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A Context-aware Radio Access Technology selection mechanism in 5G mobile network for smart city applications

Adib Habbal[a,c,*], Swetha Indudhar Goudar[b,c], Suhaidi Hassan[c]

[a] Computer Engineering Department, Faculty of Engineering, Karabuk University, Turkey
[b] Master of Computer Applications Department, KLS Gogte Institute of Technology, Belagavi, India
[c] InterNetWorks Research Laboratory, School of Computing, Universiti Utara Malaysia, Malaysia

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ABSTRACT

The Fifth Generation (5G) mobile network will revolutionize the way of communication by supporting new innovative applications that require low latency and high data rates in smart city environments. In order to meet these applications' requirements, Ultra-Dense Network (UDN) is considered as one of the promising technological enablers in 5G. 5G UDN deployments are envisaged to be heterogeneous and dense, mainly through the provisioning of small cells such as picocells and femtocells, from different Radio Access Technologies (RATs). Nevertheless, various studies have reported that the densification is not always beneficial to the network performance. As the network density increases, this will pose further requirements and complexity of determining which RAT a user should connect with at a given time. Hence, an efficient RAT selection mechanism to choose the best Radio Access Technology among multiple available ones is a must. This paper proposes a new Context-aware Radio Access Technology (CRAT) selection mechanism that examines the context of the user and the networks in choosing the appropriate RAT to serve. A simplified conceptual model of the Context-aware RAT selection is introduced. Then, a mathematical model of CRAT considering the user and network context is derived, adopting Analytical Hierarchical Process (AHP) for weighting the importance of the selection criteria and TOPSIS for ranking the available RATs. The proposed CRAT was implemented and validated in NS3 simulation environment. The performance of the proposed mechanism was tested using two different scenarios within a smart city environment, called a shopping mall and urban city scenarios. The obtained results showed that CRAT outperforms the conventional approach namely A2A4 of RAT selection in terms of the number of handovers, average network delay, throughput, and packet delivery ratio.

1. Introduction

Recently, the mobile communication has become a fundamental entity to connect people through social media, telephony, messaging, and many other online services. The horizon has been extended from just connecting people, to connecting machines and devices, facilitating the linkages for the Internet of Things (IoT) applications (Chen et al., 2017). Hence, the upcoming revolutionised digital wave of the Fifth Generation Mobile networking or simply (5G) is designed to enable efficient connection among smart devices and applications, serving the anticipated explosive growth of mobile users' data traffic in a wide range of new innovative services for many different environments.

The smart city is one of the most popular applications which represents an extensive number of ubiquitous services working and coordinating their activities towards improving the quality and lifestyle of city residents. (Akpakwu et al., 2018). The smart city is where a person can imagine driving down a city road when the red traffic light signal is switched to green so that people can cross an empty street without waiting for the signal to switch according to a preset timer. Another case is to inform the driver about the possible alternative directions/routes while driving and suggest the best road to select based on the current condition of the roads and traffic. In addition, an intelligent and sophisticated monitoring and control system can make the augmented reality true in the smart city by introducing a new way for tourist and even local people to explore their city. Moreover, a good connection speed can be assured irrespective of the location. Thus, 5G is capable of connecting with and supporting self-driving vehicles, which can improve the traffic safety levels that normally humans cannot achieve. This is

* Corresponding author. Computer Engineering Department, Faculty of Engineering, Karabuk University, Turkey.
E-mail address: adibhabbal@karabuk.edu.tr (A. Habbal).

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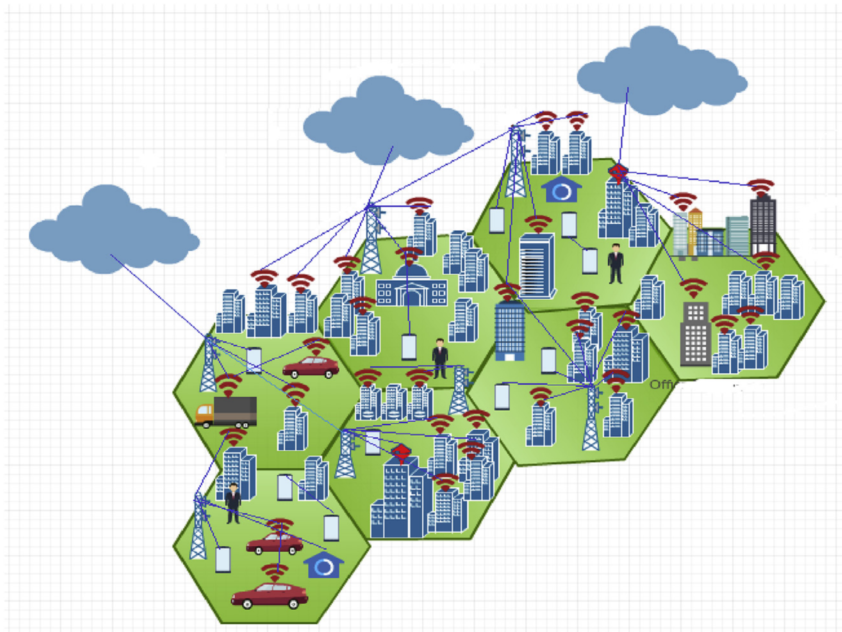

Fig. 1. 5G mobile network in smart city environment.

just from the intelligent transportation system point of view of the smart city.

The applications of a smart society connecting smart homes will be attained by dense wireless devices with intelligence that can sense and control different electrical equipment and appliances. Similarly, the health sector will have many applications that benefit from the fast mobile communications, enabling medical services from a distance. Thus, surgeons can perform a remote surgery in case of emergencies using 5G for controlling smart remote-robot, which can save people's live. Achieving this requires robust and reliable connectivity solutions as well as the capability of seamlessly connecting all the devices. Fig. 1 elaborates the idea of smart city using 5G connectivity (Agiwal et al., 2016; Condoluci et al., 2016).

In order to achieve such quality of services and realize the new connectivity requirements, this imposes technological evolutions and revolutions on the current 3G and 4G systems (Cheng et al., 2018). Consequently, 5G mobile network is expected to revolutionize the way of our today's communication by supporting a wide range of new applications that compel low latency and high data rates in both indoor and outdoor environments. 5G incorporates new features ranging from the millimeter wave (mmWave), massive MIMO concept, Spectrum sharing, D2D communication (Gandotra and Jha, 2016), and Internet of Things (IoT). All these are built on the network structure of Ultra-Dense Network (UDN) (Akpakwu et al., 2018). Fig. 2 depicts the new and revolutionised features offered by 5G networks in attaining the anticipated high demand of mobile users and future applications.

