User Association in 5G mmWave Networks

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***Abstract*—The approaching 5G era of cellular communications is posing stringent performance requirements. New groundbreaking applications can be enabled only by means of multi-Gbps data rates and ultra-low latencies. The spectrum scarcity at frequencies below 6 GHz stimulated a new wave of wireless research that focuses on higher bands, namely mmWave. Directionality and high penetration loss represent the key challenges when operating with such carriers. The resulting intermittent connectivity makes the user association problem even more complex and critical than in previous generations of cellular systems, where the channel was better behaved. In this paper, we aim at deriving an optimal and fair cell selection policy that encapsulates the reallocation cost of potential handovers, and captures the erratic nature of the mmWave channel. An important conclusion is that (i) if there is no, or minimal, reallocation cost, each user associates with a single BS, while (ii) for higher handover cost values, users tend to connect to multiple base stations simultaneously.**

***Index Terms*—Wireless; Millimeter-wave; 5G; Handover; Optimization; User Association.**

I. INTRODUCTION

Next-generation cellular networks are expected to include millimeter wave (mmWave) technology, that operates at frequencies above 28 GHz, therefore exploiting the enormous amount of spectrum available in these bands. However, the radio propagation characteristics are sharply different from their microwave counterparts. Based on the Friis transmission equation [1], attenuation can be 30-40 dB more. To cope with this poor isotropic propagation, antenna arrays with beamforming are used to obtain the desired range. Additionally, given the increased blockage and shadowing effects [2], the mmWave channel will undergo rapid quality variations, thus leading to *intermittent* link connectivity between the user and the base station.

User association is a critical procedure in cellular networks. It involves choosing which base station (BS) the user equipment (UE) should be connected to. In traditional cellular systems, which operate in the microwave bands (around 2 GHz), simple heuristics are sufficient. They are typically based on the BS that can provide the highest long-term signal to noise ratio (SNR) [3]. However, given the erratic nature of the mmWave channel, cell selection and handover decisions represent a key challenge in designing seamless next-generation cellular networks.

A critical goal is to maintain an acceptable level of service despite this intermittency, which is the reason why the density of BSs in mmWave cellular networks is expected to be an order of magnitude higher than in current systems [4]. Multiple potential surrounding BSs can be detected to rapidly switch between them in response to the fast-varying link qualities [5]. A viable approach might be to greedily pick the BS with the best instantaneous SNR value, but this approach may lead to degraded performance for other UEs [6], [7], or even to instability. Further, it introduces significant overhead because of the frequent signaling triggered in the control plane due to the large number of BS handovers. For these reasons, a better approach should capture all relevant information, such as channel conditions, cell load and signaling plus reallocation cost.

The problem of cell selection in mmWave networks has gained a lot of interest. In [8], the authors examine different user association approaches applied to mmWave WLAN networks, which operate at 60 GHz. The most appealing solution is given by G. Athanasiou et al. [9], who propose an optimal and fair client association based on Lagrangian duality theory. In [10], it is shown how the attainable throughput of mmWave networks is highly dependent on the user association. However, the authors do not propose any specific selection strategy. Interestingly, in [11], the authors show that the UE will remain associated with a mmWave BS for just a few seconds. In [12], Shokri-Ghadikolaei et al. study the implications of the mmWave PHY layer on the MAC layer, arguing that simple cell selection techniques based on SNR would lead to many handovers, as also shown in [13], [14], where the impact of multiple handovers is captured through end-to-end network simulations in multiple mmWave cellular scenarios. Finally, the authors in [7] argue that considering SINR alone leads to sub-optimal assignments, and the optimal approach is therefore to solve cell selection and resource allocation jointly.

In our previous work [15], we had proposed a framework for handover decisions based on Markov Decision Processes (MDPs) [16]–[18]. However, due to the intrinsic complexity of this mathematical model, its computational burden increased super exponentially with the number of UEs and BSs. As a consequence, rather than implementing a centralized omniscient system, we opted for a distributed approach capable of capturing the two key factors, namely, (i) *channel variability* and (ii) *reallocation cost*.

