BDAC: A Behavior-aware Dynamic Adaptive Configuration on DHCP in Wireless LANs

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***Abstract*—DHCP is widely used to dynamically allocate IP addresses to the devices on local area networks, but the explosive increases of WiFi devices and their frequent mobility pose great challenges on DHCP performance in wireless LANs. In this paper, by analyzing large scale real network traces, we observe that the dynamic WiFi user behavior (e.g., online time pattern and spatio-temporal mobility pattern) leads to the poor DHCP performance. The IP pools in some VLANs have been exhausted in rush hours although the total IP utilization in WLAN is only 24%. Therefore, we have to configure IP lease times and IP pools dynamically and make sure that they are adaptive to the WiFi user behavior. In order to achieve this goal, we characterize and model the user behavior across online time pattern and spatio-temporal mobility pattern. Then we propose BDAC, a behavior-aware dynamic adaptive configuration, which is combined of two strategies: adaptive IP lease time configuration and dynamic IP pool configuration. The former is to set adaptive lease times across user roles and area types based on online time pattern to reclaim IP addresses in time and reduce the peak IP usage, while the latter dynamically migrates the IP addresses across VLANs based on spatio-temporal mobility correlation to save the IP addresses. Using the real network traces of a different week, we conduct experiments to evaluate the performance of BDAC. Results show that BDAC can save up to 60% of IP addresses and the actual IP utilization rises from 24% to 59%. Furthermore, BDAC maintains high IP utilization when the number of VLANs in a WLAN increases.**

I. INTRODUCTION

The Dynamic Host Configuration Protocol (DHCP) [1] is used to automatically assign IP address and related configuration information to client on local area networks (LANs). Because of its convenience, DHCP is widely adopted in wireless LANs (WLANs), especially in campuses and enterprises where the networks are large scale with many WiFi devices. However, the explosive increases of WiFi devices, such as smartphones, tablets and smart watches in recent years [2] [3], and their frequent mobility increase the demand on IP addresses in WLANs. While the configuration on DHCP server remains the same in WLANs, *dynamic WiFi user behavior* (e.g., online time pattern and spatio-temporal mobility pattern) poses great challenges on DHCP performance. For example, if a user with one WiFi device use an IP address in one place for a short time and moves to another place, her device may acquire a new IP address while the previous IP address is not reclaimed. As a result, her device occupies two IP addresses for a certain period of time and it causes the waste of IP address. In addition, a user may hold several WiFi devices. This aggravates the waste of IP addresses.

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In order to pursue high efficiency of IP address utilization, we have to configure the parameters on DHCP server dynamically and make sure that they are adaptive to the WiFi user behavior. There are two important IP configuration parameters on DHCP server: ***IP Lease Time*** and ***IP Pool***. The former determines how long a device can use an IP address within one request time. If DHCP server does not receive *request* message from client within a lease time, it reclaims the IP address when the lease expires [1]. The latter determines the maximum number of IP addresses provided for clients in a Virtual LAN (VLAN). Specifically, the large scale WLAN is usually separated into multiple VLANs to reduce the broadcast traffic [4]. Each VLAN is configured with an IP pool containing a number of IP addresses. As WiFi user behaves dynamically, the current static IP lease time and IP pool configuration on DHCP server in WLANs lead to poor DHCP performance.

Existing studies have tried to improve DHCP performance by adjusting IP lease time according to mobile device operating systems [5] [6] and user online patterns [7] [8]. To best of our knowledge, no prior work has studied the impact of spatio-temporal mobility pattern on DHCP performance. In this paper, by analyzing large scale real network traces, we studied impact of user behavior on DHCP performance with static IP configuration and observed that dynamic WiFi user behavior led to poor performance. For example, users arrive with sharp increment and leave after a short stay in the VLAN of eating area. On the one hand, if we configure a large IP pool that the number of IP addresses exceeds the peak IP demand in that VLAN, a large amount of IP addresses will be wasted in other time periods. On the other hand, if we configure a small IP pool that the number of IP addresses does not meet the peak IP demand, a number of clients are unable to get IP addresses to access the Internet in rush hours. In addition, if we configure a long lease time in this area, the IP addresses are wasted because they are not reclaimed in time.

To address the challenges caused by dynamic WiFi user behavior, we propose BDAC, a **B**ehavior-aware **D**ynamic **A**daptive **C**onfiguration on DHCP server, to save the IP addresses and improve IP utilization. Specifically, we firstly model the WiFi user behavior across online time pattern and spatio-temporal mobility pattern. Then we propose two configuration strategies: adaptive IP lease time strategy and dynamic IP pool configuration strategy. The former is to set dynamic lease times across user roles and area types based on user online time pattern to reclaim IP address in time and reduce the peak IP usage, the latter dynamically migrates IP addresses across VLANs based on spatio-temporal mobility correlation to save IP addresses. The main contributions of this paper are as follows:

- To best of our knowledge, our measurement is one of the largest-scale measurements and we make the observation that the dynamic WiFi user behavior leads to poor DHCP performance. The IP pools of two VLANs are exhausted in rush hours although the total IP utilization in the WLAN is only 24%.
- We characterize the dynamic WiFi user behavior from two dimensions: online time pattern and spatio-temporal mobility pattern. We observe that online time pattern varies across user roles and area types. Specifically, 80% of online time sessions in eating area are shorter than 30 minutes while 50% of online time sessions in living area are longer than 120 minutes for students. In addition, spatio-temporal mobility pattern brings about IP demand fluctuation over time and areas. We observe that the number of online users in the VLAN of eating area increases by 24 times in rush hours compared to the average.
- We model the online time pattern with hyper-exponential distribution and model the spatio-temporal mobility pattern based on correlation of two spatio-temporal points. Then we propose BDAC, which is combined of two configuration strategies on DHCP server: adaptive IP lease time configuration and dynamic IP pool configuration. The first strategy is to set adaptive lease times across user roles and area types to reduce the peak IP usage, while the second strategy is to dynamically migrate IP addresses across VLANs to save IP addresses.
- We conduct comprehensive experiments on real network traces of a different week to evaluate the performance of BDAC. Results show that BDAC outperforms the existing methods that BDAC can save up to 60% of IP addresses and the actual IP utilization rises from 24% to 59%. In addition, BDAC shows strong robustness that it maintains high IP utilization when the number of VLANs in a WLAN increases.

The rest of this paper is organized as follows. Section II describes the background on DHCP and our collected dataset. In section III, we characterize and model the dynamic user behavior across online pattern and spatio-temporal pattern. Section IV presents the behavior-aware dynamic adaptive configuration strategies and evaluation results are presented in V. Section VI presents the related work and we conclude the paper in Section VII.

II. Background and Dataset

A. Background on DHCP

There are two important IP configuration parameters on DHCP server and we will describe them below in detail.

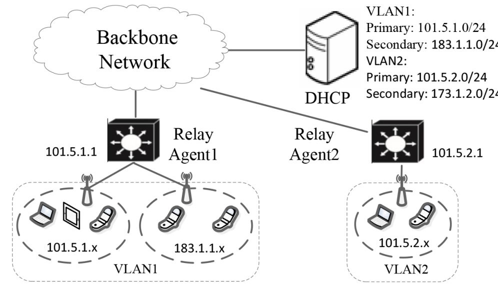


Fig. 1: The widely deployed DHCP architecture.

