An Entropy-Based WLAN Channel Allocation using Channel State Information

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***Abstract*—Low-cost access points have proliferated wireless local area networks (WLAN) providing main wireless access in many unmanaged networks. The majority of these APs rely on received signal strength indication (RSSI), known to be unreliable, as a measure of the wireless link quality. However, an accurate link measurement is a precursor to channel selection which in turn allows more efficient use of the wireless resources, especially in a crowded and dense wireless environment. In this paper, we present CSI-EWCA, an entropy-based WLAN channel allocation model using channel state information to combat the unreliability in RSSI. To develop a self-reliant system that is independent of CSI data for devices with low computational power, we develop a machine learning model to predict channel spectral entropy from physical layer network information extracted from the Linux kernel. Our experimental results show that CSI-EWCA can consistently select a channel with high throughput and low jitters and fewer retries.**

***Index Terms*—Channel Selection, Channel State Information, Entropy, Machine Learning**

I. Introduction

Wireless local area networks (WLAN) or WiFi have become increasingly pervasive over the past decade. The increasing popularity is as a result of the ubiquity of mobile devices with demand for Internet services. This has led to a corresponding growth in the production and deployment of low-cost WiFi routers providing connectivity for these devices. The vast and dense deployment of these APs in places like residential apartments and crowded public hot-spots often has a negative impact on congestion in the unlicensed spectrum. The congestion is exacerbated because many of the APs are installed by users with limited knowledge on how to effectively configure the devices to have a better utilization of the unlicensed spectrum, and thereby, relying on the manufacturer's default configurations. The sheer numbers of these scenarios have made the unlicensed band more congested and call for efficient channel allocation techniques.

The problem of channel allocation has been reasonably explored in literature and there are still many open research areas. In classic channel allocation techniques [21], a station (STA) actively scans all the available channels and then selects a channel with least STAs. The idea is to select a channel that has fewest co-channel interferers. However, having the least number of STAs does not guarantee a less chaotic channel. Other techniques like [30] uses a combination of channel traffic information and RSSI to predict the quality of a channel. It is important to note that RSSI and traffic volume are not the only determinants of channel quality. Factors like presence of STAs in the same channel (co-channel) or neighboring channel (adjacent channel) interferers, the transmission power of co-channel and adjacent channel interferer and noise from non-802.11 devices such as microwave ovens are also major causes of interference.

Several schemes have been proposed to minimize interference using different approaches like optimization techniques in [22]–[24], game theory in [29], and graph coloring techniques in [26], [27]. However, the majority of these schemes use RSSI as an indicator of the quality of a wireless link while in practice the RSSI is known to be a weak indicator of performance as it fails to capture the frequency selective fading of a wireless channel. On the other hand, the channel state information (CSI) has received more attention as a better measure of channel quality because it reflects both the time variation and frequency selectivity of a wireless link. The channel frequency selectivity property is the driver for several studies on CSI's applications toward wireless human activity detection [7]–[9], smart health monitoring systems [5], [6], dangerous driving detection, and intelligent driving assistance [10], [11]. These studies pay little attention to the wireless issue like channel allocation that affects performance. With advancement towards IEEE 802.11ax for enhanced spectrum efficiency in WLAN, the need for a robust and effective scheme for channel allocation becomes more important, especially for extremely high throughput multi-user MIMO systems.

In this work, we present CSI-EWCA, an entropy-based WLAN channel allocation scheme using CSI. In contrast to existing approaches using RSSI, the CSI-EWCA uses an in-phase (I) and a quadrature (Q) information of the channel. The entropy of the I/Q data is then used to make channel allocation due to its ability to perform well in dynamic and multi-fractal systems. For the rest of this paper, the I/Q information and CSI are used interchangeably. Our contributions in this paper can be summarized as below.

- We propose CSI-EWCA, a model based on spectral entropy using channel state information and utilize the model to analyze a given 802.11 channel.
- We benchmark the performance of CSI-EWCA with a channel allocation model using both RSSI and traffic volume.
- We present a machine learning model on how physical layer information from the Linux kernel can be used to facilitate easy prediction of channel spectral entropy without the Q/I data.

