Forecasting-based Cloud-assisted Dynamic Channel Assignment Mechanism for Mesh WiFi Networks

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***Abstract*—In this paper, we propose a cloud-assisted dynamic channel assignment system for WiFi mesh networks considering both the 2.4 GHz and 5 GHz interfaces to increase the overall performance and user experience in the WiFi network. Our solution utilizes periodic interference level measurements by the access points (AP) in all possible channels via conducting clear channel assessments. These measurements are sent to and processed by a cloud component with a forecasting module that predicts the state of each applicable channel in the near future. Finally, a channel change decision is sent to each AP if there is a better channel than its operating channel in the near future.**

We have conducted numerous field trials for a good selection of the various key parameters of the system with both the overall system's performance and impact over time-sensitive critical applications such as real-time applications in mind. We have also conducted a field trial of our proposed system over a large real-life population of fifty thousand APs and compared its performance against the widely deployed Least Congested Channel Search (LCCS) mechanism. Our results show that not only our mechanism outperforms LCCS in terms of operating channel interference level but achieves this goal with much less number of channel changes yielding a much less disruptive user experience.

***Index Terms*—WiFi, IEEE 802.11, channel assignment, cloud, forecasting**

I. Introduction

As any other wireless communication technology, WiFi has one critical real-estate: its operational frequency range. The commonly used frequency ranges of WiFi, the 2.4 GHz and 5 GHz bands, are licence-exempt frequencies, allowing other telecommunication technologies besides WiFi to also operate (i.e., Bluetooth) as well as non-telecommunication devices (e.g., microwave ovens) to generate signals in. At any given time, a WiFi network can only operate at a single channel with a given channel bandwidth whose availability has a profound performance impact over the connected users' WiFi experience. Therefore, finding the ideal channel to operate in is a crucial design decision for a WiFi network.

The frequency/channel allocation problem (FAP) has been widely studied in the general context of wireless networks as well as in the domain of cellular network technologies over the last couple of decades [1]. Although the key idea is similar, operating at licence-exempt frequencies changes the problem considerably (i.e., lack of a centralized frequency allocation entity, allowance of other technologies to generate signals in an uncontrolled fashion). Also, WiFi is considered as a secondary user in 5 GHz dynamic frequency channels (DFS), necessitating access point (APs) to conduct a long scan (i.e., 1 or 10 minutes) to make sure that no primary user signals exist before starting to operate on these channels. With these considerations, generic and cellular network specific FAP solutions cannot be directly applied to WiFi networks.

Another key difference in WiFi networks is the existence of wireless mesh networks (WMNs) over WiFi links to provide ubiquitous indoor connectivity. Although there is no standardized method for forming a WMN from multiple APs, a common technique is using one of the WiFi interfaces (usually the 5 GHz) to form mesh links between APs. Therefore, a channel allocation mechanism for WiFi networks should also consider this critical constraint on the channel selection and choose the channel of the interface used in the mesh links as the same channel in all APs within a WMN.

In the literature, WiFi network specific solutions to FAP are categorized in three groups: joint FAP and AP placement solutions, solutions for centrally managed groups of APs, and solutions for unmanaged groups of APs [2]. Solutions in the first category follow a similar approach to cellular networks and propose systems where the location of each AP as well as their assigned channels are selected before the deployment of all APs. Such solutions can be applied in industrial use-cases (e.g., factory floors) where placement of APs is done coupled with configuration of the APs. However, in urban WiFi deployments, especially in residential scenarios, placement of APs are usually conducted in an uncoordinated, distributed fashion limiting applicability of such solutions.

The second category of solutions consider groups of APs managed by a single central entity which is responsible from the channel assignment of the APs. An early and very-known method in this category is the DSATUR where the neighboring information of APs is considered as a graph and a graph-coloring based solution is applied to find ideal colors (i.e., channels) for each AP [3]. Lima et al. propose a more relaxed approach where neighboring APs can be assigned the same (i.e., interfering) channel based on their interference to each other [4]. They formalize the problem as an optimization problem and propose two heuristics: a Genetic Algorithm-based and a Differential Evolution algorithm-based. A similar approach tries to find "bad neighbors", APs generate considerable interference, and conduct the channel assignment with a higher emphasis to these neighbors [5]. In [6] a deep reinforced learning based method have been proposed focusing on maximizing the overall thoughput of the APs within the area. Iacoboaiea et al. propose another deep

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reinforced learning based solution that also adds the selection of the channel bandwidth (i.e., channel bonding) to the channel assignment problem [7]. Although more applicable to urban scenarios, the complexity of this category of solutions make them hard to implement, maintain, and operate. Moreover, these solutions usually give a fixed channel assignment without a framework for adapting to the ever-changing nature of the WiFi environment, further reducing their applicability.