IP Pool: As the network is large scale with many clients, the broadcast messages sent by the clients will consume large amounts of bandwidth. Therefore, large scale WLAN is generally separated into multiple VLANs to reduce the broadcast messages [4]. However, it is unnecessary to have a DHCP server for each VLAN. The DHCP relay agent [9] is introduced to convert the broadcast DHCP packet from the client in its broadcast domain, and forward it to DHCP server. Fig. 1 shows the widely deployed DHCP architecture in large scale WLANs. The DHCP relay agents enable one DHCP server to control multiple VLANs. The **IP pool** configured for each VLAN on DHCP server could be combined of two IP sets: primary IP set and secondary IP set. The primary IP set is static once it is configured. When the DHCP server receives DHCP *request* message from the relay agent, it firstly determines the corresponding IP pool by *ANDing* the IP address of relay agent with the primary IP set in each IP pool and then allocates the IP address in that pool to the client. The IP addresses in the primary IP set are firstly allocated and the addresses in secondary IP set are allocated only when the primary IP set is exhausted. The number of IP addresses in secondary IP set can be configured dynamically with multiple subnets, so that network administrators could manage the size of IP pool flexibly by increasing or decreasing the number of subnets in each VLAN.

IP Lease Time: The DHCP [1] enables clients to attach to network automatically. Specifically, there are three states in a complete IP lease period: initializing state, renewing state and releasing state. In the initializing state, a client acquires an IP address with a **lease time** after four message exchanges: client broadcast *discover* message, DHCP server *offer* message, client unicast *request* message and DHCP server *acknowledgement* message. In the renewing state, the client sends a *request* message to the DHCP server to extend the IP lease. The *request* message is sent periodically after half of the lease time if the client is still active. The releasing state happens in two kinds of cases. First, the client sends an explicit *release* message to the DHCP server to release the IP address before she leaves the network. Second, if the client has not sent the *request* message for a lease time, the DHCP server expires the lease and reclaims the IP address. The previous work has shown that about 1% of clients actively send *release* messages (the first case) to release the IP addresses [8]. Therefore, the network administrators should set up lease time adaptively. Long lease times can lead to the exhaustion of the IP pool while short ones increase the load of DHCP servers.

B. DataSet

The WLAN in T campus is large scale with about 40,000 individuals, 100,000 WiFi devices and 110,000 public IPv4 addresses. There are 26 VLANs covering 155 buildings with 8000 APs. All APs share the same SSID, allowing the WiFi users auto-connection when roaming in campus. We collect the real network traces for two typical weeks from 04/07/2018 to 04/20/2018. The traces in former week are used to generate the configuration strategies and the traces in latter week are used for evaluation. The dataset include about 65 million DHCP logs, 110 million SNMP logs and 1 million AAA [10] logs.

We collect DHCP logs which record the message exchanges between the clients and the DHCP servers. Each entry records an interaction *event*. A sample of DHCP log has the following format: ***timestamp, event, IP address, MAC***. The fields in the log represent that a user with *MAC* interacts with the DHCP server on the address of *IP address*. The event types, *e.g.*, offer (initializing state), renew (renewing state), release and expire (releasing state), are detailedly described in Section II-A. We correlate the event to calculate the IP usage and load of DHCP server [5]. In addition, there are a number of *scope full* events in the logs which mean that the IP pool for that VLAN is exhausted.

We setup SNMP manager program to pull SNMP logs from APs every 5 minutes. The SNMP logs provide the detailed information of each AP and their associated clients, including IP address, MAC address, AP name, Physical Channel, Interface Utilization, etc. We only extract part of the information in our work. A sample of SNMP logs has the following format: ***timestamp, IP address, AP name, client MAC***. The fields represent a client with *IP address* and *client MAC* is connecting to an AP with *AP name* at time of *timestamp*. Each AP is named with building name and a unique numeric ID, which is used for identifying the location of that AP.

Based on authentication credentials in T campus, we are able to obtain the role (e.g. student and teacher) of authenticated clients from the campus information system. A sample of authentication log has the following format: ***timestamp, IP address, client ID, role***. The fields in the log represent the client with *client ID* and *role* authenticates the *IP address* at time of *timestamp*. To best of our knowledge, we are the first to study the user online time pattern with different roles.

It is worth pointing out that the privacy issues of the dataset are seriously considered. We collaborated with the network administrators to anonymize the sensitive network traces to remove any personally identifiable information before using it in our study. Specifically, we anonymize the IP addresses, MAC addresses and client ID with the prefix-preserving anonymization as proposed in [11]. The anonymization methods and parameters are kept consistent over all logs. We then use the timestamp and client MAC address to correlate the three network traces.

As shown in previous work [12] [8], area types can provide useful information about the aggregated user behavior. We

TABLE I: The Count of VLANs and Users in Studied Campus Network

(a) VLAN count in different areas

No.	Building Type	Count
1	Studying Area	6
2	Working Area	6
3	Eating Area	1
4	Living Area	13
#	Total	26

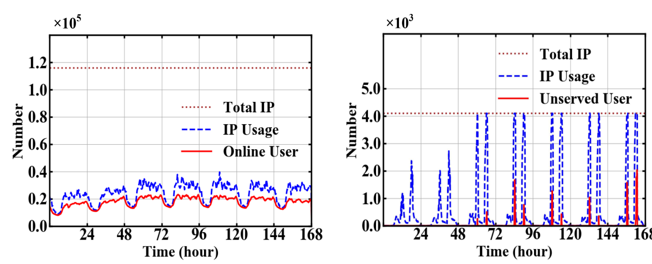
(b) User number in different roles

No.	User Role	Number
1	Student	27491
2	Teacher	9373
3	Unknown	501
#	Total	37365

divide 155 buildings into 4 area types according to their functions: studying area (including classrooms and libraries), working area (including offices and departments), eating area and living area. There are 26 VLANs and each VLAN is configured for multiple buildings with the same area type in the studied campus. The number of VLANs in each area is listed in Table I(a). Since the WiFi user behavior is similar in the VLANs of the same area type, we characterize their behavior pattern at the area level to study the aggregated behavior in VLANs [8]. In addition, we divide the users into 2 categories: students and teachers, to characterize the online time behavior with different roles. The number of users in each role is shown in Table I(b).

C. DHCP Performance Measurement

Based on the real network trace for a typical week (from Saturday to Friday), we take the first step into studying the DHCP performance in the WLAN. Fig. 2(a) shows correlation between the total number of online users and the IP usage. We observe that the number of online users follows daily pattern: the number of users is high in the day and drops at midnight. Similarly, the IP usage follows daily pattern. An interesting observation is that the peak number of online users reaches about 26,000, however, these users account for about 42,000 IP usage at the peak time. This can be explained by the reason that a client may occupy an IP address in one place and needs to apply for a new IP address when she move from a place to another. Therefore, the client occupies two IP addresses for a certain period of time. In order to quantify the IP usage efficiency in studied WLAN, we define ***IP utilization*** as the ratio of max online user vs. total IP addresses. Based on the definition, we observe that the IP utilization is quite low in the studied WLAN that the IP utilization only accounts for 24%.



