WiMove: Toward Infrastructure Mobility in mmWave WiFi

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ABSTRACT

Line-of-sight (LOS) is a critical requirement for mmWave wireless communications. In this work, we explore the use of access point (AP) infrastructure mobility to optimize indoor mmWave WiFi network performance based on the discovery of LOS connectivity to stations (STAs). We consider a ceiling-mounted mobile (CMM) AP as the infrastructure mobility framework. Within this framework, we present a LOS prediction algorithm based on machine learning (ML) that addresses the *LOS discovery problem*. The algorithm relies on the available network state information (e.g., LOS connectivity between STAs and the AP) to predict the unknown LOS connectivity status between the reachable AP locations and target STAs. We show that the proposed algorithm can predict LOS connectivity between the AP and target STAs with an accuracy up to 91%. Based on the LOS prediction algorithm, we then propose a systematic solution *WiMove*, which can decide if and where the AP should move to for optimizing network performance. Using both ns-3 based simulation and experimental prototype implementation, we show that the throughput and fairness performance of *WiMove* is up to 119% and 15% better compared with single static AP and brute force search.

CCS CONCEPTS

• **Theory of computation → Network optimization**; • **Networks → Network performance evaluation**;

KEYWORDS

Infrastructure mobility; mmWave WiFi; Machine learning

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1 INTRODUCTION

WiFi is a ubiquitous and impactful wireless technology. According to the Cisco Visual Networking Index report [1], WiFi is predicted to generate 51% of total internet traffic in 2022. Due to the significant increase of internet traffic generated by WiFi, there is a pressing need to improve the WiFi network performance. mmWave is emerging as a key technology for next-generation WiFi networks among the latest WiFi related technologies. The mmWave WiFi standard (e.g., IEEE 802.11ad) operates in the 60GHz unlicensed spectrum. It can deliver multi-gigabit (~7Gbps) performance primarily by virtue of using a large bandwidth (greater than 2GHz). While the potential performance is quite promising, mmWave WiFi is vulnerable to non-line-of-sight (NLOS) conditions compared to WiFi operating in 2.4GHz or 5GHz spectrum. The performance of mmWave communications drops significantly when the wireless link has an obstacle such as a wall or cabinet in its way. Given the fickle nature of mmWave communications, it is expected to be predominantly used in a dual-band (or tri-band) configuration that works along with legacy WiFi.

In this context, it is likely that mmWave WiFi can deliver considerably better performance, but that the performance cannot be guaranteed and will be dependent on the existence of LOS conditions. LOS conditions are a function of the physical environment, but communication technologies hitherto have had no ability to improve the physical conditions when necessary. Historically, the design of algorithms and protocols for WiFi networks has been based on the assumption that the stations (STAs) are mobile, and the AP is static. STA mobility, furthermore, is driven by user needs and behavior, which can potentially lead to NLOS connectivity. With the recent and significant advancements in robotics and embedded systems, infrastructure mobility can be meaningfully and practically devised to optimize WiFi network performance. Specifically, a WiFi AP with the freedom of mobility can discover an optimal location for itself and move to that location to offer the best possible performance for the overall WiFi network. Given that mmWave WiFi has a critical requirement on LOS connectivity, infrastructure mobility becomes an especially attractive degree of freedom for mmWave WiFi, where the creation of LOS connectivity can have a profound impact on the overall network performance.

Related works have mainly explored a floor-based mobile AP that navigates its way around obstacles for WiFi networks operating in 2.4GHz or 5GHz spectrum due to the robotic framework simplicity [2–4]. In this work, we explore a more effective framework for mmWave WiFi - *a ceiling-mounted mobile (CMM) AP that moves on an actuator platform*, where the CMM AP can potentially achieve higher LOS probability to STAs compared with floor-based AP mobility. Within this framework, we focus on the *LOS discovery problem*. Explicitly, we define the *LOS discovery problem* as how to figure out the LOS connectivity between all available AP locations and target STAs. An idealized solution to this problem is to calculate the optimal location based on a geometric problem formulation, assuming that the locations of the STAs and the locations, shapes,

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and even materials of the obstacles in the physical space are known. Then, it is trivial to identify the LOS connectivity between target STAs with all possible locations of AP on the actuator platform. However, discovering the physical attributes of STAs and the physical attributes of obstacles (especially the material of obstacles) is either non-trivial or expensive.

In this context, we present a machine learning (ML) based solution to solve the *LOS discovery problem*. Given it is likely that multiple active WiFi devices exist in a WiFi network and there is rich network state information (e.g., LOS connectivity between the AP and STAs) available, we utilize the network state information as the input to the proposed ML model. The ML model trains itself to predict the desired LOS connectivity information. When network dynamics happen (e.g., when a new STA joins the network), the algorithm can identify whether the target STA (e.g., the new STA) is likely to have LOS connectivity to all possible AP positions. We evaluate the LOS connectivity prediction accuracy of the ML-based algorithm in different network scenarios, and it achieves prediction accuracy by up to 91%. Then, we incorporate the LOS prediction algorithm in a systematic solution, *WiMove*, which is designed to maximize the number of LOS connectivity between AP and STAs given the LOS prediction results. *WiMove* can decide whether repositioning the AP is required and, if so, where to move to. Using both ns-3 based simulation and experimental prototype implementation, we show that the throughput and fairness performance of *WiMove* is up to 119% and 15% better compared with other approaches.

The following is a summary of our key contributions:

- We present heuristic-based and ML-based LOS prediction algorithms for a CMM AP to determine the LOS connectivity between all available AP locations on the actuator platform and target STAs. The algorithms use a novel methodology to recalculate the LOS connectivity when network condition changes by purely relying on network state information.
- We then incorporate the ML-based LOS prediction algorithm into a systematic solution, *WiMove*. In order to optimize network throughput and fairness, *WiMove* is able to identify the optimal AP location with a maximized number of LOS connectivity between AP and STAs. Then, we present the evaluation results for *WiMove* using both simulations and experimental prototypes. We show that the throughput and Jain's fairness index of *WiMove* performs up to 119% and 15% better compared with other approaches.