The final category of solutions focus on unmanaged groups of APs where each AP decides for its channel assignment on its own. Least Congested Channel Search (LCCS) is the most well-known as well as the most widely-deployed solution in this category [8]–[10]. In LCCS, in case the operational channel's interference level exceeds a certain threshold, the AP conducts scans in all other channels and switches to the channel with the least amount of interference. The definition of interference differs between implementations. LCCS takes an action based on an immediate set of channel scans. Therefore, it is susceptible to sudden changes in WiFi channels leading to instability and sub-optimal performance.

A similar method, proposed in [11] keeps track of selection probabilities for each channel and in case the current operating channel's quality drops below a certain threshold, a random channel is selected based on the channel probabilities. Then, if the newly selected channel does not give a satisfactory performance its probability is reduced and the mechanism selects another channel. Similar to LCCS, this method is also easy to implement, but it requires too many iterations and takes long to converge.

Athanasiou et al. propose a method that utilizes the load of a given channel to evaluate a channel's quality [12]. Here the load of a channel is calculated based on the airtime metric from IEEE 802.11s which requires input from WiFi stations (STAs) connected to the AP. Kulkarni et al. propose a similar load-based channel quality estimation by adding a load information to the beacon frames sent by APs [13]. Although, these methods yield more precise information regarding channel quality, their reliance on STAs assistance or change in beacon frame format limits their applicability in real deployment scenarios.

Kajita et al. propose utilizing more refined metrics to evaluate the quality of a channel [14]. The authors use regression methods to generate a channel score by combining estimated delay, observed throughput, received signal strength, as well as the volumes of the traffic sources. Then, the channel selection is done based on these channel scores. Although the authors have conducted exhaustive simulations to find ideal scoring functions, utilizing such complicated scoring functions in a realistic environments shall be very complex limiting the methods practicality.

These methods, although easy to implement and very suitable to urban WiFi network scenarios, utilize a reactive approach: upon detection of a performance degradation (e.g., high interference) they start investigating on a better channel and make a decision. In our previous paper, we had laid out design considerations for a pro-active, cloud-based channel selection mechanism, that is based on conducting periodic measurements on each applicable channel, predict each channel's performance via several forecasting techniques, and act upon these predicted values before the channel degrades [15].

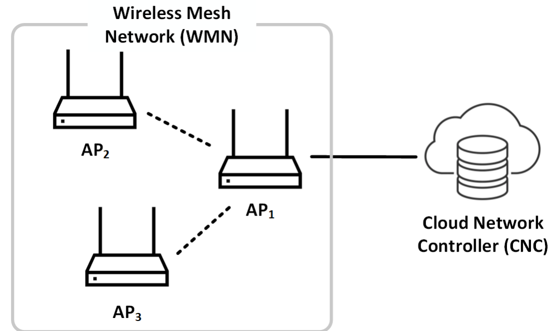


Fig. 1: Components of the proposed CACS architecture

In this paper, we expand upon our previous work and propose a complete pro-active dynamic channel assignment (DCA) solution named cloud assisted channel selection (CACS) that operates over a WMN with periodic channel scanning capabilities and utilizes forecasting techniques to determine the ideal operating channel of each AP within a WMN, both for the 2.4 GHz and 5 GHz interfaces.

In this work, the main contributions are as follows:

- First, we present an architecture for a pro-active DCA-based channel selection solution for WiFi networks considering both the 2.4 GHz and 5 GHz operating bands.
- Next, we present our analysis over several key system parameters of our solution using lab trials to tune the system for balancing measurement quality and its impact over user experience.
- We build a forecasting package consisting of several forecasting techniques that predicts the channel quality in terms of clear channel assessment (CCA) values and evaluate the accuracy of this package with lab trials.
- Finally, we evaluate the performance of the proposed CACS solution over a field trial consisting of fifty thousand real home environments in terms of operating channel quality as well as number of channel changes.

The remainder of the paper is organized as follows. In Section II, the overall architecture of our proposed channel assignment system is given. Section III and Section IV describe the responsibilities of WiFi access points and the cloud network controller respectively to the overall system. In Section V, results of a field trial of the proposed system consisting of fifty thousand real home environments is presented. Finally, Section VI concludes the paper.

