Cell Breathing Based on Supply-Demand Model in Overlapping WLAN Cells*

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Abstract. Introducing cell breathing in cellular networks into wireless local area networks (WLANs) for load balancing is beneficial since no special modification of clients. However, fairness and effectiveness is quite challenging in cell breathing. In this paper, a supply-demand model (SDM) based on cell breathing technique is proposed to allocate continuous or discrete power to APs for fair and effective load balancing. SDM classifies the beacon power of an AP into two kinds: the demand power and the supply power. The former is the ideal power that an AP is supposed to have while the latter is the power the AP actually transmits. Finding the deterministic global optimal solution, SDM makes the demand and supply power as equal as possible and the load on APs balanced. Because SDM does not need multiple iterations to compute the optimum, it can avoid frequent user handoffs resulting from frequent power change. Finally, SDM is extended to support a broader range of load definition and the generalized relationship between beacon power and load. The simulation results show the proposed scheme is fair for realizing load balancing and effective for improving throughput.

Keywords: Load balancing, cell breathing, power assignment.

1 Introduction

In WLANs, load imbalance usually comes up, which incurs two problems: lower network throughput and worse quality of service (QoS). In the carrier sense multiple access (CSMA)-based WLANs, all clients have equal rights to access the wireless medium. Thus, in a congested AP, there exists a higher probability that multiple clients access the wireless medium at the same time, resulting in a large number of transmission collisions. As a consequence, more bandwidth will be consumed for retransmissions, leading to lower network throughput. Moreover, longer backoff periods are needed to avoid collisions, thus resulting in longer transmission delay.

^{*} This work is supported by NSFC Project (no. 60873252), International S&T Cooperation Program of China (no.2008DFA11630), National Major Basic Research Program of China (no. 2007CB307105, 2009CB320501, 2009CB320503), postdoctoral foundation (no.20090450391).

N. Bartolini et al. (Eds.): QShine/AAA-IDEA 2009, LNICST 22, pp. 203-217, 2009.

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However, the IEEE 802.11 standard, the protocol of WLANs, does not provide any method for load balancing. To make up this deficiency, both industry and academia have proposed some solutions [1-10], most of which require clients to select APs based on not only the received signal strength indicator (RSSI) but also the load on the APs. This requirement needs clients to have special software/hardware supports. In real networks, WLAN clients could be heterogeneous with different AP selection policies, which make it hard to cooperate with APs for load balancing due to proprietary schemes of different device providers.

To solve the above problems, some researchers [11-13] introduce the concept of cell breathing in code division multiple access (CDMA) network into WLANs for load balancing. In fact, cell breathing is a side effect in CDMA networks in the sense that the coverage and capacity of a CDMA cell are reduced with the increase of user number. However, it can be a load balancing technique in WLANs if some optimal strategies are applied.

When cell breathing method is used in WLANs, if an AP is heavily loaded, it will reduce the power of beacons to shrink its coverage area for reducing the serving of new clients as shown in Fig. 1(a); if the AP is lightly loaded, it will increase the power of beacons to expand its coverage area for attracting new clients as shown in Fig.1 (b).



Fig. 1. Example of cell breathing (a) AP is heavily-loaded (b) AP is lightly-loaded

Reducing data transmission power of an AP will degrade the channel quality of all its associated users, not only those who tend to shift to other APs, but also those who still associate with the current AP. To solve this problem, cell breathing technique separates the transmission power of data and beacons. It only adjusts the power of beacons because the beacon power only affects the cell dimension and has no impact on the loss rate and transmission latency of data packets.

In cell breathing method, clients are not required any modification. They select an AP only according to the default mode of IEEE 802.11. Therefore, it can be realized easily and has a broader application prospect.

Although conceptually simple, implementing cell breathing is surprisingly challenging. We explain this problem through the following *Example*.

Example: Consider a WLAN with three APs, A, B and C and ten users. For simplicity, we assume that all users generate the same traffic load, and all APs have the same bit rate and data transmission power. At the beginning, due to the extremely different beacon power, the network load is quite imbalanced as shown in Fig.2 (a). To solve this problem, we use the cell breathing method that increases the beacon power of APs A and C, and decreases that of AP B. From the viewpoint of load balancing, we can obtain two optimal results as shown in Figs. 2(b) and (c). Both client-to-AP mappings can realize load balancing, but their throughput is different.