2 BACKGROUND OVERVIEW

2.1 mmWave WiFi

The essential advantage of the mmWave WiFi as compared to legacy WiFi operating in 2.4GHz or 5GHz is the availability of a large amount of unlicensed spectrum. Taking advantage of the large spectrum available, the bandwidth supported by mmWave WiFi standard 802.11ad is 12.5x larger than the bandwidth supported by the latest non-mmWave WiFi standard 802.11ax. However, achieving the multi-gigabit performance in mmWave WiFi networks is not a trivial problem, since the mmWave signal propagation characteristics significantly differ from that of the legacy spectrum. The major difference is that mmWave communication has *extremely high signal attenuation* [5] generally caused by: 1) high propagation loss: there is an additional signal attenuation of 22dB at 60GHz compared to that of 5GHz based on the free space path loss model and the properties of the propagation media can also significantly increase the signal attenuation (e.g., oxygen absorption or rain attenuation); 2) high penetration loss: the attenuation impact is amplified when there is shadow fading or NLOS between the transmitter and receiver pair; and 3) sparse multipath diversity: multipath components propagating through objects tend to have low signal power due to longer propagation paths and additional reflection loss. Due to these features of mmWave communication, NLOS can have a severe impact on mmWave WiFi performance. Note that a consequent advantage of mmWave communication compared with the legacy frequency is that the high signal attenuation naturally lowers the probability of interference.

2.2 LOS in mmWave Networks

Based on the harsh mmWave signal propagation characteristics, it is likely that robust receiver signal quality is hard to achieve. While beamforming can be utilized to combat the severe propagation loss in mmWave communication, the additional loss caused by NLOS can lead to severe performance degradation. Related work shows that SNR of NLOS path is on average 16dB lower than LOS path [6]. Note that for 802.11ad [7], a 2dB additional loss could cause a 1Gbps performance drop when the modulation and coding schemes drop from 23 to 22. Thus, providing high and robust receiver signal quality is an essential problem for mmWave WiFi. In this context, in order to achieve multi-gigabit performance, LOS connectivity is highly critical in mmWave networks. In a simple experiment to observe the impact of NLOS in mmWave WiFi, we build a mmWave link using a TP-Link Talon AD7200 AP and an Acer Travelmate P648 laptop. We observe that obstacles such as a wall, a metal cabinet, and a cardboard box can degrade the performance of an ideal link with LOS connectivity from 1Gbps to 0Gbps, 0Gbps, and 0.52Gbps, respectively. Even though LOS connectivity provides critical benefits for mmWave communication, achieving LOS connectivity is not trivial. Consider typical indoor scenarios consisting of randomly located obstacles with various dimensions and materials that could potentially block the mmWave link. Also, both mmWave STAs and the obstacles can be dynamic, which prevents the possibility of predetermining the ideal AP location with optimized LOS connectivity to STAs.

2.3 LOS and Infrastructure Mobility

To optimize LOS connectivity in a mmWave network adaptively, we consider infrastructure mobility as a promising candidate solution, as infrastructure mobility allows for changing the location of the AP adaptively. Fig. 1 shows a scenario with a CMM AP and randomly distributed obstacles, where the obstacle density and dimension follows distribution based on real-world measurements. The gray cuboids, white cuboids, and black solid circle represent the CMM AP with its platform, obstacles, and the STA, respectively. Based on the performance analysis of various platform shapes [8], the 1D linear actuator platform is considered in this work. In Fig. 1, the CMM AP initially located at the center of a linear actuator platform can't provide LOS connection to the STA. Given the degree of freedom of AP mobility, the AP can move to a location on the side of the platform where LOS connectivity can be provided. On a more

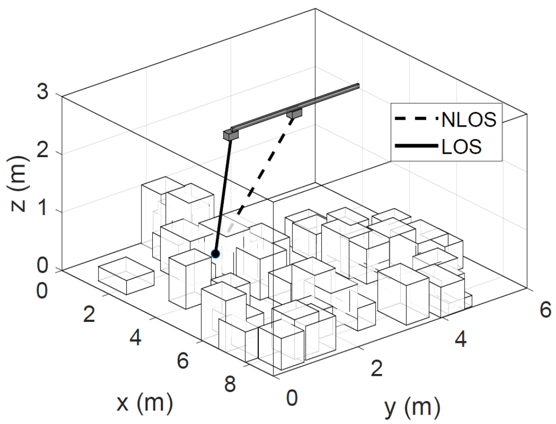


Figure 1: Infrastructure Mobility Providing LOS

generalized note, using simulation-based statistical analysis, we identify that a CMM AP operating on a 3m long linear actuator provides a 70% increase in LOS probability coverage compared with a static ceiling-mounted AP. With a larger movement range provided by the actuator platform, higher LOS connectivity probability can be achieved, but the cost also becomes more expensive. It should be noted that this work investigates the application of infrastructure mobility in the context of mmWave WiFi due to the critical impact of LOS connectivity for mmWave communication. This approach is also generally applicable to other types of wireless networks (e.g., wireless sensor networks, legacy WiFi, and robotic wireless networks), since wireless link performance generally benefits from LOS connectivity.

3 THE *LOS DISCOVERY PROBLEM*

The network scenario considered in this work is a single room with a single CMM AP serving multiple STAs, where the CMM AP platform is mounted on the center of the ceiling. The AP can move to P discrete available positions on the platform [1]. There are M STAs in this network scenario at a specific time instance t. For both the AP and STAs, it is assumed that both 5GHz and 60GHz WiFi radios are available. At another time instance (e.g., t'), there is an $(M+1)^{th}$ STA intending to connect to the AP through mmWave. We intend to predict the unknown LOS connectivity based on the available network state information, and the problem is formulated using the LOS connectivity as network state information for simplicity. At time instance t', we assume that the STA-STA LOS connectivity matrix between $M+1$ STAs and AP-STA LOS connectivity matrix between AP and first M STAs are given (the data collection methods are described in Section 6). The LOS connectivity of the new STA with all available AP locations is unknown. The information on STA's intention to connect to the AP and the connectivity information of the AP are communicated through the 5GHz band.

