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Adaptive Radio Access Technology Selection Algorithm for Heterogeneous Wireless Networks

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Abstract: *In Heterogeneous Wireless Networks (HWNs), Radio Access Technologies (RAT) can only consider the situation of one particular Radio Resource Management (RRM) which is unsuitable for managing multiple RATs. This study deployed an adaptive RAT selection scheme model to allocate users to the best RAT with the use of the cost function variable. The adopted model uses different input criteria like signal strength, network loads, service type and QoS requirement for the best access network selections. The adaptive RAT selection algorithm was executed in different service mixes (voice and data service) to access model suitability for users in Global System for Mobile Communications with Enhanced Data Rates for Global Evolution Radio Access Network (GERAN) and Universal Mobile Telecommunications System Radio Access Network (UTRAN). The proposed algorithm resulted in the call blocking probability reduction by 0.03 for GERAN and 0.14 for UTRAN as validated with the existing algorithm based on load balancing, service-based and priority-based. The drop implied an increased probability of ensuring session stability and high quality of the active service, leading to a high load distribution.*

Keywords: *Algorithm,* GERAN*, Heterogeneous Wireless Network, Radio Access Technology, Radio Resource Management, UTRAN.*

1. INTRODUCTION

In the current wireless network, it's important to ensure that end users have uninterrupted access to high-quality mobile services. This is especially true as the network becomes more diverse, with different types of devices and Radio Access Technologies (RATs) being used. To address this, we rely on multimode mobile device terminals that can integrate these different RATs and form what's known as heterogeneous wireless networks (HWNs). The Common Radio Resource Management (CRRM) platform manages integrated networks to enable simultaneous use of all available RATs. In HWNs, each RAT exhibits different qualities such as bandwidth, coverage area, service cost, and mobility management. Therefore, poor RAT selection might lead to overpopulation on a single RAT whereas activity in other RATs is only slightly occupied. Thus, RAT selection is a major challenge in the allocation of call requests to the most suitable RAT in HWN [1].

Several RAT selection algorithms such as single criteria algorithms, non-computation intelligence algorithm and computation intelligence algorithm have been proposed [2-4]. The single criterial algorithms [1-4] are load balancing algorithm service-based algorithm [6], priority-based algorithm, random selection algorithm and service cost-based algorithm [5]. The load balancing algorithm allocates users to the RAT with a lower load situation at a given time [2, 5]. As long as resources are available in the RAT, this strategy adaptively chooses the one with the least load; if not, the user will be barred. According to [7] a two-step load balancing approach was developed for multi-tier HWNs consisting of LTE-A macro cells and mmWave small cells. The approach utilizes two biases to modify the layer and RAT selection. Although this kind of algorithm improves the resource utilization of HWNs, the algorithm does not take into account the performance of the network link, and the user may be connected to the network with poor Quality of Service (QoS) [3]. Therefore, the required QoS by the users cannot be adequately guaranteed. The service cost RAT selection algorithm allocates incoming calls to the user through the RAT with the cheapest cost for the service request [6]. This technique focuses primarily on service charges differing between different RATs. Although, this algorithm helps in decreasing the service cost for each user in general but can lead to network overload [7] differentiate between CRRM RAT selection algorithms: load balancing (LB), and service-based (SB) evaluating with delay, overall throughput, and average cell load. Due to variances in attributes between each of the CRRM RAT selecting algorithms, various results emerge. According to the random-based algorithm, available RATs are chosen randomly for any call request [8]. The call is dropped or blocked when minimal radio resources are accessible in the designated RAT. The advantage of this algorithm is in the implementation simplicity but with a probability of a high level of blocking under reduced use of radio resource efficiency constraints.