Fig. 2. Challenges in Cell Breathing

The difference between Figs. 2(b) and (c) is whether user g accesses AP B or A, which leads to different throughput. When each AP's data transmission power is same and without considering other factors, the throughput of a user is proportional to its received power [12] which is in turn inversely proportional to the distance between the user and AP [14]. Because user g is nearer to AP B, the throughput when it accesses B is higher than accesses AP A.

In reality, WLANs offer more complicated scenarios. So our challenge is to propose an effective cell breathing method to find an optimal power assignment that achieves load balancing while providing higher throughput. In addition, another challenge is to avoid the frequent power change, because it will induce non-negligible handoff latency.

This paper proposes a cell breathing scheme based on the supply-demand model (SDM). It classifies the beacon power of an AP into two kinds: the demand power and the supply power. The former is the ideal power that an AP is supposed to have while the latter is the power the AP actually transmits. SDM makes the demand and supply power as equal as possible while the load on APs balanced. The proposed scheme inherits the advantages of cell breathing method, and may have the following potential contributions:

- It finds the deterministic global optimal mapping between users and APs instead of relying on local optimization heuristics. More importantly, it does not need multiple iterations for finding the optimum, avoiding frequent user handoffs caused by frequent power change.
- 2) It supports a broad range of load definition besides the user number.
- 3) It is applicable to both continuous power and discrete power assignment.

The simulation results show that our SDM-based cell breathing scheme is fair for realizing load balancing and effective for improving throughput.

The rest of paper is organized as follows: related works are shown in Section 2 while the problem formulation is given in Section 3. SDM are presented in Section 4,

and how to assign power through SDM-based cell breathing method is described in Section 5, which is extended in Section 6. The performance evaluation is discussed in Section 7 while conclusions are offered in Section 8.

2 Related Works

Load balancing in WLANs is an important issue that has attracted significant attentions from both industry and academia. From industry perspective, several vendors [1-4] have supported load balancing in their WLAN products. For example, Cisco's load balancing solution [1] is based on the client number, signal strength and bit error rates. D-link [2], Proxim [3] and Airflow [4] take into account the actual AP traffic in their solutions. In these proprietary products, APs need to broadcast their load information to clients through beacons, and each client is required to select the AP with the lightest load.

From academic perspective, several algorithms have been proposed to distribute the load based on different load metrics, such as the client number [5], the capacity available for a new station that uses the fastest modulation (AAC) [13], the aggregated downlink and uplink traffic [6], the channel idle time [7], the channel utilization estimate (CUE) [8]. Balachandran et al. [9] proposed to select an AP in light of not only its RSSI but also the minimal bandwidth that the AP can offer. Bejerano et al [10] proved the strong correlation between fairness and load balancing, and used load balancing techniques to obtain near-optimal max-min fair bandwidth allocation.

All the above schemes require the clients to have special supports for AP selection. To avoid revising clients, some researchers [11-13] introduced the concept of cell breathing in CDMA networks into WLANs for load balancing.

Bejerano and Han [11] presented a cell breathing method for load balancing in WLANs, which is based on two algorithms: one minimizes the load of the most congested AP(s), and the other produces an optimal min-max load balancing solution. These methods can maximize network throughput while providing fairness. However, if only the currently associated user set and each user's load are known, their algorithms need multiple iterations to converge to an optimum. Because each iteration will actually change the beacon power which may trigger some clients to move among the coverage areas of APs from time to time, this method may induce non-negligible handoff latency up to 1.3 seconds [7].

Bahl et al. [12] proposed another cell breathing scheme. Different from [11], this scheme does not need multiple iterations. Once the topology of APs and clients is given, an optimal mapping of clients to APs can be found with the help of linear programming. However, their method needs to know the distance between each AP-client pair, hence increasing the algorithm complexity.

Garcia et al. [13] adopted a cell breathing method to adjust the cell size according to the signal to noise ratio (SNR) received by each client in the AP's coverage area. To obtain the SNR information, their scheme needs the help of some new standards such as the IEEE 802.11k or h.

3 Problem Formulation

In this section, the problem formulation is given. As described above, cell breathing method separates the transmission power of data and beacons. So we call the beacon signal strength indicator a user receives as RSSI-B while the data signal strength indicator a user receives as RSSI-D.

