Journal of Network and Computer Applications 85 (2017) 94–105

Contents lists available at ScienceDirect

Journal of Network and Computer Applications

journal homepage: www.elsevier.com/locate/jnca

Intelligent deployment of UAVs in 5G heterogeneous communication environment for improved coverage

Vishal Sharma[a], Kathiravan Srinivasan[b,*], Han-Chieh Chao[c,d,e,f], Kai-Lung Hua[g], Wen-Huang Cheng[g,h]

[a] Computer Science and Engineering Department, Thapar University, Patiala, Punjab, India
[b] Department of Computer Science and Information Engineering, National Ilan University, Yilan County, Taiwan, R.O.C
[c] College of Mathematics and Computer Science, Wuhan Polytechnic University, Wuhan, China
[d] Department of Electrical Engineering, National Dong Hwa University, Hualien, Taiwan, R.O.C
[e] Department of Computer Science and Information Engineering, National Ilan University, Yilan, Taiwan, R.O.C
[f] School of Information Science and Engineering, Fujian University of Technology, Fujian, China
[g] Department of Computer Science and Information Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan, R.O.C
[h] Research Center for Information Technology Innovation (CITI), Academia Sinica, Taipei, Taiwan, R.O.C

A R T I C L E I N F O

Keywords:
UAVs
5G
Heterogeneous Networks
Interference
Capacity

A B S T R A C T

With hard requirements of high performance for the next generation mobile communication systems, especially 5G networks, coverage has been the crucial problem which requires the deployment of more stations by the service providers. However, this deployment of new stations is not cost effective and requires network replanning. This issue can easily be overcome by the use of Unmanned Aerial Vehicles (UAVs) in the existing communication system. Thus, considering this as a problem, an intelligent solution is presented for the accurate and efficient placement of the UAVs with respect to the demand areas resulting in the increase in the capacity and coverage of the wireless networks. The proposed approach utilizes the priority-wise dominance and the entropy approaches for providing solutions to the two problems considered in this paper, namely, Macro Base Station (MBS) decision problem and the cooperative UAV allocation problem. Finally, network bargaining is defined over these solutions to accurately map the UAVs to the desired areas resulting in the significant improvement of the network parameters, namely, throughput, per User Equipment (UE) capacity, 5th percentile spectral efficiency, network delays and guaranteed signal to interference plus noise ratio by 6.3%, 16.6%, 55.9%, 48.2%, and 36.99%, respectively in comparison with the existing approaches.

1. Introduction

Unmanned aerial vehicles (UAVs) have made a mark in the area of networking with provisioning of continuous support to the network devices. This connectivity has improved the data rate which is the primary requirement of the 5G networks. With solutions to the CAPEX/OPEX issues, UAVs allow a vast range of applications in the heterogeneous networks. The next-generation heterogeneous networks aim at providing high data rate with improved coverage and capacity by deploying network facility in all the components. The use of multiple devices is the key aspect of the heterogeneous networking. These networks can be used to resolve the problems related to high stream data transfers (Shuai et al., 2011; Cheng et al., 2007). These networks aim at increasing the data rate, serving user demands for 100% availability and lesser delays in transmissions (Bor-Yaliniz and Yanikomeroglu, 2016). These networks although gel well with the fronthaul and the backhaul of the existing network formations, yet these are not capable of providing the full connectivity and coverage to all the users in the particular area (Li et al., 2014).

A traditional heterogeneous network comprises of the macro base station (MBS), small cells, femtocells and picocells for connectivity users (Hossain et al., 2014; Bennis et al., 2013). According to the architecture suggested under METIS, METIS2, and 5GPP, small cells, Radio Access Networks (RANs), Cloud-RANs form the crucial part of the 5G deployment (Osseiran et al., 2014). These components are the backbone of the high-speed transmission in these 5G networks. However, these small cells, femtocells, and picocells are to be deployed in larger number to serve the maximum users with high data rates. This

* Corresponding author.
E-mail addresses: vishal_sharma2012@hotmail.com (V. Sharma), kathiravan@niu.edu.tw (K. Srinivasan), hcc@niu.edu.tw (H.-C. Chao), hua@mail.ntust.edu.tw (K.-L. Hua), whcheng@citi.sinica.edu.tw (W.-H. Cheng).

http://dx.doi.org/10.1016/j.jnca.2016.12.012
Received 28 July 2016; Received in revised form 13 November 2016; Accepted 2 December 2016
Available online 05 December 2016
1084-8045/

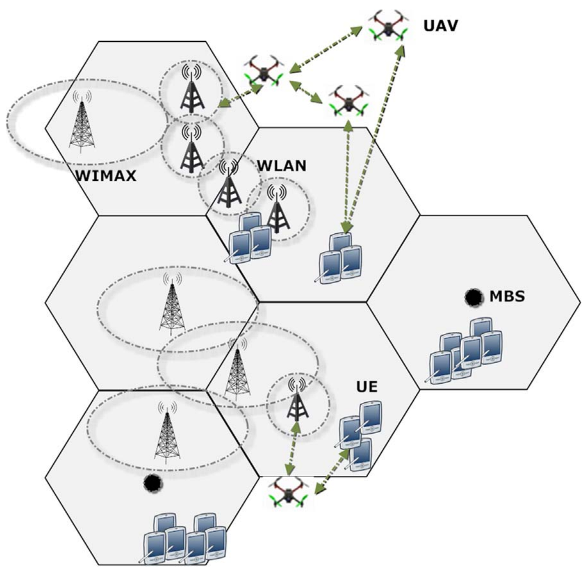

Fig. 1. An illustration of the UAV oriented heterogeneous networks.

deploying of more devices and access points can improve the capacity of the networks, but this also increases the network complexity and the cost to large extent (Curiac, 2016). It becomes relatively tough for the service providers to find the appropriate sites for the deployment of these devices and requires rigorous network planning which makes it complex to use them. An alternative approach is required which can not only improve the coordination but should be intelligent enough to take the decisions regarding the traffic regulations. Thus, UAVs can be a considered as an intelligent as well as reliable solutions to this problem of the next generation heterogeneous networks. UAVs can act as a pivot in the existing cellular infrastructure and can relay information between the stations and the cells efficiently; and can also provide direct support for connectivity between the user equipments (UEs), as shown in Fig. 1.

UAVs have already seen a lot of development and utility in the networks by acting as a centralized or autonomous device for prolonged connectivity between the users. However, the existing solutions aim only at the deployment of the UAVs as an alternative network node which can relay data and can handle extra users (Saleem et al., 2015). Positioning, mapping of UAVs to a particular area, load transfer delusions in the case of failures, cooperation and decision of deployment are still major issues which are to be resolved to provide improved coordination for increasing the capacity and the coverage of the existing cellular networks (Yaliniz et al., 2016; Galkin et al., 2016). Further, there exist some other approaches which use UAVs as ad hoc component and provide temporary connections between the other network nodes, but this does not stand with the continuous increasing demand of the users as well as does not provide a stable and a reliable solution for continuous support of high data rate demands. Handling more number of the users is one of the applications of these aerial vehicles. Deployment, mapping, and the requirement of UAVs to intelligently understand the network demand are not provided by the existing solutions. Thus, efficient approaches and models are required which can overcome these issues and can provide a stable and reliable ideology for capacity enhancement of the 5G heterogeneous networks.

In this paper, the coverage and capacity enhancement of the 5G heterogeneous networks are considered as the formal problem which is resolved using the UAVs. The proposed approach is initially derived for two different solutions. One of them focus on the formation of this as a decision problem for the MBS which has to decide where to place the UAVs, and the second focuses on the cooperative network formation which performs network bargaining between the UAVs to handle a particular demand area as well as for load balancing. The solutions to these problems are provided using the priority-wise dominance and the entropy approaches. The results obtained for the proposed approach shows significant improvement in terms of the network throughput, 5th percentile spectral efficiency, network coverage, signal to noise plus interference ratio, network delays, accuracy in the mapping of the demand areas with the UAVs, and delivery ratio. The proposed approach provides more stabilized network formations, a low-complex solution which provides a significant improvement in the gains for the above-mentioned parameters.

1.1. Network considerations and assumptions

The use of UAVs undoubtedly helps the modern day networking. But, there exist some limitations to these aerial vehicles such as the maximum load of UAV, length, and weight of the antenna, fuel/power consumption of UAV. All these issues are to be resolved for the efficient utilization of UAVs in the upcoming 5G networks (Mozaffari et al., 2015,). The load has been taken care of in this paper, but other aspects related to the physical properties such as the speed, length and payload are not evaluated and it is assumed that the UAVs are capable of supporting the network components. Although the results may vary when these issues are considered, yet the proposed approach provides an efficient ideology for the use of UAVs in the 5G networks. Apart from these, mobile handovers are assumed to be happening using the existing technologies. However, since UAVs are highly dynamic and high-speed mobile stations, these require efficient handover mechanisms for smooth transfer of services (Sharma et al., 2016a). In this paper, these handovers are operated using the existing media independent mechanisms. The actual analysis of the handovers for UAV-assisted networks will be presented in the future reports.

