Scalability Improvement of IEEE 802.11ah IoT Networks

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Abstract

In this paper, we propose a non-orthogonal multiple access (NOMA) based grouping method for IEEE 802.11ah, a promising platform for the internet of things (IoT). The grouping method improves the scalability of IoT networks, by reducing collisions in the access points (APs). The proposed method puts those IoT devices (IoT-Ds) whose channel gains are far enough from each other, i.e., who satisfy NOMA constraints, in the same group. Therefore, using successive interference cancellation (SIC), the AP is able to decode the simultaneous signal transmissions from IoT-Ds in a group. To assign IoT-Ds into groups and determine their transmission power, we formulate a total throughput maximization problem as a joint optimal grouping and power allocation problem, which is a non-convex mixed-integer programming problem. We convert it to a convex problem using quadratic fractional programming (QFP), and then we solve it using augmented Lagrange multiplier (ALM) method. Moreover, to reduce the complexity of the solution, we propose a fast grouping method to allocate power to each group in parallel. Simulation results show that the proposed methods have outstanding performance compared to conventional association identifier (AID)-based grouping method; besides, scalability of the network in terms of throughput, power consumption and channel utilization improves dramatically because of the collision reduction of IoT-Ds, which is achieved by deploying NOMA and SIC. Furthermore, the fast grouping method decreases the computational complexity greatly at the expense of a small reduction in network performance.

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1 Introduction

In recent years, the advent of IoT has caused a significant increase in wireless traffic. IoT services and applications, such as, smart metering, environmental/agricultural monitoring and automation of industrial processes, require low power technologies that support data transmission in dense networks. Wireless personal area Network (WPAN) technologies, such as, ZigBee and Bluetooth, provide throughput up to a few hundred kilobits per second in short ranges, i.e., tens of meters. In long ranges, up to several kilometers, low power wide area network (LPWAN) technologies, such as, LoRA and SigFox, support throughput up to a few kilobits per second. Due to the limited throughput, these technologies can be used only in a limited IoT scenarios [1]. In order to support large-scale networks, IEEE 802.11ah standard, known as Wi-Fi HaLow, was developed. It can support up to 8000 users, transmission ranges from 100 m up to 1 km with data rates between 0.15 Mbps to 8 Mbps [2].

According to IEEE 802.11ah standard, devices of the network contend with each other to access wireless channel. In order to decrease collision probability of a dense network, the standard introduces a group-based access method called restricted access window (RAW). Periodic beacons divide the operation time of the network, and the interval between two consecutive beacons is divided into equal length RAW slots as shown in Fig. 1. The AP divides the devices into several groups and assigns one or more RAW slots to each group. The devices belonging to the same group contend for channel access only in the assigned RAW slot and go to sleep in the other RAW slots [3]. The devices contend by choosing a random number of time slots limited by the back-off window size. By winning the contention, the device attains a transmission opportunity (TXOP) during a RAW slot. A TXOP ends with an acknowledgement (ACK) message, then the next contention starts. No transmission is allowed to cross the RAW slot boundary, so devices do not start a transmission if the remaining time in the current RAW slot is not enough to complete the transmission. Therefore, a holding period is considered at the end of each slot as much as the time interval between the start of sending and receiving the ACK.

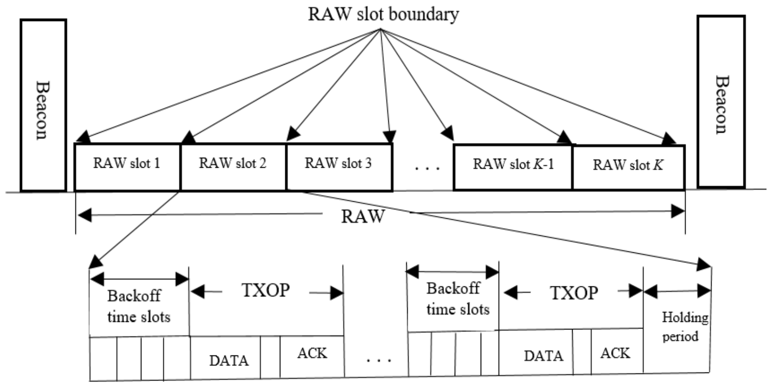


Fig. 1 RAW structure

The performance of dense networks depends remarkably to appropriate RAW configuration. The configuration parameters related to RAW include number of devices allocated to each group, number of groups, duration of RAW and number of RAW slots. Recent researches propose different analytical models of RAW or RAW-based grouping mechanisms to improve the scalability performance of IEEE802.11ah in terms of throughput, power and energy consumption.

