Linkcon: Adaptive Link Configuration over SDN Controlled Wireless Access Networks

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ABSTRACT

High throughput wireless access networks such as IEEE 802.11ac show a significant challenge in choosing link configuration parameters dynamically based on channel condition. It is due to a large pool of design set like channel bonding, number of spatial streams, guard intervals, different modulation and coding schemes, frame aggregation etc. Selection of such parameters is far challenging in mobile environment where signal strength fluctuates frequently. In this paper, we design a *software-defined networking (SDN)* framework for link adaptation in mobile environment, that engages an adaptive learning-based methodology, $\epsilon-greedy$ policy. The proposed link adaptation mechanism, *Linkcon*, explores several possible configuration options on the basis of their impact on network performance in various channel conditions. We analyze the performance of Linkcon from simulation results. We observe that this approach provides a significant better performance compared to other competing schemes proposed in the literature.

CCS CONCEPTS

•Networks →Link-layer protocols; Network experimentation; High throughput wireless access networks;

KEYWORDS

Software-Defined Networking; IEEE 802.11ac; link adaptation; mobility

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1 INTRODUCTION

High throughput amendments of IEEE 802.11 are introduced in the last few years to fulfill the demand of high data rate in wireless local area networks (WLANs). IEEE 802.11n and IEEE 802.11ac [18] are examples in this direction, and they are popularly termed as *High Throughput WLANs (HT-WLANs)*. Both physical (PHY) layer and medium access control (MAC) sublayer of IEEE 802.11n/ac are enhanced with some new features for improving the capacity of the wireless transmissions, whereas maintaining the compatibility with legacy IEEE 802.11 standards. Multiple input multiple output (MIMO) antenna technology, channel bonding, short guard interval (SGI) and advanced modulation and coding scheme (MCS) are the enhanced features in PHY. MIMO can increase transmission range and data rate by applying multiple antennas. MCS is used to regulate the coding rate and modulation of a signal with the combination of MIMO spatial streams. By using channel bonding feature, multiple channels of 20 MHz can be combined together to create 20/40/80/160 MHz channels. Physical data rate is increased theoretically by applying this enhancement. In contrast to the standard guard interval of 800ns, SGI supports guard interval of 400 ns. Similarly, MAC sublayer is enhanced with frame aggregation and block acknowledgement (BACK) technologies.

Although HT-WLANs support several advanced features at both PHY and MAC layers, each feature comes with its internal tradeoffs in performance under diverse channel conditions. While every feature shows a remarkable performance in a specific network condition, it fails in other network conditions. For example, communication with higher channel width can not sustain under weak signal strength. Consequently, wider channels are prone to increased packet losses due to external interferences and channel errors [4, 5]. MIMO throws the challenge of placing multiple antennas and design of transmitter modules for efficient communication over time varying wireless channels [22]. For high network traffic and congestion in a network, SGI may drop the overall system throughput, as inter-symbol interference may not get eliminated with 400ns guard interval under a congested network scenario. Signal fading, channel interference and signal attenuation impose a significant fluctuation in *signal to noise ratio* (SNR) of the wireless channel. High SNR is needed for sustaining of higher MCS values [20]. In case of MAC enhancements, frame aggregation transmits multiple frames in a single transmission. Thus, this feature increases packet loss for low signal level and high channel error conditions [10]. By carrying multiple acknowledgements, BACK induces high packet loss when signal strength is low [15].

Link adaptation: Considering aforesaid trade-offs, an important design objective is to transmit the data at the best suited PHY and MAC parameters for the present channel condition. A fixed set of PHY and MAC parameters can not be the optimal under all circumstances since a wireless network is a time-varying system. Therefore, it is necessary to select PHY and MAC parameters dynamically to cope up with channel condition. Considering the current channel condition, the selection of the best possible set of

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link parameters is known as *link adaptation* which is addressed in this paper.

Impact of mobility: Most of the existing mechanisms of link or rate adaptation in IEEE 802.11, such as [8, 12, 19] and the references therein, are based on static environments. In a mobile scenario, interference, signal fading and attenuation change significantly in different positions of a wireless station. Hence, a wireless device observes contrasting channel conditions repeatedly. Consequently, the link adaptation is far challenging since a selected link configuration at time t needs to be revised at time $t + 1$. Further, dynamic link adaptation in HT-WLANs is very difficult under mobile environment because of a large number of PHY/MAC parameter sets with their inter-dependencies.

