Abstract—Load balancing through cell-site selection in wireless networks has gained much attention as an efficient way to utilize scarce wireless resources. This paper considers a Point of Attachment (PoA) selection problem which is an extension of the cell-site selection problem. The PoA selection problem deals with an extended environment where each user device is with a different radio access technology (RAT) capability including multiple wireless network interface cards (WNICs). The goal of this paper is to formulate the problem that aims to maximize the network-wide utility under the environment of multi RATs and heterogeneous user device capabilities. To solve this problem, we first prove the problem is NP-Hard and propose a heuristic algorithm. Through extensive simulations, we evaluate the performance of our proposed algorithm against two received signal strength based approaches.

I. INTRODUCTION

Recently, there have been developed several kinds of advanced wireless communication systems. Examples include cellular systems such as EPS (Evolved Packet System) and Mobile WiMAX (Worldwide Interoperability for Microwave Access), and the next generation wireless local area network (WLAN) of IEEE 802.11n. Due to the distinctive characteristics of each system, e.g., capital and operating expenses, peak data rate, and mobility support, it is anticipated that they will coexist and complement each other. Accordingly, a considerable amount of efforts from industry and academia has been made in this regard especially for supporting service continuity across heterogeneous networks [1][2][3].

Along with the diversification of communication systems, user devices are becoming more and more capable owing to the continuing development of micro electro-mechanical systems (MEMS). As a result, various types of user devices equipped with more than one RAT have appeared lately. Some of them can access to more than one RAT simultaneously at a given moment, e.g., a laptop connected to both WLAN and WiMAX, while the others cannot due to several reasons such as a limitation on power consumption.

From a network operator’s perspective, such multi RATs and heterogeneous user device capabilities provide a possibility of using scarce wireless resources efficiently. Although, advanced technologies such as multiple-input multiple-output (MIMO) and orthogonal frequency division multiplexing (OFDM) greatly improve the capacity of wireless links, still the bottleneck appears to be wireless links. To utilize the wireless resources efficiently, several previous works considered load balancing through cell-site selection [3][4][5] that assigns an AP (Access Point) to each user in order to maximize the network-wide utility. In principle, this paper follows this concept with additional consideration about heterogeneous RAT environments.

In this paper, we extend a framework called GPF (Generalized Proportional Fair) [3] to consider an extended environment. We refer to the extended framework as Point of Attachment (PoA) selection. In the PoA selection framework, each user is with single or multiple WNICs and associated with one or more APs which allocate their wireless resources to all associated users according to the proportional fair (PF) scheduling policy [6]. The PF scheduling tries to achieve a balance between throughput and fairness. Consequently, the utility of each user is determined by a logarithm of its achieved throughput. The goal of the PoA selection problem is to maximize the network-wide utility which is the sum of all users’ utilities. We prove that our problem is NP-Hard, and propose a heuristic algorithm to obtain a sub-optimal solution. Through extensive simulations, we evaluate the performance of our proposed heuristic algorithm against two received signal strength based approaches.

The rest of the paper is organized as follows: In Section II, the considered system model is described in detail. In Section III, we prove the NP-Hardness of the considered PoA selection problem. To solve this problem, we propose a heuristic algorithm in Section IV, followed by the performance evaluation in Section V. Finally, we conclude this paper in Section VI.

II. SYSTEM MODEL

Without loss of generality, we assume that two types of wireless access networks operated by a network operator are deployed in the considered area. Each type covers either the whole area or only some hotspots where the traffic demand is high. The set of RAT indices employed in the wireless access networks is denoted by $K = \{1, 2\}$, and $A$ denotes the set of APs regardless of RAT.1

User devices are classified into three classes: single-mode (SM), multi-mode single-homing (MMSH), and multi-mode multi-homing (MMMH). SM devices can be connected to only one fixed RAT at a given time. We assume that SM devices can access to only RAT 1 without loss of generality. MMSH

1Throughout the paper, we simply use the term RAT to indicate a wireless access network which employs that RAT.
devices are similar to those of SM class in that they can be connected to only one RAT at a given moment. However, they distinguish themselves from SM devices according to the ability to switch between the two RATs whenever necessary. Lastly, MMMH devices are the most capable ones since they can be connected to both RATs simultaneously. It is assumed that each user has only one user device which belongs to one of the three classes. For notational brevity, we denote the sets of users with SM, MMSH, and MMMH devices by $U_1$, $U_2$, and $U_3$, respectively. The set of all users is denoted by $U = U_1 \cup U_2 \cup U_3$.

