Access Point Load Aware User Association Using Reinforcement Learning

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Abstract - The network traffic across multiple Wi-Fi access points (AP's) in high-density environments is unevenly distributed leading to an imbalance of load on these APs. Such load imbalance usually results in less responsive use of internet applications, low bandwidth distributed across the clients, along other network issues that come with increased load on the APs. Hence, there comes a need to optimally balance the load across the APs to reduce any network congestion over an area and to increase the aggregate bandwidth provided to the clients.

One solution of the many to solve this problem would be to develop an algorithm that would allow the user equipment's (UE's) to decide to associate to AP with the strongest signal by analysing the load on all the APs that are distributed across an area. Reinforcement learning (RL), which is a training method based on reward and action is a technique that has recently been in use in the networking domain as it allows the networking entities to make decisions locally to enhance the networking performance. This paper introduces an approach by incorporating reinforcement learning which takes into consideration the strength and load of APs distributed over an area to decide on which AP to connect hence increasing the network performance.

Keywords: ***RSSI, User Equipment, Q-learning, Agent, Policy***

I. Introduction

In recent years, with the advent of mobile terminals and the development of the mobile Internet, the way to reach the network using Wi-Fi has become more widespread. The use of Wi-Fi networks over a wired network is increasing year by year. Wireless Access Points (WAP's) are the networking devices that allow capable devices to connect to the wireless network. Multiple APs are generally used in large organizations to extend the coverage of the existing network which allows for simultaneous connection to these APs by a large number of users. Recent works [1],[2],[3] on operational Wire-less LANs (WLANs) have shown that the load is often distributed unevenly between the APs. Once the end devices access these AP's, the network performance depends upon its running services. However, there is a possibility of uneven distribution of users across these APs that lead to some Aps being underutilized and some APs being overly utilized [4]. The overloading of the APs might increase the response time of the server and tamper with the signal strength. Balancing the load evenly across these APs be-comes a necessity to enhance the running services of these APs. Load balancing is a method [5] used to distribute a load on a server to increase performance and speed of work directed to a specific server. Based upon the signal strength of the access point to the device and the load on the access point we need to evenly distribute the load across these APs over an area. In this article, we introduce an approach that incorporates RL for the device to connect to the optimal AP. Reinforcement learning is a domain of machine learning, where an agent learns by trial and error using feedback from its actions and experiences. So, the goal is to design the load aware user association using RL in wireless network communication to determine the optimal association between the station and access point in the wireless network environment.

II. Related Work

In [6], strategies based on the network-wide utility maximization problem are proposed. considering the cell association and resource allocation jointly, authors have formulated a logarithmic utility maximization problem where the equal resource allocation is optimal, and they have designed algorithm via dual decomposition, which gives a near-optimal solution. In [7] fractional association solution is proposed. This solution ensures the correct bandwidth allocation in terms of minute accuracy. Then the accuracy of time is considered and it introduces a polynomial time algorithm for a complete solution. In [8] Extended-LLF is proposed. Extended-LLF is a development of an existing method that can overcome weaknesses in the LLF. The RSSI variance parameter was added as a requirement for the user association decision. In the test [9] a reinforcement learning-based algorithm is proposed. The authors claim that using a reinforcement learning approach has allowed a 44.5 percent reduction in moderate access delays and improved access success opportunities. In [10] algorithm is developed for handover strategy to improve network capacity via load balancing which minimizes switching overhead. This paper [11] proposes an access point load-balancing strategy based on service attributes in wireless networks. It uses the TOPSIS algorithm to select the optimal AP. In this paper [12], load balancing in wireless LAN is done using a round-robin algorithm. Using this algorithm mobile stations are distributed among all APs to maximize the signal strength. In [13] strategies based on fuzzy logic are proposed, here fuzzy controller decides whether or not to move a client towards a less loaded access point through natural reasoning. In [14], the traffic classification using supervised learning is integrated with topology slicing in Software Defined Networks (SDN). Deep learning provides the benefit of feature extraction. In [15] the deep learning model is employed to classify traffic. In this paper [16] an algorithm for measuring the load to improve network performance is proposed. And the authors claim that the algorithm will dynamically balance the network load by distributing UEs between APs.