This remaining part of this paper is organized as following. In section II, related work on CSI and some of its applications in WiFi system as well as entropy and channel allocation are discussed. Section III presents our implementation and Section IV explains setup for the experiment. The evaluation and results for our model is presented in Section V. Finally, in Section VI, we conclude the paper.

II. Related Work

A. Channel State Information

CSI has attracted extensive attention from both the research and industrial community due to its ability to reliably capture the state of a communication channel in terms of decay, scattering, fading and other important channel properties that affect the performance of a multi-input multi-output (MIMO) systems. The procedure for its applications is also defined in communication standards for 802.11, LTE and LTE-A [2], [12].

The recent CSI extraction tools for WiFi [3], [4] have extended viability of CSI to several consumer-grade applications such as smart health [5], [6], human activity detection [7]–[9] and intelligent driving assistance [10], [11]. While these works show several applications of CSI in real-life systems, most of them fail to address the fundamental wireless network task of determining the quality of wireless channels which may significantly affect the performance of such applications. Moreover, the trend in future wireless technology like WiFi-6 requires appropriate channel estimation for interference mitigation and load balancing of multiple users. It is worthy to note that CSI is heavily relied on and exploited in current and future telecommunication systems for channel allocation and selection to achieve high throughput and spectrum efficiency [12]. However, the majority of channel allocation models for 802.11 networks are yet to take full benefits of CSI for their channel selection but rely predominantly on RSSI.

B. Entropy

The entropy [13] is an average bit of information required to efficiently represent the outcome from an information source and has found applications in a wide range of domains. In wireless systems, entropy has been employed for scheduling [14], developing a framework to represent the uncertainty in mobile network [15], measuring changes in network topology [16] and predicting Distributed Denial of Service (DDoS) attacks and link key updates in sensor networks [17]–[19]. The wide range of applications are due to its ability to represent information-theoretical characteristics of these multi-fractal systems by examining the underlying spectral power distributions and their probabilities. Although entropy has been applied to various aspects of the wireless systems to evaluate performance with proven successes, models for channel allocation in 802.11 networks using entropy are largely unavailable to the best of our knowledge. The closest work in the wireless network is [20] where the spectrum entropy prediction is used to assist in selecting a channel for secondary users in 433MHz and GSM networks. Our work presents a model using spectral entropy of CSI that is capable of modelling the WiFi system's information and its uncertainty for channel allocation.

C. Channel Allocation

Channel allocation (CA) is undoubtedly one of the major issues in a wireless network and a key determinant of its performance. The CA thereby involves designing an efficient mechanism to mitigate interference that usually results in low throughput. The issues relating to CA in WLAN have been well investigated in the literature and several techniques have been proposed. In the classic CA algorithm [21], a least congested channel with the least traffics or fewest number of associated clients is assigned to APs. Other schemes like [22]–[24] employ a diverse set of optimization approaches like linear and non-linear programming with the objective to minimize interference and maximize channel utilization. Many of these algorithms show the problem to be NP-complete and solutions are only heuristic with no guaranteed optimal solution. The algorithms in [25]–[27] address the problem as graphs using graph-coloring techniques. Schemes in [28], [29] use game theory by modeling their proposed solutions to the CA problem as game strategies. While many of these approaches present different perspectives to model the problem, most of the solutions are complex without practical feasibility. Only a few of these techniques consider CA in an uncoordinated WLAN.

The authors in [30], [31] examine CA in an uncoordinated WLAN. Similar to [21], they also focus on traffic volume and RSSI. Unlike these systems using RSSI, we show that using spectral entropy of CSI offers an effective way for CA with less complexity and suitable for practical implementation in low-cost equipment commonly used as APs in many uncoordinated WLAN.

III. Entropy Based WLAN channel allocation

The goal of CSI-EWCA is to develop a model that can efficiently allocate a channel to an 802.11 AP based on maximum spectral entropy with minimal overhead while taking into cognizance of its specific wireless environment. The CA is only possible after determining accurate information about each channel. We simplify the design and applicability of our model to consider only the CSI captured on an AP in a crowded 2.4 GHz ISM sub-band of the wireless spectrum. We believe the scope is adequate to cover most channel allocation problem experienced in an uncoordinated or non-enterprise WiFi network.