The paper is organized as follows. In Sec. II, we introduce our problem formulation. In Sec. III, we describe our approximate optimization formulation and report its solution in Appendix A. In Sec. IV, we report some results, and finally conclude the paper in Sec. V.

II. Problem Formulation

We consider a cellular network with M base stations and N UEs. Between the BSs and the UEs, there are L links. Not all BS-UE pairs have a possible connection, so L may be less than MN. For each link ℓ, we let $\sigma_{\rm UE}(\ell)$ and $\sigma_{\rm BS}(\ell)$ be the UE and BS indices associated with the link. Since we are considering an association problem, each UE has possible connections to multiple BSs. Also, each BS may serve multiple UEs. We let

$$A_n = \{\ell | \sigma_{\rm UE} = n\}, \quad B_m = \{\ell | \sigma_{\rm BS} = m\},$$

be the set of links associated with each UE n and BS m. We assume that the A_n's are disjoint for all n and the B_m's are disjoint for all m.

To model the time-varying nature of the links, we associate with eack link ℓ a time-varying state described by a Markov chain $x_\ell(k)$. We assume that there are K states for each link so that we can write $x_\ell(k) \in \{1, \ldots, K\}$. It is easy to extend this model to different values of K per link. At each time instant k, the system is to make a bandwidth allocations $w_\ell(k)$, which represents the amount of bandwidth available to link ℓ. The rate of link ℓ is then assumed to be given by

$$R_\ell(k) = \rho_\ell(x_\ell(k)) w_\ell(k), \tag{1}$$

where $\rho_\ell(x_\ell)$ is the spectral efficiency of the link as a function of the link state, $x_\ell(k)$. The total instantaneous rate delivered to UE n is then given by the sum

$$\overline{R}_n(k) = \sum_{\ell \in A_n} R_\ell(k). \tag{2}$$

We next introduce the following terminology. The state of an individual link $x_\ell(k)$ will be called the *link state*. The state across the entire network will then be given by the vector

$$\mathbf{x}(k) = [\mathbf{x}_1(k), \ldots, \mathbf{x}_N(k)], \tag{3}$$

and will be called the *network state* or *global state*. Since each link state has dimension K, the network state dimension is K^L – exponentially large. The state of all the links associated with a particular UE n will be denoted by

$$\mathbf{x}_n(k) = [x_\ell(k), \ell \in A_n], \tag{4}$$

and will be called the *UE state*. Since UE n is associated with $|A_n|$ links, its dimension will be $K^{|A_n|}$. We can define $\mathbf{w}_n(k)$ and $\mathbf{w}$ similarly.

The network problem is to select an allocation *policy*, by which we mean a function

$$\mathbf{w}(k) = g(\mathbf{x}(k)), \tag{5}$$

which selects the resource allocation for all links based on the network state $\mathbf{x}(k)$. We assume that the link states are stationary Markov chains. Thus, under a time-invariant policy of the form (5), the network state $\mathbf{x}(k)$ and resource allocation $\mathbf{w}(k)$ become stationary random processes. With these definitions, we can define the components of our optimization as follows.

Risk-averse rate time averaging: The time-averaged rate to UE n is given by

$$\mathbb{E}(\overline{R}_n(k) | g),$$

where we use the notation $\mathbb{E}(\cdot|g)$ to denote the expectation under the policy (5). However, the time-averaged rate may not be a suitable metric since short-term outages in rate can lead to a very poor experience, even though they may not influence the overall rate significantly. We thus propose to use a "risk averse" time-averaged rate given by

$$S_n(g) := -\frac{1}{\theta} \log \mathbb{E}\left[\exp(-\theta \overline{R}_n(k)) | g\right], \tag{6}$$

where $\theta > 0$ is some risk aversion parameter. When $\theta \to 0$, $S_n(g) \to \mathbb{E}(\overline{R}_n(k)|g)$, the average rate. When $\theta \to \infty$, $S_n(g) \to \min \overline{R}_n(k)$, the minimum rate. Thus, by increasing θ we can penalize the short-term drops in rate.