We define $r_{ua}$ as the expected achievable rate if all the resources of AP $a$ are solely allocated to user $u$. Let $S_u$ be the set of APs from which user $u$ can receive a nonzero rate. That is, $S_u = \{ a | r_{ua} > 0, \forall a \in A \}$. $S_u$ is divided into $|K|$ non-overlapping subsets $S_{u,k}$, $\forall k \in K$. Note that $S_{u,2} = \phi$ for all users in $U_1$.

We define an indicator variable $x_{ua}$ that equals 1 if user $u$ is associated with AP $a$, and 0 otherwise. A partial association is not allowed since $x_{ua}$ can take either 0 or 1. For users in $U_1$ and $U_2$, $\sum_{a \in S_u} x_{ua} \leq 1$ holds as they can be connected to only one RAT at a given time. On the contrary, the association constraints are imposed on each RAT independently of users in $U_3$.

Once a user is associated with an AP, he or she will be allocated wireless resources according to the proportional fair (PF) policy. To be specific, at each time $t$, AP $a$ chooses user $u^*$ for resource allocation which is in a relatively best channel state as follows:

$$u^* = \arg \max_u \frac{r'_{ua}(t)}{R_{ua}(t)},$$

(1)

where $r'_{ua}(t)$ is the instantaneous achievable rate at time $t$, and $R_{ua}(t)$ is the average rate which has been achieved by time $t$. $R_{ua}$ is updated according to the following exponential smoothing rule:

$$\begin{cases} R_{ua}(t+1) = (1 - \frac{1}{c})R_{ua}(t) + \frac{1}{c}r'_{ua}, & \text{if scheduled}, \\ R_{ua}(t+1) = (1 - \frac{1}{c})R_{ua}(t), & \text{if not scheduled}, \end{cases}$$

(2)

where $1/c$ is a smoothing factor and usually set to 0.001.

Finally, we define a multi-user diversity (MUD) gain function $G : \mathbb{N} \to \mathbb{R}$ which arises from the opportunistic behavior of the PF scheduling. The function takes the number of users associated with an AP and returns a real-valued MUD gain. In general, the MUD gain is a function of the set of associated users. However, as pointed out in [7], if the relative rate fluctuations are statistically identical, the MUD gain only depends on the number of users associated with the AP. Let $y_a$ be the number of users associated with AP $a$. Consequently, it can be expressed as $y_a = \sum_{u,a \in S_u} x_{ua}$. If user $u$ is associated with AP $a$, the actual rate $\gamma_u$ that the user receives from the AP is $\gamma_u = r_{ua}G(y_a)/y_a$ because $y_a$ users share the airtime resources. In [8], Kelly showed that the PF scheduling rule in (1) coincides with optimizing the following problem:

$$\max \sum_{u \in U} \log(\gamma_u).$$

(3)

Hence, to summarize, the PoA selection problem which aims at maximizing the network-wide utility by carefully assigning each user to one or more neighboring APs can be formulated as the following optimization problem.

**PoA selection problem:**

$$\max_{x_{ua}} \sum_{u \in U} b_u$$

subject to

$$b_u = \log \sum_{a \in S_u} x_{ua}r_{ua}G(y_a)/y_a, \quad \forall u \in U,$$

$$y_a = \sum_{u,a \in S_u} x_{ua}, \quad \forall a \in A,$$

$$\sum_{a \in S_u} x_{ua} \leq 1, \quad \forall u \in U_1 \cup U_2,$$

$$\sum_{a \in S_{u,k}} x_{ua} \leq 1, \quad \forall u \in U_3, \forall k \in K,$$

$$x_{ua} = \{0, 1\}, \quad \forall u \in U, \forall a \in A.$$

In [3], Bu et al. described two GPF problems: GPF1 and GPF2. In GPF1, a general MUD gain function was considered, whereas the special form of MUD gain function as in this paper was used for GPF2. However, both of these considered only one RAT and SM devices. Therefore, they are degenerate cases of our respective problems although the PoA selection problem with a general MUD gain function is not dealt with in this paper.

