

# Throughput Prediction on 60 GHz Mobile Devices for High-Bandwidth, Latency-Sensitive Applications

Shivang Aggarwal<sup>1</sup>, Zhaoning Kong<sup>2</sup>, Moinak Ghoshal<sup>1</sup>, Y. Charlie Hu<sup>2</sup>,  
Dimitrios Koutsonikolas<sup>1</sup>

<sup>1</sup>Northeastern University, USA <sup>2</sup>Purdue University, USA

**Abstract.** In the near future, high quality VR and video streaming at 4K/8K resolutions will require Gigabit throughput to maintain a high user quality of experience (QoE). IEEE 802.11ad, which standardizes the 14 GHz of unlicensed spectrum around 60 GHz, is a prime candidate to fulfil these demands wirelessly. To maintain QoE, applications need to adapt to the ever changing network conditions by performing quality adaptation. A key component of quality adaptation is throughput prediction. At 60 GHz, due to the much higher frequency, the throughput can vary sharply due to blockage and mobility. Hence, the problem of predicting throughput becomes quite challenging.

In this paper, we perform an extensive measurement study of the predictability of the network throughput of an 802.11ad WLAN in downloading data to an 802.11ad-enabled mobile device under varying mobility patterns and orientations of the mobile device. We show that, with carefully designed neural networks, we can predict the throughput of the 60 GHz link with good accuracy at varying timescales, from 10 ms (suitable for VR) up to 2 s (suitable for ABR streaming). We further identify the most important features that affect the neural network prediction accuracy to be past throughput and MCS.

## 1 Introduction

The past few years have witnessed the rise of a number of high-bandwidth, latency-sensitive applications including virtual reality (VR), high-resolution video streaming, live video streaming, and connected autonomous vehicles. Such applications are characterized by stringent user-perceived quality of experience (QoE) requirements, which in turn dictate high demand for the network performance in terms of ultra high throughput and low latency. Further, such applications typically run on mobile devices, which require high network performance to be supported wirelessly. For example, 8K resolution VR demands 1.2 Gbps [28] in order to satisfy the 20ms photon-to-motion latency, while live 4K video streaming at 30 FPS demands 1.8 Gbps [16] for good user QoE.

Such stringent demand for network performance could not be supported in the past decade. However, the advent of mmWave technologies in recent years has made such network performance within reach and holds the promise to enable these demanding applications. For example, the IEEE 802.11ad WLAN standard [20] governs the use of the unlicensed spectrum around 60 GHz and supports 2 GHz wide channel to provide PHY data rates of up to 6.7 Gbps.

However, 60 GHz networks also come with higher dynamics due to their vastly different propagation characteristics compared to sub-6 GHz networks. In particular, due to the high attenuation loss at 60 GHz, directional communication is needed, making the wireless link highly susceptible to human blockage and mobility [43,42]. Due to these challenges, a user watching a 360° video or playing a VR game over a 60 GHz network may experience long periods of rebuffering/stalls due to intervals of low to no connectivity [44,48,16]. For example, the user may be moving around in such a way so as to face completely away from the AP and thus self-block the link. For this reason, a 60 GHz WLAN often cannot be used as a standalone technology to enable these high resolution applications, and the legacy sub-6 GHz WiFi, which does not suffer from blockage and mobility, may be required as a backup [42,16].

Fortunately, most of the network-demanding applications already have some type of quality adaptation built-in, to deal with the network dynamics. For example, adaptive bitrate (ABR) streaming has become a de facto mechanism implemented in modern video streaming systems such as YouTube, backed by a number of adaptive streaming standards introduced over the years [40,33,3,11]. In a nutshell, ABR streaming continuously monitors the network conditions and adapts the content quality to optimize the QoE, which typically is a function of the frame resolution, frame continuity, and rebuffering time. ABR streaming has been applied in all the recent proposals for high-resolution 360° video streaming [34,18,37] as well as live video streaming [16]. Similar adaptation techniques have also been proposed for state-of-the-art mobile VR systems [26].

The very first task of network adaptation in such network-demanding applications is the estimation of network conditions for the next time interval. For example, in video streaming, most ABR systems estimate the throughput in the next time interval and choose a video quality level based on the throughput estimate and playback buffer occupancy [41,39], as both can affect the QoE. More recently, the use of deep learning (DL) to select the most appropriate quality level has gained popularity [29,46] and ML-based ABR algorithms have been shown to outperform traditional algorithms.

