On Dynamic Load Distribution Algorithms for Multi-AP WLAN under Diverse Conditions

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***Abstract*—Future wireless networks will enjoy ubiquitous connectivity by taking advantage of the IP core convergence which is seen as the *lingua franca* of heterogeneous access networks ecosystem. It is expected that the prevalence of WLAN and the advent of IEEE 802.11n standard will continue to offer compelling opportunities and therefore be considered as one of the de-facto wireless access network. However, it is known that wireless network conditions in general are diverse owing to both traffic and wireless channel variations. This raises the importance of exploiting diversity across a multiple access points (multi-AP) WLAN, which requires an advanced network control mechanism to effectuate uniform load distribution, so that QoS of users and composite capacity can be improved. Although various load distribution algorithms for WLAN have been investigated in literature, there is a lack of performance comparison between different algorithms. In this paper, we present a comparison of three dynamic load distribution algorithms, viz. predictive load balancing (PLB), predictive QoS balancing (PQB) and reactive QoS balancing (RQB) for infrastructure-based WLAN with DCF access mechanism based on OPNET simulations.**

I. Introduction

IEEE 802.11 WLAN is one of the de-facto wireless access networks offering broadband connectivity, thanks to its pervasive deployments over many diverse environments. The forthcoming 802.11n standard will further accentuate its benefits for high-speed ubiquitous broadband wireless access. However, delivering QoS demanding applications such as voice over WLAN (VoWLAN) are very challenging, particularly in the context of future IP-based wireless networking scenario where hotspot of multi-AP are physically co-located.

In general, network operators are motivated to maximize their revenue by maintaining a high system utilization while the end users demand good QoS. It is known that QoS would inevitably deteriorate when network is driven beyond its capacity limits. Hotspots are typically deployed under such circumstances to cope with heightened traffic demands. However, the composite network capacity will not scale with the increasing number of APs when stations select AP based on received signal strength only, without QoS considerations such as load control or an appropriate network control mechanism such as admission control. This problem is further complicated by the typical non-uniform load distribution across APs in public hotspots such as convention centers and airports where users tend to correlate temporally and spatially. Consequently, these cause sporadic congestions in AP with the strongest signal strength. Therefore, load and/or admission control must be incorporated in such multi-AP hotspots so that diversity could be exploited to harness composite network capacity and QoS improvements. The context of diversity in this paper refers to the dynamic network conditions in AP owing to both traffic and wireless channel variations. The former depend on the class of services e.g. real-time (RT) and non-real-time (NRT), type of traffic sources e.g. constant bit rate (CBR) and variable bit rate (VBR), and proportion of service classes whilst the latter depend on different propagation and fading environments. Particularly, wireless channel impairments are commonplace in hotspot and indoor WLAN, arising from frequent non-line-of-sight (NLOS) transmissions caused by structures and obstacles.

Traditionally, load control is concerned with load distribution to improve network QoS performance by transferring stations from heavily to lightly loaded networks. This allows stations to take advantage of the spare network capacity which would otherwise be left unused. However, it is also important to consider the state of wireless channel, which places fundamental limits on the network QoS performance, when distributing load across wireless networks [1]. Admission control is also critical for provisioning of QoS by regulating input traffic and preventing overloading of network. It works by conducting an assessment to check whether a new flow could be admitted without compromising the QoS requirements of existing flows. Hence, admission control policy dictates the provisioning of either guaranteed or predictive QoS. In fact, admission control and load control are often not dissociable. The main reason is that both rely on the knowledge of load metric in order to make their decisions. Henceforth, we treat both load and admission control interchangeably in the context of this paper.

Load distribution algorithms can be broadly classified as static, dynamic or adaptive. The main difference between static and dynamic load distribution algorithms is that the latter utilize additional system state information, which enables exploitation of short-term fluctuations, to improve the quality of their decisions. Dynamic load distribution algorithms can be further categorized as load balancing or QoS balancing algorithms. Both algorithms have the same primary function of avoiding under-utilized networks when distributing load. The subtle difference is the former attempt to equalize load while the latter attempt to equalize QoS across networks to improve QoS for all flows. Adaptive load distribution algorithms are

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an extension of dynamic load distribution algorithms with the capability to adapt their parameters or policies dynamically in response to the varying system state.