II. CACS Architecture

The overall architecture of our proposed CACS system is composed of two main components: a WMN with multiple APs and the Cloud Network Controller (CNC) (Fig 1). While the APs within the WMN are responsible from taking representative interference measurements from the channel, and

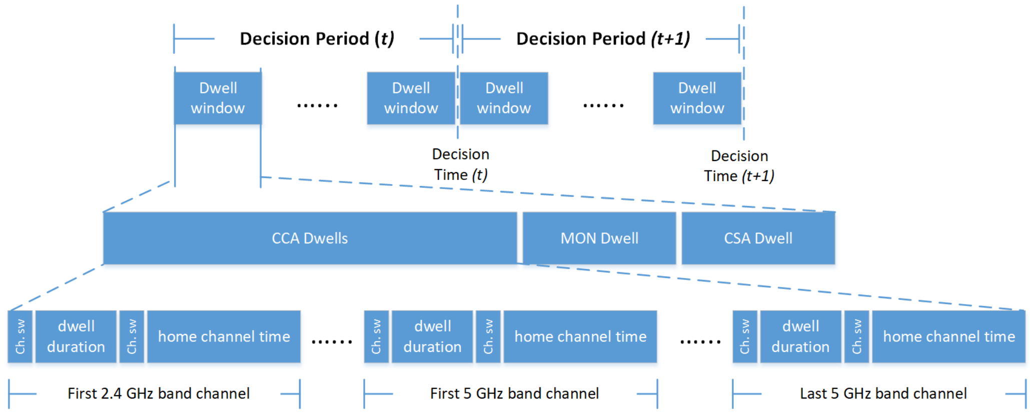


Fig. 2: CACS periodic timeline, decision period, dwell window and CCA dwells details.

acting based on the advices sent from the CNC, the CNC is responsible from utilizing the measurements provided by the APs and deciding if a channel change is needed. If so, the CNC also offers information to which channel this change should be towards.

Since CACS is a DCA solution, it works on a periodic basis we call decision periods (Fig. 2). During each decision period, the APs collect measurements and report these measurements to the CNC. At the end of each decision period, called the decision time, the CNC makes a prediction for each channel for the next decision period, and if needed generates a channel change advice. Decision periods can take any value on a minutely basis and we use a 60-minute decision periods as the default value. In the following two sections, the details of the AP requirements and CNC requirements are explained.

III. Access Point (AP) Responsibilities

On the firmware part of the CACS system, APs have three responsibilities: taking representative interference measurements from each channel, synchronizing 5 GHz measurements, and acting based on the advices sent by the CNC.

The key design decision for the first responsibility is the selection of the interference measurement metric. As part of their routine operation, each WiFi device periodically measure the availability of the operating channel and represent it in a scale of 0-255, where 0 means the medium is completely available and 255 means the medium has no availability at all. This metric, called the Clear Channel Assessment (CCA), is used by the CSMA/CA mechanism of WiFi to determine if the device can access the medium or not [16]. Since CCA is already a well-established metric and part of the core WiFi channel access mechanism, it has been chosen as the key metric in the interference measurement part of our proposed CACS mechanism.

As stated in Section I, a common technique in forming WiFi WMNs is utilizing 5 GHz interfaces of each AP within the WMN. In such WMNs, since all APs within the WMN are required to choose the same 5 GHz channel to operate in, they must coordinate their 5 GHz operating channel measurements among themselves to avoid measuring the mesh traffic as background interference.

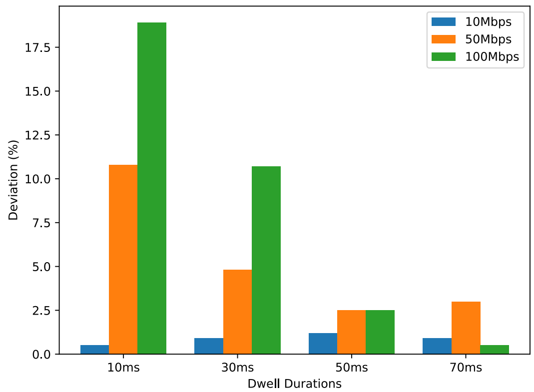
As the third responsibility, the APs must be able to receive channel change advices from the CNC and act accordingly. However, changing the operating channel is generally a disruptive operation that can lead to drops in STA connectivity. Therefore, an AP should consider such potential disruptions and decide in case of a channel change advice to either act immediately, postpone it for a while, or completely disregard it depending on its operational status.

A. *Taking Measurements*

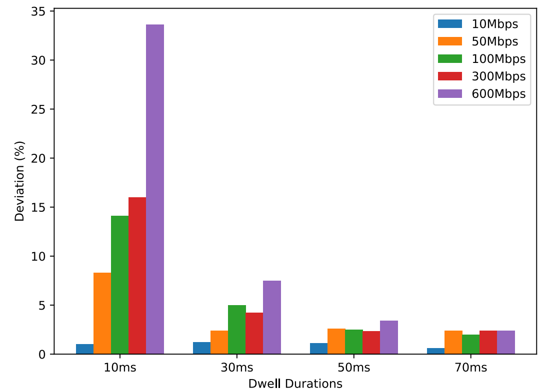
The two key aspects of CCA measurements are timeliness and completeness. In order to be timely, the measurements should be periodically repeated and to be complete all possible channels must be measured. We consider periodic dwell windows where a measurement is collected from each applicable channel (Fig. 2). Each dwell window is composed of three parts: CCA dwells where the off-channel measurements are collected; MON dwell where the in-channel measurement is collected; and the CSA dwell where the advices sent by the CNC are handled. In each CCA dwell, the AP switches to the target channel (i.e., channel switch time), collect measurements in terms of CCA levels; switches back to its operating channel; and operates normally on its own channel (i.e., home channel time) before the next CCA dwell starts.