Contribution of this Paper: In this paper, we explore automatic learning by wireless devices from the past knowledge, such that they can select the best suited link parameters adaptively when a change in channel condition is observed. We develop a software controlled architecture based on the concept of software defined networking (SDN) paradigm [9, 14], where a network controller connected with the wireless access points captures the link state configurations and decides optimal link parameters based on an online learning mechanism. We first design an optimization mechanism to select the optimal link configurations based on the underlying channel conditions. However, as it is difficult to learn the channel condition in a distributed environment, we employ the SDN controller to periodically collect channel conditions and apply a distributed online automatic learning mechanism to learn the impact of channel conditions over various link parameters. We apply ϵ-greedy [21] policy as an adaptive *machine learning approach* to design an efficient dynamic link adaptation mechanism, *Linkcon*, for HT-WLANs. The SDN control for Linkcon provides programmability support to the network administrator and makes the functionality easier by maintaining a global view of the whole network. Additionally, SDN simplifies the design of Linkcon since SDN controllers are vendor-neutral and open standards-based. We consider channel bonding, MIMO streams, MCS, SGI and frame aggregation to create the set of link parameters. SNR is engaged as the measurement of channel condition. We employ packet error rate (PER) to measure overall performance of network. The performance of Linkcon is analyzed through simulation results. The analysis shows that this mechanism improves the network performance significantly compared to other related schemes explored in the literature.

2 RELATED WORKS

In HT-WLANs, dynamic link adaptation can be classified into two categories as follows.

(i) Link adaptation in static environment: MiRA [17] is a dynamic data rate adaptation approach that selects spatial streams and rates. It is based on MIMO technology and the receiver's feedback. In poor channel condition, MiRA performs excessive rate selection. Further, RAMAS [16] is a credit-based scheme that also applies MIMO streams. So, this approach incurs overhead of assigning credit to select data rate. Deek *et al.* [4] proposed a rate adaptation scheme based on channel bonding. But, the mechanism can not utilize the full strength of all PHY/MAC new features. Minstrel [2] is the default link adaptation algorithm in Linux system and engages the statistical information for channel overhearing. However, it is suitable only for legacy IEEE 802.11 systems. Different MCS values and MIMO are used in [23, 24]. Feng *et al.* [6] developed a link adaptation scheme that applies frame aggregation. All these mechanisms do not consider all PHY/MAC enhancements of HT-WLANs along with their internal trade-offs. Thus, these approaches are not able to meet theoretical achievable data rate of IEEE 802.11n/ac in practical scenarios.

Minstrel HT [7] is the default rate adaptation methodology that is applied by the wireless driver ath9k [1]. It perceives the maximum enhancements of PHY/MAC in IEEE 802.11n, but suffers from exhaustive sampling. SampleLite [13] is a pure received signal strength indicator (RSSI) threshold-based algorithm. It can not cope up with all possible wireless network scenarios. In one of our previous works [11], a dynamic link adaptation scheme is designed for IEEE 802.11n. In this work, we consider a limited set of channel conditions measured by RSSI. In our another work [12], an adaptive learner is designed for link adaptation in IEEE 802.11ac. Sur *et al.* [19] designed MUSE that is a MU-MIMO-based rate adaptation algorithm for IEEE 802.11ac networks. ESNR is an another rate selection scheme designed in [8]. Specifically, it was designed for IEEE 802.11n (MIMO). All new features of HT-WLANs are not employed in MUSE and ESNR. Moreover, their performances were not evaluated in mobile environment.

(ii) Link adaptation in mobile environment: As per our knowledge, no work has yet considered SDN-based framework to design a dynamic link adaptation algorithm for HT-WLANs in mobile environment. However, Chen *et al.* [3] proposed a rate adaptation algorithm, RAM, for mobile environment considering only legacy IEEE 802.11 standards. Hence, it is not adjustable with HT-WLANs.

3 LINKCON: SYSTEM MODEL AND DESIGN DETAILS

Linkcon is based on the concept of SDN architecture. Therefore, we separate the control of the entire network from the underlying hardware systems. The details of the architecture are given as follows.

3.1 SDN-based Linkcon Architecture

Linkcon has a hierarchical architecture containing two layers – layer-1 and layer-2. In layer-1, a central SDN controller (CSC) is placed. SDN controller for initial experience phase (SCI) and SDN controller for experience phase (SCE) are placed in layer-2. The details of these two phases are given in Section 3.8. Figure 1 illustrates this architecture.

CSC is installed in a single centralized system. Whereas, SCI and SCE have more than one instance and they form a complete SDN controller in layer-2. Thus, SCI and SCE are implemented in several systems. They run simultaneously and control different disjoint sets of access points in distributed way. The major functionalities of the proposed framework are shown in Figure 2. As our proposed model follows SDN framework, there are three layers in this model – application, control and infrastructure.