A. Spectral Entropy

To measure channel quality, we capture the CSI as it is indicative of the current channel condition. The information is necessary to determine the channel spectral entropy across the subcarriers. For a given sample period, we collect CSI across all antenna streams. If n_t represents the number of transmission antenna and n_r represents the number of receiving antenna, then the received signal can be expressed by the following equation

$$y = Hx + n, \tag{1}$$

where $x \in C^{n_t}$ and $y \in C^{n_r}$ represent transmitted signal and received signal complex vector respectively, $n \sim NC(0, \sigma)$ is white Gaussian channel noise. The CSI, $H \in C^{n_t \times n_r}$, is the channel matrix between the transmitter and receiver.

The CSI values between the transmit-receive antenna pair contain the channel response for all the subcarriers. In our case, this represents $n_t \times n_r \times N_{sc}$ CSI values. Hence, the CSI for a single spatial link can be represented as

$$H = [h_1, h_2, \dots, h_{N_{sc}}] \tag{2}$$

where the number of subcarriers N_{sc} is 56 and each subcarrier CSI h_s, $s \in [1, \dots, N_{sc}]$, in equation (2) is a complex value containing both amplitude and phase information. The subcarrier information can be expressed as

$$\begin{aligned} h = & \quad |h| \; e^{i\phi} \\ = & \quad |h| \; (cos(\phi) + i \; sin(\phi)) \end{aligned} \tag{3}$$

where $|h|$ is the amplitude, the $cos(\phi)$ and $i \; sin(\phi)$ represent $I(\phi)$ and $Q(\phi)$ component respectively.

We calculate the channel singular value decomposition (SVD) for H according to [1] to obtain the non-negative real value across the transmit-receive antenna pair. The SVD for H is represented as

$$H = U \; \Sigma \; V^* \tag{4}$$

where $U \in C^{n_r \times n_r}$ and $V \in C^{n_t \times n_t}$ are unitary matrices, and $\Sigma \in R^{n_r \times n_t}$ is a diagonal matrix whose elements are the singular values of matrix H. The singular values $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_m$ such that $m = min(n_r, n_t)$ are used to calculate the spectral entropy according to the following equation

$$E \; = -\sum_{i=1}^{N_{sc}} p(\sigma_i) \log p(\sigma_i) \tag{5}$$

where $\sigma_i = \{\sigma_1, \dots, \sigma_{N_{sc}}\}$ is a set singular values representing the channel gains for the subcarriers and $p(\sigma_i)$ is the probability of each channel gain..

We employ two transmit and receive antennas for transmission between the transmitter and receiver using both [3] and [4] to obtain the spectral entropy for a link. Consequently, we get the spectral entropy of overall wireless environment by placing the station's network interface card (NIC) in monitor mode to passively scan all the channels and extract I/Q data in equation (3) from the spectral scan available in Atheros chipsets. The absolute value of the I/Q data for each of the 56 subcarriers is used to calculate spectral entropy according to equation (5).

The procedure used by CSI-EWCA to achieve our objective of selecting a channel with maximum spectral entropy is described in Algorithm 1. In a given measurement period, the AP scans all the available channels to obtain the subcarriers' CSI in the frequency domain and preforms measurement updates in equation (5) following each step from the previous paragraph.

Algorithm 1: CSI-EWCA procedure

```
Result: selected channel, c_i
Required;
CSI = {h_s ∈ H, ∀s ∈ N_sc}
channel, c_i : i ∈ {1, ..., len(C)}
for i ← 1 to len(C) do
    Σ_i = svd(H_i); p(σ_s) = σ_s / Σ σ_s
    E = − Σ_{s=1}^{N_sc} p(σ_s) log p(σ_s)
    c_i(E) ← max(E)
end
return c_i
```

B. Machine Learning Model

To obviate the task of collecting CSI data on memory-constrained wireless equipment and devices with low computational power, we develop a machine learning model for predicting spectral entropy by utilizing the basic WiFi physical layer information available in the Linux kernel. This is consequent upon the intrinsic relationship between the physical layer information and channel quality.

