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Smart Handover with Predicted User Behavior using Convolutional Neural Networks for WiGig Systems

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***Abstract*—WiGig networks and 60 GHz frequency communications have a lot of potential for commercial and personal use. The high-frequency bands can provide high transmission rates, but their high amplitude makes it so the signal cannot go through any walls or obstacles. The signal also has a strong path loss element caused by the high frequency, significantly limiting the reach of connections because the signal is too weak at moderate distances. Due to these issues, users can easily lose connection with the access point while moving and need to connect to a new device, making WiGig systems unstable as they need to rely on frequent handovers to maintain a high-quality service. However, this solution is problematic as it forces users into bad connections and downtime before they are switched to a better access point. In this work, we use machine learning to identify patterns in user behaviors and predict user actions. This prediction is used to do proactive handovers, switching users to access points with better future transmission rates and a more stable environment based on the future state of the user. Results show that not only the proposal is effective at predicting channel data, but the use of such predictions improves system performance and avoids unnecessary handovers.**

***Index Terms*—WiGig, 60GHz, smart networking, convolutional neural networks, network prediction, proactive handover**

I. Introduction

WIGIG has been touted as the new revolutionary standard for WiFi since at least the announcement of protocol IEEE 802.11ad in 2009. Its main benefits stem from operating in the 60GHz spectrum. The higher frequency bands allow it to provide transmission rates in the range of multiple gigabits per second. These higher transmission rates can be important to support, for example, 6G and its new applications [1], [2]. However, despite the official addition of standard 802.11ad in 2012, WiGig never really took off in popularity or usage. The main drawbacks also come from the use of high-frequency communications. Signals in those bands have high dissipation rates, causing their range to be significantly shorter than more commonly used 2.4GHz and 5GHz bands, and extremely poor penetration rates, being almost entirely negated by most obstacles [3]. This comparison is illustrated in Fig. 1, where in the scenario on the top, although A receives a high-speed connection, B cannot be reached due to the wall separating it from the access point (AP). In comparison, in the scenario on the bottom, both devices are able to connect, but now A has a lower connection speed. Such issues limit 802.11ad APs to single, small rooms where line-of-sight is guaranteed and communication distance is short [4].

In an attempt to improve on the shortcomings of 802.11ad, IEEE 802.11ay was released in 2021. Compared to its predecessor, 802.11ay introduces channel bonding, multiple-input multiple-output (MIMO) capability, and higher modulation schemes. These changes not only increase the transmission rate (from a maximum of 7Gbps to 40Gbps) but also the range of communication. With the application of low loss and high output transmitters that are already available in the market, WiGig, in the form of 802.11ay, has proven that it can deliver wireless gigabit communications even with ranges of 500 meters [5]. Nonetheless, problems still surround the stability of connections, particularly with moving targets [3]. For starters, the issue with obstacles and penetrations persists, and non-line-of-sight transmission without a relay of some sort is nigh impossible. Additionally, even variations of a 1 dBm in the signal strength can significantly decrease the achievable throughput [5]. To maintain a network connection and take advantage of the highest throughput possible, multiple WiGig APs are needed with frequent handovers between them. However, handovers come with interruption time that cuts off the connection for a short interval, degrading the quality of experience [6]. This creates a complicated dilemma and tradeoff, where handovers interrupt and de-stabilize service for the users, but avoiding them means users are in a less-than-optimal connection and may lose network access altogether.

It is in this context that we will propose a proactive handover scheme for stable and efficient connection in a WiGig environment. Our framework is based on utilizing deep learning in the format of convolutional neural networks (CNN) to predict the behavior of a user/device. Then, based on this information, handover is performed in advance, before the signal degrades or is lost. Moreover, the behavior prediction allows our system to switch the connection to an AP that provides a stable environment in the future, further decreasing the need for handovers.

