User Bandwidth Demand Centric Soft-Association Control in Wi-Fi Networks

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Abstract

Abstract—To address the challenge of unprecedented growth in mobile data traffic, ultra-dense network deployment is a cost efficient solution to offload the traffic over some small cells. The overlapped coverage areas of small cells create more than one candidate access points for one mobile user. Signal strength based user association in IEEE 802.11 results in a significantly unbalanced load distribution among access points. However, the effective bandwidth demand of each user actually differs vastly due to their different preferences for mobile applications. In this paper, we formulate a set of non-linear integer programming models for joint user association control and user demand guarantee problem. In this model, we are trying to maximize the system capacity and guarantee the effective bandwidth demand for each user by soft-association control with a software defined network controller. With the fact of NP-hard complexity of non-linear integer programming solver, we propose a Kernighan Lin Algorithm based graph-partitioning method for a large-scale network. Finally, we evaluated the performance of the proposed algorithm for the edge users with heterogeneous bandwidth demands and mobility scenarios. Simulation results show that the proposed adaptive soft-association control can achieve a better performance than the other two and improves the individual quality of user experience with a little price on system throughput.

Keywords: Association control; Load balance; Software defined network; Graph partition

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1. Introduction

With high demands for capacity, massive connectivity, high reliability and low latency, the enormous amount of mobile data is expected to be transmitted via the next generation radio access networks. An efficient solution to solve this problem is the densification of cells, known as Ultra-Dense Networks (UDN). In the EU FP METIS project **[1]**, the UDN deployment with dense small cells is envisioned as an important feature of the forthcoming 5G mobile networks. Furthermore, UDN constitutes the central pillar of IEEE 802.11ax project, also known as High Efficiency Wireless LAN standard (HEW). For the prior association and handover solutions, mobile stations are assumed to be tied to at least one serving cell. As a mobile station moves away from its serving AP, the link performance may degrade until the mobile station eventually handed over to a neighboring cell. The degraded link performance near the cell edge continues to be a limiting factor in networks. However, in the ultra-dense small cells, mobile stations normally have multiple choices of the candidate APs to associate with.

Current radio access network is cell-centric instead of user centric. Software Defined Network (SDN) and Network Function Virtualization (NFV) on the other hand is geared towards user-centric. This will reshape the next generation Internet as well as the 5G mobile network to manage ubiquitous radio resources in terms of bandwidth and transmit points with a controller towards a user-centric feature[2]. Soft-RAN is a SDN architecture defined for the heterogeneous radio access networks. This provides a promising way to manage ubiquitous radio resources in terms of bandwidth and access nodes with a SDN controller [3]. Soft-RAN architecture has the potential to enable novel infrastructure abstraction. This novelty will enable the mobile user to access its neighbor APs and perform handover to another AP without any knowledge of the network environment. However, the centralized association control will lead to unbalanced load distributions among densely deployed APs, if it is unaware of network environment.

Furthermore, the diversity of mobile and Internet of Thing (IoT) applications corresponds to different bandwidth demands, which may come from the different transmission rates, or delay requirements. The weak signal strength at the cell edge leads to a smaller transmission rate than the requirement of the edge user. The quality of experience on delay will result into vast difference in effective bandwidth, especially in a heavy-load scenario.

In this paper, an application aware soft-association approach is proposed, with three characteristics. First, it is user centric because it can guarantee the quality of user experience with a new constraint to formulate the problem. Second, it is a soft association, because it can support the dual-connectivity for each user on the data plane. The third one, it works in a centralized manner, which balances the tradeoff on system throughput and the quality of individual user experience with the consideration of diverse demands and load balance among small cells.

The rest of this paper is organized as follows. In section II, the related literature is described. In section III, we present application scenarios in software defined small cell network and formulate three soft-association problems as non-linear integer programming models with constraints. Evaluation results are provided and analyzed in a variety of scenarios in section IV. Finally, we make conclusion in section V.

2. Related Work

The concept of software defined network is proposed as one of candidate techniques for the next generation Internet as well as 5G system [2]. Openflow originally is a protocol to enable switches on wired networks programmable via a standardized interface [4]. Openflow has been standardized to reduce operation cost, simplify network management and speed up network innovation. In recent years, SDN and openflow techniques are extended from wired network to wireless network. OpenRadio provides a design to decouple control plane from data plane to support the easy migration of mobile users from one type of network to another [5].OpenRadio provides a demo that shows the seamless handover between Wi-Fi and WiMax when video is streamed with Openflow [6]. Cell-SDN enables policies for new applications in order to meet diverse subscriber needs [7]. Furthermore, SDN has already been extended to wireless mesh network [8], IoTs [9], and sensor networks [10].

The investigation of user association control is very popular in Wi-Fi networks. Because IEEE 802.11 Wi-Fi network does not support centralized network management, CAPWAP protocol is well-established. This is to address this problem and to provide mobility support among different APs with a centralized controller. The basic control principle of CAPWAP protocol is based on tunnels [11]. IEEE 802.21 is referred to as a potential enabler to query link information and trigger handovers in Openflow based wireless network [12]. However, no detailed integration of IEEE 802.21 and Openflow is addressed, and the potential tradeoffs are not even discussed. There are some works done in the area of association control under the SDN architecture. The Cloud-MAC is the first centralized association control proposed for software defined wireless network[13]. However, signal strength based association control may result in significantly unbalanced load among access points. The QoE-aware spectrum efficient and energy efficient user association and resource allocation scheme for video content delivery in a wireless heterogeneous network was equally proposed in [14]. They took bandwidth and energy consumption as main factors for optimization, however no exact factor for system's load balancing were presented. Moreover, they didn't practically consider the user–station distance as a factor of energy consumption. A load-aware and QoS-aware user association that jointly considers the load of each base station and the users' required data rates model were also proposed in [15]. The authors considered the almost blank subframe as a factor to reduce inter-cell interference while offloading macro-cells. But the algorithm didnot consider neither the user mobility nor the dynamic scenario where users spontaneously join or leave system. In [16], the load-aware user association scheme with QoS support in heterogeneous cellular networks was developed by defining the relaxed association indicator variables, where users choose the base station with the maximum indicator. Yet still the authors only foccused on data plane and effective load but never clearly defined the effective bandwidth. Moreover no user mobility nor dynamic scenario were considered. Similarly, all of them didn't consider multihomed user [14,15,16].

The topic of user association in the 5G network was surveyed and outlooked in [17], where different metrics have been presented for determining which specific base station should serve which user, furthermore five metrics are commonly used in this context were discussed: outage/coverage probability, spectrum efficiency, energy efficiency, QoS, and fairness. Although authors detailed clearly the problems and weaknesses associated to previous works, they didnot suggest any solution nor model tackling any challenge in multipath user association. In [18], a cell association scheme for heterogeneous cellular networks is proposed with the effective load balancing by implementing a load-based range expansion bias at the macro base station, and dynamically adjusts the offloading effect to the current load in order to set the bias value. Though it performed well, this scheme never presented the user experience in both single interface and multi-homed user, moreover no impact of new user on the system balance is clearly presented. The novel user association were proposed, where authors developed dynamic cell range expansion and fairness gain based load equalization for load equalization considered the minimum user rate and the total system's fairness gain to offload the macro base stations in [19], the algorithm performs well, however no user demands were taken into consideration nor the impact of new users on the system's load balance were studied.

