Toward a Self-Positioning Access Point for WiFi Networks

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ABSTRACT

The position of an access point (AP) in a WiFi network has considerable influence on the performance of the network. In this work, we consider the problem of a WiFi AP self-positioning itself adaptively based on the network conditions to deliver improved network performance. Through extensive experimental evaluation, we show that there are indeed significant performance benefits to be attained by allowing the AP to move intelligently. We also rely on theoretical analysis, simulations, and experimental studies to show that the AP optimal location search problem can be split into two parts: a macro-search problem to minimize average path loss between AP and clients, and a micro-search problem to tackle real-time multipath fading effects. We then present *Hermes*, a self-positioning WiFi AP system that relies on a suite of algorithms to compute and then move to an optimal location within the network. Using a prototype implementation, we show that *Hermes* can perform up to 117% better than WiFi with no AP mobility, and up to 73% better than related work that allows for AP mobility.

KEYWORDS

Self-positioning AP systems; WiFi; Path Loss; Multipath

ACM Reference Format:

Yubing Jian, Shruti Lall, and Raghupathy Sivakumar. 2018. Toward a Self-Positioning Access Point for WiFi Networks. In *MobiWac '18: 16th ACM International Symposium on Mobility Management and Wireless Access Oct. 28–Nov. 2, 2018, Montréal, Québec, Canada.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3265863.3265876

1 INTRODUCTION

The position of an AP in a WiFi network has considerable influence on the performance of the network. Historically, the design of algorithms and protocols for wireless networks has been based on the assumption that the clients are mobile and the AP is static. The client mobility, furthermore, is driven by user needs and behavior as opposed to optimizing the network performance. In this work, we consider the problem of an AP positioning itself dynamically based on the network conditions to deliver improved network performance. Recent and significant advances in domains such as wireless communications and robotics have made it possible to meaningfully and practically devise a solution for a self-positioning AP system.

MobiWac '18, October 28–November 2, 2018, Montréal, Québec, Canada

ACM ISBN 978-1-4503-5962-7/18/10…$15.00
https://doi.org/10.1145/3265863.3265876

An obvious question to ask before developing such a solution is the following: *are the benefits of AP self-positioning significant enough to warrant the potential overheads and complexities?* Through a detailed experimental analysis, we identify that even movements as small as a few centimeters can result in network performance improvements up to 116%. However, designing and developing a solution to leverage the possible benefits is a non-trivial problem. First, the optimal location of the AP within the physical space that maximizes performance for the network as a whole has to be first deduced. Second, the physical mobility problem of reaching the AP to the deduced location has to be solved. Further, there is also the condition of whether the theoretically optimal location is reachable in the first place, and what needs to be done if the answer is no.

This is not the first paper to identify or leverage the benefits of AP mobility. Most recently, in [1], the authors present a simple, but effective solution wherein the AP moves within a 4ft.^{2} region, and uses an optimal stopping theory (OST) strategy to find the location within that region that would maximize the aggregate throughput performance of the network. They show that the solution can deliver average performance improvements of 70%. In [2], the authors study an approach that improves throughput performance by up to 80% by simply adapting the AP's antenna and base orientations. The approach in [2] has a reduced movement complexity while achieving meaningful performance improvement. Other somewhat related works include [3] where robotic APs make adjustments to their positions to converge to an optimum position where client-specific bandwidth requirements can be satisfied, and [4] where positions of antenna elements in a multi-element array are adapted to improve link capacity (with network performance improvements of 98%).

At a high level, the key contribution of this paper is the systematic study of the self-positioning problem when the AP has both large-scale and small-scale mobility. When the scope of AP mobility is expanded, there is a search space complexity problem that has to be handled. In other words, if a 2D search space is R square units, and the possible granularity of mobility is r units, the number of potential search locations is $(\frac{R^{0.5}}{r} + 1)^2$. For a typical room of 16m^2 size, the number of search locations could vary from $50,000$ to $250,000$ depending for search granularities of 5cm and 1cm respectively. We address the search complexity problem by showing that it can be split into a macro-search problem to optimize network performance based on the *path loss* phenomenon, and a micro-search problem to further optimize network performance based on the *multipath* phenomenon. This significantly reduces the complexity of search and makes AP self-positioning solvable.

The specific contributions we make are as follows:

- We first use an extensive set of experimental results to show the benefits of AP self-positioning under a variety of conditions spanning from different environmental characteristics to different network configurations. We use these results to show that AP

Figure 1: A self-positioning AP system

self-positioning is an attractive strategy to achieve performance improvements within WiFi networks.

- We rely on systematic experimental analysis using WiFi APs, WiFi clients, an *anechoic chamber*, a *Tolomatic Programmable linear actuator*, and an *iRobot Create 2* and theoretical analysis to show that the AP location search problem can be split into two sub-problems: a macro-search problem to tackle path loss and a micro-search problem to tackle multipath.
- We then present *Hermes*, a self-positioning WiFi AP system that relies on a suite of algorithms to compute and move to an optimal location of the network. Based on the location of clients, we introduce the notion of a **communication centroid (CC)** that is akin to the geometric median but adapted for the path loss exponent. *Hermes* relies on the CC to solve the macro-position problem[1]. It then relies on a brute-force search algorithm at the CC to perform fine-grained adaptation to solve the micro-search problem. Then, we utilize ns-3 and MATLAB simulations to further analyze the algorithm performance of *Hermes*.
- Using a prototype implementation, we show that, on average, the proposed suite of algorithms can perform up to 117% better than default WiFi with no AP mobility, and up to 73% better than related work that allows for AP mobility.

In the rest of this paper, Section 2 presents the possible performance improvement that can be achieved with *AP position diversity* in various scenarios. In Section 3, the key concepts of the proposed algorithms are introduced. Section 4 and 5 present and analyze the algorithms of *Hermes*. The system is evaluated in Section 6. Section 7 discusses the related work, and Section 8 concludes the paper.

2 THE CASE FOR A SELF-POSITIONING AP

In this section, we provide experimental analysis results to illustrate the potential benefits of *AP position diversity*. We conduct **7** sets of experiments to investigate the benefits of self-positioning AP under various network conditions.

2.1 System Overview

Fig. 1 shows a self-positioning AP system, with an AP and a laptop mounted on a robotic platform. The main components of this system are as follows: 1) *Netgear AC 2350* AP, 2) *iRobot Create 2* robotic platform [6], and 3) *Lenovo Y410P* controller. *iRobot Create 2* carries both the AP and the controller, in order to enable the movement capability of the AP. A *MATLAB* toolbox provided by [6] is used by the controller to control the movement of the robot through serial communications. To monitor the AP's performance, the controller is connected to the AP via an Ethernet cable.