5G mobile networks implies connecting a large number of User Equipment (UEs), supporting massive machine to machine (M2M) communication, and enabling fast response time and the 1000-fold data traffic increase (Goudar et al., 2017; Gandotra and Jha, 2017). Ultra-Dense Network (UDN) is one of the key driving features towards fulfilling 5G main criteria. UDN is the extreme deployment of base stations and access points of different Radio Access Technologies (RATs) in a very close proximity (Cisco, 2015), that gives a uniform experience to users across heterogeneous networks, to satisfy the anticipated exponential growth of data traffic which is said to explode 1000X times more than the current by 2020 (Cisco, 2015). These requirements are difficult to be achieved by a macro-base station or the central core network method. Hence, UDN needs to initiate a holistic approach to handle the heterogeneous environment significantly, which gives rise to the concept of small cells, like micro-base, femto-base, and pico-base stations, to distribute the traffic (Bhushan et al., 2014; Samir Soliman, 2017). The small cells are comprised within the macro-cell region to handle the increased traffic in an efficient manner, where by each small cell aids in managing traffic across the network by handling the massive demand.

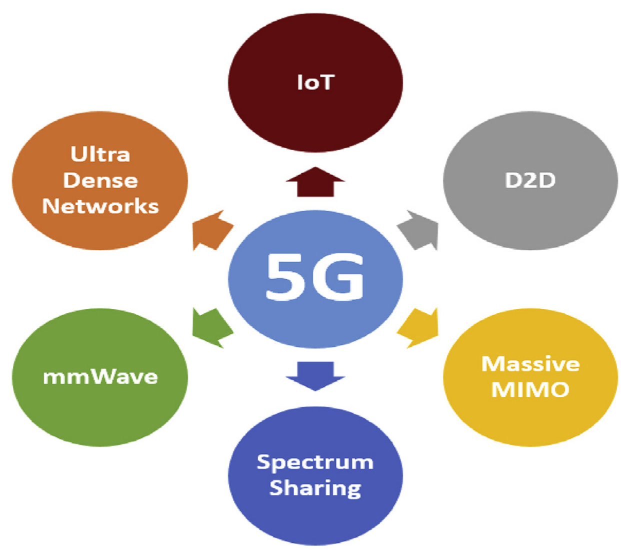

Fig. 2. 5G features.

The concept of small cells enables a better network resource utilisation and enhances the Quality of Experience (QoE) expected by mobile users (Xu et al., 2014; Wang et al., 2015). In addition, the small base stations require less power; consequently, the energy efficiency problems are inherently resolved. This situation provides a win-win opportunity to both the users and operators. However, due to the random close deployment of RAT base stations and as the network density increases, this will demand added requirements and complexity of determining which RAT a user should connect with at a given time (Wang et al., 2017). Moreover, it will by accompanied with frequent handovers among available RATs (Goudar et al., 2017). This phenomenon will not only degrade the system performance, but also consume more power. The main question to be answered in 5G UDN scenario is “How should a user select a RAT in 5G UDN at any given time?” (Wang et al., 2017). This is an open research area for introducing an efficient decision-making approach in handling unnecessary handovers and selecting the most appropriate Radio Access Technology in UDN smart city environment.

The imperative method of RAT selection based on Radio Signal Strength (RSS) quality or power will not be efficient in a multi-RAT UDN environment. In the imperative approach based decision, the RAT initiation is triggered either when the current RAT RSS value diminishes or when the RSS value of the neighbour RAT is sensed to be better than the current serving RAT. The close deployment of RATs will lead to frequent handovers with the imperative approach. As a result, this will degrade the performance of the UDN multi-RAT environment. Hence, there is a need to consider a few more aspects of utilising network resources along with preserving the user’s preference for seamlessly good service (Liu et al., 2018; Agiwal et al., 2016). The 5G technology is stated to be a more user-centric approach, co-existing with device and machine communications. As a result, it is difficult to choose the appropriate RAT with only a single or a few criteria, and an appropriate mechanism with context-awareness and multi-criteria is essential (Ahmed et al., 2006).

This paper presents a new Context-aware Radio Access Technology (CRAT) selection mechanism to choose the most suitable RAT to serve in a UDN environment. In achieving the main aim of this paper, the following contributions will be obtained:

- A brief convergence of the related works toward this proposed selection mechanism is presented (Section 2).
- A Simplified conceptual model of the Context-aware RAT selection is introduced that eases the deployment of CRAT while capturing the essential features of context management. (Section 3).
- A mathematical model of CRAT considering the user and the network context is derived, adopting Analytical Hierarchical Process (AHP) for weighting the importance of selection criteria and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) for ranking available RATs (Section 4).
- In contrast to other mechanisms which were only implemented and tested in MATLAB, the proposed CRAT was implemented in NS3 simulation environment, then its performance was evaluated in two real scenarios of smart city environments (Section 5).

2. Related work

The traditional approaches tend not to be suitable to achieve RAT selection by considering RSS or a few criteria, which are strongly intended for horizontal handover. However, this is inadequate for future wireless communications of 1000X traffic and multi-RAT heterogeneous UDN. Hence, there is a need to have an efficient RAT selection approach for the UDN environment, where context-awareness in analysing more criteria other than just RSS, is utilised for realising a user-centric paradigm. Decisions need to be made at two points, firstly to measure the need to switch from the current RAT, which is the intra-RAT assessment. Secondly, is the inter-RAT assessment, i.e., to choose the correct RAT to serve the UE demand for differentiated applications efficiently. The approach should involve effective decision making of selecting the target RAT.

The complex heterogeneous UDN with multi-RAT requires considering multi-criteria to determine the most appropriate RAT for demanded service. Yang et al. (2007) devised a QoS based approach in VHO decision by measuring Signal to Interference Noise Ratio (SINR). Comparing the SINR of WLAN to WCDMA, the handover is done to the network with a high signal. This approach is more efficient com-

Table 1
Summary of VHO algorithms.