LOS connectivity is defined as a binary variable with 1 representing LOS and 0 representing NLOS. We define $los_{i,j}$ representing the LOS connectivity between device i and device j. For example, for AP at location p (with $p \in [1, P]$) on the actuator platform, $los_{p,m}$ represents LOS connectivity status between the AP at location p and STA m (with $m \in [1, M+1]$ at t'). Specifically, we consider the LOS connectivity matrices with two pieces of information: 1) $LOS_{(ss,t')}$: it represents the LOS connectivity status between all STAs at time instance t':

$$LOS_{(ss,t')} = \begin{bmatrix} los_{1,1} & los_{1,2} & \dots & los_{1,M+1} \\ los_{2,1} & los_{2,2} & \dots & los_{2,M+1} \\ \vdots & \vdots & \ddots & \vdots \\ los_{M+1,1} & los_{M+1,2} & \dots & los_{M+1,M+1} \end{bmatrix}$$

and, 2) $LOS_{(as,t')}$: it represents the LOS connectivity status between all available AP locations with all STAs at a time instance t':

$$LOS_{(as,t')} = \begin{bmatrix} los_{p1,1} & los_{p1,2} & \dots & los_{p1,M} \\ los_{p2,1} & los_{p2,2} & \dots & los_{p2,M} \\ \vdots & \vdots & \ddots & \vdots \\ los_{pP,1} & los_{pP,2} & \dots & los_{pP,M} \end{bmatrix}$$

where, $los_{pi,j}$ represents the LOS connectivity between AP at location i and STA j. Within this scope, as network dynamics happens (e.g., a new $(M+1)^{th}$ STA joins the network), the objective is to identify AP-STA LOS connectivity vector $\vec{as}_{(M+1,p,t')}$ between AP and $(M+1)^{th}$ STA at time instance t':

$$\vec{as}_{(M+1,p,t')} = [los_{p1,M+1}, los_{p2,M+1}, ..., los_{pP,M+1}] \quad (1)$$

Given the AP-STA LOS connectivity vector $\vec{as}_{(M+1,p,t')}$, the AP can then optimize the LOS connectivity to the targeted STA. With this network problem definition, we restrict the scope of this work to the following: (i) we only consider a single WiFi network where a CMM AP serving multiple STAs in a single room; and (ii) This work aims to optimize mmWave WiFi network performance. For STA has NLOS connection with the AP, we assume 5GHz is utilized to provide WiFi connectivity.

4 LOS PREDICTION ALGORITHMS

Given the potential benefits that can be achieved by leveraging LOS connectivity in mmWave WiFi networks, we propose both heuristic and Machine Learning (ML) based algorithms to address the *LOS discovery problem* in this section.

4.1 Heuristic Intuitive Approach

Based on our observations, a deterministic solution for the *LOS discovery problem* is not feasible. We intend to solve the *LOS discovery problem* using heuristic methods from a probabilistic perspective. At a single time instance, the obstacle map (location and dimension of obstacles) is fixed but unknown. The set of network state information (e.g., LOS connectivity information of $LOS_{(ss,t')}$ and $LOS_{(as,t')}$) can reveal the information about unknown obstacle map to some extent. Assuming that $LOS_{(ss,t')}$ and $LOS_{(as,t')}$ are given, we intend to identify the LOS connectivity between the target $(M+1)^{th}$ STA with the all available AP locations at time instance t'. Similar to AP-STA LOS connectivity vector $\vec{as}_{(M+1,p,t')}$, we define the STA-STA LOS connectivity vector of $(M+1)^{th}$ STA to all STAs as $\vec{ss}_{(M+1,m,t')}$ at time instance t':

$$\vec{ss}_{(M+1,m,t')} = [los_{M+1,1}, los_{M+1,2}, ..., los_{M+1,M+1}] \quad (2)$$

Specifically, the connectivity vector $\vec{ss}_{(M+1,m,t')}$ can be collected from the connectivity matrix $LOS_{(ss,t')}$. Intuitively, if the $(M+1)^{th}$

[1]We assume the power and the Ethernet cords of the AP are delivered through the actuator platform.

STA has similar LOS connectivity vector $\vec{ss}_{(M+1,m,t')}$ with another m'^{th} STA ($m' \in [1, M]$), the location of these two STAs is likely to be closed to each other. Given the location similarity between these two STAs, the AP-STA LOS connectivity matrix $LOS_{(as,t')}$ is also likely to be similar to each other. Given the objective is to estimate $\vec{as}_{(M+1,p,t')}$, we propose the following heuristic algorithm based on the previous intuitive observation. We first identify the most similar STA-STA connectivity vector of m'^{th} STA and the target $(M+1)^{th}$ STA, and then match AP-STA LOS connectivity vector $\vec{as}_{(M+1,p,t')}$ with $\vec{as}_{(m',p,t')}$. Specifically, to identify the maximum similarity of STA-STA LOS connectivity vector between the target $(M+1)^{th}$ STA and other STAs, we identify m'^{th} STA with minimum Euclidean distance between the STA-STA LOS connectivity vectors with target $(M+1)^{th}$ STA. The equation to calculate the Euclidean distance based cost function between STA-STA LOS connectivity vectors is shown in the following equation:

$$d(M+1, m) = ||\vec{ss}_{(M+1,m,t')} - \vec{ss}_{(m,m,t')}|| \tag{3}$$

There is a possibility that multiple STAs have the same minimum Euclidean distance. We collect the set of STAs, V, with maximum similarity with the target STA. Then, we calculate the expected AP-STA LOS connectivity vector E[$\vec{as}_{(m,p,t')}$] of the set of STAs. We consider E[$\vec{as}_{(m,p,t')}$] as the predicted result for $\vec{as}_{(M+1,p,t')}$ of the target $(M+1)^{th}$ STA. The pseudo-code for this heuristic algorithm is presented in Algorithm 1.

Algorithm 1: Connectivity Similarity

Data: $LOS_{(ss,t')}$ and $LOS_{(as,t')}$ at time instance t
Result: $\vec{as}_{(M+1,p,t')}$ of $M+1^{th}$ STA
$\vec{ss}_{(M+1,m,t')}$ = Target STA-STA LOS connectivity vector;
while *Traverse all* $\vec{ss}_{(m,m,t')}$ *other than* $M+1^{th}$ **do**
  if $d(\vec{ss}_{(M+1,m,t')}, \vec{ss}_{(m,m,t')}) <$ *minimum distance* **then**
    minimum distance = d($\vec{ss}_{(M+1,m,t')}, \vec{ss}_{(m,m,t')}$);
    Initialize V to a empty set;
    Add m to V;
  else if $d(\vec{ss}_{(M+1,m,t')}, \vec{ss}_{(m,m,t')}) ==$ *minimum distance* **then**
    Add m to V;
$\vec{as}_{(M+1,p,t')}$ = E[$\vec{as}_{(m,p,t')}$] of V;