(a) (b)

Fig. 2: (a). The number of online users and the IP usage. (b). The number of IP usage and unserved users of the VLAN in eating area.

In the further step, we study the IP usage in each VLAN. We observe that the number of online users and the IP usage also follows daily pattern. Surprisingly, we observe that the IP pools are exhausted in two VLANs locating in eating area and studying area (The DHCP server declines the IP lease request and logs an *scope full* event.). Fig. 2(b) depicts the IP usage and the number of unserved users in the VLAN of eating area (The figure in the VLAN of studying area is similar and omitted due to page limit). From the figure, we find that the IP demand is extremely high in rush hours, resulting in the IP pool exhaustion for a certain period of time. Therefore, about one third of the users in that VLAN are unable to get IP addresses to access the Internet in rush hours. However, the IP demand is quite low at other times.

Summary: *We conclude that the dynamic WiFi user behavior leads to the poor DHCP performance that the IP pool in some VLANs would be exhausted in rush hours, resulting in large number of users being unable to get IP addresses, although the total IP utilization in the WLAN is quite low.*

III. Dynamic User Behavior Study

The dynamic WiFi user behavior in the WLAN poses great challenges on DHCP performance and it motivates us to take the further study to characterize the user behavior. Since the WiFi user behavior is similar in the VLANs of the same area type [12], [8], we characterize the behavior pattern at the area level to study the aggregated behavior in the VLANs. In detail, we firstly study how WiFi user behaves from two dimensions: online time pattern and spatio-temporal mobility pattern, and then present corresponding models to capture their behavior pattern.

A. Studying Online Time Pattern

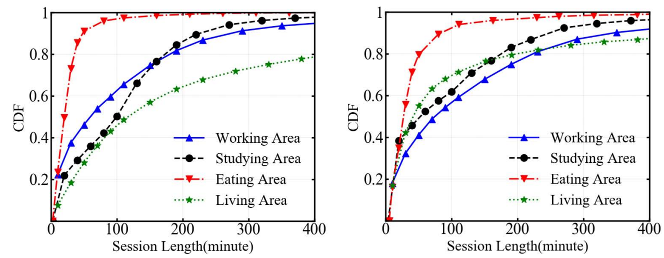
Characterizing Online Time Pattern: The *user online time* is defined as how long a client connects to the network in a session. Determining user online time is a bit challenging as the WiFi user behaves casually and they would leave the network at anytime without sending any notice message. By combining the DHCP logs and SNMP dataset, we design two rules to determine user online time. The details are shown below:

Rule1: If the client sends an explicit *release* message to the DHCP server before she leaves the WLAN, the user online time is denoted as (DHCP release time - DHCP offer time).

Rule2: If there is an *expire* message in the DHCP logs, we believe that the client leaves the network before the timestamp of the *expire* message. Then we find the timestamp when the client is last seen in SNMP dataset and approximate user online time with (SNMP last seen time - DHCP offer time).

Similar to the previous work [8], we observe that Rule1 only accounts for less than 1% of total sessions in studied WLAN. In other words, almost all users leave the network without sending the explicit *release* message. Hence, it is important to consider Rule2 in our study.

Based on these rules, we are able to characterize the user online time pattern. In order to take a further study, we divide the clients across user roles and area types. To best of our knowledge, *we are the first to study the user online time with different roles*. Fig. 3(a) and Fig. 3(b) depict the online time distributions of students and teachers across different area types respectively. We observe that the user online time pattern follows long-tail distributions across user roles and area types generally, however the pattern varies across user roles and area types. For students, we observe that the online time is long in living area that about 50% of online time sessions are more than 120 minutes. However, the online time for teachers is much shorter in living area that more than 50% of online time sessions are less than 45 minutes. As for eating area, the online time of students and teachers is similar and is very short that about 80% of online time sessions are less than 30 minutes. In studying area, the online time pattern of students is closely related to the length of a class. As for working area, the teachers are more likely to stay for a longer time than the students.

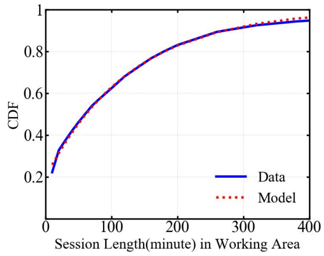


(a) Students (b) Teachers

Fig. 3: CDF of the user online time distribution in different areas with students and teachers.

Since the online time pattern varies across user roles and area types, the static IP lease time configuration on DHCP does not adapt to the dynamic online time pattern. Long lease times will prevent the DHCP server from reclaiming IP addresses in time and result in the waste of IP addresses. Short lease times will introduce much load on the DHCP server. Therefore, setting adaptive IP lease times based on the online time pattern is an appealing approach to reduce the peak IP usage while not introducing much DHCP load.

Modeling Online Time Pattern: In order to determine the proper IP lease time for each combination of user roles and area types, we first model the user online time distribution and then create the model to reveal the relationship between IP lease times and IP usage. As shown in Fig. 3 that the user online time pattern in studied WLAN follows long-tail distributions, we use *two-stage hyper-exponential distribution* [13] to model the user online time distribution for each combination of user roles and area types. The density function can be represented as follows: $f(x) = a_1 p e^{-a_1 x} + a_2(1-p)e^{-a_2 x}$, where $a_1 > 0$, $a_2 > 0$, and $p \in [0, 1]$. We then use the iterative method to determine the values of these parameters for each combination. Fig. 4 shows the modeling results compared with the real data of two combinations (i.e. students in working area and teachers in eating area) which the residual errors are 0.007 and 0.011 respectively. The results validate the effectiveness



(a) Students (b) Teachers

Fig. 4: CDF of the user online time distribution with the modeling results compared with the real data.

of our user online time distribution model. Due to the page limit, we omit the rest figures in the paper.

We define user online time as l_1 and *IP occupation time* as l_2. The l_2 means how long a client occupies the IP address for a complete IP lease period. Since Rule2 accounts for more than 99% of total sessions in studied WLAN, we focus on Rule2 in our work. The relationship of l_1 and l_2 can be determined with $l_1 + L - l_1\%(L/2) = l_2$ where L is the IP lease time and $\%$ is the symbol of modulo. For example, if the user connects to the network and leave the network after 20 minutes and the IP lease time L in the network is set to 30 minutes, the IP occupation time l_2 would be 45 minutes. Specifically, the user would send *renew* message after connecting the network for 15 minutes and then the DHCP server release the IP address while not receiving the message for a lease time. In area s, we define the density function of students and teachers as $f_s^1(x)$ and $f_s^2(x)$ respectively. Then the density function of IP occupation time can be represented as follows:

$$I_s(y) = \{\theta \sum_{y-L_s^1}^{y} p_s^1(x) f_s^1(x) \mid x + L_s^1 - x\%(L_s^1/2) = y\}$$
$$+\{(1-\theta) \sum_{y-L_s^2}^{y} p_s^2(x) f_s^2(x) \mid x + L_s^2 - x\%(L_s^2/2) = y\}$$

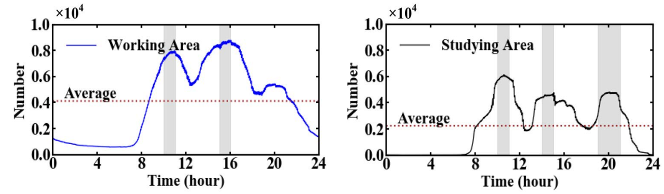
where θ is the proportion of sessions that is produced by students, L_s^1 and L_s^2 represent the IP lease times of students and teachers in the VLANs of area s respectively, and $p_s^1(x)$ and $p_s^2(x)$ represent the proportion of sessions with length of x on students and teachers in area s respectively.