Fairness across users: To model fairness across users, we take a system utility of the form

$$U(g) := \sum_{n=1}^{N} U_n(S_n(g)), \tag{7}$$

where the functions $U_n(s)$ are concave, smooth and strictly increasing. For example, for the proportional fairness metric, we take $U_n(s) = \log(s)$. The utility functions are taken as functions of the risk-averse UE rates $S_n(g)$.

Bandwidth constraint: Each BS m has a finite bandwidth $\overline{w}_m$. We require that, in every time slot k, the allocated bandwidth does not exceed this maximum

$$\begin{aligned} &\sum_{\ell \in B_m} w_\ell(k) \le \overline{w}_m, \\ &w_\ell(k) \ge 0, \forall \ell \in B_m, \forall m \end{aligned} \tag{8}$$

Reallocation cost: Critical in our formulation is that we penalize the cost of reallocating resources, trough either handover or allocation within a BS. Let $C(g)$ be the average *link reallocation* cost, given by

$$C(g) = \sum_{\ell=1}^{L} C_\ell(g),$$

where

$$C_\ell(g) := \mathbb{E}\left[\phi(w_\ell(k) - w_\ell(k-1)) | g\right],$$

for some convex, smooth function $\phi(\cdot)$.

Under these constraints, our optimization is to find a policy g that minimizes

$$\min_g J(g), \quad J(g) := -U(g) + C(g), \tag{9}$$

where the optimization is over all policies satisfying the resource allocation constraint (8).

III. Approximate Optimization

In this section, we simplify the optimization problem (9) and present a method to solve it. We replace the instantaneous resource constraint (8) with an average constraint

$$\sum_{\ell \in B_m} \mathbb{E}\left[w_\ell(k)|g\right] \leq \overline{w}_m, \tag{10}$$

for all BSs m, with $w_\ell(k) \geq 0, \forall \ell \in B_m$.

That is, we seek to minimize (9) under the constraint (10). It can be verified that this problem is convex. To prove the convexity of the objective function, we use the following two simple lemmas.

Lemma 1. *Consider a composition function $h(\mathbf{x}) = f(g(\mathbf{x}))$ where (i) $f(z)$ and $g(\mathbf{x})$ are smooth and concave; (ii) $f(z)$ has a scalar valued input and (iii) $f(z)$ is a non-decreasing function of z. Then, $h(\mathbf{x})$ is concave.*

Proof. Take the first derivative

$$h'(\mathbf{x}) = f'(g(\mathbf{x}))g'(\mathbf{x}).$$

The Hessian is

$$h''(\mathbf{x}) = g'(\mathbf{x})^T f''(g(\mathbf{x}))g'(\mathbf{x}) + f'(g(\mathbf{x})g''(\mathbf{x})).$$

Since f and g are concave, $f''(z)$ and $g''(\mathbf{x}) \leq 0$. Also, since $f(z)$ is non-decreasing $f'(z) \geq 0$. So $h''(\mathbf{x}) \leq 0$. □

Lemma 2. *Consider a function of the form*

$$f(\mathbf{x}) = \log\left[\mathbf{b}^T \exp(\mathbf{A}\mathbf{x})\right].$$

for any matrix $\mathbf{A}$ and vector $\mathbf{b}$ with $\mathbf{b} > 0$. Then $f(\mathbf{x})$ is convex.

Proof. This is a standard result of exponential families. Specifically, let

$$Z(\mathbf{x}) = \mathbf{b}^T \exp(\mathbf{A}\mathbf{x}) = \sum_i b_i e^{\mathbf{a}_i^T \mathbf{x}},$$

which is called the partition function. Define the probability distribution

$$p_i = \frac{1}{Z(\mathbf{x})} b_i e^{\mathbf{a}_i^T \mathbf{x}},$$

which is a probability distribution dependent on $\mathbf{x}$. Then, the first derivative of $f(\mathbf{x})$ is

$$f'(\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \sum_i p_i \mathbf{a}_i = \mathbb{E}(\mathbf{a}_i|\mathbf{x}).$$

