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Modeling and the Congestion Relief in WLANs using Ad hoc Networks

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***Abstract*—We consider usage of campus wireless LANs (WLANs) consisting of access points (AP) with potentially noncontiguous coverage. Through surveys on mobility patterns and wireless network usage on the college campus, we find that mobility and usage patterns exhibit significant differences across various types of locations on campus. Using the collected data we build a realistic mobility model that we call Weighted-Way Point (WWP), to better simulate wireless network user behavior in a university campus environment. Using WWP, we show that unbalanced wireless network usage and hotspots are likely to occur on campus.**

We further propose a mechanism to alleviate the local hotspot congestion by using multi-hop ad hoc networks. When a MN determines the local AP is unable to provide satisfactory bandwidth to an on-going flow, it requests the flow to be switched to a neighboring access point (NAP). Our mechanism differs from other schemes by allowing MNs to make the decision of initiating the flow-switching procedure and using bi-directional route-discovery from both the switching MN and NAP to reduce the route discovery delay. We use simulations to show that with this flow-switching mechanism, flows are more evenly distributed across APs. We also show that our mechanism reduces congestion time for popular APs and improves the user-perceived quality.

Keywords-Ad hoc network, wireless LAN, congestion alleviation

I. INTRODUCTION

Quality-of-service (QoS) degradation due to local congestion has started to emerge as a potential problem for current mid-sized wireless LANs. Wireless network collapses due to network overloads at conferences have been well-documented. Excessive requirement of bandwidth at some popular access points (APs) may lead to severe local congestion. Chances of congestion in wireless LANs are increasing as the demand for more bandwidth-consuming applications (such as streaming video) increases. However, it is possible that while some APs are overloaded, other neighboring APs are underutilized. In such situation, the whole system capacity may be enough to serve the aggregation of bandwidth requirement of concurrent users, but the unevenly distributed load results in poor QoS for wireless network users at some APs. To alleviate potential congestion in hotspots during peak hours, we introduce a mechanism that combines multi-hop ad hoc networks with access-point-based, last-hop wireless networks (wireless LANs). We propose a hybrid wireless network in which mobile nodes (MNs) under a congested AP use a multi-hop wireless route to connect to a neighboring AP.

To better understand the effects of the underlying mobility model and wireless network usage model to hotspot formation in wireless LANs, we conduct a survey on the college. Based on such data we create a Weighted Way Point (WWP) mobility model, which is a variant of the widely used RandomWay Point (RWP) model. Salient features of the WWP models include: (1) It incorporates the fact that the destinations of movement are *not* randomly picked with the same "weight" across the whole simulation area. People almost always show preference in their movements. (2) The parameters of a mobility model and network usage model (e.g. pause time, traffic flow duration, etc.) are location-dependent and time-dependent instead of constants throughout the simulation area or time. WWP model leads to more prominent uneven distribution of load on wireless LAN usage than RWP model. We further show that our flow-switching mechanism effectively reduces the problem of local congestion by allowing flows at congested APs to re-route to neighboring APs (NAP).

The rest of this paper is organized as follows. Section 2 discusses related work. Detailed survey results and the WWP mobility model are introduced in section 3. We further display the inferences of WWP model using simulation in section 4. We explain our flow-switching mechanism in section 5 and simulation results in section 6. Section 7 concludes the paper.

II. RELATED WORK

Wu et al. [1] proposed an ad hoc relaying architecture named iCAR for cellular phone system. It involves installing signal relay nodes on the boundary of cells through which a MN can access neighboring base stations. As suggested by the iCAR project, forming multi-hop path to neighboring cells is one way to alleviate local congestion. In [2] the authors use a similar mechanism, in which the AP seeks help from its NAPs if it cannot support all the requests made in its coverage area. They propose an AP-initiated mechanism in which congested AP seeks help from neighbors if its bandwidth utilization is higher than a threshold. However, if the requirements of mobile nodes are different, which is usually the case in wireless data networks, the mobile node has the best knowledge of whether its requirement is satisfied by the local access point (LAP) or it should try to switch to one of the NAP. Therefore we consider the MN more suitable to initiate the flow-switching process.

There are several other previous works on heterogeneous networks combining last-hop wireless networks and ad hoc networks. For example, a system called Sphinx [3] involves forming an ad hoc network between MNs in a cellular system to increase the throughput per unit power and fairness among flows. In [4] the authors propose a mechanism for AP to dynamically assign channels to MNs under its coverage so that they can communicate with each other without going through AP by forming an ad hoc network on another channel.

