

Partially Blind Handovers for mmWave New Radio Aided by Sub-6 GHz LTE Signaling

Faris B. Mismar and Brian L. Evans

Wireless Networking and Communications Group, The University of Texas at Austin, Austin, TX 78712 USA

Abstract—For a base station that supports cellular communications in sub-6 GHz LTE and millimeter (mmWave) bands, we propose a supervised machine learning algorithm to improve the success rate in the handover between the two radio frequencies using sub-6 GHz and mmWave prior channel measurements within a temporal window. The main contributions of our paper are to 1) introduce partially blind handovers, 2) employ machine learning to perform handover success predictions from sub-6 GHz to mmWave frequencies, and 3) show that this machine learning based algorithm combined with partially blind handovers can improve the handover success rate in a realistic network setup of colocated cells. Simulation results show improvement in handover success rates for our proposed algorithm compared to standard handover algorithms.

Index Terms—machine learning, self-organizing networks, 5g, mmwave, inter-RAT, blind handover.

I. INTRODUCTION

The fifth-generation (5G) of wireless communications, also known as *New Radio* (NR), is believed to adopt the *millimeter wave* (mmWave) frequencies in addition to sub-6 GHz band while other technologies such as LTE or LTE-A Pro (collectively LTE from now on) will continue to use frequencies in the sub-6 GHz band [1]. As a result, the need for measurement gaps prior to executing the *inter-radio access technology* (inter-RAT) handover from these technologies to 5G. The major problem with measurement gaps is their reduction of the perceived end-user throughput because data transmission ceases during these gaps [2]. In this paper, we propose a machine learning based algorithm residing in the LTE base station (eNodeB) prior to configuring the measurement gap. This step is essential before the 5G base station establishes the radio link into NR as part of the handover execution. Such a step is important because the cost of a failed handover during a measurement gap is expensive: it can cause a dropped call, an increased packet delay, or low data throughput. All of these are factors that contribute to the dissatisfaction of the end-user about the service or about the mobile network operator as a whole. Our approach learns a statistical relationship between both sub-6 GHz in LTE and mmWave frequency measurements in NR and uses it to decide whether a handover would succeed if executed. This is an enabler for *self-organizing networks* (SON) to perform as promised in 5G [3]. Fig. 1 shows the overall setup.

During measurement gaps, the data transmission ceases so the *user equipment* (UE) receiver circuitry can measure the different frequency band in which the target technology

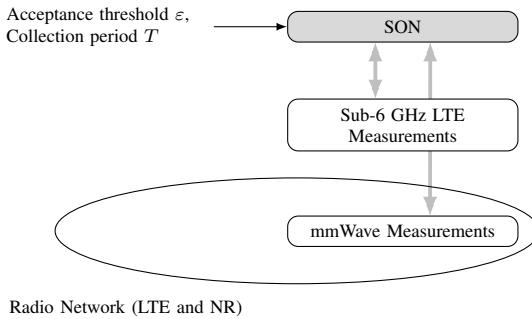


Fig. 1. The machine learning based algorithm and partially blind handovers interacting with the self-organizing network (SON).

typically operates. In our case, the target technology that the LTE-connected UE wants to measure is the 5G technology operating in the mmWave frequency range.

In [4], the authors used *correlation based adaptive compressed sensing* (CBACS) in mmWave to estimate with high-accuracy the *channel state information* (CSI) particularly the *angle of departure* (AoD) and *angle of arrival* (AoA), which are essential for hybrid beamforming. Compressed sensing is justified since mmWave radio frequency waves scatter poorly as they propagate. Their approach decides the CSI by comparing correlations of the received CSI versus the quantized sensing vectors. They obtained higher accuracy without an increase in the training overhead. We occasionally override the need for CSI by allowing the base station to make the channel estimation on behalf of the UE based on collected data.