In this time structure, the dwell duration value is a key system parameter. Since an off-channel measurement requires the device to pause its normal operation and temporarily operate at the measured channel; on one hand, the longer the device operates in the measured channel, the accuracy of the measurements increase and on the other hand, the AP cannot serve its STAs, causing QoE degradation especially in their real-time applications (RTAs).

We evaluate the quality of an off-channel measurement by the deviation percentage from the in-channel measurement in the same environment under different interfering traffic rates (in terms of Mbps) both in the 2.4 GHz band and the 5 GHz band. As seen in Fig. 3, in both bands measurements collected with 70 and 50 ms dwell duration have a slight deviation of



(a) Deviations of 2.4 GHz off-channel measurements



(b) Deviations of 5 GHz off-channel measurements

Fig. 3: Deviations of off-channel measurements based on interfering traffic rate and dwell duration

TABLE I: DF results with dwell window values

Dwell window (ms)	No dwell	10	20	30	40	50
Delay Factor (DF)	3.01	26.89	36.7	47.05	56.12	67.08

3 - 4%. A shorter duration of 30 ms gives a higher margin of error with a maximum deviation of 11%. Finally, a much shorter duration of 10 ms gives a much higher error rate with 18 - 35% maximum deviation.

As for the impact on RTAs, we investigate the maximum latency of teleconference applications and the delay factor (DF)[1] of video-on-demand (VOD) applications when our proposed periodic off-channel scan mechanism is enabled. As one might expect when there is an off-channel measurement, teleconference applications operate with a maximum latency equal to 10 ms more than the selected dwell duration value. When compared to the ITU-T standard for teleconference application delay bounds of 150 ms, delays of each considered dwell duration values are below the recommended value [17]. As for the DF values of VOD applications, we compare the results against the suggested upper bound of 50 ms (Table I) [18]. 50 and 40 ms dwells both exceed this limit while 30 and 10 ms dwells are below the suggested limit.

Based on the above investigation, we choose the dwell duration as 30 ms which does not violate QoE requirements of RTAs while the measurement quality has a upper bound of 11% deviation which only happens when the channel is extremely congested.

Following the 60-minute decision period selection, we choose a 1-minute dwell window duration to balance between keeping the overall home channel time high (95% of overall operation time) while getting as many samples as possible in each decision period[2]. In these 1-minute dwell windows, there is a single CCA dwell for each applicable 20 MHz channel based on each region's own regulations[3].

B. Measurement Synchronization

In a WMN where the backbone mesh traffic is carried over the 5 GHz interfaces, the 5 GHz in-channel measurements should be collected synchronous among the APs of the WMN to avoid considering mesh traffic as interference.

Considering dwell durations being in milliseconds, the needed synchronization resolution for this task is very high (i.e., accuracy around 1-2 ms). The well-known time synchronization methods like Network Time Protocol (NTP) have synchronization accuracy of 5 - 100 ms which is not sensitive enough for this use-case [19]. To fulfill this requirement we develop a specific mechanism called "Airclock" utilizing the "Timestamp Function (TSF)" field of beacon frames. This field stores the time elapsed after the boot of the AP in terms of milliseconds. Although, TSF is enough to synchronize APs that start operating at the same time, often times APs within a WMN do not start at the same time.

We add a new element named Time Advertisement Information Element (TAIE) to beacon frames and we call the summation of the TSF and TAIE values the Airclock value (i.e., $Airclock_i = TSF_i + TAIE_i$). At boot, each AP sets its TAIE value to 0. Then, each AP (AP_i), upon reception of a beacon frame from another AP (e.g., AP_j) within the WMN, compares $Airclock_i$ against $Airclock_j$, if $Airclock_j > Airclock_i$, AP_i updates its TAIE value as

$$TAIE_i = TSF_j + TAIE_j - TSF_i \tag{1}$$

to be synchronized with the rest of the WMN. These Airclock values are sent to the CNC coupled with the 5 GHz in-channel

[1]DF is a time value indicating how many milliseconds' worth of data the buffers must be able to contain in order to eliminate jitter. It is computed as the maximum difference in buffer size divided by the stream rate at regular intervals (typically one second).

[2]In modern WiFi RFICs, a channel change does not lead to a real switching operation. Instead, the bit sequence given to the voltage-controlled oscillator is changed which in turn produces the local oscillator signal. Therefore, there is no significant energy consumption in a channel change operation.