Handover Decision Class	Network Dynamics employed	Complexity	Handover Target Criteria	Advantages	Disadvantages
RSS based	RSS with threshold, timer and hysteresis	Simple	RSS	minimized handover failure	long packet delay, wastage of resources
Bandwidth based	Bandwidth, RSS	Simple	Bandwidth	High throughput, low latency	ping-pong effect, application blocking, connection breakdown
QoS based	Bandwidth, RSS and SINR	Usually Simple	Network candidates with highest overall performance	low HO latency, high throughput, assured QoS	high packet loss, increased HO latency, ping-pong effect
Cost based	Bandwidth, RSS, Cost, BER etc	Little Complex	Network candidates with highest overall performance	Increased user satisfaction, high throughput	difficult to make algorithm realistic, hard to estimate security and interference levels
MADM based	Variable input parameters based on technique	Complex	Network candidates with highest overall performance	high success rate in finding candidate network, reduced HO delay	training delay, high HO dropping rate, fixed weight may result in failure
Network Intelligence based	Variable input parameters based on technique	Complex	Network candidates with highest overall performance	high success rate in finding candidate network, reduced HO delay, high throughput	high latency, high signaling overhead
Context Aware	Variable input parameters based on technique	Very Complex	Network candidates with highest overall performance	low HO failure, high throughput, low ping-pong effect, low latency	Signaling cost high, might compromise on QoS if a low cost network available, handover delay

pared to the RSS based approach in terms of throughput. However, QoS based approaches are prone to more handover toggling to and fro between networks with the variation of SINR degrading the overall system performance of the network. Wang et al. (1999) considered the input criteria as network condition, user defined policies, and stability period to form a cost function, thus claiming to have a good decision for seamless handover. The adopted methodology was demonstrated to deliver the user's satisfaction with less handover blockage.

When the parameters list is increased with the collaborative approach of network and user, the single tracked assessment of criteria is less efficient to decide the RAT. Hence, a multi-criteria based approach is ideal in decision making. The Multi Attributes Decision Making (MADM) approach calculates the quantitative value for attributes with assigned weighted function to evaluate the target RAT (Chai et al., 2009). MADM chooses the best alternative among the set of alternatives based on their attribute weights (Song et al., 2009).

Obayiuwana and Falowo (2016) in their review of Multiple Criteria Decision Making (MCDM) approach in network selection analysed the different approaches and showed that the integrated approach tackles decisions by 44% better than the other two forms, namely the single and the modified MCDM approaches. The multi-criteria mechanism sometimes results in conflict, within a dynamic and complex problem in decision making. Hence, the MADM with context-awareness was considered in this study to resolve the conflict and aid in dynamic decision making in UDN. Wang et al. (2017) presented a survey on the heterogeneous networks of 5G and strongly recommended to utilize the capabilities of the network in the context of RAT selection in 5G. A detailed comparison of RAT selection (handover decision approaches) approaches together with their advantages and disadvantages is provided in Table 1.

3. Conceptual model of Context-aware Radio Access Technology selection (CRAT)

This section introduces the conceptual model of CRAT. CRAT selection was constructed to be conscious of the possibilities offered by each RAT and senses the UE movement while taking into account the QoS requirements for the demanded services. The collected context information needs to be evaluated to initiate/select the suitable RAT. Fig. 3 illustrates the main components of the Context-aware RAT Selection (CRAT) model, namely the context management, the context provider, and the context consumer. The researchers simplified the model for the purpose of this study, as the development of context-aware middleware is a vendor-specific matter. However, a network service provider can implement a common context management method to support all UEs. The three main working components of CRAT are co-ordinated in a synchronised way toward the initiation and selection of RAT with context-awareness.

3.1. Context management

Mobile Edge Computing (MEC) is an emergent architecture, where by highly distributed computing services are extended to the edge of networks (Abbas et al., 2018). It is an important component in the 5G architecture which is expected to enable the network to support extensive innovative services and applications (Liu et al., 2018). In addition, MEC can be used to store and process the content in close proximity to mobile users (Gupta et al., 2016). Moreover, the Radio Network Information Service (RNIS) module of the MEC server gives mobile's users real time network information about the cell load, subscriber's specific bandwidth, and the subscriber's location (Gupta et al., 2016). Therefore, several mobile operators are working on integrating MEC with the base station. In response to this development, MEC will be used in this study to provide enough computing resources within the locality for transferring and managing the context data.

Information is obtained about the network and user's requirements, and stored in a context repository within MEC to apply different mechanisms toward decision making for the target RAT. The initial stage involves data collection (context sensing) from both context provider, i.e., network operators, and the context consumer (user terminal). Then, the context aggregation provides basic means to aggregate the acquired context information from different dimensions. The information is the integration of the criteria pertaining to both mobile and network to attain "Always Best Connected" concept. The collaborative criteria are obtained by the network discovery of the RAT with intra and inter assessment of the short listed criteria forming a context. The network discovery and processing for context information are made dynamically. Accordingly, the context repository is updated frequently, which

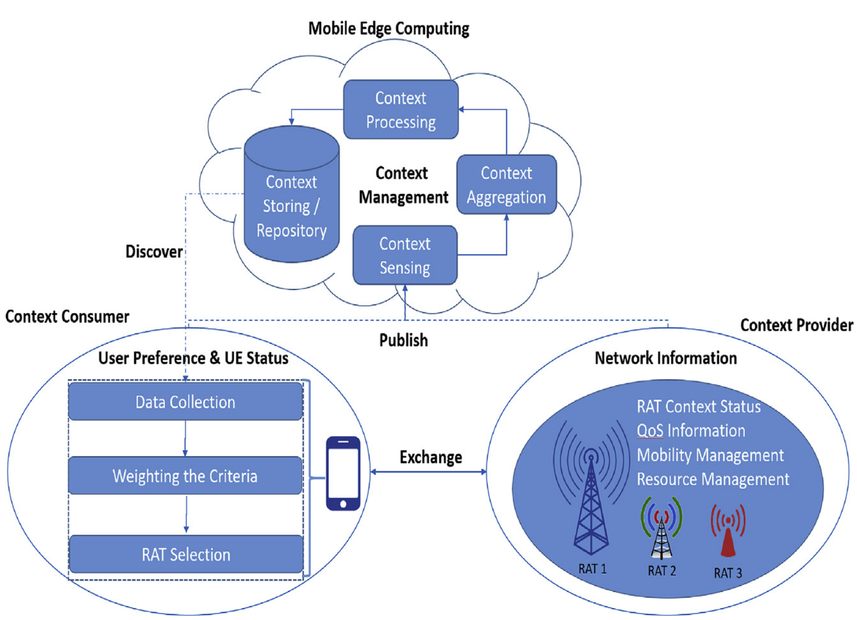

Fig. 3. CRAT overview.

aids in monitoring and measuring the need for the RAT selection. The aggregated information is matched with the requirement of the UE and network calibre in making the context-based decision.

3.2. Context provider

Context provider is most vital in making the decision of RAT selection. It needs to provide the information of inter-RAT and also intra-RAT information in decision making. The network resource and the user requirement of the heterogeneous RAT are provided to Context Consumer in weighting the criteria and ranking for further decision. The synchronised approach of balancing the network and QoS is possible if the context provider information is relatively accurate. The information offered by the provider should consider the mobility of UE, QoS factors, user profile, etc., for the huge number of smart devices in the small cell area that will be stored and manipulated in the MEC.