Rest of the paper is structured as follows: Section 2 provides insight of the existing literature for the use of UAVs in the next generation networks, Section 3 provides network model over which the proposed approach is formulated. Section 4 gives the details of the proposed approach with a complete overview of the problem. Section 5 evaluated the proposed approach and compares it with the existing state-of-art solutions. Finally, Section 6 concludes the paper with possibilities of future research.

2. Related work

The UAV oriented networking has evolved over the last decade. However, use of these aerial vehicles in the heterogeneous networks has opened new paradigms in the area of networking. With the upcoming 5GPP, UAVs will play an important role as a continuous network support device which can not only increase the capacity but will also improve the coverage of the existing networks. Coverage and capacity can also be improved without the use of the UAVs. But this will increase the operational cost of the network and will also increase the complexity as more complex algorithms will be applied to incorporate new network devices. Apart from increasing the capacity, these networks should also consider the network configurations and reliability in case of multi-UAV failures (Sharma et al., 2015a; De Freitas et al., 2010). Thus, efficient approaches are required which can provide prolonged connectivity with an increase in the network capacity and coverage along with the consideration of the network failures.

UAVs can be used in a cooperative formation to provide prolonged connectivity to the existing networks. Sharma and Kumar (2015) designed a cooperative framework which allowed the formation of a network between the aerial and the ground nodes. Their designed framework laid the foundation of guided network formations between the UAVs and the ad hoc networks on the ground. However, their work did not cover the core applications of the cellular networks and cannot be readily applied to the heterogeneous network formations. Further, the authors used the UAV oriented network to resolve various network issues such as broadcast storming in the existing network by using the proximity sensitivity routing which allows the non-redundant packet flow in the network (Sharma et al., 2015b). Another solution to the UAV oriented network is the formation of an opportunistic network which acts as a temporary network between the UAVs given by Sharma and Kumar (2015). Although this work improved the throughput, but it covers the aspects of networking only between the UAVs and not on the improvement of the ground networks.

Mozaffari et al. (2016) worked for the improvement of the network coverage by using multiple unmanned aerial vehicles. The authors proposed an approach which focuses on the altitude of the UAVs as an important factor for providing vast coverage. Although, the work is aligned with the one proposed in this paper, but the authors did not consider the mapping issues of UAVs with respect to the demand areas. Further, network dynamics are other issues which are yet to be resolved in their model. Guo et al. (2014) focussed on the use of UAVs as intermediate relays in the cellular networks. The authors focussed on the utilization of the small unmanned-aerial-vehicles (SUAV) as wireless relays for increasing the performance of the existing cellular networks. The work presented by the authors provide an insight of the experiment for network analysis covering the both stochastic geometry and multi-cell simulations. The analysis presented by the authors show that UAVs can provide more throughput even in areas of low connectivity. However, the deployment of the UAVs is not based on the intelligent approach and issues like spectral efficiency, interference is not considered in the conducted research.

Merwaday and Guvenc (2015) focussed on the increase of network capacity which improves the 5th percentile spectral efficiency of the network, especially in public safety networks. The authors considered the interference between the UEs but did not include the noise issues with the existing cellular networks. The authors also focussed on the improvement of the average throughput of the cellular network by incorporating UAVs with the traditional macro base stations. In an alternate to this work, Sharma et al. (2016a) developed an approach based on the reverse neural model for increasing the capacity of the UAV-assisted heterogeneous networks. The work presented by the authors not only improved the spectral efficiency but also lowers the delays in UAV deployment. The mapping of the UAVs and the areas is based on the cost based functions. Although the approach is more related to the one proposed in this paper, it is relatively more complex and slow as it uses neural networks to identify the demand areas. Further, this work does include the per UE capacity of the network while defining the network model.

Mozaffari et al. (2015, 2016) have provided a detailed analytical analysis on the use of drones in the existing cellular networks. The authors have presented a detailed study on the various challenges, design issues and the deployment constraints faced by the drone cell networks in the existing infrastructure. Also, the authors have clearly distinguished the tradeoff which occurs in the device to device communication when relaying through the UAVs. Various challenges and the detailed open issues presented are the key highlights of their work. Another use of the UAVs in the heterogeneous networks is for the application-oriented network formations. One of such applications in the heterogeneous wireless sensor networks using UAVs is attained by Erman et al. (2008) et al. in which the authors incorporated the UAVs with the sensor nodes to efficiently relay the information towards the base station. Considering the similar application of the UAVs, Sharma et al. (2016b) provided an efficient data dissemination in the traditional wireless sensor networks by the use of UAVs in place of the manager nodes to relay data efficiency towards the base stations. In these works, the authors improved the coverage of the existing sensor networks but the applicability is not provided for the public cellular networks. Also, the scope of their applications to other cellular networks is limited and requires further enhancement in their work to cover the aspects of the next generation networks.

3. Network model

The network comprises a set N of UAVs operating in either single or multiple layers such that each UAV has a radio range R. Each UAV is capable of handling a set K of users making continuous requests from a particular demand area. The number of requests S_r comes with an arrival rate of λ and mean packet size of each service request is $\frac{1}{\mu}$. Considering the omnidirectional antenna, the latitude of the UAVs is fixed at h. This altitude value is kept at an optimal value to allow better connectivity and coverage. No fixed formulation for the altitude is considered for the UAVs in this paper. In the analysis, h is altered to analyze the performance of the proposed approach on the varying scale. The deployment model of the UAVs in the heterogeneous networks considered two aspects; one is the single layer model with multiple UAVs, and the other is the multi-layer model with multiple UAVs in each layer. For the single layer model, the number of UAVs are decided on the basis of provisioning of the connectivity with the MBS and the number of user requests from a particular demand area. The number of UAVs for connection between the MBS and the demand area is calculated as:

$$|N| = \frac{Z}{R}, \tag{1}$$

where Z is the distance of the excessive demand area from the MBS as shown in Fig. 2, and for the full capacity link between the UAVs and the MBS, $|N|$ is given as $|N'|$ which is calculated as:

$$|N'| = \frac{S_r}{S_u}, \tag{2}$$

where S_u is the number of services requests a single UAV can handle. The set N stores the UAV-ID for each of the aerial vehicle used for intermediate connectivity. For the multi-layer model, the altitude is taken into account to distinguish between the UAVs of different layers. UAVs in the approximated equal altitude are considered to be in the same layer whereas the others are considered to belong to different layers. Each MBS has a limited number of UAVs, and in case all the UAVs are deployed in the network, the UAVs are arranged in a multi-layer model. In this model, the upper layer UAVs will act as the main pivot between the lower layer UAVs and the MBS. This pivot UAVs can support a number of UAVs by acting as an aerial base station for them. Although, this layered approach increases the cost as well as the complexity of the network formation, yet this approach provides stability and more reliable network formation in the case of limited number of UAVs. One of the scenario with multi-layered UAV is presented in Fig. 3. This model is also very useful in case of UAV failures or MBS failures. This model can also be further extended to provide the load balancing over a multi-layered UAV architecture. Now, the load/delay D_L for a user at location x in the UAV network with bandwidth ω is given by Sharma et al. (2016a), Samarakoon et al. (2014):

$$D_L(x) = \frac{\lambda}{\omega \log(1 + SINR(x)) \times \mu}. \tag{3}$$

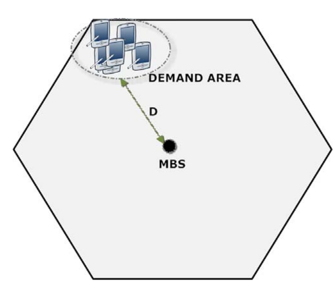

Fig. 2. An illustration of the distance calculation between the demand area and the MBS.

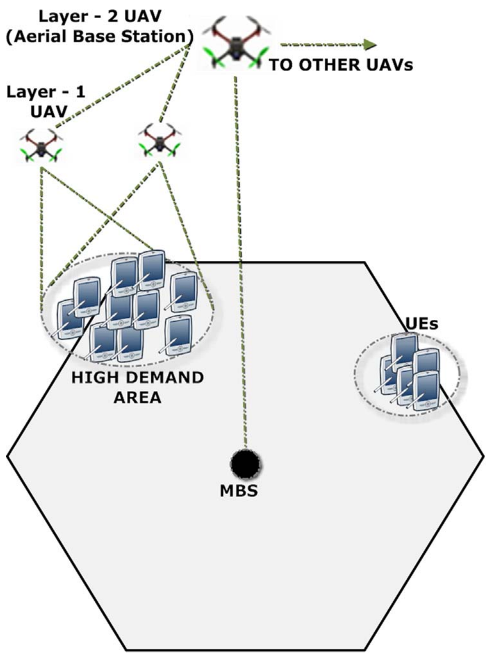

Fig. 3. An illustration of the multi-layered network formation with the UAVs.