On the other hand, the author [9] proposes an intelligent approach to RAT selection: non-computational and computational RAT selection algorithms. The algorithm for non-computational RAT selection intelligently distributes call requests to a certain RAT by considering a utility value derived from different RAT parameters. However, these algorithms have a high efficiency level and computational overheads, thus it is complicated to implement. These impending limitations led to the adoption of more robust and more intelligent-based approaches as documented in the literature. An Intelligent Network Selection Strategy based on Multi-Attribute Decision-Making (MADM) methods in HWNs was proposed according to [10]. This strategy combines two MADM methods such as the ANP method and TOPSIS method, the ANP method applied to find the different weights of available networks and the TOPSIS method is used to rank the available networks [11]. Heterogeneous wireless network selection frequently uses Multiple Attribute Decision Making (MADM) techniques as in [12-16]. Authors [15, 16] propose a mix of three MADM techniques namely the Fuzzy Analytic Hierarchical Process (FAHP), Entropy, and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to form a network selection algorithm based on the combination of network properties and user preferences. A flexible hybrid MADM method made up of FAHP, standard deviation, and Grey Relational Analysis (GRA) was also suggested by the authors [16] for the HetNet selection problem. The Analytic Hierarchy Process (AHP) was also recommended by [17] as a way for UEs to select the best RAT based on Signal to Noise Ratio (SNR), available bandwidth, delay, and jitter. An access selection technique called Relative Entropy-based Multi-service Network Selection (REMNS) was proposed by [18] to maximize the Quality of Experience (QoE) for subscribers within 5G heterogeneous networks. REMNS utilizes a relative entropy-based technique to choose the optimal network after filtering networks using a fuzzy logic-based network pre-assessment and analyzing network preferences using both the AHP and Entropy Weight Method (EWM). This method balances network traffic while maintaining steady connections and greatly enhancing user quality. Furthermore, [19] suggested a cost function that balances two factors: the blocking cost function, which considers the importance of each service class in each RAT, and the alternative acceptance cost, which reflects the diversity of RATs working cooperatively. Additionally, the author in [20] proposed a contemporary RAT selection approach based on the cost function, Particle Swarm Optimization (PSO), and Fuzzy logic system for the heterogeneous wireless network.

The reviewed aforementioned literatures only considers RAT selection under a single preference such as user preference or application types, which does not address the problem of network overloading and QoS. Therefore, to solve this problem, this paper examines an algorithm for adaptive RAT selection based on a cost function strategy that allocates users to the cheapest RAT while balancing the network load among the RATs and reducing the call-blocking probability. The proposed algorithm aims at allocating users to the cheapest RAT at low computation overhead and an RAT selection algorithm that is adaptive. Section II will discuss this algorithm in more detail.

The paper is structured as follows: section II presents the system model, and a cost function approach is used to model the suggested algorithm's radio resource allocation. In section III, we describe the proposed adaptive RAT selection algorithm. In section IV, we presented the result and compared the performance of the proposed algorithm with load balancing, service base, and priority-based algorithms in terms of call blocking probability, traffic load distribution, and average cost per call. Section V, concludes the paper.

2. SYSTEM MODEL AND PROBLEM FORMULATION

2.1 System Model

In this work, we consider a mobile network that allows numerous users to access multiple RATs due to its heterogeneous network architecture. The UTRAN and GERAN networks with co-located cells are the available RATs in the scenario under consideration. It was anticipated that the portable device terminal would perhaps be multimode and that each RAN already has its own RRM component for operations within the RAN. The challenging aspect is finding out which RAT is best for each call request. Figures 1 and 2 depict the suggested RAT selection method and its result.

The system is made up of two RATs in an overlapped coverage region, depicted in Figure 1. When a call request is placed, it is assumed that the initial strategies give a voice call to RAT2 as well as data calls to RAT1, however, since most network users utilize data, this will lead to systemic imbalance. As a result, to avoid imbalance, each RAT's RRM entity notifies the CRRM entity about its load bearing limits. The CRRM entity will then oversee the resources in each RAT and use the cost function model to make decisions based on the suggested policy. As depicted in Figure 2, based on the proposed cost function policy, the CRRM entity will distribute the available RAT to each user and calls will be allocated evenly to all user.