And the Hessian is

$$\begin{aligned} f''(\mathbf{x}) &= \mathbb{E}(\mathbf{a}_i\mathbf{a}_i^T|\mathbf{x}) - \mathbb{E}(\mathbf{a}_i|\mathbf{x})\mathbb{E}(\mathbf{a}_i|\mathbf{x})^T \\ &= \mathrm{var}(\mathbf{a}_i|\mathbf{x}) \geq 0. \end{aligned}$$

□

These lemmas can be used for our objective function by considering $f(z) = U_n(z)$, and $g(\mathbf{x}) = -S_n(\mathbf{x})$ in Lemma 1, where $S_n(\mathbf{x})$ has the same form of $f(\mathbf{x})$ of Lemma 2. Hence $U(g)$ in (9) is a concave function. Since $\phi(\cdot)$ is a convex, smooth function, our objective function (9) is convex.

The problem admits a simple dual decomposition. First, we rewrite the constraints (10) as

$$\begin{aligned} &\mathbf{F}\mathbb{E}\left[\mathbf{w}(k)|g\right] \leq \overline{\mathbf{w}}_m, \\ &\mathbf{w}(k) \geq 0, \end{aligned} \tag{11}$$

where $\mathbf{F}$ is the matrix with $A_{m\ell} = 1$ if $\ell \in B_m$ and 0 otherwise, while $\overline{\mathbf{w}}_m$ is the vector of bandwidths $\overline{w}_m$. Corresponding to the constraints in (11), and using auxiliary variables $\widetilde{\mathbf{w}}(k)$, we can write our optimization problem as

$$\begin{aligned} \min_{g, \widetilde{\mathbf{w}}} \quad & J(g) \\ \text{subject to} \quad & \mathbf{F}\mathbb{E}\left[\mathbf{w}(k)|g\right] \leq \overline{\mathbf{w}}_m, \\ & \mathbf{w}(k) = \widetilde{\mathbf{w}}(k), \\ & \widetilde{\mathbf{w}}(k) \geq 0. \end{aligned} \tag{12}$$

Let us define the Lagrangian

$$\begin{aligned} &L_0(g, \widetilde{\mathbf{w}}(k), \boldsymbol{\lambda}, \mathbf{u}) := J(g) \\ &+ \boldsymbol{\lambda}^T \left(\mathbf{F}\mathbb{E}\left[\mathbf{w}(k)|g\right] - \overline{\mathbf{w}}_m\right) + \mathbf{u}^T(\mathbf{w}(k) - \widetilde{\mathbf{w}}(k)). \end{aligned} \tag{13}$$

The augmented Lagrangian [19] for this problem is

$$\begin{aligned} L(g, \widetilde{\mathbf{w}}(k), \boldsymbol{\lambda}, \mathbf{u}) := L_0(g, \widetilde{\mathbf{w}}(k), \boldsymbol{\lambda}, \mathbf{u}) + \\ (\rho/2)||\mathbf{w}(k) - \widetilde{\mathbf{w}}(k)||^2, \end{aligned} \tag{14}$$

where $\rho > 0$ is called the penalty parameter. We solve (12) using the alternating direction method of multipliers (ADMM) [19], by repeating the optimization steps given in (15). At iteration $t+1$,

$$\mathbf{w}(k)^{t+1} \leftarrow g^{t+1} \leftarrow \arg\min_{g} L(g, \widetilde{\mathbf{w}}(k)^t, \boldsymbol{\lambda}^t, \mathbf{u}^t), \tag{15a}$$

$$\widetilde{\mathbf{w}}(k)^{t+1} \leftarrow \arg\min_{\widetilde{\mathbf{w}}(k) \geq 0} L(g^{t+1}, \widetilde{\mathbf{w}}(k), \boldsymbol{\lambda}^t, \mathbf{u}^t), \tag{15b}$$

$$\boldsymbol{\lambda}^{t+1} \leftarrow \boldsymbol{\lambda}^t + \alpha\left[\mathbf{F}\mathbb{E}\left[\mathbf{w}(k)|g^{t+1}\right] - \overline{\mathbf{w}}_m\right], \tag{15c}$$

$$\mathbf{u}^{t+1} \leftarrow \mathbf{u}^t + \rho(\mathbf{w}^{t+1}(k) - \widetilde{\mathbf{w}}^{t+1}(k)). \tag{15d}$$

Since the original problem is convex, strong duality holds and (15) will converge to the solution of the primal problem (9) subject to (11).