[3]For example in North America in the 2.4 GHz frequency band, applicable 20 MHz channels are channels 1 - 11.

measurements to check the synchronization between the APs of the WMN.

C. Channel Change Advice Handling

The incoming channel change advices are handled in the CSA dwells. An advice is composed of channel switch flags, one for each interface, and predicted score values for each applicable channel whose calculations are as explained in Section IV. If the 2.4 GHz channel switch flag has a “true” value, the 2.4 GHz channel with the highest score is selected as the new target channel. Then, the AP checks if there is considerable ongoing traffic over its 2.4 GHz interface (i.e., traffic exceeding a $thr_{traffic}$ value). If so, the advice is postponed until the next CSA dwell with a maximum number of $retryCount$ times. If not, it triggers a channel change to the target channel. These controls aim to avoid service disruption to users due to a channel change when there is considerable ongoing traffic.

If the 5 GHz channel switch flag has a “true” value, only the master node within the WMN takes an action similar to the 2.4 GHz case. If it decides to instigate a channel change, it relays this change via a channel switch announcement message to all other APs within the WMN so that the whole WMN switches to the new 5 GHz channel together.

IV. Cloud Network Controller (CNC) Requirements

The cloud side of the CACS system, CNC also has three responsibilities: aggregating interference measurements, conducting a time series analysis to predict the quality of each channel in the next decision period, and deciding on a channel change action based on the predicted values.

A. Data Processing and Aggregation

As described in Section III.A, each AP measures each applicable channel periodically in terms of CCA values and send these information to the CNC to be processed. CNC aggregates these measurements collected within the last decision period and generate a decision period representative CCA value to be used in the subsequent prediction process. This aggregation uses a simple arithmetic mean to eliminate the short-term fading effects and smooth out the measurement data.

In contrast to the aggregation of the 2.4 GHz measurements where the simple arithmetic mean is used, the aggregation of the 5 GHz measurements is done on a WMN basis considering the 5 GHz measurements of all APs within the WMN. First, for each channel and each dwell window, the highest CCA value reported by the APs of the WMN is selected. These values are called the WMN-wide measurement vector. Then, the arithmetic mean is calculated over these WMN-wide measurement vector and WMN-wide decision period representative CCA values are found. As for the special case of the 5 GHz in-channel measurements, while forming the WMN-wide measurement vector, the Airclock values are also checked. If there are more than $2ms$ of discrepancy between the Airclock values of the measurements belonging to the same dwell window, these measurements are considered as unreliable and discarded.

B. Channel Prediction

After aggregating the last decision period’s measurement data into a single representative value, we employ a prediction mechanism over the past representative CCA values to forecast the CCA level of all applicable channels in the next decision period.

We have collected representative CCA level time-series data from a variety of homes with different WiFi usage patterns to investigate their patterns. Since the CCA value is a bounded value between 0-255, there cannot be any trend. As for seasonality and cyclicity, different APs have different behaviors. Some APs exhibit seasonal behaviour in terms of hours (e.g., all evening data have similar behavior whereas all morning data also have a similar behavior) others in terms of days of the week. Another group of APs lack any seasonality in their CCA data but exhibit cyclic patterns (e.g., when there are guests in a neighboring home, channels used by that neighbor have a similar pattern for several hours). As such, finding one ideal forecasting technique that is applicable to all possible scenarios is not very practical. Instead, in each decision period for each AP and for each channel, we employ several forecasting techniques with different parameters, compare the forecasting qualities of each technique/parameter pair in terms of mean square error (MSE) and choose the technique/parameter with the smallest MSE values.

In our previous work, we consider exponential smoothing and moving average techniques [15]. In this work, we also investigate bi-directional exponential smoothing, ARIMA, as well as LSTM techniques.

1) Exponential Smoothing: Exponential smoothing is one of the simplest and well-known yet powerful forecasting techniques. It has a single parameter: the smoothing factor α. In exponential smoothing, if $X^t_{i,j}$ represents the actual measured CCA value of channel i for AP j during decision period t, and $\delta^t_{i,j}$ represents the predicted value for the same channel, AP, and decision period. The predicted value at the next decision period can be found as:

$$\delta^{t+1}_{i,j} = \alpha\delta^t_{i,j} + (1-\alpha)X^t_{i,j} \tag{2}$$

where α can take any values between [0-1]. A low α value puts much more focus on the one previous actual measurement whereas a high α value puts more focus on the historical predicted values.

2) Moving Average: Another well-known forecasting technique, the moving average also has a single parameter, the window size wnd. Following the same notation as above, the predicted value at the next decision period is defined as follows:

$$\delta^{t+1}_{i,j} = (\sum_{n=t-wnd+1}^{t} X^n_{i,j})/wnd \tag{3}$$

where wnd can take any positive integer value.