The above algorithm requires only $LOS_{(ss,t')}$ and $LOS_{(as,t')}$ at a single time instance t'. In fact, the $LOS_{(ss,t)}$ and $LOS_{(as,t)}$ can be continuously monitored and collected. Here, we leverage the benefits of a total of T data samples to further improve the performance of the heuristic algorithm. To utilize T data samples, it is important to notice that not all historical data samples provide useful information for LOS prediction. The key methodology is that we first identify the most similar $LOS_{(ss,t)}$ from T data samples with the current $LOS_{(ss,t')}$. Ideally, if $LOS_{(ss,t)}$ of two data samples are similar, it is likely that the location of STAs from different data samples are also similar to each other. Thus, we utilize $LOS_{(ss,t)}$ as a representation for scenario features. We can then utilize Algorithm 1 to find the best matched $\vec{ss}_{(M+1,m,t)}$ from the most matched $LOS_{(ss,t)}$ and the current $LOS_{(ss,t')}$. Specifically, to achieve such an objective, we calculate the Euclidean distance between $LOS_{(ss,t)}$ of the target data sample with that of T data samples using equation 4. To further increase the possibility to identify the most similar scenarios, it is possible to permute the STA-STA LOS connectivity matrix $LOS_{(ss,t')}$ of the target scenario to identify similar matrices with STAs in different orders. Then, we find the set of $LOS_{(ss,t)}$ with minimum Euclidean distance with the current $LOS_{(ss,t')}$.

$$d(LOS_{(ss,t')}, LOS_{(ss,t)}) = ||LOS_{(ss,t')} - LOS_{(ss,t)}|| \tag{4}$$

Having identified a set of $LOS_{(ss,t)}$ with maximum similarity with the target $LOS_{(ss,t')}$, S, we perform Algorithm 1 to identify the most matched STA-STA LOS connectivity vectors from the set of best matched set of $LOS_{(ss,t)}$ to identify the expected E[$\vec{as}_{(m,p,t)}$] as Algorithm 1. The pseudo-code for the identify most similar scenario is presented in Algorithm 2.

Algorithm 2: Scenario Similarity

Data: T sets of $LOS_{(ss,t)}$ and $LOS_{(as,t)}$
Result: most matched STA-STA LOS connectivity matrix set S
$LOS_{(ss,t')}$ = Target LOS STA STA connectivity matrix;
while *Traverse all* $LOS_{(ss,t)}$ *other than the target* **do**
  if $d(LOS_{(ss,t')}, LOS_{(ss,t)})) <$ *minimum distance* **then**
    minimum distance = $d(LOS_{(ss,t')}, LOS_{(ss,t)})$;
    Initialize S to a empty set;
    Add t to S;
  else if $d(LOS_{(ss,t')}, LOS_{(ss,t)})) ==$ *minimum distance* **then**
    Add t to S;

4.2 ML Framework

Based on our simulation analysis, we identified that the heuristic algorithm can achieve 77% LOS prediction accuracy with LOS based network state information. In order to further improve LOS prediction accuracy, we identify three limitations in the heuristic algorithm that can be addressed. 1) Performance optimality: the heuristic algorithm is only capable of identifying the most similar scenario or STA-STA LOS connectivity vector. The second, third or other similar STA-STA LOS connectivity vectors may also provide valuable information that can be captured to improve the LOS prediction performance; 2) Given there is a rich set of network state information other than LOS, it is not trivial for the heuristic algorithm to jointly consider multiple types of input data (e.g., LOS connectivity, RSS, and location of STAs); 3) When data samples are limited, the data set may not provide enough information for the algorithm to achieve reasonable prediction accuracy. However, the time complexity of the heuristic algorithm with permutation will be high O((M+1)!), considering the permutations of the training set. Hence, with a large number of STAs and data samples, the heuristic algorithm is infeasible to operate in a real-time manner.

Therefore, to further improve the prediction accuracy and reduce time complexity, we consider an ML based approach to address the aforementioned limitations. The proposed ML approach can take into account multiple network state information as input, and the

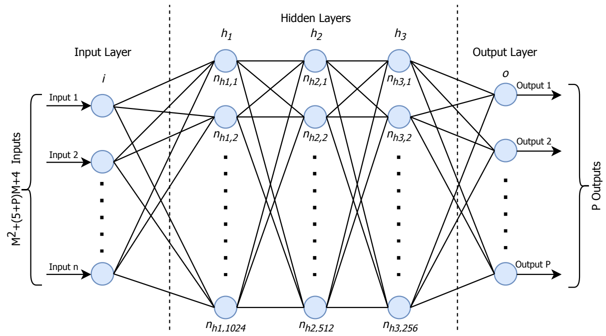


Figure 2: Neural network architecture

time complexity will be constant for an offline trained model. The problem to predict the LOS connectivity of the $(M+1)^{th}$ STA with the AP is represented and solved in a supervised fashion. Thus, keeping the fact in mind that the underlying relationship between input and output is actually a skewed representation of the fixed obstacle map, we utilize parametric function approximation approaches to learn this latent structure. While we are aware that it might not be possible to learn the full obstacle map, we aim to extract as much possible information in an attempt to maximize the prediction accuracy. In our ML-based LOS connectivity prediction framework, we use Artificial Neural Networks (ANNs) as a recipe for parametric function approximation.

Input Features and the Output: We consider two representative input features: 1) the LOS connectivity information, which can be collected using LOS estimation technique [9], which explores space and antenna diversity to identify LOS connectivity; 2) localization information of STAs, that can be obtained with reasonable accuracy based on [10], which utilizes RSSI-based location-clustering techniques. The input data is present in the format of 1) LOS connectivity matrix between STAs, $LOS_{(ss,t)}$, LOS connectivity matrix $LOS_{(as,t)}$ between AP and STAs, and 2) the localization matrix of STAs in the form of three-dimensional cartesian coordinates. The input data is generated in accordance to practical estimation techniques for both LOS and localization prediction and hence accounts for the uncertainty involved. The labels (ground truth) for training are present in the format of $\vec{as}_{(M+1,p,t)}$ i.e., the LOS connectivity matrix of $(M+1)^{th}$ STA with the P possible locations of the AP.

Given the network has $M+1$ STAs, the $LOS_{(ss,t)}$ matrix has total $(M+1)*(M+1)$ features and the $LOS_{(ss,t)}$ matrix has $M*P$ features. The localization matrix for $(M+1)$ STAs consists of $3(M+1)$ features. The input feature vector X is obtained by concatenating these three feature vectors into a single vector of size $(M^2+(5+P)M+4)$. The network outputs $\hat{Y} \in [0,1]^P$, a P sized probability vector representing the probability of LOS connectivity of $(M+1)^{th}$ STA with P locations.