Our main contributions are listed as follows:

- We provide a framework for collecting user data and

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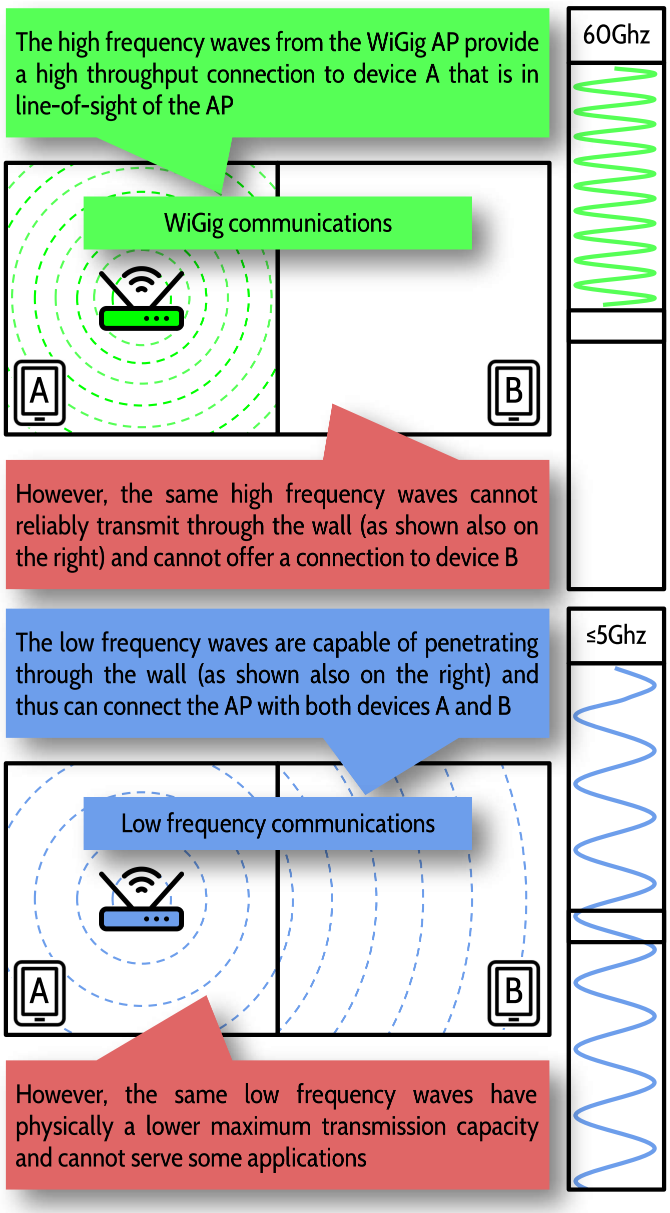

Fig. 1. Simplified comparison between WiGig and low frequency communications, and the tradeoff between speed and coverage.

training a CNN model capable of identifying patterns and predicting the future behavior of user devices in a WiGig environment.

- We propose a novel handover decision scheme capable of choosing APs with stable and efficient connections for each user device based on the predicted information.
- We provide simulation results based on experimental measurements that attest to how our proposal is capable of increasing the provided transmission rate and decreasing the number of handovers needed.

The rest of this article is organized as follows. In the next section, we review what are the existing works on network prediction and handling handovers. After that, we present our proposed architecture to provide users with WiGig network access while simultaneously collecting the data needed to improve system efficiency. Following that, we will propose a framework that analyzes the collected data and smartly performs handovers. Finally, we evaluate the performance of our proposal and discuss some promising future directions while concluding the article.

II. Proactive Handover and Network Prediction

Conventionally, networks and research on computer communications utilize a reactive approach to handovers, where the connection from the user to the network is only changed to a new AP after the service is detected to have deteriorated [7]. A big problem with this is that it forces the user to remain in a low-quality connection until the handover is completed. Such an issue is not ignored in the literature. Existing works have pointed out that networks with mobile users lead to frequent handovers and that using a deterministic and reactive scheme to control such handovers causes poor performance [8]. Especially in dense networks (which can be seen in WiGig, since the AP reach is easily blocked), a lot of redundant handovers (where a user is switched back and forth between APs) can happen, leading to high signaling overhead, handover latency, and service interruption, lowering the stability of the service [9]. Current literature (e.g., [7], [8], and [10]) addresses this by using a proactive handover based on predicting future network states through machine learning (ML). However, this is often done while ignoring the application profile and requirements of the users [6].