Using *orthogonal matching pursuit* (OMP), the authors in [5] formulated a sparse signal recovery problem, which exploits the sparse nature of mmWave channels. They performed channel estimation based on a parametric channel model with quantized AoAs and AoDs. They bounded their results by the guaranteed OMP performance as an upper bound and the oracle estimator which assumes perfect knowledge of the AoAs and AoDs. They asserted that estimating the CSI in mmWave with massive MIMO systems is challenging because the signal-to-noise ratio (SNR) before beamforming is low and the number of antennas is generally high. This is an important finding that we overcome in our paper by using measurements from the sub-6 GHz system to estimate the received signal powers in the mmWave band.

The authors in [6] attempted to exploit the use of out-of-band information to estimate the mmWave signal powers.

They proposed using three categories of out-of-band information: 1) position information such as global positioning system (GPS) signals, cameras, or even radars, 2) sub-6 GHz signals coming from Wi-Fi or cellular deployments, and 3) wireless sensor networks. The authors did not consider the use of statistical learning or the reuse of the mmWave measurements for the same users within a temporal window, which we are proposing. Further, the paper does not cover the various radio protocols of the technologies they referenced (e.g., the handover procedure).

Handovers in 5G wireless systems are expected to resemble what LTE offers at the *radio resource control* (RRC) layer [2]. These handovers can be broadly grouped into:

- *Measured*: the UE measures the source cell and, in specific cases, the target cell radio conditions and reports its measurement as an event to the base station.
- *Blind*: the UE has performed an action (other than a UE-reported radio measurement, such as requesting a service) which triggers the base station to reconfigure the radio bearers to a new cell offering this service. This cell can be in a different frequency or a different technology.

Estimating the mmWave frequencies from the *colocated* LTE serving cell measurements in the sub-6 GHz band helps in preempting the handover procedure if it is likely to fail due to weak mmWave signal levels. This is done without having the UE explicitly measure the mmWave carrier prior to the handover. We call this handover “*partially blind*” because it still requires target technologies measurement reports for *both* technologies for a certain period of time T (the *collection period*) to build the training data required for the machine learning algorithm to operate. It is blind in that the measurement gap configuration is temporarily unnecessary after the collection period has passed (details in Section II). Owed to the partially blind handovers, the UE data rates are not reduced due to a superfluous measurement gap. We have chosen LTE sub-6 GHz and mmWave bands for this paper; however we believe that this approach works for any inter-frequency pairs provided the cells are colocated and their radio environment parameters are known. For the particular case of mmWave and sub-6 GHz frequencies in this paper, since the mmWave wavelengths shrink by an order of magnitude relative to sub-6 GHz frequencies, the material penetration incurs greater attenuation as stated in [7]. This therefore elevates the importance of line-of-sight (LOS) propagation in both bands, with a difference that the path loss model in mmWave frequencies [7], [8] is a random blocking model unlike the model in the sub-6 GHz frequencies.

Our main contributions in this paper are as follows:

- 1) Introduce the new concept of partially blind handovers.
- 2) Employ machine learning to perform handover success predictions from sub-6 GHz to mmWave frequencies.
- 3) Show that this machine learning based algorithm combined with partially blind handovers can improve the

handover success rate in a realistic network setup of colocated cells of both frequencies.

II. SYSTEM MODEL

This system comprises two components:

- 1) A network of two colocated cells and connected users in an outdoor setting in a dense-urban environment.
- 2) A machine learning algorithm using *extreme gradient boosting* (XGBoost) classifier to override the handover decision if needed based on the estimation inferred using the history of the handover success for that user.

For the model to be valid, the collection period T cannot exceed the *channel coherence time*. This is the temporal window during which measurements are collected. As not all the UEs require handovers, the number of data points collected cannot exceed the number of handover attempts. The eNodeB reruns the algorithm for a given UE every time the UE establishes a radio connection or hands off to a new eNodeB.

A. Radio Network

The radio network is comprised of two colocated cells (i.e., an overlay) with a circular geometry with a radius r in a dense urban setting. Each cell operates a different technology and frequency band.