Due to without any special modification of clients, default WLAN users select APs only according to RSSI-B of APs However, RSSI-D of APs that they receive actually affects the data link quality. In our scheme, to reflect the relationship between AP and users' data link quality, users are classified into two types:

Definition 1: A primary user of AP i (i = 1, 2, ..., N) is defined as a user whose RSSI-D sensed from AP i is the loudest, where N is the maximum AP number in the network.

Definition 2: A handoff user of AP i is defined as a primary user of other APs, who currently associates with AP i (i = 1, 2, ..., N).

Obviously, a user of AP i (i = 1, 2, ..., N) is either a primary user or a handoff user. In our scheme, time is divided into equal length intervals. The number of primary users belonging to each AP at any time interval makes up the primary user vector, which is defined as:

Definition 3: The primary user vector $P(k) = [p_1(k) \quad p_2(k) \quad \dots \quad p_N(k)]$, where $p_i(k)$ is the primary user number of AP i(i = 1, 2, ..., N) during the k^{th} time interval, k = 1, 2, ...

In addition, despite the user type, the number of users connecting to each AP at any time interval makes up the user vector, whose definition is:

Definition 4: The user vector $U(k) = [u_1(k) \ u_2(k) \ \dots \ u_N(k)]$, where $u_i(k)$ is the number of users that associate with AP $i(i = 1, 2, \dots, N)$ during the k^{th} time interval, $k = 1, 2, \dots$.

Obviously, both $\sum_{i=1}^{N} p_i(k)$ and $\sum_{i=1}^{N} u_i(k)$ are the total user number in the network

during the k^{th} time interval.

For the sake of simplicity, we assume that the AP deployment ensures a high degree of overlaps among the range of adjacent APs as in [11]. And then our problem is when the primary user vector is given, how to find the optimal user vector to make each user associate with the AP providing the data link quality as good as possible while guaranteeing the load balancing on APs. To solve the problem, we propose SDM as described in the next section.

4 Supply-Demand Model

4.1 Formulations of Demand and Supply Power

SDM classifies the beacon power of an AP into two kinds: the demand power and the supply power. The former is the ideal power that an AP is supposed to have while the latter is the power the AP actually transmits.

According to the definition of primary users, an AP should serve its primary users as many as possible to provide better data link quality to users. At the same time, when the AP is light-loaded while its neighbors are congested, it should serve some users of its neighbors to relieve their load. So, an AP should have enough beacon power to attract the primary and handoff users.

According to [12], the larger the beacon power is, the more users that request to associate with an AP. Here, we assume the relationship between the associated user number and the beacon power to be linear correlation. Actually, our model is still workable when this assumption is replaced by other relationship as described in Section 6. Therefore, the demand power of AP *i* at the k^{th} time interval, denoted as $d_i(k)$, can be formulated as follow:

$$d_i(k) = \alpha p_i(k) + f_i + \sum_{j=1}^{N} q_{ij} \cdot (d_j(k-1) - s_j(k-1)) \quad (i = 1, 2, ..., N)$$
(1)

Formula (1) includes two parts. The first part $\alpha p_i(k) + f_i$ is the power of AP *i* needed to attract the primary users at the k^{th} time interval. This part is proportional to the primary user number. Here, $\alpha > 0$ is the proportionality coefficient and f_i is a constant reflecting the external factors (e.g., geomorphology, buildings or trees) that affect AP *i* to provide power for attracting users.

The second part $\sum_{j=1}^{N} q_{ij} \cdot (d_j(k-1) - s_j(k-1))$ is the power provided by AP *i* to

attract handoff users at the k^{th} time interval, where $d_j(k-1)$ and $s_j(k-1)$ are the demand power and supply power of AP *j* at the $(k-1)^{th}$ time interval respectively. This part is closely related to the power provided by the neighbor APs at the $(k-1)^{th}$ time interval. During the $(k-1)^{th}$ time interval, if the demand power in the neighbors of AP *i* is larger than the supply power, i.e. $d_j(k-1) > s_j(k-1)$, their primary users will be compelled to shift. As a result, AP *i* should increase its power to attract these handoff users, and vice versa. In Formula (1), q_{ij} is the power-impact factor of AP *j* to AP *i*. The power-impact factors of all APs constitute the power-impact factor matrix, whose definition is:

Definition 5: The power-impact factor matrix $Q = \{q_{ij}\}_{N \times N}$, where q_{ij} is the power-impact factor of AP *j* to AP *i*. In particular, q_{ij} is the fraction of primary users in AP *j* who shift to AP *i* due to power deficiency in AP *j* resulting from its congestion; or q_{ij} is the fraction of handoff users in AP *j* who comes from AP *i* due to the excessive power in AP *j* because of its light load. Note $q_{ij} = 0$, if AP *j* is not the neighbor of AP

i or *i*=*j*. Apparently, $\sum_{i=1}^{N} q_{ij} = 1 \ (j = 1, 2, ..., N)$.

In our scheme, a WLAN client requires neither special support nor change in the standard. It chooses APs only according to the received RSSI-B. As a result, q_{ij} is

only related to those factors that affect the RSSI-B received by users, such as the distance between APs, the geomorphology, buildings, trees and other obstacles.

Likewise, we also assume that the supply power of AP *i* during the k^{th} time interval, denoted as $s_i(k)$, is proportional to the number of its associated users, $u_i(k)$. So $s_i(k)$ can be formulated as follow:

$$s_i(k) = \alpha u_i(k) + f_i \quad (i = 1, 2, ..., N; k = 1, 2, ...)$$
 (2)

4.2 Optimal User Vector Solution

According to Formulas (1) and (2), we obtain the following definition:

Definition 6: The supply-demand deficit vector is $M(k) = [m_1(k) \ m_2(k) \ \dots \ m_N(k)]$, where $m_i(k)$ is the supply-demand deficit of power in AP *i* during the k^{th} time interval. With respect to Formulas (1) and (2), $m_i(k)$ (i = 1, 2, ..., N; k = 1, 2, ...) can be calculated as:

$$m_{i}(k) = d_{i}(k) - s_{i}(k) = \alpha p_{i}(k) + \sum_{j=1}^{N} q_{ij} \cdot (d_{j}(k-1) - s_{j}(k-1)) - \alpha u_{i}(k)$$

$$(i = 1, 2, ..., N; k = 1, 2, ...)$$
(3)

Formula (3) can be rewritten using vector form:

$$M(k) = \alpha P(k) + M(k-1) \cdot Q - \alpha U(k)$$
⁽⁴⁾

Aiming at our problem described in Section 3, we need to find U(k) that realizes two objectives: (i) minimizing the supply-demand deficit of power to make the supply power and demand power as equal as possible; (ii) making the load of each AP approach to the mean load of its neighbors to realize load balancing. So we can get the following formula:

$$\min (1 - \varphi)M(k)M(k)^{T} + \varphi(U(k) - U(k))(U(k) - U(k))^{T}$$

s.t. $U(k)A = P(k)A$
 $A = [1 \quad 1 \quad \dots \quad 1]^{T}$ (5)

In Formula (5), the first part guarantees the objective (i) while the second part guarantees the objective (ii). $\varphi \in [0,1]$ is the weight coefficient. $\overline{U}(k) = [\overline{u_1}(k) \quad \overline{u_2}(k) \quad \dots \quad \overline{u_N}(k)]$ is the mean value vector. $\overline{u_i}(k) = \sum_{j=1}^{A_i} p_j(k) / A_i$, where A_i is the neighbor number of AP i (i = 1, 2, ..., N). In addition, the constraint condition guarantees $\sum_{i=1}^{N} p_i(k) = \sum_{i=1}^{N} u_i(k)$ = the user number in the network. By taking the derivative of Formula (5), the optimum is obtained as:

$$U(k) = \frac{\alpha^{2}(1-\varphi)(P(k)+M(k-1)(Q+\overline{Q}))+\varphi\overline{U}(k)}{\alpha^{2}(1-\varphi)+\varphi}$$
(6)
where $\overline{Q} = \begin{bmatrix} q_{1}/N & q_{1}/N & \dots & q_{1}/N \\ q_{2}/N & q_{2}/N & \dots & q_{2}/N \\ \dots & \dots & \dots & q_{2}/N \\ \dots & \dots & \dots & \dots \\ q_{N-1}/N & q_{N-1}/N & \dots & q_{N-1}/N \\ q_{N}/N & q_{N}/N & \dots & q_{N}/N \end{bmatrix}$ and $q_{i} = \sum_{j=1}^{N} q_{ij}$ $i = 1, 2, \dots N$.