In [4], the effect of grouping strategy on saturated throughput of the network is studied. The AP assigns the devices to the groups randomly and adjusts allocated time to each group according to its number of devices. Later, the authors show that centralized grouping, where the AP allocates equal number of devices to groups, outperforms the random grouping, where the devices choose a RAW slot randomly [5]. To enhance the success probability of uplink access, a method is introduced in [6] which estimates the number of competing devices and determines the optimal number of RAW slots. In [7], assuming that each device transmits one packet on each RAW slot and the back-off windows are reset in the next RAW slot, the authors calculate the probability of successful transmission for a specified RAW duration. The authors of [8] propose a mathematical approach to find the relationship between energy efficiency, number of devices and RAW slot duration. Then, the authors propose an adaptive access window algorithm to find the optimal combination of the number of competing devices and the size of RAW slots. With the target of load balancing in groups and channel efficiency improving in a heterogeneous network, an optimized device grouping solution is proposed in [9]. A numerical analysis of physical and medium access control (MAC) layer of IEEE802.11ah for a dense IoT scenario is presented in [1], where the effect of traffic load, number of devices and duration of

RAW slots on the optimal number of RAW groups is investigated. In [10], the authors propose a RAW mechanism with a retransmission algorithm. The algorithm improves energy and channel efficiency by retransmitting the collided packets in the next empty RAW slot in the same RAW. The authors in [11] suggest an optimization algorithm which regulates the number and duration of RAW slots in real time based on the current traffic condition. The authors propose a regression-based analytical model to estimate the probability of success to improve channel utilization in [12]. In [13], a grouping algorithm is developed which prioritizes the groups based on the estimated transmission time of their devices. The group of high-priority devices achieves longer access time than the group with low-priority devices. To minimize unfairness across groups, a fair scheduling problem based on the contention window size selection of nodes is formulated as an optimization problem in [14]. A dynamic frequency allocation to improve channel utilization and to reduce contention in a base service set (BSS), the area where devices communicate with each other via the AP, is suggested in [15]. Based on the interferences in each BSS, the AP divides the devices dynamically between frequency sub-bands to increase reusing frequencies in the BSSs. To balance the energy efficiency of different groups, a traffic distribution-based grouping is proposed in [16]. To improve the fairness and throughput, a data rate based grouping is proposed which devices operating at the same data rate are grouped together [17]. The authors of [18] predict the service interval of a monitoring application and schedule the subsequent frames before their arrivals without requiring any further contention. To increase the saturation throughput of the network and the relative service differentiation ratio of the lower priority class devices, the authors in [19] propose a priority-based grouping in which the devices belonging to the same priorities are grouped together. In [20], the authors propose an optimization model by using adaptive neuro-fuzzy inference system to find the optimal number of RAW slots. The model is trained with network size, modulation and coding schemes to increase the unsaturation throughput of the network. Although all mentioned studies propose a grouping method to reduce the contention and increase the throughput, none of them considers physical layer features to solve the collision problem of IEEE802.11ah MAC effectively. The devices have to double their back-off counter after each collision. This fact increases the waiting time for channel access and, consequently, decreases the throughput and increases the power consumption specifically when the number of devices is high. Therefore, to enhance scalability, a grouping method to mitigate the collision is required when dense IoT networks deploy IEEE802.11ah as their platform.