3) Bi-directional Exponential Smoothing: A variant of the exponential smoothing, the bi-directional exponential smoothing is basically conducting the exponential smoothing both in forward and backward directions (i.e., backcasting), and then taking the average of the two results.

4) ARIMA: ARIMA is one of the most general techniques in the forecasting literature. It requires higher computational complexity than the first three methods, and has to be tuned depending on the given time-series. The standard notation for ARIMA is $Arima(p, d, q)$ where p,d,q are lag order, degree of differencing, and the size of the moving average respectively. For a given problem, the ideal p and q values are generally found with grid search. As for the d value it can be inferred following a KPSS test. For stationary time series, d is fixed as 0. For non-stationary time series following operations are done for time series t_i to find the ideal d value.

Algorithm 1 Selection of d for ARIMA

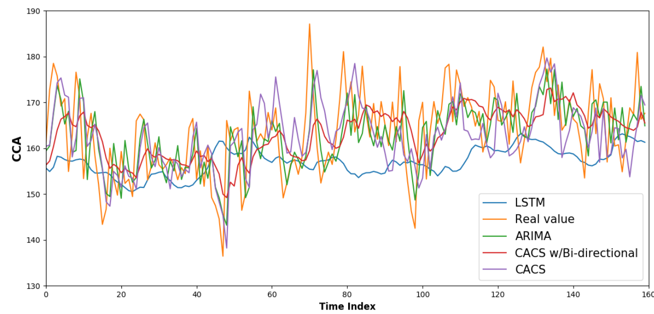
```
for all t_i do
    index, d = 0
    threshold = 0.05
    p_value = kpss_test(t_i)
    while p_value ≠ threshold do
        p_value = kpss_test(t_i)
        t_i = t_i.diff(index)
        d = d + 1
        index = index + 1
    end while
end for
```

5) LSTM: Long short term memory (LSTM) is an artificial neural network-based deep learning method, also used in the forecasting solutions. Unlike the previous techniques, LSTM has functions (e.g., activation functions), number and behavior of layers to be selected as well as too many parameters to be optimized for a given problem. We have investigated several well-known LSTM layer designs namely stacked LSTM, vanilla LSTM, and bi-directional LSTM with different activation functions. We have trained LSTM with a training set composed of 40 CCA time series collected among different APs and devices. Among the investigated LSTM designs, the single layer bi-directional LSTM with 'relu' activation function yielded the best results.

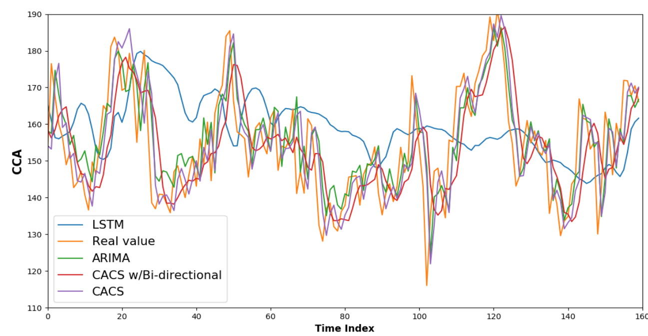
The first three methods have fairly low computational complexity and the range of their method specific parameters are also pretty limited. In contrast, ARIMA and LSTM requires much more computational complexity as well as numerous parameters required to be optimized. Moreover, as a deep-learning based technique, LSTM requires huge amount of data for its training set to yield a good prediction accuracy. Therefore, we design two forecasting packages combining the three low complexity solutions with a set of parameters as: exponential smoothing with $\alpha \in [0.2 : 0.2 : 1]$, moving average with $wnd \in [2 : 2 : 16]$, and bi-directional exponential smoothing where $\alpha \in [0.2 : 0.2 : 1]$. We also add a similar package without the bi-directional exponential smoothing

TABLE II: Error values of different forecasting methods

	MAE	MSE	RMSE
CACS	7.353	107.069	10.347
CACS w/o bi-direct.	7.593	108.124	10.398
ARIMA	6.984	95.529	9.774
LSTM	11.294	220.751	14.858



(a) AP/channel pair where the channel quality is generally within a certain range



(b) AP/channel pair where the channel quality have occasional sharp changes

Fig. 4: CCA Time-series representations of different forecasts with the actual data

method included to investigate the additional benefit of this third method. Then, we compare the accuracy of these two packages with parameter optimized results of ARIMA and LSTM with data sets of 80 different AP/channel pairs over a period of 1 week of forecasting.