The common ground of proactive handover research is predicting future network states. This has been done through user mobility and data transmission behavior, which are highly predictable as users commonly follow a limited number of patterns [8], [10]. This has also been done by predicting signal strength, which is tied strongly with user mobility [6]. Luckily for this field, the prediction of network states is widely studied, even unrelated to handover. The method is often the collection of past user data (packets generated, location, speed, signal strength, etc.) and identifying patterns for predicting future actions [11], [12]. Additionally, the literature concludes that ML is the best method for making these predictions [11], [13]. The ML models are trained on past user data and then used for predicting the future behavior of new users, based on the assumption that new users follow similar behaviors as past ones [10]. Moreover, the ML models are also updated during live use of the system, through reinforcement learning, which allows the models to stay updated even if the environment changes and continuously improve their accuracy [14]. Particularly, CNN has been identified as especially effective in finding patterns in network states and predicting future network parameters [12]. However, many of these works (e.g. [11] and [13]) focus on just providing better predictions, without proposing any systems that can work on these predictions to improve practical network performance.

In this work, we address the shortcomings of the literature by providing a proactive handover scheme for WiGig networks. Our proposed system not only provides a method to collect user data, analyze it for patterns, and predict future network states but also how to use this prediction to provide practical performance improvement through better overall

TABLE I
SELECT LITERATURE ON NETWORK PREDICTION AND PROACTIVE HANDOVER

References	ML Methods	Objectives	Predicted Data	WiGig?
[6]	Neural network	Avoid handovers	Signal strength	No
[7]	Recurrent neural network	Improve prediction	Signal strength	No
[8]	Markov model, long short term memory	Improve prediction	Transmitted data	No
[9]	Assumes complete data knowledge	Improve data rate, avoid handovers	User location	No
[10]	Bayesian additive regression tree	Improve data rate, avoid handovers	Signal strength and user location	No
[11]	Random forest, deep learning	Improve prediction	Signal strength, transmitted data, and user location	No
[12]	CNN	Improve data rate	Signal strength and transmitted data	No
[13]	Particle swarm optimization, long short term memory	Improve prediction	Transmitted data	No

throughput. This is done while taking into consideration signal strength and also traffic generated by user applications. Prediction is done using CNN, following literature recommendation [12]. Lastly, as far as we know, this is the first study on network prediction-based handover management specifically for WiGig networks, as evidenced in Table I, which summarizes the key points of some works in the literature (this is not an exhaustive list, due to space limitation, but it is a faithful representation of the state-of-art). This is important as WiGig has such high transmission and obstruction rates that conventional solutions should not be applied without careful investigation and adjustments [3], [4].

III. WiGig Environment and Data Collection

In this section, we will explain what is our assumed scenario that will outline the design and implementation of our proposed framework and handover scheme. Consider a room (or any area where the network is to be established) with multiple APs, all capable of offering WiGig access. The room also has what we will define as "points of interest" or PoIs. A PoI is somewhere where users are likely to stop and stand still for some time. For example, a bench in a park, a table in a restaurant, and a cashier at a store are all possible PoIs since users will probably walk toward those places and stop moving for a while.

Users will enter this room following a Gaussian distribution with a pre-determined average rate. Each user that enters the room will have a set of PoIs it wants to "visit" before leaving, and thus will move to each of those PoIs in sequence. Additionally, once they reach a PoI, they will stand still in that place for an amount of time, where the actual amount is influenced by the PoI (some PoIs, like a cashier line, have short staying time, while others, like a table in a restaurant, have long staying time). Finally, each user is using an application that fits into a pre-determined list of application types [2]. Think of these types as video streaming, messaging, gaming, etc. Each type has its own, particular profile of data downloaded, data uploaded, and connection time. Additionally, we will also assume that some users are not compatible with some PoIs due to the application they are using and thus would not include those PoIs in their set of places to "visit". For example, a user watching a video or taking part in a video conference will probably not stand in a cashier line.

The scenario described is not only a realistic one but also provides a believable source of user behavior patterns. Since applications have particular profiles of data transmission and connection time [6], analysis of these features makes it possible to identify the type of each user. Additionally, because there are a limited number of PoIs, there is also a limited number of paths between them. We can use user data to infer the location of the user as it moves and identify the path being taken [10]. Moreover, by knowing at which PoI the user is through this location information, it is possible to estimate how long the user will stay there due to the nature of that PoI. Finally, because each application type has a subset of compatible PoIs, the number of paths possible is also similarly further limited by the application being used, fortunately decreasing the number of possible patterns.