What is important is that the minimization in (15a) is simple. Specifically, the optimal policy g that minimizes $L(g, \cdots)$ is of the form

$$\mathbf{w}_n(k) = g_n(\mathbf{x}_n(k)). \tag{16}$$

That is, the resource allocation for UE n depends only on the UE state $\mathbf{x}_n(k)$, not the global state $\mathbf{x}(k)$, and is therefore much more tractable.

The function $L(g, \cdots)$ can be written explicitly as follows. Fix a UE n and let $d = |A_n|$ be the total number of links associated with the UEs. The UE space has size K^d and we index all the UE states, $i = 1, \ldots, K^d$. For any policy $g_n(\cdot)$, we can define

$$\mathbf{w}_{ni} = g_n(\mathbf{x}_n = i),$$

which is the allocation of $\mathbf{w}_n(k)$ when the UE state $\mathbf{x}_n(k) = i$. Each $\mathbf{w}_{ni}$ is an allocation of bandwidths across the links associated with the UE

$$\mathbf{w}_{ni} = \{w_{ni\ell}, \ell \in A_n\},$$

and can be represented as a d-dimensional vector. The policy g_n is then completely described by the matrix $\mathbf{W}_n = [\mathbf{w}_{n1}, \ldots, \mathbf{w}_{nK^d}]$.

By taking the terms in $L(g, \cdots)$ in (14) that depend on UE n, we get that g_n should minimize

$$\begin{aligned} &L_n(g_n, \widetilde{\mathbf{w}}_n(k), \boldsymbol{\lambda}, \mathbf{u}) := -U_n(g_n)+ \\ &\sum_{\ell \in A_n} \left[C_\ell(g_n) + v_\ell \mathbb{E}\left[w_\ell(k)|g_n\right]\right] \\ &+ \sum_{\ell \in A_n} \sum_i u_{ni\ell}\left[w_{ni\ell}(k)|g_n - \widetilde{w}_{ni\ell}(k)|g_n\right] \\ &+ (\rho/2) \sum_{\ell \in A_n} \sum_i ||w_{ni\ell}(k)|g_n - \widetilde{w}_{ni\ell}(k)|g_n||^2, \end{aligned} \tag{17}$$

where $\mathbf{v}$ is the transformed dual parameter

$$\mathbf{v} = \mathbf{F}^T \boldsymbol{\lambda}.$$

Further, we can write each component of the Lagrangian in (17) in terms of the vectors $\mathbf{w}_{ni}$. For example, the risk-averse rate in (6) is given by

$$S_n(g_n) = -\frac{1}{\theta} \log\left[\sum_i p_{ni} \exp(-\theta \mathbf{w}_{ni}^T \rho_{ni})\right],$$

where p_{ni} is the steady state probability $p_{ni} = \Pr(\mathbf{x}_n = i)$ and ρ_{ni} is the vector of the spectral efficiencies in UE state i. Similarly, the link reallocation term is given by

$$C_\ell(g_n) = \sum_{ij} P_{nij} \phi(w_{ni\ell} - w_{nj\ell}),$$

where P_{nij} is the joint probability distribution of the UE state,

$$P_{nij} = \Pr(\mathbf{x}_n(k) = i, \mathbf{x}_n(k-1) = j).$$

Finally, the expected resource usage is given by

$$\mathbb{E}\left[w_\ell(k)|g_n\right] = \sum_i p_{ni} w_{ni\ell},$$

and

$$\mathbb{E}\left[\widetilde{w}_\ell(k)|g_n\right] = \sum_i p_{ni} \widetilde{w}_{ni\ell}.$$

We can then use these terms to rewrite (17) in terms of $\mathbf{W}_n$ and solve for the optimal matrix via standard convex optimization techniques. Please refer to Appendix A for more details on the solution for $\mathbf{W}_n$.