Based on the density function of IP occupation time in area s, we model the IP usage at each time based on the user arrival rate on the assumption that the user arrival is subject to a Poisson distribution with a constant arriving rate over a short period of time [14]. The IP usage at specific temporal point t in area s can be formulated as:

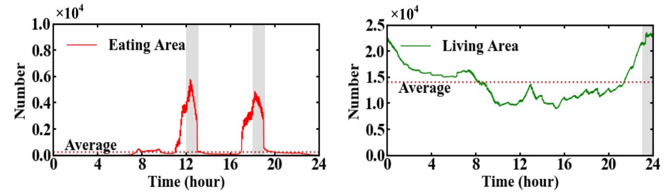
$$m_s(t) = \sum_{t_0=1}^{t} \lambda_s(t) - \sum_{t_0=1}^{t} [I_s(t-t_0) \sum_{t_1=1}^{t_0} \lambda_s(t_1)]$$

where $\lambda_s(t)$ is the number of users arriving at time t. Then the total IP usage $M(t)$ at time t can be represented by:

$$M(t) = \sum_{s \in S} m_s(t) \tag{1}$$



(a) Working area (b) Studying area



(c) Eating area (d) Living area

Fig. 5: The number of online users with temporal mobility pattern. The peak time periods are indicated by shading.

Our IP usage model is able to calculate the IP usage with different lease time settings across user roles and area types. As a result, we can choose the optimal configuration combination of IP lease time according to the requirement and constraint on DHCP servers. The details will be described in Section IV-A.

B. Studying Spatio-temporal Mobility Pattern

Characterizing Spatio-temporal Mobility Pattern: The user spatio-temporal mobility pattern brings about the IP demand fluctuation among areas with the change of time. In order to conduct an efficient IP pool configuration strategy, we characterize the temporal pattern and spatial pattern of user behavior and the detail is shown below.

Fig. 5 depicts the number of online users across areas for a typical day. The four curves show that the temporal behavior of online user varies: 2 peaks a day in working area and eating area; 3 peaks a day in studying area and 1 peak in living area. The online user numbers in working, studying and living area are doubled in the peak compared to the average. Surprisingly, we find that the online user number in eating area increases by 24 times in the peak compared to the average. Then, we derive certain periods of time when the online users reach the peak for each area which are indicated by shading in Fig. 5. We find that the peak time are intersected across different areas. If the number of online user in one area reaches the peak, while the number of online user reaches the valley in the rest of areas. For example in 23:00-24:00, the online user reaches the peak in living area, while the online user reaches the valley in the rest of areas. These phenomena motivate us to study the spatial mobility pattern of online users.

We use the anonymized client MAC and the associated AP to track the user spatial mobility pattern. Fig. 6 depicts the mobility pattern of online user across areas for typical time periods. We observe that the mobility between different areas is large scale with thousands of users and their mobility pattern is closely related to their daily life regularity. A large number of users move to the studying area and working area

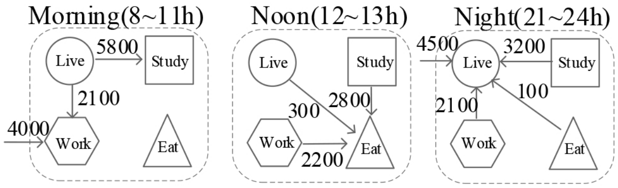


Fig. 6: The typical time periods of user spatial mobility pattern.

from living area in the morning. This can be explained by the fact that one part of users should attend the morning class and the rest should go to working area. There are additional 4,000 online users in the working area which can be explained by the reason that teachers always go to work from outside campus. At noon, the clients in working area, studying area and living area all move to eating area for meals and at night, the clients all return to the living area. Another interesting observation is that there are additional 4,500 online users in living area at night. This can be explained that an individual usually connects the WiFi with several WiFi devices at the same time in living area [15].

The spatio-temporal mobility pattern brings about the IP demand fluctuation across areas with change of time. The static IP pool configuration does not meet the dynamic mobility pattern of online user. If the number of IP addresses in the pool is configured merely exceeding the peak IP usage, a large amount of IP addresses are wasted at spare time. However, if the number of IP addresses is not configured to meet the peak IP demand, a number of clients are unable to get IP addresses to access the Internet in rush hours. The spatial-temporal redundancies of IP address result in the waste of valuable IP addresses. Therefore, dynamic IP pool configuration based on user spatio-temporal mobility pattern is an appealing approach to save IP addresses.

Modeling Spatio-temporal Mobility Pattern: In order to conduct the dynamic IP pool configuration strategy, we create the user mobility model to reveal the relationship between the spatial and temporal correlation. The number of online user at specific spatial-temporal point can be represented by a random variable $y_s(t)$ where s and t denote spatial and temporal index respectively. Assuming $y_s(t)$ is derived from a stochastic process $Y_s(t)$, we formulate the online user number with the form as follows:

$$\{Y_s(t) : s \in S, t \in T\}$$

where $S = \{s_1, \cdots, s_N\}$ and $T = \{t_1, \cdots, t_P\}$ denote spatial and temporal domain respectively. In our work, the spatial domain is divided into N and the temporal domain is discretized into P segmentations to aggregate the mobility statistics with equivalent segmentations. Based on our method, the spatial and temporal online user behavior can be captured in a unified manner.

We then introduce the spatial-temporal covariance function to study the spatio-temporal interaction of online users. Given a stochastic process in location s that is temporally first order stationary, thus, $E[Y_s(t)] = \mu$ and $Var[Y_s(t)] = \sigma^2$, we define the covariance for two spatial-temporal points:

$$Cov(Y_{s_i}(t_p), Y_{s_j}(t_q)) = \frac{1}{L}\sum_{L}((Y_{s_i}(t_p) - \mu_{s_i})(Y_{s_j}(t_q) - \mu_{s_j}))$$

where L is a set of time points that fall into the time t_p (or t_q), and μ_{s_i} and μ_{s_j} represent the average value of a stochastic process $Y_s(t)$ in s_i and s_j respectively.

Finally, its correlation function can be defined as:

$$\rho(Y_{s_i}(t_p), Y_{s_j}(t_q)) = \frac{Cov(Y_{s_i}(t_p), Y_{s_j}(t_q))}{\sigma_{s_i}\sigma_{s_j}} \tag{2}$$

where σ_{s_i} and σ_{s_j} represent the standard deviation of a stochastic process $Y_s(t)$ in s_i and s_j respectively. The correlation of two spatial-temporal points is significant when the correlation value approaches -1. This means that the user mobility happens between the two spatio-temporal points.