CSC divides the number of available access points (APs) in the controllers of layer-2 (SCI and SCE). For example, if we have n

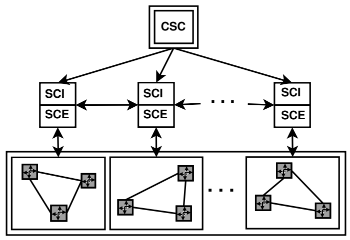

Figure 1: System Architecture

number of layer-2 controllers and m number of available APs, CSC assigns $\lfloor \frac{m}{n} \rfloor$ number of APs to first $(n-1)$ layer-2 controllers. The remaining $(m - \lfloor \frac{m}{n} \rfloor)$ APs are given to the control of the n^{th} controller. Further, the layer-2 controllers can interact with each other when a controller wants to transfer the control of an AP to an another controller.

3.2 Policy Generation for Setting Link Parameters

Policy generator for setting the values of different link parameters resides in the sub-module – *configuration setting rule*. We formulate an optimization problem where we try to minimize a utility function. While a station (STA) connects to an AP, a traffic flow is maintained by that AP on the behalf of the STA. Hence, we represent the number of STAs by the number of flows controlled by APs. Let us consider p_i denotes the PER of flow i. In our proposed mechanism, we consider channel bonding, MIMO streams, guard interval, frame aggregation and MCS to construct the link configuration set that will control data transmission. Let c_i, s_i, g_i, a_i and m_i be the values of channel bandwidth, number of MIMO spatial streams, guard interval, level of frame aggregation and MCS value for i^{th} flow. c_i ranges from $minBand$ to $maxBand$, and s_i varies from $minStream$ to $maxStream$. g_i can be either $minGi$ (400 ns) or $maxGi$ (800 ns). The level of frame aggregation varies from $minLevel$ to $maxLevel$, where we include four levels of frame aggregation. m_i varies from $minMcs$ to $maxMcs$. Each of these configuration parameters (c_i, s_i, g_i, a_i and m_i) is normalized by a *sigmoid function*. For variable t, sigmoid function is defined as $f(t) = \frac{1}{1+e^{-t}}$.

Any soft real-time traffic has a saturation point, but since such traffic has flexible delay tolerance, their utility graph is concave in nature. Without much loss of generality, we can assume that soft real-time traffic has logarithmic utility pattern. As traffic increases, PER in the network also increases and thus, our aim should be to minimize PER of the network. At the same time, we must try to increase the values of the configuration parameters to obtain a high throughput. Let z_i denote the sum of the normalized values of four configuration parameters of flow i. Hence, z_i can be represented as follows.

$$z_i = f(c_i) + f(s_i) + f(g_i) + f(a_i) + f(m_i)$$

Here, $f(c_i)$, $f(s_i)$, $f(g_i)$, $f(a_i)$ and $f(m_i)$ represent normalized values of c_i, s_i, g_i, a_i and m_i respectively. Moreover, assume x_i is the normalized version of z_i such that $x_i = f(z_i)$. In our approach, we consider PER and x_i as the metric of traffic utility measurement. Thus, our objective is to maximize x_i and minimize p_i. We define a function $\mathcal{F}$ considering p_i and x_i such that the objective will be the minimization of $\mathcal{F}$. Therefore, for n number of flows, the objective function with a set of constraints are given in the following.

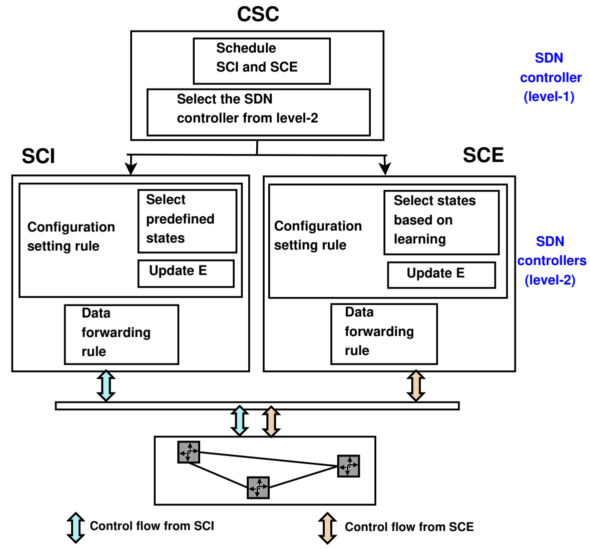

Figure 2: Functional components of CSC, SCI and SCE

$$\text{Minimize} \quad \mathcal{F} = \sum_{i}^{n} \frac{log(p_i)}{x_i} \tag{1}$$