IV. Results

In this section, we present some numerical and simulation results obtained by applying the bandwidth allocation technique derived in Section III. We studied a heterogeneous scenario with 1 macro BS and 3 mmWave BSs, while varying the number of UEs. The results presented in this section are generated by taking the average over different topologies. In each topology,

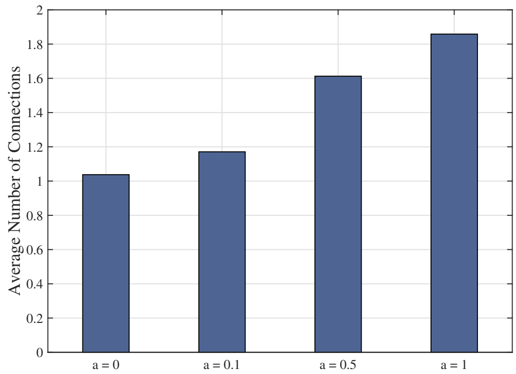

Fig. 1. Average number of connections with different handover cost with 6 UEs

TABLE I
NETWORK PARAMETERS

Parameter	Value
mmWave BS Bandwidth	1 GHz
Macro BS Bandwidth	1 MHz
Path loss (dB) with macro BS (R in km)	$128.1 + 37.6\ \log_{10}(R)$
Path Loss (dB) with mmWave BS (LOS, d in m)	$61.4 + 20 \log_{10}(d)$

the BSs and the UEs are randomly dropped in a 10^4 m^2 area. Each link between a mmWave BS and a UE is characterized by two possible states, (i) outage, where no mmWave link is available; (ii) LOS, where a direct LOS mmWave link is available. The presence of the outage state, which occurs due to blockage, and the highly dynamic behavior of the channel, which can move in and out of the outage state on a very short time scale, are unique to the mmWave model. The channel conditions seen by each UE towards a mmWave BS are modeled with a transition probability matrix,

$$\mathbf{P} = \begin{bmatrix} p_{out-out} & p_{out-LOS} \\ p_{LOS-out} & p_{LOS-LOS} \end{bmatrix}. \tag{18}$$

In our simulations, for each UE, we use the following three different transition matrices to model the links with the three mmWave BSs.

$$\mathbf{P_1} = \begin{bmatrix} 0.05 & 0.95 \\ 0.1 & 0.9 \end{bmatrix}, \mathbf{P_2} = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}, \mathbf{P_2} = \begin{bmatrix} 0.9 & 0.1 \\ 0.95 & 0.05 \end{bmatrix}$$

In the first and third matrix, the dominant channel states are LOS and outage, respectively, whereas for the second matrix, both conditions are equally likely. The other simulation parameters are given in Table I [20].

To better assess the performance of the proposed model, we generate the results for different handover costs. First we see the effect of varying the handover cost on the system utility (7). To vary the handover cost, we use different values of a to compute $C_\ell(\mathbf{w}_n)$ as defined in (21). As we increase the values of a, i.e., increasing the handover cost, the value of the system utility decreases. For example, with 6 UEs, the system utility is decreased by 3% and 5% when $a = 0.5$ and $a = 1$, respectively, compared to the value with no handover cost. From the bandwidth allocation given by

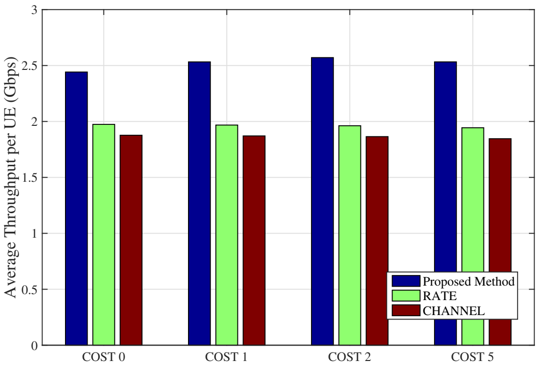

Fig. 2. Average throughput with different handover cost with 6 UEs. Here Cost 0, Cost 1, Cost 2, and Cost 5 correspond to 0%, 1%, 2%, and 5% handover cost, respectively.