In contrast, radio access virtualization and advanced cloud computational platform are proposed in the future user-centric 5G network. This is to exploit densification at both network and mobile user sides [20]. This paves the way towards overcoming the limitation of cell boundary and breaking away from the cell concept, thereby achieving cell-less radio access and getting rid of the cell-edge curse. A typical work is the dual-connectivity that has been supported for heterogeneous macro-small cells in the 3GPP Release 12[21]. An enhanced solution to this problem is known as multipath soft-association control, in which each mobile user with multiple interfaces is partially associated with a virtual cell [22]. This virtual cell is mapped to a set of multiple APs dynamically. The optimized serving AP set is transparent to mobile user. The existing user association and bandwidth allocation strategies are however proposed based on an assumption that each user has a huge bandwidth demand [23] [24]. It means that the demand of users could not be satisfied, no matter how much bandwidths are allocated proportionally to the transmission rate of users. Users can use up their allocated bandwidths. In fact, the effective bandwidth demand of each user differs vastly due to their various preferences on network applications. This is lacking in existing user association strategies. They never consider a diversity of bandwidth demands on mobile applications. Although the bandwidth demand is mentioned in [25], it is assumed that the bandwidth demand depends on transmission rates and did not analyze user experience and traffic characteristics. In sum, the joint consideration of multipath association and diverse user demands is the main new feature in this paper.

3. The Proposed Approach

3.1 System model

We present an example to illustrate how the soft-association control works in the **Fig. 1**. We consider a typical SDN based layered system architecture with a typical access controller, a macro-cell AP and multiple small-cell Transmission Points (TPs). TP is a different AP without control plane but data plane. The common control layer via a macro-cell AP is well suited to integrate different layers of frequency and spatial transmission paths. Here, multiple TPs of small-cells can offload data traffic from macro-cell. The controller collects signal strength measurements, user demands in terms of effective bandwidth for each user and load distribution among multiple TPs in small-cell radio access network. We assume the controller can assign one Virtual Transmission Point (VTP) to each user and this VTP includes at least one TP as the serving cell set for this user. This dynamic mapping from VTP to TP is transparent to mobile users. The appraisal mechanism on load balance and user demand change works via network scanning. If the analysis module detects events happened, the controller makes decision on operations of data plane, such as flow combine, split and handover. Similarly, the soft-association manager will issue the specific command to network devices on the data plane to redirect data flows of users. We use Open-flow protocol to manage the flows across network devices in the Open-flow wired backbone. The ultra-dense heterogeneous network is composed of one macro-cell and some small cells. Mobile user connects with controller via control plane of macro-cell AP via the Secure Socket Layer (SSL). With the dual-connectivity, mobility among small cells within the same macro cell is not going to trigger handover. Each virtual cell has a VTP-ID and an optimized set of TPs dynamically.

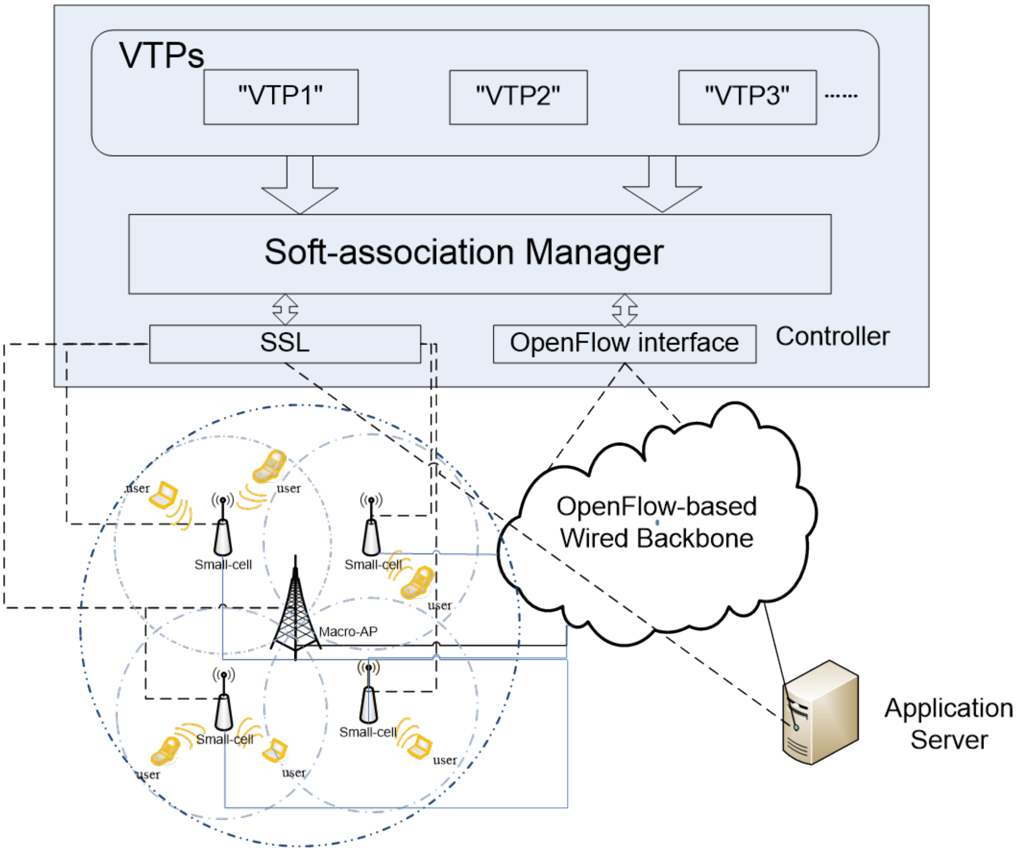


Fig. 1. The virtual-cell based soft-association control

Firstly, we defined the relationship among user, TP and interface. Here we assume that each user can have T interfaces. Actually, in the simulation, T is equal to two. A user can be associated with one VTP that is mapping to several TPs, however each of those TPs can allocate no more than one interface for that user. The coefficient β_{ij} indicates specific association relationship between user *i* and TP *j*. We define the coefficient as follows:

$$\beta_{ij} = \begin{cases} 1, & \text{if user i associated to TP j,} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where *i*=1, 2, …, I, *j*=1,2,…, J. I is the number of users, and J is the number of TPs.

Definition 1: Link Capacity
Based on Shannon theory, the link capacity φ_{ij} from user *i* and TP *j* can be calculated as.

$$\varphi_{ij} = \frac{w_j * log2(1+SINR_{ij})}{\partial_j} \quad (2)$$

Where, w_j is the system bandwidth of each TP *j*. ∂_j is the load of the TP *j*, in terms of the number of mobile users. Therefore, we can get the system capacity τ as the sum of expectation throughput of each user in this system:

$$\tau_{total} = \sum_{i=1}^{i=I} \sum_{j=1}^{j=J} \frac{w_j * log2(1+SINR_{ij}) * \beta_{ij}}{\partial_j} \quad (3)$$

We define a variable *l* to indicate the index of interfaces in the system with *i* users, which ranges from 1 to *i**T. In this way, we can get the expected throughput for user *i* as follows.

$$\psi_i = \sum_{l=(i-1)*T+1}^{l=i*T} \sum_{J=1}^{j=J} \frac{w_j * log_2(1+SINR_{lj})}{\partial_j} * x_{lj} \quad (4)$$

Where, x_{lj} is a specific association relationship between the TP *j* and the interface *l*, different with β_{ij}. In order to guarantee the experience of user, the expected throughput must be larger than the demand of the user *i* with *T* interfaces. For example, the bandwidth demand can be calculated with the Effective Bandwidth defined in the theory of network calculus [26]. In the Network Calculus, which is a queue theory with the traffic characteristics analysis, the effective bandwidth δ relies on both the transmit rates *R* and the delay requirement *D*. Intuitively, the effective bandwidth sometimes depends on the transmission rate *R*, sometimes depends on the maximum packetsize *M* over the delay requirement *D*.

$$\delta = maximum\{R, M/D\} \quad (5)$$

However, the *signal interference and noise ratio(SINR)* values in equation (2) are not available in Wi-Fi networks. Similar to the work in [27], transmissions in each cell would be independent of other cells using orthogonal channels. The background noise is constant, i.e. typical white noise follows the Gaussian distribution with a constant mean. Therefore, we consider the expectation throughput replaced by the so-called equivalent goodput with the Received Signal Strength Indicator (RSSI) measurement in Wi-Fi network.