Our user mobility model reveals the relationship between the spatial and temporal correlation of WiFi user behavior. So we can design the corresponding algorithm to configure the IP pools flexibly (*i.e.*, migrating IP addresses) based on the demand of IP addresses in each spatial domain. The details will be described in Section IV-B.

IV. Dynamic Adaptive IP Configuration Algorithm

Based on the detailed WiFi user behavior study, we propose BDAC, which is combined of two configuration strategies on DHCP server: adaptive IP lease time configuration and dynamic IP pool configuration. The first strategy is to set adaptive IP lease times in VLANs across user roles and area types to reclaim IP address in time and reduce the peak IP usage. The second strategy is to dynamically configure the IP pool in each VLAN based on spatio-temporal mobility correlation.

A. Configuring Adaptive Lease Time

Since online time pattern varies across user roles and area types, conducting the static IP lease time configuration on DHCP server does not accommodate to the dynamic online time patterns. Therefore, we should set adaptive IP lease times to reduce the peak IP usage. Equation (1) provides the IP usage at each temporal point with different IP lease times. The objective of adaptive lease time configuration strategy is to minimize the peak IP usage while the increment of peak DHCP load is under a threshold since overload in DHCP server would influence the IP address allocation. The DHCP load can be computed from the message exchanges between the clients and the DHCP server which is widely used in previous work [5], [8]. Then the problem can be written as the following optimization problem with DHCP load constraint:

$$min \qquad max[M(t)] \tag{3}$$

$$s.t. \qquad Load_{now} \leq (1+\beta) \cdot Load_{ini} \tag{4}$$

where $Load_{now}$ and $Load_{ini}$ represent the maximum DHCP load based on the adaptive IP lease time strategy and original

Algorithm 1 Dynamic Lease Time Configuration Strategy

Input: $\mathcal{L}$, N, β
Output: $\mathcal{S}$, P

1: **Initialization:** $d \leftarrow 0$, $\overrightarrow{MinIP}$, $\overrightarrow{MinLoad}$, $R \leftarrow new[N]$
2: **function** $Search$(d, res, $\overrightarrow{MinIP}$, $\overrightarrow{MinLoad}$)
3:     **for** each (l_i, l_j) in $\mathcal{L}$ **do**
4:         add (l_i, l_j) to R;
5:         $\overrightarrow{MinIP}$ [d], $\overrightarrow{MinLoad}$ [d] $\leftarrow (l_i, l_j)$;
6:         **if** ComputeLoad($\overrightarrow{MinLoad}$) $\geq (1+\beta) \cdot Load_{ini}$ **then**
7:             **continue**;
8:         **if** ComputeIP($\overrightarrow{MinIP} \geq P$) **then**
9:             **continue**;
10:        **if** d = N **then**
11:            $\mathcal{S} \leftarrow R$;
12:            $P \leftarrow$ Compute($\overrightarrow{MinIP}$);
13:            **continue**;
14:        $Search$($d+1$, res, $\overrightarrow{MinIP}$, $\overrightarrow{MinLoad}$)

static IP lease time configuration respectively. The β refers to the maximum increment of the load on DHCP server while not affecting the DHCP server performance.

To get the optimal lease time setting strategy, the basic idea is to construct the solution tree of each combination of user roles and area types, and then traverse the solution space to get the optimal lease time strategy. To reduce the searching process of solution space, we first give two properties:

Property 1: When the lease time of only one role in one area is decreased and the lease times of the rest are not changed, the number of IP address used at time t will decrease and the DHCP load at time t will increase, and vice versa.

Property 2: If the solution needs more IP addresses than the current optimal solution or the DHCP load exceeds the threshold, the subtree whose root is the current node is not the optimal solution.

According to the above two properties, we introduce a load-aware dynamic lease time optimization algorithm with the DHCP load constraint. The specific description is shown in Algorithm 1. We let the lease time array $\mathcal{L}$ represent all potential lease time combinations of teachers and students in each area, N represents the depth of the solution tree which depends on the number of area types. The VLANs in the same area will share the same lease time. To improve the efficiency of the algorithm, we construct the $\overrightarrow{MinIP}$ and $\overrightarrow{MinLoad}$ to represent the lease time strategies of the smallest peak address usage and the smallest peak DHCP load at the current node respectively. The depth d is the layer of the solution tree and initialized to 0 (line 1-2). In each layer d, we check every pair of combined lease time in $\mathcal{L}$ (line 3-6). If the increment of maximum DHCP load of $\overrightarrow{MinLoad}$ strategy exceeds the threshold (line 7-8) or the maximum IP usage of $\overrightarrow{MinIP}$ strategy exceeds the current optimal usage P (line 9-10), the subtree whose root is the current node is not the optimal solution. If the leases of the last lease time pair are determined, the current strategy is the temporary optimal solution. Then the optimal lease strategy $\mathcal{S}$ and the minimum IP usage based on $\mathcal{S}$ are updated (line 11-14). Otherwise, we conduct the recursive search of the solution tree (line 15). The time complexity of Algorithm 1 is $O(\mathcal{L}^N)$.

Algorithm 2 Dynamic IP pool configuration Strategy

Input: $Y_s(t)$,γ, $\mathcal{I}$, B, T, S
Output: $\mathcal{N}$

1: **Initialization:** $\mathcal{N} \leftarrow sum(\mathcal{I})$
2: **for** (t_p, s_i) in (T, S) **do**
3:     $R = Y_{s_i}(t_{p+1}) - Y_{s_i}(t_p)$;
4:     **if** $R > 0$ **then**
5:         **for** (t_q, s_j) in (T, S) **do**
6:             **if** $\rho(Y_{s_i}(t_p), Y_{s_j}(t_q)) < \gamma$ **then**
7:                 $Move$ IP addresses from (t_q, s_j) to (t_p, s_i);
8:                 **update** R;
9:         **update** $\mathcal{N}$ with R, B;

B. Configuring Dynamic IP Pool

Since the user spatio-temporal mobility pattern brings about the IP demand fluctuation among areas with the change of time, conducting static IP pool configuration may bring about two extreme phenomena: low IP address utilization in spare time and IP pool exhaustion in rush hours. The spatio-temporal redundancy of IP addresses and the changeability of number of IP addresses motivate us to dynamically configure IP pool accordingly to save the IP addresses. Equation (2) provide the correlation between two spatio-temporal points, so we can design dynamic IP pool configuration strategy to dynamically migrates the IP address across VLANs to meet the IP demand of each spatio-temporal point.

The detailed description is shown in Algorithm 2. The γ is the threshold to determine if any two spatio-temporal points have spatio-temporal mobility correlation. The $\mathcal{I}$ is an array to represent the number of IP addresses in the primary IP set of each VLAN. The B represents block size which is defined as IP address number of a subnet in secondary IP set. The primary IP set is static once it is configured, and we are able to change the number of subnets in secondary IP set to configure the size of IP pool in each VLAN. We calculate the total IP usage $\mathcal{N}$ after initializing a fixed number of IP addresses in each VLAN (line 1). For each spatio-temporal point (t_p, s_i), we calculate the change of online users based on $Y_s(t)$ (line 2-3). If the number of online users increases by R in area s_i and the primary IP set is exhausted, we start to search for the spatio-temporal point. If the correlation ρ of two points is under a threshold γ, we believe that the users in area s_j move to s_i. The correlation ρ is calculated based on Equation (2). Note that the correlation of two spatial-temporal points is significant when the correlation value approaches -1. Then we directly move the IP subnets from s_j to s_i by configuring the pool in two VLANs and update R (line 4-8). If there is no such a point or the number of IP addresses configured from other points is not enough, we configure the new IP subnets in s_i and update the $\mathcal{N}$ (line 9). The time complexity of Algorithm 2 is $O(S^2T^2)$.