III. Proposed Model

The agent/actor in the proposed RL model as shown in fig.1 is the user equipment. The agent's goal is to learn and associate with optimal AP within its environment. The agent performs the task by taking actions (e.g., associating with AP1, AP2, AP3..., APn) as suggested by a policy. So, after performing that specific action the agent gets the reward for the action. This reward is then utilized by the RL algorithm to upgrade/improve the existing strategy (or policy), for better performance in the future. RL algorithm suggests optimal AP.

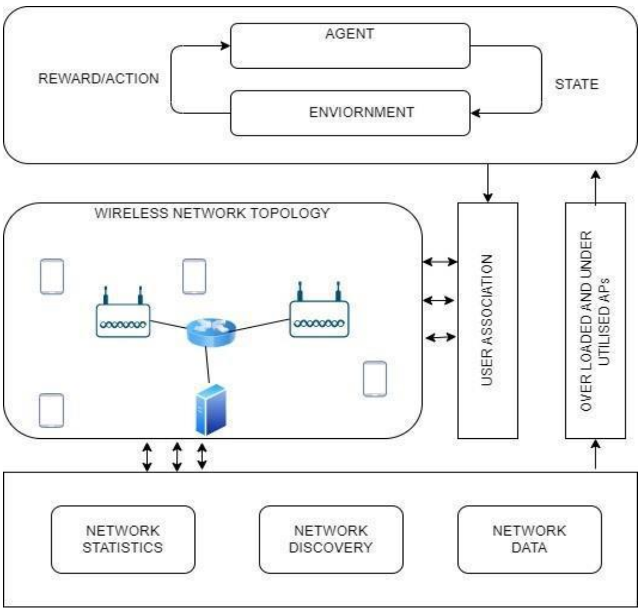


Fig.1: Proposed system for load aware user association using RL

The UE discovers APs around it. And retrieves the network statistics of all APs. Using these network data (Signal strength and load) and Q-learning (performing an action and earning reward) AP with good signal strength, bandwidth, latency is selected. If the UE does not get connected, then the process will repeat. If the UE gets connected, then the UE association is successful.

IV. Dataset

A. Dataset for signal strength

Signal strength at the UE's location is shown in table 1. Here the SSID and the signal strength are considered for assigning the reward. Similarly for all the AP's in the environment this data is collected.

Table 1. UE network parameter details

SSID 1: LIBRARY	
DATA	TYPE
Network ID	Infrastructure
Authentication	WPAP2-Personal
Encryption	CCMP
BSSID 1	26:8b:bf:xx:xx:xx
Signal	100 percent
Channel-Number	1
Basic-rates (Mbps)	1, 2, 5.5, 11

B. Dataset for load on AP

Table 2. AP network parameter details

BSSID	ESSID	#IV	Privacy
52:AB:A7:XX:XX:XX	KLETech	290	WPA
70:BB:E9:XX:XX:XX	Library	51	WPA2

Data shown in the table 2 shows the information of the APs around the UE. #IV represents the load on the AP. This load along with the signal strength helps in assigning the reward to the agent.

V. Methadology

Reward function describes how the agent must behave. In other words, stipulating what you want the agent to accomplish. Rewards are assigned based on the signal strength of AP at the UE location and by the load on AP.

Table 3. Reward based on RSSI

RSSI retrieved in percentage		
UE RSSI	Reward	Remarks
>75%	100	Excellent
>50%	50	Good
≤50%	0	Poor

Table 4: Reward based on load of AP

AP Load	Reward	Remarks
>75%	0	Extremely loaded
>50%	25	Moderately loaded
>25%	50	Slightly loaded
≤25%	100	Least loaded

In table 3, we can observe that the Agent gets a reward of 100 if the agent gets associated with AP having signal strength greater than 75 percent which is an excellent signal. Agent gets a reward of 50 if it gets associated with the AP having signal strength in the range of 50 percent and 75 percent which is good signal strength. Agent gets a reward of 0 if it gets associated with the AP having signal strength less than 50 percent which is a poor signal or no signal.

Rewards for load on AP are shown in the table 4. If the normalized load is greater than 75 percent additional reward is 0, in the range of 50 percent to 75 percent additional reward is 25, while if the normalized load falls in the range of 25 percent and 50 percent the additional reward is 50, and if the normalized load is less than 25 percent additional reward is 100.

State-space S is a set of all the states that agents can transit to. Here the number of states depends on the number of APs in the environment i.e., if there are n AP's then the agent can transit n states.