[1]Although [5] identifies the macro-search problem, it simply searches for the optimum position (maximum throughput) and does not specify how to systematically or theoretically derive the optimal macro position.

Table 1: Default Experimental Settings

	Default Settings
AP	Netgear AC 2350
Client	Lenovo Y700
Client Number	1
Traffic Direction	Downlink
Transport Protocol	UDP
Experimental Scenario	Apartment
WiFi Spectrum	5GHz

2.2 Methodology

The major goal of this section is to identify the gain of *AP position diversity* under the following **7** sets of experiments: 1) 2D Locations, 2) Spectrum, 3) 2D vs. 3D Locations, 4) Traffic Direction, 5) Multiple Clients, 6) Wireless Backhaul, and 7) Anechoic Chamber.

Metrics: The main metric we focus on is the **aggregate throughput** between AP and clients. The traffic and corresponding throughput is controlled and measured by *Iperf3* [7]. The throughput is measured over a period of 20s, and an average result is obtained over three 20-second periods. We present the gain based on the following formula:

$$Average\,Gain = \frac{Max(throughput_i)}{\sum_{i=1}^{x} throughput_i/x} \tag{1}$$

where, i represents AP located at position i, and x is the total number of tested AP locations. More specifically, for every single set of experiment, the maximum throughput represents the achievable optimum throughput as a result of the advantages brought by *AP position diversity*.

Experimental Settings: We categorize the AP's location into the following two types: 1) *Standard location*: AP is located at the corners or the center of a room; 2) *Intelligent bad location*: If obstacles (with a minimum size of $0.2625m^3$ and a minimum penetration loss of ~15dBm) prevent Line-of-sight (LoS) condition between AP and its clients, we define the corresponding AP location as an intelligent bad position.

To validate the benefits of *AP position diversity* in different indoor scenarios, three different environments are chosen; namely, a research lab ($58.5m^2$), an apartment ($62.5m^2$), and a classroom ($119m^2$). Since these scenarios are presented in uncontrolled environments, the experiments are predominantly performed during the night and over the weekends so as to avoid dynamic channel conditions caused by dynamic environments or interference (e.g. unpredictable neighboring WiFi traffic and people moving around). For each set of experiment, we test the throughput performance at 5 *intelligent bad locations* and 5 *standard locations* (4 corners and 1 center of the room). For all the experiments, clients are placed within 10m away w.r.t. the AP. The default experimental parameters are listed in Table 1. If not otherwise mentioned, the experimental settings follow Table 1. In the interest of brevity, we present only a subset of all the experimental results and focus on the most important conclusions.

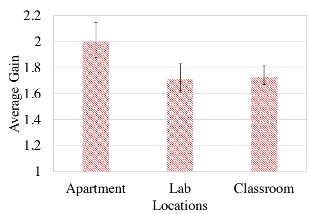

Figure 2: 2D Locations

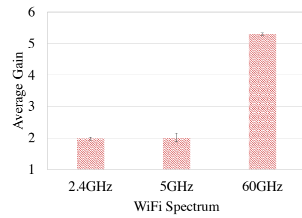

Figure 3: Spectrum

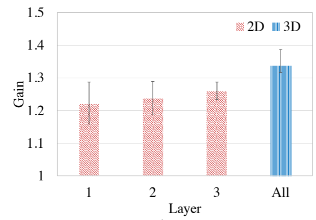

Figure 4: 2D/3D Locations

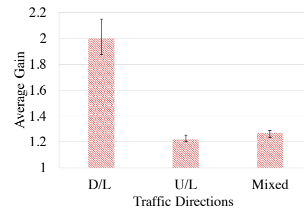

Figure 5: Traffic Direction

2.3 Evaluation Results

2D Locations: Here, we vary the AP's location to identify its impact on the network performance. To vary the AP's location, we follow the AP location categories identified in Section 2.2. The AP is placed at 5 standard and 5 intelligent bad locations. The throughput between the AP and its client is measured at the 10 AP locations.

Fig. 2 illustrates the *Average Gain* as the AP is located at the aforementioned 10 locations. It can be observed that the ideal AP location provides *Average Gain* of almost 2x. More specifically, the average throughput is 159Mbps, and the optimal throughput is 320Mbps. Also, 2D *AP position diversity* can achieve more than 1.7x *Average Gain* in all three environments, which validates the fact that the location of the AP does have a large impact on the network performance. We can also identify that the throughput improvement brought by *AP position diversity* is very site-specific. *This experiment indicates AP position diversity promises significant benefits, as the AP moves in a 2D plane.*

Spectrum: Here, we investigate the performance benefits of *AP position diversity* when WiFi carrier frequency varies among 2.4GHz, 5GHz and 60GHz. The experimental methodology is the same as the 2D locations experiment methodology. For 2.4GHz and 5GHz bands, we follow the default devices configurations given in Table 1. For the 60GHz experiment, we utilize a *TP LINK AD7200* as AP, and an *Acer TravelMate P648-M-59KW* laptop as client.

Fig. 3 shows 2x, 2x, and 5.3x *Average Gain* as a result of *AP position diversity* for 2.4GHz, 5GHz, and 60GHz, respectively. There is no difference between the *Average Gain* of 2.4GHz and 5GHz. Since 2.4GHz and 5GHz spectrum are close to each other, there is no significant difference in signal propagation characteristics. However, *AP position diversity* is able to provide 5.3x performance improvement for 60GHz (mmWave spectrum). The major reason is that both propagation loss and penetration loss of mmWave signals are significantly higher than that of 2.4GHz and 5GHz [8]. It reveals the fact that location (especially, LoS condition) matters substantially for mmWave. *The key observation here is* AP position diversity *is a significantly promising application for mmWave.*

2D vs. 3D Locations: From the 2D locations experiments, it can be seen that *AP position diversity* can bring significant network performance improvement. Here, we additionally study the impact on network performance while moving the AP in a 3D space. We construct the experiment using a 3-layer platform with size $1 * 1.25 * 1.75\text{m}^3$. The AP can be placed on any layer of this platform, where AP is in LoS or Non-LoS (NLoS) with its client on layer 3 or layer 1 and 2, respectively. The AP is placed at 9 different positions on each layer. The gain of 3D locations is defined as the maximum throughput identified from all 3 layers divided by the lowest average throughput among 3 layers. The similar concept is applied for the gain of 2D locations, where maximum and lowest throughput is constrained within a specific layer. Fig. 4 presents the comparison results as the AP location varies in a 2D plane or a 3D space; the performance improvement ranges from 1.22x to 1.33x. Even though moving the AP in a 3D space can provide LoS conditions in this set of experiment, the 3D movement does not achieve significant improvement as compared with 2D movement. The first reason is that 3D movement (allowing an additional z-axis change for AP position) does not significantly change the distance between the AP and the client. Thus, the 3D movement does not have a notable impact on the path loss. Another reason is that multipath can be mitigated with either 2D or 3D movement of an AP. *This experiment indicates that the AP's 3D movement does not provide considerable benefits over AP's 2D movement regarding reducing path loss or mitigating the multipath effect.*

Traffic Direction: Here, we investigate the benefits of *AP position diversity*, when the traffic direction varies among uplink (UL), downlink (DL), and hybrid of UL and DL.