On the relationship between uneven load distribution and hotspots in wireless networks, in [5] the authors have demonstrated that in cellular phone systems mobility preference

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Volume No.2, Issue No. 7, pp : 410-417 01 Oct. 2013

based hotspots have global influence on network performance. In [6] the authors have suggested that an MN may choose different locations on a campus with different preferences (different "weights") as its next destination in future works. As people move toward the "popular spots" on campus, preference-based hotspot may form. We investigate this further and discover that it is indeed the case by carrying out a mobility pattern survey first, then synthesizing the WWP mobility model and using it to investigate its effect on hotspots.

While this paper focuses on the mechanism to re-distribute the load of wireless LANs across APs, there is no absolute guarantee that the switching will be successful, or the bandwidth on the ad hoc path is enough for the flow. QoS guarantees in ad hoc network is an interesting problem. In [9] the authors proposed a mechanism called SWAN, which is basically a stateless decentralized flow admission control to achieve QoS in ad hoc networks. Mechanisms like SWAN can work in parallel with our mechanism to ensure there is enough bandwidth on the ad hoc route.

III. Preference-Based Mobility Model for Campus Environments

There are wide families of mobility models in ad hoc network studies [6][7]. However, these works did not address one important issue: Human beings usually do not pick a destination randomly. Some locations are more popular than others for a given environment, such as classrooms, libraries and cafeterias during lunch time on a campus. We investigate this issue and propose a preference-based mobility model based on a mobility survey performed on the campus.

A. Modeling Preferences of Movement

We seek to model the movement of MNs on campus as transition from building to building. From our observation, the general pattern of daily activities on campus is a repetitive pattern of going to one location, staying for a while to finish a task, then moving on to another location. In our context we call each movement from location to location as a *transition*.

We divide the buildings on campus into 3 categories based on its functionality: *classrooms, libraries*, and *cafeterias*. These buildings are referred as *locations* henceforth. The places that do not belong to the above 3 categories on campus are defined as *other* areas, and the campus is surrounded by *off-campus* area. The off-campus area is added to model the fact that some nodes may leave the simulation area (i.e. the campus) but come back later. This feature is not modeled in most simulation studies on ad hoc networks. In this paper we use the simulation environment as shown in Fig. 1. This virtual campus topology is adopted from a small part of the actual campus. In this scenario we define noncontiguous locations: 3 classrooms, 2 libraries, and 2 cafeterias.

While MNs move in the virtual campus, their behavior may vary according to the location type at which it stops. We model such location-dependent behavior by using different pause time distributions, weights for selecting next destination, and network usage for different location types. We get these parameters from a mobility survey on COLLEGE campus. From the collected data, we derive pause time distributions for the 3 *locations* and *other* areas on campus. We find that these distributions vary significantly across the different location types. The pause time distribution of classrooms is bell-shape distributed with the peak at about 90 minutes, which is the general duration of classes. For cafeterias and *other* areas on campus, the distribution is skewed toward the shorter pause interval, similar to exponential distribution. Distribution for pause time at libraries displays long-tail characteristic (see Fig. 2 below for details). We assume off-campus pause time is a roughly estimated fixed value. For next destination selection, we use a Markov model in which MN chooses its next destination with different sets of weights depending on its current location. In our survey result, it also shows the weights are time-variant. For example, MNs will be more likely to choose cafeterias as the next destination around lunchtime. The weight-distribution now depends on both MN's current location and time. Hence the mobility model is a time-variant Markov model. We call this mobility model the Weighted-Way point (WWP) model. We believe this model is more realistic than traditional mobility models that treat the simulation area as a homogeneous area throughout.

The characteristics of wireless usage are captured by *flow-initiation probability* and *flow duration distribution*, both are location-dependent parameters. We assume only the locations (classrooms, libraries, and cafeterias) are covered by the access point. Here, we are interested in wireless LAN usage, hence we assume that MNs use the wireless LAN only when they stop within AP coverage. MNs can only start a flow to the local AP when they stop within locations with a location-dependent flow-initiation probability. A MN never tries to start a flow outside of the locations, as those areas are not covered by APs. Through our survey we find that different locations have different popularity for wireless LAN users. The libraries are the most likely potential hotspot, since the flow-initiation probability is higher, and the flow duration is longer than the other location types.

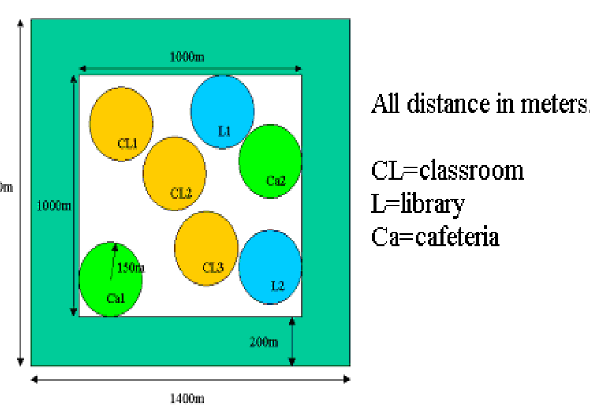

Figure 1. Topology of virtual-campus

International Journal of Engineering Research (ISSN : 2319-6890)
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B. Detailed Mobility Survey Results

Following results are based the analysis of the surveys of the mobility patterns and wireless network usage throughout COLLEGE campus. We gave the survey to randomly sampled respondents on campus during the time period from March 22nd to April 16th, 2011. The total number of surveys we got is 268. The survey from is attached below in appendix A.