Recently, NOMA and SIC techniques have enhanced wireless channel utilization by resolving the collisions which happen by simultaneous transmissions to a receiver. From physical layer perspective, if the simultaneously received signal strength of one transmission is much higher than the ones of others, then the receiver is able to decode the transmission. In uplink, if several devices transmit their signals non-orthogonally but with different levels of power, which satisfies NOMA constraints, then the AP can distinguish the received interfered signals upon deploying SIC technique. In the AP, the strongest received signal is decoded first. Then, the second strongest signal is decoded. This process continues to decode the weakest signal [21]. Several optimization-based methods have been proposed to enhance the performance of NOMA and SIC techniques in Wi-Fi networks. In [22], an optimization problem is solved to allocate optimal power to each device and to maximize throughput in an unsaturated IEEE 802.11 network. In [23], a k-SIC MAC protocol is proposed which the devices are divided into $2k$ groups using different carrier sensing thresholds for scheduling up to k devices simultaneously. In [24], an analytical model is developed to compute the average throughput of a device in a WLAN with the SIC technique in presence of pathloss, Rayleigh fading and log-normal shadowing. In [25], the authors propose a SIC-aware CSMA MAC protocol for uplink access which the AP waits to receive requests from a certain number of devices and then selects the highest number of potential devices for uplink data transmission. To increase downlink throughput by utilizing the NOMA technique, an algorithm is developed in [26] to select an optimal device-set from a randomly selected device-set for downlink transmission with appropriate power allocation. An algorithm is proposed in [27] which determines optimal size of the contention window and adjusts the devices power level and transmission rates based on their channel condition. Papers [20] to [25] consider Wi-Fi networks with a few number of devices and short transmission range, but neither of these papers propose a solution to resolves the collision problem completely in dense and geographically distributed networks.

IoT-Ds experience different channel gain in IEEE 802.11ah standard due to widespread distribution of the devices, so the received signal power at the reception is highly different. On the other hand, the performance of NOMA and SIC techniques depends on the difference among simultaneous received signals strength. Accordingly, the required difference for deploying NOMA and SIC, can be maintained among the signals by controlling the transmitted power of IoT-Ds and assigning appropriate RAW slot to them, i.e., put them in appropriate groups. In this paper, we propose a new grouping method to improve the scalability by mitigating the collisions in IoT networks whose platform is IEEE802.11ah. We group the devices whose received signal strength in the AP are very different from each other. Therefore, the detection error or collision does not lead to information loss, i.e., collision is resolved completely. We solve an optimization problem for grouping and power allocation to maximize the total throughput of IEEE802.11ah network. We transform the integer and non-convex programing problem into a convex problem by relaxing integer variables and using QFP. Then, we propose an iterative approach to solve the transformed problem using ALM algorithm. Finally, we propose a fast grouping algorithm to decrease the complexity of the proposed optimal solution.

The rest of this paper is organized as follows. In Section 2, we introduce the scenario of the IoT network. The joint grouping and power allocation problem is formulated in Section 3. In Section 4, we propose a fast grouping algorithm to decrease the computational complexity. Simulation results are presented in Section 5, and we conclude the paper in Section 6.

2 Network Scenario

We consider an IEEE 802.11ah network with a single AP and N IoT-Ds denoted by $\mathcal{N} = \{1, 2, ..., N\}$. The AP is responsible for assigning some IoT-Ds to each group and determines their uplink transmission power based on NOMA and SIC techniques. The queue length at IoT-Ds are full and they always have equal length packets to transmit. We assume that one RAW in each beacon interval is divided into K RAW slots with indices k belongs to set $\mathcal{K} = \{1, 2, ..., k, ..., K\}$. One group is formed on each RAW slot. The maximum number of IoT-Ds in each group is $N_{\max}$ and is determined according to the complexity of the SIC receiver. At least two groups should exist, so we set $N_{\max} = N/2$. The AP is equipped with a SIC receiver that can detect $N_{\max}$ packets simultaneously in each RAW slot. Therefore, if several IoT-Ds of a group select the same back-off counter, their packets can be decoded at the AP correctly. Consequently, no collision occurs as long as fewer than $N_{\max}$ IoT-Ds in the group satisfy NOMA constraints.

The complex channel coefficient on the k-th RAW slot from the i-th IoT-D is $g_{i,k}$, which is constant during each RAW slot and is i.i.d among beacon intervals. The set of allocated transmission power to the i-

th IoT-D in the *k*-th RAW slot is $\mathbf{P} = \left\{ p_{i,k} \ge 0 : \forall i \in \mathcal{N}, \forall k \in \mathcal{K} \right\}$. The transmitted data symbol of the *i*-th IoT-D on the *k*-th RAW slot is $s_{i,k}$, and the received symbol on the *k*-th RAW slot at the AP is

$$y_k = \sum_{i \in \mathcal{N}} \sqrt{p_{i,k}}\, g_{i,k} s_{i,k} + z \qquad \forall k \in \mathcal{K} \tag{1}$$

where z is additive white Gaussian noise with variance σ^2. By allocating non-zero and zero transmission power, we determine dynamically which IoT-Ds are able to transmit data at each RAW slot.