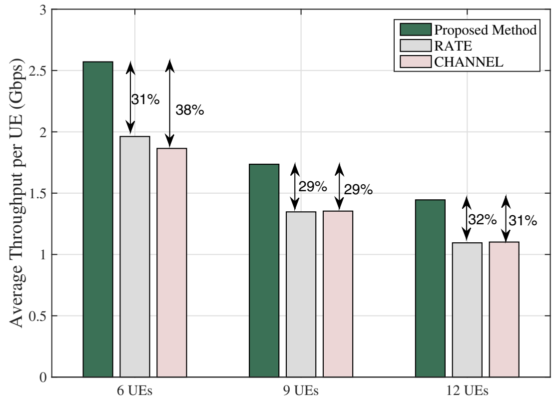

Fig. 3. Average throughput at increasing number of UEs (2% handover cost).

the proposed optimization, we can also calculate the number of BSs on which a UE has non-zero bandwidth allocation for each state. With this result we compute the average number of connections for each UE over all states. In Fig. 1, the average number of connections for a UE is shown with different values of a. For higher handover costs, our policy suggests to keep multiple connections at the same time.

To further assess the performance of the proposed method, we compare its performance against other cell selection approaches, namely:

- **Rate:** UEs associate with the BS that can offer the best instantaneous rate, which depends on both channel and load information;
- **Channel:** Traditional approach where UEs select the BS offering the best channel (SNR-based).

Under the aforementioned deployment setting and the channel transition matrix, we run our simulation for 10 seconds for each topology and apply the cell association policy derived in our proposed method, *Rate*, and *Channel*. In our method, for each state, we assume that a UE is connected to all the BSs with which it has non zero bandwidth allocation. For all the three approaches, we assume that the total bandwidth is equally divided among all the associated UEs. We calculate the average throughput a UE achieves in all the approaches with different handover costs. For a given handover cost, we deduct a fixed percentage of the rate a UE achieves when it changes its BS association. In Fig. 2, Cost 0, Cost 1, Cost 2, and Cost 5 mean 0%, 1%, 2%, and 5% handover cost, respectively. For example, in case of Cost 2, when a UE moves from its current BS to another BS, i.e., target BS, a 2% deduction from the achievable rate on the target BS will be incurred for this UE, for that specific slot. Fig. 2 shows that the proposed cell association technique outperforms the other approaches. On average, *Rate* based and *Channel* based approaches achieve 22% and 25% lower throughput compared to our approach, respectively. In our method, for Cost 0, Cost 1, Cost 2, and Cost 5, we use $a = 0$, $a = 0.1$, $a = 0.5$, and $a = 1$ while deriving the corresponding policies, respectively.

In Fig. 3, the average throughput is plotted versus the number of UEs with 2% handover cost. In all cases, the proposed method provides significant throughput gains compared to other schemes.

V. Conclusion

Intermittent mmWave links make user association particularly critical in the design of 5G mmWave cellular networks. In this paper, we have derived an optimal and fair cell selection policy that encapsulates the reallocation cost of potential handovers, and captures the erratic nature of the mmWave channel. Interestingly, we note that (i) if there is no, or minimal, reallocation cost, each user associates with a single BS, while (ii) for higher handover cost values, users tend to connect to multiple base stations simultaneously.

Appendix A
Approximate solution of $\mathbf{W}_n$

Using (15a) and (17), we can write

$$\begin{aligned}
\mathbf{w}_n(k)^{t+1} \leftarrow & \arg\min_{\mathbf{w}_n(k)} -U_n(g_n) + \\
& \sum_{\ell \in A_n} \left[C_\ell(g_n) + v_\ell \mathbb{E}\left[w_\ell(k)|g_n\right]\right] \\
& + \sum_{\ell \in A_n} \sum_i u_{ni\ell}\left[w_{ni\ell}(k)|g_n - \widetilde{w}_{ni\ell}(k)|g_n\right] \\
& + (\rho/2) \sum_{\ell \in A_n} \sum_i ||w_{ni\ell}(k)|g_n - \widetilde{w}_{ni\ell}(k)|g_n||^2
\end{aligned} \tag{19}$$