Table II shows the accuracy of the four investigated forecasting methods: the two proposed CACS packages, ARIMA, and LSTM. As examples, Fig. 4 present the detailed time-series representation of the four methods' forecasts compared against the real CCA values in two AP/channel pairs among the 80 investigated AP/channel pairs. Among these methods, ARIMA gives the lowest error followed by the two proposed CACS packages while LSTM gives the worst performance in all three error metrics. Although ARIMA yields the best performance, its improvement over the CACS packages is not high. Among the two proposed packages, the package with bi-directional exponential smoothing yields a slightly better performance. LSTM gives by far the worst performance which can be attributed to the limited data set used for its training. As seen in Fig. 4, LSTM captures the long-term pattern quite well however it misses out quite a lot regarding the short time fluctuations reducing its accuracy.

When we look at these accuracy results combined with the required computational complexity for each method, we select the most comprehensive CACS forecasting package to be used in the channel prediction component of our system. Due to its huge data requirement, investigating for a much more accurate LSTM model is left as a future work.

C. Channel Change Advice Generation

After the quality of each applicable channel during the next decision period has been predicted, CNC decides on whether to instigate a channel change for a given interface or not based on these predicted values.

First, all predicted channel CCA values are converted into channel scores between 0-100 by a linear transformation as below for ease of use

$$Score_{ij}^{t+1} = ((255 - \delta_{i,j}^{t+1})/255) \cdot 100. \quad (4)$$

Then, each score is converted into a weighted score based on a weight (w_i) for each channel as below:

$$WScore_{ij}^{t+1} = \frac{Score_{ij}^{t+1} + w_i}{100 + \max_{j \in \mathcal{C}}(w_j)} \quad (5)$$

where $\mathcal{C}$ represents the set of applicable channels. These weights can be used for favoring a particular channel over other channels for non-interference related reasons such as maximum transmission power of a channel or a channel being a DFS channel or not. Note that DFS channels have a longer channel switch time requirement causing longer service disruptions.

Finally, the weighted score of the current operating channel is compared against the weighted score of the best channel in terms of weighted scores. If the improvement is higher than an improvement threshold (thr_{impr}), then the CNC sends a "true" advice to the AP. Otherwise, no channel change advice is sent; either due to the current channel being the best channel or the improvement is not deemed to be too much for the disruption of a channel change.

V. Field Trial Results

We have conducted a field trial of our proposed CACS system over a population of 50 thousand real home APs. The trial base is composed of WMNs of sizes between 1-3. We have utilized our system in both the 2.4 GHz and 5 GHz interfaces of these APs where the operating bandwidth of the 2.4 GHz interface is selected as 20 MHz, and the operating bandwidth of the 5 GHz interface is selected as 80 MHz. The applicable channels are selected as the first 11 overlapping channels in the 2.4 GHz band and twenty 80 MHz channels in the 5 GHz band where 80 MHz channels with different primary channels are considered as separate channels.

TABLE III: CACS Field trial parameters

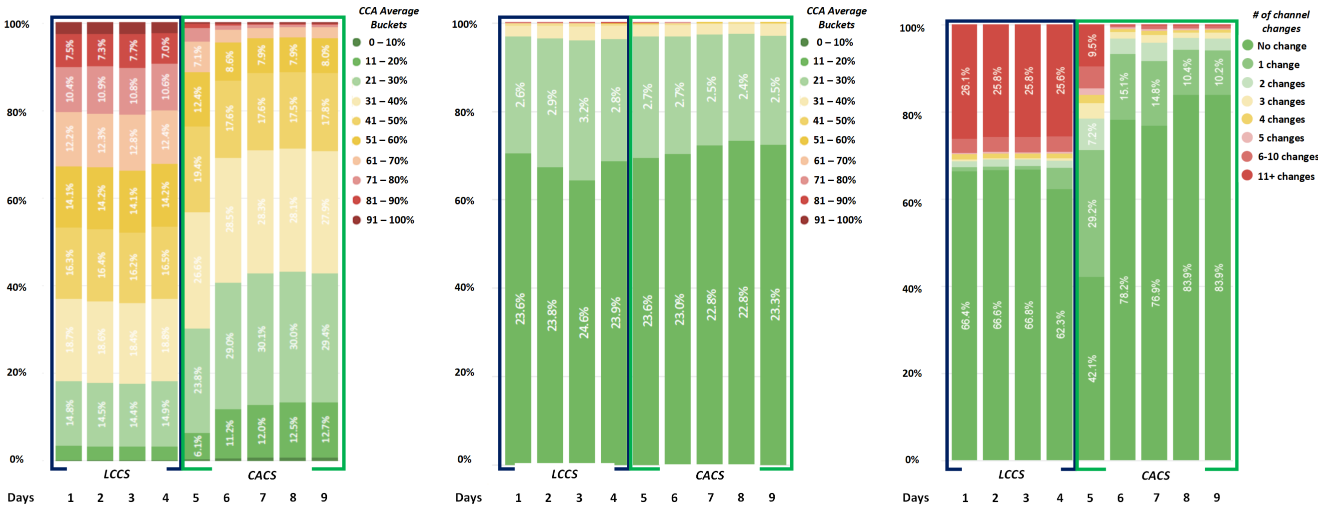
Parameter	Value
Applicable 2.4 GHz channels	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Applicable 5 GHz channels	36, 40, 44, 48, 52, 56, 60, 64, 100 104, 108, 112, 132, 136, 140, 144, 149, 153, 157, 161
2.4 GHz channel bandwidth	20 MHz
5 GHz channel bandwidth	80 MHz
Decision period	60 minutes
Dwell window	1 minute
Dwell duration	30 ms
α	[0.2:0.2:1]
wnd	[2:2:16]
$thr_{traffic}$	5 Mbps
$retryCount$	60
thr_{imp}	25%
w_i for 2.4 GHz channels	10
w_i for DFS 5 GHz channels	10
w_i for non-DFS 5 GHz channels	40