Although various load distribution algorithms for WLAN have been investigated in literature, there is a lack of performance comparison between different algorithms. In this paper, we present a comparison of three dynamic load distribution algorithms, viz. one belonging to the class of load balancing algorithm and the other two belonging to the class of QoS balancing algorithm for infrastructure-based WLAN with DCF access mechanism under diverse network conditions. The remainder of the paper is organized as follows. Section II discusses the related work. Section III describes the different dynamic load distribution algorithms. Section IV illustrates the comparative performance evaluation. Section V presents the conclusions and future work.

II. Related Work

A key issue in designing any load or admission control algorithms is to identify a suitable load metric to estimate the available network capacity accurately. Bianchi and Tinnirello [2] first introduced the notion of 'packet level' load metric and showed that load balancing of WLAN can be improved.

Derivation of packet level load metrics could be categorized in two main threads, viz. model-based and measurement-based. In model-based approach, packet level load metrics are obtained by analyzing the WLAN DCF using the two-dimensional Markov chain model either with or without the aid of theoretical queueing models. Zhai *et al.* [3] integrated Bianchi's model [4] with $M/M/1/K$ and $M/G/1/K$ queueing models to give non-saturation throughput, packet delay and loss bounds. The authors also showed that although $M/G/1/K$ provides better accuracy than $M/M/1/K$ in general, they do not exhibit significant difference in the non-saturation region. Malone *et al.* [5] extended Bianchi's model to non-saturation conditions by incorporating post-backoff states under bufferless network assumption. The authors also considered stations with different arrival rates but with same packet lengths. In measurement-based approach, packet level load metrics are obtained by either direct measurements or estimations from the system itself. Velayos *et al.* utilized throughput of AP to reflect the load of a network. Ong and Khan [6] employed packet delay of AP to capture both network and wireless channel variations which are indicative of the network load. Above all, channel utilization estimation first proposed by Garg and Kappes [7] gave the best representation of the effective network load.

The level of centralization also plays a crucial role in dynamic load distribution algorithms. Balachandran *et al.* [8] presented an adaptive load balancing solution where a centralized admission control server contains load information of all APs. Velayos *et al.* [9] proposed a decentralized load balancing scheme where APs are then classified based on their throughput in one of the three states, viz. underloaded, overloaded or balanced. It is known that both centralized and decentralized architectures have their pros and cons. Recently, a terminal-oriented network-assisted (TONA) handover architecture, which is a compromise between centralized and decentralized ones, is proposed in [6].

III. Dynamic Load Distribution Algorithms

The comparison of the three dynamic load distribution algorithms is summarized in Table. I. Since these algorithms span across different levels of centralization, their performance is investigated based on IP-based TONA handover architecture [6] which can be configured to support different levels of centralization. Here, we draw a distinction between different radio resource management (RRM) distributions according to the levels of centralization. Accordingly, network-centralized RRM refers to RRM decisions made in a central access point controller (APC), network-distributed RRM refers to RRM decisions distributed between APs, and network-device distributed RRM refers to RRM decisions distributed between AP and stations. In what follows, we give an overview of the three dynamic load distribution algorithms which aim to redistribute load across a multi-AP WLAN by exploiting diversity of dynamic network conditions to trigger vertical handovers. References to the respective models used in each of the dynamic load distribution algorithms are provided as it is beyond the scope of this paper to exposit their intricacies.

A. Predictive QoS Balancing Algorithm

In PQB algorithm, the load metric is based on packet delay and packet loss rate which are derived by combining two analytical models, viz. Markov chain model which analyzes the WLAN DCF operation and $M/M/1/K$ queueing model to analyze the WLAN QoS performance under varying traffic and wireless channel conditions. Here, we modify Zhai's model [3] to reflect the unbalanced load situation of an infrastructure-based VoWLAN in a wireline-to-wireless topology. The VoWLAN consists of one AP, $N-1$ WLAN stations and $N-1$ ethernet stations, which are connected through a wireline backbone. When considering 2-way voice conversations between WLAN and ethernet stations, the traffic load flowing through the AP is $N-1$ times that of a WLAN station since AP transmits half of the voice traffic to WLAN stations. In addition, we introduce traffic variability between WLAN stations by considering heterogeneous voice codecs of different packetization intervals and packet length. Furthermore, we consider wireless channel variability between BSSs by factoring in transmission failures in both medium access control (MAC) data frame and acknowledgment (ACK) frame. We assume a Gaussian wireless channel where each bit has the same bit error probability and bit errors are *i.i.d.* over the entire frame. We ignore the effects of distance and assume that all stations have same bit error rate (BER) and frame error rate (FER) as in Ni's model [10]. We also model the freezing of backoff counter during times when medium is busy according to Ziouva's model [11]. Collectively, our analytical model accounts for: (i) unbalanced traffic load between stations and AP of an infrastructure-based WLAN; (ii) diverse traffic flows