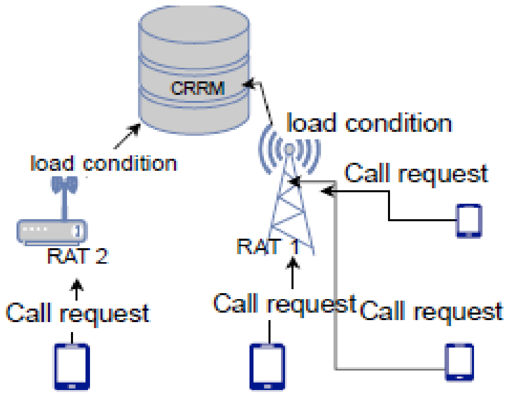

Figure 1: Proposed call request

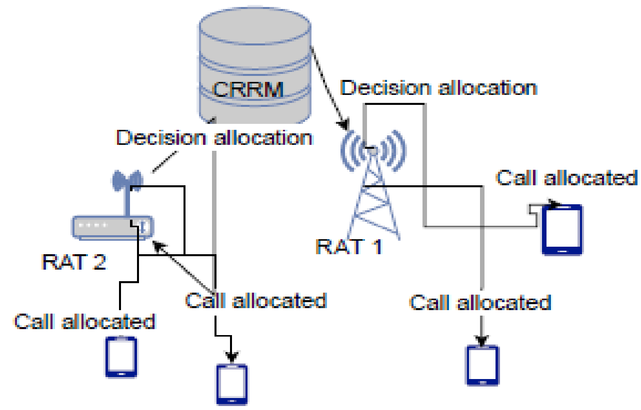

Figure 2: Proposed call allocation

2.2 Problem Formulation as Cost Function Model

To assign radio resources in the adaptive RAT selection process, a cost function model has been proposed. The objective is to balance the network load among the RATs, lower the likelihood of a call-blocking problem, and assign each user's call request to the RAT that gives the best price. The network and user cost function are the two costs that make up the cost function model.

For every RAT j, the function of the total costs can be written as:

$$F_j = N_j(L_j) + U_n \quad j = 1, 2, \ldots, |J| \quad n = 1, 2, \ldots, |N| \tag{1}$$

where

$N_j(L_j)$ = network cost function for RAT j,

L_j = current number of active calls in RAT j,

U_n= cost function for user service type n (voice or data).

The network cost function shows two thresholds for loads and network cost which are defined as L_{max} and L_{min} and N_{max} and N_{min} denoting optimal loads on the network, as well as the associated cost. The load L_j is determined based on active calls request in RAT j between L_{max} and L_{min}.

$$N_j(L_j) = \left[\frac{L_j - L_{min}}{L_{max} - L_{min}} \times (N_{max} - N_{min})\right] + N_{min} \tag{2}$$

Therefore, the total cost function for RAT j is expressed as follows:

$$F_j = \left[\left[\frac{L_j - L_{min}}{L_{max} - L_{min}} \times (N_{max} - N_{min})\right] + N_{min}\right] + U_n \tag{3}$$

3. PROPOSED ADAPTIVE RATS SELECTING ALGORITHM

The proposed adaptive RATs selection technique is explained in this section. The technique takes into consideration a range of variables, including the amount of traffic, kind of service, received signal intensity, and network cost. Because maintaining a fair load distribution on all networks with overlap coverage regions and choosing the least expensive RAT are the major goals. The networks and users under consideration are presumed to support the CRRM entity that is covered by [21]. Figure 3 shows the proposed algorithm flow chart. In the first step, new call user $|n|$ arrives in accordance with a mean rate Poisson process λ_n and mean holding time μ_n. The RRM then measured receive signal strength of user n from RAT j denoted as R_j and then make a list M_j which is a list of RATs whose received signal strengths measured by user n are above a threshold R_{min}.