To finalize the assumed network system, we will consider that there is a server of some sort connected to all APs [15]. At periodical intervals, every WiGig AP in the room will collect the following information: the signal strength between it and each user in the room, and how much data users connected to it have downloaded/uploaded in this time slot. The amount of transmitted data can be logged easily during communication with users. The signal strength does require an extra step, but it is not a troublesome one: the APs can broadcast a small message to all users that require a short acknowledgment, and this acknowledgment will be used to measure the signal strength (in fact, IEEE 802.11ay already has a similar mechanism implemented for beamforming training that can be adapted for this use). Note that the amount of transmitted data is logged only for connected users, while signal strength is logged for all users. This is done because the signal strength is useful for determining the estimated location of the user and having multiple data points allows for a rough triangulation [12]. This is not exact, but an approximate position should be useful in its own merit. All this collected information is sent to the server, which will aggregate it in a single tuple for each user for each time slot that contains: the amount of data downloaded/uploaded, and the signal strength between the user and each AP.

IV. Proposed WiGig Handover Scheme

By accumulating and logging user information in our server, we have created a suitable environment for learning-based

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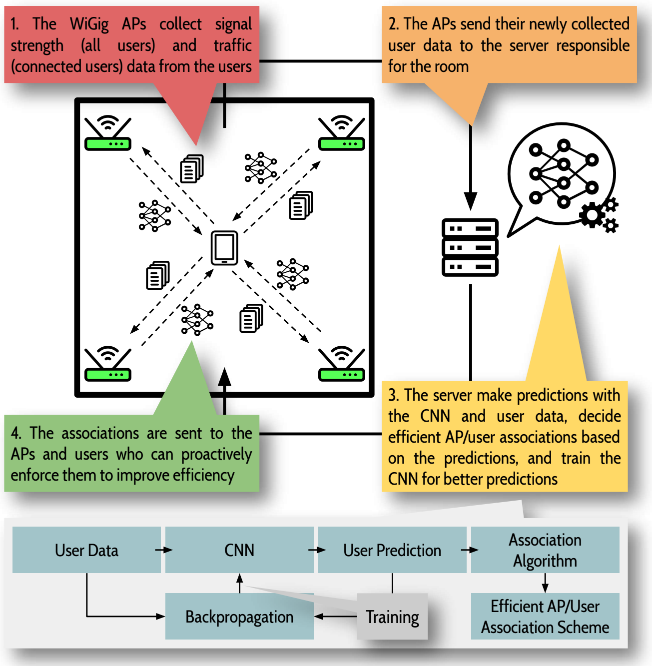

Fig. 2. The main loop of the proposed framework, showing how data is obtained to train the ML model, and how decisions based on the model are sent back to the agents.

analysis of the data collected from our network. The service model is shown in Fig. 2, where we show two APs collecting data from one user and sending that data to the server. The server will use these data to train an ML model which is then used to predict future user behavior. This prediction is used for deciding how to realize handovers for the user, with the handover scheme being relayed back to the APs and the user so they can enact it. The chosen model for our proposed system will be a CNN due to its proven capability in predicting user behavior in networks and communication systems. CNNs have mechanisms called convolution and pooling that allow the learning model to intelligently select which features are more relevant from the input and use those to generate the desired output. In simple terms, CNNs can, better than human operators, identify which information is important to consider when trying to predict future user actions [12]. This information is fed into a regular neural network for generating the output desired. The output generated by the CNN is compared with what would be the correct output for the provided input and the difference between the values is used to update the weights of the whole model (neural network, pooling, and convolution sections) to produce more accurate outputs in the future.

In more specific terms, in our proposed framework, at each time slot, the server will, for each user, collect the most recent X tuples of information to serve as input to the CNN. The output of the CNN will be the predicted information for the next Y tuples for that particular user. That is, the CNN will output what it predicts will be the future signal strength between the user and all APs as well as the transmission data for that user in the next future Y time slots. The reason such prediction is possible is that there is a limited number of likely walking patterns that each user can take [10]. By looking at a big enough sample X of historic data for that user, the pattern of information can be matched to one of the existing patterns, thus allowing for predicting the future behavior of that user. The way the model will learn of these patterns is through live training and reinforcement learning. Weights are set randomly at first. Then, as users connect to the system and information is collected, the model will make predictions. Because information continues to be collected, past predictions can eventually be compared with real collected data. For example, a prediction made at time slot i will predict data up until time slot $i+Y$. Then, if the system collects data from the user up until time slot $i+Y$, the prediction made at i can be compared with the corresponding "correct answer." This difference between the prediction and the correct result will be the basis for backpropagation that adjusts the weights [14]. Repeat the process enough times, with data from enough users, and the weights will be set so that patterns in that room can be identified.