Fig. 1 illustrates an example of the PoA selection problem. In this example, there are two user devices in the field: one SM device and one MMMH device denoted by $u$ and $v$, respectively. AP $a$ employs RAT 1 which has a wider coverage, yet offers a lower rate compared to RAT 2 employed in AP $b$. A typical example of this scenario would be the case that RAT 1 is WCDMA (Wideband Code Division Multiple Access) and RAT 2 is WLAN. For association, user $u$ has no choice but getting attached to AP $a$. On the other hand, user $v$ can attach to one or both of the APs. From user $v$’s
In terms of throughput, additional throughput in RAT 1 does not compensate for the decrease in user $u$'s utility caused by sharing the wireless resource of AP $a$ with user $v$. As shown in this example, the PoA selection problem is even more complicated than the GPF problem due to the environment of multi RATs and heterogeneous user device capabilities.

III. NP-HARDNESS OF POA SELECTION PROBLEM

In this section, we prove the NP-Hardness of the PoA selection problem. In [3], it was proved that GPF1 is NP-Hard and that there does not exist a polynomial time algorithm that can approximate the problem with a factor of $\rho$, $\forall \rho > 0$. On the contrary, in GPF2 where the MUD gain function depends only on the number of associated users, there exists an algorithm that can find an optimal solution in polynomial time. However, if multi-RAT environments and simultaneously accessible user devices are considered together, the optimization problem becomes NP-Hard even though it uses the special form of MUD gain function.

To show the NP-Hardness of our problem, we reduce the 3-dimensional matching problem, which is known as an NP-Complete problem, to a special case of our problem. The 3-dimensional matching problem is stated as follows: Let $X = \{x_1, x_2, ..., x_n\}$, $Y = \{y_1, y_2, ..., y_n\}$, and $Z = \{z_1, z_2, ..., z_n\}$ be finite and disjoint sets. Additionally, let $T$ be a subset of $X \times Y \times Z$. There are $m$ elements in $T$, and each element $T_i$ is a triple $(b_i, c_i, d_i)$ such that $b_i \in X$, $c_i \in Y$, and $d_i \in Z$. A subset of $T$, say $T^*$, is called matching if $|T^*| = n$ and $\bigcup_{T_i \in T^*} T_i = X \cup Y \cup Z$. To cover the set $X \cup Y \cup Z$ with only $n$ elements, it is required that, for any two distinct triples $T_i = (b_i, c_i, d_i)$ and $T_j = (b_j, c_j, d_j)$ in $T^*$, we have $b_i \neq b_j$, $c_i \neq c_j$, and $d_i \neq d_j$. The 3-dimensional matching problem is a decision problem which is to determine whether there exists a matching in the given $T$. We assume $n < m$ since it is trivial to check whether there is a matching when $n \geq m$.

**Theorem 1:** The PoA selection problem is NP-Hard.

**Proof:** We assign each triple $T_i \in T$ to a user with an MMMH device. As a result, there exist a total of $m$ users. Two RATs, RAT $y$ and RAT $z$, are deployed in the field, and each AP belongs to one of the two RATs. In particular, $y_1, ..., y_n$ are mapped to APs of RAT $y$. Likewise, $z_1, ..., z_n$ are regarded as APs of RAT $z$. These $2n$ APs are called normal APs. Each user receives the rates $R_y$ and $R_z$ (constants) from APs $c_i$ and $d_i$, respectively. In other words, among $n$ normal APs of RAT $y$, the user can be connected to only AP $c_i$ which is a component of the corresponding triple $T_i$. The same thing is applied to AP $d_i$ of RAT $z$. On the contrary, the achievable rates from normal APs other than $c_i$ and $d_i$ are all zeros.