For the complete network, the overall load is taken to be discrete as the user distribution varied with time and cannot be continuously similar in all the demand area, and thus, the complete area load A_L is calculated as:

$$A_L = \sum_{i=1}^{|B|} D_L(i). \tag{4}$$

$|B|$ denotes the number of demand areas formulated over the complete area A. Here, signal to noise plus interference ratio is considered from a particular UAV to a UE at location x is given as Sharma et al. (2016a):

$$SINR(x) = \frac{\frac{P\delta}{R^\eta}}{\sum_{i=1, i\neq x}^{n} \frac{P\delta}{R^\eta} + O}, \tag{5}$$

where P is the transmission power, δ is the antenna characteristic constant, η is the network pathloss, O is the noise. Thus, the spectral efficiency S_e for the user at location x is given as:

$$S_e = \omega. \frac{\log_2(1 + SINR(x))}{|K|}. \tag{6}$$

This spectral efficiency accounts for the entire users which make requests during the connectivity between the MBS and the UAVs. However, with increase in number of UAVs in the layered architecture, the network capacity suffers and this is presented in terms of per UE capacity U_C which is given by:

$$U_C = \frac{\omega}{\beta} \log\left(1 + \frac{\beta\frac{P\delta}{R^\eta}}{\sum_{j=1, j\neq i}^{|N|} \beta\frac{P\delta}{R^\eta} + O}\right), \beta < |K| \tag{7}$$

where β is the number of users below threshold SINR. The decrease in the β will improve the connectivity which will guarantee higher data rates to the users.

4. Proposed approach

The proposed approach aims at increasing the capacity and the coverage of the next-generation heterogeneous wireless networks by using UAVs as the coordinating node between the devices. The proposed approach aims at enhancing the mapping of the UAVs to a particular demand area with minimum delay and increased coordination. The network model presented in the previous section forms the basis of the UAV deployment and is further evaluated over two different problem sets. The problem targeted in this paper focuses on two different aspects; one is the UAV deployment considering the decisions from the MBS and the other is the UAV reconfigurability and arrangements allowing the formation of the self-sufficient UAV coordinated 5G network. These two problems and their solutions are presented as separate subsection and are then resolved by defining the efficient strategy to disseminate the services which can also relay even in the case of network errors and failures. The detailed solutions for these two problems are presented below.

4.1. UAVs deployment as a decision problem

In the traditional networks, the MBS is the controller of the macro cell which coordinates the deployment of the all other cell type formations such as small cell deployment. In this part, the MBS is considered to be the in-charge of tall the UAVs and also act as their charging station. In this initial approach for the capacity and coverage enhancement, the problem of the UAV deployment and the mapping to the particular demand area is subjected to the decision of the MBS. The MBS is considered to be the central authority which regulates the positioning of the UAVs in the macro cell so as to increase the data rate as well as the coverage. MBS takes a decision regarding the deploying of the UAVs and also decides on the strategy to be used for deploying. The final selection of the demand area for a UAV mapping is also performed by the MBS.

In this decision-based approach, the MBS divides the complete area into the priority zones on the basis of the user requests from them. The upper range of the user requests is accounted by the upper limit of the requests a UAV can handle as defined in the network model. For an area A, let A_1, A_2, …$A_{|B|}$ be the demand areas generating requests for extra users. Now, the complete request areas are assigned a priority value based on the number of requests pending in the particular zone provided that the number of requests pending is always less than or equal to the number of requests supported by a single UAV. The decision of the network topology is for the areas and is totally based on the priority value. The part of the area which is not included as the demand zone will either be handled using the multi-layer model or will be assigned a number of UAVs for direct connectivity with the MBS.

For the single layer network, the UAVs deployment has to be efficient such that maximum coverage and capacity is attained for the complete network. This priority-based approach defined on the number of the user requests gives a formal ideology for deploying UAVs and also provides a support for the selection of the continuous relay. Consider the example shown in Fig. 4, the figure presents the three demand areas with notation A_1, A_2 and A_3, in the order of priority $A_1 > A_3 > A_2$ decided on the basis of the number of user requests generated at the same instance. Now, considering this priority, the UAVs are allocated to these areas in the same order of the priority. This approach is a decision-based approach and is completely dependent upon the MBS's active involvement. The accurate assignment of the priority is the key to the success of this approach. This decision approach provides a stabilized solution to the single layer deployment where the total demand is always less than or equal to the total users a single UAV can support. However, these can be a case when the number of UAVs is limited and there is a large possibility that some of these UAVs are not actively available to be deployed. In such cases, the multi-layered model provides a stable connectivity for the areas with higher demands than that supported by the single UAV. These areas/zones require a highly stable and self-sufficient network which can be intermittently used to relay with the final MBS. One of the UAV will act as the aerial base station providing a pivotal support to the other UAVs, thus, increasing the capacity of the overall network. However, there is

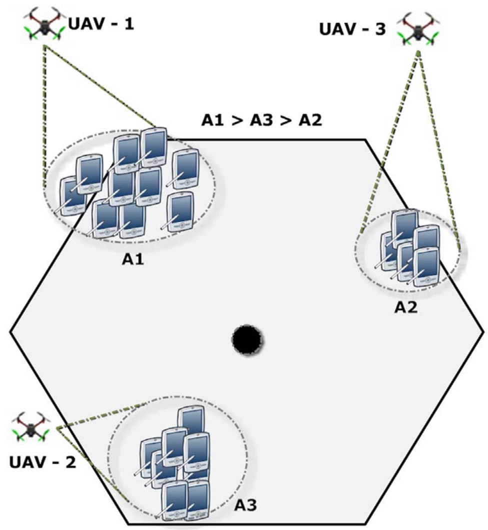

Fig. 4. An illustration of priority wise UAV allocation.

always a chance of more consumption of the network resources in case of the multi-layer deployment, but the CAPEX/OPEX issues with these multi-layer deployments are not large enough to affect the network performance. As UAVs are rechargeable and re-configurable, the deployment of the UAVs as the multi-layered node can be efficient and reliable in most of the cases except for those in which the pivotal UAV or the aerial base station fails.

4.2. UAVs deployment as a cooperative problem

The cooperative problem deals with the independent network formation using the UAVs without any dependency on the MBS for deployment decision. This deals with the main aspect of deploying the UAVs autonomously by their own decisive power. The UAVs are fed with the demand areas and the requests generated over these areas, and then these aerial vehicles take an intelligent decision to deploy themselves; and also decides on relaying even in the case of UAV failures or network losses. This problem of the cooperative network formation is derived from the “Game Theory” as the “Network Bargaining Problem” and is solved the aspects of game theory by defining the entropy of each UAV and the demand areas (Nagaraj, 2009; Gupta and Kapoor, 1997). The goal of the network is to minimize the entropy of the network which is carried out by minimizing the entropies of the UAVs and the demand areas altogether.

The entropy of the area E_A is defined as the request entropy and is calculated on the basis of the demand areas with pending service requests as:

$$E_A = -\sum_{i=1}^{|B'|} \frac{1}{|B'|} \log\left(\frac{1}{|B'|}\right), B' \subseteq B. \tag{8}$$

Here, B' is the demand areas with pending service requests. The entropy for the UAV E_U is defined as the number of UAVs which are available for handling the service requests and the number of users in the demand areas which is calculated as:

$$E_U = -\sum_{i=1}^{|K'|} \frac{1}{|K'|} \log\left(\frac{1}{|K'|}\right), K' \subseteq K. \tag{9}$$

Here, K' is the number of users which are to be handled by the UAV from the pending demand areas. The network entropy is dependent upon the UAV and the area entropy which aims at minimizing them which results in the formation of a stable network with improved coordination and capacity. This allocation strategy provides an efficient cooperative solution to the UAVs mapping with the desired demand area with a low-complexity.

4.2.1. Network bargaining for UAV allocation

The network bargaining refers to the decision formation between the agents (UAVs) to decide on the location for supporting the excessive demand of users over the particular geographical location. The entropy based formulation helps in the controlled and optimized positioning the UAVs considering the entropy of the both the area and the UAVs. The procedure for the network bargaining allows the formation of the decision matrix which is then used to take the final decision regarding the UAV positioning and mapping to a particular demand area. Network bargaining value N_B is derived on the overall network entropy. When the overall network entropy acquires minima, the N_B converges towards the maximum i.e.,

$$N_B \propto \frac{1}{E_T}, \quad E_T = \gamma_1 E_A + \gamma_2 E_U, \tag{10}$$

where γ_1 and γ_2 are the probabilistic entropy constant with values in the range $(0, 1)$.