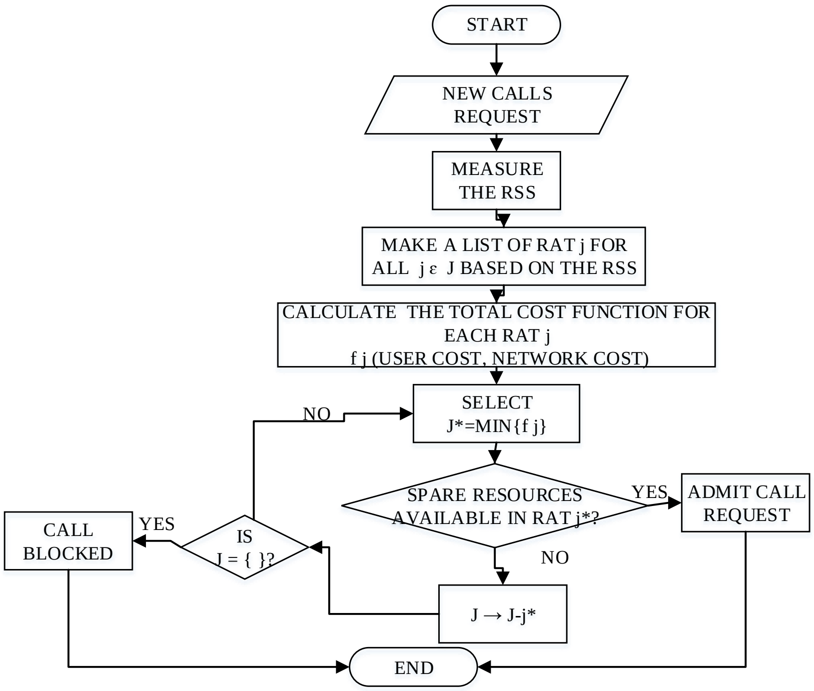

Figure 3: Adaptive RAT selection technique flow chart

The list of RATs whose received signal strengths measured by user n are above a threshold $R_{min.}$ is expressed as:

$$\bigcup_{j\in J, R_J > R_{min}} M_j \tag{4}$$

where
R $_j$ = receive signal strength for RAT j of user n,
R $_{min}$ = minimum receive signal strength threshold.

$$M_j \subseteq J$$

The second step is derivation of the total cost function $F_{j,n}$ which has been shown previously in Equation (3).

The third step is selection of RAT j with minimum cost,

$$j^* = \arg\min\{F_{j,n}\} \qquad j^* \epsilon M_j \tag{5}$$

The final step is to check if resources are available in the selected RAT from the step above i.e.

$$j^* = \begin{cases} 1 & \text{accept if resources is available} \\ 0 & \text{otherwise go back to the third step} \end{cases} \tag{6}$$

The load factor equation for GERAN is estimated as [22],

$$L_G = \frac{\min(n_{VG} + n_{DG}), C_{max}}{C_{max}} \tag{7}$$

where:
L_G = GERAN load,
$n_{VG} \& n_{DG}$ = amount of data and voice users in GERAN,
C_{max} = overall channel capacity in GERAN

For UTRAN, the uplink load factor is estimated as in [23, 24]

$$L_{UP}^{U} = (1 + i)\sum_{n=1}^{N} \frac{1}{1 + \frac{W}{\left(E_b/N_o\right)_n \cdot R_n \cdot V_n}} \tag{8}$$

where:
W = chip rate (Mcps)
i = interference ratio between own and other cells
R_n = bit rate for n user (Kbps)
V_n = activity factor for n user

The signal-to-noise ratio for n user is expressed as:

$$\left({}^{E_b}/_{N_0}\right)_n \tag{9}$$

In order to determine the call blocking probability of the algorithm, in equation 10 is calculated according to [25] as:

$$\mathrm{P_B} = \frac{\text{Number of blocked calls}}{\text{Number of call requests}} \tag{10}$$

4. NUMERICAL RESULTS AND DISCUSSIONS

4.1Simulation Parameters

The performance evalution of the proposed adaptive RATs selection technique was compared with priority-based policies, load balancing and service-based, simulations were done on the MATLAB program R2021a. Seven Omni-direction cells for both RATs were considered in an integrated GERAN and UTRAN network concept. Both speech and data call services are taken into consideration. The Poisson approach was supposed to produce the calls at a mean rate of λ.. In addition, a call duration time with an exponential distribution and a mean of $\frac{1}{\mu}$.was projected for each call. UTRAN uses WCDMA for voice calls at 12.2Kbps. Unused voice capacity is shared with data calls up to 128Kbps, but reduced if UTRAN bandwidth is insufficient. GERAN uses TDMA with 24 physical channels from three carrier frequencies. UTRAN has only one carrier frequency. In comparison, the cluster of seven GERAN cells and UTRAN practically share the same amount of total bandwidth [26]. Voice users in GERAN have a bit rate of 12.2Kbps. 59.2Kbps is the bit rate of the data consumer. In comparison to data services, voice services are given precedence. Table 1 summarises the parameters used in the simulation.