TABLE I
COMPARISON BETWEEN DYNAMIC LOAD DISTRIBUTION ALGORITHMS.

Attributes	Model-Based	Measurement-Based	
Algorithm Type	QoS balancing	Load balancing	QoS balancing
Load Metric	Packet delay, packet loss [3],[10],[11]	Channel utilization [7]	Packet delay [6], channel utilization [7]
Traffic Profiling	Mean arrival rates, collision probability, queue characteristics	Estimated peak and/or mean channel utilization	Measured packet delay, estimated mean channel utilization
Admission Control	Hard Limit	Hard Limit	Soft Limit
Centralization	Network-centralized RRM	Network-distributed RRM	Network-device distributed RRM
Information Exchange	Between APC-APs	Between APs	Between APC-AP-Stations
Utilization	Medium	Low	High
Handover Events/Complexity	High	Low	Medium
QoS Provision	Predictive QoS		
Stability Period	10 Beacon Intervals		
Candidate Selection	QoS satisfaction factor ($QSF < 1$)		
Network Selection	Greedy Approach		

between stations; and (iii) diverse wireless channel conditions between BSSs of a multi-AP hotspot scenario. The load metric is then used as upper bounds of admissible traffic load, which include the new flow and any existing flows of an AP, in a centralized admission control to provision predictive QoS. We remark that these bounds are more proper as compared to those used in PLB algorithm since collision probability and queue characteristics of the AP are considered. However, PQB will generally result in higher complexity.

B. Predictive Load Balancing Algorithm

In PLB algorithm, the load metric is based on channel utilization which estimates the fraction of channel occupation time per observation interval. Accordingly, the channel utilization of each flow and the corresponding network capacity are estimated as

$$\begin{aligned} CU^n_{total} = \sum_{j \in flows} CU^n_j, \quad n = 1, \ldots, N, \\ CU^n_j + CU^n_{total} < CU_{max}, \end{aligned} \tag{1}$$

where $0 \leq CU^n_{total} \leq 1$ is total channel utilization of nth AP, CU^n_j is channel utilization of jth flow and CU_{max} is the admission threshold. A new RT flow can be accepted without affecting QoS of existing flows if (1) is true. For error-prone wireless channel, we need to consider the average FER and account for the factor of $(1 - FER)$, when computing the channel utilization of each flow i.e. $CU^n_j/(1 - FER)$, since the entire transmission will fail. This load metric is widely used for both load and admission control algorithms due to its simplicity. Here, we implement PLB in a decentralized fashion as in [9]. Guaranteed QoS can be provisioned when both peak and mean channel utilization are used as upper bounds of admissible traffic load. Network utilization is usually acceptable when flows are smooth with CBR sources. However, when flows are bursty with VBR sources, such guaranteed QoS inevitably results in low utilization. Higher network utilization can be achieved by relaxing the bounds to use mean channel utilization only but this means that only predictive QoS can be provisioned. Furthermore, the admission threshold for RT flows is typically restricted to $80-90\%$. It is often argued that this buffer caters for variability of VBR sources and ensures that NRT flows can be accommodated within the buffered capacity. However, finding an optimal admission threshold in not trivial since the saturation point of WLAN depends on the proportion of traffic mixes e.g. RT vs. NRT flows and CBR vs. VBR sources. In other words, there will be a different impact on the network load *even* for the same average data rate. Hence, a better approach might be removing the admission threshold and rely on measurements of the existing flows to regulate input flows. Such measurements should be conservative by using historical knowledge of the fluctuations in network conditions.