Lemma 1. *With an increase in the network interference, the per UE capacity of the network decreases, which results in the increase of the pending service requests from a particular demand area. This causes an increase in the overall network entropy resulting in decrease in the network bargaining causing poor mapping between the UAVs and the demand areas.*

Proof. Considering the relation between the U_C and the SINR from the Eq. (7),

$$U_c \propto SINR \tag{11}$$

and

$$U_c \propto \frac{1}{\beta} \tag{12}$$

SINR is the signal to noise plus interference ratio. This is defined in the Eq. (5). According to this equation, the SINR will decrease with increase in the network interference by a UAV for a particular user. Also, with more users not getting the appropriate SINR, the U_C decreases (Ref. (7)). Now, considering the Eqs. (8) and (9), it is clear that with increase in users with unhandled service requests, the number of demand areas will increase which will increase the overall entropy resulting in the decrease in the N_B (Ref. (10)). With this decline in value of N_B, the solution of the cooperative problem converges towards the maxima resulting in very high entropy which causes poor mapping between the UAVs and the demand areas. Thus, the arguments given in this text justifies the context of the Lemma 1 regarding the mapping between the UAVs and the demand areas. □

Thus, it can be concluded from this lemma that the success of the proposed cooperative problem depends on the accurate mapping of the UAVs to the demand areas which will not only increase the per UE capacity of the network but will also cause less interference, resulting in the increase in the users above the threshold SINR.

4.2.2. Mapping procedure for reducing the network entropy

The mapping of the area for the cooperative problem is performed over the game theory application of the entropy. According to this approach, the entropy of the UAVs and the demand areas are used to calculated the final entropy of the network with each UAV marked to all the demand areas. The values of these mapping are stored in the matrix as shown in Table 1.

Algorithm 1. UAV to Area Mapping: Decision and Cooperative Solution

Input: $|K|$, $|A|$, $|N|$
Output: UAV to Area mapping
Initialize Network
Compute $|A|$ /* the demand areas for the entire

Table 1
Decision matrix for E_U and E_A ($E_{T,1,1} = \gamma_1 E_{A,1} + \gamma_2 E_{U,1}$).

E_U / E_A	U_1	U_2	U_3	U_4	U_5
A_1	$E_{T,1,1}$	$E_{T,2,1}$	$E_{T,3,1}$	$E_{T,4,1}$	$E_{T,5,1}$
A_2	$E_{T,1,2}$	$E_{T,2,2}$	$E_{T,3,2}$	$E_{T,4,2}$	$E_{T,5,2}$
A_3	$E_{T,1,3}$	$E_{T,2,3}$	$E_{T,3,3}$	$E_{T,4,3}$	$E_{T,5,3}$
A_{Total}	$E_{T,1,1-3}$	$E_{T,2,1-3}$	$E_{T,3,1-3}$	$E_{T,4,1-3}$	$E_{T,5,1-3}$

network */
5: Sort ($|A| \longleftarrow S'_r$, $descend'$) /* Arrange the demand areas in descending order of the user requests*/
6: **if** ($S_r < S_u$) **then**
7: Proceed with either decision problem or cooperative problem
8: **if** (UAVs already at the MBS) **then**
9: A=Prioritize(A) /*Compute the priority of the demand area*/
10: max (Prioritize(A)) $\longleftarrow U$ /* Allocate UAVs in higher order of priority*/
11: Launch and trace the UAV activity
12: **else**
13: Proceed with the cooperative solution
14: $E_A = -\sum_{i=1}^{|B'|} \frac{1}{|B'|} \log(\frac{1}{|B'|})$, $B' \subseteq B$ /*Calculate the entropy for the area */
15: $E_U = -\sum_{i=1}^{|K'|} \frac{1}{|K'|} \log(\frac{1}{|K'|})$, $K' \subseteq K$ /*Calculate the entropy for the UAV */
16: $E_T = \gamma_1 E_A + \gamma_2 E_U$ /*Calculate the network entropy */
17: $D_{\mathcal{M}}$=matrix ($E_{\mathcal{U}}$,$E_{\mathcal{A}}$) /*Mark the values and store in the decision matrix */
18: $U = \min(D_{\mathcal{M}}, E_A)$ /*Select the UAVs with minimum entropy values with respect to area*/
19: $U \longrightarrow \max E_T$ /*Allocate UAVs in the descending order of entropy*/
20: Use the free UAVs as a backup or for aerial base station
21: Iterate till all the areas are not mapped
22: **end if**
23: **else**
24: Find area with $A_L \geqslant S_r$ /* Mark the area with excessive service demands*/
25: perform the steps (7)–(21) with other area with less service demands
26: **If** (More UAVs are available with MBS) **then**
27: allocate more UAVs to the excessive service demand area
28: **else**
29: Re-arrange the nearest UAVs into the layered topology
30: Select the saved UAV as the aerial base station
31: iterate till all the areas are not mapped
32: **end if**
33: **end if**
34: Exit and start transmission

Algorithm 2. Selection of the Cooperative Decision Controller.

1: **Input**: $|K|$, $|N|$, $|A|$
2: **Output**: Cooperative Decision Controller
3: Initialize Network
4: **while** (transmission is not completed) **do**
5: Find U, A /*the number of UAVs deployed and the demand areas*/
6: $E_A = -\sum_{i=1}^{|B'|} \frac{1}{|B'|} \log(\frac{1}{|B'|})$, $B' \subseteq B$ /*Calculate the entropy for the area */
7: $E_U = -\sum_{i=1}^{|K'|} \frac{1}{|K'|} \log(\frac{1}{|K'|})$, $K' \subseteq K$ /*Calculate the entropy for the UAV */
8: $E_T = \gamma_1 E_A + \gamma_2 E_U$ /*Calculate the network entropy */
9: $D_{\mathcal{M}}$=matrix ($E_{\mathcal{U}}$,$E_{\mathcal{A}}$) /*form the decision matrix */
10: find $U = \min(E_T)$ /*Find the UAV with the minimum entropy value and maximum occurrences*/
11: **if** (UAV is not allocated to demand area) **then**
12: Mark the UAV
13: **else**
14: Mark Next $U = \min(E_T)$
15: **end if**
16: Select the marked UAV as the cooperative decision controller
17: **if** ($E_{\mathcal{T}}$(current)!= $E_{\mathcal{T}}$(previous)) **then**
18: iterate
19: **else**
20: exit
21: **end if**
22: **end while**

(a) The mapping formed from the entropy of the network allows accurate positioning of the UAV over a demand area resulting in the increase in the capacity and the coverage of the heterogeneous networks. For the considered example, as shown in Table 1, let the values attain the following rules after final calculations: For the area A_1, $E_{T,1,1} < E_{T,2,1} < E_{T,4,1} < E_{T,5,1} < E_{T,3,1}$. For the area A_2, $E_{T,2,2} = E_{T,4,2} < E_{T,5,2} < E_{T,3,2} < E_{T,1,2}$, and for the area A_3, $E_{T,2,3} = E_{T,5,3} < E_{T,4,3} < E_{T,1,3} < E_{T,3,3}$.

(b) Select the UAVs and the areas with the minimum combination for the overall network entropy i.e. check for the column and identify the UAVs which attain minimum for the particular area. From the considered example, A_1: U_1, A_2: U_2, U_4, and A_3: U_2, U_5. This approach can also be reversed to allocate the area to the UAVs. However, allocation of the UAVs to the area is low-complex as UAVs can be assigned to any area whereas the inverse requires calculation of the UAV load as well.

(c) Now, select the area with the minimum entropy value. The area with the highest entropy gets a UAV first so as to stabilize the complete network. In the considered example, $A_1 > A_3 > A_2$. Thus, the same order is used for allocating the UAVs.

(d) Allocation is performed to satisfy the minimum entropy requirement of the network as this will satisfy the one complete demand zone and then the free UAV can be used as layered for the network with extremely large entropy.

(e) Considering the allocation scheme described above, the UAVs will be allocated as follows: A_1 will be directly assigned the U_1. In the case of the area not survived by the single UAVs, the next UAV in the order of priority is selected which is not requested by the other demand areas. For A_3, there are two possibilities between the U_2 and U_5. Out of these two, the one with distance closer to the demand area is select. For this example, U_5 is mapped to the A_3. Now, because of this allocation, A_2 is also left with two possibilities, following the same distance rule, U_2 is allocated to the A_2 with UAVs U_4 acting as a reserve which can act as an aerial base station in case of requirement of the multi-layered network model.