Table 1: Parameters for simulation

Base station parameters	**GERAN**	**UTRAN**
Maximum power transmitted	43 dBm	43 dBm
Thermal noise	-117 dBm	-104 dBm
Quantity of carriers	3	1
Total number of channels on TS	24	N/A
Bandwidth of transmission	1 .6 MHZ	5 MHZ
Load Max.	60 users	70 users
Load Min.	0	0
Network cost Max.	#25/min	#30/min
Network cost Min.	#4/min	#7/min
Voice call bit rate	12.2 Kbps	12.2 Kbps
Data rate Max.	59.2 Kps	128 Kbps
Average rate of call arrivals (λ)	10 calls/h/users	
Average call holding time (μ)	80 s	

4.2 Average Cell Load Distribution

The load of the cell is the average load distributed by each RAT to different users. Figures 4 and 5 show the distribution of average cell load for data users in both RATs when the traffic from voice users is much. The graphs depicts that as number of call arrivals increases the load in all the policies increases. Figure 4 presents the result obtained for comparing the proposed algorithm with load balancing, priority based, and service policies algorithm for GERAN load distribution. In Figure 4, it was observed that load balancing, priority-based and service policies algorithms have a minimal call acceptance when compared to our proposed algorithm that is able to accept more call request. Figure 5 presents the result obtained for comparing the proposed algorithm with load balancing, priority based, and service policies algorithm for UTRAN load distribution. As shown in Figure 5, the load balancing, priority-based and service policies algorithms gave a lower call acceptance when compared to our proposed algorithm that is able to accept more call request. Also, the two Figures depict that, the proposed algorithm and load balancing keep the load evenly distributed in both RATs. On the other hand, as the UTRAN network illustrates, the proposed approach uses network capacity more effectively than load balancing. In contrast to load balancing, the proposed approach permits additional calls in the network from a similar quantity of call requests. Due to insufficient load information in both the priority-based and service policies, they have the lowest load.

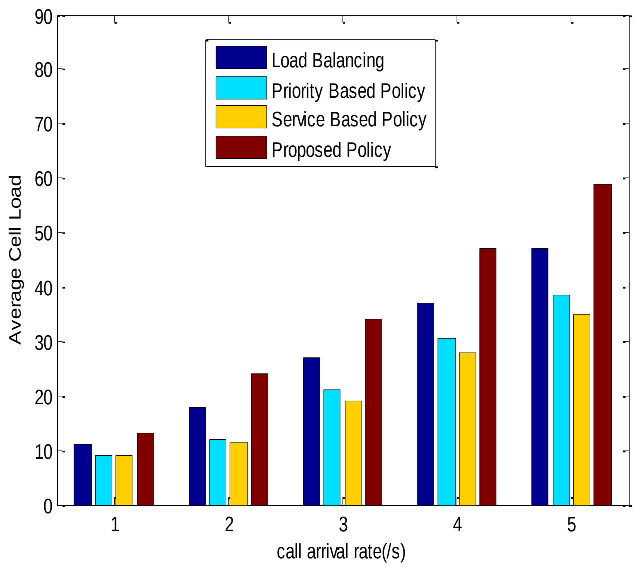

Figure 4: Load (GERAN)