Action space A is a set of all actions the agent can take in the environment. If there are n APs in the environment then the agent can perform n actions. The action space is discrete in this case and given as [associating with AP1, AP2……, APn].

Policy: The UE must get associated with an AP with the least load and highest signal strength.

Environment is the Agent's world in which it lives and interacts.

Algorithm:

UE executes the following algorithm and sends the signal strength and BSSID to the remote controller.

Algorithm: User Association for Balancing (UE side)

Begin

Get the WLAN SSID and signal strength using 'netsh wlan show networks mode= BSSID'
Create list containing BSSID and Signal strength corresponding to index numbers (Lists: AP [], strength [])
Send the list to remote controller.
Wait for the reply from the remote controller.

End

Now remote controller extracts the load on the AP's and uses the signal strength at the user location to assign reward and finds the optimal AP using Q-learning for the UE to associate. The algorithm for remote controller is described below:

Algorithm: User Association for Load Balancing (Controller side)

Begin
Accept connection from the UE.
Create reward matrix R [No. of AP discovered * No. of AP discovered]
Get BSSID and signal strength from the UE.
Get Load associated with respective AP in the list of APs
Assign strength and load rewards to the matrix
Begin: (Reward for Signal Strength)
if Signal Strength >75%
Assign reward 100
else if Signal Strength >50%
Assign reward 50
else if Signal Strength ≤ 50%
Assign reward 0
End: (Reward-Signal Strength)
Begin: (Reward for Load on AP) Controller gets the normalized (min-max normalization) load rewards
if Load > 75%
Assign reward 0
else if Load >50%
Assign reward 25
else if Load > 25%
Assign reward 50
else if Load ≤ 25%
Assign reward 100
End: (Reward-Load on AP)
ADD signal strength reward and load reward and store in reward table
Begin: (Training)
Train the agent by iteratively updating the Q matrix.
Randomly select any state, called current state.
Find all the possible next states.
Select any random state from the above step called next state.
Find the max value from the (next state) row of Q matrix.
γ=0.8
Initialize max value to max (Q [s'])
Q [s, s'] = R [s, s'] + γ * max value [17]
Repeat this step to train (700 epochs)
End: (Training)
Begin: (Testing)
Set the current state = initial state (State0) Set the goal state to destination state Find the states, with maximum value in the current state row of Q matrix
if: state is the goal state
return sequence of (AP- WAPn - Destination)

where WAPn indicates optimal AP

Send the optimal AP to UE to associate.

End: (Testing)

End

Testbed setup: Sample topology is show in fig2, here UE 8 is associated with the optimal access point (AP 2) chosen by the proposed RL algorithm.

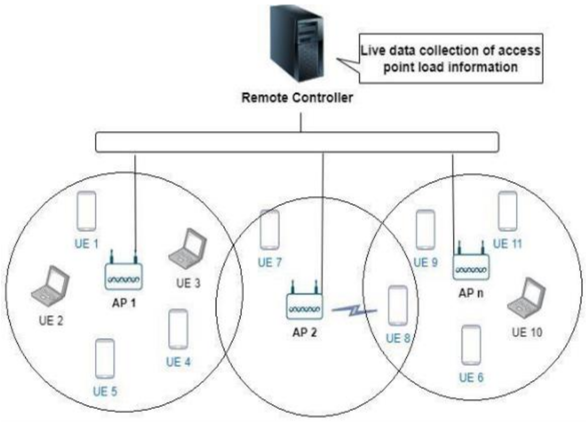


Figure.2: Testbed setup for load-aware user association

VI. Evaluation

A. Performance metrics

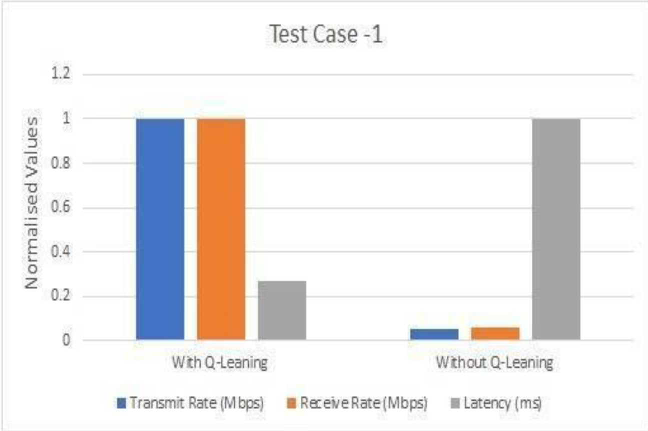
Metrics used to evaluate the algorithm are transmit and receive rate, download and upload speed and latency. Transmit and receive rate are obtained through command "netsh wlan show interfaces", and latency, download speed, upload speed is obtained through speed test. Here all the values are normalized using equation (1).

