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RL-Based Load Balancing for Software-Defined WiFi Networks

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Abstract. Due to the popularity of mobile devices, more WIFI access points (APs) are being installed in public spaces, including train stations, airports, campuses, and shopping centers. Any station in WiFi networks will often connect to the AP that is closest to it based on the RSSI value that is the strongest. This user association approach will result in unfair bandwidth distribution and load imbalance when WiFi networks have many stations and an uneven distribution of those stations. By separating the control plane and data plane, software-defined networks (SDN) enable WiFi networks that are programmable, controllable, measurable, and manageable. This paper represents a novel load balancing mechanism based on reinforcement learning and SDN. In our proposed scheme, the center controller collects the number of associated stations with APs and traffic information on each AP's backhaul link. Then the controller decides the optimal station migration scheme to achieve load balancing among APs, based on collected information and reinforcement learning algorithm. The simulation results illustrate that our algorithm outperforms the RSSI method in terms of throughput of stations and average station number of each AP.

Keywords. reinforcement learning, user association, load balancing, SDN, WiFi networks

1. Introduction

Mobile voice and video traffic in the wireless network has grown significantly over the past few years as a result of the widespread use of smart mobile devices. For the increased mobile traffic, WiFi access points (APs) are widely used in public spaces (such campuses, shopping malls, and airports). When WiFi APs are widely spread in a public space, the WiFi network's performance degrades as a result of interference or an unbalanced load.[1].

According to the IEEE 802.11 standard's user association method, stations choose the AP closest to them, with the highest Received Signal Strength Indicator (RSSI) value, to achieve a high data rate[2,3]. This association strategy will cause the load imbalance of the AP and congestion of the backhaul link since it ignores the load of the APs. Some APs have a high number of associated stations, and other APs may have fewer stations. The

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imbalance reduces network utilization, causes congestion at overloaded APs, and lowers the QoS of stations[4]. Due to IEEE 802.11 standard does not provide any solutions to mitigate the overload of APs caused by the imbalance of users, many schemes are proposed to solve this issue. In [5], a load balancing algorithm is proposed where stations do not connect the APs with the greatest transmission power. Literature [6] models the load balancing problem to a bipartite graph matching problem.

A revolutionary network architecture that separates the data plane and control plane is known as software defined networks (SDNs). In SDNs, a logically centered network controller can collect a global view of the whole network and make intelligent control decisions[7]. Recently, some studies have applied SDNs to the wireless network to make it programable, controllable, measurable, and manageable [8,9,10].In [8], OpenRoads is proposed to support heterogeneous wireless networks.Literature[9] implemented Odin, a WIFI management platform, handles scheduling wireless traffic.In [10], T. Zahid et al. proposed a software deinfied WIFI testbed.

Reinforcement Learning(RL) is a subfield of machine learning. As Fig. 1 shows, the agent observes the surrounding environment(state), takes action, and receives the environment's reward, in which the RL agent continuously interacts with the environment to maximize the cumulative reward[11].Reinforcement learning can provide machine learning enabled scheme for issues in wireless network[12], such as rate controller[13],resource management in cell network[14],channel selection and power adaptation for cognitive radio network[15].

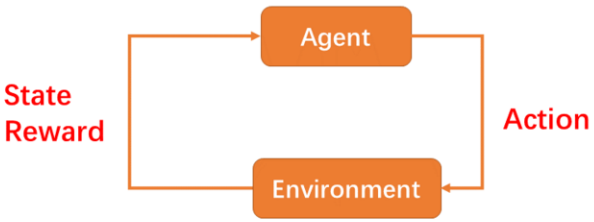

Figure 1. Renforcement Learning Model

In this paper, we propose a novel load balancing algorithm based on reinforcement learning and SDNs. First, the SDN controller periodically collects the number of stations connected to per AP and traffic information per AP's backhaul link. Then the optimal stations migration is decided by reinforcement learning algorithm according to the state of the system, including load information and traffic information of each AP. The simulation results show that the RL-based load balancing algorithm improves throughput of stations and average station number of each AP.