where

$$U_n(g_n) = \log\left(-\tfrac{1}{\theta}\log\left[\textstyle\sum_i p_{ni}\exp(-\theta \mathbf{w}_{ni}^T \rho_{ni})\right]\right) \tag{20}$$

and we assume a quadratic cost function as

$$\phi(z) = a|z|^2, \tag{21}$$

where $a > 0$ is a weighting factor used to vary the weight of the reallocation cost. Thus,

$$C_\ell(\mathbf{w}_n) = a \sum_{ij} P_{nij}(w_{ni\ell} - w_{nj\ell})^2. \tag{22}$$

We write (19) as

$$
\begin{aligned}
\mathbf{W}_n(k)^{t+1} \leftarrow & \underset{\mathbf{W}_n(k)}{\arg\min}\, F_1(\mathbf{W}_n(k)) + F_2(\mathbf{W}_n(k)) \\
& + \mathbf{v}^T(\mathbf{A}\mathbf{W}_n(k)) + \mathbf{u}_n^T(\mathbf{W}_n(k) - \widetilde{\mathbf{W}}_n(k)) \\
& + (\rho/2)||\mathbf{W}_n(k)) - \widetilde{\mathbf{W}}_n(k)||^2,
\end{aligned} \tag{23}
$$

where $F_1(\mathbf{W}_n(k)) = -U_n(\mathbf{W}_n(k))$, and $F_2(\mathbf{W}_n(k)) = \sum_{\ell \in A_n} C_\ell(\mathbf{w}_n))$. We replace F_1, and F_2 with their second order approximations as

$$
\begin{aligned}
& F(\mathbf{W}_n(k)) = F(\mathbf{W}_n(k)^t) + [F^{'}(\mathbf{W}_n(k)^t)]^T \\
& .(\mathbf{W}_n(k) - \mathbf{W}_n(k)^t) + 0.5(\mathbf{W}_n(k) - \mathbf{W}_n(k)^t)^T \\
& .[H(\mathbf{W}_n(k)^t)]^T(\mathbf{W}_n(k) - \mathbf{W}_n(k)^t),
\end{aligned} \tag{24}
$$

where H is the hessian matrix of F. Then the $\mathbf{W}_n(k)$ which provides the minimum value of (23) can be derived as

$$
\begin{aligned}
& \mathbf{W}_n(k)^{t+1} = \left[H_1(\mathbf{W}_n(k)^t) + H_2(\mathbf{W}_n(k)^t) + \rho\ \mathbf{I}\right]^{-1} \\
& \times \left[H_1(\mathbf{W}_n(k)^t)\mathbf{W}_n(k)^t + H_2(\mathbf{W}_n(k)^t)\mathbf{W}_n(k)^t\right. \\
& - F_1^{'}(\mathbf{W}_n(k)^t) - F_2^{'}(\mathbf{W}_n(k)^t) + \rho\widetilde{\mathbf{W}}_n(k) - \\
& \qquad \left.\mathbf{A}^T\mathbf{v} - \mathbf{u}_n\right].
\end{aligned} \tag{25}
$$

The solution for $\widetilde{\mathbf{w}}_n(k)$ in (15b) can be obtained by solving

$$
\begin{aligned}
\widetilde{\mathbf{w}}_n(k)^{t+1} \leftarrow & \underset{\widetilde{\mathbf{w}}_n(k) \geq 0}{\arg\min} -\mathbf{u}^T\widetilde{\mathbf{w}}_n(k)^t \\
& + (\rho/2)||\mathbf{w}_n(k)^{t+1} - \widetilde{\mathbf{w}}_n(k)||^2,
\end{aligned} \tag{26}
$$

which gives

$$
\widetilde{w}_{ni\ell}^{t+1} = (w_{ni\ell}^{t+1} + (1/\rho)u_{ni\ell}^t)\mathbb{1}_{\{(w_{ni\ell}^{t+1} + (1/\rho)u_{ni\ell}^t) > 0\}}. \tag{27}
$$

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