5 Power Assignment Based On SDM

5.1 Continuous and Discrete Power Assignment

In actual scenario, some APs can adjust their power to any values, while others only to certain discrete values. In this section, we explain how to use SDM to realize cell breathing when the power of AP is continuously adjustable and only a set of discrete values as shown in Figs. 3 and 4 respectively.

1 initialize $D(0), S(0)$ and time slot sequence number $k \leftarrow 1$;				
2 IF(a time interval terminates)				
2.1 obtain the neighbors' supply-demand deficit in power;				
2.2 estimate $P(k)$ and compute $D(k)$, $U(k)$, $S(k)$;				
2.3 FOR $(j = 1; j \le N; j + +)$				
2.3.1 IF $(u_j(k) > u_j^{MAX})$ $u_j(k) \leftarrow u_j^{MAX}; s_j(k) \leftarrow \alpha u_j(k) + f_j;$				
2.3.2 IF $(s_j(k) > Pow_j^{MAX})$ $s_j(k) \leftarrow Pow_j^{MAX};$				
2.4 $k \leftarrow k+1;$				

Fig. 3. Cell Breathing for Continuous Power

1 initialize $D(0), S(0)$ and time slot sequence number $k \leftarrow 1$;			
2 IF (a time interval terminates)			
2.1 obtain the neighbors' supply-demand deficit in power;			
2.2 estimate $P(k)$ and compute $D(k)$, $U(k)$, $S(k)$;			
2.3 FOR $(j = 1; j \le N; j + +)$			
2.3.1 IF $(u_j(k) > u_j^{MAX})$ $u_j(k) \leftarrow u_j^{MAX}; s_j(k) \leftarrow \alpha u_j(k) + f_j;$			
2.3.2 FOR each power in $[Pow_j^1 Pow_j^2 \dots Pow_j^{MAX}];$			
2.3.2.1 find a power level which is closest to $s_j(k)$;			
2.4 $k \leftarrow k+1;$			

Fig. 4. Cell Breathing for Discrete Power Level

In both figures, u_j^{MAX} is the maximum user number that AP *j* can serve. In Fig.3, the power of AP *j* can change from 0 to Pow_j^{MAX} ; however, in Fig. 4, the power level of AP *j* is a set of discrete values, say $[Pow_j^1 Pow_j^2 \dots Pow_j^{MAX}], (j = 1, 2, ..., N)$.

5.2 Some Key Parameters

From the figures, each AP needs to initialize its demand power and supply power. To obtain the primary users, we set both $d_i(0)$ and $s_i(0)$ of beacons equal to the data transmission power of AP *i*.

When each AP transmits beacons with the same power as that of data, the beacons' RSSI is the same as that of data, i.e. RSSI-D=RSSI-B. Because cell breathing does not need any modification of clients, RSSI-D may be the most easily obtained parameter reflecting data link quality. Thus, when RSSI-D=RSSI-B, the strongest RSSI-B received by a user from an AP means that the AP can provide the best data link quality to the user. Because the primary users of an AP are those who can obtain the loudest RSSI-D, when $d_i(0)$ and $s_i(0)$ of beacons equal to the data transmission power of AP *i*, the users who request to associate with AP *i* according to RSSI-B are just its primary users.

In addition, except the first time interval, at the beginning of other time intervals, our scheme needs to estimate the number of primary users in AP i. For this purpose, we use the following formula:

$$p_i(k) = p_i(k-1) + p_{ni}(k) - p_{li}(k) \quad (i = 1, 2, ..., N)$$
(7)

In Formula (7), $p_{ni}(k)$ is the number of newly arrival primary users in AP *i* during the k^{th} time interval and $p_{li}(k)$ is the number of primary users who leave AP *i* during that interval. Now $p_{ni}(k)$ and $p_{li}(k)$ can be estimated from some empirical data, while $p_i(k-1)$ can be calculated in terms of $u_i(k-1)$, and the power supply-demand deficit of AP *i* and its neighbors.