Fig. 5 presents the *Average Gain* for the various traffic directions. Intuitively, it would be expected that the *Average Gain* for DL and UL traffic condition is similar due to channel reciprocity. However, in the experimental results, the *Average Gain* for DL traffic is much higher than the *Average Gain* of UL. The reasons are: 1) different features of network interface controller (NIC) of AP and client (e.g., transmission power), 2) different multipath characteristics of UL and DL, and 3) different interference characteristics (e.g., hidden terminals). *This experiment implies that channel reciprocity cannot be assumed for WiFi networks.*

Multiple Clients: In this section, we will identify the *Average Gain* as the number of clients varies from 1 to 3 (clients selection priority: *Lenovo Y700 > Dell E6520 > MacBook Air*).

In Fig. 6, the *Average Gain* is more than 1.6x, as the client number varies from 1 to 3. We can also observe that the performance improvement decreases as the number of client increases. When the AP is located at a standard location, the overall network performance of multiple clients scenario is likely to perform better than the single client scenario. The major reason is that there is a higher probability that the AP will have good channel condition between itself and any of the clients, which in turn leads to slightly higher overall performance at standard locations for multiple clients scenario. For multiple clients scenario, it is not trivial to identify the optimum position for AP. It indicates the necessity for developing an intelligent AP self-positioning algorithm. *This experiment indicates there can also be significant performance improvement of AP position diversity for multiple clients scenario.*

Wireless Backhaul: The key advantages of wireless backhaul are to eliminate the Ethernet cable physical constraints of a self-positioning AP, and to extend the boundaries of the AP's transmission and movement range. A specific application case is embedding

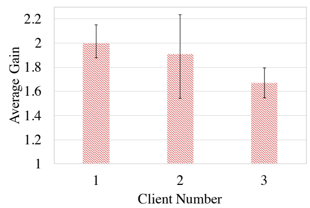

Figure 6: Number of Clients

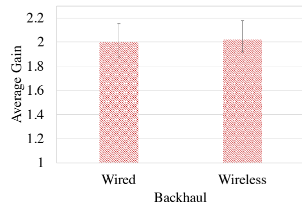

Figure 7: Wireless Backhaul

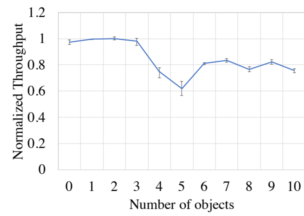

Figure 8: Multipath Effect

Figure 9: Micro-Mobility

the self-positioning functionality in household robots to improve corresponding network performance.

To conduct this experiment, we utilize a *Dell E6250* to mimic wireless backhaul and a *Lenovo Y700* as a client. The minimum throughput of the link from wireless backhaul to AP and the link from AP to the client is defined as the performance metric for wireless backhaul. We utilize the performance of wired backhaul AP as the baseline. The position of AP is varied among the aforementioned 10 locations (with a fixed client and the wireless backhaul in this set of the experiment).

From Fig. 7, it can be observed that *AP position diversity* can provide around 2x throughput improvement for both wireless and wired backhaul. Here, *AP position diversity* can provide significant *Average Gain* improvement for both wireless and wired backhaul. The *Average Gain* of wireless backhaul is slightly higher than that of wired backhaul. Theoretically, *AP position diversity* matters more in wireless backhaul scenario, since both links are impacted by the location of AP. Either of the links with bad channel condition can limit the performance of wireless backhaul. *The results from this experiment indicate that the benefits of AP position diversity can also be attained in wireless backhaul scenarios.*

Anechoic Chamber: In an effort to have a fully controlled environment, the following experiments were performed in a $4m^2$ anechoic chamber. The anechoic chamber is equipped with 90dBm attenuation walls which are used to eliminate any outside interference. Also, the inside of the anechoic chamber is fully covered with radio absorption materials to eliminate multipath. Thus, this chamber provides an ideal environment with no dynamic channel conditions or multipath effects.

Multipath effect investigation: The AP movement of even a few centimeters can appreciably increase the received signal quality due to multipath [5, 9]. More specifically, for WiFi networks, multipath can have a large impact when the signal quality change resulted by multipath leads to the change of modulation and coding rate due to signal quality achieving various minimum sensitivity requirements. Here, our methodology is to put various numbers of metallic objects (with a minimum size of $0.005m^3$) in the chamber to simulate scenarios with different multipath conditions. Fig. 8 illustrates how networks are impacted by different multipath conditions. As can be seen from Fig. 8, when no object is in the chamber, the throughput is at its maximum. As the number of objects inside the chamber is increased, the throughput varies significantly. E.g., for five objects, throughput drops to 60% of the maximum throughput. *It can conclusively be seen that the multipath has a large impact on the network performance.*

Micro-mobility investigation: Here, the number of objects in the anechoic chamber is fixed as 4. The micro-positioning is achieved by changing the position of the AP with an interval granularity of 2cm. As can be seen from Fig. 9, micro-positioning can introduce significant performance impact for throughput performance in an ideal environment, which further indicates interference is not the major reason which leads to performance variance for all the experiments. *Here, we observe that micro mobility of AP has a large impact on the network performance.*

Summary: We investigated how *AP position diversity* can improve *Average Gain* in various network scenarios. It was found that *AP position diversity* provides significant network performance improvement, ranging from 1.22x to 5.3x on an average. It is also worth to notice that spectrum efficiency is also improved as *Average Gain* increases. Additionally, the maximum throughput improvement observed is up to 52.8x. Thus, the results clearly motivate further investigation on how to utilize the benefits brought by *AP position diversity*. The experiments presented in this section are conservative (tested with a limited number of locations), and hence the optimum network performance can be even higher.

2.4 Problem Statement and Scope

The problem addressed in this paper is to determine the optimal location for a self-positioning AP system where the network performance is optimized, and how to practically reach the optimal location. For the initial study of a self-positioning AP system, the scope of the problem investigated is the following: (i) Non-mmWave spectrum (e.g., 5GHz) is considered. (ii) A single AP scenario is considered.