C. Reactive QoS Balancing Algorithm

In RQB algorithm, the load metric is based on measured packet delay and mean channel utilization which are utilized as upper bounds of admissible traffic load in network-device distributed RRM implementation found in [6]. RQB leverages on link layer measurements, such as packet delay, as QoS metric to characterize the perceived quality of each AP. The key advantages of adopting link layer measurement are: (i) it could be used to quantify both QoS explicitly and wireless channel variations implicitly, since QoS metric in general varies accordingly to wireless channel conditions; and (ii) it mitigates the difficulty of estimating the actual bandwidth occupancy for each flow, particularly in the presence of dynamic traffic patterns and wireless channel conditions when employed as load metric for soft admission control. Accordingly, *soft* refers to the number of admissible connections which is not fixed but variable depending on the class of services e.g. RT and NRT flows, type of traffic sources e.g. CBR and VBR, proportion of service classes, and prevailing wireless channel conditions. This differs from the traditional hard admission control, which is typically used for homogeneous voice traffic, where the number of admissible connections can be easily predetermined. These bounds are more relaxed as compared to the previous two algorithms, thus are referred as soft limits. Here, the mean channel utilization is used without imposing any admission threshold to RT flows. This essentially removes the hard limit and encourages higher network utilization. However, additional packet delay measurements need to be incorporated to account for the past network traffic variations. Accordingly, the measurements directly optimize the expected packet delay, making it adaptive to dynamic network conditions. This improves the flexibility of the admission control but at the expense of occasional violations, which limit it to provision predictive QoS, and moderate complexity. The network utilization gain would become more significant when there is a high degree of statistical multiplexing e.g. in broadband WLANs.

D. Candidate Selection and Network Selection

To facilitate candidate selection, we quantify QoS requirements of the stations as a function of two QoS metrics. Each QoS element is the ratio of the required QoS metric threshold and the measured QoS value. QoS satisfaction factor (QSF) is defined as the minimum between the two QoS elements,

$$QSF = \min_{i \in Links} \left[\frac{PD^t}{PD_i^m}, \frac{PLR^t}{PLR_i^m} \right], \tag{2}$$

where PD^t is packet delay threshold and PLR^t is packet loss rate threshold while PD_i^m is measured packet delay and PLR_i^m is measured packet loss rate of ith links i.e. both uplink and downlink. $QSF < 1$ when QoS requirements of stations cannot be met. This condition is used by stations in all three dynamic load distribution algorithms to trigger QoS-based vertical handover.

The network selection in all three dynamic load distribution algorithms is based on the greedy approach. The reason being obtaining an optimal allocation of stations to available APs that maximize the composite network capacity is a combinatorial problem which is NP-hard. For PQB (PLB) algorithm, the AP which maximizes the difference between the estimated bounds and predefined QoS metric (load metric) thresholds is selected. For RQB algorithm, network selection is implemented according to [6] where AP with the highest network quality probability, which is based on packet delay measurement, is selected. A Bayesian learning process is used to capture historical variations of network traffic conservatively, making it reliable for use in soft admission control.

IV. Comparative Performance Evaluation

We simulate a hotspot of three 802.11b APs in a wireline-to-wireless topology as in [6], operating with data rate of $1Mbps$ under error-prone wireless channel conditions using OPNET™ Modeler® 14.5 wireless module. VoIP traffic is generated using heterogeneous voice codecs as in Table. II and VBR source is simulated using ON-OFF model according to ITU [12]. We introduce an unbalanced load of five G.711, five G.729, five G.723.1 stations in BSS 1 and two G.711, two G.729, two G.723.1 stations in each of BSS 2 and BSS 3. An error-prone Gaussian wireless channel is simulated where BER of wireless channels in BSS 1, 2 and 3 are 10^{-9}, 10^{-5} and 10^{-6}, respectively. The motivation is to examine the worst-case scenario when the total offered load approaches the composite network capacity of three BSSs under diverse wireless channel conditions. We assume no hidden terminals and exclude RTS-CTS mechanism. All stations are roaming to support handover events which are coordinated to one event at a time.

For QoS performance evaluation, we adopt Jain's fairness index to quantify the effect of different dynamic load distribution algorithms on QoS fairness among APs. Suppose x_i is the QoS metric i.e. packet delay or packet loss rate of AP i, then the QoS balance index (QBI) is defined as,

TABLE II
Traffic generation parameters.