V. Performance Evaluation

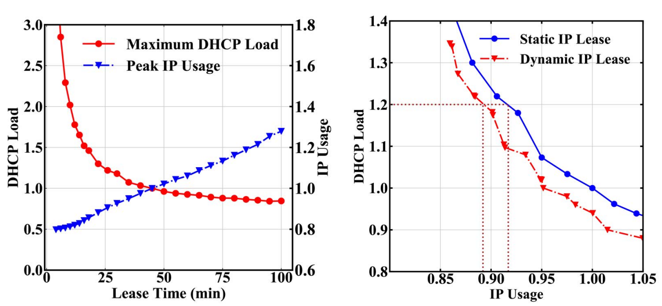
The real network traces collected for two typical weeks are used to conduct our experiment. The traces in the first week are used to determine the value of IP lease time configuration parameters and IP pool configuration parameters, while the traces in the second week are used to evaluate the effectiveness of BDAC.

A. Evaluation of Adaptive IP Lease Configuration

To evaluate the adaptive IP lease time configuration on DHCP performance, we firstly conduct the static IP lease time strategy (all areas share the same lease time) to depict the maximum DHCP load and peak IP usage with different IP lease times, and then we show the superior of adaptive IP lease time configuration with the same DHCP load constraint, comparing with the static IP lease time strategy.

Fig. 7(a) depicts the relationship between the maximum DHCP load and peak IP usage with the static IP lease time strategy when the IP lease time is set form 5 minute to 100 minutes. The DHCP load and IP usage are normalized by dividing the values generated by the default IP lease time. We observe that if the IP lease time increases, the peak IP usage increases while the maximum DHCP load decreases, and vice versa. Therefore, if we want to save the IP address, we could reduce the IP lease time at the expense of increasing the DHCP load. However, if the IP lease time is set too small, the DHCP load increases exponentially while the peak IP usage has not decreased too much. For example, if the lease time is set to 10 minutes, the maximum DHCP load increase by 100% while the peak IP usage is only reduced by 20%.

Then, we study the correlation between the maximum DHCP load and the peak IP usage with the static and adaptive IP lease configurations. Fig. 7(b) depicts the comparison between adaptive IP lease times and static IP lease time. We observe that the static IP lease configuration is not able to reach the optimal results since our method need less IP addresses with the same DHCP load constraint or occupy less DHCP load with the same IP usage constraint. For example, if the threshold of DHCP load is set to 10%, the peak IP usage by our method could be reduced by 9% while the peak IP usage by static strategy is only reduced by about 5%. Based



(a) (b)

Fig. 7: (a). The peak IP usage and maximum DHCP load configured with different static IP lease times. (b). The comparison of adaptive IP lease times with static IP lease times.

on the network administrators' feedback and consideration, the increment of DHCP load in studied WLAN should not exceed 20%. The peak IP usage based on our method could be reduced by 12%, which is 50% better than the static IP lease configuration strategy. The optimal lease time strategy across user roles and area types is shown in Table II.

TABLE II: Adaptive Lease Time configuration across User Roles and Area Types.

	Studying	Working	Living	Eating
Student	40 min	25 min	45 min	5 min
Teacher	20 min	45 min	15	5 min

B. Evaluation of Dynamic IP Pool Configuration

Dynamically configuring IP pool not only improves the efficiency of IP usage, but also reduces the risk of IP pool exhaustion. However, the dynamic IP pool configuration will bring about two network issues: the network topology change and the client re-association. In each step of configuration, the network topology will be changed since the IP pools of VLANs are reconfigured to migrate the IP addresses. This process will only take few seconds to maintain the link-state information [16] [17]. The other problem is that the client should re-associate the networks to apply for a new IP address when the previous IP address is not available due to the migration of IP subnets between VLANs. This process will also take few seconds [5]. The main idea of dynamic IP pool configuration is to improve the IP utilization while not introduce much network problem. To evaluate the performance, we change the parameters used in Algorithm 2 (i.e., initial IP number in the primary IP set and the block size in the second IP set). The initial IP number is set as multiplying a factor (i.e., [0, 1.0]) to the maximum IP usage in each VLAN. The block size is set from 4 to 2048.

Fig. 8 depicts the IP utilization with different block sizes and initial IP numbers. In the upper figure, we observe that the IP utilization decreases when the block size is larger than 256. Therefore, setting a large block size is not an efficient way to improve IP utilization because the number of arriving users is not much and the rest of IP addresses are wasted. Surprisingly, we find that the IP utilization decreases when the block size is smaller than 32. This can be explained by the reason that the first IP address and the last IP address in a block are used for netmask address and broadcast address respectively which can not be used by the clients. In the lower figure, we observe that the IP utilization maintains stable when the initial IP number is set to less than 60% of the maximum IP usage in each VLAN. However, if the initial IP number is set to more than 60% of the maximum IP usage, the IP utilization decreases.

Then we study the two issues introduced by dynamic IP pool configuration. Fig. 9 depicts the daily configuration number with changes of block size and initial IP number. In upper figure, we find that the daily configuration number decreases rapidly when the block size increases. For example, the configuration number is more than 100 when the block size is 8. However, the configuration number is less than 10 times when