3 DESIGN BASICS

3.1 A Case for Hierarchical Mobility

The key argument that we make in this paper is that the impact of the AP location on the network performance is actually related to a juxtaposition of two different phenomena - path loss and multipath. *We posit that the search complexity problem can be tackled by decoupling the two phenomena, and solving them independently.* The first step is to find the optimal macro-position of the AP so that the average path loss between AP and client is minimized. Upon reaching the optimal macro-position, the second step involves performing a brute force search to find the optimal micro-position. We now theoretically and quantitatively validate our argument.

Macro-mobility: Path loss in a network is the attenuation of a transmitted signal as it propagates through a medium. While it happens because of a variety of factors such as penetration loss, absorption, and propagation loss, it is strongly inversely proportional to the distance between the transmitter and receiver. The goal of this part is to establish that adapting AP based on path loss phenomenon through macro-mobility will improve network performance. To model the path loss between AP and clients, we utilize a widely accepted log-distance based path loss model as shown in Equation

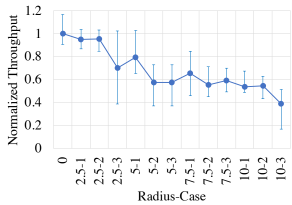

Figure 10: Throughput

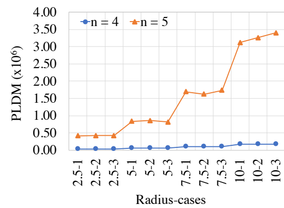

Figure 11: PLDM

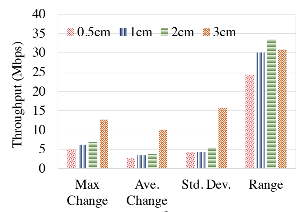

Figure 12: Granularity Statistics

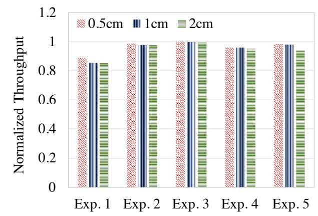

Figure 13: Optimum Throughput

2 (the impact of shadow fading on the self-positioning system will be discussed in Section 5). Traditional log normal shadowing model and, more recently, advanced practical indoor path loss model [10] are based on the log-distance path loss model. Path loss exponent is a key parameter in this model, which can be roughly estimated based on scenario type or accurately calibrated using the Cayley-Menger determinant based algorithm [11].

$$Path\ Loss = PL_0 + 10 n_i log \frac{d_i}{d_0} \tag{2}$$

where, d_i, PL_0, and n_i is the distance between AP and client i, the path loss at the reference distance d_0, and path loss exponent between AP and client i, respectively.

Here, we intend to minimize average path loss between AP and clients which can maximize average link quality. Average link quality is an important metric for WiFi networks because any link in WiFi networks with low-quality consumes extra transmission resources (e.g., time) due to its low modulation and coding rate. Utilizing low modulation and coding rate will not impact the distributed coordination function MAC algorithm of WiFi networks. Thus, from the MAC perspective, low-quality WiFi links have the same transmission opportunity as high-quality WiFi links. Also, considering DL transmission in WiFi networks, low-quality links may even need to retransmit due to transmission failure. In such case, AP increases its contention window and waits extra time to complete the transmission which leads to even worse spectrum efficiency (while other high-quality links also need to wait for the completion of the retransmission). Based on the above discussion, we intend to minimize the average path loss between AP and clients to maximize average link quality. To minimize average path loss, we use a simplified metric - path loss distance metric (PLDM) ($\Sigma {d_i}^{n_i}/k$), where k is the total number of clients. Average path loss between AP and clients are minimized when PLDM is minimized since PL_0 and d_0 in Equation 2 are constant parameters.

In the macro-mobility experiment, 3 clients are located on the arc of a circle with 10m radius in the lab scenario. The clients are placed equidistant on the circle. We change the position of the AP from the center of the circle to positions along concentric circles with different radii - 2.5m, 5m, 7.5m, and 10m (3 different AP locations on each concentric circle are tested). The experiment also follows the experimental methodology of Section 2. From Fig. 10, it can be identified that as the AP moves away from the center, the network exhibits lower performance. The macro optimal location is the center of the circle, and at that point, the PLDM is also minimized (with the path loss exponent n_i is estimated as 4 for each client). The results indicate the macro-position has a significant impact on the overall network performance, and specifically, minimizing PLDM improves network performance. Fig. 11 shows how the PLDM changes across with different path loss exponent for the 3 clients scenario. It can be observed that there is a strong inverse relationship between the PLDM and throughput, thus further motivating the idea of minimizing the average path loss between AP and clients.

Micro-mobility: In an effort to encompass micro-mobility of a self-positioning AP system, the granularity by which the AP moves needs to be determined in the first place. Identifying a desired micro search granularity interval is important for reducing the search cost and complexity. Any practical self-position AP would need to find an optimal solution in reasonable time while still ensuring satisfactory network performance improvement.

Related works have suggested that multipath will have an impact if the movement distance is greater than 1/4 to 1/2 of the wavelength of the transmitted signal [12, 13]. In particular, [13] states that when the distance between two locations is greater than 1/4 wavelength, the phase difference between the responses on the two locations changes by $\pi/2$, which causes a significant change in the overall received signal strength. This implies that movement of the AP between 1/4 to 1/2 of the wavelength is sufficient to mitigate multipath. For a 5GHz signal, the movement of an AP between 1/4 to 1/2 of the wavelength translates to movement between 1.5cm to 3cm. To validate this claim, we perform experiments that involved moving the AP by small intervals and measuring throughput between the client and AP. The AP was moved by the granularities of 0.5cm, 1cm, 2cm and 3cm using the *Tolomatic Programmable linear actuator*. The actuator system allows mobility along the x, y, and z axes, and ensures micro-mobility with an accuracy of 3.175μm. The throughput at each point was evaluated for movements of up to 10cm in x and y axes, and 6cm along the z axis (with a physical limitation of 6cm along the z-axis).

In this granularity experiment, a single client scenario is considered with 5 different client location settings. A 0.5cm interval movement means that the AP moves with an interval of 0.5cm in the x, y and z directions in a $2.5 * 2.5 * 2.5\text{cm}^3$ cube, which equates to 216 points. Similarly, for 1cm, the AP moves in a $5 * 5 * 5\text{cm}^3$ cube with 216 points. To fairly compare the performance for the different intervals, a rectangular prism with dimensions $16 * 10 * 6\text{cm}^3$ for the 2cm interval, and $24 * 21 * 6\text{cm}^3$ for the 3cm was evaluated by moving the actuator. This ensures that there are 216 points in the cube at which measurements can be made for various granularity.