When the power of AP i is enough at the $(k-1)^{th}$ time interval, the power of its neighbors have two statuses: (i) the power of all neighbors is enough; (ii) the power of a part of or all neighbors is shortage. In status (i), evidently, $p_i(k-1) = u_i(k-1)$; in status (ii), some users of AP j ($j \in C_i$) will roam to the range of its neighbors, where C_i is the set of AP i's neighbors with power shortage. We denote the number of such users as $H_j(k-1)$. Because the power of AP i is lightly loaded, it should serve a fraction of users coming from AP j. In light of the definition of power-impact factor, we know the number of handoff users from AP j is $q_{ij}H_j(k-1)$. As a result, in status

(ii),
$$p_i(k-1) = u_i(k-1) - \sum_{j=1}^{C_i} q_{ij}H_j(k-1)$$
. When the power of AP *i* falls short during

the $(k-1)^{\text{th}}$ time interval, the primary users of this AP will shift to other APs. In this scenario, $p_i(k-1) = u_i(k-1) + H_i(k-1)$. Here, $H_i(k-1)$ (i = 1, 2, ..., N) can be

obtained according to the power supply-demand deficit of AP *i* and its neighbors, and the relationship between power and the number of users.

6 SDM Extension

As shown in Formulas (1) and (2), SDM has two main assumptions: (a) the user number is linearly direct proportional to the beacon power transmitted by an AP; (b) the load metric is user number. In fact, our model can work without the above assumptions. In this section, we extend SDM to a broader application range. The extended demand power is defined as follow:

$$d_{i}(k) = \overline{d_{i}(k)} + \sum_{j=1}^{N} q_{ij} \cdot (d_{j}(k-1) - s_{j}(k-1))$$
(8)

where $\overline{d_i(k)}$ is defined as the primary demand power, formulated as:

$$\overline{d_i(k)} = G_1(\overline{L_i}, f_i) \quad (i=1, 2, \dots, N)$$
(9)

In Formula (9), the definition of f_i is the same as that in Section 4. $\overline{L_i}$ is the load which has two kinds: the *primary* load and the minimum expected load, as defined as follow:

Definition 7: The primary load of AP i is the load that can obtain the best QoS when it is served by AP *i* (*i*=1, 2,..., *N*) instead of other APs.

Apparently, the primary user is a special case of the primary load.

Definition 8: The minimum expected load of AP i is the minimum load that AP i (i=1, 2, ..., N) expects to serve.

The extended supply power is given in Formula (10), where L_i is the actual load served by AP *i*.

$$s_i(k) = G_2(L_i, f_i)$$
 (i=1, 2,..., N) (10)

Formulas (9) and (10) show that $\overline{d_i(k)}$ is the function of $\overline{L_i}$ and f_i , and $s_i(k)$ is the function of L_i and f_i . The form of $G_1(\bullet)$ and $G_2(\bullet)$ can be fitted by the empirical data about the relationship between power and load.

Besides generalizing the relationship between power and load, another key extension is load definition. The load in the extended SDM is not tied to the user number, but supports a broad range of load definition. For example, the load can be traffic, the channel idle time [7], CUE [8]. Correspondingly, $\overline{L_i}$ can be the primary traffic (generated by primary user), the minimum expected channel idle time, the minimum expected CUE. In the extended model, APs can get its load through real-time measurement, or through users by means of some new standards, such as the IEEE 802.11 k or h.

After extending the definitions of demand power and supply power, the optimal mapping between the APs and users can be solved through the method introduced in Sections 4 and 5.

7 Performance Evaluation

In this section, we compare the performance of our scheme with the default WLAN AP selection scheme. As described above, default WLAN users select APs only according to their RSSI-B. Although our scheme has the same AP selection criterion, the APs adjust their beacon power dynamically according to the network load.

In our simulation, we randomly place 20 APs in a 500m×500m area. The distributions of clients have two scenarios: random pattern and hotspot pattern. To realize these distributions, we number all APs and appoint APs 19 and 20 as the serving APs in hotspot areas. The probability that clients are nearest to these two APs is P_{hot} , while the probability that other clients are nearest to APs 1-18 are equal, i.e. $(1-P_{hot})/18$. Therefore, the user-distribution is in random pattern when the fraction of primary users in each APs is 1/20, while it is in hotspot pattern when $P_{hot} > 0.1$.

