Fairness Maintenance in IEEE 802.11ah Networks for IoT Applications with Different Requirements

L. Rajya Lakshmi and Biplab Sikdar
Department of Electrical and Computer Engineering
National University of Singapore, Singapore

***Abstract*—The IEEE 802.11ah standard can provide cost-effective Internet access to a large number of devices in newly evolving Internet-of-Things (IoT) and machine-to-machine (M2M) networks. To handle high collision probability caused by a large number devices, it adopts a group-based protocol at the MAC layer and divides nodes into a number of groups. The formed groups may not be uniform in terms of data rate requirements, since each group is a combination of sensors with different data requirements. To achieve fair resource utilization across the groups which in turn maximizes the channel utilization, this paper formulates fair grouping in IEEE 802.11ah networks as an optimization problem, and to solve the problem in real-time we develop a heuristic method. In addition, to ensure fair channel utilization by the nodes in each group, a contention window selection and adjustment method is proposed. Results from the extensive simulations conducted in a dense IoT network show that the proposed fairness model achieves a superior performance than the existing methods in terms of throughput, packet delay, energy efficiency, and fairness.**

I. Introduction

The revolutionary Internet-of-Things is rapidly evolving and changing many industries such as advertising, farming, smart buildings, hospitality, manufacturing, finance, retail, health-care, smart homes, etc. On the other hand, machine-to-machine communications consist of a large number of intelligence machines capable of automatic data generation, exchange, processing and actuation, have brought revolutionary changes in fields such as electricity grids, smart cities, industrial automation, etc. One issue that influences the performance of these two technologies is the ability to connect a large number of power constrained devices to the Internet. To address this issue, cellular networks are not a cost-effective solution, and the current standards of WLANs focus on achieving high throughput in small networks, but not serving extremely dense IoT and M2M networks. When it comes to low power communication technologies, wireless personal area networks (WPANs) can achieve medium throughput at short ranges and low power wide area networks (LPWANs) can support long range communications with low data rates. Hence these technologies can support a limited set of IoT and M2M scenarios.

The IEEE 802.11ah standard [1] has the potential to support most of the IoT and M2M scenarios. It operates in the unlicensed sub-1 Ghz band and has the capability to provide a trade-off between throughput, range, and energy efficiency. Thus, it supports transmission ranges from 100 m to 1 km or more and data rates from 150 kbps to 1 Mbps. With this standard, each access point (AP) can support up to 8192 devices. To handle high contention from a large number of devices, IEEE 802.11ah adopts a group-based MAC protocol, and to realise this protocol it introduces a *restricted access window (RAW)* mechanism. With RAW, nodes are divided into groups, and the airtime is divided into RAW slots of the same length. In each RAW slot, member from a single group contend for channel access, hence, the collision probability and power consumption reduce significantly.

Even though the RAW-based access mechanism results in a great reduction in the collision probability, the way the groups are formed is going to have a significant impact on the channel utilization [2]. Since IoT and M2M technologies can support a wide variety of applications, we can expect devices with diversified data rate requirements in IoT and M2M networks. When these devices are partitioned into groups, we may end up with groups that are not uniform in terms of size, data requirements, etc. Following the current resource allocation strategies, if we allow each group to utilize one RAW slot each, then we may expect unfair channel utilization by the groups, which ultimate increases unfairness among the devices. Allocating RAW slots in proportion to the requirements of groups may solve the problem partially, but, to achieve better results, fairness has to considered during group formation also.

Fair scheduling is an important issue in every network, thus we find many studies both in wireline and wireless networks [3], [4]. However, most of the existing centralized methods assume perfect knowledge about the packet arrivals at nodes, and perform data flow scheduling on per-slot basis. These methods are not directly applicable in IEEE 802.11ah networks due to lack precise information about the data flows at the scheduler, and resource allocation in terms of big chunks that are capable to accommodate data transmissions from multiple devices. On the other hand, the existing grouping methods mainly focus on even distribution of nodes, load balancing, etc [2], [5]. The groups with the same size (in terms of number of nodes) but with different data requirements [5] as well as the groups with the same load but with different sizes [2] may lead to unfair channel utilization across groups. Based on the above analysis, this paper aims to develop new scheduling and grouping methods optimized for fairness maintenance IEEE 802.11ah networks. The main contributions of the paper are:

- To achieve fairness channel utilization across the groups, fair grouping in IEEE 802.11ah networks is formulated as an optimization problem, and then to solve the problem in real-time, a heuristic method is developed.