The choice of features in our sample is influenced by [2] and channel utilization for the QoS enhanced basic service set (QBSS) information element in IEEE 802.11e used by an AP to inform the QoS wireless clients about channel usage. The feature vector includes the following elements.

(a) *channel busy*: $CH_{CCA} = t_{busy}/t_{total}$ is measured as a ratio of time the scanning station's NIC detects the channel as busy as a result of channel assessment for carrier sensing or energy detection, and the total time spent by the station on the channel.

(b) *channel transmit*: $CH_{TX} = t_{transmit}/t_{total}$ is calculated from the ratio of the time used by scanning AP for transmitting data on the channel and the total time spent by the scanning AP on the channel.

(c) *channel receive*: $CH_{RX} = t_{receive}/t_{total}$ is the ratio of the time used by the station's NIC for receiving data on the monitored channel and the total time it has spent on the channel.

(d) *co-channel interferer signal strength*: computes the total power of other APs sharing the same channel from the standpoint of the current AP using the equation in (6).

The other elements are average data rate for transmissions on the channel, percentage of retries, and average bytes per packets during scanning.

$$L_T = 10 \; log_{10} \sum_{i=1}^{N} 10^{p_i/10} \tag{6}$$

Each feature vector is matched with its corresponding CSI spectral entropy target to form training data for machine learning. The model training process is a regression supervised learning using linear regression, support vector regression and random forest regressor algorithms. The trained model is used for predicting the CSI entropy. The influence of each feature on the trained model and its importance to prediction is presented in section V.

Linear Regression: model assumes linear relationship between feature vector and its target value. If a training data set of size m with n–dimensional feature vector and a target variable is represented as $S = \{(x_i, y_i)\}_{i=1}^{m}$ where $x \in R^n$ and $y \in R$, then the linear relationship between x and y is defined as

$$y = f(x) = w^T x + b \tag{7}$$

$$min \sum_{i=1}^{m} (y_i - f(x_i))^2 = \quad \sum_{i=1}^{m} (y_i - (w^T x + b))^2 \tag{8}$$

where w represents coefficients and b represents the bias or intercept. The linear regression algorithm aims to fit the training data to the linear function in equation (7) and finds a function with the best fit by minimizing the sum of squared errors according to equation (8).

Support Vector Regression: is an epsilon regression algorithm to find a function with at most ε deviation from the target for all data in the training set. The optimization problem is written as

$$\begin{aligned} min \quad & \frac{1}{2} \|w\|^2 \\ & \text{s.t.} \begin{cases} y_i - (w^T x_i + b) \leq \varepsilon \\ (w^T x_i + b) - y_i \leq \varepsilon \end{cases} \end{aligned} \tag{9}$$

The discriminant function obtained from equation (9) is used to predict the target variable from the test data.

Random Forest: the algorithm reduces high variance in training data by generating decision trees. Each tree is formed by a random sampling of training data and tree nodes are split based on elements of the feature vector. The quality of a split is determined by its mean squared error. The final model is the averaging of decision trees produced by the sub-samples of the dataset. The detailed process of model training and CSI entropy prediction from each trained model is presented in section V(B).

IV. Experimental Setup

In this section, we give a brief description of our testbed as well as the steps involved in our experiments. We performed our experiments in several locations on a university campus and a residential apartment indoor environment with a dense AP deployment. Each environment has about 50 APs on average. The experiments were performed during different hours of the day to capture varied wireless channel utilization during the "peak" and "off-peak" hours with different traffic and number of users.

A. Testbed Description

The experiment for this work was performed in the 2.4 GHz band of the unlicensed spectrum. The bandwidth for transmission is 20 MHz using 56 OFDM subcarriers. Our testbed includes a TL-WR4300 AP and a laptop running Ubuntu Linux 4.1.10 kernel. The TL-WR4300 is a dual-band AP with Atheros wireless NIC Ar9344 and Ar9580. The Ubuntu Linux machine is a 64-bit (x86_64 version) installation on HP ProBook 4540s with Atheros wireless NIC Ar9462. These NICs have 802.11n capabilities and support MIMO technologies. The scanning station is put in a monitor mode to passively scan all the available channels and extract I/Q data from the spectral scan information on the Atheros NIC.