Similar to any cellular network today, the UEs measure the downlink radio frequencies and report them to the base stations. The difference here is that the base stations can decide whether to configure a measurement gap in LTE, since they now know by means of our machine learning based algorithm that the 5G mmWave band will not have sufficient signal power levels to maintain a session in that band. Further, we have handovers to facilitate service continuation as the UE reaches to edge of coverage.

We distribute the UEs in the network according to a *homogeneous poisson point process* (PPP) [9]. The process Φ has an *intensity parameter* λ representing the expected number of users served per unit area. We define the point process Φ for the number of users N in the network service area W . The UEs are sampled from a Poisson distribution with mean $\lambda W \triangleq \lambda \pi r^2$, where r is the cell radius.

The i -th UE position is i.i.d. sampled from a continuous uniform distribution in \mathbb{R}^2 using the polar coordinates (r_i, θ_i) where $0 \leq r_i \leq r$, $0 \leq \theta_i \leq 2\pi$, and $i = 1, 2, 3, \dots, N$. Fig. 2 shows the layout of the PPP in the serving area of the colocated cells just before simulation starts. The radio parameters of this network are in Table III.

B. Machine Learning

We have chosen the XGBoost classifier for our predictions because it can perform parallel computing on trees hence making the proposed algorithm suitable for distributed base stations. It is also invariant to input scaling and can learn higher order interaction between features. XGBoost is a scalable ensemble learning technique discussed in [10].

XGBoost minimizes an objective function which has a differentiable convex loss function and regularization terms

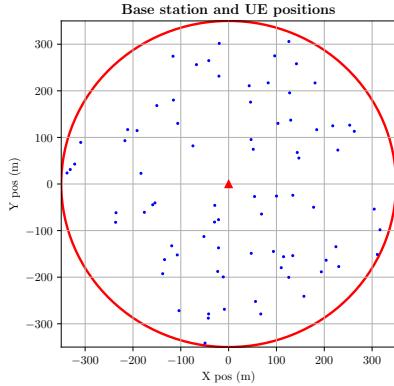


Fig. 2. The network layout simulated at $t = 0$. UEs are blue dots and the base station is the red triangle in the origin. The blue dots move throughout $1 \leq t \leq T_{\text{sim}}$ by resampling from the poisson point process.

TABLE I
MACHINE LEARNING FEATURES \mathbf{X}

	Parameter	Type	Description
\mathbf{x}_1	(x, y)	Float	Coordinates of UE.
\mathbf{x}_2	Distance	Float	The Euclidean distance from the base station based on the coordinates of UE.
\mathbf{x}_3	RSRP_X	Float	RSRP in $x = \{\text{LTE, mmWave}\}$ bands.
\mathbf{x}_4	Gap_Closed	Boolean	Did UE report event A1 based on its RSRP measurement?
\mathbf{x}_5	Gap_Open	Boolean	Did UE report event A2 based on its RSRP measurement?

$\alpha\|\mathbf{w}\|_1 + \frac{1}{2}\lambda\|\mathbf{w}\|_2^2 + \gamma T$, where \mathbf{w} is the vector containing the leaf weights in the boosted tree and T is the number of leaves. Regularization controls the complexity of the model and therefore helps avoid overfitting.

The $m \times n$ matrix of learning features $\mathbf{X} \triangleq [\mathbf{x}_i]_{i=1}^n$ is listed in Table I where n is the number of features and each feature \mathbf{x}_i is an m -dimensional vector obtained during the measurement collection period. The supervisory label vector is \mathbf{y} . The supervisory label is an integer with 0 being handover not executed and 1 being executed.

The features \mathbf{x}_3 , \mathbf{x}_4 , and \mathbf{x}_5 are obtained directly from UE measurements. However, features \mathbf{x}_1 and \mathbf{x}_2 require additional modification to the standards to enable the UEs to report their coordinates through RRC messaging. These coordinates can come from the positioning methods such as *global navigation satellite systems* (GNSS) or *observed time difference of arrival* (OTDOA) as defined in the LTE positioning protocol [11].