- To achieve fair channel utilization among the nodes within a group, a weight-based contention window selection method, and a method that dynamically updates the contention windows of nodes in accordance with their channel utilization are developed.
- The performance of the proposed methods is evaluated in a dense IoT scenario and compared with the existing methods.

The rest of the paper is organized as follows. Section II discusses the related research. Section III describes the considered system model. Section IV formulates fair grouping in IEEE 802.11ah networks as an optimization problem and presents a heuristic grouping method as well as the other components of the proposed fairness model. Section V describes the simulation settings and discusses the simulation results. Section VI concludes the paper.

II. Related Work

In the existing literature on IEEE 802.11ah, we can find studies that aim to address a variety of related issues such as throughput analysis, grouping, RAW size selection, power saving, etc. To achieve balance across the groups in terms of their loads, group formation in IEEE 802.11ah networks is formulated as an optimization problem in [2]. Then, a greedy group formation method is also proposed to assign sensors to groups in such a way that the channel utilization of each group improves. In the centralized grouping method proposed in [5], the AP assigns n sensors to k groups so that each group accommodates (n/k) sensors. To avoid regrouping upon the arrival of new devices, a decentralized grouping method is also proposed in [5]. With this method, each sensor randomly chooses one of the K RAW slots with probability $1/K$.

A method has been developed for the optimal RAW size selection in [6]. Based on the success probability observed in the network, the number of stations contending for the uplink access are estimated. Then, the optimal RAW size is computed utilizing the relationship between the number of contending devices and RAW size. In [7], the stations are virtually divided into contending and non-contending groups based on their random arbitration inter frame space numbers. Only contending stations decrease their backoff counter and participate in contention, so as to improve the network throughput. Since the throughput in each RAW slot is dependent on the number of contending stations, in [8], it is argued that the duration of each RAW slot should be selected based on the number of stations contend for channel access in that RAW slot.

In contrast to the existing literature on IEEE 802.11ah networks, this paper targets to achieve fair channel utilization across the groups and among the sensors within each group. Fairness-ensuring group formation in IEEE 802.11ah networks is formulated as an optimization problem. Owing to the hardness of this problem, a heuristic method is proposed to assign sensors to groups in such a way that the fairness across the groups improves. In addition, to maintain fairness among the nodes within a group, mechanisms have been developed to find the contention windows of various sensors according to their data rate requirements and to adjust these windows based on the channel utilization of sensors.

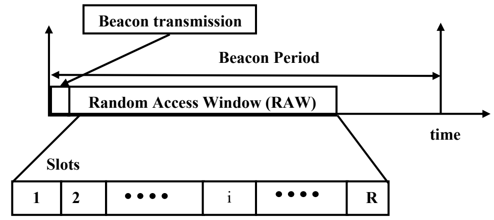

Fig. 1. Beacon period structure.

III. System Model

The considered architecture of IEEE 802.11ah networks consists of one AP and a number of sensors that want to send data to application servers through the AP. By adopting a group-based MAC protocol, these sensors are assigned to groups. Figure 1 depicts how the network time is divided into beacon periods and how the RAW of each beacon period is subdivided into a number of RAW slots. In each RAW slot, only the member of a single group can contend for channel access, thus the collision probability decreases tremendously. At the beginning of each beacon period, the AP schedules the available RAW slots to various groups and communicates the information about the number of slots allocated to each group and the start time of the allocated slots to the sensors through a beacon frame.

The sensor winning the last transmission opportunity in a RAW slot, may or may not be allowed to utilize that opportunity depending upon whether "cross slot boundary" is enabled or not. If it is, then the sensor can utilize the transmission opportunity even though the remaining duration in the allocated RAW slot cannot accommodate the data transmission and the corresponding acknowledgement. Otherwise, the winning sensor can access the channel provided the transmission opportunity does not cross the allocated RAW slot boundary. To contend for channel access, sensors use the enhanced distributed channel access (EDCA) of IEEE 802.11.