3.3. Context consumer

The information in the context repository facilitates the measurements taken from the residing RAT according to the UE requirement. If the current serving RAT is unable to meet the requirements at that moment the handover is initiated, the measurement is performed with the importance of criterion, which is quantified to be in accordance to its weight. The weights of the criteria determine the importance of each criterion with respect to the context, as shown in Fig. 3. The input to the context repository comes from the MEC and the mechanism to assign the weight is executed to obtain the importance of the criteria. The relative importance of the criteria is represented by weight using Saaty's scale to mark the importance of the criteria (Hwang and Yoon, 1981a). The details of the procedure are briefed in the following section.

Furthermore, determining the best RAT among the available ones in UDN is a critical challenge. The handover initiation is an intra-RAT analysis, however in contrast, the decision making is the inter-RAT analysis to decide the best fit among the available ones. This is attained by the mechanism comparing the importance of the criteria and the RAT capability matching the user needs. A mechanism is required that makes the collaborative assessment of the criteria from the repository with the networks, i.e., the assessment of RATs available in the neighbourhood is made by choosing the best one among the available that best suits the UE requirement at the particular context of decision making. The fact is reiterated that the CRAT approach is not imperative or biased to the criteria or the RAT, rather it is a context-awareness based decision approach.

4. Design of CRAT selection mechanism

The overview of the CRAT conceptual model is presented in the previous section, and this section introduces the design and mathematical model of CRAT. The new request is transmitted from the UE at different instances of time continuously and the base station is supposed to serve the request. When the current serving RAT fails to meet the context requirement of UE, the handover is triggered. The triggering of handover is not imperative based, but rather based on the context constraint to trigger the handover. Once the handover over is triggered, the next phase is to determine the point of attachment i.e, the new RAT.

Determining the RAT phase is when there is a need to measure the capability of each RAT with respective criteria for decision making in order to choose among all available RATs, thus instigating a network discovery. This event helps to map the criteria to alternatives. Once the match is found, a new target RAT is determined and the control of UE is attached to the new target RAT. If the RAT is not determined, the UE is bound to continue with the current serving RAT. The CRAT to determine the target RAT comprises of two methods, the first method determines the importance of selection criteria for the particular request by transforming the UE requirement and RAT capability to weight. This is attained by the Analytical Hierarchy Process (AHP). Further, another method is required to decide the best RAT among the available once by mapping the UE request and the capabilities of each RAT in the vicinity. During this process of transiting phases, the complete performance of the designed approach is measured in terms of throughput, packet delivery ratio, delay, and number of devices.

Table 2
Saaty's scale of importance, (Saaty and Vargas, 2012).

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

4.1. Analytical Hierarchy Process (AHP)

The AHP method was introduced by Saaty (Saaty and Vargas, 2012) with an aim to divide and conquer complicated problems in decision making by dividing the problem into sub-problems into a hierarchical model of goal, criteria and alternatives. The AHP primarily refers the integers from 1 to 9 from Saaty's Table 2 to confer the criteria importance ranging from 1 to 9 in constructing the pairwise matrix. The AHP is integrated with context-awareness to form CAHP in assigning the weight. The context-awareness determines the dynamic importance of criteria in decision making. Assuming the consistency, weight ordering of the factors in each level is computed and then synthesize them into the overall weight ordering of all criteria towards the main goal (Sgora et al., 2010). This method consists of following steps:

Step 1: Determination of the objective and decision factor A pairwise matrix (n∗n) is constructed comparing the criteria against each other based on the Saaty's scale for pairwise comparisons. Table 2 defines the Saatys 1–9 scale of the pairwise comparison matrix (Saaty, 1990; Saaty and Vargas, 2012). Let C = [Cj; j = 1,2, …,n] be the set of criteria. The resulting (n∗n) pairwise matrix A in which every element a_{ij} (i,j = 1,2, …,n) is the quotient of the weight of the criteria.The priorities assigned are of different units, hence the values are normalized and converted to dimensional values. The elements of the constructing pairwise matrix are weighted against the each other based on the application preference. The weights obtained at the end of the CAHP process for each category of criteria is validated mathematically by computing the Coherence Ratio (CR) to check for consistency which can be derived from Equations (1)–(7). The eigenvector method used by CAHP can determine the weights (Hwang and Yoon, 1981a). The value 0.1 is the accepted upper limit for CR (Saaty, 1990). If the CR value > 0.1 the process need to be repeated for attaining consistency. The measured consistency can be used to evaluate the consistency of decision making. The pairwise matrix is expressed as,

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} where, a_{ii} = 1, a = \frac{1}{a_{ij}} \tag{1}$$

Where a_{ij} represents the importance of criterion versus another criterion in the constructed pairwise matrix A based on the intensity of importance drawn from Table 2. Determining the co-relation of the criteria against each other are known. In each level, the decision factors are compared in the pairwise matrix according to their level of influence w.r.t to the Tables 2 and 3.

Table 3
Value of random index.

Criteria	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Step 2: Normalization and calculation of the relative weights: The pairwise matrix comprises of different units of measurement, hence it needs to normalize for harmonizing the process. The normalized matrix A_{norm} is constructed from Equation (1). In short, divide each element of the comparison matrix A by its respective column sum to obtain elements of the normalized matrix in Equation (2).

$$A = \begin{bmatrix} \frac{a_{11}}{\sum_{a_{i1}}} & \frac{a_{12}}{\sum_{a_{i2}}} & \cdots & \frac{a_{1n}}{\sum_{a_{i1}}} \\ \frac{a_{21}}{\sum_{a_{i1}}} & \frac{a_{22}}{\sum_{a_{i2}}} & \cdots & \frac{a_{2n}}{\sum_{a_{in}}} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{a_{n1}}{\sum_{a_{i1}}} & \frac{a_{n1}}{\sum_{a_{i2}}} & \cdots & \frac{a_{nn}}{\sum_{a_{in}}} \end{bmatrix} where, a_{ii} = 1, a = \frac{1}{a_{ij}} \tag{2}$$

Calculating the weight of the criteria, the decision factor, Wi is computed by,

$$W_i = \frac{\sum_n^{j=1} a_{ij}}{n}, W = \begin{bmatrix} W_1 \\ W_2 \\ . \\ . \\ . \\ W_n \end{bmatrix} Where, W_k = Avg(k^t h row of A_{\text{norm}}) \tag{3}$$

Where n is the number of comparable criteria. The column sum should yields 1 has in Equation (3), signifying the consistency in weight computing else needs to revise the pairwise matrix until the attainment of consistency. To check the consistency of the pairwise matrix Coherence Ratio (CR) is calculated. The values of Random Index (RI) are taken from Table 3 depending upon the number of input criteria the RI value is picked. In this proposed research magnitude of criteria is five. Hence the chosen RI value is 1.12 for the further computation of CR. CR is calculated as the ration of CI, which is the consistency Index to the RI which signifies based on the chosen magnitude of the criteria.

$$CR = \frac{CI}{RI} \tag{4}$$

Where, Consistency Index (CI) and is the Random Index (RI) are determined by following steps,

$$\lambda = \frac{A * W}{W} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ . \\ . \\ . \\ \lambda_n \end{bmatrix} \tag{5}$$

$$\lambda_{\max} = \frac{\lambda_1 + \lambda_2 + \cdots + \lambda_n}{n} \tag{6}$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{7}$$

If the CR < 0.1, the pairwise comparison is acceptable. Thus, the relative weights are calculated by finding the right Eigen vector (W) corresponding to the largest Eigen vector $\lambda_{\max}$.