Network: We use a Multi-Layer perceptron network [11] with the number of hidden layers and neurons configured to work across different network scenarios. The flattened input feature vector of size $(M^2+(5+P)M+4)$ is fed to a fully connected network as shown in Fig 2 with 3 hidden layers. The l^{th} hidden layer has a total of n_{H_l} neurons. The k^{th} neuron in $(l-1)^{th}$ layer is connected to j^{th} neuron in l^{th} layer with a weight of w^l_{jk}. b^l_j represents the bias of the j^{th} neuron in the l^{th} layer. The activation of the j^{th} neuron in the l^{th} layer, i.e. a^l_j, is calculated through the forward propagation rule as below,

$$a^l_j = \sigma(\sum_k w^l_{jk} a^{l-1}_k + b^l_j) \tag{5}$$

where, σ applies the non-linearity in the model using the ReLU activation function,

$$\sigma(h) = max(0,h) \tag{6}$$

Finally, we use softmax layer [12] before the output layer to transform the output logits to the probability vectors. The model is trained through the backpropagation rule, using weighted cross-entropy loss, defined as:

$$H_y(p) = \sum_i^P -(y_i \log(p_i) * w + (1-y_i)\log(1-p_i)) \tag{7}$$

Here, p represents the softmax probability of output logits, and w is calculated as the ratio of NLOS vs. LOS connectivity using training data. As the ratio of NLOS to LOS connectivity in the data samples may be imbalanced, the weighted cross-entropy loss with weight w, balances the loss function to avoid any local minima. Using the available training data bank, $DB = \{(X_1,Y_1),(X_2,Y_2),\ldots(X_N,Y_N)\}$, of N samples, the loss function is minimized using stochastic gradient descent (SGD) with momentum optimizer [13]. In SGD, a batch of B training samples is randomly selected out of N training samples, and the weights and biases are updated through the backpropagation rule. A fraction of the gradient in the previous iteration is retained with the "coefficient of momentum". At each learning iteration, the learning rate is decreased over time to optimize performance and to increase the convergence rate [14] of the algorithm. While training, we also augment the training set by a random permutation over the sequence order of the STAs in the input features. This not only increases the training set size but also improves the convergence of gradient descent by avoiding any STA-order based local minima. The random permutations prevent the ML architecture to extract features based on the STA ordering.

Based on the proposed ML framework, we identify the following two potential trade-offs: 1) as the number of data sample increases, the prediction accuracy also increases, and 2) as potential locations of STAs decreases, the prediction accuracy also increases due to fewer input possibilities.

5 LOS PREDICTION EVALUATION

In this section, we evaluate the performance of both heuristic and ML-based LOS prediction approach through simulations. We utilize customized ns-3 simulator [8] to generate network scenarios to collect the required data samples. By tuning network scenarios, we are able to generate a large number of data samples and measure corresponding network performance.

5.1 Simulation Platform

To incorporate the features of indoor configurations and 802.11ad, we make the following modifications to the default ns-3 simulator.

Simulation of Indoor Scenarios: Due to the lack of an indoor scenario model in ns-3, we used the following indoor model. A room is simulated as a specific three-dimensional space with a given obstacle distribution model. To simplify the simulations, we

Table 1: Default Parameters

	Settings
Size of room (m)	(9, 4, 3)
(μ_x, μ_y, μ_z) (m)	(1.08, 0.28, 0.61)
$(\sigma_x, \sigma_y, \sigma_z)$ (m)	(0.46, 0.08, 0.21)
Platform location	Center of the ceiling
Platform orientation	Parallel to shorter edge
Platform length (m)	3
P	30
M	5
n_{pl}	2
σ_{fading}	2.24
T	7,000

assume that the obstacles are modeled as cuboid.To simulate practical scenarios, we consider that the placement of the STA follows the following distribution: an obstacle is uniformly selected as the base location for the STA, and the STA is uniformly distributed on top or sides of the selected obstacles.

To accurately simulate indoor obstacles, the implemented obstacle model has the following features:

- The center of the obstacle follows a Poisson point process. It defines the probability for obstacles to be uniformly placed in an indoor scenario.
- The x, y, and z dimension of obstacles follow a truncated normal distribution to constrain the maximum and minimum of obstacle dimension.
- The material of the obstacle is uniformly chosen from [15] to represent materials with various penetration losses.

We show the default parameters used in the simulation in Table 1. The parameters are derived by using a real-life physical space (a lab environment) as a guiding example. To build a cuboid-based obstacle model, the x, y, and z dimensions are collected based on the largest dimension of a measured obstacle. We then collect the number of obstacles in the lab space as n. To calculate the x, y, z dimension distribution parameters, we use distribution fitter in MATLAB to calculate the best fit normal distribution with mean μ_x, μ_y, μ_z, and standard deviation $\sigma_x, \sigma_y, \sigma_z$. The maximum and minimum of x, y, and z dimensions of obstacles are utilized as the range limitation in the truncated normal distribution.

Simulation of 802.11ad: We use the 802.11ad model based on [16]. The simulator provides all techniques that are essential for 802.11ad, such as beamforming training and steering, hence providing an accurate simulation environment for 802.11ad. The mmWave channel is another essential component of simulating the performance of 802.11ad. To incorporate shadow fading based on information of mmWave WiFi devices and obstacles, we consider the impact of shadow fading and multipath separately. Based on experimental evaluation [17], we consider the log-distance based path loss model as follows:

$$L(d) = L(d_0) + 10 * n_{pl} * log_{10}(\frac{d}{d_0}) + X_s + X_{\sigma_m} \tag{8}$$

where, $L(d_0)$ is the path loss at a reference distance d_0, n_{pl} is the path loss exponent, d is the distance between two communication devices, X_s represents shadow fading where the penetration loss is calculated based on the obstacles' location, dimension and material between mmWave WiFi devices, and X_{σ_m} represents the normally distributed multipath fading with σ_m as the standard deviation. Particularly, X_s is 0 when the communication link is in LOS connectivity. We collected the average of 5 sets of experimental estimations of the log-distance based path loss model to collect n_{pl} and σ_m based on [17], which are presented in Table 1.

Data Samples Generation: To generate data samples using the above ns-3 model, we initialize the network scenario by generating a random network scenario like Fig 1. Then we deploy M STAs following the STA distributions mentioned above. At each time step, network dynamics (e.g., STAs join or leave the network) happens based on the Poisson distribution with an expected rate of one unit per time step. We then collect network state information (i.e., STA-STA LOS connectivity matrix, AP-STA LOS connectivity matrix, and STA location matrix) for each time instance t. Specifically, we incorporate the error model of LOS estimation and localization based on the prediction cumulative distribution function (CDF) presented in [9] and in [10], respectively. The default parameters of the number of STAs M, the number of data samples T, the number of available AP locations P are described in Table 1.