Using SIC technique and canceling the interference of higher channel gains than those of the desired signal with channel coefficient $g_{i,k}$, Eq. 1 transforms to Eq. 2:

$$y'_{l,k} = \sqrt{p_{l,k}}\, g_{l,k} s_{l,k} + \sum_{i \in C} \sqrt{p_{i,k}}\, g_{i,k} s_{i,k} + z \qquad \forall l \in \mathcal{N}, \forall k \in \mathcal{K}, \tag{2}$$

In Eq.2, $C = \left\{ i : \left| g_{i,k} \right| < \left| g_{l,k} \right|, \forall i \in \mathcal{N}, \forall k \in \mathcal{K} \right\}$ is the set of network interference signals received by the *l*-th IoT-D on the *k*-th RAW slot; channel gains of interference signals, $g_{i,k}$, are smaller than that of the desired signal, $g_{l,k}$.

To decode received signals correctly using SIC technique, signal to interference and noise ratio (SINR) of the *l*-th IoT-D at the AP must be higher than a threshold. Considering Γ as the SINR threshold, the SIC constraints are defined at the AP:

$$\gamma_{l,k} = \frac{p_{l,k} \left| g_{l,k} \right|^2}{\sum_{i \in C} p_{i,k} \left| g_{i,k} \right|^2 + \sigma^2} \ge 1_{\left(p_{l,k} > 0\right)} \Gamma \qquad \forall l \in Q_k, \forall k \in \mathcal{K}, \tag{3}$$

where $Q_k = \left\{ l : \left| g_{l,k} \right| \ge \left| g_{j,k} \right|, \forall l \in \mathcal{N}, j = \text{argmin}_{r \in \mathcal{N}} g_{r,k}, \forall k \in \mathcal{K} \right\}$. By defining $1_{(p_{l,k} > 0)}$, if the *l*-th IoT-D is not allocated to group *k*, $p_{l,k} = 0$, inequality (3) remains valid.

If several IoT-Ds select the same back-off counter, the AP receives y_k, the summation of multiple number of signals simultaneously. First, the IoT-D with the strongest channel gain is decoded at the SIC receiver.

Then, the second strongest signal is decoded by subtracting the reconstructed strongest signal from y_k. The detection procedure proceeds until the signal of the IoT-D with the lowest channel gain is decoded without any interference.

3 Dynamic NOMA-based Grouping

To improve scalability of IoT networks implemented by IEEE 802.11ah platform, we take advantage of NOMA and SIC to reduce the collisions and increase the number of IoT-Ds being serviced. Accordingly, we solve a throughput maximization problem to perform grouping, RAW slot assignment and transmission power allocation.

3.1 Problem Formulation

In order to maximize the throughput, the AP places the competing IoT-Ds in different groups so that the power levels of the received signals at the AP are sufficiently different from each other. Let $x_{l,k}$ be a RAW slot allocation decision variable indicating that the k-th RAW slot is dedicated to l-th IoT-D if $x_{l,k} = 1$, otherwise $x_{l,k} = 0$. We represent the joint NOMA-based grouping and power allocation problem for the uplink throughput maximization as

$$\max_{p_{l,k}, x_{l,k}} \sum_{k \in \mathcal{K}} \left\{ \sum_{l \in \mathcal{N}} x_{l,k} log_2 \left(1 + \frac{p_{l,k} \left| g_{l,k} \right|^2}{\sum_{i \in C} p_{i,k} \left| g_{i,k} \right|^2 + \sigma^2} \right) \right\} \tag{4a}$$

$$\frac{p_{l,k} \left| g_{l,k} \right|^2}{\sum_{i \in C} p_{i,k} \left| g_{i,k} \right|^2 + \sigma^2} \geq 1_{\left(p_{l,k} > 0\right)} \Gamma \qquad \forall l \in \mathcal{N}, \forall k \in \mathcal{K}, \tag{4b}$$

$$\sum_{l \in \mathcal{N}} x_{l,k} \leq N_{max} \qquad \forall k \in \mathcal{K} \tag{4c}$$

$$\sum_{k \in \mathcal{K}} x_{l,k} = 1 \qquad \forall l \in \mathcal{N} \tag{4d}$$

$$p_{l,k} \le p_{max} \qquad \forall l \in \mathcal{N}, \forall k \in \mathcal{K}, \tag{4e}$$

Constraint (4b) ensures that the IoT-Ds are placed in the *k*-th group are sufficiently different in terms of received power level at the SIC receiver and their transmitted signals can be decoded correctly. Constraint (4c) limits the maximum number of IoT-Ds, $N_{\max}$, which can be placed in the *k*-th group. Constraint (4d) ensures assigning each IoT-D to only one group. Constraint (4e) limits the transmission power of each IoT-D into the maximum admissible value of uplink transmission power, $p_{\max}$.