Let’s define $Q_{x_i}$ as a set of users that have $x_i$ in the corresponding triple. Therefore, $\sum_{x_i \in Q_{x_i}} |Q_{x_i}| = m$. For each $Q_{x_i}$, we introduce $2(|Q_{x_i}| - 1)$ extra APs with half of them being APs of RAT $y$ and the other half being APs of RAT $z$. These extra APs are denoted by $y_k^{(i)}$ and $z_k^{(i)} (1 \leq i \leq n, 1 \leq k \leq |Q_{x_i}| - 1)$. Each user in $Q_{x_i}$ can receive the rates $R'_y$ and $R'_z$ (constants) from these extra APs using RATs $y$ and $z$, respectively. However, users in $Q_{x_i}(j \neq i)$ cannot be connected to these APs, thus having zero achievable rates.

Fig. 2 shows an example of the above-mentioned reduction. The left part of the figure illustrates an instance of the 3-dimensional matching problem where $T_1 = \{x_1, y_1, z_1\}$, $T_2 = \{x_1, y_2, z_2\}$, $T_3 = \{x_2, y_1, z_2\}$, and $T_4 = \{x_2, y_2, z_2\}$. In the right part which is the corresponding PoA selection problem, users and APs are represented by squares and circles, respectively. The connectivity between users and APs are shown as lines, and the rate that can be achieved when only one user is associated with an AP is represented above or below the corresponding AP.

Now, let us assume that $R_y + R_z = R'_y + R'_z$ and $R_y = R'_y + \epsilon, \exists \epsilon > 0$. Correspondingly, $R_z = R'_z - \epsilon$. Then, for a given MUD gain function $G(\cdot)$, we can choose $\epsilon$ such that $R_y G(k) < R'_y, \forall k > 1$ since $G(k) < 1, \forall k > 1$. Likewise, $R'_z G(k) < R_z, \forall k > 1$. We claim that a matching exists in the original problem iff the optimal network-wide utility is $m\log(R_y + R_z)$ in the corresponding PoA selection problem.

Suppose that there exists a matching $T^* \subset T$. Then, we assign the users in $T^*$ to the normal APs. This makes each
normal AP occupied by exactly one user. For the remaining \( m - n \) users in \( T \setminus T^* \), we assign them to the extra APs in such a way that no AP is occupied by two or more users. This is possible because there are \( 2(|Q_x| - 1) \) extra APs for each \( Q_x \), and they can be connected to all the users in \( Q_x \). As a result of this assignment, the network-wide utility becomes \( m \log(R_y + R_z) \). In Fig. 2, the bold lines represent an optimal assignment.

Conversely, in order to achieve the optimal network-wide utility, it is necessary that each AP should not be occupied by two or more users. This is because a user cannot receive more rate by sharing an AP with other user(s) due to the condition of \( \epsilon \) mentioned above. In addition, two APs with which a user is associated, i.e., one AP of RAT \( y \) and the other AP of RAT \( z \), should be the same type; normal or extra. This is because all users should receive the same total rate through the both RATs in order to maximize the network-wide utility. Recall that we are trying to maximize the product of rates, i.e., the sum of logarithms, whose sum is fixed. Therefore, if we can assign the users to the APs such that the network-wide utility becomes \( m \log(R_y + R_z) \), a matching can be found by choosing the users that are associated with the normal APs. Since the 3-dimensional matching problem which is reduced to our problem is NP-Complete, the decision version of our problem is also NP-Complete. Hence, the PoA selection problem is NP-Hard.

IV. PROPOSED HEURISTIC ALGORITHM

In this section, we propose an offline algorithm which is an extension of the LocalSearch algorithm proposed in [3]. The LocalSearch algorithm is a greedy algorithm which alters the current assignment to a best one among “nearby” configurations. As a result, the algorithm returns a local optimum.

The LocalSearch algorithm consists of two atomic operations: change and swap. The change operation chooses a user which results in the largest increase in the network-wide utility if it is associated with one of the other APs. If the increase is larger than a pre-defined threshold, the algorithm executes the operation. On the other hand, the swap operation considers the change of two APs with which two chosen users are associated respectively. It is noteworthy that the swap operation may not be decomposed into two sequential change operations due to the greedy characteristic of the algorithm.