Traffic Type	Packet Size (Bytes)	Inter-arrival (ms)	Avg. Data Rate (kbps)
G.711	80	10	64
G.729	20	20	8
G.723.1	24	30	6.4

$$QBI(x) = \left(\sum_i x_i\right)^2 \Big/ n \left(\sum_i x_i^2\right), \tag{3}$$

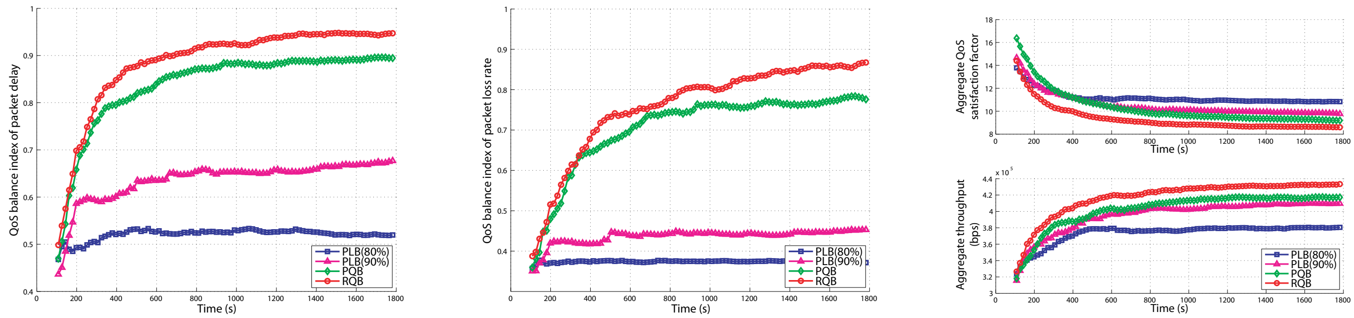
where n is the number of APs over which the load will be redistributed. The QoS balance index $0 \leq QBI \leq 1$ is a continuous function which is independent of scale. It has a value of 1 when all APs have the exactly the same QoS metric and a value of $1/n$ when APs are extremely unbalanced, which is 0 in the limit as $n \to \infty$.

A. Simulation Results

In this study, we investigate the impact of three different dynamic load balancing algorithms on QoS, throughput and handover performance. PLB is evaluated under different admission thresholds of $CU_{max} = 0.8$ denoted as PLB(80%) and $CU_{max} = 0.9$ denoted as PLB(90%). PQB is evaluated with a packet delay threshold of $60ms$ and a packet loss rate threshold of 1%. RQB is evaluated with $CU_{max} = 1.0$ i.e. no admission threshold for RT flows and also a packet delay threshold of $60ms$. The key motivation is to compare the QoS fairness between APs and number of handover events when different dynamic load distribution algorithms are deployed. In addition, we reveal an interesting relationship, which is the cornerstone of QoS balancing algorithms, between aggregate QSF of stations defined in (2) and aggregate throughput of stations as well as QoS fairness between APs defined in (3).

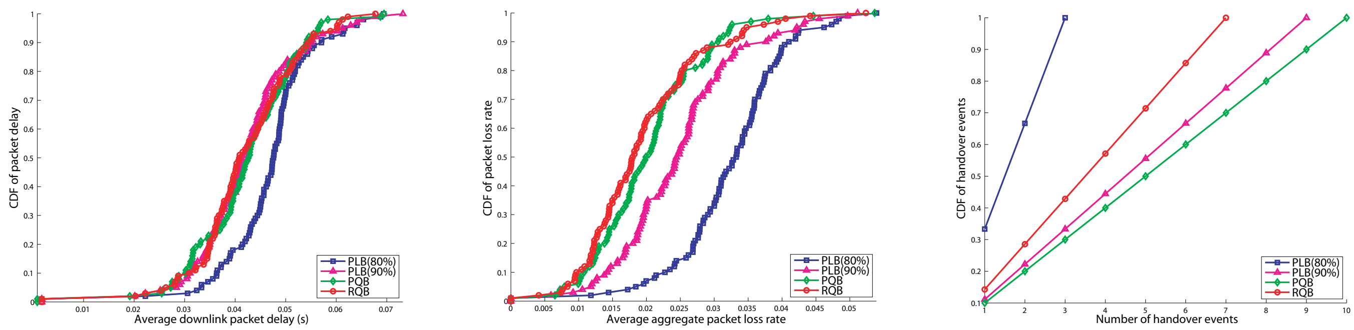
We analyze our results starting from $100s$ ($0 - 100s$ is the warm-up period). According to the definition of (3), QBI should be close to one ideally to offer QoS fairness. From Fig. 1 (a), we observe that RQB outperforms PLB(80%) by 67%, PLB(90%) by 39% and PQB by 5% in terms of QBI of packet delay between APs. Similarly from Fig. 1 (b), we observe that RQB outperforms PLB(80%) by 100%, PLB(90%) by 72% and PQB by 7% in terms of QBI of packet loss rate between APs. Clearly, the state of balance i.e. QoS fairness between APs is dependent on the type of dynamic load distribution algorithms which we would now discuss.