4.2. Ranking using the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS)

Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is a classic MADM approach based on Euclidian Theory (Hwang and Yoon, 1981b), which confers the chosen outcome is near to the best ideal solution while far from the negative ideal solution. This TOPSIS is integrated with context-awareness concept and forms CTOPSIS. The context refers to the situation of decision making for the collaborative requirement of the user equipment. CTOPSIS method works well in obtaining the rank of the available RAT at the junction of decision making. The CTOPSIS gives the dynamics to the input criteria and also reflects in determining the best RAT. The procedure to compute the rank of RAT through the TOPSIS method should adhere to the following steps:

The decision matrix D is formed by the co-ordinated mapping of alternatives (RAT) to the shortlisted criteria of this proposed research. Each element is the intersection of the alternative (A) with the respective criteria (C) i.e A_iC_j where i = 1, …, total number of available RATs and j = 1, …, total number of selected criteria.

$$D = \begin{bmatrix} A_1C_1 & \cdots & \cdots & A_1C_n \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ A_nC_1 & \cdots & \cdots. & A_nC_n \end{bmatrix} \tag{8}$$

Normalizing the pairwise decision matrix: The decision matrix is normalized to apply the CTOPSIS method. The normalization is done as in Equation (9).

$$R_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m}}} where, i = 1, \ldots m; j = 1, \ldots, n \tag{9}$$

d_{ij} corresponds to the value of action i for j in decision matrix. Generating the normalized matrix by multiplying the normalized decision criterion R_{ij} with its assigned weight W_k. The weights obtained from CAHP method in is the input to obtain V_{ij} matrix. The V_{ij} is the actual data formed with the integration of alternatives and criteria weights. Further, computation compute the ideal positive and negative solution for the formed data. The computations are done through the Equations from 10 to 17.

$$V_{ij} = R_{ij} * W_k \; where, \sum_{k=1}^{m} W_k = 1 \tag{10}$$

Determine the positive ideal solution A^+ and negative ideal solution A^-

$$A^+ = V_1^+, \ldots, V_m^+ \; and \; A^- = V_1^-, \ldots, V_m^- \tag{11}$$

For desirable criteria,

$$V_1^+ = \max V_{ij}, j = 1, \ldots, n \tag{12}$$

$$V_1^- = \min V_{ij}, j = 1, \ldots, n \tag{13}$$

For undesirable criteria,

$$V_1^+ = \min V_{ij}, j = 1, \ldots, n \tag{14}$$

$$V_1^- = \max V_{ij}, j = 1, \ldots, n \tag{15}$$

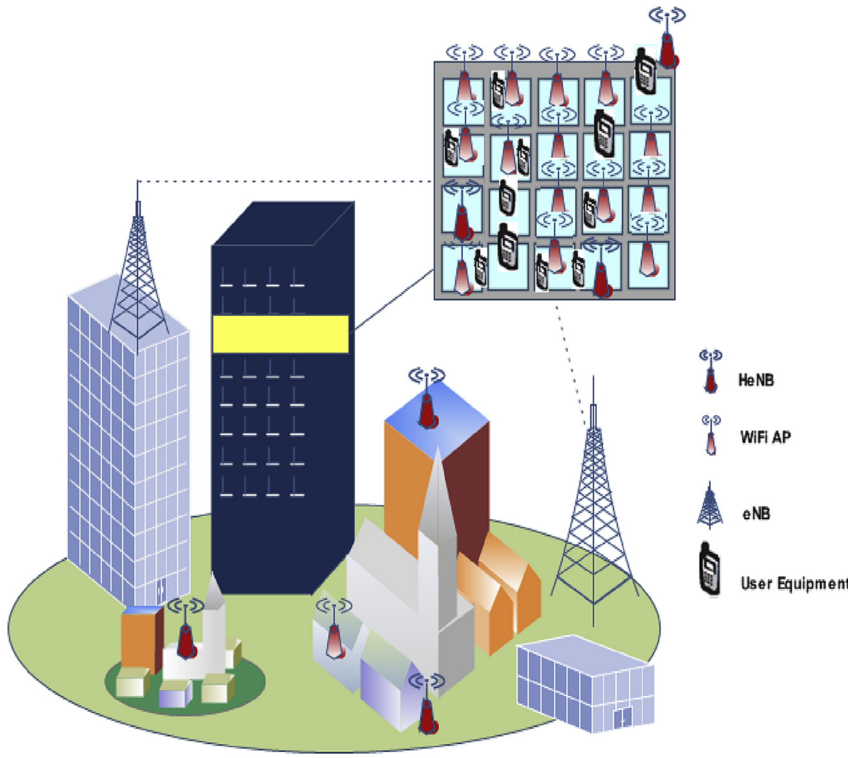

Fig. 4. Shopping mall scenario.

Calculate similarity distance

$$S_j^+ = \sqrt{\sum_{j=1}^{n} (V_i^+ - V_{ij})^2} \; where, j = 1, \ldots, n \tag{16}$$

$$S_j^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_i^-)^2} \; where, j = 1, \ldots, n \tag{17}$$

Ranking: Once the positive and negative ideal solutions are obtained the final rank vector C is computed as in Equation (18). The rank vector determines the ranking order of the RATs among the available once. The best RAT from the vector is chosen in descending order of ranking. The one with highest rank is the best RAT.

$$C_j^* = \frac{S_j^-}{S_j^+ + S_j^-} \; where, j = 1, \ldots, n \tag{18}$$

5. Performance evaluation

The proposed CRAT is implemented and validated in NS3 simulation environment. Then, Its performance is evaluated in smart city environment considering two scenarios, namely shopping mall which depicts the small area of UDN environment and urban city which replicates the wider area of UDN environment. It is contemplated that in UDN environment of 5G networks smart city, many small cells will be available to handle UEs connections (3GPP, 2013), Specifically, femto WiFi (IEEE 802.11n) and Home evolved Node Base Stations (HeNBs) are integrated to form UDN environment.To represent an actual smart city environment, The proposed system comprises Long Term Evolution release 13 (LTE) macrocell, HeNBs, and WiFi as a femtocell in RAT selection.