In IoT and M2M networks, we can find sensors supporting different applications with varying data rate requirements. Thus, the traffic patterns of sensors are usually specific, but their sampling rates and packet sizes are typically very different [2]. We assume that the AP has information about the sampling rates (i.e. packet generation rates) and packet sizes of all sensors in the network. r_i and ρ_i denote the sampling rate and payload size of s_i, respectively. Usually, the sensors supporting the same or similar kind of applications have the same sampling rates and payload sizes. Thus, the sensors can be divided into q different service classes, Φ_1, Φ_2 $\cdots$ Φ_q, such that the sampling rates and payload sizes of all sensors in each class are the same. The sampling rate and the payload size of the sensors in class Φ_1 are represented as r^{Φ_1} and ρ^{Φ_1}, respectively. Now the weight of Φ_u is set as: $\omega^{\Phi_u} = \frac{\rho^{\Phi_u} r^{\Phi_u}}{\sum_{v=1}^{q} \rho^{\Phi_v} r^{\Phi_v}}$. The weight of each sensor $s_i \in \Phi_v$ is the same as that of ω^{Φ_v}, that is, $\omega_{s_i} = \omega^{\Phi_v}$. Assume that the sensors are partitioned into K groups (the group formation method is explained later). The weight of groups g_i is set as: $\omega^{g_i} = \frac{\mu_i}{\sum_{j=1}^{K} \mu_j}$, where μ_i is the aggregate weight of all sensors in g_i.

In the process explained above, weight assignment has been achieved by utilizing the amount of data generated by each sensor per second. Different from this method, weights can also be assigned to sensors and groups based on some other criteria such as the applications the sensors currently supporting, the priority of the data they carry, etc.

A. Analytical Throughput of a Group

In this section, we obtain the normalized throughput of group g and sensor s_1. Assume that the collision probability p_c of each packet is constant and independent of the other packets. Now, we can represent the bi-dimensional process {s(t),b(t)} as a DTMC, where $s(t)$ and $b(t)$ represent the stochastic process for the backoff stage and the backoff counter of the considered node at time t, respectively. Then, we can obtain p_t, the transmission probability of a single node as [9]:

$$p_t = \frac{2(1-2p_c)}{(1-2p_c)(CW_{min}+1)+p_c CW_{min}(1-(2p_c)^{\psi})}, \tag{1}$$

where CW_{min} and ψ denote the initial contention window size and the maximum number of retransmission attempts, respectively. In any RAW slot, a node encounters a collision, if at least one of the remaining $(|g|-1)$ nodes also transmit, where $|g|$ is the cardinality of g. Hence, the collision probability can be expressed as:

$$p_c = 1-(1-p_t)^{|g|-1}. \tag{2}$$

By solving Eq. (1) and (2) using nonlinear methods, we can obtain p_t and p_c. Now, the probability for at least one node to initiate transmission in a RAW slot can be computed as [9]:

$$P_{tr} = 1-(1-p_t)^{|g|}. \tag{3}$$

Now, subjected to the condition that at least one node initiates transmission, the probability that exactly one station (s_1) transmits on the channel is:

$$p_s(s_1) = \frac{p_t(1-p_t)^{|g|-1}}{1-(1-p_t)^{|g|}}. \tag{4}$$

Using $p_s(s_1)$, we can get the success probability of g as [9]:

$$p_s(g) = \frac{|g|p_t(1-p_t)^{|g|-1}}{1-(1-p_t)^{|g|}}. \tag{5}$$

Then, the normalized throughput of g can be obtained as [9]:

$$T_g = \frac{p_s(g)P_{tr}P_l}{(1-P_{tr})S_{time}+P_{tr}p_s(g)su_l+P_{tr}(1-p_s(g))c_l}. \tag{6}$$

where, P_l is the average packet payload size, su_l is the average length of a successful transmission, c_l is the average length of a collision, and S_{time} is the duration of an idle slot.