On the whole, both QoS balancing algorithms achieve better QoS fairness as compared to load balancing algorithm. QoS balancing algorithms exhibit better performance for two main reasons. First, the load metrics of both PQB and RQB contain at least one of the QoS metrics under study. This directly optimizes the expected packet delay and packet loss rate while the load metric of PLB is indirectly related to the investigated QoS metrics. Second, the load metric of PLB is based on mean channel utilization where the admission threshold is set to 80% (90%) of an AP maximum capacity. Since only



(a) QBI of packet delay. (b) QBI of packet loss rate. (c) Aggregate QSF and throughput of stations.

Fig. 1. QoS balance index between APs, and aggregate QoS satisfaction factor and throughput of stations.



(a) CDF of average downlink packet delay. (b) CDF of average aggregate packet loss rate. (c) CDF of number of handover events.

Fig. 2. CDF of average downlink packet delay and aggregate packet loss rate, and number of handover events in a multi-AP WLAN.

BSS 1 is overloaded in the simulated scenario, the admission threshold creates an aggregate buffer capacity of 40% (20%) preemptively in BSS 2 and BSS 3. This places a hard limit which prevents opportunistic exploitation of possibly spare capacity. Although this strategy attempts to protect existing flows, it inevitably results in higher blocking probability for incoming handover attempts. Hence, BSS 1 suffers sustained overloading which degrades the QoS fairness between APs. This impact will be magnified with decreasing admission threshold which acts to create more buffered capacity which is evident from Figs. 1 (a) and (b). Moreover, choosing an optimal admission threshold in not trivial since the saturation point of WLAN depends on class of services e.g. RT and NRT flows, type of traffic sources e.g. CBR and VBR, proportion of service classes, and prevailing wireless channel conditions. Therefore, it is very difficult to obtain accurate characterization of RT flows as a priori knowledge in presence of such dynamic network conditions. We note that PQB also utilizes hard limit but admission threshold is not required. Hence, QoS fairness of PQB comes in between RQB, and PLB(80%) and PLB(90%).

On the other hand, RQB also employs mean channel utilization as one of its load metric but relaxes the bounds by eliminating the admission threshold. Instead, it operates on a soft admission control using packet delay measurement. The salient advantage of measurement-based soft admission control is that it relies on historic variations of network conditions captured through measurements to mitigate the difficulty in characterizing bandwidth occupancy of RT flows. Hence, a higher network utilization can be achieved by allowing exploitation of spare capacity opportunistically which is evident in the case of RQB over PLB(80%) and PLB(90%), where both are design to provision predictive QoS. Although there would be sporadic violations of packet delay as shown in Fig. 2 (a), this would be outweighed by the remarkable QoS fairness improvements as shown in Figs. 1 (a) and (b) which are direct consequences of the packet loss rate improvements as shown in Fig. 2 (b).

In terms of handover performance as shown in Fig. 2 (c), PLB(80%) has the least number of handover events as compared to PLB(90%), RQB and PQB. When comparing between the two QoS balancing algorithms, PQB has the most number of handover events while RQB has moderate number of handover events which comes in between PLB(80%) and PLB(90%). In general, QoS balancing algorithms tend to accrue more handover events as compared to load balancing algorithm since their load metric does not impose any admission threshold to create buffered capacity preemptively. However, QoS balancing algorithms provide better overall QoS performance in terms of packet delay and packet loss rate as compared to load balancing algorithms since their load metrics contain at least one of the QoS metrics under study.