$$L' = \frac{L - \min(L)}{\max(L) - \min(L)} \tag{1}$$

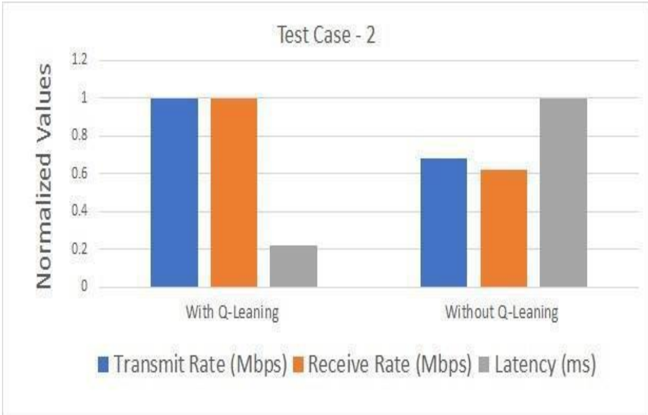
B. Result Analysis

Results are analyzed using the metrics mentioned in section VI(A).

In fig.3a and fig. 3b, graphs show the comparison of transmit rate, receive rate, latency for AP that is chosen with Q-learning algorithm with the one that is chosen manually by the user. From these graphs we can infer that AP chosen with algorithm has a higher transmit and receive rate and low latency when compared to AP that is manually chosen by the user.



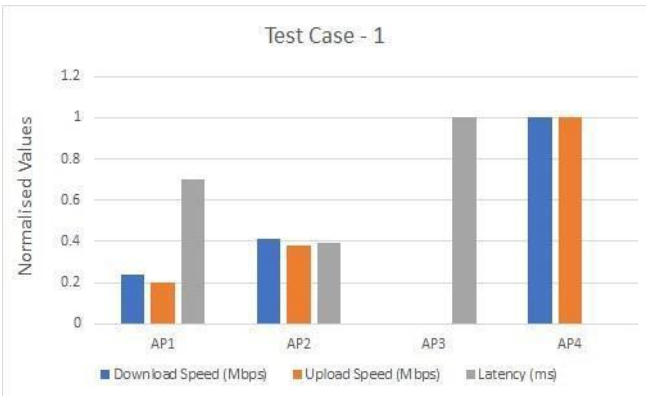
(3a)



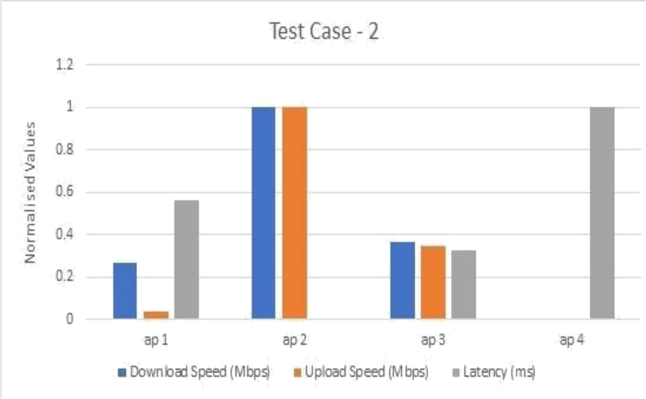
(3b)

Fig.3: Comparison for network performance with and without RL

Fig.4a and fig.4b graphs show the comparison of upload speed, download speed, latency for AP that is chosen by Q-learning algorithm with all APs in the environment. From the graphs we can infer that AP2 and AP4 respectively have the highest download and upload speed and low latency when compared to all the APs in the environment.



(4a)



(4b)

Fig.4: Selection of optimal AP in comparison with other APs.

VII. Conclusion

By incorporating reinforcement learning for the association of the user to an access point, our algorithm can associate the user to an access point that has signal strength >75% and has a load < 25%. The user device is getting associated with AP that has less load and high signal strength. Through this algorithm load-aware user association is achieved using RL.

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