subjected to

$$minBand \leq c_i \leq maxBand \qquad i = 1, 2, \ldots, n \tag{2}$$

$$minStream \leq s_i \leq maxStream \qquad i = 1, 2, \ldots, n \tag{3}$$

$$minGi \leq g_i \leq maxGi \qquad i = 1, 2, \ldots, n \tag{4}$$

$$minLevel \leq a_i \leq maxLevel \qquad i = 1, 2, \ldots, n \tag{5}$$

$$minMcs \leq m_i \leq maxMcs \qquad i = 1, 2, \ldots, n \tag{6}$$

This problem is a variant of the popular *bin-packing* problem. In the traditional bin-packing problem, the objective is to find the minimum number of bins. If we consider each flow as a *bin*, we do not want to reduce the number of bins in our case. This is because reduction of the number of flows will reduce the total network utilization. Thus, we need to determine the maximum possible values of our four configuration parameters such that overall PER of network will be reduced. As bin-packing is a combinatorial *NP-Hard* problem, we had no choice but to use an approximate algorithm for the estimation of link parameters. Exploiting this feature of the proposed optimization framework, we apply ϵ-greedy policy [21] as an approximate algorithm to set the values of the configuration parameters.

3.3 Metric Selection

Linkcon uses two channel metrics for selecting link parameters – (i) SNR of the channel and (ii) PER; considering channel bonding, MIMO streams, SGI, frame aggregation and advanced MCS values. SNR is a good measurement of signal quality since it indicates an additive effect from both interference noise and channel noise.

3.4 Model Description

In Linkcon, we consider channel bonding (c), MIMO spatial streams (s), SGI (g), level of frame aggregation (a) and MCS (m). It can be represented by a tuple $T < c, s, g, a, m >$. Level of channel bonding ranges from $minBand$ to $maxBand$. s takes number of MIMO streams ranging from $minStream$ to $maxStream$. g is either 800 ns or 400 ns. Let us consider a has n_a values. If $n_a = 1$, the maximum number of aggregated frames is considered and it is $maxLevel$. This value is decremented by the value of dec in successive higher values of n_a i.e., $minLevel = maxLevel - (n_a - 1) \times dec$. m ranges from $minMcs$ to $maxMcs$. The value of c is changed as follows.

$$c = 2^i \times minBand, \qquad i = 0, 1, \ldots, maxIndex - 1 \tag{7}$$

Here, $minBand$ is selected when $i = 0$ and $maxBand$ is chosen for $i = maxIndex - 1$.

Considering different values of T, a configuration set C is formed. Assume there are K number of configurations in C and thus, we have $|C| = K$. Two phases are proposed in this scheme – *configuration selection* and *data transmission*. In the configuration selection phase, the best possible values of link parameters are chosen. After that, data transmission begins for a time interval t. Let us consider $\mathcal{L}$ is the learner that applies ϵ-greedy policy to gain the knowledge about wireless environment. Based on the past experience, the learner takes decision in the selection phase. Hence, $\mathcal{L}$ performs the configuration selection phase and initiates data transmission. At the end of time t, $\mathcal{L}$ calculates PER and starts the next selection phase.

3.5 ϵ-greedy Policy

It is a well-known policy in machine learning [21]. A parameter ϵ, known as exploration probability, is used to control the learning rate. The policy enforcement employs two phases as follows.
Exploration: In this phase, a configuration is selected randomly and the probability of this selection is ϵ.
Exploitation: The configuration which has produced the best performance (in our case, it is PER) in the past is chosen in this case. The probability of exploitation is $(1 - \epsilon)$. These two approaches can be combined as a *Strategy*. Hence, a Strategy is defined as $Strategy = \epsilon \times Explore + (1 - \epsilon) \times exploit$.

3.6 SNR Estimation

To cope up with a mobile environment, at any time t of data rate estimation, we calculate the SNR value using *exponentially weighted moving average (EWMA)*, as follows.

$$S_{avg}(t) = \gamma \cdot S_{curr}(t) + (1 - \gamma) \cdot S_{avg}(t - 1) \tag{8}$$

In Eq. (8), $S_{curr}(t)$ is the present SNR value of the channel measured by $\mathcal{L}$ and $S_{avg}(t)$ represents the value of the EWMA which is treated as the estimated value of the SNR at t for selecting the data rate. $S_{avg}(t - 1)$ denotes the EWMA at $(t - 1)$. Here γ is a parameter representing the degree of decrease of weightage, and it lies between 0 and 1. At t, the deviation denoted by $Dev(t)$ is calculated between $S_{curr}(t)$ and $S_{avg}(t - 1)$ as follows.