The survey form consists of 2 parts. Part one is a mobility pattern survey. We asked the respondent to fill in his last, current, and predicted next location to stay at. For each location the respondent also fills in the time duration he stays at the location. We then categorize the locations on surveys into 5 pre-defined categories: *classrooms*, *libraries*, *cafeterias*, *other area* on campus, and *off-campus* area. We determine the pause time distribution for each category using the pause time samples provided by the respondents. For off-campus area, there are comparatively few samples, and the samples vary significantly. (For example, some respondent writes that he will go home and stay until the next morning.) Hence we make the rough assumption that if a MN is going to come back to campus it stays at off-campus area for a fixed interval of 120 minutes. We show the pause time distribution of the other 4 categories in Fig. 2 below.

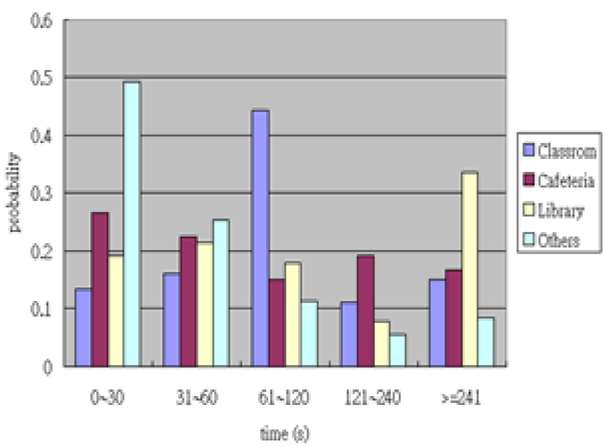

Figure 2. Pause time duration for each location

From the last, current, and next locations the respondent fills in the survey, we get 2 transitions between locations (i.e. last location to current location and current location to future location). We tally all the transitions to obtain the probabilities of going from category to category. The resultant model is a 5-state Markov chain model, as illustrated in Fig. 3. When the pause for the MN at the current location ends, the MN chooses its next destination based on the Markov model. After deciding the next destination category, the MN picks a random coordinate within the next destination category and starts moving toward the coordinate. Note that the probability of going from one category to the same category can be non-zero. (e.g. It is possible to go from classroom to classroom on campus.) We also discover the weights change according to the time in the day. However, due to limited number of surveys, we are not able to have fine-grained resolution of weights variation. We only tally the transition probability separately for the morning (9AM-1PM) and afternoon (1PM-5PM) period. The results are listed below in Table 1.

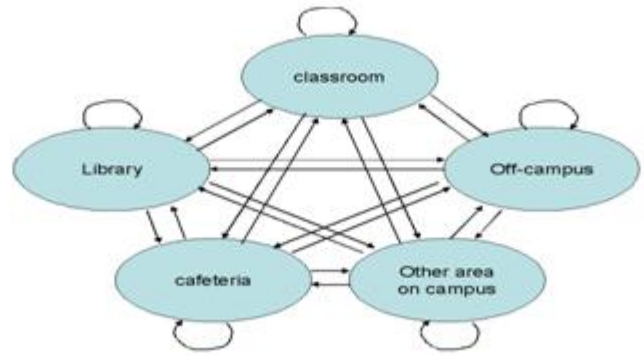

Figure 3. 5-state Markov model for MN transition between categories

TABLE I. TRANSITION PROBABILITY MATRIX

source (and time) \ Destination		Classroom	Library	Cafe	Others	Off Campus
Classroom	**9~13**	0.257	0.314	0.229	0.143	0.057
	13~17	0.174	0.302	0.000	0.186	0.337
Library	**9~13**	0.143	0.143	0.257	0.029	0.429
	13~17	0.364	0.227	0.045	0.125	0.239
cafeteria	**9~13**	0.156	0.438	0.000	0.219	0.188
	13~17	0.200	0.500	0.000	0.300	0.000
Others	**9~13**	0.091	0.121	0.242	0.303	0.242
	13~17	0.200	0.429	0.086	0.143	0.143
Off Campus	**9~13**	0.693	0.216	0.045	0.045	0.000
	13~17	0.642	0.245	0.019	0.038	0.057