LTE A2A4-RSRQ (Kaloxylos et al., 2014) approach was chosen to compare with our proposed CRAT selection mechanism. The A2A4-RSRQ approach is formed by two events, namely event A2 which occurs when serving cell Radio Signal Receiving Quality (RSRQ) becomes greater than the threshold, and event A4 occurs when the neighbour cell RSRQ becomes better than the threshold. In short, A2A4-RSRQ mainly is an imperative approach in RAT selection merely based on the link quality. In contrast, the CRAT amalgamates the multiple criteria in RAT selection. The following sub-sections measure the performance of CRAT and A2A4-RSRQ approaches in terms of number of handover, packet delivery ratio, throughput, and delay by varying the number of devices with time.

5.1. Shopping mall scenario

The shopping mall is one of the scenario chosen to replicate the smaller UDN environment with multiple RATs. Fig. 4 represents the graphical view of shopping mall scenario. The detailed description of the simulation parameters is provided in Table 4.

The shopping mall test case is formed with four rows of femto cells, assuming each shop there is an access point and a pedestrian corridor in the middle. The femtocell is formed from HeNB or WiFi AP. The macrocell is the LTE release 13 central base station that co-exists at a distance of around 1200 m in a typical urban suburb location. It is further assumed that several UE's are either static or moving at pedestrian speed varying from 0.4 m/s, 0.8 m/s, and 1.4 m/s randomly. The shopping mall single floor is considered for implementation simplicity. The focus is purely on RAT selection during the handover and the impact of the proposed CRAT on the number of handovers, attainment of throughput, packet delivery ratio, and the delay.

The performance of CRAT is compared with the A2A4-RSRQ approach within the same environment. The Fig. 5 articulates the impact of varying the UEs on the packet delivery in both approaches. The graph represents the number of devices on the x-axis and the respective PDR on the y-axis. The time of simulation is fixed to 600 s to measure the PDR. The PDR is the ratio of the data packets delivered to destination to the packets sent from the source. The results taken for the presented scenario of varying UE exhibit better hit rate of PDR in the given time slice of CRAT approach.

Table 4
Simulation parameters for shopping mall scenario.

Environment	Shopping mall 1 floor 100*200 m per floor 20 rooms per floor (2 rows of 10 equal rooms)
User Equipment	Number of user equipment (mobile - smart phone) vary with time between 50 and 300
RATs	LTE-A and 802.11n
Number of WiFi Access points	20
Number of (H)eNBs	2 eNBs,3 HeNBs
Simulation Time	600s
UE mobility	Random walk ranging: 0.4 m/s, 0.8 m/s, 1.4 m/s
HeNB load	Varying depending on the number of associated UEs (very low, low, medium, high, very high)

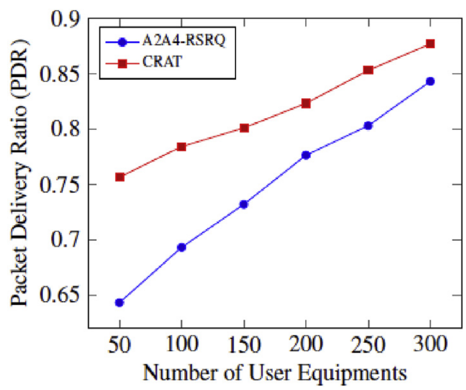

Fig. 5. The impact of varying user equipment in PDR.

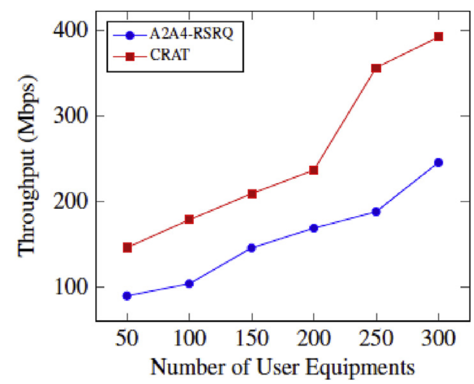

Fig. 6. The impact of varying user equipment for throughput.

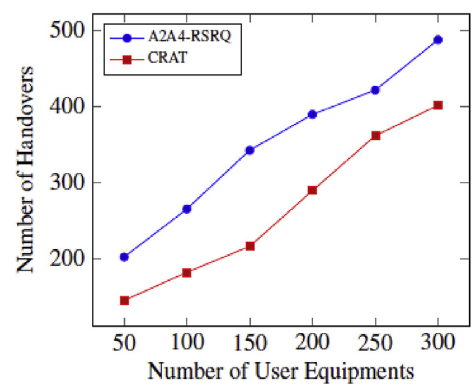

Fig. 7. The impact of varying user equipment for handover event occurrence.

It can be inferred that CRAT, in spite of combining multiple attributes, outperformed the imperative link based approach in RAT selection. The increase in the number of UEs does not affect the performance of the CRAT. This is because the priority of the criteria sensitivity at the instance of taking the call to trigger the initiation and decision making, overrides the increase in UE criteria within the mechanism to achieve better PDR. The context prioritises the flow of packets based on the traffic type, which is maintained by the Quality Channel Index (QCI) indicated from the standard for any type of flow to attain better PDR, in turn serving the user demand efficiently across the small cell.

Fig. 6 describes the throughput attained within the time slice of 600 s by the UE ranging from 50 to maximum 300, CRAT with the increase in devices attains better throughput comparatively. The A2A4-RSRQ throughput is also increasing with the devices increase, however it was not able to attain the performance of CRAT, iterating the fact that imperative A2A4-RSRQ is fundamentally depending on the link quality only. The CRAT approach prioritises the application requirement and collaboratively determines the triggering and determining the RAT. The attainment of throughput is due to the priority to the UE demand and also, right map of the demand to network resource which can serve better rather than just switching RATs and assuming the signal strength is sufficient to provide satisfactory services. The proposed CRAT serves the UE with better service attaining a higher throughput in comparison to the A2A4-RSRQ approach.

Fig. 7 depicts the number of handover measurement in the case of both the approaches, which is one of the important metrics in UDN heterogeneous scenario. The CRAT reduces the number of handovers caused by the imperative link based handover in A2A4-RSRQ approach. The traditional approach handover is imperative, meaning the system is programmed such that first, the handover is triggered if the current serving RAT signal strength is diminishing or second, if the neighbouring RAT signal is better than the current RAT. In both the cases handover is triggered irrespective of the requirement of the event at that moment of UE and network. This is a serious issue in case of UDN because the RATs are closely deployed and imperative approach will cause unnecessary handovers very frequently. This can be checked by the proposed context-aware MADM approach, where the decision is based on different criteria and priorities with the collaborative assessment of network resource availability and UE demand. As a result of the CRAT approach, the number of handover is reduced comparatively with the imperative approach.