Definition 2: Equivalent Goodput

The equivalent goodput is a proportion of the theoretical upper-bound capacity, which is expressed by the Shannon-like equation:

$$\text{Goodput} = \text{c} * \text{w}_j * log2(a + b * r_{ij}) \quad (6)$$

Where, a, b, c, are coefficients to be decided. We use the nonlinear least squares curve fitting in MATLAB to fit this equation with the observed data to decide them. This model suits the tendency of the observed instantaneous goodput and approaches the mean of goodput well. Then, we formulate the problem of multipath user association as a model of non-linear integer programming, which is shown in section 3.2, 3.3 and 3.4. In the formulation 1, we assume a user can use one or two interfaces alternatively for transmission in an adaptive manner, which is allocated by the controller. In the formulation 2, we assume a user can only use single path transmission. In the formulation 3, one user can only use its maximum number of interfaces, T, to transmit its information. Both formulation 2 and formulation 3 are evolved from formulation 1.

3.2 Formulation 1: Adaptive multipath method

A soft-association controller makes the decision on single-path or multipath transmission for each user. This is with the goal to maximize system capacity for all users with multiple interfaces via a soft-association control method. We formulate an objective function in the equation (7) and a set of constraint conditions from equation (8) to equation (13) as a non-linear integer programming model. The solver of branch and bound is used in our simulation with the support of MATLAB toolbox. Though computational complexity for a large scale network may impose a challenge to the algorithm, the network of TPs can be divided into independent small groups and be computed in parallel.

$$\boldsymbol{max} \quad \boldsymbol{T} = \sum_{l=1}^{l=I*T} \sum_{j=1}^{j=J} \frac{w_j * log2(a + b * r_{lj}) * x_{lj}}{\partial_j} \tag{7}$$

$$\partial_j = \sum_{l=1}^{l=I*T} x_{lj} \tag{8}$$

$$\sum_{j=1}^{j=J} x_{lj} \leq 1 \quad \forall\, l \in [1, I * T] \tag{9}$$

$$\sum_{l=i*T-T+1}^{l=i*T} x_{lj} \leq 1 \quad \forall\, (i,j) \in ([1,I],[1,J]) \tag{10}$$

$$\sum_{l=i*T-T+1}^{l=i*T} \sum_{j=1}^{j=J} \frac{w_j * log2(a + b * r_{lj})}{\partial_j} * x_{lj} \geq \delta_{\mathrm{i}} \quad \forall\, i \in [1, I] \tag{11}$$

$$\sum_{l=1}^{l=I*T} x_{lj} \geq floor(I/J) \quad \forall\, j \in [1, J] \tag{12}$$

$$\forall\, x_{lj} \in \{0,1\} \tag{13}$$

where, Equation (8) means the number of users on one TP is the sum of elements on a column of association matrix. Equation (9) indicates that one interface can only be associated with one TP. Equation (10) assumes that T interfaces on the user *i* cannot be associated with a common TP at the same time. Equation (11) indicates the link capacity for the user *i* should be larger than its required bandwidth δ_i. In the equation (3), the variable *l* is defined as the index of interface in the whole system with *I* users, which ranges from 1 to *i**T. We assume each user has T interfaces. Therefore, the index of interfaces for the user *i* ranges from (*i**T-T+1) to (*i**T). Here, T is common for all of users. Equation (12) balances the load distribution on multiple TPs. It assumes the number of users associated with each TP must be less than the average load capacity of the whole system, which depends on the ratio of user number and TP number. The function of $floor(A)$ rounds the elements of A to the nearest integer less than or equal to A. Equation (13) indicates variables in the association relationship matrix can be 0 and 1, therefore this is integer programming of 0-1 programming problem.

3.3 Formulation 2: One-path method

In order to show the advantage of adaptive soft-association method, we define another formulation for the soft-association problem and assume a single interface can be used. The soft-association controller still makes decision in a centralized manner. Equation (14) still keeps the same objective function as with Equation (7) in formulation 1. In this new formulation, we replace Equation (9) and Equation (10) with a new constraint Equation (16). Equation (16) indicates that a single interface can be used for the user *i* in this formualtion. The formulation 2 is defined with Equation (14)- (19):

$$\boldsymbol{max} \quad \boldsymbol{T} = \sum_{l=1}^{l=I*T} \sum_{j=1}^{j=J} \frac{w_j * log2(a+b*r_{lj}) * x_{lj}}{\partial_j} \tag{14}$$

$$\partial_j = \sum_{l=1}^{l=I*T} x_{lj} \tag{15}$$

$$\sum_{l=i*T-T+1}^{l=i*T} \sum_{j=1}^{j=J} x_{lj} = 1 \quad \forall\, i \in [1, I] \tag{16}$$

$$\sum_{l=i*T-T+1}^{l=i*T} \sum_{j=1}^{j=J} \frac{w_j * log2(a+b*r_{lj})}{\partial_j} * x_{lj} \geq \delta_i \quad \forall\, i \in [1, I] \tag{17}$$

$$\sum_{l=1}^{l=I*T} x_{lj} \geq \text{floor}(I/J) \quad \forall\, j \in [1, J] \tag{18}$$

$$\forall\, x_{lj} \in \{0,1\} \tag{19}$$

3.4 Formulation 3: T-path method

In the problem formulation 3, we assume all of the T interfaces for each user should be used in order to satisfy its bandwidth demand. In this method, T interfaces must be associated with T TPs for each user. The new formulation replaces Equation (9) in the formulation 1 with Equation (22), which has a different range of index l. This formulation is a non-linear integer programming problem. In the simulation, T is set as two, so it is a *two-path* method.

$$\boldsymbol{max} \quad \boldsymbol{T} = \sum_{l=1}^{l=I*T} \sum_{j=1}^{j=J} \frac{w_j * log2(a+b*r_{lj}) * x_{lj}}{\partial_j} \tag{20}$$

$$\partial_j = \sum_{l=1}^{l=I*T} x_{lj} \tag{21}$$

$$\sum_{j=1}^{j=J} x_{lj} = 1 \quad \forall\, l \in [1, I*T] \tag{22}$$

$$\sum_{l=i*T-T+1}^{l=i*T} x_{lj} \leq 1 \quad \forall\, (i,j) \in ([1, I], [1, J]) \tag{23}$$

$$\sum_{l=i*T-T+1}^{l=i*T} \sum_{j=1}^{j=J} \frac{w_j * log2(a+b*r_{lj})}{\partial_j} * x_{lj} \geq \delta_i \quad \forall\, i \in [1, I] \tag{24}$$

$$\sum_{l=1}^{l=I*T} x_{lj} \geq \text{floor}(I/J) \quad \forall\, j \in [1, J] \tag{25}$$

$$\forall\, x_{lj} \in \{0,1\} \tag{26}$$

3.5 Algorithm: Graph partition

With the fact of computational complexity, we generate subgraphs by graph partition using the KLA (Kernighan Lin Algorithm), which is explained by authors in [20]. When an optimized graph partition for a large-scale cellular network is finished, we solve the non-linear integer-programming model by a branch and bound algorithm to optimize the user association for each small-portioned network. Starting our partitioning, we begin with finding TPs in good cooperation in a partition by calculating their Bonding Level (BL). We define the bonding level in a pair of TPs [20],

$$\mathrm{e}^{*}_{\mathrm{g,h}} = \sum_{\mathrm{k}\in\mathrm{TP(g)}} f_k \frac{\mathrm{P_{k,g}}}{\mathrm{P_{k,h}}} + \sum_{\mathrm{k}\in\mathrm{TP(h)}} f_k \frac{\mathrm{P_{k,h}}}{\mathrm{P_{k,g}}},\ \forall\, \mathrm{g,h} \tag{27}$$