B. Measurement Tools and Setup

The hardware enables us to obtain channel conditions for the 56 OFDM subcarriers from the scanning AP. We disable network utility for automatic station connection management on the AP and configure the NIC to scan all the 13 channels in 2.4 GHz in turns. The control for the spectral scan facility in the Atheros NIC is set to operate in *chanscan* mode. We configure the spectral scan count to return 16 samples for each channel when performing a scan. The physical layer passes the captured frame to the media access control layer every 64 μsec and a complete cycle for scan successive entry point through all the channels is 2.87×10^{12} Hz. The I/Q information obtained from the subcarriers is used to compute spectral entropy according to equation (2). We only use a subset of spectral entropy results since transmission is only permitted in 11 channels in the United States. We evaluate packet delivery performance on each channel by using *iperf3* UDP traffic testing available in OpenWRT.

V. Evaluation

In this section, we experimentally evaluate the proposed CSI-EWCA model for channel allocation in our testbeds. The evaluation is vital to determine whether the model is suitable for the intended task and comparable in performance to an existing model for channel allocation. We first perform a UDP test on a channel to determine the achievable throughput and jitter for transmission on the channel. Then we present the results of the machine learning model which we develop using the physical layer wireless information available in the Linux kernel.

A. RSSI and CSI-EWCA

To evaluate our model with a model using the RSSI, we perform a UDP test and obtain the result for Regression Scoring (RS) in [30]. This serves as a benchmark for our performance evaluation because several models for CA in an uncoordinated WLAN rely on RSSI and traffic volume. The RS is a suitable candidate because the model considers both normalized RSSI and traffic volume. The result from the UDP test for CSI-EWCA is then compared to the result from RS. The evaluation is strictly restricted to non-overlapping channels by making the inter-channel distance between APs in [30] to be greater than 3.

The plot in Fig. 1 and 2 show results for the UDP test for both RS and CSI-EWCA. It is evident that the CA decision by CSI-EWCA leads to a choice for a better channel that achieves higher throughput than the RS model as shown in Fig. 1. The average throughput for RS and CSI-EWCA is 21.73 Mbits/sec and 25.24 Mbits/sec respectively resulting

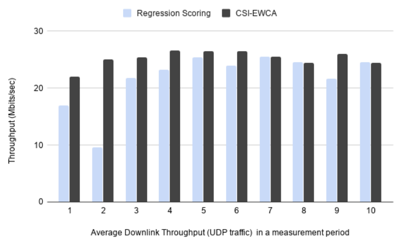

Fig. 1: Average throughput for UDP test.

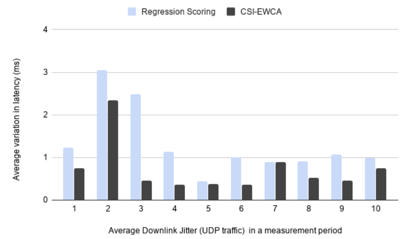

Fig. 2: Average jitter for UDP test.

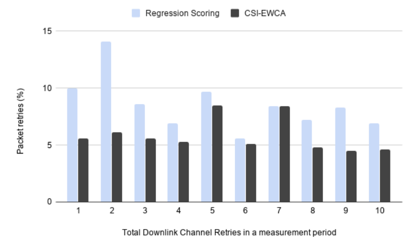

Fig. 3: Average channel transmission retries.

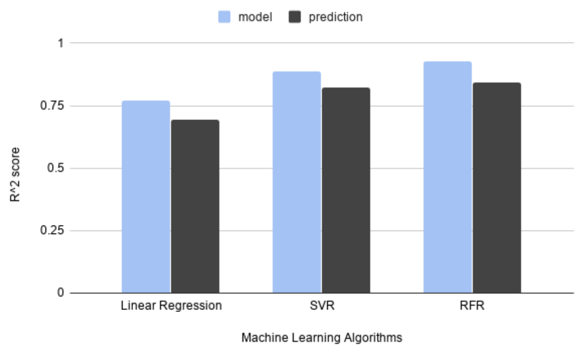

Fig. 4: CSI Entropy Prediction.

in about 16.15% increase. This is as a result of CSI-EWCA model's ability to capture the channel's underlying information theoretic characteristics that may not be reflected by RSSI and traffic volume. The plot of average variation in latency (jitter) for the UDP test between RS and CSI-EWCA in Fig. 2 shows average jitter to be consistently less than 1% for the majority of the CA decisions by CSI-EWCA making the model suitable for low latency applications. The jitter shows a 44.87% decrease in overall average for CA decision from RS to CSI-EWCA.