We draw some interesting inferences from the transition probability matrix. Showing the transition matrix for the two intervals side-by-side, we can see that after finishing a class people prefer to go from classrooms to home (off-campus) in the afternoon but they tend to go stay on campus in the morning. Also we can see that people in libraries tend to go to classrooms in the afternoon while they prefer to go to the cafeterias or off-campus (perhaps some off-campus restaurants) in the morning. However, people in both the intervals tend go from the classrooms to libraries with nearly equal probability in both intervals. Surprisingly, library is by far the most popular next stop after people visit the cafeterias. At last, people from off-campus tend to go Classroom or to the Library with higher probabilities as compared to other locations in both intervals. This can be explained by considering that people come to school when they

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Volume No.2, Issue No. 7, pp : 410-417 01 Oct. 2013

have classes to attend or want to use the libraries hence these locations are usually their "first stop" on campus.

For the second part of the survey, we ask if the respondent has ever used wireless LAN at some location categories and, if so, the most likely duration of using wireless LAN at the location. We calculate the location-dependent flow-initiation probability by dividing the number of respondents ever use wireless LAN at the location category to the total respondents (268). The results are shown in Fig. 4. We get the flow duration distribution by tally the most likely duration of using wireless LAN at the location category. Results are shown in Fig. 5. We can see that durations of using wireless LAN in classroom or in cafeteria tend to be short, but the durations of using wireless LAN are long in library.

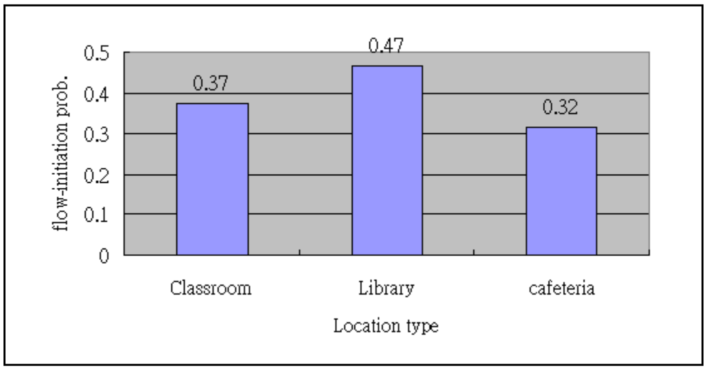

Figure 4. Flow-initiation probability of different locations

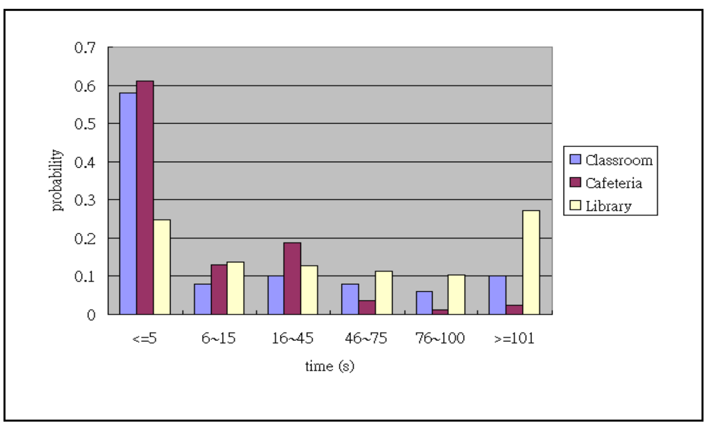

Figure 5. Flow duration distribution of different locations

IV. Impact of Preference-Based Mobility Model

A. Uneven Spatial Distribution and Lack of Steady State

One direct impact of WWP model is that MNs tend to have an uneven distribution in the simulation area. MNs tend to move to locations rather than *other* areas with the WWP model. In Fig. 6 we show the MN density distribution of 200 MNs during 500-second simulation run. (In the simulations in this paper, we scale down the time so that 1 second in simulation time corresponds to 1 minute in real time. A 500-second simulation run corresponds to 8 hours and 20 minutes simulation of a day from 9AM to 5:20PM, as weights for choosing the next destination change during the day. According to the scaling factor, MN moving speed is uniformly distributed between 30m/s to 75 m/s – scaled up 60 times from normal human walking speed 0.5m/s to 1.25m/s.) We can see that the node densities at locations are much higher than *other* area or off-campus area. This is an artifact that in WWP model, the weights for choosing the locations as destination is much higher than choosing *other* area or off-campus area.

From Fig. 6 we also can see that the node density at library 1 has not reached its steady state for the morning Markov model when we switch to afternoon Markov model at time 240 (still increasing). Also, at the end of simulation, node density at cafeteria 1 has not reached its steady state (still decreasing) for the afternoon Markov model. This suggests that the density of MNs converge slower to its steady state than the rate at which preferences of underlying mobility model change. The consequence of this is that at least for some locations the density of MNs never reaches the "steady state". Considering that the preferences of movement should be a function of time throughout the day time, the transition probability matrix should be in fact a time-variant matrix. While the "morning" and "afternoon" notion is proposed in this work to ease data manipulation, if more survey data is available, we may further divide the time boundaries and have many different matrices instead of only two. The consequence is that there would be no "steady state" of MN distribution-before the node density converges, the transition matrix changes, and the node distribution will move toward another potential steady state, which it may never reach.