The unique characteristics of the 60 GHz links, however, make throughput prediction in 60 GHz WLANs a much more challenging problem than in legacy WLANs. Although throughput estimation/prediction has been studied in the past in the context of sub-6 GHz WLANs [23,38,22] and cellular networks [27], no previous work, to our best knowledge, has studied throughput prediction at 60 GHz networks. In this work, we carry out the first measurement study of the throughput predictability in 60 GHz WLANs using ML.

There are two main challenges to conduct this measurement study. First, in order to reliably train and test any ML model, we need to collect a significant amount of data. Since 60 GHz WLANs are not widely deployed (the first 802.11ad-enabled smartphone model was only launched in 2019), we cannot collect data from real networks, as in previous ABR studies [29,46]. Further, the only two phones that support 802.11ad, the ASUS ROG Phone [5] and the ASUS ROG Phone II [6], are not VR Ready; hence, we cannot perform real VR experiments

with volunteers, as in previous VR studies [26,45]. Thus, we need to develop a methodology to collect traces in a controlled environment efficiently and in an automated way, in order to obtain a large amount of data while covering a wide variety of realistic mobility patterns. To meet these conflicting requirements, we mounted the 802.11ad phone on a programmable 3-axis motion controller typically used by professional photographers. Using this setup, we collected more than 100 hours of traces while running different applications under random mobility patterns. Second, unlike in previous works, which make predictions only on coarse-grained timescales, e.g., in the order of a few seconds for ABR video streaming [47,46], we study throughput prediction at timescales as fine as 10 ms, which are needed by some of the demanding applications such as VR. To support throughput prediction at such fine timescales, we need ML models that strike a good balance between being accurate as well as being lightweight enough to run on mobile devices within such short timescales. To overcome this challenge, we started with a neural network model previously shown to work well at the 2-second timescale [46], and performed multiple iterations of grid search on the two configuration dimensions (number of layers and number of nodes) to find the smallest configuration, beyond which the performance increase is marginal, to derive a model configuration that balances accuracy and inference latency. We also considered a recurrent neural network (RNN) model, Long Short Term Memory (LSTM), which is suitable for processing time series data, as is the case with throughput prediction. We again went through configuration search to arrive at a cost-effective LSTM model for our throughput prediction problem. We then experimentally compared both models throughout our measurement study.

In summary, our work makes the following contributions.

- We conducted the first measurement study of the throughput predictability of a 60 GHz WLAN to a mobile device. The dataset is publicly available [1].
- We tuned the parameters of state-of-the-art throughput-prediction DNNs to strike a balance between prediction accuracy and lightweightness usable for online throughput prediction. Our two models run in 0.41ms and 4.02 ms on the ASUS ROG Phone II and require less than 4 MB of memory.
- We found that TCP throughput prediction in static scenarios is highly accurate for 40 to 2000 ms, with 95th percentile error ranging between 10.6% for 40 ms and 5.7% for 2 s. For 10-20 ms, the accuracy drops but still remains at satisfactory levels.
- However, the accuracy drops in random mobility scenarios, typical of real applications. The 95th percentile error increases to 38.1% for 10 ms and 19.4% for 2 s timescales.
- We performed a feature selection study and found that only a few features are important to make accurate throughput predictions. At timescales smaller than 100ms, past throughput is the most important, but for larger timescales, MCS becomes more useful.
- Our study suggests that VR apps should be conservative in the use of throughput prediction. In particular, at the 10ms timescale the prediction error is above 10% for 40% of the time, and the 95th percentile prediction error is 38%.

## 2 Experimental Methodology

**Devices** We used a Netgear Nighthawk X10 Smart WiFi router [12] and an ASUS ROG Phone II [6] for our measurements. The Netgear router has a 10-Gigabit SFP+ Ethernet port, which we use to connect to a powerful desktop acting as the server in our experiments. The ASUS ROG Phone II has an octa-core Snapdragon 855 Plus processor with a maximum CPU frequency of 2.96 GHz, a 6000 mAh battery, and an 8 GB RAM, and runs the Android OS 10. Both devices support all 12 802.11ad single carrier MCSs, yielding theoretical data rates up from 385 Mbps to 4.6 Gbps. However, similar to previous studies using laptops as 802.11ad clients [35,16,36], the maximum TCP throughput is limited to 1.65 Gbps in practical scenarios.