Where $\boldsymbol{e}^{*}_{\boldsymbol{g,h}}$ is the bonding level of (*g*,*h*) TPs pair. $\boldsymbol{f_k}$ is the weight of user *k*, associated with for TP *g* or *h*. In fact, $\boldsymbol{f_k}$ is a function for *k*, $\boldsymbol{P_{k,g}}$ is the RSSI of TP *g* at user *k*, and TP (*g*) is the set of users that are associated with TP g. By considering explicitly the load of TP in terms of the number of users to be connected, we defined the BL of each pair of TPs in a subgraph and therefore we measured the cooperation level in a partition as follow.

$$e_{g.h} = \sum_{k\in TP(g)} \frac{1}{n_g} * \frac{p_{k,g}}{p_{k,h}} + \sum_{k\in TP(h)} \frac{1}{n_h} * \frac{p_{k,h}}{p_{k,g}}, \forall\, g \neq h,\ \forall\, k \tag{28}$$

Where TP g and TP h are two arbitrary vertices in the graph G, and $e_{g.h}$ is the bonding level between TP g and TP h. The TP(*g*) and TP(*h*) are sets of users associated to TP g and TP h respectively. Then, n_g and n_h denote the load of the TP g and the TP h respectively. $\mathrm{P}_{k,g}$ and $\mathrm{P}_{k,h}$ denote the RSSI value received by the k^{th} user from the TP g and the TP h respectively. The equation (29) indicates that any graph G is partitioned into two subgraphs G_1 and G_2 with an equal size. We define a function *gain* as

$$gain(\hat{\mathrm{g}}, \hat{\mathrm{h}}) = \left(\sum_{t\in G_1} e_{\hat{\mathrm{g}},t} - \sum_{t\in G_2} e_{\hat{\mathrm{g}},t}\right) + \left(\sum_{t\in G_2} e_{\hat{\mathrm{h}},t} - \sum_{t\in G_1} e_{\hat{\mathrm{h}},t}\right) - 2 * e_{\hat{\mathrm{g}},\hat{\mathrm{h}}}, \tag{29}$$

$$\hat{\mathrm{g}} \in G_1, \hat{\mathrm{h}} \in G_2$$

Where, $\hat{\mathrm{g}}$ and $\hat{\mathrm{h}}$ are two arbitrary vertices in the G_1 and G_2 respectively. The $\mathrm{gain}(\hat{\mathrm{g}}, \hat{\mathrm{h}})$ means the brought gain to swap $\hat{\mathrm{g}}$ and $\hat{\mathrm{h}}$, in which the new cost function is calculated based on the distance between the sum of bonding levels inside a subgraph and the sum of bonding levels outside a subgraph.

The algorithm description of the KLA-based graph partition is shown in the **Fig. 2**. In the first step, we first compute the RSSI values between user *k* and all of TPs, which are taken as the raw data set to do the graph partition. In the step 2, we draw a weighted graph G, which takes each TP as the vertex, and the BL $e_{g.h}$ in the equation (28) as the edge for TP *g* and TP *h*. The goal of the proposed algorithm is trying to partition the graph G into two disjoint subgraph G_1 and G_2 of equal size, in such way that minimizes the sum of the edge weights across the subgraph G_1 and G_2. The algorithm iterates and improves a partition using a greedy strategy to pair up vertices of G_1 and vertices of G_2, so that exchange of the paired vertices from one group to the other group will improve the sum of the partition gain defined in the equation (29). After vertices matching $\{(\hat{\mathrm{g}}, \hat{\mathrm{h}})\}$ is found, that leads to a maximized C_v, as shown in the **Fig. 2**, it then swaps two vertices in the selected *v* pairs. Then, step 3 is repeated until no improvement can be got on the sum of gains. In step 4, repeat the operations in step 2 and 3, G finally can be partitioned into λ sub-graph and the maximum number of vertexes for each sub-graph will be limited to a small threshold.

KLA-based graph partitioning method

INPUT: A pair of sets {set(*TP*), set(*user*)},

Step 1: Acquire RSSI value that between TP h or g and user k in a graph

Step 2: TPs is considered as a graph Vertices, Calculate the $e_{g,h}$ from Eq(28) as the graph edge weight between g and h; g and h represent any vertices in the graph

Step 3: Divide the network that need to partition into 2 sub-graph G_1 and G_2

For i:= 1 to y/2, that y is the number of TPs

from the unlocked(unexchanged) vertices,

choose a pair($\hat{g}$, $\hat{h}$) that $\hat{g} \in G_1$, $\hat{h} \in G_2$ s.t. *gain* ($\hat{g}$, $\hat{h}$) is largest.

exchange $\hat{g}$ and $\hat{h}$. lock $\hat{g}$ and $\hat{h}$.

let $gain_i = gain(\hat{g}, \hat{h})$ from the formula(29).

$C_i = C_{i-1} + gain_i$

find the v s.t. C_v is maximized.

switch the first v pairs.

Repeat Step 3 until there is no improvement($\Delta C = 0$)

Step 4: **Repeat** step 2, step 3 until there is the number of TP every sub-graph is lower than a threshold value

OUTPUT: λ pairs of sets.

$\{set(TP), set(user)\}^1, \{set(TP), set(user)\}^2, \ldots, \{set(TP), set(user)\}^\lambda$

Fig. 2. KLA-based graph partitioning method

In order to show the advantage of KLA-based graph partitioning method, we introduce another graph partition based on geometry, which divides the whole zone into sub-zone equally and group the users based on their position distribution. With such a simple intuition, we evaluate the different graph partitioning methods with simulations.

Geometry-based graph partitioning method

INPUT: A pair of sets {set(*TP*), set(*user*)},

Step 1: Divide the entire area into λ subareas with equivalent size randomly,

Step 2: Calculate the coverage of each subareas,

Step 3: Compare the location of each node(*TP* or *user*) and the coverage of subareas, Determine which subarea the node(*TP* and *user*) falls in;

Step 4: **Repeat** step 3 until every *TP* or *user* has been processed.

OUTPUT: λ pairs of sets.

$\{set(TP), set(user)\}^1, \{set(TP), set(user)\}^2, \ldots, \{set(TP), set(user)\}^\lambda$

Fig. 3. Geometry-based graph partitioning method

4. Experimental Results and Analysis

4.1 Scenario Configuration

In order to evaluate the performance of the proposed adaptive soft-association control approach. The simulation is done in a scenario of small cell Wi-Fi networks. It can be extended to other heterogeneous wireless network. With the consideration on computation complexity of the non-linear integer programming, we assume a large scale network of TPs can be divided into groups in a small scale. In this case, three independent cells are deployed in an indoor scenario. Here, we assume each user has two interfaces. The system bandwidth of each TP is 20MHz, and three TPs are deployed in the center of an area with a fixed distance 34 meters, as shown in the **Fig. 4**.