IV. Fairness Maintenance in IEEE 802.11ah Networks

The important factors that play a vital role in fairness maintenance across the groups and among the nodes with each group are: group formation, contention window selection, and resource allocation. This section investigates each of these factors and presents our proposed methods. All proposed methods together called "group and sensor fairness maintenance model (GS-FMM)".

A. Fair Grouping

The weight of a group represents the aggregate data rate requirement of all sensors in that group, and to maintain fairness across groups, the channel utilization of each group should be in proportion to its weight. Since the channel utilization of a group is dependent on its success probability, the grouping method should form groups in such a way that the success probability of each group is in proportion to its weight. Consider a network that consists of n sensors, and assume that these sensors are to be partitioned into K groups. Let A be a matrix of size $n \times K$, and let a_{ix} be the element in the i-th row and the x-th column of A. a_{ix} is set to 1, if sensor s_i is assigned group g_x, otherwise, it is set to 0. Now, fair grouping in IEEE 802.11ah networks can be formulated as an optimization problem (**P1**) as follows:

$$\min_{A} \left[\sum_{x=1}^{K}\sum_{y=1}^{K} \left| \frac{p_s(g_x)}{\omega^{g_x}} - \frac{p_s(g_y)}{\omega^{g_y}} \right| \right], \tag{7}$$

such that

$$a_{ix} \in \{0,1\},\ \forall\ i,x \tag{8}$$

$$\sum_{x=1}^{K} a_{ix} = 1, \forall\ i. \tag{9}$$

Constraint (8) and (9) indicate that each sensor should be assigned to only one group. Problem (**P1**) is a variant of the *exact cover problem*, which is NP-complete. Hence, we develop a greedy group formation method that targets to achieve fairness in the success probabilities of groups.

Let $g_1,\ g_2,\ \cdots,\ g_K$ be the groups and assume that the success probabilities of these groups are maintained in Υ_{g_1}, $\Upsilon_{g_2}, \cdots, \Upsilon_{g_K}$, respectively. Assume that, Υ_{min} and κ are the temporary variables used in the group formation process. To find a suitable group for s_i, first, Υ_{min} and κ are initialized with ∞ and -1 respectively. Then, the groups are considered one by one, and for each group g_x, s_i is temporarily included in g_x. Then, using nonlinear methods, p_t and p_c are computed first, and then $p_s(g_x)$ is computed. Now, the highet difference between the normalized success probability of g_x and the other groups is computed in Υ_{diff} as: $\Upsilon_{diff} = \max_{g_y \in (G-\{g_x\})} \left| \frac{p_s(g_x)}{\omega^{g_x}} - \frac{\Upsilon_{g_y}}{\omega^{g_y}} \right|$. If $\Upsilon_{diff} < \Upsilon_{min}$, then Υ_{min} and κ are updated as $\Upsilon_{min} = \Upsilon_{diff}$ and $\kappa = x$, respectively. After repeating the same process with the other groups, s_i is assigned to group g_κ, and Υ_{g_κ} is updated to reflected the new success probability of g_κ after the inclusion of s_i. The pseudo-code of this method is given in Algorithm 1. The worst-case complexity of this algorithm is $O(nK^2)$.

B. Contention Window Selection

To achieve fair channel utilization, the sensors with a higher weight should have a higher success probability than the sensors with a lower weight. One parameter that influences the

Algorithm 1 Fair Grouping

BEGIN:

initialization: g_1, g_2, $\cdots$, g_K are the groups, and Υ_{g_1}, Υ_{g_2}, $\cdots$, Υ_{g_K} be their respective success probabilities;
for $i = 1$ to n **do**
  $\Upsilon_{min} = \infty$; $\kappa = -1$;
  for $x = 1$ to K **do**
    temporarily include s_i in g_x;
    solve Eq. (1) and (2) for p_t and p_c;
    using p_t and p_c compute $p_s(g_x)$;
    $\Upsilon_{diff} = \max_{g_y \in (G-\{g_x\})} \left| \frac{p_s(g_x)}{\omega^{g_x}} - \frac{\Upsilon_{g_y}}{\omega^{g_y}} \right|$
    if $\Upsilon_{min} > \Upsilon_{diff}$ **then**
      $\Upsilon_{min} = \Upsilon_{diff}$; $\kappa = x$;
    end if
  end for
  $g_\kappa = (g_\kappa \cup s_i)$;
end for

END;

success probability of a sensor is its contention window. For fairness maintenance, the sensors with a higher weight should use a smaller contention window than the sensors with a lower weight [10]. By setting CW_{min} and CW_{max} of each sensor in inverse proportion to its weight, a reasonably good fairness can be maintained among the sensors in each group. Below we obtain CW_{min} and CW_{max} of various service classes.