The findings for average network delay of RAT selection is compared between both approaches, and CRAT reduces the delay in spite of multiple criteria, due to the priority in criteria and context base decision, whereas, the link based approach delay is noticeably high in comparison with CRAT for 300 UEs. The findings in terms of network delay is the end-to-end delay of network since the beginning of the simulation to the end to find the RAT selection within the execution duration of the proposed approach. The delay is reduced because the decision is based on UE and network context as well as according to the availability, the selection is done without waiting for signal quality alone. Hence, all these lead to minimum delay and better performance is achieved. The findings are described in Fig. 8.

The traditional RAT selection is based on RSS and its constituent components. Where's the context-aware aggregates the information about the network and the user to form a context has explained in Fig. 3.

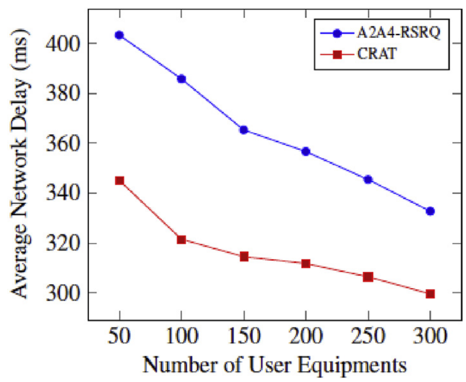

Fig. 8. The impact of varying user equipment for average network delay.

The context-aware RAT selection in this article is proposed for the Ultra-Dense Network, i.e the densified user devices in a cell area. The UE to the RAT cannot just get connected arbitrarily. It needs a mechanism to connect based on certain constraint. This constraint is the context aggregation in this article based on formulating criteria. The provider's information is stored in the context database and matched with the user requirement for the context management. The heap of data collected need to prioritize based on the priority of the requirement. In general the time complexity is the unit of time taken to accomplish the whole task. In general the time complexity is, If m criteria are formulated based on the context described. And, n RATs are available for the selection for the UE. Input: n RATs in the vicinity and m criteria pertaining to each of the RAT for UE to make choice. Output: Choice of best RAT for the UE requirement. The computing for the exhaustive search and sorted match would take O(n) computations.

5.2. Urban city scenario

The Urban City is another case taken to demonstrate the performance of the CRAT in smart city environment, where this scenario is UDN with wider area and more number of macro and femto cells present as compared to shopping mall case. Also, the UEs are more and scattered more than the shopping mall. The urban city consists of UE movement from building to building, home offices, and across roads in a larger city location. Fig. 9 demonstrates the urban city scenario graphical representation and Table 5 describes the simulation parameters for the urban city scenario.

The performance evaluation of the CRAT in comparison to the A2A4-RSRQ approach was made. Also, the performance was measured in terms of packet delivery ratio, throughput, number of handovers, and delay. Figs. 10–13 present the performance evaluation for urban city scenario for the above mentioned metrics. The detailed network parameters of the simulation are mentioned in Table 5. Unlike to the shopping mall scenario, the urban city scenario illustrates a larger area of UDN with different RATs across a wider range. The shopping mall was confined to a single floor. However, the urban city considers a wider area to measure the performance of CRAT against the traditional A2A4-RSRQ approach. The results are drawn for the varying number of user equipment from 200 to a maximum of 1200 devices at the time interval of 600 s.

From the findings it was noticed that even though there was an increase in the number of devices, the CRAT performed well in terms of both metrics. The packet delivery ratio is comparatively better in CRAT approach than the link approach. Due, to the priority to the class of traffic, the context approach yields better PDR, consequently the through-

Fig. 9. Urban city simulation scenario.

Table 5
Simulation parameters for urban city scenario.

Environment	The bureaucrat offices
User Equipment	Number of user equipment vary with time between 150 and 1000
RATs	LTE-A and 802.11n
Number of WiFi Access points	30
Number of (H)eNBs	4 enBs, HenBs- 20
Simulation Time	600s
UE mobility	Random walk ranging: 0.4 m/s, 0.8 m/s, 1.4 m/s
HeNB load	Varying depending on the number of associated UEs (very low, low, medium, high, very high)

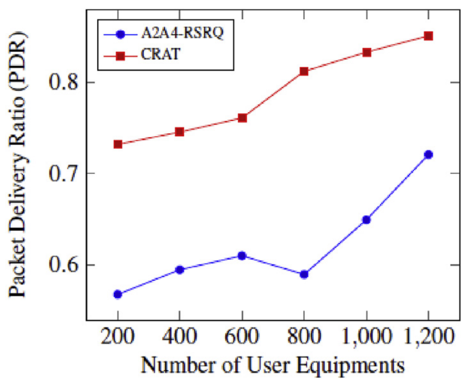

Fig. 10. The impact of varying user equipment in PDR.

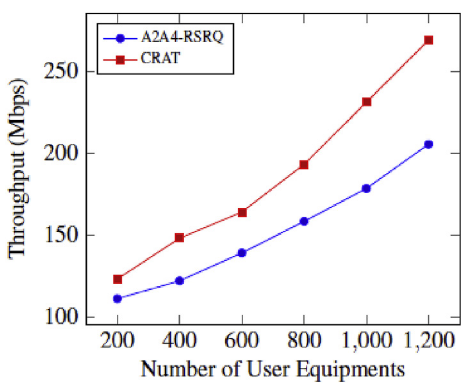

Fig. 11. The impact of varying user equipment for throughput.

put is also improved. The imperative method falls short in both the metrics because it merely considers link quality in the selection process. The results of PDR can be seen in Fig. 10 and the throughput in Fig. 11.

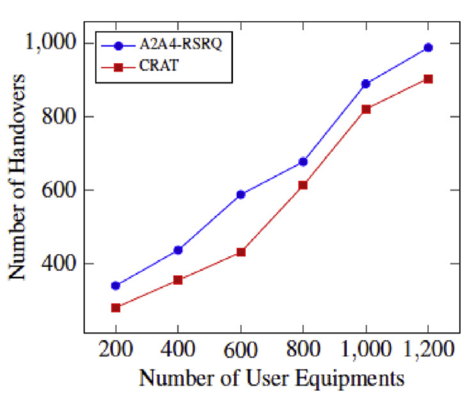

Fig. 12. The impact of varying user equipment for handover event occurrence.