The rest of this paper is structured as follows: Section II presents the RL-based load balancing algorithm. The simulation and performance are evaluated in section III. Section IV end the paper by summarising conclusions and future works.

2. RL-based balancing algorithm

2.1. System Model

This study considers an SDN-based multi-station WiFi network for indoor communication with WiFi APs. N_A stands for the total number of APs, and N_S stands for the total number of stations. The associated stations list STA_i^K={STA_1^K,STA_2^K,STA_3^K,...,STA_N^K} defines the stations within the communication range of the AP K, where K $\in$ A={A_1,A_2,...,A_{N_A}}. We assumed an SDN controller center located in the network, which collects traffic and load information from each AP. A decision Agent make optimal AP assigenement,using reinforcement learning algorithm, based on information from SDN controller.

We propose that the load of the AP, in contrast to the Least Load First (LLF) method, should take into account more factors, not only the number of stations connected to the AP but also the sorts of applications running on the stations that affect traffic flow on the AP's backhaul link. Few stations running high throughput applications, such as video on demand, live video, virtual reality, or augmented reality, have a larger chance of experiencing congestion on the connected AP than more stations running low throughput applications, like email, web pages, or messages. So we assumed the load of the AP mainly comes from two aspects:(i) the number of stations associated with the AP;(ii) the traffic on the AP's backhaul link. As Eq.1 shows, the load consists of the number of stations N_i and traffic T_i on AP's backhaul link . α and β are weight factors, the sum of α and β is 1. N_i is sum of stations connected the AP i. T_i is the sum of all traffic throughput on AP's backhaul link.

$$\begin{aligned}
&L_i = \alpha \times N_i + \beta \times e^{T_i} \quad , \quad \alpha + \beta = 1 \\
&N_i = \sum_{j=1}^{n} STA_j^i \quad , \quad i \in \{AP_1, AP_2, \ldots, AP_{N_A}\}, \\
&STA \in \{STA_1^i, STA_2^i, \ldots, STA_n^i\} \\
&T_i = \sum_{j=1}^{n} flow_j^i \quad , \quad flow \in \{flow_1^i, flow_2^i, \ldots, flow_n^i\}
\end{aligned} \tag{1}$$

In addition, the mean load of all APs controlled by an SDN controller:

$$\bar{L} = \frac{\sum_{i=1}^{N_A} L_i}{N_A} \tag{2}$$

The degree of imbalance of an AP is described by Eq.3. The bigger the positive value of IMD_i, the greater the overload of AP. Our method uses the degree of imbalance metric to find overload APs where this metric is greater than the threshold value.

$$IMD_i = \frac{L_i - \bar{L}}{\bar{L}}, i \in \{AP_1, AP_2, \ldots, AP_{N_A}\} \tag{3}$$

The relative degree of imbalance between an AP and its adjacent AP within its communication range is described by Eq.4. The value of $RIMD_i$ is positive, which indicates the load of AP i is greater than AP j, and vice versa. We use this metric to decide which AP to be selected to afford unassociated stations from overload AP.

$$RIMD_i = \frac{L_i - L_j}{\bar{L_{i,j}}}, i, j \in \{AP_1, AP_2, \ldots, AP_{N_A}\} \tag{4}$$

In our method, the SDN controller collects the number of associated stations and traffic information from all APs in the WiFi network. By computing the degree of imbalance of each AP, we find the overload APs. Then we compute the relative degree of imbalance among overload AP and its adjacent APs to decide which we migrate stations to. The station migration algorithm, which we implement using the reinforcement learning algorithm.

2.2. RL-based station migration algorithm

Reinforcement learning can be modeled by Markov Decision Process(MDP),which is described by (S,A,P,r,s_0,γ). S is the set of states. A is the set of actions. P is state transition probability. r is the reward function.s_0 is the initial state.At step t,an agent at state s_t,takes an action a_t,receives a reward $r_t = r(s_t, a_t)$,then transits to next state $s_{t+1} \sim P(.|s_t, a_t)$.$\pi : a \to P(s)$ is the policy. The cumulative discounted reward under policy π is presented by Eq.5.