Consider a group g_x, and assume that the members of g_x can be partitioned into q sets, θ_1, θ_2, $\cdots$, θ_q, such that all sensors in θ_m belong to service class Φ_m. Let p_m, be the probability of a sensor belonging to class Φ_m to initiate a transmission in a RAW slot. Now, the probability of at least one node to initiate transmission is:

$$P_{tr} = (1 - \prod_{m=1}^{q} (1 - p_m)^{|\theta_m|}). \tag{10}$$

The success probability of $s_i \in \Phi_u$, $p_s(s_i)$, is:

$$(p_u(1-p_u)^{(|\theta_u|-1)} \prod_{v \neq u} (1-p_v)^{|\theta_v|}) / (1 - \prod_{m=1}^{q} (1-p_m)^{|\theta_m|}). \tag{11}$$

Similarly, the success probability of g_x, $p_s(g_x)$, is:

$$\frac{\sum_{u=1}^{q} \Big(|\theta_u| p_u (1-p_u)^{(|\theta_u|-1)} \prod_{v \neq u} (1-p_v)^{|\theta_v|} \Big)}{1 - \prod_{m=1}^{q} (1-p_m)^{|\theta_m|}}. \tag{12}$$

Now, consider two sensors $s_i \in \Phi_u$ and $s_j \in \Phi_v$. To maintain fairness between s_i and s_j, we must have

$$\frac{p_s(s_i)}{\omega_{s_i}} = \frac{p_s(s_j)}{\omega_{s_j}}, \quad \frac{p_s(s_i)}{\omega^{\Phi_u}} = \frac{p_s(s_j)}{\omega^{\Phi_v}}. \tag{13}$$

The second part of Eq. (13) follows from the fact that the weight of each sensor is the same as that of its service class. Now, using the new definition of $p_s(s_i)$ given in Eq. (11), Eq. (13) becomes,

$$\frac{p_u(1-p_v)}{\omega^{\Phi_u}} = \frac{p_v(1-p_u)}{\omega^{\Phi_v}}. \tag{14}$$

After simplification, we get:

$$p_v = \frac{\omega^{\Phi_v} p_u}{\omega^{\Phi_u}(1-p_u) + \omega^{\Phi_v} p_u}, p_v = \frac{\omega^{\Phi_v} p_1}{\omega^{\Phi_1}(1-p_1) + \omega^{\Phi_v} p_1}. \tag{15}$$

Using (6), (12) and (15), the normalized throughput of g_x can be represented as a function of p_1. By solving $\frac{dT_{g_x}}{dp_1} = 0$, the optimal value of p_1 that maximizes the throughput can be obtained. Using the optimal value of p_1 and Eqs. (1) and (2), we can calculate CW_{min} of each service class. However, it is difficult to solve $\frac{dT_{g_x}}{dp_1} = 0$ for the optimal p_1 [10], hence, we adopt an approximate solution.

The sensors belonging to the service class Φ_u use the same maximum and minimum contention window sizes. We denote CW_{min} and CW_{max} of the sensors belonging to Φ_u as CW^u_{min} and CW^u_{max}, respectively. We fix CW^1_{min} at some value and set CW^1_{max} as αCW^1_{min}, where α is a constant. Using CW^1_{min} and Eq. (15), we solve Eqs. (1) and (2) for p_1 and p_c, which are in turn used to obtain p_v, $v = 2 \sim q$. Based on the values of p_c, p_v and using Eq. (1), CW^v_{min}, $v = 2 \sim q$, can be obtained, and then CW^v_{max} is set as αCW^v_{min}, $v = 2 \sim q$. The sensors of each service class Φ_u set their set their CW_{min} and CW_{max} as CW^u_{min} and CW^u_{max}, respectively.