The standard deviation, range, as well as maximum and average changes between adjacent points, are shown for the different intervals of movement in Fig. 12. The maximum and average changes as shown in Fig. 12 are obtained by calculating the difference in throughput for each point in space and all adjacent points near it. For example, if we imagine a 3D coordinate system, then at point (1,1,1), all adjacent points with a granularity of 1cm is (0,1,1), (2,1,1), (1,0,1), (1,2,1), (1,1,0) and (1,1,2). The range is calculated as the maximum throughput value subtracted by the minimum throughput value obtained within the entire search cube. From Fig. 12, the standard deviation increases as the granularity increases. There is, however, a significant increase in the standard deviation for a granularity interval of 3cm, which indicates significant impact by multipath can be observed for 3cm granularity. Also, the range metric can achieve up to 33.6Mbps within a small searching cube. The maximum and average change of the throughput between adjacent points for the different intervals further seeks to verify the claim that micro-mobility makes a notable impact on the network performance. The results shown in Fig. 12 effectively substantiate that moving the AP, by intervals of as small as 3cm, has a considerable impact on the throughput performance.

It is obvious that the smaller the interval by which the AP is moved, the larger the likelihood of finding the optimum position. However, there is a trade-off between the time spent searching and the highest throughput obtained. As shown in Fig. 12, a movement of 3cm causes a large performance variation which may lead to missing the optimal location. Therefore, movement intervals of less than 3cm should be considered for 5GHz signal. Moving the AP with intervals of 0.5cm, 1cm and 2cm yields the results shown in Fig. 13 for 5 different client positions. The highest throughput obtained is for a search space that is exhaustively searched for an interval of 0.5cm. However, the optimum throughput value obtained when searching with a granularity of 0.5cm, is on average approximately 1.03% and 2.08% higher for granularities of 1cm and 2cm, respectively. This means that a micro-search with a granular interval of 2cm reduces the search time by 75% while having a minimal impact in identifying the optimal position. The interval of 2cm is in line with the notion that the movement of the AP of between 1/4 and 1/2 of the wavelength is sufficient for significant impact through multipath.

3.2 CC and Brute-force Search

CC: For the macro-search problem, we consider optimizing the path loss phenomenon for WiFi networks. We, therefore intend to minimize the average path loss between an AP and clients. As the average path loss is minimized, the average link quality is then maximized. We term this optimal macro position as *CC*. The CC is related to the geometric centroid in that the latter minimizes the average distance to a given set of vertices. Here, CC is adapted with the path loss exponent. This renders the computation of the optimal location that minimizes average path loss between AP and all the clients as a convex optimization problem which will be discussed in Section 4.

Brute-force Search: Once the CC is determined in a particular network, a brute-force micro-search approach can then be used to search a finite number of points in the vicinity to further improve the network performance to combat multipath.

3.3 Practical System Design and Discussion

To practically enable mobility of an AP, we propose a self-positioning AP system with the following requirements and features: 1) *Robotic platform:* any robotic system has floor movement capability; 2) *Power source of AP:* the robotic platform or the controller can provide port to power the AP in order to eliminate power outlet (e.g., mini APs can be powered by any power sources with micro USB port). 3) *Wireless backhaul:* wireless backhaul can be utilized to eliminate the Ethernet cable. To maintain the performance of such a system, the wireless backhaul communication channel should be different from the front end communication channel. 4) *Movement range:* we assume that the AP can only move in a limited area where no obstacle exists in this region, and we also consider the limited area as a convex set for simplicity, where, for every pair of points within the region, every point on the straight line segment that joins the pair of points is also within the previously defined region (in such case, the path planning problem is simplified as moving in the straight line); 5) *Location calibration:* the AP can utilize localization technique to measure its relative position w.r.t. wireless backhaul to calibrate its position and strictly restrict the system to move in the previously defined limited area.

4 HERMES — A SELF-POSITIONING WIFI ACCESS POINT

Based on the design insights of Section 3, we propose *Hermes*, a self-positioning WiFi AP in this section. The following items are the major components that constitute *Hermes*: 1) localization of Clients; 2) computation of the macro-optimal CC based on clients' positions; 3) brute force micro-search.

4.1 Localization of Clients

Localization techniques: Recently, many studies have been done for WiFi-based indoor localization [14]. Specifically, [15] presents *SpotFi*, which is an accurate indoor localization system that can be deployed on off-the-shelf WiFi infrastructure. This system can achieve a median accuracy of 40*cm*. *SpotFi* incorporates super-resolution algorithms that can accurately compute the angle of arrival (AoA) of multipath components and estimate the location of the target by using the direct path AoA estimates and RSSI measurements. As AP is equipped with comparatively large number of antennas, [16] can be applied to *Hermes*, which utilizes multipath suppression algorithm to achieve a median accuracy of 23*cm*.

Robotic Trilateration: Typically, localization techniques require at least three receivers to localize clients' position. Given the benefit of movement capability of *Hermes*, localization techniques can be applied to single AP *Hermes*. Trilateration is a process by which the location of a transmitter can be determined by measuring the distance between the transmitter and three different receivers with known locations [17]. Although the target environment for *Hermes* does not have three receivers with known locations, *Hermes* itself has moving capability. Thus, we propose a technique called *robotic trilateration*, in which *Hermes* moves to m number of positions (with $m \geq 3$) to measure the distance between itself and its clients m times to estimate the clients' positions. Also, given the mobility advantage, *Hermes* can rotate in rn number of directions, and collect average distance estimation to reduce measurement error. As m and rn increase, the estimation accuracy increases, but the time complexity also increases.