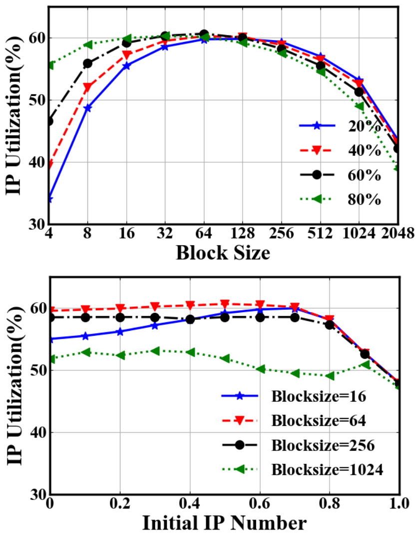


Fig. 8: IP utilization

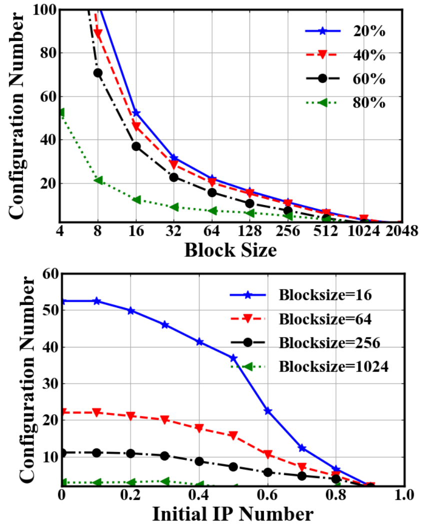


Fig. 9: Configuration number

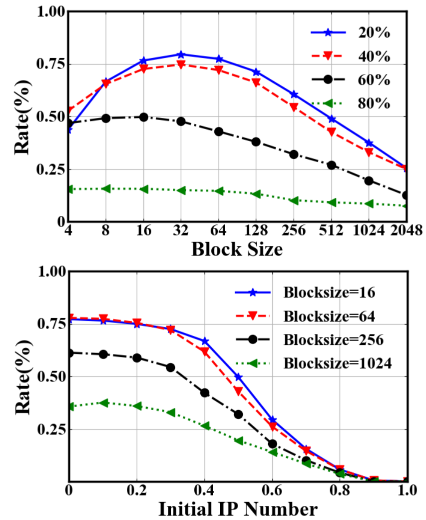


Fig. 10: Client re-connection rate

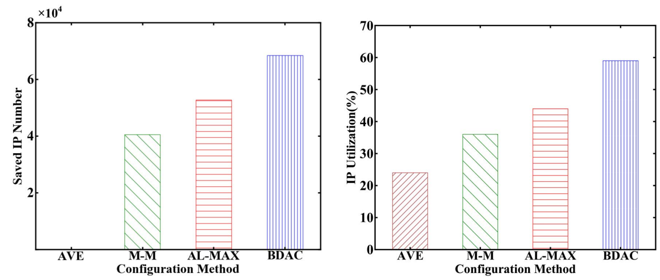
the block size is larger than 256. The lower figure shows that the initial IP number also greatly influences the configuration number when the block size is small. However, when the block size is larger than 256, the configuration number is not sensitive to the initial IP number. Fig. 10 shows that the client re-connection rate is very low that only less than 0.8% of clients need to re-connect the network when we reconfigure the IP pool in VLANs. It only take few seconds to re-connecting to the Internet. Note that the static IP configuration results in that one third of users in VLAN of eating area are unable to get IP addresses to access the Internet for hours.

Based on our analysis, we find that setting block size at 256 and initial IP number at 60% of maximum IP usage respectively in each VLAN are the most suitable parameter values. The results in the figures show that setting the two values reaches high IP utilization (the IP utilization reach about 60%) while not introducing much network issues (the network topology only changes 6 times in each VLAN and the clients' re-association rate is less than 0.4%). These parameters could be updated periodically (such as a week, a month or a semester) to meet the change of WiFi network patterns.

C. Comparing BDAC with Existing Approaches

With the traces in the first week to determine the configuration parameters, we use the traces in the second week to compare the **BDAC** with the traditional methods. The traditional methods fall into three main categories: (1) configuring the average number of IP addresses in each VLAN (**AVE**) which is used in studied WLAN; (2) configuring number of IP addresses merely exceeding the maximum IP usage in each VLAN (**M-M**); (3) configuring the adaptive IP lease time to reduce the maximum IP usage in each VLAN [8] and then configuring the number of IP addresses merely exceeding the maximum IP usage (**AL-MAX**).

Fig. 11(a) depicts the saved IP number with each method. The AVE method is the easiest way to configure the IP pool for each VLAN which is also used in studied WLAN. However,



(a) Saved IP Number

(b) IP Utilization

Fig. 11: (a). The saved IP number with 4 configuration methods. (b). The IP utilization with 4 configuration methods.

this method leads to the poor DHCP performance. Note that the clients in studying area and eating area are unable to get IP addresses to access the Internet in rush hours. The M-M method could save about 40,000 IP addresses and AL-MAX method could save about 52,000 IP addresses by configuring the different lease times across user roles and area types. However, the above two methods are not able to reduce the spatio-temporal redundancy of IP address. Therefore, the IP addresses are wasted in spare time of the VLAN. Our method could save 68,000 IP addresses by setting adaptive lease time across user roles and area types and configuring the IP pool in each VLAN dynamically based on spatio-temporal behavior. We only use about 4,7000 IP addresses to meet the IP demand in studied WLAN.

Fig. 11(b) depicts the IP utilization among four methods. It is obvious that the AVE method leads to quite low IP utilization that the IP utilization is 24%. The M-M method which considers the maximum number of users in each VLAN improves the IP utilization by 1.5 times and the actual IP utilization is about 36%. The AL-MAX method reduces the peak IP usage by setting adaptive IP lease time in each VLAN so that the IP utilization reaches 44%. Our method shows the best performance that the actual IP utilization is 59%.

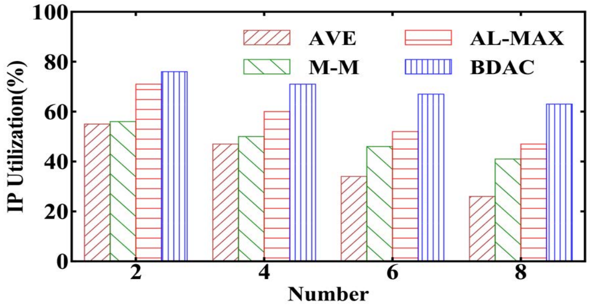


Fig. 12: The IP utilization of four methods with different number of VLANs

D. Evaluation of Robustness

In order to evaluate the robustness of our method, we redivide the WLAN in studied campus with different number of VLANs. Fig. 12 depicts the IP utilization when the number of VLANs changes from 2 to 8. We find that the performance of BDAC is best when the number of VLAN changes. An interesting observation is that the IP utilization gap between M-M and AL-MAX is large when the VLAN number is 2, however, the gap between AL-MAX and BDAC is not large. This phenomenon can be explained by the reason that majority of IP addresses are wasted due to the improper IP lease time settings since the user mobility between VLANs is not apparent when the number of VLAN is small. It motivates us to set the adaptive IP lease time in each VLAN to save IP addresses and improve IP utilization when the number of VLAN in a WLAN is small. As the number of VLAN grows, the IP utilization gap between AL-MAX and BDAC is gradually growing. This is because that the AL-MAX is not able to reduce the waste of IP addresses caused by spatio-temporal mobility pattern. The spatio-temporal redundancy results in the waste of IP addresses. Our method dynamically configures the IP pool to migrate the IP subnets between VLANs to reduce the spatio-temporal redundancy. In other words, our method reuses the same IP address across VLANs in different time periods and largely improves the IP utilization. Therefore, our method maintains high efficiency of IP utilization even if the number of VLANs is large in a WLAN.

VI. Related Work

Understanding User Behavior: The collection and analysis of datasets from mobile devices have attracted a number of researches understanding the user behavior. X. Wei et.al [18], [19] profiled the handheld devices and group users into intuitive H-M-L groups based on the time-variance and traffic behavior.Zhang et al. [20] combined with multi-source data and designed three-layer mPat to explore the correlation and divergence among the multi-source data to analyze and infer human mobility. Another work by Alipour et al. [21] quantified the correlation between the mobility pattern and the network traffic pattern across device types, time and space with integrated datasets. Previous works only provided interesting measurement results or presented mathematical models on the characteristics of user behavior. C. Miao et [22] conducted a multi-dimension measurement study of large-scale campus and provided the potential strategies from network administrator point of view. Different from previous works, our work observed the impact of the dynamic user behavior on DHCP performance, and then we preset models and design the behavior-aware dynamic adaptive IP configuration strategy to improve the DHCP performance.