5.2 ML Network Configurations

We use Tensorflow to implement and run the ML models. We use three hidden layers in the model with 1024, 512, and 256 neurons, respectively. A default batch size of 256 is considered except for the cases where the total training sample size is smaller than 256. The learning rate is initialized as 0.15 and decreased with a factor of 0.9 every 5000 steps. For the LOS connectivity prediction of all AP locations, the performance metrics are found very similar with insignificant variance. Hence, in subsequent analysis, we only present the average performance over all the AP locations.

We split the available data into two sets: 1) the training set comprises of 70% of the data and is used to learn the network weights, and 2) the remaining 30% set is used for testing. We use three different metrics to evaluate algorithm performance, namely overall accuracy, precision, and recall for LOS connectivity. Precision for LOS connectivity is defined as the fraction of actual LOS connections out of total predicted LOS connections. Recall informs how accurately the model can predict LOS connections out of actual LOS connections. For each configuration, we ensure the evaluation correctness through random permutation tests. It is to be noted that this is a binary classification problem (predicting the presence of LOS connection) and hence, a random classifier will have an accuracy of 50%. As LOS connectivity and NLOS connectivity are not equally distributed, an evaluation based only on accuracy will represent biased results. Hence, we provide precision and recall along with accuracy. Additionally, we also randomly permute the labels of test sets to validate that the ML model is learning meaningful latent structure in terms of the relationship between inputs features and output labels.

5.3 Comparison of ML and Heuristic

In this section, we evaluate the performance of both heuristic and ML algorithms. In a 6 STAs scenario, we test 2 different input features: LOS, and location, separately with heuristics algorithm, and

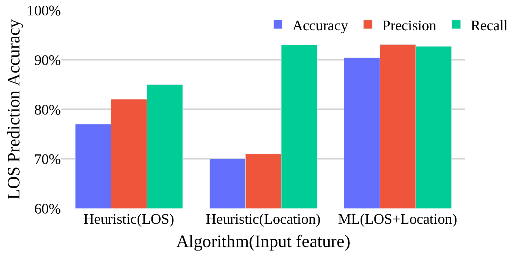


Figure 3: Comparison of heuristic and ML

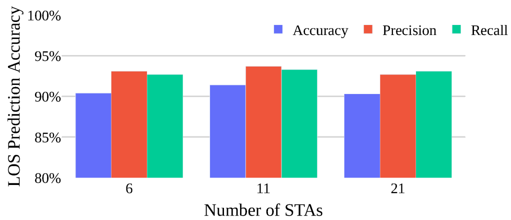


Figure 4: ML with different number of STAs

we consider both inputs as the ML inputs. From Fig.3, we can see that accuracy of three settings achieves 77%, 70%, and 91%, respectively. Overall, we identify that ML performs significantly better than the heuristic algorithm described. The average prediction accuracy of ML with a single input feature achieves 80%. These results validate that ML can take advantage of multiple input features and gain more insightful information from jointly considering LOS and location input features. Specifically, LOS connectivity matrices provide network-level relative information of each STA and location matrices provide the physical information of each STA. Even with prediction error, the ML model is able to jointly learn the location of each STA and identify the corresponding LOS connectivity with all available AP locations. Ideally, increasing the number of input features can further improve ML prediction accuracy. In the case of the heuristic algorithm, the introduction of estimation error in data in accordance with error models reduces the performance since it only tries to identify the AP-STA LOS connectivity vector based on the best matching metrics. In the following section, we will mainly evaluate ML performance due to its high prediction accuracy.

5.4 Impact of Number of STAs

We test the ML performance with different number of STAs. Specifically, the number of STAs $M + 1$ is configured as 6, 11 and 21. Surprisingly, from Fig 4, we identify that the prediction accuracy saturates when the number of STA is as low as 6. The prediction accuracy is 91%, 91%, and 90% for 6, 11, and 21 STAs, respectively. It indicates the ML performance is invariant with the number of STAs. However, we identified that as the number of STA increases, the minimum required network size also increases. If the minimum required network complexity is not used, the performance drops. Therefore, we conclude that ML performance is largely invariant with the number of STAs as long as the network size is large enough.

5.5 Impact of Obstacle Maps

To analyze the impact of different obstacle maps, and hence quantify the applicability of the ML algorithm to different indoor scenarios, we obtain the performance metrics for 3 different obstacle maps for

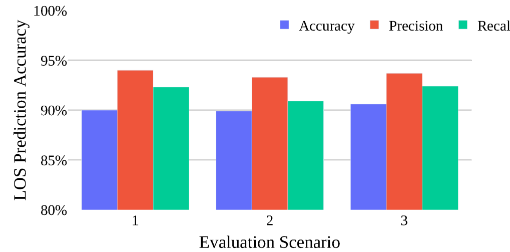


Figure 5: ML with different Obstacle maps

default scenarios. From Fig. 5, we observe that the mean accuracy is 90% with a standard deviation of 0.4%. The low variance demonstrates that the proposed algorithm is generalizable to different scenario instances (e.g., different STA locations within different obstacle maps).

5.6 Dynamic Environments

The ML framework presented above requires the environment to be static (e.g., fixed obstacle map). We first classify dynamic scenarios and evaluate ML in different dynamic scenario settings. Specifically, we classify network dynamics into two types: 1) STA dynamics: an active STA changes its location, or a static STA joins the network or leaves the network, and 2) obstacle dynamics: an obstacle in target scenario moves to another location. These dynamics can be identified based on network state information available. STA dynamics can be identified by the change of STA location and the connectivity matrix to other static connected STAs. Obstacle dynamics can be identified by the change of STA LOS connectivity matrix without changes in STA location. STA dynamics do not skew ML model prediction accuracy as the underlying obstacle map is unaffected. However, obstacle dynamics change the obstacle map, which can lead to decreased performance of the ML model. Thus, we will target obstacle dynamics in the rest of this section. Considering the case in which the ML model is retrained after an obstacle movement is detected, the performance is now limited by the frequency of obstacle movements. On average, if there is an obstacle movement event for every k time steps, then the achievable performance of the ML model after training from data of k time steps is of interest. The methodology to study the continuous obstacle dynamics scenarios is to train using the data set collected at each k time steps. Specifically, we change the number of data samples collected k from 100 through 10000.

Fig. 6 shows the prediction accuracy when the number of samples increases from 100 to 10000. Clearly, we can observe that there is a tendency that the prediction accuracy increases as the number of data sample increases. Specifically, the prediction accuracy increases from 84% to 90% as the number of data samples increases from 100 to 10000, respectively. Similarly, the recall rate also increases with the number of time steps. However, increasing the time steps does not have a significant impact on the precision metric. The precision varies in the range of 93% to 95%. We also observe that the prediction accuracy for data set from as low as 100-time steps is reasonably accurate.