We tune the hyperparameters in Table II using grid search on K -fold cross-validation. Cross-validation is required to tune the model for accuracy.

The time complexity of our algorithm is $O(mn \cdot (d_{\max}E + n \log n))$ using [10] where d_{\max} is the maximum depth of the boosted tree and E is the total number of trees or estimators. The complexity is a function of the number of UEs covered in the cell and the measurement reporting frequency, but not the number of cells in the network.

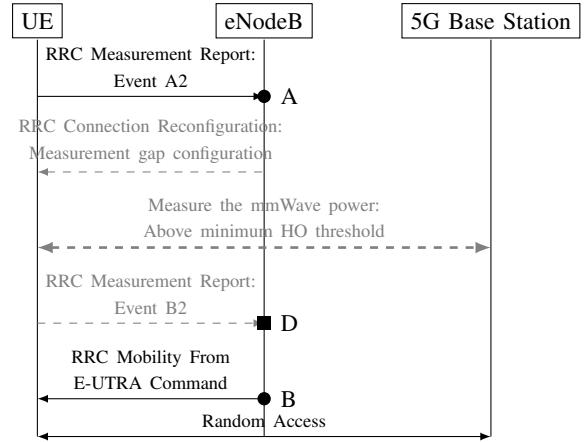


Fig. 3. Handover signaling procedure adapted after [2]. The handover decision point D and the metric trigger points A and B are also shown. (RRC stands for *radio resource control*, HO is short for handover, E-UTRA is the *evolved universal terrestrial radio access*, eNodeB is the LTE base station). Signals in dashed gray are ones impacted by the proposed algorithm.

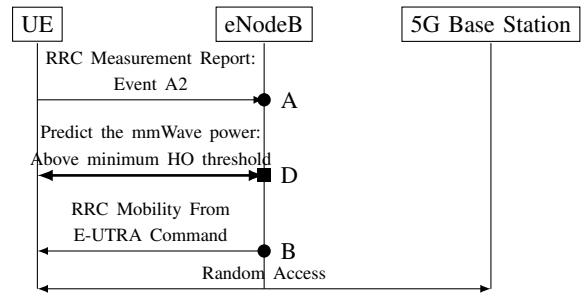


Fig. 4. Proposed handover signaling procedure changing the decision point D earlier in the procedure and allowing the eNodeB to predict the mmWave band measurement.

III. HANDOVER ALGORITHMS

A. Baseline Inter-RAT Handover Algorithm

Industry standards [2] specify that when the UE measures the *reference symbol received power* (RSRP) of a cell which is worse than a threshold, it triggers RRC event A2. This allows inter-RAT measurements to start for this UE through measurement gaps. Also, when the UE measures an RSRP better than a threshold, it triggers RRC event A1 ending inter-RAT measurements for this UE. If mmWave power is above a certain threshold, UE triggers RRC event B2 and proceeds with random access towards the mmWave carrier. The handover is then successfully executed. Fig. 3 shows the baseline procedure through which a handover is prepared and executed. Trigger point A is where the handover attempt is stepped and trigger point B is where the handover execution counter is stepped after eNodeB decides to allow handover.

B. Proposed Inter-RAT Handover Algorithm

In the proposed Algorithm 1, the decision of whether to accept the UE measurement or override it is based on *receiver operating characteristic* area under the curve (ROC

Algorithm 1 Partially blind handover success estimation

Input: Parameters listed in Table II and Table III, ε the acceptance threshold, and the simulation time T_{sim} .

Output: An output table for all UEs containing a time sequence showing whether the handover to 5G must be overridden or not based on estimated mmWave received signal level.