[17] proposes an enhanced trilateration algorithm that simplifies the trilateration problem by limiting the receivers locations. Based on the proposed algorithm, by solving quadratic equations, the

number of solutions for quadratic equations is reduced to 2. Utilizing the same methodology, we let *Hermes* move to three specific types of coordinates to measure the distance between itself and a client: 1) A1(0,0,0), A2(x_2,0,0), and A3(x_3,y_3,0), where A1, A2, and A3 are non-collinear. *Hermes* relies on a virtual coordinate system where the initial position of the AP is defined as the origin with coordinates (0,0,0), and the initial direction that the AP faces to is defined as the x positive direction. The unit length in the coordinate system should be less than the granularity of micro-positioning. *Hermes* measures the distance between the AP and a given client at the initial position (A1). Then, the AP moves to A2 (x_2,0,0) and A3 (x_3,y_3,0). Then, the following quadratic equations can be formed:

$$r_1^2 = x^2 + y^2 + z^2 \tag{3}$$

$$r_2^2 = (x - x_2)^2 + y^2 + z^2 \tag{4}$$

$$r_3^2 = (x - x_3)^2 + (y - y_3)^2 + z^2 \tag{5}$$

Where, r_1, r_2, and r_3 are distances measured from positions A1, A2, and A3. x, y, z are the coordinates of the client of interest. The following equations are then used to calculate the location of the client of interest for that set of positions:

$$x = \frac{r_1^2 - r_2^2 + x_2^2}{2x_2} \tag{6}$$

$$y = \frac{r_1^2 - r_3^2 + x_3^2 + y_3^2 - 2x_3x}{2y_3} \tag{7}$$

$$z = \sqrt{r_1^2 - x^2 - y^2} \tag{8}$$

Note that, if $m > 3$, the above equations can be formed for each unique combination of positions of the form A1, A2, A3. For example, if m is 5, and say each coordinate type A1/A2/A3 has 1/2/2 positions, the number of equation sets becomes 4. For each equation set, a corresponding client location can be calculated. The average of all possible client locations is then computed to improve the location estimation accuracy. As can be seen from Equation 8, z can be either positive or negative. For a 2D robotic platform, there is no need to calculate the unique client coordinate, since both negative or positive z solution will let the robotic platform converge to the same CC. For a 3D robotic platform, as the robotic platform can move in z direction, the distance between the AP and its client can be utilized to identify unique client location. Specifically, if the robotic platform moves in the positive z direction, and the distance between the robotic platform and its client decreases, it means that the client location has a positive z coordinate.

Monitoring System: In order to adapt for dynamic client scenario, in *Hermes*, we propose the following monitoring system to constantly monitor the clients' mobility status using the localization methods discussed in this section. We categorize clients mobility as 4 types: 1) *Fixed*: client with no change in position, 2) *micro-movement*: client with movement less than *mr* meter, 3) *macro-movement*: with movement larger than *mr* meter , and 4) *constantly moving*: client does not stay still. More specifically, a client will be categorized in each type, when the client is monitored as the specific type for *mt* seconds. The tradeoff to set low *mr* or *mt* is higher optimized network performance but more frequent AP movement. The default of *mr* and *mt* are set as 50x of wavelength and 20s.

4.2 Computing CC

Given the algorithm to identify locations of the clients, the next step is to identify the CC within the predefined movement range. CC is the position with minimum average path loss between AP and its clients. Thus, we intend to minimize the following equation as discussed in 3:

$$\frac{sum_{i=1}^{k} w_i |\vec{p_o} - \vec{p_i}|^{n_i}}{k} \tag{9}$$

where k is the total number of clients. w_i is the weight for the link between AP and client i which is in the range of [0,1] (the higher the weight is, the higher the QoS is given to client i). $\vec{p_o}$ and $\vec{p_i}$ are the coordinates of the optimum AP position and the coordinates of client i, and n_i is the path loss exponent. If a client is identified as a constantly moving client, a weight 0 is given to such client. We intend to show that this is a convex optimization problem. The mathematical objective is to prove the following statement:

$$\frac{sum_{i=1}^{k} w_i |\vec{p_o} - \vec{p_i}|^{n_i}}{k} \quad is\ a\ convex\ function$$

The first step is to show that the nth power of a non-negative convex function, as the distance is non-negative, is still a convex function, where n is always larger than 1. The second step is to show that the sum of convex functions is still a convex function, and the third step is to show the convex function divided by a non-zero constant is still a convex function. The proof for the second and third steps are trivial and can be found in [18]. The convex function definition is given in Equation 10, where c(x) is the convex function and x_1/x_2 are arbitrary variables of c(x). Then, important proof steps are given below for the first step, where f(x) follows the definition of a convex function.

$$\forall t \in [0,1], c(tx_1 + (1-t)x_2) <= tc(x_1) + (1-t)c(x_2) \tag{10}$$

Proof. Assume f(x) = h(g(x)), where h(z) = z^n and g(x) is a non-negative convex function.

$$Since\ g(x)\ is\ non-negative:$$
$$[g(tx_1 + (1-t)x_2)]^n <= [tg(x_1) + (1-t)g(x_2)]^n$$
$$Since\ n > 1\ and\ z\ is\ non-negative:$$
$$h''(z) = n_i(n-1)z^{n_i-2} > 0$$
$$Since\ h(z)\ is\ convex:$$
$$h(tz_1 + (1-t)z_2) <= th(z_1) + (1-t)h(z_2)$$
$$By\ substitution: \ f(tx + (1-t)x) <= f(x) + (1-t)f(x)$$

□

Assume the locations of all clients are given. Algorithm 1 can be utilized to identify the location of the CC. The initial position of the AP is defined in line 1. The sum of nth power of distances between initial AP position and all its clients is calculated in line 2. We define *Step* as the pace to search in line 3. If *Step* is larger than the movement granularity of *Hermes*, defined as *gran*, continue the search in line 4. Search in 6 different directions, and if the sum of nth power of distance between the new AP position and all clients are smaller, replace AP's coordinate with the new AP's position as shown in line 5-line 8. Step becomes half of the previous value in each loop (loop is formed in line 4 to line 11) as shown in line 10. Finally, the CC is identified with the minimum average of $n_i{}^{th}$ power of the distance between the new AP position and all clients in line 12. When a new client joins the network or a client is detected with macro-movement using the monitoring system, or if an existing client either becomes active or deactivate, the macro-search will commence once again.

Algorithm 1 Computing CC

$AP = (cx, cy)$
$Ave = \sum w_i |AP - clients|^{n_i} / k$
$Step = InitialStep$
while $Step > gran$ **do**
  $Change\ AP\ with \pm Step$ for x, y and z
  $NewAve = \sum w_i |NewAP - clients|^{n_i} / k$
  if $NewAve < Ave$ **then**
    $AP = NewAP$
  End if
  $Step = Step/2$
End while
$CC = AP$

4.3 Brute-force Search

After identifying the CC, the next step in *Hermes* is to utilize a brute force search to identify the optimal micro-location. Specifically, *Hermes* considers CC as the center of searching space.At each position, AP and clients perform both UL or DL throughput measurement, due to the channel asymmetric issue discussed in Section 2.3. The tradeoff of measurement duration is that long duration leads to high reliability but also high time complexity. The throughput measurements from clients are reported to AP. AP utilizes the following T metric to identify the optimal micro position:

$$T = \sum_{i=1}^{k} (w_l * Throughput_{UL_i} + (1 - w_l) * Throughput_{DL_i}) \quad (11)$$

where, the weighed factor w_l (in the range of [0,1]) and $1 - w_l$ is used to assign weights for DL and UL measurement. AP identifies the position with maximum T as optimum position. The micro-search will be performed at the initial stage and the measurement at the p micro-positions will be recorded as history data, in particular, the lowest value of T obtained over the p positions will also be noted. Once the AP is moved to the optimal micro position, the AP will only move to a new micro position when the measured T metric drops to less than half of the sum of optimum and lowest T. The brute force search will then commence once again.