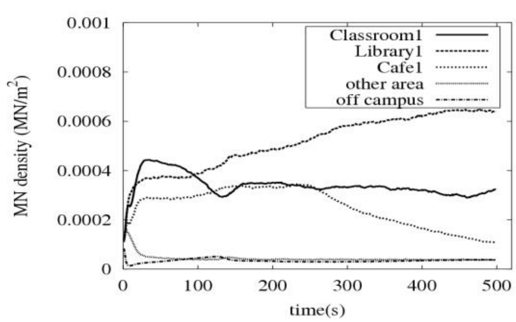

Figure 6. MN densities much higher at locations – clustering effect

B. Local Congestion at the APs

As the MNs cluster at the locations, more flows are generated toward local APs. However, since the distribution of MNs is uneven across locations, the distribution of flows is also uneven across APs. We show the number of simultaneous flows at 3 APs located in the upper-right corner of the virtual campus (Fig. 1) as a function of time in Fig. 7 for the 200 MN case. While the AP at library 1 has large number of flows, APs at classroom 2 and cafeteria 2 are quite underutilized. This uneven distribution of flows suggests the possibility of using ad hoc techniques to re-route some flows to the underutilized neighboring APs in order to alleviate local congestion. We explore this possibility further in the next section.

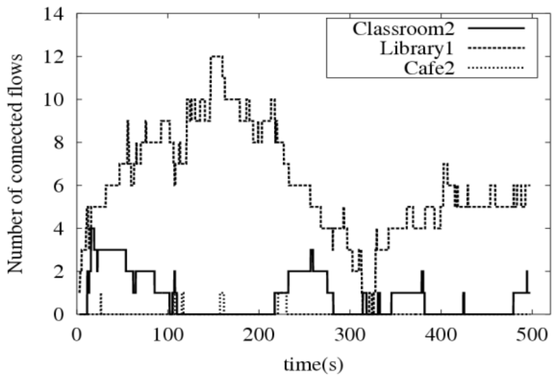

Figure 7. Uneven flow distribution across APs

We further compare the difference between congestion patterns caused by WWP mobility model and RWP mobility model. In the simulation study below, we assume that each AP operates at bit rate of 2Mb/s. Each MN flow requires 200Kb/s throughput. To simplify the simulation, the MNs identify LAP congestion by counting current number of flows connected to LAP. The local AP becomes congested and throughputs for local flows start to drop if 7 or more simultaneous flows are connected to the LAP (This number was obtained via detailed simulations. The wireless channel cannot reach 100% utilization because of contention in wireless channel.) We rum the same simulation using WWP and RWP mobility model and compare the results. All the simulation results are average of 6 independent simulation runs.

In Fig. 8, as the number of MNs increases, both models generate more flows. However, for the same simulation duration, twice the number of flows is generated by the MNs if WWP model is used instead of RWP model. The explanation is that in WWP model, MN is more likely to stay at the locations hence it has higher likelihood of generating a flow. In Fig. 9, we define congested flow ratio as the number of congested flows divided by number of total flows. WWP obviously has a much higher congested flow ratio compared to RMP. This result reflects that when WWP model is used more MNs stay at locations and generate flows that can congest the network.

In addition, in Fig. 10, as we plot number of flows versus congested ratio, it reveals another interesting result. Even when both models have a similar number of total flows, WWP always has a higher congested flow ratio than RWP model. The reason is the MN’s location preference. Here the total number of flows is counted throughout entire simulation environment instead of a single AP. In WWP model the locations are chosen as destination of MN according to non-uniform weights. If a location is more popular than others, it will be likely to attract more MNs hence a greater proportion of flows are initiated at the location. This situation results in an un-even distribution of flows at different locations, as shown in Fig. 7 above. Some locations have more flows and these flows are likely to face a congested local AP. On the other hand, in RWP model the destination is randomly chosen, so all the locations are equal likely to be picked as the destination since they have the same area. The generated flows are evenly distributed among the locations hence the congested flow ratio is not as high given the same number of total flows. In conclusion, RWP model has the intrinsic property of evenly distribute the load. WWP model can truly reflect the scenario with location preferences, which usually happens in realistic world. Preference usually leads to more severe local congestion, as the results above suggest.

We argue that WWP model is a more realistic mobility model for campus environment than RWP model is. Hence, the local congestion problem on campus should be evaluat ed using WWP model.