From Fig. 1 (c), it is interesting to observe that both QoS balancing algorithms have lower aggregate QSF but higher aggregate throughput as compared to load balancing algorithm, from the stations' perspective. More specifically, the aggregate throughput increases with decreasing QSF. Similarly from Figs. 1 (a) and (b), QoS fairness also increases with decreasing aggregate QSF. This suggests that tradeoffs exist between aggregate QSF and throughput of stations as well as QoS fairness between APs. For every decrease in aggregate QSF of stations, there is a corresponding increase in aggregate throughput of stations and QoS fairness between APs. In other words, QoS balancing algorithms trade aggregate QSF of stations for QoS fairness between APs in order to maintain a QoS-balanced system which in turn yields a higher aggregate throughput of stations. When comparing between the two QoS balancing algorithms, it is clear that RQB is able to achieve higher QoS fairness between APs and aggregate throughput of stations, and generate lesser handover events as compared to PQB but at the expense of lower aggregate QSF of stations. Although RQB results in a lower aggregate QSF, we notice from Figs. 2 (a) and (b) that both RQB and PQB have similar average downlink packet delay and aggregate packet loss rate from the composite system's perspective. This reiterates the advantage of using a measurement-based soft admission control which improves its flexibility in presence of dynamic network conditions by exploiting spare capacity in an opportunistic manner while allowing occasional violations.

B. Discussions

The performance of all three dynamic load distribution algorithms, which depends largely on their load metrics, has various tradeoffs. Load balancing algorithm which uses mean channel utilization as load metric has the advantages of lower complexity and lesser handover events. However, it results in lower utilization due to the required admission threshold for RT flows which creates buffered capacity that may not be utilized efficiently. Furthermore, how to choose an admission threshold for RT flows optimally or adaptively is non-trivial since it is very difficult to obtain accurate characterization of RT flows as a priori knowledge in presence of dynamic network conditions. On the other hand, QoS balancing algorithms use QoS metric as load metric which has the advantages of higher utilization, QoS fairness and aggregate throughput of stations since its load metric directly optimizes the expected packet delay and packet loss rate of the system. However, they tend to be more complex, generate more handover events and result in lower aggregate QSF of stations which is a tradeoff for achieving higher utilization.

When comparing between the two QoS balancing algorithms, we note that the measurement-based soft admission control employed in RQB has evident advantages over the hard admission control found in PQB. Particularly, RQB yields higher utilization, QoS fairness and aggregate throughput of stations with lesser handover events, thanks to the Bayesian learning process which captures historical variations of network conditions reliably for use in soft admission control to exploit any available capacity opportunistically and adapt to dynamic network conditions. Another significant advantage of RQB is that it uses a generalized measurement-based approach which can be deployed in any wireless networks since it requires only link layer measurements to quantify both QoS explicitly and wireless channel variations implicitly. On the contrary, PQB employs a model-based approach where generalization for different wireless networks is challenging and generally requires remodeling efforts. We note that IEEE 1900.4 standard [13], which has gained much attention recently, is an example of such measurement-based system.

V. Conclusion and Future Work

We evaluate the comparative performance between three dynamic load distribution algorithms, viz. predictive load balancing (PLB), predictive QoS balancing (PQB) and reactive QoS balancing (RQB) in terms of QoS fairness between APs, aggregate QSF and throughput of stations, and number of handover events. The QoS metrics considered are packet delay and packet loss rate which are typically used to characteristic the quality of VoIP traffic. Initial results suggest that performance of all three algorithms depends largely on their load metrics. Particularly, RQB achieves higher (significantly higher) network utilization and QoS fairness, and similar (much better) QoS performance as compared to PQB (PLB evaluated at both admission thresholds of 80% and 90%). Results also show that the generalized measurement-based approach employed in RQB is adaptive to dynamic network conditions, arising from both traffic and wireless channel variations. For future work, we plan to investigate the class of adaptive load distribution algorithm where load metrics can be dynamically adjusted according to prevailing system states.

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