For simplification, constraints (4b)-(4e) are rewritten with (5)-(8):

$$F_{l,k} = 1_{(p_{l,k}>0)}\Gamma\left(\sum_{i\in C} p_{i,k}\left|g_{i,k}\right|^2 + \sigma^2\right) - p_{l,k}\left|g_{l,k}\right|^2 \le 0. \tag{5}$$

$$S_k = \sum_{l\in\mathcal{N}} x_{l,k} - N_{max} \le 0. \tag{6}$$

$$O_l = \sum_{k\in\mathcal{K}} x_{l,k} - 1 = 0. \tag{7}$$

$$M_{l,k} = p_{l,k} - p_{max} \le 0. \tag{8}$$

Problem 4 is non-convex, since the SINR expressions appeared in the objective function contains interference terms. As the SINR expressions have fractional form and the logarithm is a non-decreasing convex function, the optimization problem (4) is an FP problem. In [28], a solution is proposed for FP problems based on the quadratic transform. In this solution, the numerator and denominator of each fractional expression are separated by a quadratic transform. Then, convex FP problems are converted to a sequence of convex optimization problems which ensure the convergence. In particular, an FP problem is solved using iterative algorithms through transforming the original problem into a sequence of convex expression. In this case, each fractional expression of the original problem relates to a convex expression by introducing additional variables updated during the iterations.

3.2 Solution Methodology

We define the set of quadratic transform variables for IoT-Ds with $\mathbf{Y} = \left\{Y_{l,k}, \forall l \in \mathcal{N}, \forall k \in \mathcal{K}\right\}$. Using quadratic transform, problem (4) is rewritten as problem (9).

$$\max_{p_{l,k}, x_{l,k}, \mathbf{Y}} \sum_{k \in \mathcal{K}} R_k \tag{9a}$$

$$\text{s.t.} \quad 0 \le x_{l,k} \le 1 \tag{9b}$$

(5), (6), (7) and (8). (9c)

Here R_k is the throughput of devices on the k-th RAW slot, i.e.,

$$\begin{aligned} R_k &= \sum_{l \in M_k} x_{l,k} R_{l,k} + \sum_{l \in \mathcal{N} \setminus M_k} x_{l,k} R_{l,k} = \sum_{l \in M_k} x_{l,k} log_2 \left(1 + \frac{p_{l,k} \left|g_{l,k}\right|^2}{\sigma^2}\right) + \\ &\sum_{l \in \mathcal{N} \setminus M_k} x_{l,k} log_2 \left(1 + 2Y_{l,k} \sqrt{p_{l,k} \left|g_{l,k}\right|^2} - Y_{l,k}^2 \left(\sum_{i \in C} p_{i,k} \left|g_{i,k}\right|^2 + \sigma^2\right)\right). \end{aligned} \tag{10}$$

In Eq. 10, $M_k = \left\{l = \text{argmin}_{r \in \mathcal{N}} \left|g_{r,k}\right|, \forall l \in \mathcal{N}, \forall k \in \mathcal{K}\right\}$ is the set of desired signals on each RAW slot with the lowest channel gain among interfering signals. The AP cancels all interfering signals having higher channel gains than that of the desired signal. As a result, the SINR expressions corresponding to these signals are convex functions, i.e., without interference. Hence, Eq.10 is divided into two expressions. The first expression includes the SINR of transmitters that are interference-free and the second expression refers to the sets of signals that experience interference.