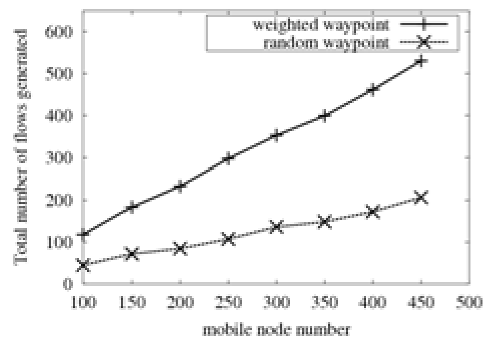

Fig8: WWP model generates more flows than RWP model, due to the high probabilities MN visit locations

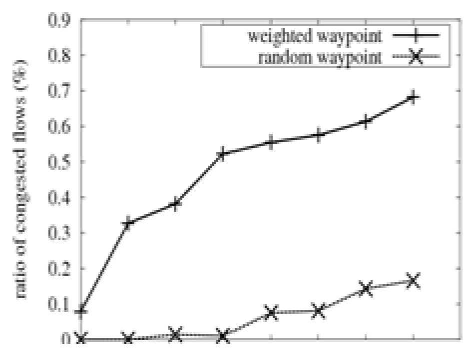

Fig9:Ratio of congested flows is much higer in WWP model

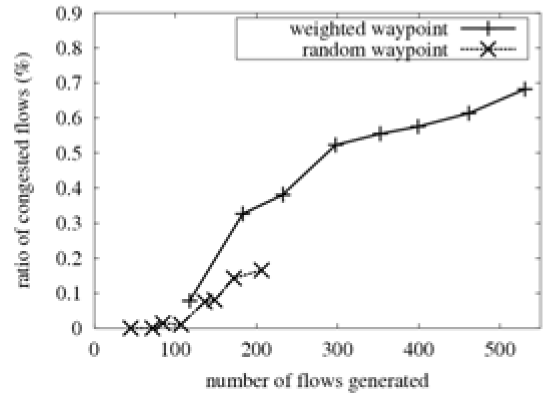

Fig10:WWP model results in higher ratio of congested flows even if the number of flows is similar to RWP model, due to uneven distribution of flows

V. Congestion Alleviation Mechanism

As suggested by the highly uneven distribution of flows among APs illustrated in Fig. 7, it is feasible to improve the QoS of the flows at the congested AP, if we can find a multi-hop ad hoc route to redirect it to underutilized NAPs. We propose the following MN-initiated flow-switching mechanism to achieve this goal.

The nodes with on-going flows keep monitoring the average end-to-end throughput to the local access point (LAP). If the average throughput is lower than an application-defined threshold, the MN notifies the LAP that it would like to be re- routed to a NAP using ad hoc multi-hop route, in the hope of getting better average throughput.

The MN notifies the LAP of its request to be switched to other APs by sending a “re-route request” to the LAP. Upon receiving this message, the LAP requests help from its neighbors by sending “help” message to one of them. The choice of the neighbor is based on AP’s geographical knowledge of the topology. The AP will make a random choice from its close by neighbors. It is possible to make a better choice by looking at the current loads of NAPs. The NAP replies with a “help ACK” message. The local AP then notifies the two parties (MN and NAP) about ID of each other. Based on this information, the neighbor AP and the MN can send out a route request packet (We adopt DSR [8] as the ad hoc routing protocol.) for each other simultaneously. This is achievable because the wired network provides a “tunnel” to exchange information between the MN and the NAP before they actually establish an ad hoc route to each other. The intermediate nodes at which the bi-directional searches meet will concatenate the partial routes from both ends and send back route reply messages to the MN and NAP. Such “meet in halfway” behavior is possible because DSR caches the partial route a route-request packet traversed before reaching the node, therefore an intermediate node is able to establish the end-to-end path if it is visited by route-request packets from both ends one after the other. The bi-directional search for the ad hoc route can potentially reduce the route discovery time.

In our work we assume that MNs uses a dedicated wireless channel to communicate with other MNs, so that the ad hoc network does not interfere with congested local wireless channel used by LAP and other MNs. This can be achieved by reserving a dedicated channel for ad hoc communication. All APs and MNs in the system must agree on using this reserved channel only for ad hoc communication. The channel is not used locally by any AP.

If the LAP assigns a MN to be switched to one of its neighbor, but there is no available multi-hop route from the MN to NAP, the switching is considered a failure and the MN will reestablish its connection to the LAP after a fixed period of time. If the MN is able to establish route to the designated NAP, but the route breaks later due to movement of intermediate nodes, the MN will also reestablish the connection to the LAP. Such fall-back-to-LAP behavior is necessary to avoid a MN waiting indefinitely for an ad hoc route to the designated NAP, which may not appear for a long time. If the LAP is still congested, the MN may start another switch trial later, possibly to another NAP. Note that for the duration of the flow to LAP, the MN stays stationary, so the route to the LAP is always available. The MN switches the flow to NAP only for better throughput, not because route to LAP is unavailable.