(f) These steps allow allocation of the UAVs to the demand area in single iterations. However, with an increase in the demand areas and the number of users in the particular area, these steps are repeated again till minima is attained for the overall entropy.

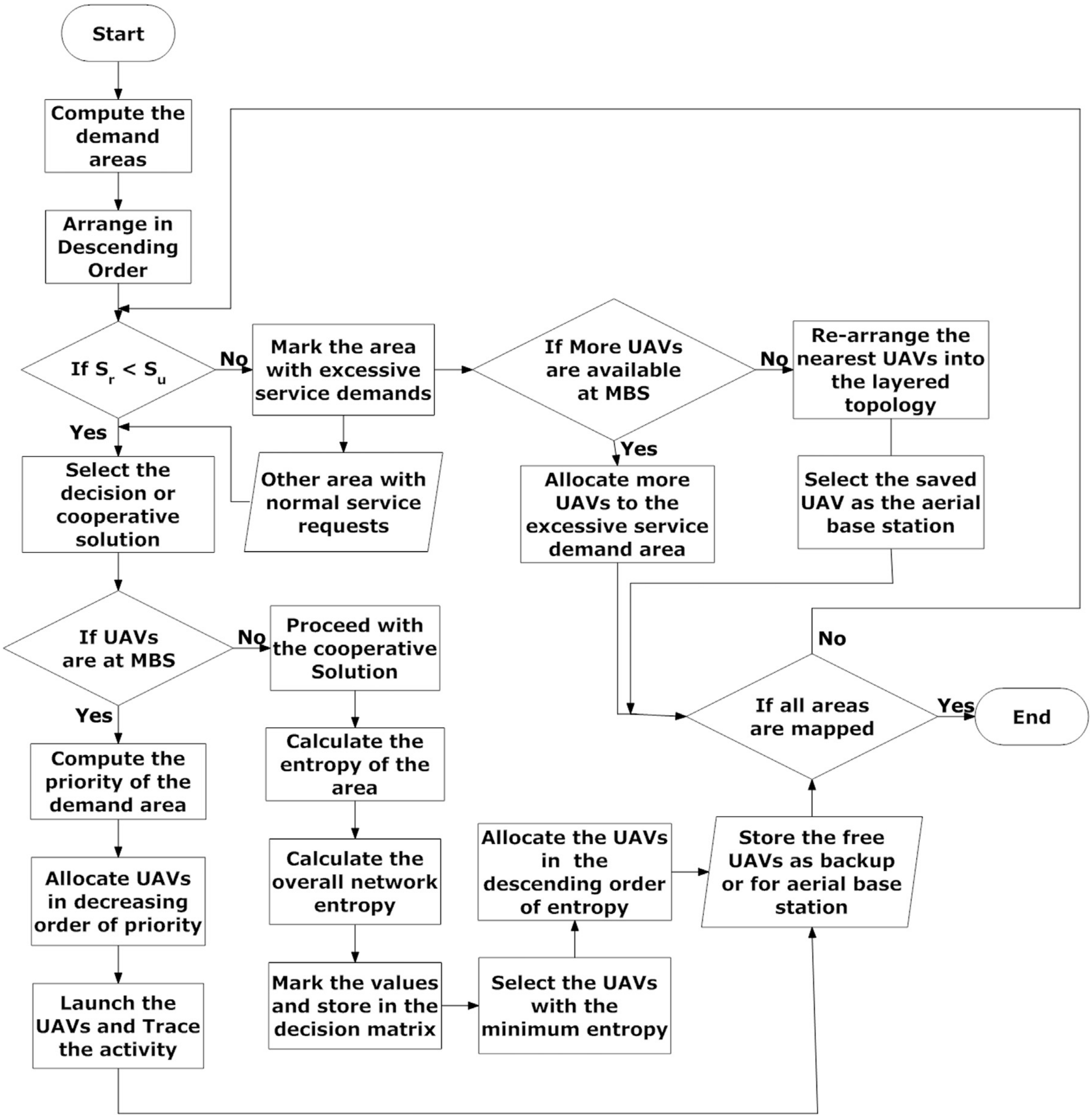

Fig. 5. Flow chart for UAV to area mapping.

4.2.3. Selection of the UAV controllers over the demand area

The complete solution to the above-defined approaches is derived either over the MBS or the UAVs depending upon the type of solution adopted for the solution of UAV to demand area mapping. The complete procedure for the mapping of the demand areas to the UAVs considering the both UAV and the MBS is presented in Algorithm 1 and as a flow chart in Fig. 5. For the cooperative solution to the demand area mapping with the UAVs, the UAV with the least entropy value at the start of the network and with a maximum number of occupancy in the decision matrix is taken as the cooperative decision controller. All the calculations, command, and control are performed by this decision controller. The UAVs with varying number of users and service requests will undergo update rule to allow the selection of the next optimal UAV as the decision controller during the entire network operations. The steps for the selection of the cooperative decision controller during the entire network sessions are presented in Algorithm 2.

4.2.4. Lifetime enhancement for prolonged connectivity

The lifetime of UAVs play a key role in the next generation wireless networks. These aerial vehicles are battery operated. Even the best of available UAVs are not capable of long-duration flights, and thus, requires strategies either to improve the battery performance or alternatives during battery recharging. Three different approaches can be used to overcome these issues. First is the optimized usage of batteries for UAVs as suggested by Saha et al. (2012). The authors have carried out research to optimize the battery performance of the UAVs by predicting the lifetime of batteries depending upon the load. This approach can be directly integrated with the proposed approach and the battery performance can easily be monitored depending upon the network load. The prognostic framework given as a function of load can actually help in optimizing the network lifetime as well as the load effect on the UAV batteries. Further, use of multiple batteries is another suggestion in this framework. However, this directly affects the payload of the aerial vehicles. The second solution is the energy efficient deployment of UAVs considering the energy resources available with the UAVs. This is suggested by Sharma et al. (2016b). The model suggests the energy efficient deployment can enhance the lifetime of UAVs-assisted networks. This approach can be directly applied to the selection of the demand zones which would not consume much of the UAV energy resources. Also, this selection can be done on the basis of the available energy resources. According to the system model defined in Sharma et al. (2016b), the energy consumption E_C of the network assisted by UAVs is given as:

$$E_C = \sum_{i=1}^{|N|} \left(\sum_{j=1}^{|K|} PC_j \right) \times t, \tag{13}$$

where PC_j is the unit power consumption for j^{th} UE for the time t. Also, the energy depletion E_d for entire network assisted by UAVs is given as:

$$E_d = \frac{E_{TX} + E_P}{A_L}, \tag{14}$$

where E_{TX} is the transmitter energy and E_P is the receiver processing energy. The Eqs. (13) and (14) can be used to identify the areas which would lead to more depletion of UAV energy resources. On the basis of these calculations, a decision can be taken to serve the demand areas with the energy requirement within the available range despite the priority as stated in the proposed approach. This should be applied only when the energy is a critical issue during deployment. The third approach is the charge and serves approach. In this approach, the MBS monitors each of the deployed UAVs for their left out battery resources. As soon as the battery of a UAV reaches a critical mark, the MBS instructs the UAV to return back to base for recharging and at the same time, the already charged UAV is sent in its place. Although this approach is a slightly complex as it involves shift of services and more handovers, but this can serve the purpose of prolonging the lifetime of the UAV-assisted networks.

All the three approaches suggested in this section can serve the purpose of prolonging the lifetime of UAV-assisted networks. However, energy harvesting in these networks can be targeted as a separate issue and battery optimization can be considered as a vast area of research.

5. Performance evaluation

The proposed approach aims at improving the coordination as well as the capacity and coverage of the heterogeneous wireless networks by providing an efficient approach for UAV to area mapping. The proposed approach uses entropy based decision policies to locate the UAVs in the area of a macro base station to support the extra users over the network operational time. The proposed approach is analyzed using the numerical simulations over an area of 10000×10000 sq.m. maneuvered by a maximum of 12 UAVs per MBS. The service requests from the users are considered to be following Poisson Distribution with users attaining a mean of 400 over the network with an initial rate of 256 Kbps. The other parameters configured for analyzing the performance of the proposed approach are shown in Table 2.

Table 2
Parameter configurations.