Studying DHCP Performance: The existing works on DHCP focused on improving the DHCP performance by setting the proper IP lease time. M. Khadilkar et al. [7] proposed single adaptation strategy and exponential adaptation strategy by dynamically adjusting IP lease times to reduce the DHCP traffic. I. Papapanagiotou et al. [5] proposed an operating system based on IP lease setting strategy to improve the IP utilization. Chen et al. [14] characterized the use behavior and provide an analytic model to study the relationship between the session lengths and IP address usage. Li et al. [8] built an emulation technique among the lease, address utilization and DHCP overhead and proposed a load-aware IP lease strategy to set different leases for each area. Wang et al. [6] analyzed the mobility of users with different operating system and consider both area types and operating system types to improve DHCP performance. These works only focused on setting adaptive lease time according to operating system or area type to improve the DHCP performance. Different from previous works, our work focused on two dimensions: user online time pattern and spatio-temporal mobility pattern. We modeled the dynamic user behavior and proposed two configuration strategies with adaptive IP lease time configuration and dynamic IP pool configuration to save IP addresses and improve IP utilization.

VII. Conclusion

In this paper, we observe that the dynamic WiFi user behavior (i.e. online time pattern and spatio-temporal mobility pattern) leads to poor DHCP performance based on the large scale real network traces. In order to address this problem, we firstly characterize and model the WiFi user behavior across online time pattern and spatio-temporal mobility pattern. Then we propose BDAC, a behavior-aware dynamic adaptive configuration which is combined of two strategies: adaptive IP lease time configuration and dynamic IP pool configuration. The former is to set the adaptive lease time across user roles and area types based on online time pattern to reclaim IP in time and reduce the peak IP usage, and the latter dynamically migrates the IP addresses between VLANs based on spatio-temporal mobility correlation to save IP addresses. We compare the BDAC with other methods using the real network traces from a different week. Results show that BDAC can save up to 60% IP addresses and the actual IP utilization rises from 24% to 59%. Furthermore, our method shows strong robustness that it maintains high IP utilization when the number of VLANs grows large.

VIII. Acknowledgement

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REFERENCES

[1] R. Droms, "Dynamic host configuration protocol," 1997.

[2] M. U. 2018, www.stonetemple.com/mobile-vs-desktop-usage-study/.

[3] D. Lund, C. MacGillivray, V. Turner, and M. Morales, "Worldwide and regional internet of things (iot) 2014–2020 forecast: A virtuous circle of proven value and demand," *International Data Corporation (IDC), Tech. Rep*, vol. 1, 2014.

[4] F. E. Ross, "Hub for segmented virtual local area network with shared media access," Feb. 28 1995, uS Patent 5,394,402.

[5] I. Papapanagiotou, E. M. Nahum, and V. Pappas, "Configuring dhcp leases in the smartphone era," in *Proceedings of the 2012 ACM conference on Internet measurement conference*. ACM, 2012, pp. 365–370.

[6] H. Wang, J. Wang, W. Dang, J. Xue, and F. Li, "Squeezing the gap: An empirical study on dhcp performance in a large-scale wireless network," in *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*. IEEE, 2018, pp. 1628–1636.

[7] M. Khadilkar, N. Feamster, M. Sanders, and R. Clark, "Usage-based dhcp lease time optimization," in *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement*. ACM, 2007, pp. 71–76.

[8] F. Li, X. Wang, J. Cao, R. Wang, and Y. Bi, "How dhcp leases meet smart terminals: Emulation and modeling," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 56–68, 2018.

[9] M. Patrick, "Dhcp relay agent information option," 2001.

[10] S. Glass, T. Hiller, S. Jacobs, and C. Perkins, "Mobile ip authentication, authorization, and accounting requirements," Tech. Rep., 2000.

[11] J. Xu, J. Fan, M. H. Ammar, and S. B. Moon, "Prefix-preserving ip address anonymization: Measurement-based security evaluation and a new cryptography-based scheme," in *Network Protocols, 2002. Proceedings. 10th IEEE International Conference on*. IEEE, 2002, pp. 280–289.

[12] K. Sui, Y. Zhao, D. Pei, and L. Zimu, "How bad are the rogues' impact on enterprise 802.11 network performance?" in *Computer Communications (INFOCOM), 2015 IEEE Conference on*. IEEE, 2015, pp. 361–369.

[13] A. Feldmann and W. Whitt, "Fitting mixtures of exponentials to long-tail distributions to analyze network performance models," *Performance evaluation*, vol. 31, no. 3-4, pp. 245–279, 1998.

[14] X. Chen, L. Lipsky, K. Suh, B. Wang, and W. Wei, "Session lengths and ip address usage of smartphones in a university campus wifi network: Characterization and analytical models," in *Performance Computing and Communications Conference (IPCCC), 2013 IEEE 32nd International*. IEEE, 2013, pp. 1–9.

[15] A. K. Das, P. H. Pathak, C.-N. Chuah, and P. Mohapatra, "Characterization of wireless multidevice users," *ACM Transactions on Internet Technology (TOIT)*, vol. 16, no. 4, p. 29, 2016.

[16] P. Francois, M. Shand, and O. Bonaventure, "Disruption free topology reconfiguration in ospf networks," in *INFOCOM 2007. 26th IEEE International Conference on Computer Communications. IEEE*. IEEE, 2007, pp. 89–97.

[17] F. Clad, P. Mérindol, S. Vissicchio, J.-J. Pansiot, and P. Francois, "Graceful router updates in link-state protocols," in *2013 21st IEEE International Conference on Network Protocols (ICNP)*. IEEE, 2013, pp. 1–10.

[18] X. Wei, N. Valler, H. V. Madhyastha, I. Neamtiu, and M. Faloutsos, "A behavior-aware profiling of handheld devices." in *INFOCOM*, 2015, pp. 846–854.

[19] X. Wei, N. C. Valler, H. V. Madhyastha, I. Neamtiu, and M. Faloutsos, "Characterizing the behavior of handheld devices and its implications," *Computer Networks*, vol. 114, pp. 1–12, 2017.

[20] D. Zhang, J. Huang, Y. Li, F. Zhang, C. Xu, and T. He, "Exploring human mobility with multi-source data at extremely large metropolitan scales," in *Proceedings of the 20th annual international conference on Mobile computing and networking*. ACM, 2014, pp. 201–212.

[21] B. Alipour, L. Tonetto, A. Y. Ding, R. Ketabi, J. Ott, and A. Helmy, "Analyzing mobility-traffic correlations in large wlan traces: Flutes vs. cellos," *arXiv preprint arXiv:1801.02705*, 2018.

[22] C. Miao, J. Wang, H. Wang, J. Zhang, W. Zhou, and S. Liu, "A multi-dimension measurement study of a large scale campus wifi network," in *2018 IEEE 43rd Conference on Local Computer Networks (LCN)*. IEEE, 2018, pp. 351–359.