The values for X and Y need to be chosen carefully. If they are too big, then the complexity of the CNN model will be big and may cause too much of a computational overhead to the system, which is a problem as it may delay handovers and defeat its initial purpose. Additionally, if Y is too large, then it will be difficult to make accurate predictions, as predicting farther into the future is a more daunting task since there are more possibilities for the user to make choices to alter the pattern it fits into. However, if Y is too small, then there is little benefit to be gained, as we are not seeing enough of the user's future behavior to make the best decisions for a stable association. Moreover, if X is too small, then we risk not providing enough input data to properly identify the user's pattern. So, while CNN is a proven adequate model for pattern prediction, it must be properly tuned. In this work, we performed multiple experiments, under different scenarios, to empirically determine not only the optimal values of X and Y but also for all other CNN hyperparameters. These values are explained in the performance evaluation section. Note that the use of empirical experimentation to optimize Machine Learning parameters is the conventional method used in the literature [12].

It is worth pointing out that the ML model has no prior knowledge about the scenario. There is no need to have predetermined data regarding the location of PoIs [1], details of the applications, which application each user uses, etc. The CNN will detect these features live, as the network is used and data is collected. This results in a feasible deployment plan, as the system can just be plugged in and learn the patterns by itself [1]. Moreover, the server mentioned here just needs enough processing capabilities to execute one forward run and one backpropagation of the CNN for each currently connected user

[1]Note that PoIs are very important as they determine user movement and are correlated to user behavior (i.e., data transmitted and application used). Thus, they will affect handover as movement will force other APs to offer better connection, and application requirements may necessitate migrating to a different AP as well. Although the PoI information is not provided directly, as that would not be realistic, the scheme still must infer and learn about it through user behavior analysis based on the collected data to efficiently perform handovers.

Algorithm 1 AP association based on prediction.

start with all APs having 0 associated users
for user i from 0 to $N-1$
  for AP j from 0 to $P-1$
    calculate throughput of i with j based on prediction
    update max throughput appropriately
  if max throughput $-$ current throughput $>$ threshold
    associate i with AP with max throughput
  else
    associate i with current AP

TABLE II
PARAMETERS USED IN THE PERFORMANCE EVALUATION

Parameter Names	Parameter Values
Room Size	300m x 300m
Time Slot Length	1s
Number of APs	4
Number of Input Time Slots	25
Number of Output Time Slots	10
User Interarrival Time Rate	10s
Number of Application Types	3
User Data Generation	10 - 1000Mbps
User Movement Speed	0.1 - 2.0m/s
Total Number of PoIs	4
PoI Stay Time	1 - 100s
Number of PoIs per User	1 - 3
Throughput Threshold for Handover	200Mbps
Achieved Throughput Rate	From IEEE 801.11ay [5]

per timeslot. If there are N users and the CNN has M values to process, the total complexity is $O(NM)$. Depending on the size of the room and CNN, this can be done with a small-scale server or even one of the APs standing in as a server.

Finally, it is important to explain how the predicted data is used for deciding user/AP association and handover. In our system, the output of the CNN for all users is fed into an auxiliary algorithm. This algorithm, shown in Algorithm 1 (where P is the number of APs), receives as input the predicted signal strength and transmitted data for each user and the current AP association of each user, and greedily checks all APs for the one that offers the highest transmission rate in the future Y time slots. This is done iteratively, going through each user and associating it with the best AP available based on the user's future behavior. As APs get connected to more users, the actual throughput that can be provided to each user decreases (since access is provided in a time-division way in WiGig, more connected users mean less access time per user, which leads to lower rates [4]). The algorithm will take this, the number of connected users, alongside the predicted future behavior into account when choosing the AP that offers the highest rate for each user [15]. Lastly, the algorithm will also refrain from making users change APs if the resulting improvement in transmission rate is not significant. Overall, considering the execution and training of the CNN, the whole scheme has a complexity of $O(NM + NYP)$.