Problem (9a)-(9c) is convex when the quadratic transform variables are constant. Thereby, quadratic transform variables $\mathbf{Y}$ and decision variables, $p_{l,k}$ and $x_{l,k}$, are obtained and updated in each iteration. Since the optimization problem (9) has several constraints, ALM method is deployed to release the constraints [29]. Methodology of ALM is based on the combination of the penalty method and Lagrange multiplier method [30]. ALM outperforms the Lagrange multiplier method in convergence speed, so it suits real time applications. Moreover, ill-conditioning problem that appears in penalty method does not happens in ALM anymore.

According to ALM method, to maximize an optimization problem with the objective function $f(x)$, equality constraint $A(x)$, and inequality constraint $B(x)$, the augmented Lagrangian function is

$$L = f(x) + \lambda A(x) + \frac{m}{2} A(x)^2 + \frac{1}{2m} \sum_{j=1}^{r} \left\{ \left(\mu_j + mB_j(x) \right)_+^2 - \mu_j^2 \right\}. \tag{11}$$

In Eq.11, λ and μ are multipliers of equality and inequality constraints, respectively, and m is the penalty parameter. Finding the solution of augmented Lagrangian function is equivalent to obtaining the answers of the primal problem. To this end, by initializing the variables λ, μ and m, the Lagrangian multipliers are computed and updated with Eq.12 and Eq.13 in each iteration a. The index symbol + in Eq.13 means the parameter μ must be positive. This process continues until the augmented Lagrangian function converges.

$$\lambda^{(a+1)} = \left(\lambda^{(a)} + m^{(a)} A(x)^{(a)} \right) \tag{12}$$

$$\mu_j^{(a+1)} = \left(\mu_j^{(a)} + m^{(a)} B_j(x)^{(a)} \right)_+ . \tag{13}$$

We consider $\mu_{l,k}$, $\alpha_{l,k}$ and $\beta_{l,k}$ as the multipliers of the SINR, transmission power and RAW slot allocation decision variable, respectively, for the l-th IoT-D on the k-th RAW slot. We define δ_k and ∂_l as the multipliers of constraints (6) and (7), respectively. Accordingly, the augmented Lagrangian function is

$$L = -\sum_{k \in \mathcal{K}} R_k + r. \tag{14}$$

Considering m as the penalty parameter, we define r as

$$r = \sum_{k \in \mathcal{K}} \left\{ \sum_{l \in \mathcal{N}} A_{l,k} + \frac{1}{2m} \sum_{l \in \mathcal{Q}_k} \left\{ \left(\mu_{l,k} + mF_{l,k} \right)_+^2 - \mu_{l,k}^2 \right\} + \frac{1}{2m} \left\{ \left(\delta_k + mS_k \right)_+^2 - \delta_k^2 \right\} + \frac{1}{2m} \sum_{l \in \mathcal{N}} \left\{ \left(\alpha_{l,k} + mM_{l,k} \right)_+^2 - \alpha_{l,k}^2 \right\} \right\}$$
$$+ \sum_{l \in \mathcal{N}} \left\{ \partial_l O_l + \frac{m}{2} O_l^2 \right\}. \tag{15}$$

Constraint (9b) is represented by

$$
A_{l,k} = \begin{cases} \beta_{l,k}\left(x_{i,k} - 1\right) + \dfrac{m}{2}\left|x_{i,k} - 1\right|^2 & \text{if } \beta_{l,k} + m\left(x_{i,k} - 1\right) > 0, \\ \beta_{l,k} x_{i,k} + \dfrac{m}{2}\left|x_{i,k}\right|^2 & \text{if } \beta_{l,k} + m x_{i,k} < 0, \\ -\dfrac{\beta_{l,k}^2}{2m} & \text{otherwise.} \end{cases} \tag{16}
$$

The transformed problem (9a)-(9c) is convex, so the optimal solution of original problem (4a)-(4e) is achieved by minimizing the augmented Lagrangian function (14). We propose an iterative approach for simultaneous optimization of transmission power and RAW slot allocation. For this purpose, first, by initializing the transmission power and multipliers, variables $Y_{l,k}$ are computed

$$
Y_{l,k} = \frac{\sqrt{p_{l,k}\left|g_{l,k}\right|^2}}{\sum_{i \in C} p_{i,k}\left|g_{i,k}\right|^2 + \sigma^2} \qquad \forall l \in \mathcal{N}, \forall k \in \mathcal{K}, \tag{17}
$$

Afterward variables $x_{l,k}$ are obtained using Newton method. Then, having $x_{l,k}$, we find the transmission power by optimizing the augmented Lagrangian function. The Lagrangian multipliers are updated in each iteration a by Eq.18 to Eq.22 [30].