5 *HERMES* ANALYSIS

In this section, we utilize simulation-based analysis to study: 1) Impact of dynamic Shadow fading: the impact of obstacles on channel quality while *Hermes* computes CC, and 2) CC vs. Optimal Location: the performance gap of CC versus optimal location.

5.1 Impact of Dynamic Shadow Fading

Shadowing effect is an important phenomenon to be considered in the path loss model. For indoor scenarios, there is a very high probability that the link between AP and client is impacted by shadowing and leads to NLoS channel condition. In *Hermes*, to compute CC, the shadowing parameter is not considered in Equation 2. The reason will be explained herein.

In *Hermes*, as the system will constantly move, the number of obstacle between AP and each client may change. Thus, to accurately identify CC, the exact location, size, and even the material of each obstacle need to be known by the AP, which incurs very high complexity for the AP to collect these parameters. To quantitatively analyze the impact of shadowing effect on *Hermes*, we utilize MATLAB simulations to identify how likely the number of obstacle between AP and each client changes as *Hermes* moves.

Table 2: MATLAB Simulation Configurations

	Settings
Number of Obstacle	33
Minimum Obstacle Size (m)	(0.75, 0.25, 0.1)
Maximum Obstacle Size (m)	(1.75, 1.25, 1.75)
Average Obstacle Size (m)	(1.24, 0.59, 0.47)
Standard Deviation of Obstacle Size (m)	(0.36, 0.32, 0.45)
Size of Room (m)	(9, 6.5, 3)

Table 3: ns-3 Simulation Configurations

	Settings
Client Number	3
Distance between AP and client	10m
Traffic Direction	Dl
Transport Protocol	UDP
WiFi Spectrum	5GHz
Experimental Duration	20s

The simulation parameters are summarized in Table 2. The obstacle information is collected based on the obstacle layout in the lab scenario (only obstacles with large size or high penetration loss are considered). We have run 10 sets of simulations with different obstacle configurations with obstacle size follows the distribution with average and standard deviation obstacle size shown in Table 2, and the size is limited by max and min of obstacle size. In each scenario, the movement range (with the center located at the center of the floor) of AP is configured as $2.25m^2$, $9m^2$, and $20.25m^2$. For each scenario, 1000 clients are simulated. As AP moves in each predefined area, we intend to identify the number of obstacle change between AP and each client. In fig. 14, the results show how the number of obstacle changes while the AP moves. To be noticed, the higher the number of obstacle change is, the larger the impact it has on the CC computing algorithm. We categorize the number of change of obstacle of 0, 1, and 2 or above as *no impact*, *low impact* and *high impact* cases, respectively. As the movement range changes between $2.25m^2$, $9m^2$, and $20.25m^2$, the high impact cases appears in 1%, 1.4% and 4.4% of overall cases, respectively. Thus, it can be seen that the high impact cases rarely happen. Thus, we conclude that the impact of shadowing effect on computing CC algorithm is very limited. Also, due to the extremely high complexity and cost to consider shadowing effect in *Hermes*, we intend to eliminate the shadowing parameter in CC computing algorithms.

5.2 CC vs. Optimal Location

In this work, CC is defined as the position with minimized average path loss (to maximize average link quality), which does not directly lead to maximal throughput performance. Here, we utilize ns-3 [19] simulations to study the performance gap of CC versus optimal location. The simulation scenario is configured as shown in Table 3. Each client is randomly distributed around the AP. The default log-distance path loss model is utilized (without modeling the multipath effect).

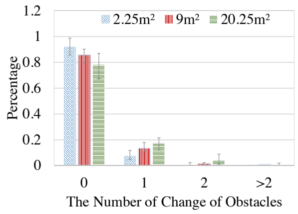

Figure 14: Dynamic Shadowing

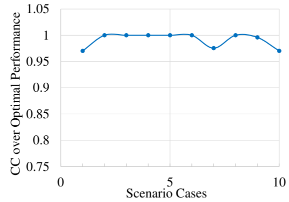

Figure 15: CC Performance Analysis

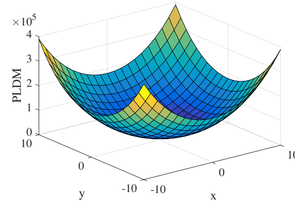

Figure 16: Path Loss Distribution

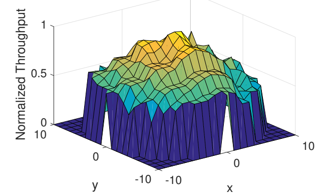

Figure 17: Throughput Distribution

We have run the simulation 10 times with random clients location configurations. As shown in Fig. 15, the normalized aggregate throughput performance of CC ranges from 0.97 to 1 compared with optimal location. This further validates that minimizing average path loss can almost achieve optimal network performance. To further illustrate the performance of CC, fig. 16 and 17 show the average path loss distribution and aggregate throughput performance distribution of a specific scenario, where AP is located at (0, 0), and three clients are located at (9.8, 0), (-5, 8.5) and (-4.8, -8.8). In this example, the CC is located at (0, 0). The normalized aggregate throughout performance within 10m of AP ranges from [0.33, 1]. As the AP is located at any location where the link quality of a specific link has bad channel quality, the aggregate performance of the network becomes extremely bad due to the bad quality link consuming extra transmission resources. More specifically, as AP is located at (10, 0), the aggregate performance is 0.48 (each client contributes 0.18, 0.16, and 0.14). In this example, it is clear that even one of the client has extremely good link quality, it only performs 0.18, since it has to share the channel with the other two low-quality links. If modulation, coding, and transmission success rate of each link can be predicted at each AP location, the network performance can be further improved.