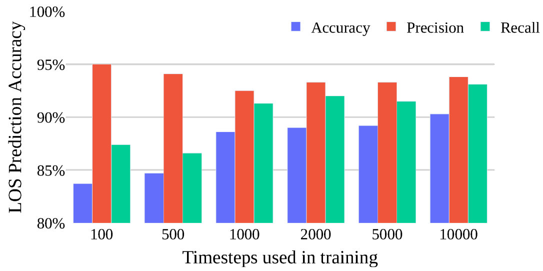


Figure 6: ML in Dynamic Scenarios

6 *WIMOVE*: A SYSTEMATIC SOLUTION

In this section, a systematic solution of *WiMove* is first discussed. In this solution, we intend to optimize the mmWave WiFi network performance in the perspective of throughput and fairness. We assume STAs with NLOS with AP can be served using the 5GHz band (the joint 5GHz and 60GHz network optimization is considered as future work). With the assumption of equal transmission probability of each WiFi device, network fairness is maximized when the number of LOS connectivity links between AP and STAs is maximized. Therefore, the objective function for AP to identify the optimal location is to *maximize the number of LOS connectivity links between AP and STAs*. Given this objective function, we will then evaluate *WiMove* using both simulations and experiments.

6.1 Trivial Solutions

Before we introduce the solution of *WiMove* for the CMM AP in mmWave WiFi, we will first briefly discuss two trivial approaches to provide mmWave service to STAs and the corresponding trade-offs:

- *Single static AP:* The static AP is mounted at the center of the ceiling to maximize the overall LOS probability with randomly deployed STAs. This approach has the simplest strategy and minimum cost, but the non-adaptive solution can only achieve limited performance.
- *Brute-force:* Another trivial but adaptive approach is a brute-force solution which enables the AP periodically traversing the entire platform in order to collect network status information. At each available AP location, the AP utilizes LOS estimation or localization techniques to collect network status information. Based on the collected global knowledge, the location with the maximum number of LOS STAs can be identified and then the AP moves to the ideal location. This approach is straight forward, but it introduces a significant amount of time complexity. Thus, the large convergence time to achieve the ideal location leads to a degradation of network performance.

6.2 *WiMove* Overview

Given the LOS prediction algorithm presented in Section 4, we intend to employ the algorithm in a practical system to evaluate the overall system performance. To perform such an ML algorithm, we assume there is a cloud server which connects with AP with Ethernet. The cloud server can collect network status information from the AP and train the ML model and inform the AP about AP-STA LOS connectivity vector with a target STA. In this context, to achieve the objective of maximizing the number of LOS connectivity

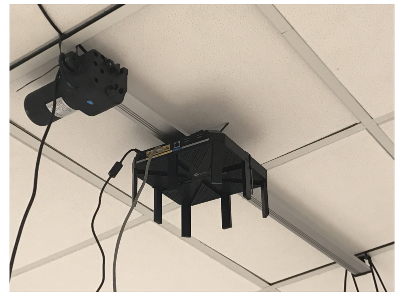


Figure 7: Experimental Platform

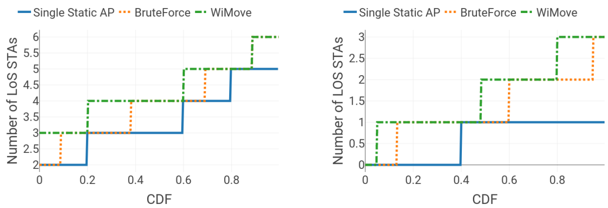
between AP and STAs, the overall systematic solution of *WiMove* is presented as follows:

- *Initialization brute-force:* The AP uses the brute-force discovery to collect global data of network status information through 5GHz band. The AP then informs the cloud server with the collected network status information at the current time instance. The collected network status information is then fed to the ML model for training. If network dynamics happens, the algorithm goes into the phase of *Network dynamics*.
- *Network dynamics:* As discussed in Section 4, there are two types of network dynamics: STA dynamics and obstacle dynamics. The system deals with each dynamic scenario in the following manner: 1) STA dynamics: the AP collects the current time step network state information and sends the information to cloud server, and then the AP collects LOS prediction results from the cloud server and then identifies the closest optimal location and goes into *AP Movement* phase; 2) obstacle dynamics: re-initialization of the ML algorithm is required, it goes into *Initialization brute-force phase* to retrain the ML model.
- *AP movement*: AP moves to the identified target location and goes into the *Reach Target* phase. Note that, the AP will collect ground truth network status information with the target STA during movement [2]. If the current location satisfies the objective function due to false negative prediction, the AP will stop at the current location.
- *Reach Target*: If the AP reaches the target location with a correct prediction, *WiMove* goes into idle mode. If the prediction is wrong, *WiMove* goes into *AP movement* phase with a newly identified nearest optimal location.

6.3 Evaluation Methodology

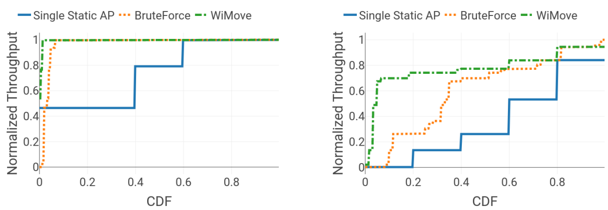
Consider a room with the CMM AP platform mounted at the default location on the ceiling with parameters following the configurations in Table 1. There are M STAs in the scenario at a specific time instant. We consider instant STA dynamics in the evaluation. STAs join or leave the network based on a Poisson distribution with an expected rate of one unit per minute. The overall evaluation time is 5 minutes. Similar to LOS prediction evaluation, we incorporate LOS estimation and localization error in the network status collection phase.

[2] When the percentage of ground truth data is smaller then a threshold of 90%, the *WiMove* goes into the *Initialization brute-force* phase.