In the MATLAB simulation, we take an indoor office as the application scenario. First, we get the real measurements in our office for Wi-Fi networks. The real measurements include RSSI, SINR, and link throughput. We develop a simple signal measurement application on andriod system for mobile phone MIUI 6, which is based on Android OS 4.4, and its CPU is Snapdragon 801 MSM8974AC. We get the RSSI measurements and the SINR measurements based on the class *wifiInfo*, provided by Android system. We measure the link throughput in terms of *bit_ per_second* with *iperf tool*.

WifiManager wifi_service = (WifiManager)getSystemService(WIFI_SERVICE);

WifiInfo wifiInfo = wifi_service.getConnectionInfo();

We calculate the coefficients *a*, *b* and *c* in Equation (6) based on the curve fitting. Finally, we generate the RSSI values based on a path-loss model.

$$\mathrm{RSSI} = \mathrm{Pt} - \mathrm{Shadowing} - \mathrm{PathLoss} \tag{27}$$

Where, the transmit power Pt is -10dBm, and M is a random value for the shadowing effect because of the obstacles, which ranges from 0 to 40 in dB. The PathLoss model is set up for our office enviroments based on real RSSI measurements：

$$\mathrm{PathLoss} \ = 20\lg(\mathrm{F}) + 20\lg(\mathrm{distance}) + 32.4 \tag{28}$$

Fig. 4. Scenario configuration for a small-scale network

Where, F is equal to 2.4GHz, *distance* is the distance between the user and one of TPs. We evaluate our approach in three cases: edge/central users, homogeneous change of user demands, and heterogeneous user demands. Two metrics defined for evaluation are system throughput and individual throughput. A common configuration list is given in the **Table 1**.

Table 1. PARAMETERS CONFIGURATION

Parameter with units	Values
Number of TPs J	3
Number of users I	9
Number of interface T	1 or 2
Radius of coverage(meter)	150
Distance of neighbor TPs(meter)	34
Frequency band(GHz)	2.4
Transmit power(Pt, dBm)	-10
Shadowing effects(dB)	(0,40)
Bandwidth (MHz)	20
The coefficient *a*	1.733
The coefficient b	0.005429
The coefficient *c*	5
RSSI threshold for Edge user (dBm)	-120
RSSI threshold for Central user(dBm)	-90

4.2 Coefficient Fitting

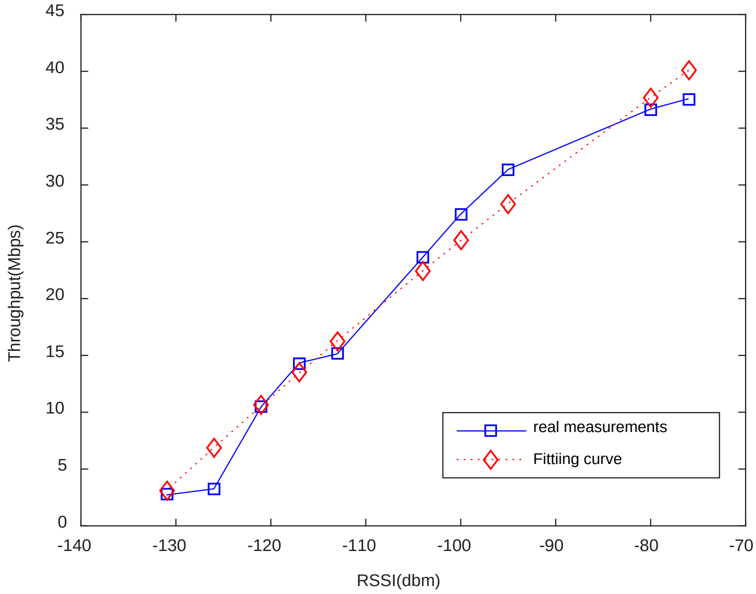


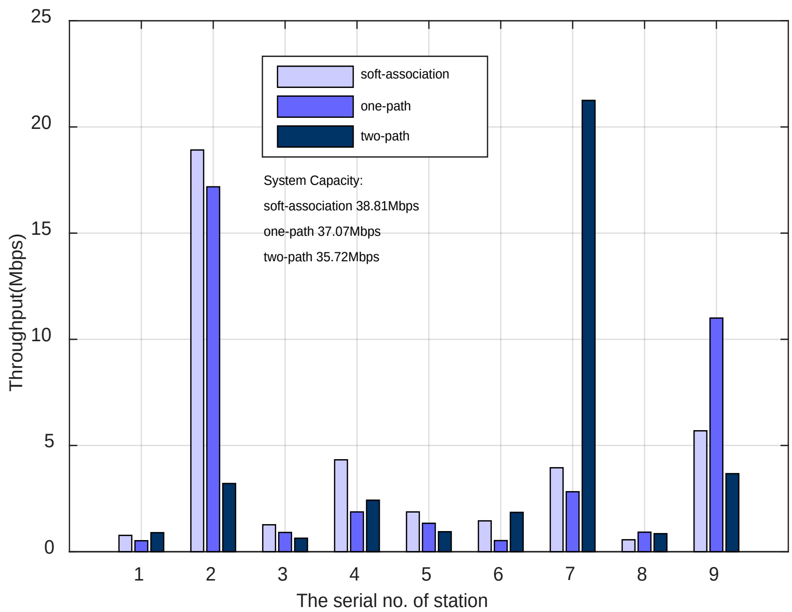
Fig. 5. The model fitting with real measurements

We follow the methodology provided in [10] and set up an approximate model between RSSI and SINR measurements, as shown in the **Fig. 5**. The unknown coefficients of *a*, *b* and *c* are calculated with MATLAB. a=1.733, b=0.005429, c=5.0. Then, the real RSSI measurements are used to fit the goodput in the equation (6). The comparison of model fitting and real measurement is shown in the **Fig. 5**. The real measurements match the fitting curve very well. Therefore, the value of a, b and c can be used in simulation to evaluate the performance of our proposed algorithms.

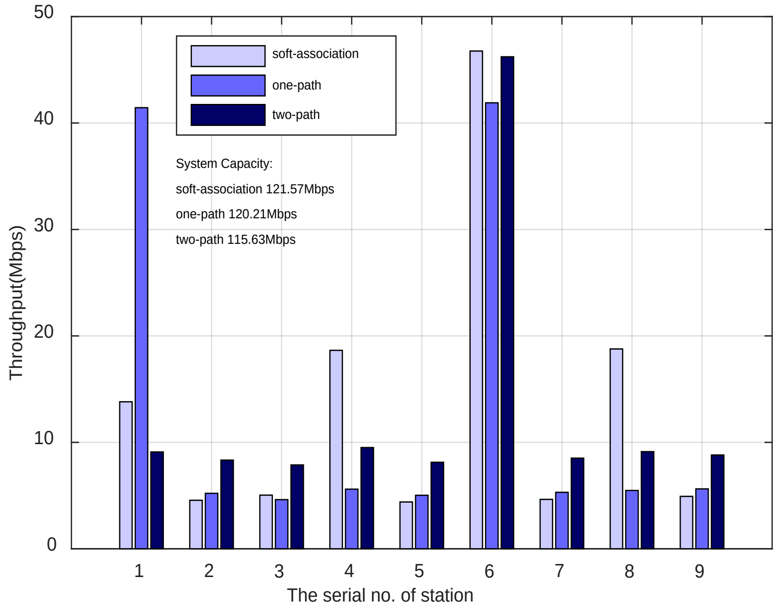
4.3 Case study: Edge/Central users without Load balance