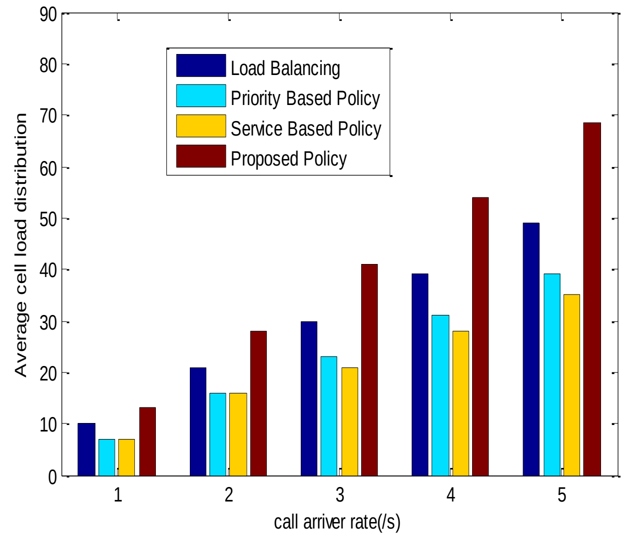

Figure 5: Load distribution (UTRAN)

4.3 Call Blocking Probability

Call blocking probability is the situation whereby a user call request is not allowed due to lack of resources in the available network. Figure 6 and 7 depict the blocking probability (P_B) as expressed in equation 10 for GERAN and UTRAN respectively plotted against number of call request. The results shows how the call blocking probability for each algorithm increases with increase in session. Figure 6 present the result obtained for comparing the proposed algorithm with load balancing, priority based, and service policies algorithm for GERAN blocking probability. In Figure 6, for 9 call requests, the blocking probability obtained value is 0.14 for the proposed policy, 0.28 for load balancing, 0.67 for priority based and 0.75 for service policies algorithm. Also, Figure 7 present the result obtained for comparing the proposed algorithm with load balancing, priority based, and service policies algorithm for UTRAN blocking probability. In Figure 7, for 9 call requests, the blocking probability obtained value is 0.004 for the proposed policy, 0.142 for load balancing, 0.223 for priority based and 0.35 for service policies algorithm. However, Figure 6 and 7 shows that the proposed policy gave the smallest blocking probability while service-based policies have the highest blocking probability. Therefore, the proposed method, however, lowers the potential of call blocking in heterogeneous wireless networks.

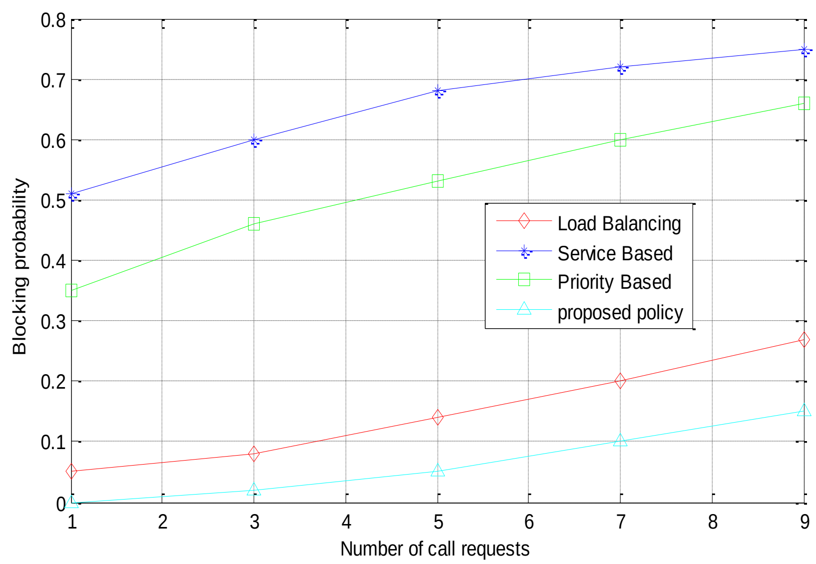

Figure 6: Blocking probability (GERAN)