**Experimental Setup and Trace Collection** In all our experiments, except for those with real applications in §3.4, we used nuttcp [13] with the default CUBIC congestion control to generate backlogged TCP traffic from the server to the phone and logged throughput every 10 ms. We developed an Android app that runs on the phone and logs sensor and link state information. This information is used as input in the ML models, described in §2. Specifically, the app uses the Android Sensor API [4] to log information from the `TYPE_ROTATION_VECTOR/TYPE_GAME_ROTATION_VECTOR` sensors, which report the phone’s rotation angle in the azimuth and pitch dimensions (Fig. 1), and from the accelerometer (`TYPE_ACCELEROMETER`) sensor, which gives the acceleration of the phone (in  $m/s^2$ ) on the x-, y-, and z-axis. Sensor data are logged every 10 ms. The app also logs 60 GHz link information reported by the `wl16210` driver on the phone every 20 ms. This includes the MCS used by the AP for data transmission, link quality estimators (SQI, RSSI), the link status (OK, RETRYING, FAILED), and the selected beamforming sectors.

Since 60 GHz WLANs are not widely deployed, we cannot collect data from real networks, as in previous ABR studies over the Internet [29,46]. In addition, our phone is not VR Ready and we cannot perform real VR experiments with volunteers, as in previous VR studies [26,45]. Hence, we used the following methodology to collect a large amount of data, while covering a wide variety of realistic mobility patterns in a controlled environment efficiently and in an automated way. For all our experiments, we kept the phone in a Google Cardboard [9] headset at a distance of 4 m from the AP, to emulate a realistic signal propagation environment. For the experiments involving mobility, we mounted the headset on a Cinetics Lynx 3-Axis Slider [7], used by professional photographers (Fig. 1). This setup enabled us to perform full  $360^\circ$  rotation in the azimuth and pitch dimensions at a speed of up to  $48^\circ/s$  and translational motion of up to 1 m. We used the Dragonframe software [8] to program custom mobility patterns (e.g., emulating a user playing a VR game or watching a  $360^\circ$  video). Using this methodology, we collected over 100 hours of traces.

**Trace Processing** Applications have diverse requirements on the timescale of throughput prediction. For example, VR applications need to predict the

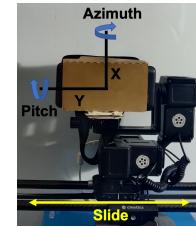


Fig. 1: Mobility Experiments Setup

throughput in the window of the next tens of milliseconds. On the other end of the spectrum, video streaming applications usually fetch video chunks of several seconds in length and therefore need to predict the average throughput in the window of the next few seconds. As such, we study the throughput predictability over 802.11ad covering the full range of practical timescales, including timescales of 10 ms, 20 ms, 40 ms, 100 ms, 400 ms, 1000 ms, and 2000 ms.

To support the above study of multiple timescales, we always log throughput samples at the finest timescale, i.e., every 10 ms, and then offline convert the logged throughput into multiple coarser timescales, by combining consecutive samples using their mean value. For example, to obtain 20 ms traces, every 2 adjacent data points are combined. For all other features, which consist of categorical values, and are not meaningful when averaged, we consider the last data point in each window. In addition, the last value in the window can more accurately reflect the up-to-date state of the feature. To make a consistent comparison of throughput predictability across different timescales, we always use the first 15,000 data points for training, and the following 3,000 for testing.

**Machine Learning-based Prediction** Recent work has shown that simple DNN can predict throughput well at the 2-s timescale [46]. We therefore focus on a number of DNNs for making throughput predictions. In addition to prediction accuracy, we also need the DNN to be lightweight so that it can be used in even the most-latency sensitive applications, such as VR, when running on mobile devices. We experimented with three neural networks. For each network, we performed multiple iterations of grid search on the two configuration dimensions (number of layers and number of nodes) to find the smallest configuration, beyond which the performance increase is marginal, to derive a model configuration that balances accuracy and inference latency.

*BP8*: a fully-connected neural network with 3 hidden layers, each of 40 neurons. It takes as input the actual throughput in the past 8 windows, pose information (azimuth and pitch) in the past 1 window, and link layer information (MCS, transmit beamforming sector, link status, SQI, and RSSI) in the past 1 window. *RNN8*: a recurrent neural network with 3 hidden layers, each with 20 neurons. It takes as input the actual throughput, pose information, and link layer information in the past 8 windows.