Initially, we mimic the work of Cloud-MAC proposed in [13] in this use case. We delete the constraints of Equation (12), (18), and (25) in the proposed formulation. We assume all of the mobile users have one flow, and each flow has a common effective bandwidth 0.5Mbps. The performance of the three proposed models are appraised. We consider the distribution of users in two scenarios. One scenario assumes all of users are edge users with RSSI less than -120dBm. The results for edge users are shown in the **Fig. 6 (a)**. The other scenario assumes that all of users are central users with RSSI more than -90dBm. The results for central users are shown in the **Fig. 6(b)**. Here, the definition of threshold for the edge user and the central user are not the standard parameters. However, they are the token to identify and differentiate the user demands on the bandwidth. Based on the equation (6), we try to create a scenario with the edge users, whose RSSI values are less than -120dBm. Their bandwidth demand cannot be met with one-path association. Therefore, they resort to multipath association. However, for the central users, whose RSSI values greater than -90dBm, their bandwidth demand can be easily satisfied with the one-path association. We can calculate RSSI based on pathloss model with a shadowing effect in a range of 0~40dB. The bandwidth demand of users can not be met for edge users, shown in the **Fig. 6(a)** and **Fig. 7(a)**.

In two scenarios above, the adaptive soft-association method performs better on system capacity than the other two. On individual capacity, the soft-association has not achieve better performance than the other two. Furthermore, it achieve the best system throughput by maximize the capacity for one of the stations, e.g. station 2 in the **Fig. 6(a)** and station 6 in the **Fig. 6(b)**. The objective function tries to maximize the system capacity by satisfying the station with the best RSSI value leading to unbalanced load distribution among multiple TPs. This unbalanced load distribution accounted for a lot of rounds in our observations. The constraint of load balance is therefore necessary in our proposed model of soft-association.



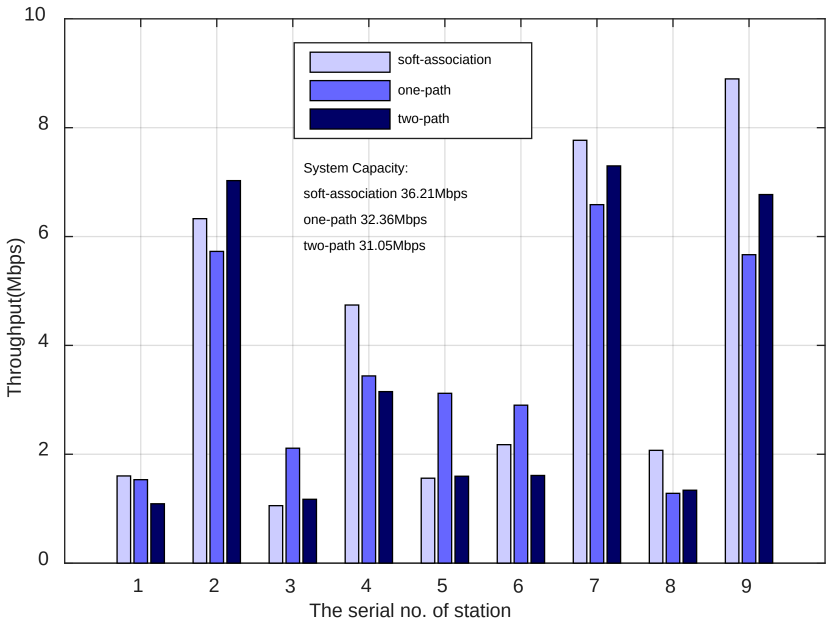
(a)



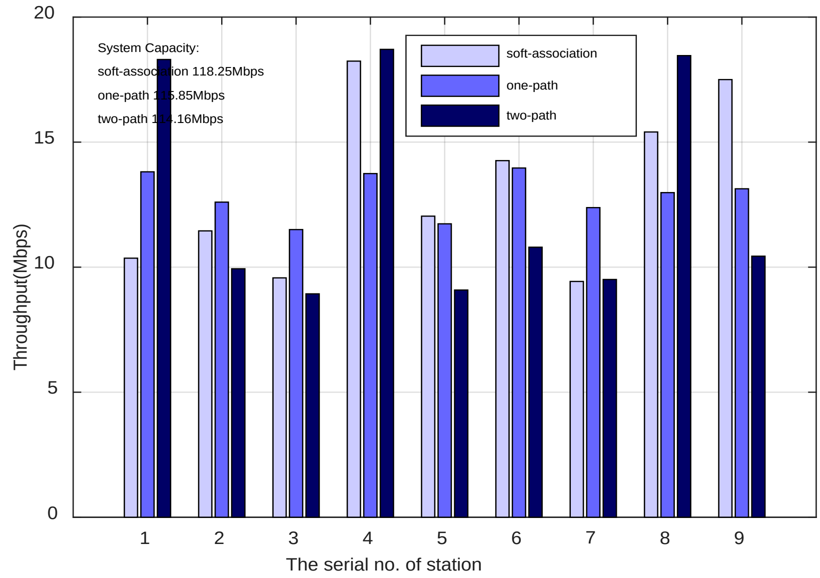
(b)

Fig. 6. Edge vs central users without load balance

4.4 Case study: Edge/Central users with Load balance



(a)



(b)

Fig. 7. Edge user vs Central user with load balance

In this case, a constraint for load balance is added, e.g. Equation (12), (18) and (25). The load is modeled with the number of stations for each TP, which is reasonable with an assumption that each station has one flow. The results are shown in the **Fig. 7 (a)** and **(b)**. It still shows that the adaptive soft-association performs better than the other two on system capacity. It achieves a better performance on individual experience and fairness because it guaranteed load balance. The improvement however is achieved with a little price of system capacity.