6 HERMES EVALUATION

In this section, the performance of *Hermes* is experimentally evaluated in different environments with varying restrictions. The throughput is measured over a period of 20s, and an average result is obtained over three 20-second periods. Algorithms of *Hermes* follow specifications in Section 4. For client localization, the distance between the client and AP are assumed to be known to the AP. For communication centroid, the number of positions *Hermes* moves to, m, is chosen as 3, path loss exponent n_i is chosen as 4 for each client based on the scenario type, and weighted factor w_i is set as 1 for each client. To determine the micro-optimal position, the brute force search technique is used in which, the possible number of locations to search, p is chosen as 9. DL traffic is assumed for the experiments, so w_l is set as 1. For simplicity, a wired backhaul system is configured for performance evaluation. Experimental results are also compared with the *iMob* system proposed in [1]. The system in [1] searches for an optimal position in a 4ft.^{2} region using the OST to find the position of the AP such that the aggregate throughput is maximized in real-time without having the AP to retrace its path. In essence, if there are N total number of points that the AP can be positioned within the 4ft.^{2} plane, OST specifies that the AP finds the maximum aggregate throughput in the first $\frac{N}{e}$ points. It further stipulates that the AP should stop at the first point after the $\frac{N}{e}$ points that yields a greater aggregate throughput than the maximum throughput found in the first $\frac{N}{e}$ points. In case the OST is unable to find a point that yields a higher aggregate throughput, the expectation is reduced in proportion to the number of points it has already traversed. We utilize the actuator system as the platform for the *iMob* system.

6.1 Number of Clients

In this experiment, the starting position of the AP is located in the circle with 10m distance to the CC. The optimal aggregate throughput obtained for 1, 2 and 3 clients of *Hermes* is compared to the results obtained through the implementation of the *iMob* [1].

The aggregate throughput for 1, 2 and 3 clients over three different configurations are shown in Fig. 18. As can be seen, there is a significant aggregate throughput improvement of 66%, 17%, 20% of *Hermes* compared with *iMob* for 1, 2 and 3 clients scenarios, respectively. It reveals the benefit of the macro optimization algorithm of *Hermes*. Furthermore, it is important to mention that there are on average over 110 points that *iMob* needs to traverse before it stops at a position that it considers optimal. For *Hermes* however, there are on average 10 micro-position stops it makes before finding the position that results in the highest aggregate network throughput.

6.2 Location of Clients

To further evaluate the performance of *Hermes* in a multi-client scenario, the optimal positions obtained by *Hermes* and *iMob* are analyzed for three different topology configurations where three clients are randomly placed around a circle with a radius around 10m. For configurations *1* and *2*, the starting position of the AP is randomly located inside the circle. For configuration *3*, the starting position of the AP is located on the circle with 10m distance to CC.

In Fig. 19, the performance improvement of *Hermes* over *iMob* is up to 73% for configuration *3*. In configuration *3*, the starting position of the AP is on the circle along which the clients are placed on. As *Hermes* performs both macro-positioning to identify CC and micro-positioning to identify the optimal micro position, *Hermes* can optimize both path loss and multipath phenomenon. *iMob* mainly considers micro-positioning to benefit from mitigating multipath but not from path loss phenomenon. Also, the efficient micro-searching algorithm in *Hermes* at the CC reduces the search complexity. The results further indicate the promising improvement achieved by macro-mobility of *Hermes*. To be noticed, the performance improvement of *Hermes* compared with *iMob* increases as the distance between starting point and CC increases.

6.3 Constrained Mobility

In real-life environments, various constraints can limit the movement of *Hermes*, and it needs to be taken into account. This can prevent *Hermes* from moving towards the CC. Following the same

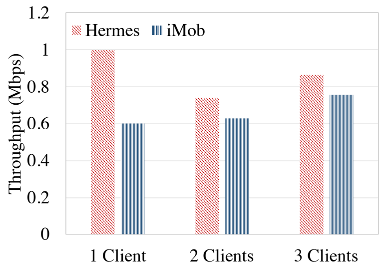

Figure 18: Number of Clients

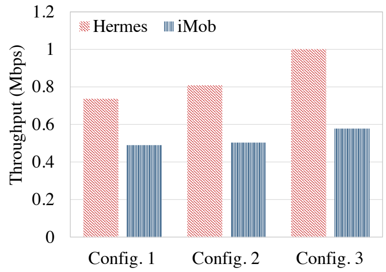

Figure 19: Clients Configurations

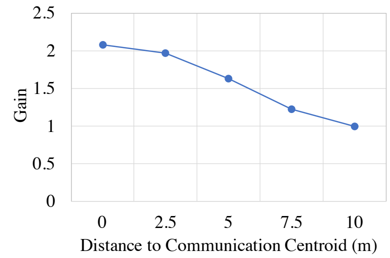

Figure 20: Constrained Mobility

experimental configurations of macro-mobility experiments in Section 3.1, the impact on the aggregate network throughput of various distances the AP is away from the CC is shown in fig. 20. It shows the network throughput performance as the AP is away from CC with distance ranging from 0m to 10m with a step size of 2.5m.

From fig. 20, the overall network performance is approximately less than a half when it is placed as far as 10m from CC. It exhibits a nearly linear relationship in terms of the overall network throughput degradation as the AP is moved away from the CC. This implies that if the AP is not able to precisely move to the CC due to barriers, *Hermes* will still exhibit acceptable performance improvement compared with an arbitrary starting position of the AP.

7 RELATED WORK

With respect to device position, phenomena that impact network performance are path loss and multipath effect. For indoor wireless communication, recent works suggest that path loss prediction is able to provide decent m. level accuracy [10]. On the other hand, multipath has always been identified as an important contributor to the unreliability of wireless links, due to the richness of the multipath effect for wireless transmission for indoor scenario [9]. More specifically, the movement of a transmitter or a receiver of even several centimeters can appreciably increase the received signal quality [1, 5].

As intelligent robotics become well-performed and cost-effective, self-positioning wireless systems become an attractive solution to combat both multipath and path loss issue in both micro and macro level. [1, 3, 4, 12] present promising results for self-positioning mechanisms which can achieve significant network performance improvement. Inspired by the previously mentioned works, *Hermes* first considers both utilizing macro-positioning achieving CC to minimize average path loss and maximize average link quality between the AP and clients, and afterward utilizing micro-mobility to combat multipath effect based on the brute force searching.

8 CONCLUSIONS

In this paper, we present a self-positioning AP system - *Hermes. Hermes* performs positioning by sequentially solving two related, but independent problems which aim to improve network performance. The first problem is to find the CC so that path loss phenomenon is optimized from the network perspective. The second problem involves finding an optimal micro position around the CC to optimize the multipath phenomenon. In addition, the notions of finding a CC and using brute force search can be directly applied to multiple APs scenario, as long as the optimum pairing set of APs and clients are given. Other than expanding the scope of this work, the following are the most important future work to be considered: 1) self-positioning time complexity analysis, 2) leveraging network fairness utilizing AP mobility, and 3) mitigating interference utilizing AP mobility.

ACKNOWLEDGEMENT

This work was funded in part by the National Science Foundation under grants CNS-1513884 and IIP-1701115, and the Wayne J. Holman Endowed Chair.

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