*RNN20*: same as RNN8, but takes information in the past 20 windows as input.

We also experimented with the BP8 model to take as input all information in the past 8 windows like RNN8, but the results were very similar.

The neural network outputs the probability distribution (PD) of the throughput in the current window  $T_t$ . The PD  $P_1, \dots, P_{21}$  is over 21 bins of throughput in Mbps:  $B_1 = [0, 50], \dots, B_{21} = [1950, 2000]$ . We calculate the expected throughput based on the PD as the prediction output:

$$\text{Throughput} = 0 \times P_1 + \sum_{i=2}^{20} \text{median}(B_i) \times P_i + 2000 \times P_{21} \quad (1)$$

**Accuracy Metrics** We evaluate the performance of the throughput prediction models in terms of 3 metrics: (i) *RMSE*: The root mean squared error between

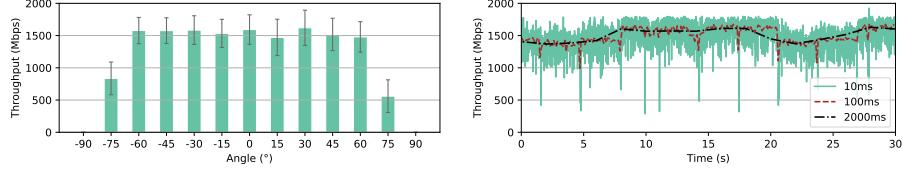


Fig. 2: Throughput at different azimuth angles. Fig. 3: Throughput timeline within the FoV ( $0^\circ$ ) at different timescales.

the prediction and the actual throughput; (ii) *ARE95*: The absolute relative error of the prediction at the 95% percentile; and (iii) *PARE10*: The percentage of predictions with absolute relative error below 10%. To gain insight into which input features are the most useful for a high prediction accuracy, we also run a feature pruning algorithm which ranks the importance of the features.

### 3 Results and Analysis

In this section, we present the results using our neural network models. We consider three scenarios: (i) static scenarios, where the phone is fixed at a given azimuth and pitch at a distance of 4 m in front of the AP, (ii) random mobility scenarios, where the phone simultaneously moves along all three dimensions (azimuth, pitch, slide) at different speeds, and (iii) real application scenarios, where we use real application traces – VR and ABR video streaming – instead of backlogged TCP traffic generated by nuttcp, under random mobility.

#### 3.1 Impact of the Phased Array Field of View

Practical phased arrays used by COTS devices have a limited angular coverage area on the receiving end, called field-of-view (FoV) in [44], outside of which throughput drops sharply. Previous studies using 802.11ad APs and laptops [44,35] showed that the FoV is around  $170^\circ$ . We begin our study by measuring the throughput when the AP stays within/outside the phone’s FoV. We place the phone facing the AP from a distance of 4 m, and rotate it to change its azimuth with respect to the AP. Our results in Fig. 2 show that, when the azimuth is within  $(-60^\circ, 60^\circ)$ , the average throughput is always  $\sim 1.5$  Gbps. Once the azimuth moves outside this region, the throughput drops below 1 Gbps and becomes 0 for angles greater than  $\pm 90^\circ$ . Hence, the FoV is even smaller in the case of these first generation 802.11ad smartphones. In the rest of the paper we focus on predicting throughput when the AP is within the phone’s FoV.

Interestingly, Fig. 3 shows that throughput can vary significantly over time even within the FoV, especially at fine timescales. At the 10 ms timescale, the throughput varies between 1 Gbps and 1.8 Gbps and sometimes drops even below 500 Mbps. Such large variations are caused by the 802.11ad MAC layer mechanisms, including the periodic beaconing by the AP every 100 ms, beamforming between the phone and the AP (triggered periodically, every 3 s, as well as in case of missing ACKs), and the interplay between beamforming and rate adaptation [35], all of which make throughput prediction quite challenging at fine timescales. At the coarser timescales of 100 ms and 2000 ms though, the variations are averaged out and throughput appears much smoother.

### 3.2 Static Scenarios

We first explore the throughput predictability when the phone is stationary. In this section, we aim to understand how well we can predict throughput changes caused by channel variations and MAC layer mechanisms only.

We collected 5 static traces, listed in Table 1, by placing the phone at various azimuth and pitch angles with respect to the AP. We trained and evaluated a separate model on each trace. Since the phone is static for the duration of each trace, we do not use the azimuth, pitch, and link status data in training and testing our models as these features remain constant. The results shown in Figs. 4a-4c are averaged over the 5 traces.

