 2017, doi: 10.1109/MWC.2017.1600304WC.

[16] S. Chinchali *et al.*, "Cellular network traffic scheduling with deep reinforcement learning," in *32nd AAAI Conference on Artificial Intelligence, AAAI 2018*, 2018, pp. 766–774, doi: 10.1609/aaai.v32i1.11339.

[17] L. Yan *et al.*, "Machine learning-based handovers for sub-6 ghz and mmwave integrated vehicular networks," *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4873–4885, 2019, doi: 10.1109/TWC.2019.2930193.

[18] B. Ma, W. Guo, and J. Zhang, "A survey of online data-driven proactive 5g network optimisation using machine learning," *IEEE Access*, vol. 8, pp. 35606–35637, 2020, doi: 10.1109/ACCESS.2020.2975004.

[19] S. I. Majid, S. W. Shah, S. N. K. Marwat, A. Hafeez, H. Ali, and N. Jan, "Using an efficient technique based on dynamic learning period for improving delay in ai-based handover," *Mobile Information Systems*, vol. 2021. 2021, doi: 10.1155/2021/2775278.
[20] R. Sanchez-Iborra, L. Bernal-Escobedo, and J. Santa, "Machine learning-based radio access technology selection in the Internet of moving things," *China Communications*, vol. 18, no. 7, pp. 13–24, 2021, doi: 10.23919/JCC.2021.07.002.
[21] Y. Cao, S. Y. Lien, Y. C. Liang, K. C. Chen, and X. Shen, "User access control in open radio access networks: A federated deep reinforcement learning approach," *IEEE Transactions on Wireless Communications*, vol. 21, no. 6, pp. 3721–3736, 2022, doi: 10.1109/TWC.2021.3123500.
[22] B. Galkin, E. Fonseca, R. Amer, L. A. Dasilva, and I. Dusparic, "REQIBA: Regression and deep q-learning for intelligent uav cellular user to base station association," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, pp. 5–20, 2022, doi: 10.1109/TVT.2021.3126536.
[23] B. Zhang, S. Liu, J. L. Yu, and Z. Han, "A learning aided long-term user association scheme for ultra-dense networks," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, pp. 820–830, 2022, doi: 10.1109/TVT.2021.3127367.
[24] J. Chen *et al.*, "Joint task assignment and spectrum allocation in heterogeneous uav communication networks: A coalition formation game-theoretic approach," *IEEE Transactions on Wireless Communications*, vol. 20, no. 1, pp. 440–452, 2021, doi: 10.1109/TWC.2020.3025316.
[25] H. Hu, C. Ma, and B. Tang, "Channel allocation scheme for ultra-dense femtocell networks: Based on coalition formation game and matching game," 2019, doi: 10.1109/IEEE-IWS.2019.8803970.
[26] L. Le Magoarou, "Efficient channel charting via phase-insensitive distance computation," *IEEE Wireless Communications Letters*, vol. 10, no. 12, pp. 2634–2638, 2021, doi: 10.1109/LWC.2021.3109295.
[27] H. Tong, T. Wang, Y. Zhu, X. Liu, S. Wang, and C. Yin, "Mobility-Aware seamless handover with mptcp in software-defined hetnets," *IEEE Transactions on Network and Service Management*, vol. 18, no. 1, pp. 498–510, 2021, doi: 10.1109/TNSM.2021.3050627.
[28] X. Tan, G. Chen, and H. Sun, "Vertical handover algorithm based on multi-attribute and neural network in heterogeneous integrated network," *Eurasip Journal on Wireless Communications and Networking*, vol. 2020, no. 1, 2020, doi: 10.1186/s13638-020-01822-1.
[29] J. S. Liu, C. H. R. Lin, and Y. C. Hu, "Joint resource allocation, user association, and power control for 5g lte-based heterogeneous networks," *IEEE Access*, vol. 8, pp. 122654–122672, 2020, doi: 10.1109/ACCESS.2020.3007193.
[30] S. Manap, K. Dimyati, M. N. Hindia, M. S. Abu Talip, and R. Tafazolli, "Survey of radio resource management in 5g heterogeneous networks," *IEEE Access*, vol. 8, pp. 131202–131223, 2020, doi: 10.1109/ACCESS.2020.3002252.
[31] J. Y. Lai, W. H. Wu, and Y. T. Su, "Resource allocation and node placement in multi-hop heterogeneous integrated-access-and-backhaul networks," *IEEE Access*, vol. 8, pp. 122937–122958, 2020, doi: 10.1109/ACCESS.2020.3007501.
[32] S. Kim, "Heterogeneous network spectrum allocation scheme for network-assisted D2D communications," *Mobile Information Systems*, vol. 2020. 2020, doi: 10.1155/2020/8825119.
[33] A. Khodmi, S. Ben Rejeb, N. Agoulmine, and Z. Choukair, "Joint user-channel assignment and power allocation for non-orthogonal multiple access in a 5g heterogeneous ultra-dense networks," in *2020 International Wireless Communications and Mobile Computing, IWCMC 2020*, 2020, pp. 1879–1884, doi: 10.1109/IWCMC48107.2020.9148116.
[34] M. Zukerman, "Introduction to queueing theory and stochastic teletraffic models." 2013, [Online]. Available: http://arxiv.org/abs/1307.2968.
[35] M. A. Al-Absi, A. A. Al-Absi, T. Y. Kim, and H. J. Lee, "An environmental channel throughput and radio propagation modeling for vehicle-to-vehicle communication," *International Journal of Distributed Sensor Networks*, vol. 14, no. 4, 2018, doi: 10.1177/1550147718772535.
[36] M. A. Al-Absi, A. A. Al-Absi, Y. J. Kang, and H. J. Lee, "Obstacles effects on signal attenuation in line of sight for different environments in V2V communication," in *International Conference on Advanced Communication Technology, ICACT*, 2018, vol. 2018-February, pp. 17–20, doi: 10.23919/ICACT.2018.8323630.
[37] M. Manzano, F. Espinosa, Á. M. Bravo-Santos, and A. Gardel-Vicente, "Cognitive self-scheduled mechanism for access control in noisy vehicular ad hoc networks," *Mathematical Problems in Engineering*, vol. 2015, pp. 1–12, 2015, doi: 10.1155/2015/354292.
[38] T. V Saroja, L. L. Ragha, and S. K. Sharma, "A dynamic spectrum access optimization model for cognitive radio wireless sensor network," *ICTACT Journal on Communication Technology*, vol. 8, no. 3, pp. 1559–1565, 2017, doi: 10.21917/ijct.2017.0230.

BIOGRAPHIES OF AUTHORS

Nishatbanu Nayakwadi is a research scholar at KBN College of Engineering, Kalaburgi, Karnataka. She earned her MTech degree from Banasthali University Rajasthan, in the year 2015. She has more than 10 years of experience in teaching. She has served as a lecturer for AEIP college Gadag. Her research areas are Machine learning, Internet of Things, and Facial Recognition. She can be contacted at email: nishtabanu7777@gmail.com or nishatbanunayakwadi123456789@rediffmail.com.

Dr. Ruksar Fatima is serving as a Dean of Faculty for Engineering and Technology at Khaja Bandanawaz University. She has earned her Ph.D. in Computer Science from Jawaharlal Nehru Technological University, Hyderabad, India. She is serving as a technical Committee Member for various international conferences. She has published papers in various international journals and publications. She has also registered two patents under her name. She can be contacted at email: ruksarf@gmail.com.