V. PERFORMANCE EVALUATION

Simulation tests were carried out to evaluate the performance of the proposed solution. 10000 simulation runs were done, with the random deployment of APs and PoIs, and the results shown are the average across all runs. The users' features, such as which application they use or which PoIs they visit, are also determined randomly. Which PoIs are available for each application is also determined randomly. This is all done to achieve enough statistical relevance for our results. Finally, the signal strength between users and APs is determined by distance and was derived based on real-life measurements performed using a "Fujikura 60GHz mmWave (millimeter wave) Wireless Communications Module" [5]. These experiments measured the signal strength while varying the distance between the two devices. The values obtained were used in the simulation to add more realism to the results seen in this paper. Unless stated otherwise, the parameters used for all graphs shown here are in Table II, which were obtained from the literature [3], [4]. The CNN hyperparameters come from extensive empirical studies looking for the best performance, omitted here for brevity.

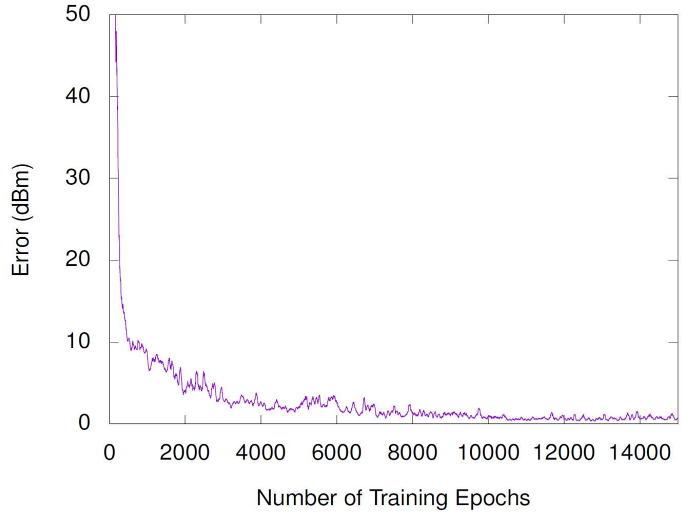

Fig. 3. How the model improves in its prediction accuracy as it is allowed to train and see more data from the environment.

First, we measured what is the error value given by the CNN when predicting signal strength between a user and the APs. Signal strength is very important for determining transmission rate and estimating user location, plus it can vary significantly while the user is moving, which is why it was selected to highlight the prediction performance [11]. Epoch here is determined by one time slot, where on each time slot, the most recent 25 tuples of each user are used as input to determine the next 10 tuples. Results can be seen in Fig. 3. As expected, the error is high at the beginning since the CNN is predicting randomly without any a priori learning. However, this quickly changes. After 5000 epochs, the average error is below 5 dBm. After 10000 epochs, the error is below 1 dBm. This gives us two insights. First, it is better to not use the AP association generated from the CNN predictions until learning reaches an acceptable level. Second, the CNN is definitely capable of learning the patterns of any room that follows our assumed scenario and predicting future user behavior with minimal error.

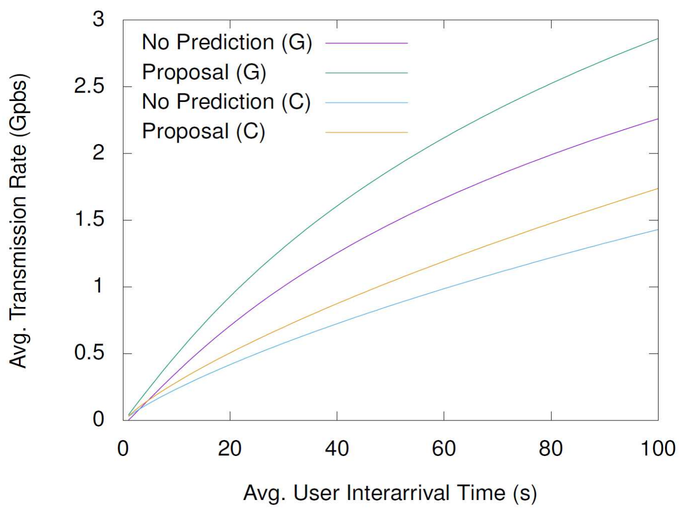

Fig. 4. What are the transmission rates provided by all schemes for different values of network workload represented by user interarrival time.