Table 1: Static Traces Collected

Trace #	Azimuth	Pitch	Length	Average Throughput
Static 1	0°	0°	10hr	1588 Mbps
Static 2	30°	0°	10hr	1575 Mbps
Static 3	60°	0°	10hr	1568 Mbps
Static 4	0°	40°	10hr	1566 Mbps
Static 5	0°	-40°	10hr	1585 Mbps

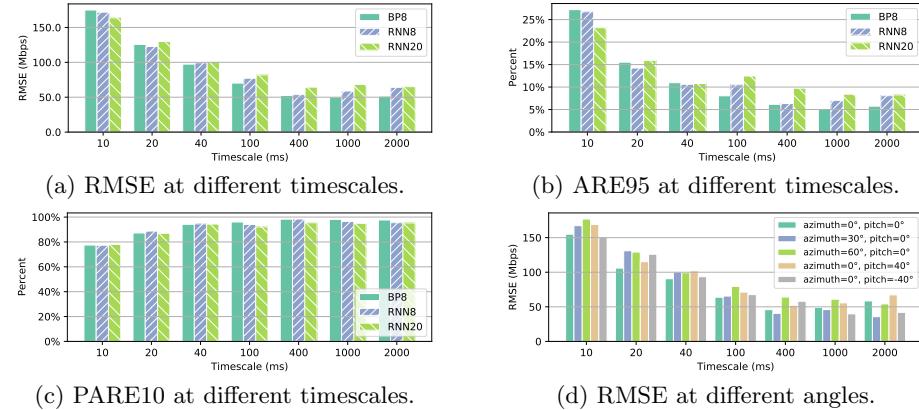


Fig. 4: Model performance for static traces. The input for timescales above 100ms does not include throughput, see Feature Selection in this section.

Figs. 4a, 4b, 4c show that the accuracy with all three models and for all three metrics generally improves as we move from finer to coarser timescales. Overall, the accuracy is very high at timescales coarser than 40 ms, where there are no significant throughput variations, as we saw in Fig. 3. The RMSE remains below 100 Mbps, the ARE95 metric remains below 12%, and the PARE10 metric above 92% at those timescales. For the fine timescales (10-20 ms) required for VR applications, the 95th percentile of the error is higher, 14-16% at 20 ms and 23-27% at 10 ms, due to the the large throughput variations at such short timescales, which we observed in Fig. 3. Nonetheless, the RMSE remains at satisfactory levels (122-175 Mbps) and 78-88% of the prediction errors are still lower than 10%. Overall, *DNN models can make accurate throughput predictions at all timescales in static conditions*.

When we compare the three DNN models, we observe that there are no significant differences among them. The RNN models perform slightly better in

terms of the RMSE and ARE95 metrics at 10 ms, but the BP model becomes slightly more accurate at coarser timescales. All three models perform similarly in terms of the PARE10 metric. Between the two RNN models, RNN8 outperforms RNN20 at all timescales except for 10 ms.

To study the impact of the different angles that the phone is kept at within the FoV, we picked the best model for each angle at each timescale and plotted the RMSE in Fig. 4d. For timescales up to 100 ms, the prediction is most accurate when the phone is facing exactly towards the AP ( $0^\circ$  azimuth,  $0^\circ$  pitch). At coarser timescales, there is no clear trend. In most cases, the  $60^\circ$  azimuth trace has the worst RMSE, which is most likely due to the fact that at  $60^\circ$  azimuth the AP is very close to the edge of the phone’s FoV (§3.1) and hence experiences higher throughput variations. In terms of the pitch,  $+40^\circ$  has lower RMSE for some timescales but  $-40^\circ$  for other timescales. Overall, *in static conditions, the model performance is not affected significantly by the azimuth or pitch angles.*

**Feature Selection** To understand which of these features are more useful in the prediction, we perform the following iterative feature removal exercise.

We start with all  $N$  features. For each feature, we temporarily remove it from the input, and train a model using the remaining  $N-1$  features. We then compare the resulting models and identify the least useful feature among the  $N$  features as the one removing which results in the model with the least prediction accuracy reduction. We permanently remove this feature from the input, and iteratively perform the same procedure on the remaining  $N-1$ ,  $N-2$ ,  $N-3\dots$  features, until all but one features have been removed. Effectively, this algorithm ranks the features by their importance to the model’s accuracy. We run this algorithm for all the timescales. The results, averaged over all 5 datasets in Table 1, are shown in Table 2 only for the BP8 model and 3 representative timescales (10 ms, 100 ms, and 2000 ms) due to the page limit.