In addition to these two operations, we add two more operations, attach and detach, which can be applied to MMMH devices in our environments. The attach operation makes an MMMH device attached to an AP using one of its available WNICs. On the contrary, the detach operation allows one of an MMMH device’s active WNICs to be turned off, thus detaching it from the associated AP. Hereafter, we refer to our proposed algorithm as LocalSearchExt algorithm.

Besides the added two new operations, the change and swap operations in the LocalSearchExt algorithm should be modified properly in order to reflect the considered environments. For example, suppose that the LocalSearchExt algorithm tries to change an MMMH device’s associated AP. In this case, it is possible to choose any AP in proximity as a target AP. However, the situation may become restrictive in case of MMMH devices. Suppose that the algorithm tries to change the AP an MMMH device is connected to using WNIC 1 (i.e., RAT 1). If the device is also attached to a RAT 2 AP using WNIC 2, only RAT 1 APs are eligible for being a target AP in this operation. The same principle is applied to the swap operation although the details are not presented in this paper.

Due to the dynamic nature of network topology incurred by user mobility, traffic arrival and departure, and so on, it is required to devise an online algorithm which has a low computational overhead. Basically, an online algorithm can originate from its offline version. This kind of approach is adopted in [3][5]. In [3], the proposed online algorithm called greedy-\( k \) is based on its offline version, i.e., the LocalSearch algorithm. In the greedy-\( k \) algorithm, it is allowed to perform at most \( k \) existing association changes, i.e., the change and swap operations, when the network topology changes. In [5], Son et al. suggest to use simple criteria for handover, i.e., association change. According to their proposed handover criteria, it is sufficient to check whether a user’s utility will be increased by the handover, rather than calculating the net change of all the affected users’ utilities. Unfortunately, these criteria cannot be used in our problem due to the simultaneous-access capability of MMMH devices. For the details, see [5]. Although the computational complexity in their problem can be reduced by the proposed criteria, it is essentially the same as the LocalSearch algorithm which gradually finds a local optimum by iteratively performing association changes. In this paper, we claim that an online algorithm can be readily obtained from the LocalSearchExt algorithm as in the case of the greedy-\( k \) algorithm. Since it has been already shown in [3][5] that the online algorithms can achieve the similar performance to those of the corresponding offline versions, we focus on the performance comparison of the offline algorithms in the following section.

V. PERFORMANCE EVALUATION

A. Compared Algorithms and Performance Metrics

We compare the performance of the LocalSearchExt algorithm against two heuristic algorithms: BestSignal-1 and BestSignal-2. Both algorithms are based on the received signal strength (RSS). In these algorithms, each user is associated with one or more APs whose RSS is the strongest. The difference between the two algorithms is that, for MMMH users, the BestSignal-1 algorithm chooses only one AP across all RATs, whereas one AP is chosen for each RAT in the BestSignal-2 algorithm. SM and MMSH users are handled in the same way in the both algorithms since they can be associated with at most one AP.

We use aggregate throughput and Jain’s fairness index [9] as performance metrics. Jain’s fairness index indicates how fair a resource allocation is, and it is calculated as follows:

\[
f(x_1, x_2, ..., x_n) = \frac{(\sum x_i)^2}{n \sum x_i^2},
\]

(4)
where \( n \) is the number of users, and \( x_i \) represents the amount of resources allocated to user \( i \). We let \( x_i \) be the number of time slots allocated to user \( i \) via both RATs over the entire simulation duration.

Besides (4) which is referred to as fairness index 1, we introduce two more fairness indices. The first one, fairness index 2, uses \( x'_i = x_i/n_i \) instead of \( x_i \) in (4) where \( n_i \) denotes the number of simultaneously associated APs with user \( i \). Hence, \( n_i \) is always 1 for SM and MMSH users, while it can be either 1 or 2 for MMMH users. Unlike the two fairness indices, fairness index 3 is calculated on a per-RAT basis. For instance, users attached to RAT 2 are taken for the calculation of the fairness index 3 of RAT 2 with \( x_i \) being the number of time slots allocated to user \( i \) via RAT 2.