The decision period is selected as 60 minutes, dwell window has a duration of 1 minute, and dwell duration is selected as 30 ms. As for the parameter values for the predictor techniques, all the values given in Section IV.B are considered. The channel change related parameters, traffic threshold ($thr_{traffic}$) and retry count ($retryCount$) parameters are selected as 5 Mbps and 60 respectively. The improvement threshold, thr_{impr} is selected as 25%, w_i values for all 2.4 GHz channels are selected as the same value not to favor any 2.4 GHz channel over the other, and w_i values for non-DFS 5 GHz channels are selected higher than the DFS 5 GHz channels to slightly favor non-DFS 5 GHz channels over the DFS channels.

The field trials are conducted against an LCCS implementation that considers the number of basic service sets (i.e., WiFi networks) as the channel quality metric and if a channel change is needed it selects the channel with the fewest number of basic service sets. The first four days of the trials, the LCCS is selected as the channel selection system. Starting with the fifth day, CACS is selected as the channel selection system. The field trial parameters are as given in Table III.

In Fig. 5a, we see the distribution of APs operating at different 2.4 GHz CCA buckets where the green buckets represent APs operating at low CCA levels whereas the red buckets represent APs operating at very high CCA levels. After enabling CACS, the CCA levels of the whole population improves significantly. APs formerly operating at very high levels move to mid-CCA levels while APs previously operating at mid-CCA levels move to low-CCA levels. When we focus on the percentage of devices operating at 50 CCA level or worse, while in LCCS nearly 65% of the population is operating at these levels, in CACS after the first day, only less than 30% of the population remains at this level.

In Fig. 5b, we see the same distribution regarding the 5 GHz CCA buckets. Here we see that regardless of the selected channel selection system pretty much all of the population is operating at very low CCA levels. Our solution only makes



(a) 2.4 GHz Daily CCA Average buckets (b) 5 GHz Daily CCA Average buckets (c) 2.4 GHz Channel change

Fig. 5: Daily CCA average bucket and channel change distributions of the field trial

a small improvement. This can be attributed to the fact that there are much fewer 5 GHz non-WiFi interference sources in regular home environments. As for the potential WiFi interference sources, the reduced transmission power of the 5 GHz WiFi signals compared to the 2.4 GHz WiFi signals also limits the potential interference between nearby APs.

As for the second performance metric, Fig. 5c shows the channel change counts of the two systems. Since LCCS acts solely on immediate channel qualities, it incurs a very high amount of channel changes for nearly one quarter of the whole population. CACS on the other hand conducts some number of channels changes on its first day after which it only makes very few channel changes in the vast majority of the population giving a much more stable performance.

VI. Conclusion and Future Work

In this paper we have described a pro-active DCA solution for WiFi networks that utilizes CCA information for the channel quality indicator and uses forecasting techniques for selecting the ideal channel for a given AP within a WMN. Our solution focuses on both the 2.4 GHz and the 5 GHz band of the WiFi networks while it can be easily expanded to the newly ratified 6 GHz WiFi channels. We have evaluated the performance of our proposed solution against an implementation of the widely-deployed LCCS solution, lacking any forecasting capabilities in terms of improvement in daily average CCA buckets as well as number of channel changes using a real field trial consisting of 50 thousand home APs. Results of the field trial show that our proposed solution vastly outperforms LCCS in both performance metrics in the 2.4 GHz frequency band. Since the performance of the 5 GHz frequency band does not have much room for improvement to start with, our proposed solution only has a small improvement in the 5 GHz frequency band.

As a future work we plan to extend our proposed system to also decide on the channel bandwidth of the WiFi interfaces based on the interference levels. Moreover, we also plan to build a coordinated centralized channel selection system for a group of APs within a given geographical area which are controlled by the same networking entity (e.g., an internet service provider).

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