At the 10 ms timescale, we observe that removing SQI, MCS, and Tx Sector marginally improves the RMSE. However, when we remove RSSI (and hence we only use the past throughput), the RMSE increases by  $\sim 5$  Mbps. Thus, *at the 10 ms timescale, the past throughput is the most important feature that contributes to the model’s accuracy* followed by RSSI.

Surprisingly, *at the coarser timescales of 100 ms and 2000 ms, we observe that throughput actually is the least important feature.* In particular, at 2000 ms, excluding throughput from the input features improves the RMSE by 6 Mbps. On the other hand, MCS, which was not very important at the 10 ms timescale, now becomes the most important feature. In fact, we observed that for all timescales less than 100 ms, throughput is the most important feature while for all coarser timescales MCS becomes the most important feature.

Table 2: Features Selection for Static Traces

Removal Step	10ms		100ms		2000ms	
	Removed	RMSE	Removed	RMSE	Removed	RMSE
1	-	175.01	-	71.75	-	57.38
2	SQI	174.33	Throughput	70.26	Throughput	51.56
3	MCS	174.34	Tx Sector	69.47	RSSI	51.85
4	Tx Sector	173.79	SQI	70.46	Tx Sector	52.80
	RSSI	178.17	RSSI	70.17	SQI	52.28
Last Feature	Throughput		MCS		MCS	

### 3.3 Mobile Scenarios

In this section, we explore the impact of realistic smartphone motion patterns (typical with applications like VR and 360° video streaming) on throughput prediction. We collected a 10 hour long trace, where the phone simultaneously moved in the azimuth, pitch, and slide dimensions at different speeds. In the azimuth dimension, the phone moved in the  $[-60^\circ, 60^\circ]$  range at various speeds between  $10^\circ/\text{s}$  and  $40^\circ/\text{s}$ . In the pitch dimension, the phone moved in  $[-40^\circ, 40^\circ]$  range at speeds between  $6^\circ/\text{s}$  and  $20^\circ/\text{s}$ . These speeds were picked as they represent typical VR motion speeds [26,48]. In the slide dimension, the phone moved at a speed of 0.05 m/s (the maximum speed supported by the Cinetics slider). We found that, at such low speeds, translational motion along the 1 m slider has no impact on throughput. Hence, we do not include the y-coordinate or the acceleration along the y-axis in our feature set.

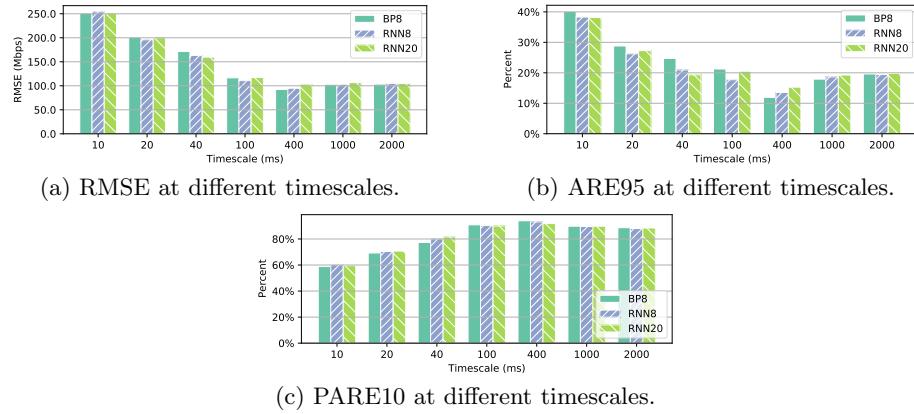


Fig. 5: Model Performance for Random Motion Traces. The input for timescales above 100 ms does not include throughput.

As expected, the prediction accuracy under mobility worsens (Fig. 5) with all three models and for all three metrics compared to the static scenarios (Figs. 4a, 4b, 4c). The RMSE ranges from 92-258 Mbps (vs. 50-175 Mbps in Fig. 4a), the ARE95 metric ranges from 12-40% (vs. 5-27% in Fig. 4b), and the PARE10 metric from 59-94% (vs. 78-98% in Fig. 4c). Nonetheless, prediction at timescales of 100 ms or higher retains high accuracy. Interestingly, we observe a "sweet spot" at 400 ms with respect to all three metrics, which was not present in the static scenarios. This suggests that motion introduces an interesting trade-off between the length of history as input, and the prediction window in the future.