The simulation sets the proportional coefficient $\alpha = 1$ and the weight coefficient $\varphi = 0.6$. For simplicity, we assume the constant reflecting the external factors f_i (i = 1, 2, ..., N) = 0 and let the power-impact factor only relate to the distance among APs. In addition, we assume that all APs have the same transmission power of data. As a result, the primary user of one AP is the user whose distance to this AP is the closest. Each element in the power-impact factor matrix can be calculated by Formula (11), where dis(i, j) is the distance between AP *i* and *j*.

$$q_{ij} = \begin{cases} dis(i,j) / \sum_{k \in A_j} dis(j,k) & j \in A_i \\ 0 & otherwise \end{cases} \quad i = 1, 2, ..., N$$

$$(11)$$

We compare SDM with default WLAN scheme in terms of load balancing and the normalized system throughput, T_N , which is defined as the fraction of time that the channel is used to successfully transmit payload bits. T_N can be calculated using Formula (12) [15].

$$T_{N} = \frac{P_{s}P_{tr}E[P]}{(1-P_{tr})\sigma + P_{s}P_{tr}T_{s} + P_{tr}(1-P_{s})T_{c}}$$
(12)

where P_{tr} and P_s can be calculated as:

$$P_{tr} = 1 - (1 - \tau)^n \tag{13}$$

$$P_s = n\tau (1-\tau)^{n-1} / P_{tr}$$
⁽¹⁴⁾

$$\tau = \begin{cases} 2(1-2\rho)/((1-2\rho)(W+1)+pW(1-(2\rho)^m)) & \rho \neq 0.5\\ 2/(W+1) & \rho = 0.5 \end{cases}$$
(15)

Here P_{tr} denotes the probability that there is at least one transmission in a given slot and P_s denotes the probability that the transmission is successful; τ is the probability that a user transmits data; *n* is the number of clients that associate with an AP. The meanings and values of other parameters are shown in Table.1 [15].

Para.	Description	Value
E[P]	Average packet payload size (measured in	163.68 slot time units
	$50 \mu s$ slot time units)	
σ	Duration of an empty slot time	50 µs
T_{s}	Average time the channel is sensed busy	179.64 slot time units
5	because of a successful transmission	
T_{c}	Average time the channel is sensed busy during	174.26 slot time units
	a collision	
ho	Conditional collision probability	0.6 <i>n</i>
W	Minimum contention window	128
т	Maximum backoff stage	5

Table 1. Sim	alation Parameters
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In addition, for the sake of simplicity, we assume the data transmission power and the frequency of APs are set reasonably so that the interference among APs can be ignored.

Figs. 5, 6 and 7 show the load on the APs in SDM and default WLAN scheme when the total user number in the network is 30, 60 and 90 respectively. The load in the simulation is measured by the number of users. In Fig.5, $P_{hot} = 0.1$, which means that the distribution of users is in random pattern. In Figs.6 and 7, $P_{hot} = 0.3$ and 0.5



Fig. 5. Load on APs ($P_{hot} = 0.1$)



Fig. 6. Load on APs ($P_{hot} = 0.3$)



Fig. 7. Load on APs ($P_{hot} = 0.5$)

respectively, implying that the distributions of users are in hotspot pattern and the probabilities that users are closest to APs 19 and 20 are 30% and 50%. Note that the APs are sorted by their load in increasing order.

Fig. 8 shows how the sum of normalized system throughput of all APs changes with the total number of users in the network. It can be seen that the throughput increases as the increase of total user number. Moreover, the throughput in our method is greater than that in the default WLAN scheme. The reason is that the default WLAN users prefer to connect to the nearest APs. As a consequence, when many clients are nearest to one AP, they do not connect to other APs even though this AP is heavily loaded. In the CSMA-based WLAN, the more users converge to one AP, the larger is the transmission collisions, which leads to lower throughput. While in our method, the near-average load in each AP reduces the transmission collisions, thus enhancing the overall throughput.



Fig. 8. Throughput comparison

8 Conclusion

We propose a cell breathing scheme based on SDM for continuous and discrete power assignment. It finds an optimal mapping between users and APs for providing better data link quality to users and realizing load balancing. To this end, our scheme makes the demand power and supply power as equal as possible and the load on the APs balanced. Finally, we extend SDM by generalizing the relationship between power and load and defining the load in a broader sense. The simulation results demonstrate that our scheme is fair for realizing load balancing and effective for improving throughput.

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