In order to avoid the situation that all MNs sense the congestion at LAP at the same time and try to switch, potentially leaving the LAP underutilized and the NAPs congested, we add a randomization factor in making switching decisions. When a MN sense local congestion, it does not always try to switch immediately. Instead, it sends the re-route request with switching-initiation probability *p*. By adjusting the switching-initiation probability, we can reduce the ping-pong effect at the cost of slower response to local congestion. The operation of our proposed mechanism is summarized in fig 11. Detailed illustration of the bi-directional route discovery is shown in Fig. 12.

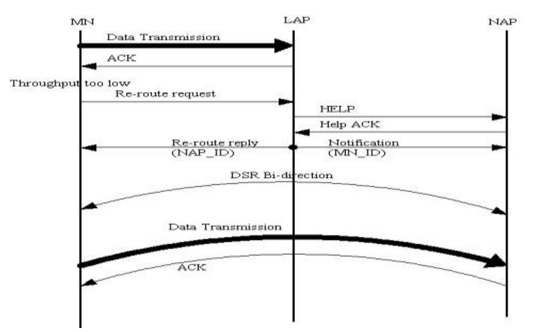

Figure 8. The control flow chart of proposed flow-switching mechanism

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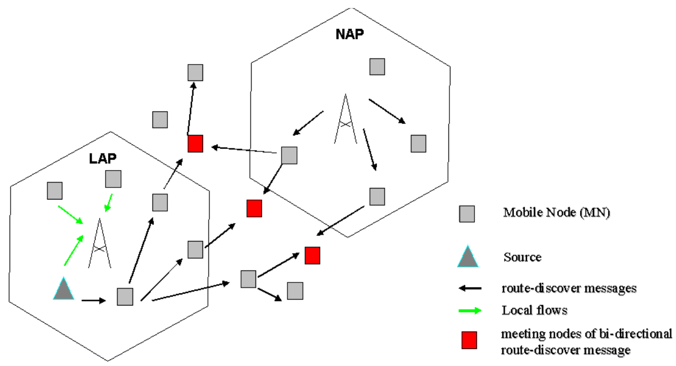
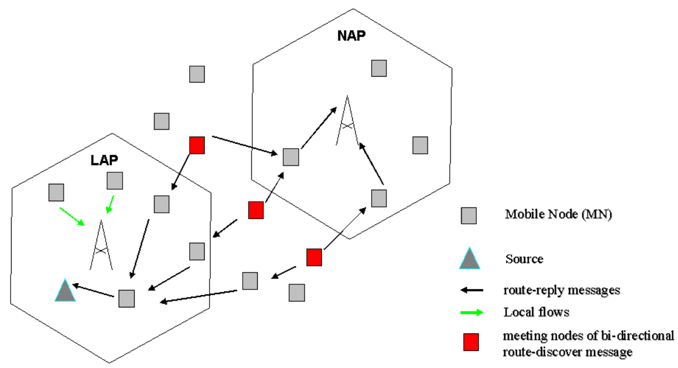


(a) Switching MN and NAP send out route discovery messages simutaneously



(b) route discovery messages meet at intermediate nodes and route reply messages are sent back to switching MN and NAP

Figure 9. Details of bi-directional route discovery behavior

VI. Simulation Results

We use *ns-2* network simulator to simulate our proposed flow switching mechanism. We vary the total number of MNs in the simulation area from 100 to 200 to illustrate different degree of congestion. The mobility model used by the MNs is the proposed WWP model introduced in section 3. In the simulation, we assume that each AP operates at bit rate of 2Mb/s. Each MN flow requires 200Kb/s throughput. To simplify the simulation, the MNs identify LAP congestion by counting current number of flows connected to LAP. The local AP becomes congested and throughputs for local flows start to drop if 7 or more simultaneous flows are connected to the LAP (This number was obtained via detailed simulations. The wireless channel cannot reach 100% utilization because of contention in wireless channel.) We simulate the scenario both with and without the flow switching mechanism.

The effect of the flow-switching algorithm is primarily to re-distribute the load of traffic across the APs. If some AP becomes congested, the MNs sense the congestion by observing degradation in the throughput of the on-going flow and try to switch the flow to NAP. If some of the MNs succeed in flow switching, the excessive flows at the LAP will shift to its neighbors, and both the flows that are switched and the flows that stay at the LAP can have uncongested wireless channel and better throughput. This idea is illustrated by comparing Fig. 7 to Fig. 13, where we illustrate the number of flows at the same 3 APs located in the upper-right corner of the virtual campus (Fig. 1), with the flow-switching mechanism. We see that some flows at library 1 are switched to classroom 2 and cafeteria 2, so the congestion at library 1 is not as bad as the case without flow-switching show in Fig. 7.