We now look at the results at the two ends of the spectrum. *At timescales of 1 and 2 s, corresponding to video streaming applications, the accuracy remains at satisfactory levels; the 95th percentile of the error is below 20% and about 89% of the errors are lower than 10%. On the other hand, the accuracy drops significantly at VR timescales, 10 and 20 ms. In particular, the ARE95 metric ranges between 38-40% and 26-29%, and the PARE10 metric is below 60% and 70%, respectively.*

Finally, when we compare the accuracy of the three models, we observe that the RNN models perform slightly better for up to 40 ms and the BP model performs better at coarser timescales. However, the difference in the performance among the three models is even smaller compared to the results in Fig. 4.

**Feature Selection** Table 3 shows the feature selection results in random mobility scenarios. Similar to the results in Table 2, we observe that throughput is the most important feature for only the 10 ms and 20 ms timescales, while for all coarser timescales, MCS becomes the most important feature. At 10 ms, RSSI remains the second most important feature, same as in Table 2, while the phone’s pitch and azimuth interestingly do not contribute much to the accuracy. In contrast, at 2000 ms, azimuth and pitch are the most important features after MCS. At 100 ms, the contribution of all features other than throughput and MCS is marginal.

Table 3: Features Selection for Random Motion Traces

Removal Step	10ms		100ms		2000ms	
	Removed	RMSE	Removed	RMSE	Removed	RMSE
1	-	250.98	-	117.30	-	110.39
2	MCS	258.18	Throughput	110.34	Throughput	98.56
3	Pitch	252.39	RSSI	108.50	RSSI	97.57
4	Azimuth	254.36	SQI	107.62	Link Status	97.87
5	SQI	255.01	Azimuth	108.01	Tx Sector	99.69
6	Link Status	256.10	Link Status	109.12	SQI	101.69
7	Tx Sector	261.69	Tx Sector	109.95	Pitch	105.32
	RSSI	270.20	Pitch	112.67	Azimuth	112.81
Last Feature	Throughput		MCS		MCS	

### 3.4 Applications

To further understand the throughput predictability using real applications, which may not always be sending backlogged traffic, we collected throughput traces for 2 applications: VR and video streaming. Both applications stream video frames encoded with H.264 compression over TCP. For both traces, the phone moved along all 3 dimensions at various speeds as described in §3.3. In the case of VR, we pre-encoded a 60 FPS Viking Village scene at 8K and we wrote a client app that requests frames from a local server. Assuming that the VR application wants to make quality adaptation decisions on a per-frame basis, it would require a throughput prediction every 16 ms at a frame rate of 60 FPS. We considered 8K VR, because 4K VR does not demand throughput more than 300 Mbps, which can be supported even by legacy WiFi [24,30]. In the case of streaming, we used a 4K, 50 FPS video from the Derf’s collection under Xiph [2], encoded at a bitrate of 1.3 Gbps, and used the same app to request video chunks of 2 s from the local server, in order to emulate ABR video streaming applications, which generally download chunks of 2 s and would need throughput predictions at that timescale.

The performance of the three models is shown in Table 4. For VR, in terms of the ARE95 and the PARE10 metrics, the performance is similar to what was shown in §3.3 at a 20 ms timescale, while the RMSE is  $\sim$ 156-164 Mbps. We conclude that 60 FPS VR applications can benefit from throughput prediction only if they use it conservatively and can tolerate a certain margin of error.

Table 4: Model Performance for Real Applications

	VR			ABR		
	BP8	RNN8	RNN20	BP8	RNN8	RNN20
RMSE	156.78	163.65	163.66	114.54	115.77	113.87
ARE95	29.08%	28.82%	27.92%	18.15%	17.72%	17.58%
PARE10	72.79%	70.52%	69.24%	86.93%	86.10%	87.03%

For ABR video streaming, as expected, the models perform better due to the much coarser timescale. With  $\sim$ 86-87% of the errors being within 10% of the actual throughput and having a prediction error of  $\sim$ 17-18% at the 95th percentile, ABR video streaming applications can use these predictions with much more confidence to ensure a high user QoE.