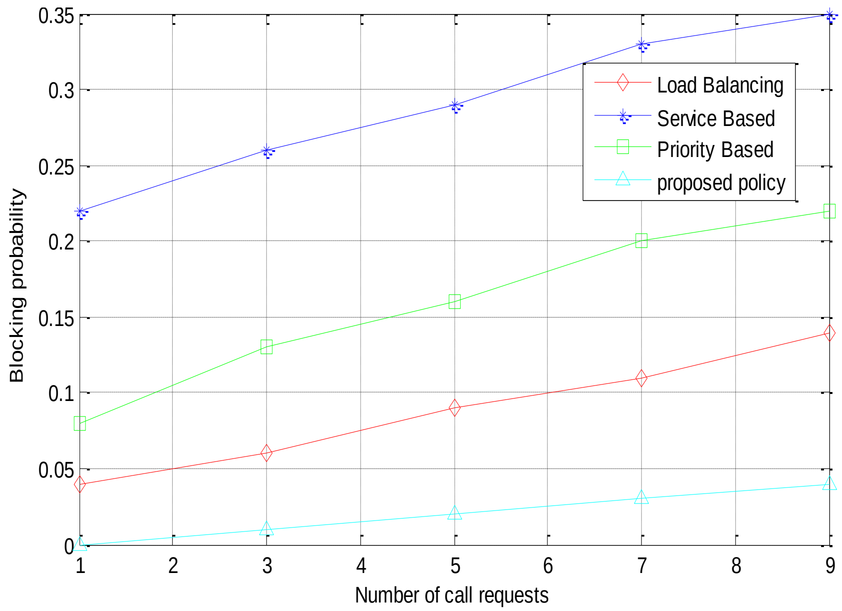

Figure 7: Blocking probability (UTRAN)

4.4 Average Cost Function and Users Distribution among each RAT

To evaluate the behavior of the proposed technique, Figure 8 depicts the average cost function for GERAN and UTRAN as a standalone RAT. Figure 9 shows the user distribution among the RAT. From Figure 8, the graph depicts that GERAN offers a lower average cost per call than UTRAN because the data rate in GERAN is higher than that of UTRAN data users. Important part of Figure 8 is the higher sensitivity of the UTRAN cost per call to an increment in the number of users admitted to GERAN, as shown in Figure 9, which forces UTRAN to admit the increase in users.

4.5 Average Cost Per call for each Policy

Figure 10 compares the average call cost for the existing RAT selection policy with the adaptive RAT policy in heterogeneous network The average cost per call for the load balancing, service-based and adaptive RAT policy are illustrated in Figure 10 of the user terminal that preferred lowest cost RAT. The simulation result showed that the adaptive RAT and service-based policy performed better than load load-balancing policy. This is because load balancing is not user centric but only considers the network load. The service-based policy allocated calls to the user based on it service type but the adaptive RAT policy balanced both the network load and the users service type. Therefore, the adaptive RAT policy has better average call cost.