$$Dev(t) = |S_{curr}(t) - S_{avg}(t - 1)|$$

Algorithm 1 Linkcon – Algorithmic Description

1: **Input:** C, E.
2: **Initialization:** Let us consider t_{init} is the number of rounds needed for building up initial statistic table. For $t = 1, 2, 3, \ldots, t_{init}$, calculate EWMA SNR of channel and select the configurations corresponding to the minimum and the maximum MCS of each $< c, s, g_{min}, a_{max}, m >$ from C and execute data the data transmission phase for a time period of (t_{dur}). Observe PER and update E.
3: **while** $t > t_{init}$ **do**
4:     Calculate ϵ_t by $\epsilon_t = min(1, rK/t^2)$.
5:     Calculate EWMA SNR of the channel. Assume $x \leftarrow$ EWMA SNR.
6:     Let $\gamma \leftarrow$ Random(0,1).
7:     **if** $\gamma \leq \epsilon_t$ **then**
8:         **if** $[(x - \alpha), (x + \alpha)] \in$ S in E **then**
9:             Choose $E_x \subset E$, such that E_x contains all the entries from E where the SNR $x \in [(x - \alpha), (x + \alpha)]$.
10:             Select configuration $y \in C$ from E_x, that produces the highest PER in E_x.
11:         **else**
12:             Select configuration $y \in C$ from E that produces the highest PER in E.
13:         **end if**
14:     **else**
15:         Select a configuration y uniformly at random in C.
16:     **end if**
17:     Initiate data transmission phase with the selected configuration y. After t_{dur}, calculate EWMA SNR x' and PER p.
18:     Update E with x', y and p.
19: **end while**

3.7 Statistics Table

As a statistic-based learning approach is followed by Linkcon, a statistics table E is created and maintained by $\mathcal{L}$. Let $E =< S, C, P >$, where S denotes the value of S_{avg} and P is PER. Hence, E contains the past experience of data transmission.

3.8 Linkcon: Algorithm

Execution steps of Linkcon is presented in Algorithm 1. A detailed description of this algorithm is given in the following.
(1) Initial experience phase (Step 2): This module is executed in the SCI instance of the SDN controller. $\mathcal{L}$ changes the value of c following Eqn.(7). Therefore, c is initially set to $minBand$ and ends with $maxBand$. $\mathcal{L}$ measures EWMA SNR and selects the configurations for the minimum and maximum value of MCS of each set $< c, s, g_{min}, a_{max}, m >$. After a time period t_{dur}, PER is calculated and E is updated accordingly. In this context, g_{min} refers to SGI and a_{max} specifies $maxLevel$ level of a. Here, t_{dur} should be chosen by the network administrator in such a way that the variation of channel condition (EWMA SNR) is least within that duration. In this way, the system is able to gather information about wireless environment for the best and the worst configurations. This phase is executed periodically to obtain the experience of system performance for different channel conditions.
(2) Experience phase (Step 3 - Step 19):

This module is executed in the SCE instance of the SDN controller. At the beginning of this phase, EWMA SNR is calculated, and let this value be x at time t. Based on the value of ϵ, $\mathcal{L}$ applies exploration and exploitation approaches. At time t, $\mathcal{L}$ calculates ϵ_t and searches for a value of SNR between $(x - \alpha)$ and $(x + \alpha)$ in E, for $\alpha > 0$. If the search is successful, the configuration that has provided the lowest PER for this range is chosen with probability $(1 - \epsilon_t)$. Otherwise, the learner selects the configuration in E with probability $(1 - \epsilon_t)$. If x is not present in aforesaid range of SNR, a configuration is selected uniformly at random in C by applying probability of ϵ_t. By considering these two cases (exploitation and exploration), let the chosen configuration be y. After that, data transmission is initiated with the chosen configuration. At the end of transmission phase

Table 1: Simulation Parameters

Parameter	Value
Channel bandwidth	20/40/80/160 MHz
Guard interval	400/800 ns
MIMO spatial streams	1/2/3
Traffic source	TCP traffic
TCP payload	1448 Bytes
Data and control mode	Constant rate wifi manager
Size of each MPDU	2 KB
A-MPDU length	$minLevel = 10$, $maxLevel = 40$
Maximum physical data rate	2340 Mbps
Path loss model	Log-normal (path loss exponent=0.3)
Propagation delay model	Constant speed propagation
Simulation time	10 mins
Number of repeated experiments under a scenario	10

(time period t_{dur}), EWMA SNR and PER are calculated and let these values be x' and p respectively. Then, E is updated with x', y and p.