$$
\mu_{l,k}^{(a+1)} = \left(\mu_{l,k}^{(a)} + m^{(a)} F_{l,k}^{(a)}\right)_+ , \tag{18}
$$

$$
\alpha_{l,k}^{(a+1)} = \left(\alpha_{l,k}^{(a)} + m^{(a)} M_{l,k}^{(a)}\right)_+ , \tag{19}
$$

$$
\delta_{k}^{(a+1)} = \left(\delta_{k}^{(a)} + m^{(a)} S_{k}^{(a)}\right)_+ , \tag{20}
$$

$$
\partial_{l}^{(a+1)} = \left(\partial_{l}^{(a)} + m^{(a)} O_{l}^{(a)}\right). \tag{21}
$$

$$
\beta_{l,k}^{(a+1)} = \begin{cases} \beta_{l,k}^{(a)} + m^{(a)}(x_{i,k} - 1) & \text{if } \beta_{l,k} + m\left(x_{i,k} - 1\right) > 0, \\ \beta_{l,k}^{(a)} + m^{(a)} x_{i,k} & \text{if } \beta_{l,k}^{(a)} + m^{(a)} x_{i,k} < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{22}
$$

When Eq. 14 converges, the iterative procedure is terminated. Algorithm 1 describes the procedure of NOMA-based grouping and power allocation of the IoT-Ds.

Algorithm 1 NOMA-based Grouping and Power Allocation

1: **Initialize P**, $\mu_{l,k}$, $\alpha_{l.k}$, $\beta_{l.k}$, ∂_l , δ_k and m
2: Compute **Y** using Eq.17
3: **repeat**
4: Compute $x_{l,k}$ by solving Eq.14
5: **repeat**
6: Compute **Y** using Eq.17
7: Compute **P** by solving transformed problem (14) for fixed **Y**
8: Update $\mu_{l,k}$, $\alpha_{l.k}$, $\beta_{l.k}$, ∂_l and δ_k using Eqs. 18, 19, 20, 21 and 22
9: **until** (14) converges
10: **until** (14) converges

4 Fast Grouping Solution

In this section, we propose a low complexity and fast method for grouping and power allocation. In this method, operations related to grouping and power allocation are divided into two separate parts. In the first part, we sort the gains in descending order and then group the devices according to Algorithm 2. According to this algorithm, IoT-Ds whose channel gains are as much as far from each other are placed in the same group. We generate *K* groups and put each one of the first *k* IoT-Ds in each group. We repeat the same approach for the second *k* IoT-Ds and so on. If the number of IoT-Ds is not a multiple of the number of groups, some groups contain fewer devices. The set of IoT-Ds which are placed in group *k* is represented by

G_k . In the second part, optimal transmission power is computed to maximize the total throughput of each group, i.e.,

$$\max_{p_i} \sum_{i \in G_k} log_2\left(1+\frac{p_i |g_i|^2}{\sum_{l \in v} p_l |g_l|^2 + \sigma^2}\right) \qquad \forall i \in G_k, \forall k \in \mathcal{K} \tag{23a}$$

$$\frac{p_i |g_i|^2}{\sum_{l \in v} p_l |g_l|^2 + \sigma^2} \geq 1_{(p_{i>0})}\Gamma \qquad \forall i \in G_k, \forall k \in \mathcal{K} \tag{23b}$$

$$p_i \leq p_{max} \qquad \forall i \in G_k, \forall k \in \mathcal{K}, \tag{23c}$$

where, $v = \{l : |g_l| < |g_i|, \forall i \in G_k, \forall k \in \mathcal{K}\}$ is the set of network interference signals, on *i*-th IoT-D and the *k*-th RAW slot so that the desired signal has a higher channel gain than that of interfering signals. Constraint (23b) indicates that the AP received power level of IoT-Ds placed in group *k* are far enough, so their transmitted signals can be decoded correctly. Constraint (23c) shows that the transmission power of the *i*-th IoT-D on the *k*-th RAW slot should be less than the maximum transmission power, $p_{\max}$.