- 1: Compute N the total number of UEs in the cell per Section II-A.
- 2: **for** $i \in \{1, \dots, N\}$ **do**
- 3: Obtain the generated simulation data for UE i for all times $t = 1, \dots, T_{\text{sim}}$, which are the features \mathbf{X} listed in Table I.
- 4: Compute the handover success of this UE: measurement gap opened AND mmWave power greater than threshold, which is the supervisory label $[\mathbf{y}]_i$ for UE i .
- 5: Split UE i data to training data and test data. Training data is collected over a period $1, \dots, T$, where $T \triangleq \min(T_{\text{coherence}}, \lceil r_{\text{training}} \cdot T_{\text{sim}} \rceil)$.
- 6: Train the XGBoost model using the training data and use grid search on K -fold cross-validation to tune the hyperparameters.
- 7: Using the trained model obtain the proposed handover execution decision $\hat{\mathbf{y}}$.
- 8: Obtain the area under the ROC curve for this model (ROC AUC).
- 9: **if** (ROC AUC $\geq \varepsilon$) **then**
- 10: Use $\hat{\mathbf{y}}$ as a valid estimate of handover execution decision (follow Fig. 4).
- 11: **else**
- 12: Use the UE reported measurements (baseline algorithm).
- 13: **end if**
- 14: **end for**

AUC) of true positive rate vs false positive rate. This curve is obtained from the machine learning technique which uses training and cross-validation data to predict whether handover will succeed or fail. Then if the LTE received power is worse than the same threshold in the baseline algorithm and the *predicted* mmWave received power is above a certain threshold or if the ROC AUC is inadequate, the algorithm proceeds as the baseline. Alternatively, if the predicted mmWave received power is lower than the threshold, the eNodeB will preempt the request from the UE to handover to mmWave thereby saving the UE from a handover likely to fail. Fig. 4 shows that the number of steps in the proposed procedure has been reduced due to the machine learning prediction.

IV. SIMULATION RESULTS

The performance of our algorithm has been tested using a computer simulation written in Python on GitHub [12]. The machine learning hyperparameters and the radio environment parameters are in Tables II and III respectively. We showed graphical outputs of an arbitrarily selected UE. Fig. 5 shows the RSRP for the same UE over the simulation time, for signals in both sub-6 GHz and mmWave frequencies, with the RRC event thresholds shown as horizontal lines. Fig. 6 shows the corresponding handover execution of both algorithms versus simulation time where the handover decisions are identical for a period equal to 28 ms ($= 0.7 \times 40$ ms). The machine learning algorithm has

TABLE II
MACHINE LEARNING HYPERPARAMETERS FOR XGBOOST

Parameter	Value
Training data split r_{training}	0.7
Objective	{logistic, linear}
K -fold crossvalidation K	5
Number of estimators E	500
ℓ_1 regularization term α	{0, 0.5, 1}
ℓ_2 regularization term λ	{0, 0.5, 1}
Complexity control γ	{0, 0.02}
Sample weights	{0.5, 0.7}
Child weights	{0, 1, 10}
Max depth d_{max}	{6, 8}

TABLE III
RADIO ENVIRONMENT PARAMETERS

Parameter	Value
LTE bandwidth	20 MHz
LTE center frequency	2.1 GHz
LTE cyclic prefix	normal
5G mmWave bandwidth	100 MHz
5G mmWave center frequency	28 GHz
LTE Propagation model	COST 231 (LOS; no shadowing)
5G mmWave Propagation model	[8]
Morphology	urban
PPP intensity parameter λ	$2 \times \{10^{-5}, 10^{-4}\}$
Simulation time T_{sim}	{40, 400, 800} ms
Cell radius r	350 m
LTE base station power	46 dBm
5G base station power	46 dBm
Antenna pattern	omnidirectional [†]
Antenna height	20 m
Antenna sub-6 GHz gain	17 dBi
Antenna mmWave gain	24 dBi
Cellular geometry	circular
UE height	1.5 m
RRC event A1 trigger	-125 dBm
RRC event A2 trigger	-130 dBm
RRC event B2 trigger	-95 dBm
RRC events time-to-trigger	0 sec.