4 PERFORMANCE ANALYSIS

Linkcon has been implemented in network simulator (NS) version NS-3.25 and we analyze the performance through infrastructure IEEE 802.11ac WLAN. There are multiple wireless STAs in the network. They are contending for accessing channel and transmitting data among themselves. Type of frame aggregation is A-MPDU. α, dec and r are set to 5.0, 10 and 1.0 respectively. The details of the simulation set-up are presented in Table 1. We compare the performance of Linkcon with respect to RAM [3], MUSE [19], ESNR [8], SampleLite [13] and Minstrel HT [7].

4.1 Analysis of Throughput

Figure 3 demonstrates the performance of Linkcon with respect to average throughput. Consideration of EWMA SNR enables Linkcon more adjustable with abrupt change of signal strength. $\mathcal{L}$ makes Linkcon intelligent to cope up with channel condition. The exploration technique applied by $\mathcal{L}$ leads to the examination of the performance of unexplored configurations. Exploration becomes valuable in highly congested network. When $\mathcal{L}$ applies different set of parameters in congested scenario, it gains knowledge about the performance of these sets. In the future, this experience helps to select the best suited configuration in a crowded environment. For selecting data rate, MUSE focuses on the selection of MU-MIMO antenna and ESNR applies MIMO technology. However, none of them consider the frequent change of signal quality in wireless environment. Similarly, SampleLite and MinstrelHT were mainly developed for static station. RAM deals with mobility, but it does not engage enhanced features of HT-WLANs. From Figure 3(b), Linkcon has a throughput of 1.7 and 12 times higher than that of MUSE and ESNR respectively in congested environment (20 stations). Whereas, the other competing schemes are lagging far behind of Linkcon.

4.2 Analysis of Packet Loss Ratio (PLR) and Packet Delay

Application of both exploration and exploitation helps to maintain a balance between unexplored configurations and the best suited

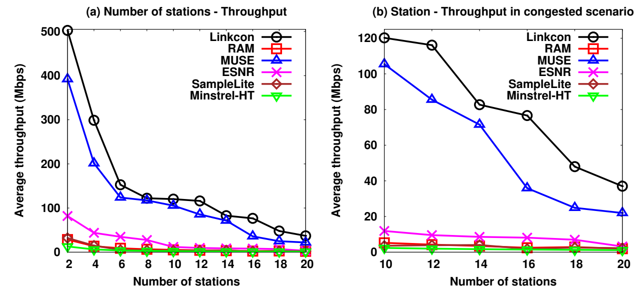

Figure 3: Performance in terms of throughput

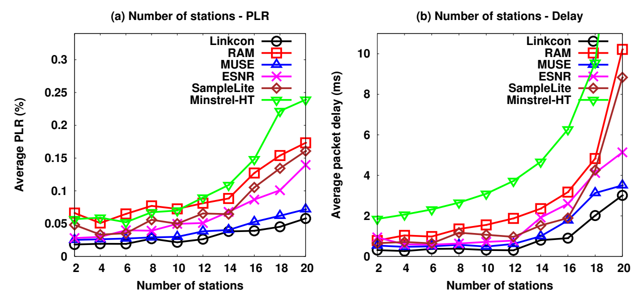

Figure 4: Performance in terms of PLR and packet delay

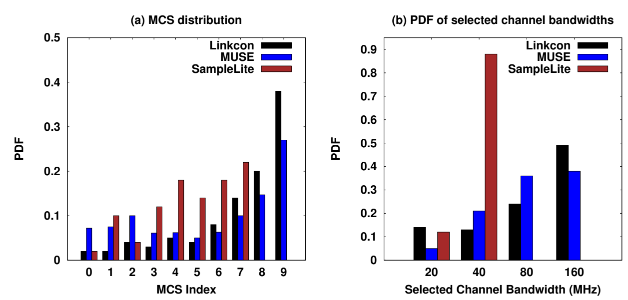

Figure 5: Analysis of Linkcon in selecting parameters: (a) PHY rate distribution; (b) channel bandwidths

configurations. As time progresses, exploitation increases. As a consequence, the system becomes able to choose parameter set as per the signal level. Hence, packet loss is reduced (Figure 4(a)). Further, due to low PLR and the increase of average throughput, packet delay is reduced as demonstrated in Figure 4(b). From Figure 4(a), Linkcon has PLRs of 52.31% and 75.43% less than that of MUSE and ESNR respectively (20 stations).