### B. Simulation Setup

Fig. 3 depicts the considered simulation topologies. Figure 3(a) which is adopted from [3] shows a part of a major service provider’s 3G network in United States. It is employed as a RAT 1 topology in our simulation. In the topology, total 34 APs are deployed in the area of 30 \( \times \) 50 km\(^2\). The achievable rate at each location is inversely proportional to the brightness of that point; the darker the point is, the higher the achievable rate is. We omitted the details of the used channel model and the supported data rates. The exact parameter values can be found in [3] and the references therein.

Fig. 3(b) shows the RAT 2 topology which covers only a limited area. But, it is configured to offer higher data rates compared to RAT 1. A log-distance path loss model of \( PL = -110 - 30\log_{10}d \) is used, where \( d \) is the distance between an AP and a user in km. In addition, log-normal shadowing with a standard deviation of 4dB and Jake’s Rayleigh fading model [10] are also applied. The transmission power of an AP and the noise power are set to 43dBm and -111dBm, respectively. The supported data rates by RAT 2 are shown in Table I.

In the simulations, users are distributed randomly over the entire area following a specific probability distribution.

According to the probability distribution, it is 4 times more probable that a user is located in the hotspots, i.e., the area covered by RAT 2, than the other areas. The simulation time is 1000 time slots, and the duration of each time slot is 1ms.

### C. Results

Fig. 4 shows empirical cumulative distribution functions (CDFs) of the aggregate throughput and the fairness indices. There are a total of 150 users (100 SM users and 50 MMMH users), and 100 different instances are generated in order to obtain the CDFs. As shown in the figures, the proposed algorithm outperforms the two RSS based algorithms in terms of aggregate throughput and fairness. The two RSS based algorithms show almost the same performance except for the fairness index 1. The BestSignal-2 algorithm performs the worst with respect to the fairness index 1 because MMMH users receive resources from the both RATs at the same time, which results in an imbalance of the amount of allocated resources between SM users and MMMH users.

Fig. 5 reveals the impact of user ratio on the discussed metrics. In this simulation, the number of MMMH users is increased from 0 to 150, and the number of SM users is decreased from 150 to 0, while maintaining the total of 150 users. Although the aggregate throughput of all the algorithms show little difference, the fairness indices of the LocalSearchExt algorithm are consistently better than those of the two RSS based algorithms. Again, it is observed that the fairness index 1 of the two RSS based algorithms becomes reversed with the number of MMMH users.

### VI. Conclusion

In this paper, we dealt with the PoA selection problem that arises from a multi-RAT environment with heterogeneous device capabilities. First, the problem was formulated as an optimization problem where the objective is to maximize the network-wide utility. The network tries to maximize the utility by judiciously associating each user with one or more APs which are not necessarily to be closer. We proved the

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**TABLE I**

<table>
<thead>
<tr>
<th>Supported data rate (kbps)</th>
<th>Required SINR</th>
</tr>
</thead>
<tbody>
<tr>
<td>614</td>
<td>-3.95</td>
</tr>
<tr>
<td>1229</td>
<td>-1.65</td>
</tr>
<tr>
<td>2458</td>
<td>1.5</td>
</tr>
<tr>
<td>3686</td>
<td>4.3</td>
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<td>18.45</td>
</tr>
<tr>
<td>18432</td>
<td>24.8</td>
</tr>
</tbody>
</table>

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2To be specific, the whole area is divided into several zones of 1 \( \times \) 1km\(^2\). Zones within and outside the hotspots are assigned uniformly chosen values from \([0, 20]\) and \([0, 5]\), respectively. The probability that a user is located in a certain zone is proportional to its assigned value.

3These are the users who generate heavy traffic which is considered in this paper.
NP-Hardness of our considered problem, and proposed a
heuristic algorithm called LocalSearchExt. Through extensive
simulations, the performance of the LocalSearchExt algorithm
was compared to those of the two RSS based algorithms. The
evaluation results revealed that our proposed algorithm out-
performs the two RSS based algorithms in terms of aggregate
throughput and fairness.

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