To better understand the effect of the flow-switching mechanism on the overall improvements of the system, we propose to use the metrics “AP congested time ratio” and “flow quality time ratio”. The former is defined as the time ratio an AP has at least 7 flows connected to it. This is the time ratio that the AP cannot provide adequate QoS to the connected flows. The latter is defined as the time ratio of a flow connected to any AP with less than 7 flows connected simultaneously. This is the proportion of time the flow can receive adequate throughput. Note that between the time a MN decides to switch a flow to NAP until the time it finds a route to the designated NAP, the flow is not connected to any AP hence this time period will not be counted toward the quality time ratio. Results shown below are averages of 6 independent simulation runs, using random mobility scenario for each.

Fig. 14 shows the average of AP congested time ratio of all APs. Fig. 15 shows the average of AP congested time ratio of the most congested AP in each simulation run. We can see that due to the uneven MN distribution resulting from the WWP model, the overall congested time ratio is low for the whole system. However, the most congested AP is quite overloaded. This is exactly the situation when flow-switching to NAPs should be helpful. From the figures we see that the congested time ratio of the most congested AP is reduced by more than 50% in all except for the 100 MN case. This implies flow-switching helps to reduce the local congestion of wireless LANs more than half of the time when congestion exists.

The flow quality time ratio is the metric to observe the improvement we get by employing flow-switching from user’s perspective. In Fig. 16 we show the flow-switching mechanism improves the quality time ratio for all cases.

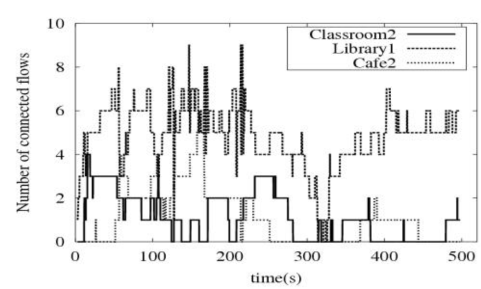


Figure 10. Flows re-distributed across APs, relieving congestion at library 1

We observe in the case for lower MN numbers (100 or 125 MNs) the effect of flow-switching is not so pronounced. This is because when the network is sparse, there is less chance to find a route to NAPs for switching flows. Hence the effectiveness of flow-switching is limited. The success rate for a switching flow to find a route to the chosen NAP is about 0.27 when there are

100 MNs, and the success rate increases to 0.43 when there are 200 MNs.

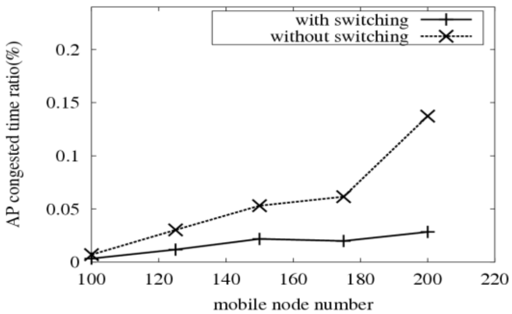


Figure 11. Average AP congested time ratio of all APs

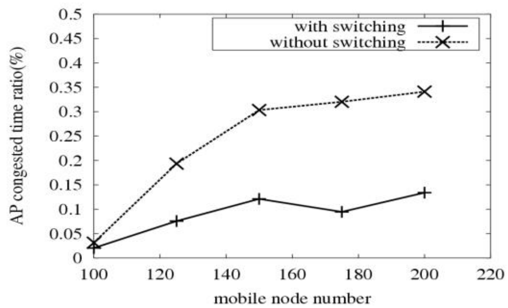


Figure 12. Average AP congested time ratio of the most congested AP

Figure 13. Average quality time ratio of all flows

VII. CONCLUSIONS AND FUTURE WORKS

We propose the WWP model to capture the location-based preferences in mobility model and network usage. Under this more realistic mobility model, distribution of MNs is uneven, leading to uneven usage of wireless LANs and congestion at some APs. However, the whole system in aggregation still has the capacity to serve the aggregated load. We propose a MN-initiated flow-switching mechanism, which involves the use of ad hoc networks to redistribute some flows from congested AP to its NAPs. Simulation results show that the mechanism improves AP congested time ratio and flow quality time ratio.

Handing out surveys is a good way to collect information about mobility pattern on campus quickly. However, such an approach is not easy to scale to obtain large amount of data. We turn our attention to the association pattern traces of wireless LAN users on campus and try to find ways to extract the parameters needed for WWP model from the traces. We are also trying to generalize this method to other environments.

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