4.3 Selection of Configuration

Selection of an appropriate configuration according to channel condition is the key issue for adapting with mobile environment. To analyze it, we examine which configurations are being selected at different time instants by Linkcon, MUSE and SampleLite. In this case, we compute probability density functions (PDFs) of the parameters. Since RAM does not choose such configuration set, we do not include it in this analysis. Since ESNR uses MIMO technology, we consider EWMA SNR in evaluating the selection of MIMO antennas.

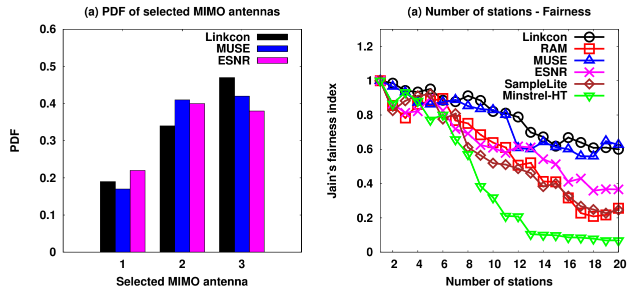

Figure 6: (a) Performance of Linkcon in selecting MIMO antennas; (b) Fairness comparison

Linkcon: $\mathcal{L}$ gains experience about mobile environment and it always tries to apply the highest possible values of these parameters. During exploration, $\mathcal{L}$ gains knowledge about the performance of configurations. On the basis of it, Linkcon tries to adjust with network condition by exploiting the maximum possible values of these parameters. As a result, probabilities of using the maximum values of these features are higher in Linkcon than the other schemes shown in Figure 5 and Figure 6(a).

MUSE and SampleLite: Due to the lack of intelligent learning, MUSE can not cope up with mobile environment. Thus, it applies all PHY rates, channel bandwidths and MIMO streams with an average probability distribution as shown in Figure 5 and Figure 6(a). Since SampleLite was designed for IEEE 802.11n, all MCS values and channel bandwidths of IEEE 802.11ac are not used by this scheme. SampleLite can not cope up with variation of SNR values because its threshold-based scheme does not fit in all network scenarios. Therefore, from Figure 5 and Figure 6(a) Linkcon outperforms others. In Linkcon, PDFs at MCS 9 and channel bandwidth 160 MHz are 1.41 and 1.29 times higher than that of MUSE, respectively (Figure 5). As shown in Figure 6(a), Linkcon applies 3 MIMO streams 1.12 times more than that of MUSE.

4.4 Fairness comparison

A comparative analysis of Jain's fairness indices of throughputs of all competing mechanisms is presented in Figure 6(b). Linkcon also provides better fairness than other schemes. In a congested network, after some runs, $\mathcal{L}$ finds parameter sets which have the best performance so far. Considering the past information about the congested scenario along with EWMA SNR, Linkcon improves the fairness in a network.

5 CONCLUSION AND FUTURE DIRECTION

Linkcon applies a machine learning policy, ϵ-greedy to select the best possible link parameter set for transmitting data. We design a SDN architecture that executes our proposed mechanism. In the SDN framework, SCI and SCE run as a single unit in multiple systems in a distributed way.The distributed nature of the proposed SDN framework enable Linkcon to run for multiple wireless stations simultaneously. Moreover, the centralized module helps to provide a global view of the entire network. In mobile environment, due to the rapid change of signal strength, EWMA SNR is employed as the measurement of channel condition. The performance of Linkcon is evaluated through simulation. We show that our scheme boosts up the performance of a system significantly compared to other competing schemes mentioned in the literature. In future we plan to deploy Linkcon over a testbed and extend its capability under various mobility scenarios.

REFERENCES

[1] 2017. ath9k 802.11n Wireless Driver. http://linuxwireless.org/en/users/Drivers/ath9k. (2017).

[2] 2017. Madwifi: Multiband Atheros Driver for WiFi. http://sourceforge.net/projects/madwifi/. (2017).

[3] Xi Chen, Prateek Gangwal, and Daji Qiao. 2012. RAM: Rate Adaptation in Mobile Environments. *IEEE Transactions on Mobile Computing* 11, 3 (March 2012), 464 – 477.

[4] Lara Deek, Eduard Garcia-Villegas, Elizabeth Belding, Sung-Ju Lee, and Kevin Almeroth. 2013. Joint Rate and Channel Width Adaptation for 802.11 MIMO Wireless Networks. In *Proceedings of the 10th Annual IEEE SECON*. 167 – 175.

[5] Lara Deek, Eduard Garcia-Villegas, Elizabeth Belding, Sung-Ju Lee, and Kevin Almeroth. 2014. Intelligent Channel Bonding in 802.11n WLANs. *IEEE Transactions on Mobile Computing* 13, 6 (june 2014), 1242 – 1255.