4.5 Case study: Homogeneous user demands

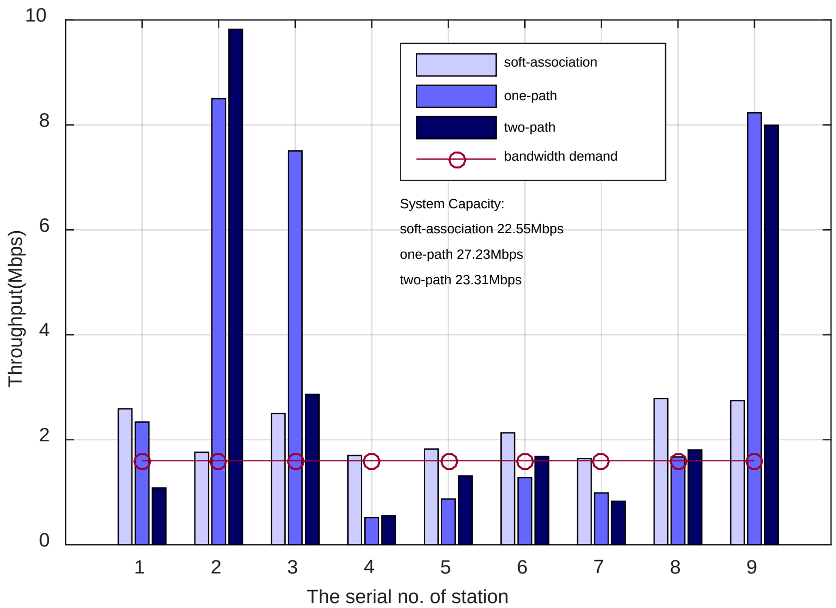


Fig. 8. Trade-off of system capacity and individual user experiences

Based on the results provided above, it seems the adaptive soft-association is not worse than the centralized association with fixed one-path or two-path. However, it is always true, if we increase the bandwidth demands of each user from 0.5Mbps to 1.6Mbps for edge users. Till now, we still assume each station has a common bandwidth demand. Unfortunately, Formula 2 and 3 often can not find the solution because of the limitation on the number of connectivities. The adaptive soft-association however, always works in a flexible manner. For this, we assume the initial association control doesn't consider user demands as long as it doesn't have applications running yet. The constraint of Equation (17) and (24) will be deleted. The results in the initial association are taken as the solution, when Formula 2 and 3 can not get a solution. In such a situation, the centralized one-path and two-path can achieve the improved system capacity but individual bandwidth requirement cannot be guaranteed. As shown in the **Fig. 8**. The adaptive soft-association control therefore performs better on the guarantee of individual bandwidth demand.

4.6 Case study: Heterogeneous user demands

In this case, we consider the scenario of heterogeneous bandwidth demand resulted by the latency requirements. The effective bandwidth δ depends on parameters *M, D* and *R*. We take the *elephant* flows as an example, e.g. interactive video services. We assume the packet size is set as $M = 1 \times 10^4$bits. The delay requirements for each flow D_i are set as [2, 4, 6, 8, 12, 16, 20, 50, 100] in million-seconds, R is set as 0.5Mbps in this case. The effective bandwidth δ is calculated as [5, 2.5, 1.67, 1.25, 0.91, 0.625, 0.5, 0.5, 0.5] in Mbps. Similar to the case of homogenous user demand, when the centralized one-path and two-path methods cannot find a solution, the results of the initial association can be adopted. Results are shown in the **Fig. 9**. The one-path RSSI based association cannot meet the requirements for flows 2 and 3. The two-path association approach could not meet the requirements of quality of service for flows 2, 3 and 9. The proposed adaptive multi-path soft-association achieves a better performance on both the system throughput and individual demand on quality of service.

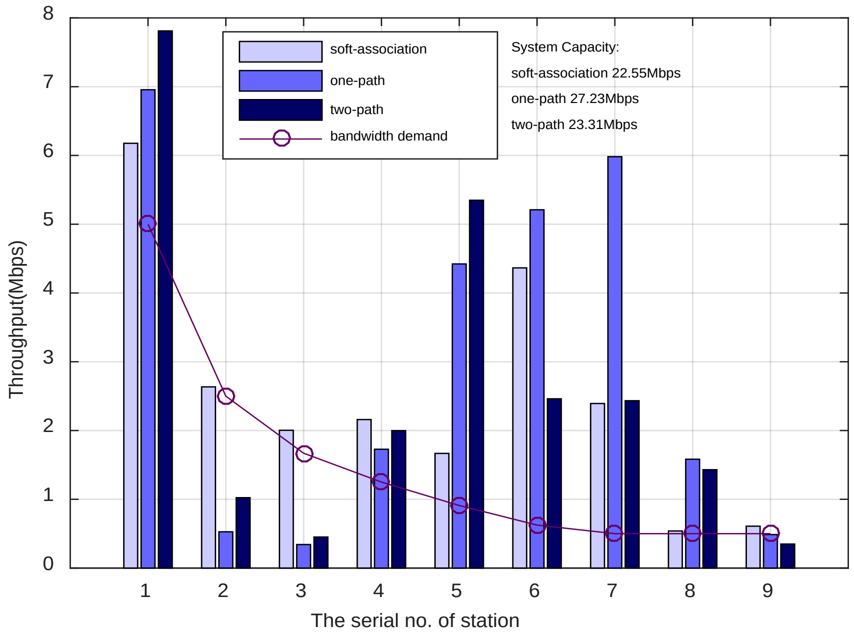


Fig. 9. Heterogeneous user demands

4.7 Case study: Mobility scenario

In this use case, we assume a user moving on a predetermined route and the other eight users keep the initial location without movement. We take some position samples on this route to observe the operations of data flow for the moving user. The set of sample positions is defined as (50,50), (100, 100), (150, 150), (200, 200), (250, 250), (300, 300), (350, 350), (400, 400), (450, 450), as shown in **Fig. 2**. In this simulation, we calculate the independent capacity achieved on each TP. At the first position, this mobile user attaches with TP1 and TP2 with two paths. Then on the second sample, it handovers link 2 to link 3 and attaches with TP1 and TP3. On the fourth position, it combines link 1 and link 3 as one connectivity with TP1. Furthermore, it handovers from TP1 to TP3 in the central of the area. When it moves from the central to the edge, flow splitting happens to attach with two independent TPs, e.g. TP2 and TP3. It therefore indicates that soft-association actually works in a user demand centric manner.

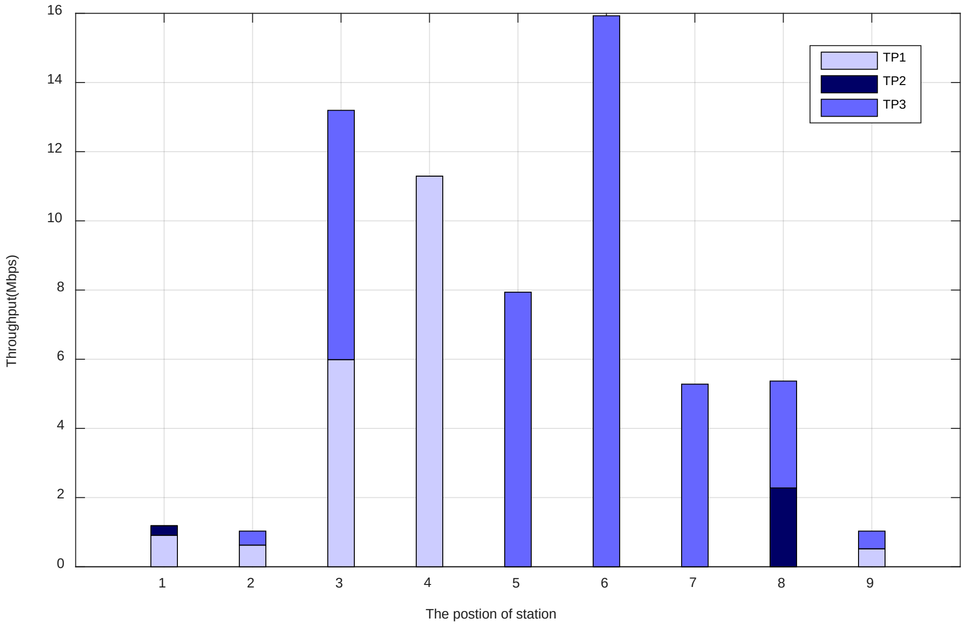
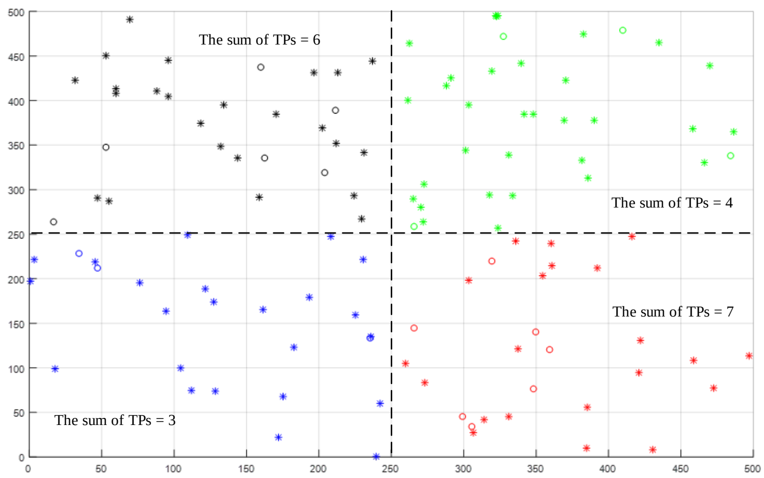