### 3.5 Prediction time (NN Inference Delay)

We wrote an Android application that uses the jpmml-evaluator [10] and tensorflow [14] modules to make predictions for BP8 and RNN(s), respectively, and ran it on the phone’s GPU to measure the inference delay and memory consumption for each model. We ran each model 100 times and the averaged inference delay and memory consumption results are shown in Table 5. We observe that BP8 runs in less than 0.5 ms and thus can be used by both VR and streaming applications. In contrast, the RNN models run in 2-4 ms and can only be used for streaming applications. The memory consumption is negligible for all 3 models.

Table 5: Inference time and memory consumption of the 3 NN models

Model	Inference delay (ms)	Memory Consumption (MB)
BP8	0.41	3.71
RNN8	1.94	0.20
RNN20	4.02	0.29

## 4 Related Work

**Throughput prediction over the Internet.** Traditional ABR algorithms were classified into two categories: rate-based [21,25,31] and buffer-based [19,39]. Recently, control-theoretic, data-driven approaches, using Model Predictive Control (MPC), e.g., [15,41,47], became the state-of-the-art approach to ABR, as they combine the use of both throughput prediction and playback buffer occupancy. More recent studies [29,46] have shown that DNN-based algorithms outperform all previous approaches. Our work differs from [29,46] in two key ways. First, we focus on 60 GHz throughput prediction, thus making predictions at the Gbps scale compared to the Mbps scale in those works. Second, while those works make predictions at timescales of a few s, we also look at timescales as low as a few ms, for low latency applications such as VR.

**Throughput prediction over wireless networks.** Past works focused on throughput prediction for sub-6 GHz mobile networks at much coarser timescales [17,27]. Lumos5G [32] is a recent work that explores using ML to predict mmWave 5G throughput. However, since cellular networks have very different characteristics from WLANs, the ML models developed in [32] have completely different input features (e.g., geographic coordinates, cellular tower-related features, handoffs, etc.) compared to our models and, similar to previous works, target much longer timescales, from a few seconds up to a few days. Recent works on mobile 360° video streaming [18,34] consider timescales of a

few seconds, similar to their Internet counterparts. Firefly [26] is a recently proposed approach for mobile VR that performs adaptation at the frame level (a few ms). However, Firefly modifies the AP firmware to obtain accurate available bandwidth statistics. In contrast, we consider client-side adaptation and our prediction models only use features readily available in the user space.

**High-bandwidth, latency-sensitive applications over 60 GHz.** The work in [44] was the first to show that performance drops drastically when the AP falls outside the client’s FoV. Based on this observation, the authors proposed a binary predictor to predict whether the AP will fall inside the client’s FoV in the next 500 ms. Our work showed that throughput variations are non-negligible at fine timescales, even for static clients. The work in [48] argues that typical VR/Miracast motion is highly unpredictable and can lead to large and sudden drops in signal quality. The work in [16] used the average throughput of the previous 40 ms window to predict the average throughput of the next 30 ms window and showed that it leads to prediction errors of up to 500 Mbps even in static conditions. Based on this result, the authors concluded that throughput cannot be predicted in 60 GHz WLANs. In contrast, our study shows that it is feasible to use 60 GHz throughput prediction for quality adaptation, especially for video streaming applications (the target application of [16]).

**Viewport prediction.** Several recent works have looked at viewport prediction for 360° video streaming, e.g., [18,34,37]. Those works are orthogonal to our work, as we show from our feature selection study that the user’s angular position with respect to the AP has little to no correlation with the resulting throughput when the AP falls within the client’s FoV.

## 5 Conclusion and Future Directions

We presented the first measurement study of the throughput predictability on 802.11ad-enabled mobile devices. Our study shows the throughput in general can be predicted well in real time using carefully designed small neural network models, and further has several implications to the predictor design. First, our feature selection study shows that using scaled throughput history (keeping the ratio of the history window and the prediction window constant) helps prediction accuracy at the 10 ms timescale but hurts at the 2000 ms timescale. This suggests that a new design that limits the length of history as the model input can potentially achieve good accuracy for all timescales. Second, our feature selection study further shows that, for different timescales, using different sets of features gives the best prediction accuracy. This suggests that a single neural network for use in different applications can potentially improve its prediction accuracy by adapting the set of features according to application latency requirements. Further, in this work we performed all our experiments in a single environment. An interesting avenue for future work is to study the impact of different environments on throughput predictability.

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