[6] Kai-Ten Feng, Po-Tai Lin, and Wen-Jiunn Liu. 2010. Frame-aggregated link adaptation protocol for next generation wireless local area networks. *EURASIP Journal on Wireless Communications and Networking* 2010, 10 (April 2010).

[7] Felix Fietkau. 2010. Minstrel HT: New Rate Control Module for 802.11n. http://lwn.net/Articles/376765/. (March 2010).

[8] Daniel Halperin, Wenjun Hu, Anmol Sheth, and David Wetherall. 2010. Predictable 802.11 packet delivery from wireless channel measurements. *ACM SIGCOMM Computer Communication Review - SIGCOMM '10* 40, 4 (October 2010), 159 – 170.

[9] Israat Tanzeena Haque and Nael Abu-Ghazaleh. 2016. Wireless Software Defined Networking: A Survey and Taxonomy. *IEEE Communications Surveys & Tutorials* 18, 4 (May 2016), 2713 – 2737.

[10] Kawther Hassine and Mounir Frikha. 2014. MAC aggregation in 802.11n: Concepts and impact on wireless networks performance. In *Proceedings of the 2014 ISNCC*. 1–6.

[11] Raja Karmakar, Samiran Chattopadhyay, and Sandip Chakraborty. 2015. Dynamic link adaptation for High Throughput wireless access networks. In *in Proceedings of IEEE ANTS*. 1–6.

[12] Raja Karmakar, Samiran Chattopadhyay, and Sandip Chakraborty. 2016. Dynamic Link Adaptation in IEEE 802.11ac: A Distributed Learning Based Approach. In *Proceedings of the 41st IEEE LCN*. IEEE.

[13] Lito Kriara and Mahesh K Marina. 2015. SampleLite: A Hybrid Approach to 802.11n Link Adaptation. *ACM SIGCOMM Computer Communication Review* 45, 2 (April 2015), 4–13.

[14] Chengchao Liang and F. Richard Yu. 2015. Wireless Network Virtualization: A Survey, Some Research Issues and Challenges. *IEEE Communications Surveys & Tutorials* 17, 1 (2015), 358 – 380.

[15] Wen-Jiunn Liu, Chao-Hua Huang, Kai-Ten Feng, and Po-Hsuan Tseng. 2014. Performance analysis of greedy fast-shift block acknowledgement for high-throughput WLANs. *Wireless Networks* 20, 8 (2014), 2503–2519.

[16] Duy Nguyen and J.J Garcia-Luna-Aceves. 2011. A practical approach to rate adaptation for multi-antenna systems. In *Proceedings of the 19th IEEE ICNP*. 331 – 340.

[17] Ioannis Pefkianakis, Yun Hu, Starsky H.Y Wong, Hao Yang, and Songwu Lu. 2010. MIMO rate adaptation in 802.11n wireless networks. In *Proceedings of the 16th MobiCom*. 257–268.

[18] Eldad Perahia and Michelle X Gong. 2011. Gigabit wireless LANs: an overview of IEEE 802.11ac and 802.11ad. *ACM SIGMOBILE Mobile Computing and Communications Review* 15, 3 (2011), 23–33.

[19] Sanjib Sur, Ioannis Pefkianakis, Xinyu Zhang, and Kyu-Han Kim. 2016. Practical MU-MIMO user selection on 802.11ac commodity networks. In *Proceedings of the 22nd Annual MobiCom*. ACM, 122 – 134.

[20] Masato Taki, Mandana Rezaee, and Maxime Guillaud. 2014. Adaptive modulation and coding for interference alignment with imperfect CSIT. *IEEE Transactions on Wireless Communications* 13, 9 (2014), 5264–5273.

[21] Christopher Watkins. 1989. Learning from Delayed Rewards. PhD thesis, University of Cambridge, Cambridge, England. (May 1989).

[22] Shanshan Wu, Wenguang Mao, and Xudong Wang. 2014. Performance Study on a CSMA/CA-Based MAC Protocol for Multi-User MIMO Wireless LANs. *IEEE Transactions on Wireless Communications* 13, 6 (2014), 3153–3166.

[23] Weihua Helen Xi, Alistair Munro, and Michael Barton. 2008. Link Adaptation Algorithm for the IEEE 802.11n MIMO System. In *Proceedings of the 7th IFIP-TC6 Networking*. 780–791.

[24] Qiuyan Xia, M Hamdi, and K Ben Letaief. 2009. Open-Loop Link Adaptation for Next-Generation IEEE 802.11n Wireless Networks. *IEEE Transactions on Vehicular Technology* 58, 7 (January 2009), 3713 – 3725.