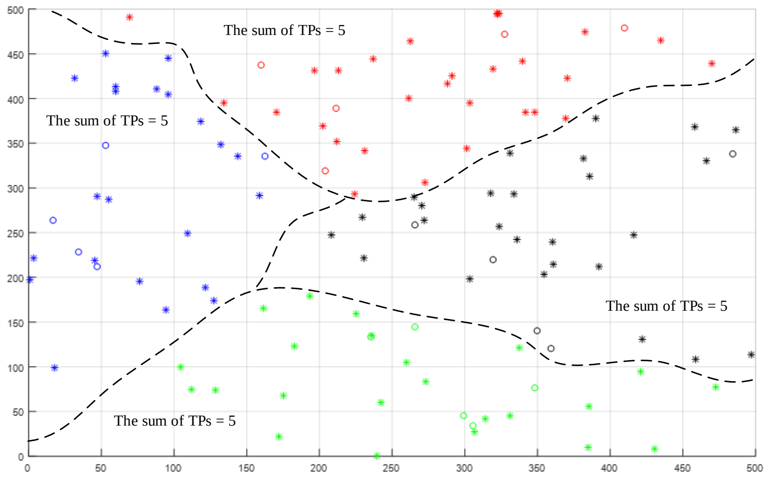
Fig. 10. Resource view for mobility scenario

4.8 Computation complexity

As shown in **Fig. 4**, The network topology with a fixed bandwidth of 20MHz TP is only one of the application scenarios to show the basic effects of the proposed adaptive multipath soft-association scheme. The graph partitioning method is taken as a potential solutin for the computational complexity of NP-hard problem presented by our formulated association model. In this paper, we consider two graph partition schemes the geometry distribution-based and the KLA-based. We provide two independent metrics to appraise the performance: system throughput and computation time. In this scenario, 20 TPs are deployed in an area of 500m $*$ 500m uniformly and new users join it in a random manner. For both two graph partitioning methods are used, we take the system throughput and the computational time as the results, as shown in the **Fig. 11 (a)** and **(b)** respectively. The sign ‘o’ represents TPs, and the sign ‘*’ represents users.



(a) Geometry-based graph partition



(b) KLA based graph partition

Fig. 11. Graph partition for a large-scale network

In order to compare two graph partitioning method on the performance of system throughput, we show the result achieved by the proposed KLA based graph partitioning algorithm in the **Fig. 12**. There is not too much difference on throughput. However, on the comparison of computational time shown in the **Fig. 13**, the KLA based partition performs better than the geometry-based graph partition. Therefore, the KLA-based algorithm can help the proposed association scheme to be extended to a large-scale network.

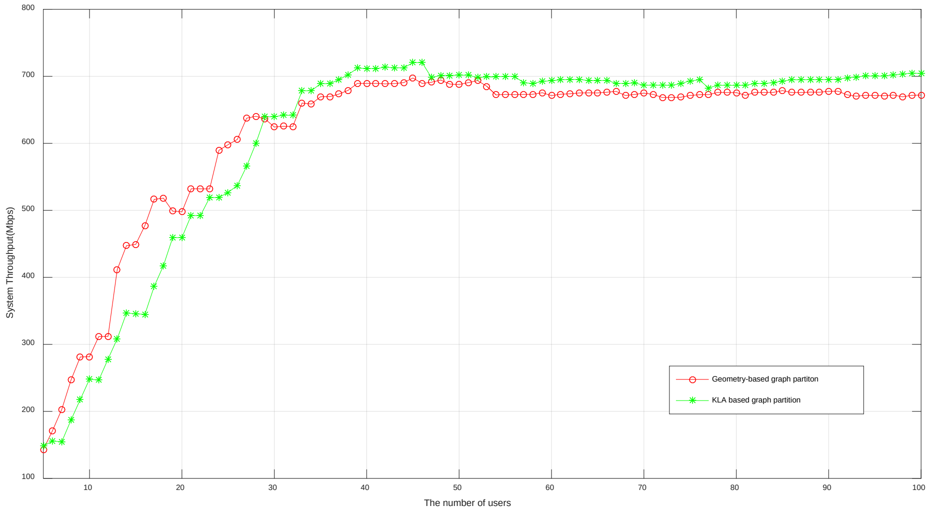


Fig. 12. The performance on system throughput

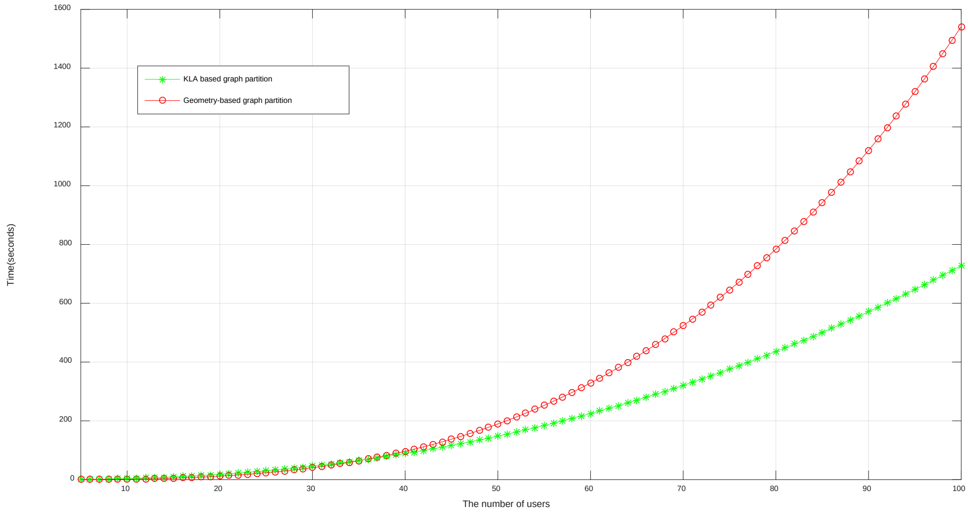


Fig. 13. The performance on computation complexity

5. Conclusion

In the paper, we propose a user demand centric soft-association control scheme in software defined small cell network. We allow that mobile users with several radio interfaces can associate with multiple TPs and transmit information in an adaptive multipath manner. We formulate such a soft-association problem as a constrained non-linear Integer Programming model. With the fact of NP-hard complexity, we extend it to a large-scale network with a KLA based graph-partitioning method. Furthermore, we investigate this problem with scenarios of heterogeneous user demands and user mobility. Simulation results show that the proposed soft-association control achieve a better performance on user experience, fairness and load balance, with a little price of system capacity.

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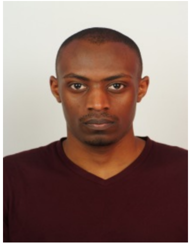

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