Parameter	Value	Description
A	10000×10000 sq. m.	Simulation area
MBS	10	Number of macro cell base station
$\|N\|$	12 (per MBS)	Maximum number of UAVs
R	500–800 m	Radio range of UAVs
S_u	200	Service requests handled by each UAV
O	−174 dBm/Hz	Noise
$\frac{1}{\mu}$	1024 B	Packet Size
h	200,500 Feet	UAV altitude
$\frac{\lambda}{\mu}$	256 kbps	Offered traffic
η	4	Path loss exponent
δ	−11 dB	Transmission constant
P	35 dBm	UAV transmission power
S_r	100 per zone	Maximum service requests
ω	10–12 MHz	System bandwidth
$\|K\|$	400–500	Active users
$SINR$ Threshold	0.5	Probabilistic SINR Threshold

The proposed approach was evaluated for the extra number of users which generates service requests for network operational time of 1000 s. A total of 50 runs were taken to evaluate the average performance of the proposed approach with altitude varying between 200 and 500 feet. Altitude of UAVs is a major concern for the networks depending upon the use of UAVs as these flying devices have to follow the guidelines and cannot fly beyond the specified range. Thus, fixing the altitude for the UAVs is altogether an issue yet to be handled. Further, the tradeoff between the quality of service/experience to the UEs and the altitude needs to be further analyzed before deploying the actual networks. However, this tradeoff is beyond the scope of this paper and it evaluates the proposed approach only in a specified altitude for the UAVs. The network performance was recorded for the parameters defined in the network model and was compared with one of the similar neural-based approaches (Sharma et al., 2016a) which also aims at enhancement of the capacity of the heterogeneous networks. Performance evaluation and comparative plots for the evaluation of the proposed approach with the neural-based approach are presented considering the average values attained for 50 runs:

5.1. Throughput coverage

Throughput is the important measure of performance for a network when dealing with the capacity and coverage issues. Throughput coverage provides the increase in the network capacity when an extra number of users are added to the network which generates service requests by utilizing the same bandwidth. The throughout coverage is measured in a number of bits transferred per second per hertz. The proposed approach utilizes the mapping of UAVs to the area by defining the network entropy which takes less time in computations than the neural approach which is considered for the comparison. The proposed approach allows efficient network formation by allocating the UAVs to the demand areas in either single cooperative formation or the multi-layered arrangement depending upon the scenario and network conditions. The comparison for improvement in the throughput coverage with respect to the increase in the UAVs is shown in Fig. 6. The proposed approach utilizes the network bargaining and cooperative formations which allow serving of the UEs with higher data rates. The proposed approach is an intelligent greedy approach that aims at serving UEs at higher data rates. However, the existing neural approach depends only on the accurate identification of the demand areas. Thus, does not always guarantee higher throughput coverage. Also, the analysis presents that the proposed approach provides better throughput coverage with an increase in the users in the particular macro cell. Although the throughput coverage decreases with increase in the users in the same area, but this decrease in the proposed

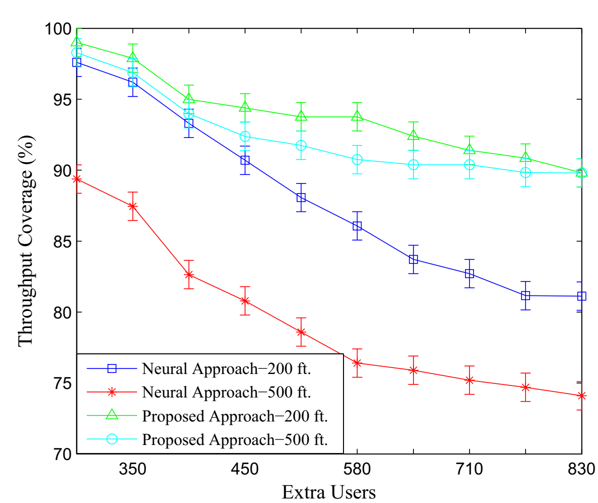

Fig. 6. Throughput coverage vs. extra users.

approach is very less in comparison with the existing neural approach. Further, the proposed approach provides an improvement of 6.3% in comparison with the neural based UAV allocation with varying altitude of the UAVs. Altitude also affects this coverage. With an increase in the height of the UAVs from a demand area, the distance increases and with its range beyond the radio range, throughput coverage decrease. Thus, a limited number of users are provided with the appropriate data rate.

5.2. Network delays

Network delays are the other important metric to be evaluated for analyzing the performance of the proposed approach. Delays account for the transmission, processing, queuing, and propagation delay. The network delays allow the analysis of the quality of service which will be provided to the end users. The network delays should be less enough that the service of the network is not affected. If the delays are allowed to increase beyond a certain range, the network may suffer from losses which may result in the final shutdown. This may affect the entire cellular system and will also decrease the quality of service to the end users. The proposed approach was evaluated over the similar network model as that of neural-based approach. The transmission and the propagation delay does not account for the much effect on the network performance of both the approaches. The major difference is caused by the processing delays. Since the other approach is based on the neural model, it is relatively slow and requires more time to perform the necessary computations. However, the proposed approach provides the UAVs to area mapping in a single iteration, thus, causing fewer delays over the complete connectivity time even with the increase in the number of users. Fig. 7 shows the comparison plot for the network delays between the proposed approach and the neural approach over the varying altitude. The analysis suggests that the altitude has much effect on the delays, as the increase in the height decreases the throughput coverage and also limits the packets arriving at the users, thus, increasing the delays with the increase in extra users as well as the altitude. However, the proposed approach causes 48.2% lesser delays than the neural based UAV deployment. This gap in the delay further increases with the height, as the increase in altitude has less effect on the proposed approach. Thus, it can be evaluated that the proposed approach is capable of providing better services to the end users with fewer delays.

5.3. Probability of guaranteed SINR to users

The signal to noise plus interference ratio is the key parameter which identifies the type of link services allocated the end users. With accurate mapping, the signal quantity must be high to sustain heavy traffic without any loss especially due to the device to device interference. Using UAVs as relays cause interference between the users from the same demand area. Thus, the approach should be capable of providing high SINR to end users. The proposed approach was evaluated for the probability of guaranteed SINR to end users with an increase in extra users in the same area. This probability denotes the service level to each user. The plot presented in Fig. 8 shows that the proposed approach allowed coverage of the complete area, thus, provides appropriate SINR to every user in the network. With better throughput coverage, signal to noise ratio is improved despite the increase in a number of users. The network bargaining allows selection of the entropy state which offers better SINR than the existing solution. For the analysis of the network, the threshold for the SINR was fixed at 0.5. Any approach that provides this value below the threshold cannot provide a reliable connectivity in the network. The SINR is also affected by the altitude of the UAVs. UAVs operating over more height offer lesser capacity enhancement because of poor signal quality than those operating at an appropriate height as that of their radio range. The proposed approach provided 36.99% better probability for SINR to extra users than the neural approach. Further, with better SINR to the end users, the capacity of the network also increases which make the network stable and reliable.

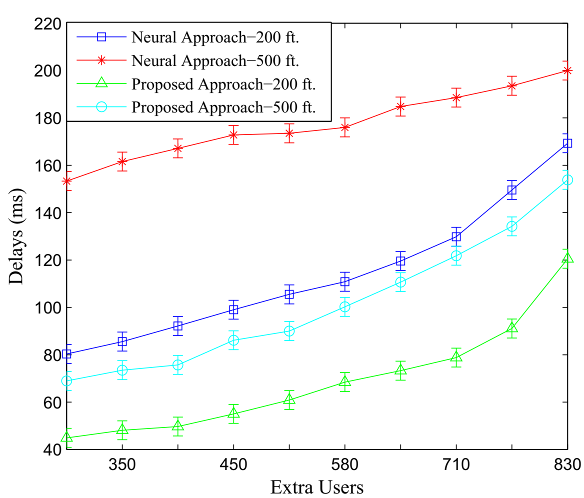

Fig. 7. Network delays vs. extra users.

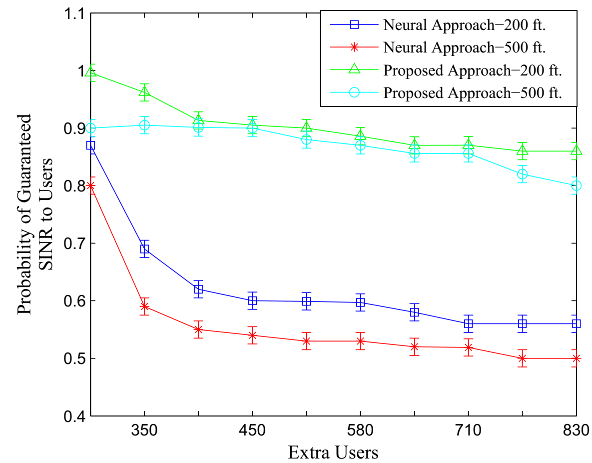

Fig. 8. Probability of guaranteed SINR vs. extra users.