We analyze the traffic captured on the monitor station during each channel scan and the result for channel retries for the channel selected for RS and CSI-EWCA is presented in Fig 3. The average retries are 8.57% and 5.85% for RS and CSI-EWCA respectively.

B. CSI Entropy Prediction

We collect sample data from different locations on the university campus and apartment residence. The sample feature is as described in Machine Learning Model in *Section III*. We obtain the physical layer information and specific channel characteristics for 30 seconds for each feature on the channel during the scan. The spectral data for the frequency band is stored during the scan and used to calculate channel spectral entropy. Our sample set consists of 300 wireless information observations from the Linux kernel and their corresponding CSI entropy. We trained the dataset using machine learning regression models. The summarized result of the coefficient of determination (R^2) for the trained model and prediction is shown in Fig 4.

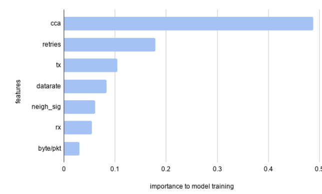

Fig. 5: Feature importance in RFR model.

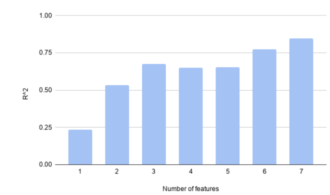

Fig. 6: Features contribution to prediction.

The machine learning algorithms that we use are ordinary least square regression (LS), support vector regression (SVR) and random forest regressor (RFR). To start the training process, we preprocess the data using a *standard scaler* to normalize the features by removing the mean and bringing the data to unit variance. Then, we engage in training the model using each of the algorithms. The sample data is split into 80% for training and 20% for testing. The results of the regression model when we fit a polynomial curve with different degrees on the training data set are shown in Table 1. We also obtain a coefficient of determination (R^2) for the SVR model. The SVR model is an epsilon regression model with a radial basis function kernel. The R^2 score for the SVR is 88.79% and 82.34% for the model and prediction data respectively. The result implies that the SVR model could explain up to about 89% of the variability in the CSI entropy from the training features. To mitigate bias, we employ a random forest regressor model with ensemble properties.

We notice a slight improvement in testing and prediction results when we use the ensemble model for training the data. The decision tree for the RFR model has a depth of 4 and a minimum split of 2. The results for the RFR model show the R^2 score for the model and prediction to be 92.73% and 84.31% respectively. The perceived improvement can be explained by the averaging of predictive power for each estimator (decision tree) in the RFR model to control over-fitting during training.

Finally, we examine the contribution of each component of the feature vector to the CSI spectral entropy prediction and present the results in Fig. 5 and Fig. 6. Here, we notice that the channel busy, CH_{CCA} has the largest impact and showing a 48% contribution to the RFR prediction. As shown in Fig 6., only three components account for about 0.77 percent of the overall R2 of 84.31 for the RFR model prediction.

VI. Conclusion

In this paper, we present a strategy for channel allocation in a dense uncoordinated WLAN and propose an alternative to RSSI for determining the best channel. The CSI-EWCA utilizes spectral entropy of the I/Q information of the channel to determine how a channel is used and its implementation is on 802.11 NIC of a commodity AP. In essence, we consider (i) selection of channel using CSI-EWCA and performance of the selected channel and (ii) alleviating spectral scan on devices with low computational power by predicting spectral entropy from wireless information available in the Linux kernel. We believe that using this strategy on a low-cost AP can significantly improve decision about channel allocation in a chaotic WLAN and help achieve a high-throughput required by users in multi-user MIMO systems.

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