C. Fair Resource Allocation

Different from the existing literature that assigns one RAW slot to each group, we assign RAW slots to groups by considering the cumulative service each group has received until now. The AP maintains the cumulative service received by each group g_x in W_{g_x}, and whenever a packet is received from a sensor in g_x, W_{g_x} is incremented by the size of that packet. Adopting the concept of providing immediate service to the group that is contributing more towards unfairness [11], the first RAW slot is allocated to the group, g_1, that has received the least normalized cumulative service than others. Then, W_{g_1} is temporarily incremented by the expected per-slot normalized throughput of g_1 that can be computed using Eq. (6). Following the same process, the remaining RAW slots are also allocated to various groups.

The contention window selection method explained in Section IV-B achieves better fairness than when all sensors use the same CW_{min} and CW_{max}. However, this method may not obtain optimal results, since it computes CW_{min} and CW_{max} of various service classes by fixing CW^1_{min} at some value which may not be optimal. The fairness performance can be improved further by providing prioritized service to some sensors while controlling contention from the others. We should maximize the scope for the sensors that have received a lower normalized service than others to get served. This is achieved through channel utilization driven contention window adjustment described below.

The AP maintains the cumulative service received by each sensor s_i, in δ_i, and this counter is incremented by ρ_i whenever the AP receives a packet from s_i. Similarly, each

TABLE I
MAC PARAMETERS FOR SIMULATIONS.

Parameter	Value
Frequency	900 MHz
Beacon Interval	0.2 s
RAW interval	0.2 s
Node distribution	Random
CW^1_{min}	15
CW^{max}	255
α	4
AIFSN	3
MAC header	legacy header
RTS/CTS	not enabled
Cross slot boundary	enabled
Wi-Fi mode	MCS2, 2Mhz
Number of slots per group	variable

sensor s_i accumulates the cumulative service it has received in σ_i. After completing RAW allocation, the AP considers each group g_2 that is allocated one or more RAW slots and executes the following process. From g_2, the least and the highest normalised services among all sensors, $\delta^{'}_l$ and $\delta^{'}_h$, are computed as: $\delta^{'}_l = \min_{s_i \in g_2}\ (\delta_i/\omega_{s_i})$, $\delta^{'}_h = \max_{s_j \in g_2}$ (δ_j/ω_{s_j}). If $(\delta^{'}_h - \delta^{'}_l) > 1$, then a threshold for controlling contention in g_2, $\delta^{''}_2$, is set as $\delta^{'}_h/2$, otherwise, it is set as $\delta^{'}_h$. Then, the AP includes the following information in a beacon: the slots allocated to g_2 and $\delta^{''}_2$. After repeating the above explained process with the other scheduled groups, the AP transmits the beacon. Each $s_i \in g_2$, after receiving the beacon, computes its cumulative normalized service, (σ_i/ω_{s_i}), and if $(\sigma_i/\omega_{s_i}) \leq \delta^{''}_2$, then it resets CW_{min} and CW_{max} to CW^v_{min} and CW^v_{max}, respectively, where Φ_v is the service class of s_i. And each $s_j \in g_2$ for which $(\sigma_j/\omega_{s_j}) > \delta^{''}_2$, increment their contention window by doubling the current values of CW_{min} and CW_{max}, and do not contend for channel access in the current beacon period. Also, each sensor doubles the values of CW_{min} and CW_{max} after successfully transmitting a packet. After any increment, if the value of CW_{max} of $s_i \in \Phi_u$ crosses a threshold, CW^{max}, then CW_{min} and CW_{max} of s_i are reset to CW^u_{min} and CW^u_{max}, respectively.