5.4. Spectral efficiency

Spectral efficiency accounts for the improvement in the 5th percentile spectral efficiency of the network which provides better connectivity to the end users at higher data rates. With the accurate and optimized mapping of the UAVs to the demand areas and the low iteration based solution, the proposed approach provides better spectral efficiency for the complete network even with the increase in the number of users. However, with an increase in the number of users and the altitude varying towards the high value, the spectral efficiency decreases and attains a minimum. Thus, the placement of the UAVs at the appropriate location can overcome this issue and can increase the spectral efficiency of the network by efficient utilization of the network bandwidth and by increasing the signal to interference plus noise ratio. Fig. 9 presents the comparison of the proposed approach and the neural approach for the improvement in the 5th percentile spectral efficiency of the network. The low-iteration and high accuracy in mapping increases the SINR which in turn improves the spectral efficiency by 55.9% in comparison with the neural approach. Also, this improvement justifies the term of capacity and coverage enchantment of the heterogeneous networks by the proposed approach.

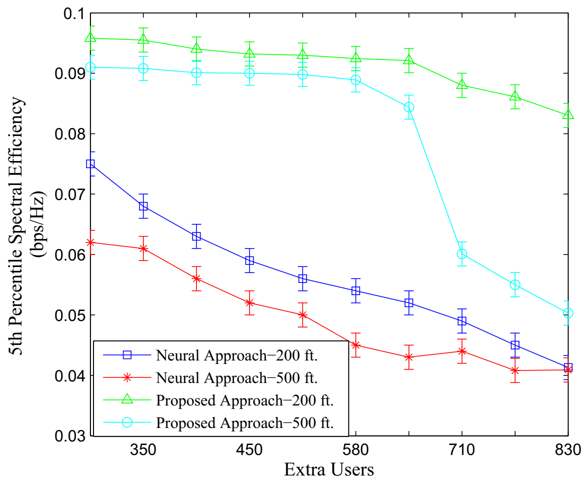

Fig. 9. 5th Percentile spectral efficiency vs. extra users.

5.5. Packet delivery ratio

Packet delivery ratio (PDR) is the measure of the successful packets received by the users to the total packets transmitted towards it. With the improvement in the throughput coverage, better data rates are attained in the network which in turn improves the packet delivery ratio. In the existing solutions, data dissemination is treated as a separate entity and the entire focus is given to the routing and relay selection for the transfer of packets in order to improve the PDR. However, PDR can be improved to a large extent by improving the network data rate which can be attained by improvement in the bandwidth utilization. The proposed approach provides better throughput coverage, better utilization of the network bandwidth which allows attainment of the higher data rates resulting in the increase in the network PDR. The analysis was traced for the comparison of the PDR with the network operational time. With time, the UAVs cover more areas and provide better SINR to most of the users, thus, more UEs are covered with higher data rates. This increases the overall PDR and allows the formation of the high capacity network. Fig. 10 presents the comparison of the PDR with respect to the network operational time with variation in the UAV altitude and number of users for the proposed and the neural approach. With the increases in operational time, more users are covered by the UAVs which show an approximate exponential growth for the PDR. The proposed approach increases the network PDR by 11.59% even with variation in the UAV altitude.

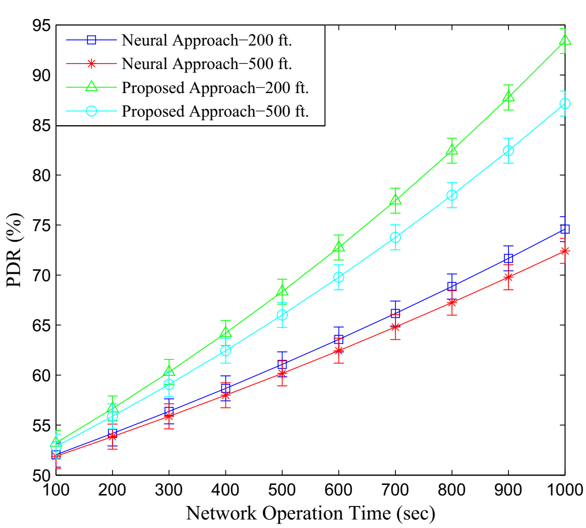

Fig. 10. Packet delivery ratio vs. network operational time.

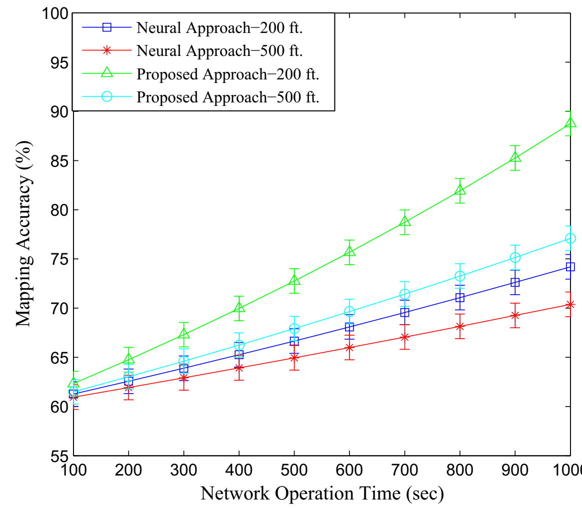

Fig. 11. Accuracy in UAV to area mapping vs. network operational time.

5.6. Accuracy in mapping

The success of the proposed approach lies in the accurate mapping of the UAVs to the demand area. Two approaches are used in the proposed model for accurate mapping of the UAVs to the demand areas depending upon the siltation and the network scenario. With decision and cooperative solutions based on the priority and the entropy of the network and area, the proposed approach placed UAVs more accurately in the entire network providing maximum coverage. The proposed approach places the UAVs in the single iteration provided there is no abrupt increase in the number of users in a particular demand area. The accuracy can be attained by other approaches also, but the proposed solution uses a single iteration based entropy decision matrix to allocate the UAVs to the demand areas, thus, decreasing the time of allocation along with the increase of the accuracy in mapping. Fig. 11 shows the comparison for the accuracy in the mapping of UAVs to the demand area. The proposed approach provides 5.2% more accuracy than the neural approach for allocation as the neural approach has to rely on its learning for the allocation of the UAVs to the demand areas whereas the proposed approach uses the entropy-based decision matrix for allocating the UAVs.

5.7. Enhancement in the per UE capacity

The other measure of the performance is per UE capacity of the network. With the increase in the SINR for most of the users, the per UE capacity of the network increases. Lower interference also accounts for an efficient network formation which improves the capacity of the network. A network with higher capacity links to the UE provides better data rates and more stable and reliable connections with improved coordination. The per UE capacity of the network is dependent on the number of users below the defined threshold SINR. Fig. 12 shows that with the increase in the SINR to the users in the macro cells, the number of users below the threshold SINR decreases which increases the per UE capacity of the network. Also, this increase is more than that provided by the neural approach by 16.6%. Further, this increase in capacity improves connectivity which enhances the coverage of the heterogeneous wireless networks. Also, this capacity enhancement can be further exploited to handle more users in the same area.

5.8. Extra users handled

All the results presented above are submerged into this parameter which tells about the extra number of users handled by the UAVs by accurate mapping over the desired demand area. With lesser iterations,

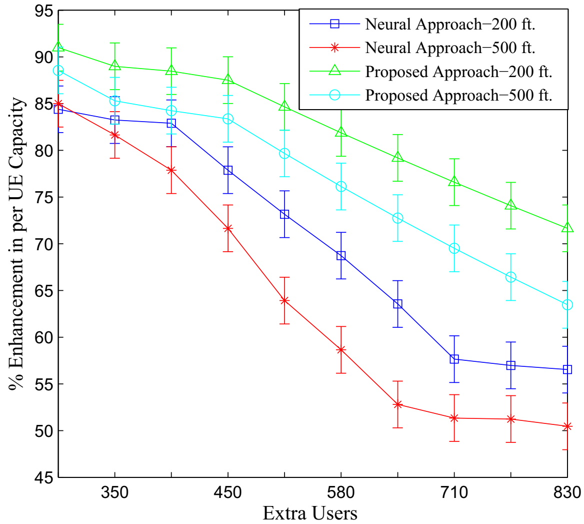

Fig. 12. Enhancement in the per UE capacity vs. extra users.

