Poster: Link Adaptation in 60 GHz WLANs using PHY Layer Information

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OVERVIEW

Rate adaptation (RA) has been traditionally considered as the main link adaptation mechanism in 802.11-based WLANs. However, the small wavelength and high directionality of 60 GHz links introduce new challenges – vulnerability to blockage and mobility – which cannot be addressed with RA alone. Hence, 60 GHz radios employ a second link adaptation mechanism, beam adaptation (BA), to maintain TX-RX beam alignment. Interestingly, the 802.11ad/ay do not specify when each of the two adaptation mechanisms, RA and BA, should be used or in what order, and vendors resort to simple heuristics to select the right mechanism.

In this work, we conducted the first experimental study of these two adaptation mechanisms in 60 GHz WLANs and explored for first time the feasibility of leveraging PHY layer information to guide link adaptation. Using a large data set collected with the X60 testbed [2] in a campus building, we investigated the effectiveness of a number of PHY layer metrics (such as SNR, CSI, time-of-flight, power delay profile) in predicting which of the two mechanisms should be triggered in a variety of scenarios involving linear and angular displacement, blockage, and interference. While some metrics appeared to be more useful than others, our study revealed that no metric works in all scenarios, suggesting that a combination of metrics is required.

We then explored for first time ML-based link adaptation approaches. We utilized 3 popular ML models – decision trees, random forests, and SVMs. Using our dataset and 5-fold cross validation, we showed that all 3 models achieve very high accuracy, ranging from 91% (SVM) to 98% (random forests). Since the PHY layer metrics can be heavily influenced by the environment, we collected a new dataset in two different campus buildings and tested the models, which are trained in the initial dataset, on this new dataset. All three models retained satisfactory accuracy (86-88%).

Even though the accuracy drops, we point out that triggering the wrong adaptation mechanism does not always have the same performance impact. To evaluate this impact, we used trace-based simulations to compare the amount of bytes delivered and the recovery delay (time to discover the first working combination of beam pair and MCS) with our ML-based solution, an oracle solution, as well as 2 heuristics: always performing RA first, which is what all COTS devices do today, and always performing BA first [1].

Figure 1: Difference of bytes delivered with the oracle and each of the other three solutions.

Fig. 1 shows that our ML-based solution performs close to the oracle 84-88% of the time irrespective of the BA overhead, frame aggregation time (FAT), and the duration of the data flow. With a flow duration of 1 s, “BA First” and “RA First” deliver the same number of bytes as the oracle in only 65-85% and 45-50% of the cases, respectively. With a short flow of 0.4 ms, “BA First” becomes the worst of the three in the case of long BA duration (Fig. 1b). We also found that “RA First” has the worst recovery delay for low BA duration and “BA First” has the worst delay for high BA duration. In contrast, our ML model strikes a good balance, achieving optimal delay in at least 70% of the cases.

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REFERENCES