V. SIMULATION RESULTS

To implement GS-FMM, the IEEE 802.11ah module for ns-3 (version 3.23) [12] is used. Performance evaluation is conducted in a sensor-based IoT network as the number of sensors and the number of groups vary. To test the effectiveness of GS-FMM under different loads, two traffic generation scenarios, “saturated mode” and “overloaded mode”, are considered. In each of these scenarios, four different combinations of sampling rates and payload sizes are considered, and each combination is assigned to an even number of sensors, thus ultimately, the sensors can be divided into four service classes. The “load balancing group formation (LBGF)” method [2], and “random grouping (RAND)” method that assigns sensors to groups randomly are considered for performance evaluation of GS-FMM. In addition, a version of GS-FMM called “GS-FMM partial, GS-FMM (PART)”, that performs only fair grouping is also considered to test the effectiveness of fair grouping method exclusively. Network throughput, packet delay, node active time, and fairness [13] are considered as the performance metrics. The results shown in the following sections are averaged over 10 simulation runs, and each simulation lasts for 300 secs. Table I shows some more simulation parameters.

A. Saturated Mode

In this mode, the cumulative traffic generated by all sensors is around the maximum capacity of the channel. The sampling rate (in Hz) and payload size (in bps) combinations of the sensors of classes I to IV are, $(1, 256)$, $(0.4, 256)$, $(1, 512)$, and $(0.8, 128)$, respectively. The number of groups vary between 5 and 50 as the number of sensors is fixed at 500. The network throughput with the four methods is shown in Figure 2. GS-FMM and GS-FMM (PART) form groups in such a way that the success probabilities of all groups is almost the same, which may not be the case with LBGF and RAND. Thus, we observe a better throughput with GS-FMM and GS-FMM (PART), compared to LBGF and RAND. Figures 3, 4, and 5 show the average packet delay, active time, and fairness of the sensors of class-I, respectively. The average active time indirectly represents the average power consumption of a sensor. Because of the uniform success probabilities across groups, GS-FMM and GS-FMM (PART) result in better packet delays, node active times, and fairness, compared to LBGF and RAND. With weight based contention window selection and adoption according to channel utilization by various sensors in each group, GS-FMM results in a slightly better delay and active time compared to GS-FMM (PART). Since the number of nodes is fixed, with increasing groups, the contention within each group reduces. Hence, we observe a gradually converging trend in the active times of all four methods, as the number of groups increases.

B. Overloaded Mode

In this set of simulations the throughput and fairness of the four methods are evaluated when the capacity is less than the cumulative traffic demand. Since demand is more than supply, all nodes are active throughout the most of the simulation runs, hence, we do not consider delay and active time in this mode. The sampling rate (in Hz) and payload size (in bps) combinations of the sensors of class-I to IV are, $(5, 256)$, $(1.5, 256)$, $(5, 512)$, and $(1, 128)$, respectively. Two node and group combination scenarios are considered for performance evaluation. In the first scenario (scen-I), the number of nodes is fixed at 500 and the number of groups vary between 5 and 50; in the second scenario (scen-II), the number of groups is fixed at 50 and the number of nodes vary between 50 and 500. Figures 6 and 7 show the throughput of all four method in scen-I and scen-II, respectively. By forming groups with even success probabilities, GS-FMM and GS-FMM (PART) achieve much better throughput, compared to LBGF and RAND. In both high contention (e.g. when the number of groups vary between 10 and 20 in scen-I) and low contention (e.g. when the number of sensors vary between 100 and 200 in scen-II) scenarios the proposed grouping method, GS-FMM

(PART), achieves significantly better throughput than LBGF and RAND. Figures 8 and 9 show the fairness results of class-I and II in scen-I, respectively. Similar results are observed for class-III and IV, hence omitted due to space limitations. By dynamically adjusting contention windows and prioritizing access to the sensors that have received a lower service than others, GS-FMM achieves significantly better fairness than LBGF and RAND even in high contention situations such as when the number of groups vary between 5 and 20. However, the performance GS-FMM (PART) is only slightly better than LBGF and RAND in such situations, since it performs only fair grouping. Figures 10 and 11 show the fairness results of class-I and II in scen-II. Due to its fairness maintenance at various levels, GS-FMM achieves significantly better fairness than other three methods, in scen-II also. Lack of contention control causes GS-FMM (PART) to result in a steeper trend in the fairness results, as the number of nodes increases.