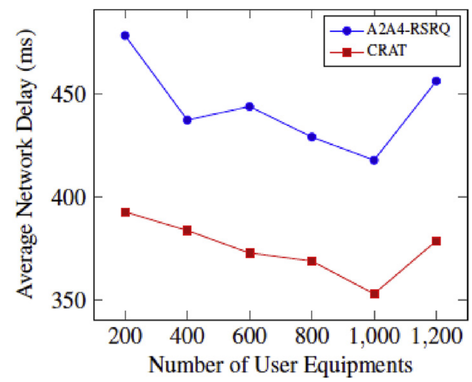

Fig. 13. The impact of varying user equipment for average network delay.

Fig. 12 reflects the number of handovers in CRAT and A2A4-RSRQ approaches for UDN in urban city scenario. The number of handovers are less in CRAT approach than the traditional A2A4-RSRQ event based approach. Hence, the results reiterate the fact that the context based decision is more efficient in RAT selection for the next wireless wave of UDN heterogeneous environment.

Fig. 13 shows the average network delay which is calculated for the RAT selection process since the beginning of the simulation to end only. The delay is less compared to the imperative approach because the handovers occur less and it is reduced when the decision is context based. In turn, the throughput also increases.

The findings with varying devices and fixed time revealed that the CRAT is better in all of the four measured metrics. In summarising the findings of both scenarios and the four metrics, the CRAT performed relatively well in spite of the increase in UEs. In general, the PDR is enhanced by 21.22%, and throughput is better by 42.68%. The number of handovers are reduced by 46.66% and the delay is reduced by 17.19% for the given scenario of shopping mall and urban city configuration by CRAT as compared to the A2A4-RSRQ approach.

6. Conclusion

This paper describes the development of an efficient RAT selection mechanism for UDN smart city environments, and evaluation of its performance via NS3 network simulation. We propose a simplified conceptual model of the Context-aware RAT selection, which eases the deployment of CRAT while at the same time keeps the essential features of the context management. Furthermore, we introduce a mathematical model of CRAT considering the user and the network context, using AHP for weighting the importance of the selection criteria and TOPSIS for ranking the available RATs. Then, we implement the proposed CRAT mechanism in NS3 network simulator and validate its performance by comparing the obtained experiments' results of CRAT with the conventional A2A4 approach. We evaluate CRAT using two different scenarios, namely the shopping mall and the urban city by varying the environment parameters to measure the performance of the proposed mechanism in a close to real situation. The obtained results show that CRAT outperforms A2A4 in terms of throughput, packet delivery ratio, number of handovers and average network delay. In summary, CRAT can help to enhance user experience within the smart city environment. In the future work, we plan to consider different selection criteria, such as security, cost, operator's revenue and evaluate CRAT performance with other RAT selection approaches.

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Adib Habbal (SM'15) is a Professor (Associate) of Computer Engineering at Karabuk University, Turkey. Before joining Karabuk University in 2019, he was a senior lecturer at Universiti Utara Malaysia (ten years) and head of InterNetWorks Research Platform (three years). He also served as IEEE UUM Student Branch Founding Counselor and Executive Council Member of the Internet Society Malaysia Chapter. Dr. Habbal received his Ph.D. degree in Computer Science (specializing in Networked Computing) from Universiti Utara Malaysia.
Dr. Habbal has received a number of recognitions from Universiti Utara Malaysia (UUM) for his outstanding educational and research activities including the Excellent Service Award (2010), Best Research Award (2014), Prolific Writer Award (2016) and many others. He has been the recipient of Internet Society Fellowship to the Internet Engineering Task Force (IETF), an IEEE Malaysia Section Best Volunteer Award, and an Asia-Pacific Advanced Network (APAN) Fellowship. Dr. Habbal is a senior member of the Institute of Electrical and Electronic Engineers (IEEE).
Dr. Habbal's research projects have been funded by several organizations, including IEEE R10, IEEE Malaysia Section, Internet society, Malaysian Ministry of Higher Education, Universiti Utara Malaysia and others. He has over 80 publications in journals and conference proceedings in the areas of Future Internet, and performance evaluation. His professional experience includes being a speaker at a number of renowned research conferences and technical meetings such as IEEE, internet2, APAN, and APRICOT, an editor for top tier and refereed journals, a technical program committee for IEEE conferences on computing networks as well as an examiner for postgraduate scholars in his research areas. His research interests include Future Internet protocols and architecture, 5Th Generation Mobile Networks, as well as Blockchain Technology and Digital Trust.

Swetha Indudhar Goudar (S'14) Dr. Swetha Indudhar Goudar is an Associate Professor in Department of MCA, Gogte Institute of Technology, Belagavi, Karnataka, India. She received a BCA degree from Karnataka University, India and MCA degree from Visvesvaraya Technological University, India in 2005 and 2008 respectively. Obtained PhD in Computer Science from InterNetWorks Research Laboratory, Universiti Utara Malaysia, Malaysia in 2017. She was fellow for SANOG XXIV, held at Greater Noida, India in 2014. She is actively involved in IEEE activities, also was an executive member of the student chapter for two consecutive terms. She was a student delegate of the Japan-Asia Exchange Program in Science administered by Japan Science and Technology, held at the Shibuara Institute of Technology, Tokyo, Japan, 2016. She has carried out many industrial and academic projects in computer applications. Her current research activities focus on Future Internet, Data Science and 5G mobile networks. She is the author of many research articles Published in good journals.

Suhaidi Hassan received his BS degree in Computer Science from Binghamton University, New York, his MS degree in Information Science (with concentration in Telecommunications and Networks) from the University of Pittsburgh, Pennsylvania and his PhD degree in Computing (specializing in Networks Performance Engineering) from the University of Leeds in the United Kingdom. He is the Professor of Computing Networks and the founding chair of the InterNetWorks Research Laboratory, at the School of Computing, Universiti Utara Malaysia (UUM). Prof. Suhaidi Hassan is a senior member of the Institute of Electrical and Electronic Engineers (IEEE), and actively involved in both IEEE Communications and IEEE Computer societies. He is also the Internet Society (ISOC) Fellow alumni to the Internet Engineering Task Force (IETF). In 2006, he was nominated as a WKD Foundation (Switzerland)'s Young Scientist Fellow at the World Knowledge Dialogue, in Crans-Montana, Switzerland. In the same year, he led a task force for the establishment of the ITU-UUM Asia Pacific Centre of Excellence (ASP CoE) for Rural ICT Development, a human resource development initiative of the International Telecommunication Union (ITU) which serves as the focal point for all rural ICT development initiatives across the Asia Pacific region. He has authored and co-authored more than 200 refereed technical publications, successfully supervised 18 PhD scholars in the area of computer and communication networks, served as reviewer and referee for journals and conferences on computing networks as well as the examiner for more than eighty doctoral and postgraduate scholars in his research areas