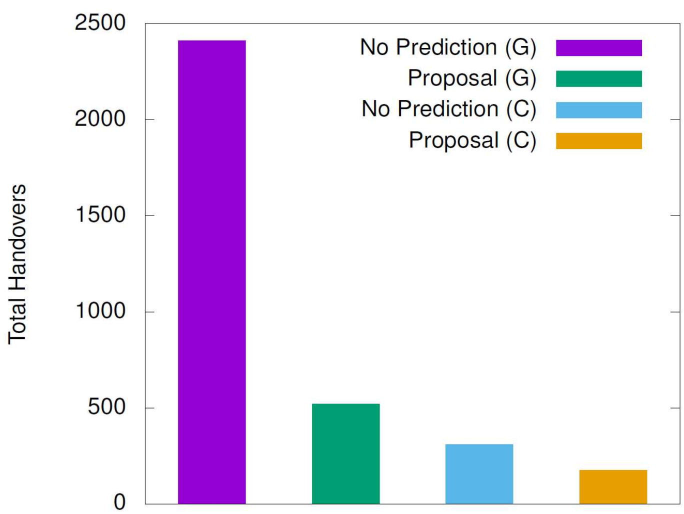

Fig. 5. The number of handovers that were performed with each method.

Next, we measured what is the average transmission rate achieved by the proposal. For comparison, 3 other methods are presented. First, we have a ”No Prediction” method, where the system does not attempt to predict future user behavior. Instead, user/AP association is decided at each time slot based solely on the current signal strength and maximizing current achievable transmission. In contrast, the proposal tries to maximize the achievable transmission rate in the future 10 time slots instead of the current one only. Additionally, for both the proposal and the ”No Prediction” method, two variations were tested. The greedy variation (represented by G in the graphs) will always perform handovers if a better transmission can be achieved, regardless of whether the improvement is big or not. The conservative variant (represented by C in the graphs), on the other hand, avoids making handovers unless the transmission rate can be improved by at least 200 Mbps. Results are shown in Fig. 4, where we varied the user interarrival time (high interarrival values mean more time between the arrival of each user and thus fewer users in the system). As expected, fewer users mean less competition for network access and higher achievable transmission rates. The conservative variants offer lower rates than their greedy counterparts. This shows that, in WiGig, switching to the best AP, to some extent, offers better performance as the system keeps trying to optimize the offered service. However, some stability is needed, and this is illustrated by how the proposal outperforms the No Prediction method in both variants, offering upwards of 1 Gbps extra. To explain why, we calculated how many handovers are done in each method, shown in Fig. 5. As expected, the conservative solutions do fewer handovers, since there is a more strict trigger for changing APs. Moreover, the No Prediction method has more handovers as it makes no effort to look for a stable connection (just the best one at the moment). Meanwhile, both figures tell us that the proposal not only is effective in finding APs that demand fewer handovers and offer a more stable environment (a reflection of how the CNN is capable of predicting future user actions) but also that having fewer handovers does have a significant impact in the performance of the system. Moreover, the conservative methods seem to lean too heavily toward avoiding handovers and the transmission rates suffer as a result, behaving even worse than the greedy No Prediction solution despite the high number of handovers. This points toward a careful tradeoff between handovers and transmission rate optimization. Nonetheless, it is clear from all results that the proposal is the best solution for predicting user behavior and finding optimal AP association.

VI. Conclusion and Future Directions

In this paper, we presented a new framework aimed toward WiGig systems that improve the average transmission rate through smart prediction of user behavior. A CNN was utilized for learning user patterns in a room and then predicting channel data surrounding a user in the form of signal strength in relation to APs and transmitted data. This prediction was used for choosing user/AP associations in a way that the transmission rate is improved while handovers are avoided and users are presented with stable connections. Additionally, by predicting future user behavior, handovers could be done proactively, before the connection degraded. Performance evaluation showed that not only the CNN effectively predicts user behavior, but the proposed algorithm based on this prediction is successful in improving the transmission rate and avoiding unnecessary handovers.

There are still a lot of challenges for network prediction and handover management in WiGig, however. This work assumed a static room layout, including PoIs. In real life, the scenario can change following a pattern (think of different routines in a classroom depending on the subject being taught, or how a restaurant environment can change between lunch hour and the middle of the afternoon) or even permanently (adding new furniture to a room, for example). This can also change where line-of-sight can be achieved for each AP. ML models have trouble with these scenario modifications, so future works should focus on how to optimize learning so the handover and prediction schemes can adapt in such situations.

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BIOGRAPHIES

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