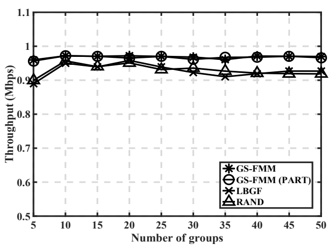

Fig. 2. Number of groups vs network throughput.

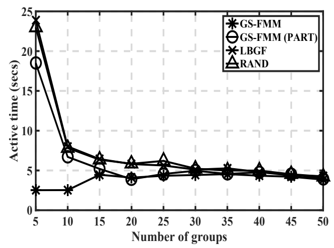

Fig. 3. Number of groups vs node active time (class-I).

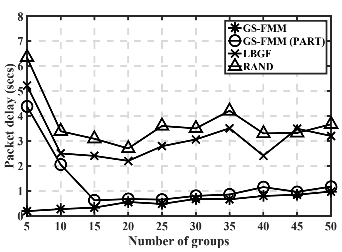

Fig. 4. Number of groups vs packet delay (class-I).

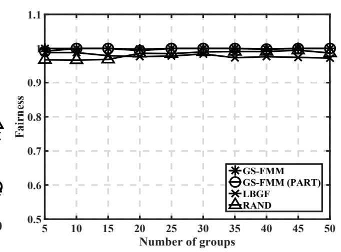

Fig. 5. Number of groups vs fairness (class-I).

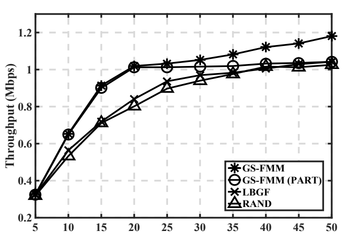

Fig. 6. Number of groups vs network throughput.

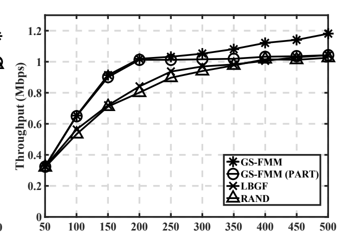

Fig. 7. Number of nodes vs network throughput.

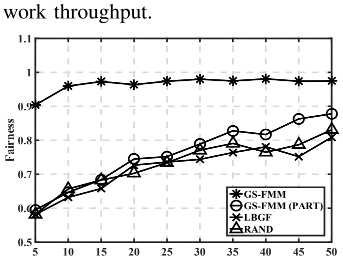

Fig. 8. Number of groups vs fairness (class-I).

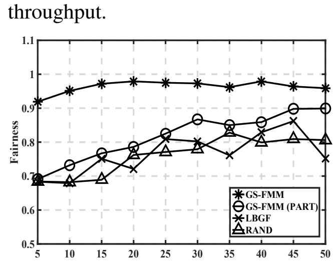

Fig. 9. Number of groups vs fairness (class-II).

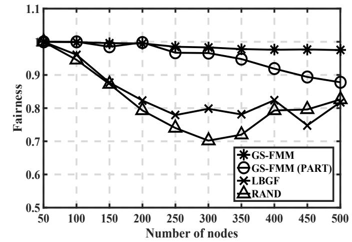

Fig. 10. Number of nodes vs fairness (class-I).

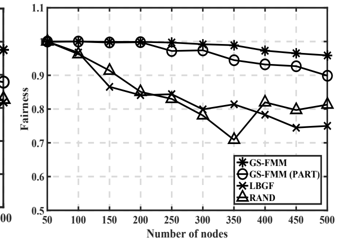

Fig. 11. Number of nodes vs fairness (class-II).

VI. Conclusions

The IEEE 802.11ah standard is a potential and promising solution to provide Internet connectivity to a large number of nodes in newly emerging IoT and M2M networks. It introduces a restricted access window mechanism and partitions nodes into groups, to handle high contention from a large number of nodes. For fair channel utilization across the groups, this paper formulates fair grouping in IEEE 802.11ah networks as an optimization problem, and then, to form groups in real-time, a heuristic method is also proposed. To achieve fairness among the sensors in each group, a contention window selection and a contention window adjustment methods are proposed. Results from the simulations that are conducted in a dense IoT network, show that the proposed fairness model achieves significantly better throughput, delay, power efficiency, and fairness, compare to the existing methods.

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