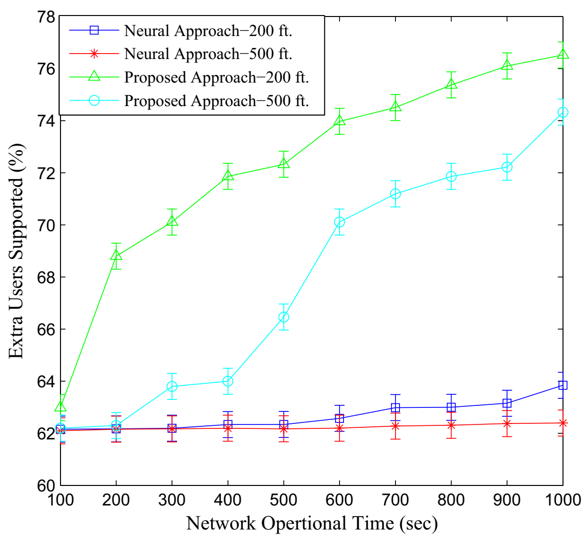

Fig. 13. Extra users handled vs. network operational time.

the changes in the network can be immediately handled by the proposed approach. Also, the increase in the SINR and the per UE capacity allows more UEs to be accommodated in the same area with higher data rates. The proposed approach utilizes this feature of improved throughput coverage and better spectral efficiency to cover more users in the complete network. Fig. 13 presents the comparative plot with varying height of the UAVs with respect to the network operational time for the proposed and the neural approach. The neural approach is quite slow because of its learning phase whereas the proposed approach can provide a low-complex solution with lesser iterations causing an increment of 8% in the number of extra users handled by the proposed UAV network.

The results presented for the throughput coverage, network delays, spectral efficiency, SINR to users, and the increase in the per UE capacity of the network presents the efficient formation of the UAV network for capacity and coverage enhancement of the existing heterogeneous wireless networks. Further, the 5GPP is accounted for the use of UAVS to improve the coordination and connectivity between the end users resulting with higher data rates. This approach can be used to map the demand areas with the UAVs on the basis of requests generated by the users either at the MBS level or autonomously using the proposed decision and the cooperative approach.

6. Conclusion

Coverage and capacity enhancement of the next-generation heterogeneous wireless networks are the biggest issues as more and more devices are making requests at the same time. Unmanned aerial vehicles (UAVs) can provide a pivotal support to regulate the data in these networks to improve the coordination as well as the coverage. UAVs can be used to relay information as well as can be used as an aerial base station to facilitate the users for data sharing with the macro base station. In the worst case of base station failures, these UAVs can provide a layered support for data sharing with other macro base stations. In this paper, an MBS based decisive and the cooperative approach is presented for the accurate mapping of the UAVs to the demand areas resulting in the increase in the capacity and coverage of the heterogeneous networks. The proposed approach utilizes the entropy-based network formation to select the UAV controller and performs network bargaining which results in the improvement of the network throughput, SINR, per UE capacity and decrease in the network delays and the errors in the mapping of UAVs to the demand areas. The performance of the proposed approach is presented in terms of the significant improvement in these parameters with variation in the number of users and altitude of the UAVs. In future, energy efficient UAV deployment and load balancing can be taken as other issues for further enhancement of the demonstrated results.

Apart from this, UAVs dynamics like speed, altitude and heading can be further investigated before their actual deployment in 5G networks.

References

Bennis, M., Simsek, M., Czylwik, A., Saad, W., Valentin, S., Debbah, M., 2013. When cellular meets wifi in wireless small cell networks. IEEE Commun. Mag. 51 (6), 44–50.

Bor-Yaliniz, I., Yanikomeroglu, H., 2016. The new frontier in ran heterogeneity: Multi-tier drone-cells. arXiv preprint arXiv:1604.00381arXiv:1604.00381.

Cheng, W.-H., Wang, C.-W., Wu, J.-L., 2007. Video adaptation for small display based on content recomposition. IEEE Trans. Circuits Syst. Video Technol. 17 (1), 43–58.

Curiac, D.-I., 2016. Towards wireless sensor, actuator and robot networks: conceptual framework, challenges and perspectives. J. Netw. Comput. Appl. 63, 14–23.

De Freitas, E.P., Heimfarth, T., Ferreira, A.M., Pereira, C.E., Wagner, F.R., Larsson, T., 2010. Decentralized task distribution among cooperative uavs in surveillance systems applications. In: Wireless On-demand Network Systems and Services (WONS), 2010 Proceedings of the Seventh International Conference on, pp. 121–128, IEEE.

Erman, A.T., Hoesel, L.v., Havinga, P., Wu, J., 2008. Enabling mobility in heterogeneous wireless sensor networks cooperating with uavs for mission-critical management. IEEE Wirel. Commun. 15 (6), 38–46.

Galkin, B., Kibilda, J., DaSilva, L.A., 2016. Deployment of uav-mounted access points according to spatial user locations in two-tier cellular networks. In: 2016 Wireless Days (WD), pp. 1–6, IEEE.

Guo, W., Devine, C., Wang, S., 2014. Performance analysis of micro unmanned airborne communication relays for cellular networks. In: Communication Systems, Networks & Digital Signal Processing (CSNDSP), Proceedings of the 9th International Symposium on, pp. 658–663, IEEE.

Gupta, S., Kapoor, V., 1997. Fundamentals of applied statistics. Sultan Chand & Sons, ISBN: 8180545288.

Hossain, E., Rasti, M., Tabassum, H., Abdelnasser, A., 2014. Evolution toward 5g multi-tier cellular wireless networks: an interference management perspective. IEEE Wirel. Commun. 21 (3), 118–127.

Li, C., Zhang, J., Letaief, K., 2014. Throughput and energy efficiency analysis of small cell networks with multi-antenna base stations. IEEE Trans. Wirel. Comm. 13 (5), 2505–2517.

Merwaday, A., Guvenc, I., 2015. Uav assisted heterogeneous networks for public safety communications. In: Wireless Comm. Conference Workshops (WCNCW), pp. 329–334, IEEE.

Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2016. Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs. arXiv preprint arXiv:1509.01187arXiv:1509.01187, pp. 1–32.

Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2015. Drone small cells in the clouds: Design, deployment and performance analysis. In: IEEE Global Communications Conference (GLOBECOM), Wireless Networks Symposium, pp. 1–6.

Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2016. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage, arXiv preprint arXiv:1606.01962arXiv:1606.01962.

Nagaraj, S.V., 2009. Entropy-based spectrum sensing in cognitive radio. Signal Process. 89 (2), 174–180.

Osseiran, A., Boccardi, F., Braun, V., Kusume, K., Marsch, P., Maternia, M., Queseth, O., Schellmann, M., Schotten, H., Taoka, H., et al., 2014. Scenarios for 5g mobile and wireless communications: the vision of the metis project. IEEE Commun. Mag. 52 (5), 26–35.

Saha, B., Quach, C.C., Goebel, K., 2012. Optimizing battery life for electric uavs using a bayesian framework. In: Aerospace Conference, 2012 IEEE, pp. 1–7, IEEE.

Saleem, Y., Rehmani, M.H., Zeadally, S., 2015. Integration of cognitive radio technology with unmanned aerial vehicles: issues, opportunities, and future research challenges. J. Netw. Comput. Appl. 50, 15–31.

Samarakoon, S., Bennis, M., Saad, W., Latva-aho, M., 2014. Opportunistic sleep mode strategies in wireless small cell networks. In: Communications (ICC), 2014 IEEE International Conference on, pp. 2707–2712, IEEE.

Sharma, V., Kumar, R., 2015. A cooperative network framework for multi-uav guided ground ad hoc networks. J. Intell. Robot. Syst. 77 (3–4), 629–652.

Sharma, V., Kumar, R., 2015. An opportunistic cross layer design for efficient service dissemination over flying ad hoc networks (fanets). In: Electronics and Communication Systems (ICECS), 2015 Proceedings of the 2nd International Conference on, pp. 1551–1557, IEEE.

Sharma, V., Kumar, R., Rana, P.S., 2015a. Self-healing neural model for stabilization against failures over networked uavs. IEEE Commun. Lett. 19 (11), 2013–2016.

Sharma, V., Kumar, R., Rathore, N., 2015b. Topological broadcasting using parameter sensitivity-based logical proximity graphs in coordinated ground-flying ad hoc networks. J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl. (JoWUA) 6 (3), 54–72.

Sharma, V., Bennis, M., Nagdev, R., 2016a. Uav-assisted heterogeneous networks for capacity enhancement. IEEE Commun. Lett. 99, 1.

Sharma, V., You, I., Kumar, R., 2016b. Energy efficient data dissemination in multi-uav coordinated wireless sensor networks. Mob. Inf. Syst. 2016.

Shuai, H.-H., Yang, D.-N., Cheng, W.-H., Chen, M.-S., 2011. Mobiup: an upsampling-based system architecture for high-quality video streaming on mobile devices. IEEE Trans. Multimed. 13 (5), 1077–1091.

Yaliniz, R., El-Keyi, A., Yanikomeroglu, H., 2016. Efficient 3-d placement of an aerial base station in next generation cellular networks. arXiv preprint arXiv:1603.00300arXiv:1603.00300.