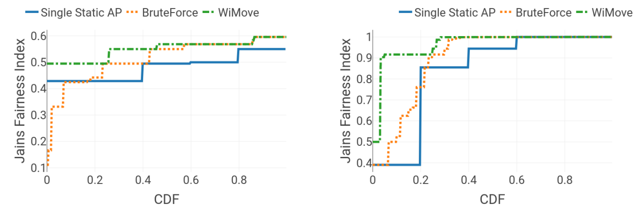
(a) Simulation (b) Experiment

Figure 8: Number of LOS STAs



(a) Simulation (b) Experiment

Figure 9: Throughput



(a) Simulation (b) Experiment

Figure 10: Jain's Fairness Index

We evaluate three different approaches for providing 802.11ad service in the network: 1) static AP, 2) brute-force, and 3) *WiMove*. For *WiMove* and brute-force, the goal is to identify the nearest location on the platform that maximizes the number of LOS STAs connectivity. The metrics to be studied are 1) the number of LOS STAs, 2) aggregate throughput performance, and 3) Jain's fairness index. Specifically, for Jain's fairness index, it ranges from $1/M$ (single STA has aggregate network throughput) to 1 (each STA has equal throughput).

Simulation configurations: We evaluate the performance of the aforementioned 3 approaches through ns-3 simulations. *WiMove* approach decides whether to adapt the AP location at every time instance when the network dynamics happen. We consider the number of STAs to be 10 at the first time step. The ML prediction accuracy achieves 91% given 7000-time steps of input data samples.

Experimental configurations: In order to evaluate the performance of *WiMove*, brute-force, and single static AP experimentally, we mounted a 1m long Progressive Linear Actuator PA-18 [18] on the optimal location of the ceiling in a lab environment utilizing cable zips. This unit is controlled by a central controller through Arduino UNO [19] and Mega Moto Plus [20]. The AP mounted on the actuator is Tp-link Talon ad7200 [21]. The experimental platform is shown in Fig. 7. We use 3 Acer Travelmate P648 laptops [22] as STAs. To collect training data for ML, the LOS and distance matrices of all possible locations are hard-coded. For *WiMove*, the controller controls the location of the AP in the discrete dynamic scenario based on the ML feedback. The ML prediction accuracy achieves 90% with 100-time steps of input data samples.

6.4 Simulation Evaluation

Initially, 10 STAs are active. Based on the Poisson distribution of STA events, the STA number changes at each minute as {-1, -2, +1/-1, +1}, where +1 means a new STA joins the network and -1 means an active STA drops off.

Fig. 8a, 9a, and 10a show the number of LOS STAs, throughput, and Jain's fairness index for the aforementioned three approaches at various time instants. For the initial 60s, the average performance of the three approaches is very similar. From 120s to 240s, the throughput performance and Jain's fairness index of *WiMove* is 115% and 33% better compared with a single static AP case. This time period clearly reveals the drawback of static AP, which has very limited performance when AP does not have a good channel connection with STAs. Overall, *WiMove* throughput performance is 30% and 110% better compared with brute-force and single static AP, and Jain's fairness index is 14% and 7% better compared with single static AP and brute-force. Since neighboring LOS locations are highly correlated (appears as a group), the AP moves toward the correct location as long as *WiMove* predicts the single correct location connectivity in one of the grouped locations.

6.5 Experimental Evaluation

For the environment setup for experimental evaluation, initially, there are 2 STAs in the network and the STA numbers change at each minute as {+1, -2, +1/-1, +1}.

Fig. 8b, 9b, and 10b illustrate the number of LOS STAs, throughput, and Jain's fairness index for the aforementioned 3 approaches at various time instants. For *WiMove* and brute-force with an initial location at the edge of the platform, there is 1 STA in LOS condition. For the single static AP case, the 2 STAs are both in NLOS condition. Initially, *WiMove* tries to explore the entire platform to collect network information (same as brute-force). In the first 60s, *WiMove* and brute-force take 25s to reach the location that has LOS w.r.t. to both STAs. Clearly, at the location with maximum LOS STAs, the network has high fairness and throughput. The network performance might drop during the movement phase, but the performance gain can be considerable when *WiMove* reaches the optimal location. For example, during the first 60s for *WiMove*, the number of LOS STA is increased by 50%, the throughput is increased by 10%, and Jain's fairness index is also increased by almost 50%. For the period between 180s to 240s where only 1 STA is active, single static AP is in NLOS with that specific STA which leads to no throughput. With mobility advantage, severe cases such as this can possibly be avoided. From this set of experiments, the throughput performance of *WiMove* is 119% and 29% better compared with brute-force and single static AP, and Jain's fairness index is 15% and 8% better compared with brute-force and single static AP. Overall, we can observe *WiMove* dynamically adapts to network conditions and achieves the best performance among brute-force and single static AP.

7 RELATED WORK

As LOS connectivity becomes a critical bottleneck for mmWave communication, there are many research works that can be employed to compensate for the challenging issue. We categorize related works that have addressed the challenges related to LOS connectivity into three types: 1) multi-band, 2) improving channel quality, and 3) establishing indirect LOS connectivity.

For multi-band approaches, the methodology is that mmWave is only utilized for good (e.g, LOS) connections, and the legacy 2.4GHz and 5GHz frequency bands are utilized when the mmWave connections experiencing poor propagation (e.g., NLOS) conditions. [23] utilizes localization of tracking angle change to steer the beam to a new location for mobile STAs, and re-directing ongoing user traffic to the robust interface (e.g., from 60GHz to 5GHz). [24] presents a dual connectivity protocol that enables mobile user equipment devices to maintain physical layer connections to 4G and 5G cells simultaneously.

To provide good signal reception between AP and STAs, some possible approaches are: 1) infrastructure mobility, 2) multiple APs, and 3) relays. For conventional WiFi, some work has studied mobility based wireless systems to boost WiFi network performance [2–4, 25]. Other related works include [26] where robotic APs make adjustments to their positions to converge to an optimum position. Another approach is to deploying more than one AP to increase the probability of LOS between AP and STAs. For the multi-AP based approach [27–29], [29] presents an infrastructure side predictive AP switching solution which can identify a proper AP for a specific STA to connect. The third approach is to utilize relays to improve signal quality at the receiver end. [30, 31] presents an optimal and efficient algorithm for choosing the relay-assisted path with maximum throughput.

The third approach is to utilize the indirect LOS connectivity between AP and STA, which typically has a higher requirement in terms of the propagation environment [6].

8 CONCLUSIONS

In this work, we present *WiMove* that uses ML techniques to predict LOS status between an AP and STAs. Upon a network dynamic happens, *WiMove* predicts the location that maximizes the number of LOS connections. Using a simulation and prototype evaluation, we show that *WiMove* can perform up to 119% and 15% better than a static AP and brute force search. The following are the essential future work to be considered: 1) AP mobility cost analysis, 2) jointly optimization of mmWave and conventional WiFi, and 3) instead of predicting the LOS connectivity, considering a multi-classifier ML model to predict MCS between AP and STAs, which can be utilized to optimizing the network performance in a finer fashion.

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