[†]Synthesized omnidirectional pattern using directional antennas.

then gathered enough information to be able to predict if an upcoming handover is likely to fail or succeed. It therefore generates handover decisions different from the baseline. Finally, Fig. 7 shows the ROC curve for the same UE, where the algorithm performance measured by the area under this curve (ROC AUC) has passed the $\varepsilon = 0.7$ threshold. This area is a measure of the ability of our algorithm to predict an IRAT handover success. This area ranges between 0.5 and 1 and is represented by ε in Algorithm 1. While the threshold at which the area deems a prediction valid in our algorithm is arbitrary, an area that is equal to 0.5 means the model is providing random guesses and cannot be used.

Table IV shows the results of the simulation. We ran the simulation for three different durations ranging from short to long. The coherence time of the channel falls in the range. These different time durations and different number of UEs in the cell also show the robustness of the algorithm. The improved numbers are in **boldface**.

With the least number of users and shortest duration, we see that the number of failures in both algorithms is similar. However, as the number of users or the simulation time increases, the number of failures by the proposed algorithm

TABLE IV
HANDOVER SUCCESS RATE SIMULATION RESULTS

Sim. Time	Algorithm	Attempts	Failures	Success rate	
$T_{\text{sim}} = 40 \text{ ms}$	$\lambda = 2 \times 10^{-4}$ ($N = 78$)	Baseline	1,259	58	95.39%
		Proposed	1,259	55	95.63%
	$\lambda = 2 \times 10^{-5}$ ($N = 8$)	Baseline	135	6	95.56%
		Proposed	135	6	95.56%
$T_{\text{sim}} = 400 \text{ ms}$	$\lambda = 2 \times 10^{-4}$ ($N = 78$)	Baseline	12,601	695	94.48%
		Proposed	12,601	450	96.43%
	$\lambda = 2 \times 10^{-5}$ ($N = 8$)	Baseline	1,254	70	94.42%
		Proposed	1,254	13	98.96%
$T_{\text{sim}} = 800 \text{ ms}$	$\lambda = 2 \times 10^{-4}$ ($N = 78$)	Baseline	25,070	1,378	94.50%
		Proposed	25,070	757	96.98%
	$\lambda = 2 \times 10^{-5}$ ($N = 8$)	Baseline	2,535	132	94.79%
		Proposed	2,535	19	99.25%

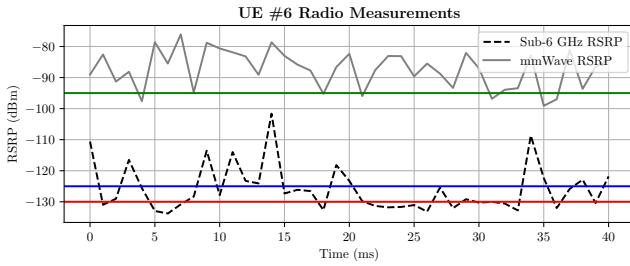


Fig. 5. Simulated received power for UE #6. The blue, red, and green lines are the RRC events (A1, A2, and B2) thresholds respectively.

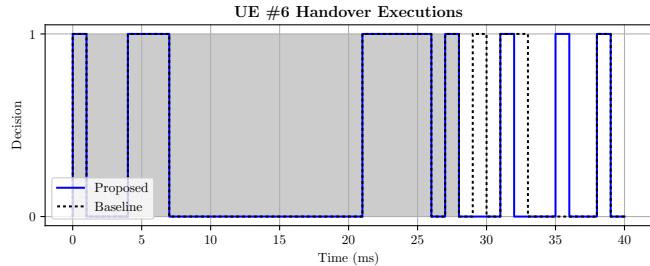


Fig. 6. Handover executions for UE #6 over the simulation time. The dotted black line denotes the baseline and the solid blue line is the proposed algorithm. The shaded region is the region corresponding to the collection period T in which the handover execution decisions are identical and excluded from results. Outside the shaded region the handover execution decisions differ.

are improved. Empirically, we observe that the baseline algorithm represents an upper bound of the number failures.