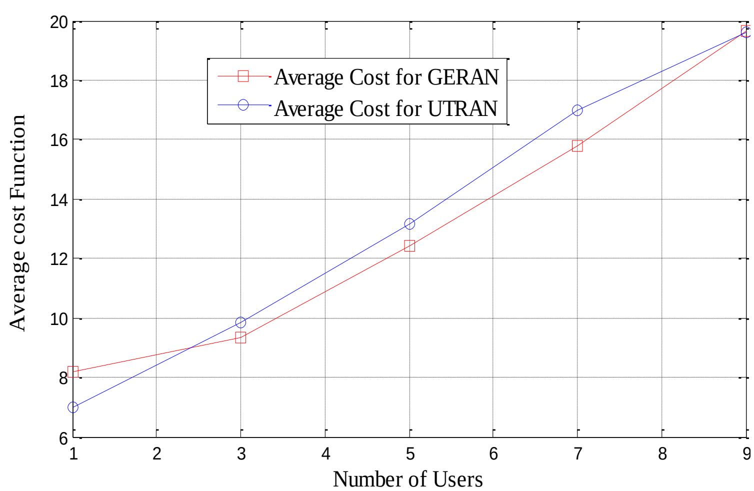

Figure 8: RATs average cost function

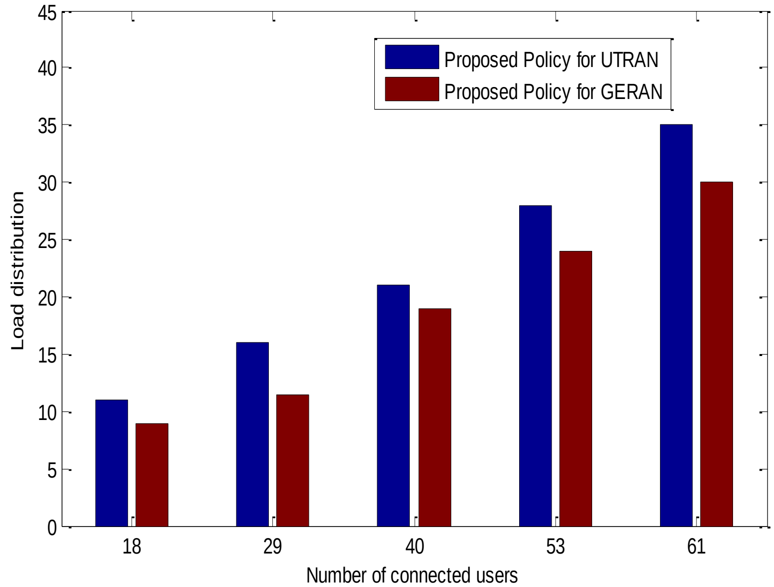

Figure 9: RATs users Load

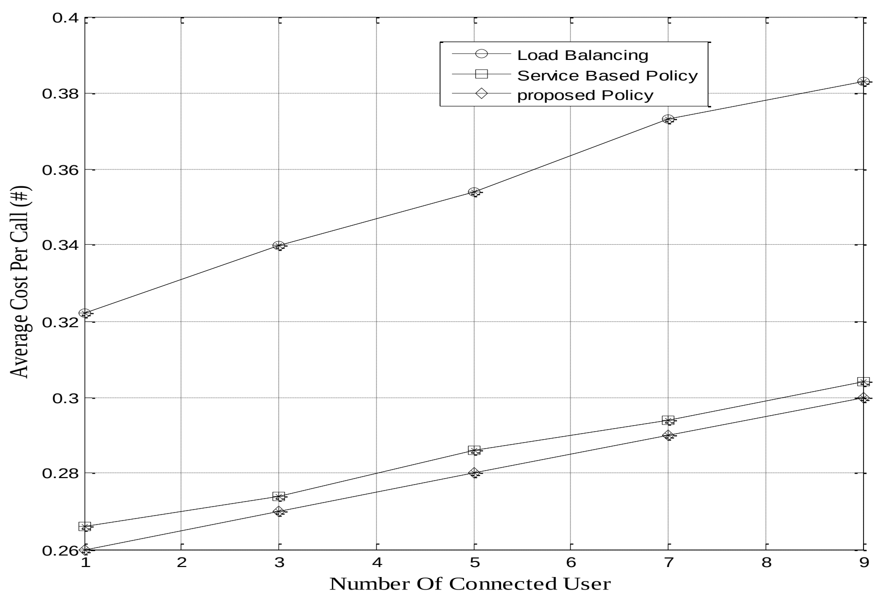

Figure 10: Average cost per call for each policy

5. CONCLUSION

An adaptive RAT selection technique has been developed in this work for HWNs and evaluated its performance via simulation. We proposed a simplified cost function model of the adaptive RAT selection that allocates the user to the cheapest RAT among UTRAN and GERAN networks. Furthermore, we introduce a mathematical model considering user and network context for voice and data service. Then, we implement the proposed algorithm in MATLAB R2021a software and validate its performance by comparing the expected result of the propose model with load-balancing, service-based, and priority-based policy. We evaluate the proposed model with the average cost of each RAT and the user distribution among the available RATs. The obtained results indicated that load-balancing and the adaptive RAT algorithm ensured a fair load spread in HWNs, while priority-based and service-based approaches displayed sudden load variations that reduced performance in overloaded networks with high congestion and a high probability of call blocking. The available radio resources were effectively exploited via adaptive RAT selection. Therefore, choosing an adaptive RAT is a preferable strategy because it offers high radio link utilization with a low likelihood of a call being blocked and the capacity to maximize network availability with an average load distribution in a co-located network.

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