$$\mu(\pi) = \sum_{t=0}^{\infty} \gamma^t R_{t+1} \tag{5}$$

The goal of reinforcement learning is to maximum $\mu(\pi)$ to find an optimal policy π^*.

$$\pi^* = \arg\max_{\pi}(\mu(\pi)) \tag{6}$$

We formulate the station migration problem as a reinforcement learning problem. In our method, the set of state S includes the load information of overload AP and adjacent APs within its communication radius. A is a set of discrete actions, which is station migration which A station migrates from overload AP to its neighboring AP. $r \to S \times A$ is reward function, which is described by Eq. 7. $\bar{L}$ is mean load of the whole network.L_t^{AP} is the current load of overload AP at step t;L_{t+1}^{AP} is the current load of overload AP at step $t+1$;

$$R(s,a) = \frac{L_{t+1}^{AP} - \bar{L}}{L_{t+1}^{AP} - L_t^{AP}} \tag{7}$$

3. Simulation and Performance

The simulation is performed by NS3-gym,which is a framework that integrates both OpenAI Gym and ns-3 in order to encourage usage of RL in networking research[16]. All the key parameters of the simulation are summarized by table 1.

Algorithm 1 station migration algorithm using RL

Input: current state s_t,including load of overload AP and other APs and optimal policy $\pi^*(a_t||s_t)$

1: using $\pi^*(a_t||s_t)$ for s_t to priedict a_t
2: migrating a station from overload AP to other AP based on a_t
3: after migration , computing the current load of overload AP and mean load of whole network
4: obtaining r_{t+1} and s_{t+1}

Output: r_{t+1} and s_{t+1}

Table 1. Simulation Parameters

Parameters	Values
Area	$300 \times 300m^2$
Number of APs	10 WiFi
Location of APs	Uniform
Number of Stations	100
Request data rate of stations	0-50Mbps
RL algorithm	DQN
Episode length	1000
Learning rate	0.01
Discount factor	0.95

Figure 2 indicates the average station number of 10 APs in network. RSSI method results in imbalance of stations connected to APs,due to all stations pefer to associate the strongest signal AP. Our proposed RL-based method can balance the station number of all APs in network.

Figure 3 shows that the RL method can get higher throughput on most APs than the RSSI method because our proposed method can migrate stations from overload AP to light load AP so that stations can achieve higher throughput.

Figure 4 depicts the rewards of the RL method with respect to the number of iterations, which shows that rewards keep increasing over the iterations and our proposed algorithm converges fast as rewards are stable.

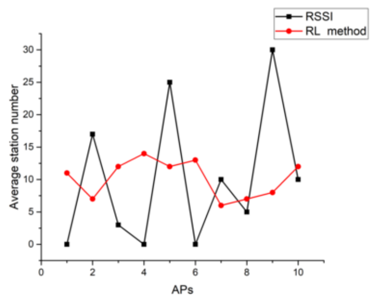

Figure 2. Average Station Number of Each AP

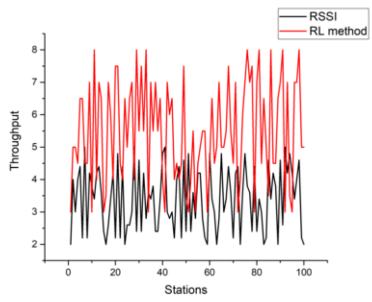

Figure 3. Throughput of Each Station

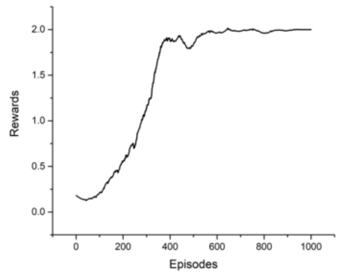

Figure 4. Training Curve of RL Method

4. Conclusions

This paper proposes a load balancing algorithm for a software-defined WiFi network. In the proposed scheme, the SDN controller first finds overload APs based on the global view of the network, load balancing, and traffic information. Then we use the RL-based stations' migration algorithm to decide the optimal stations' reassociation scheme to alleviate overload APs.Simulation results illustrate that our method achieve better performancethe than RSSI method in terms of throughput of stations and average station number of each AP.

5. Acknowledgement

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