V. CONCLUSION

In this paper, we proposed the use of machine learning in making base stations predict handover success using both sub-6 GHz and mmWave prior measurements, effectively overriding the UE measurements using data collected within the coherence time. The proposed contribution improved the inter-RAT handover success rate keeping sessions in the optimal band for longer amount of time. If incorporated in 5G SON, this predictive algorithm can help facilitate the strong demand of high availability, high bandwidths, and low latencies promised by 5G by keeping away UEs likely to experience degraded service at the handover time through the machine learning based prediction algorithm we proposed.

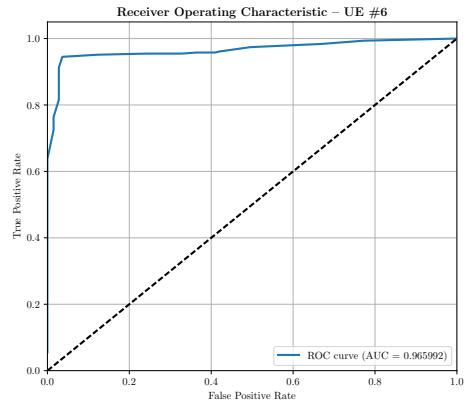


Fig. 7. Receiver operating characteristic (ROC) curve for UE #6 using $T_{\text{sim}} = 800 \text{ ms}$ and $\lambda = 2 \times 10^{-4}$.

REFERENCES

- [1] T. S. Rappaport and et al, "Millimeter Wave Mobile Comm. for 5G Cellular: It Will Work!" *IEEE Access*, 2013.
- [2] 3GPP, "Evolved Universal Terrestrial Radio Access; Radio Resource Control," 3rd Generation Partnership Project, TS 36.331, Dec. 2016.
- [3] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," *IEEE Network*, 2014.
- [4] J. Yang, Z. Wei, X. Zhang, N. Li, and L. Sang, "Correlation based adaptive compressed sensing for millimeter wave channel estimation," in *Proc. IEEE Wireless Comm. and Networking Conf.*, 2017.
- [5] J. Lee, G. T. Gil, and Y. H. Lee, "Channel Estimation via Orthogonal Matching Pursuit for Hybrid MIMO Systems in Millimeter Wave Communications," *IEEE Trans. on Communications*, Jun. 2016.
- [6] N. Gonzalez-Prelcic, A. Ali, V. Va, and R. W. Heath, "mmWave Comm. with Out-of-Band Information," *IEEE Comm. Mag.*, 2017.
- [7] T. S. Rappaport, Y. Xing, G. R. MacCartney, A. F. Molisch, E. Mellios, and J. Zhang, "Overview of mmWave Comm. for Fifth-Generation (5G) Wireless Networks With a Focus on Propagation Models," *IEEE Trans. on Antennas and Propagation*, Dec. 2017.
- [8] S. Sun, G. R. MacCartney, and T. S. Rappaport, "Millimeter-wave distance-dependent large-scale propagation measurements and path loss models for outdoor and indoor 5G systems," Apr. 2016.
- [9] F. Baccelli and B. Blaszczyszyn, *Stochastic Geometry and Wireless Networks, Volume I - Theory*. NoW Publishers, 2009.
- [10] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," *Proc. ACM Int. Conf. on Knowledge Discovery and Data Mining*, 2016.
- [11] 3GPP, "Evolved Universal Terrestrial Radio Access; LTE Positioning Protocol," 3rd Generation Partnership Project, TS 36.355, Jan. 2011.
- [12] F. B. Mismar. Source code. [Online]. Available: <https://github.com/farismismar/Handover-Improvement-ML>