Algorithm 2 Fast Grouping

1. **Initialize** Number of IoT-Ds (*N*) and Number of groups (*K*)
2. **Initialize** the gain-set H_i for $i = 1, ..., K$ as empty
3. **Initialize** the device-set G_i for $i = 1, ..., K$ as empty
4. **Initialize** $Z = 0$ **,** $j = 1$
5. **Sort** gains $g_1 > g_2 > g_3 > ... > g_N$
6. **repeat**
7. **for** $i = 1 : K$ **do**
8. $H_i \leftarrow H_i \cup g_{i+j-1}$
9. **end**
10. $j \leftarrow K + j$
11. $Z \leftarrow K + j - 1$

12. **until** $Z = N$

13. After completing each set H_i, devices that belong to each gain-set form group G_i

Problem (23) is solved for each group separately using the quadratic transform and the Lagrange multiplier methods. As the transmission power of IoT-Ds in different groups are independent, the computation complexity of the optimization problem is reduced.

5 Simulation Results

In this section, we evaluate the scalability performance of the proposed grouping methods in terms of the throughput, total transmission power and channel utilization. The performance of the proposed methods is compared with the ones of Association ID based (AID-based) grouping method. AID-based grouping has been introduced in IEEE 802.11ah standard for RAW slot allocation [3]. According to this method, each RAW slot is indexed from 0 to K-1. The index of each slot, i_{slot}, is calculated by

$$i_{slot} = \left(\mathrm{AID} + N_{offset}\right) \bmod K, \tag{24}$$

where, N_{offset} is a fixed parameter to improve fairness among the IoT-Ds in a RAW.

We consider an IoT network with IEEE 802.11ah as the platform with a radius of 1km wherein IoT-Ds are uniformly distributed. The fading channel is i.i.d, complex Gaussian with zero mean and unit variance. Pathloss is $8 + 37.6\log_{10}(d)\,\mathrm{dB}$, where d is the distances between the IoT-D and the AP. The interval between two consecutive beacons is 400 ms which is divided into K RAW slots. Each specific group acquires a RAW slot. Table 1 shows the other simulation parameters.

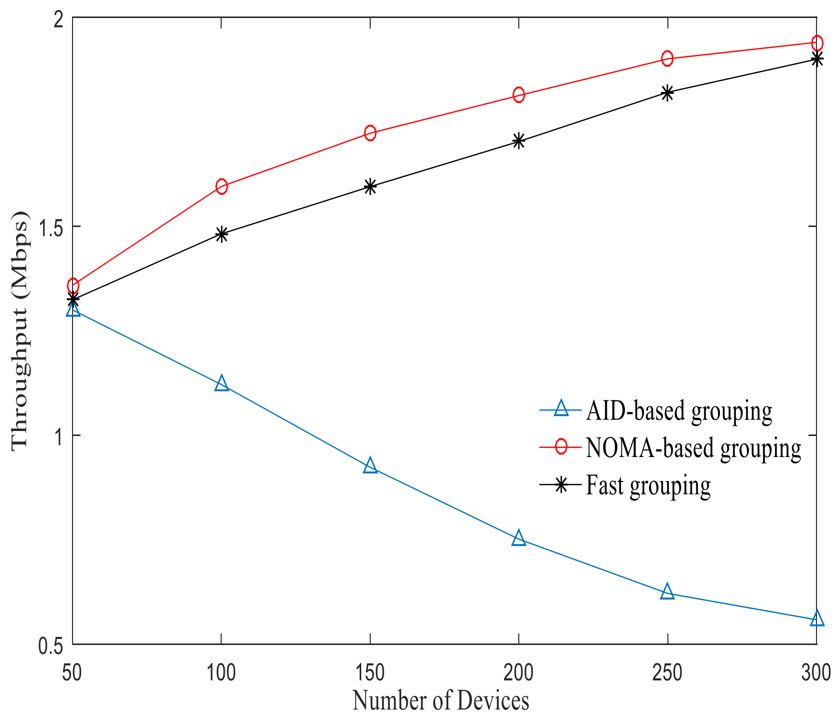
Table 1 Simulation Parameters

Parameters	Value
DIFS	264 µs
Backoff time slot	52 µs
Packet size	256 bytes
SIFS	160 µs
CW_{min}	15
MAC header	272 bits
PHY header	128 bits
ACK frame	240 bits
N_{offset}	2
Bandwidth	2 MHZ
σ^2	-110 dBm
Γ	5 dB
p_{max}	255 mW

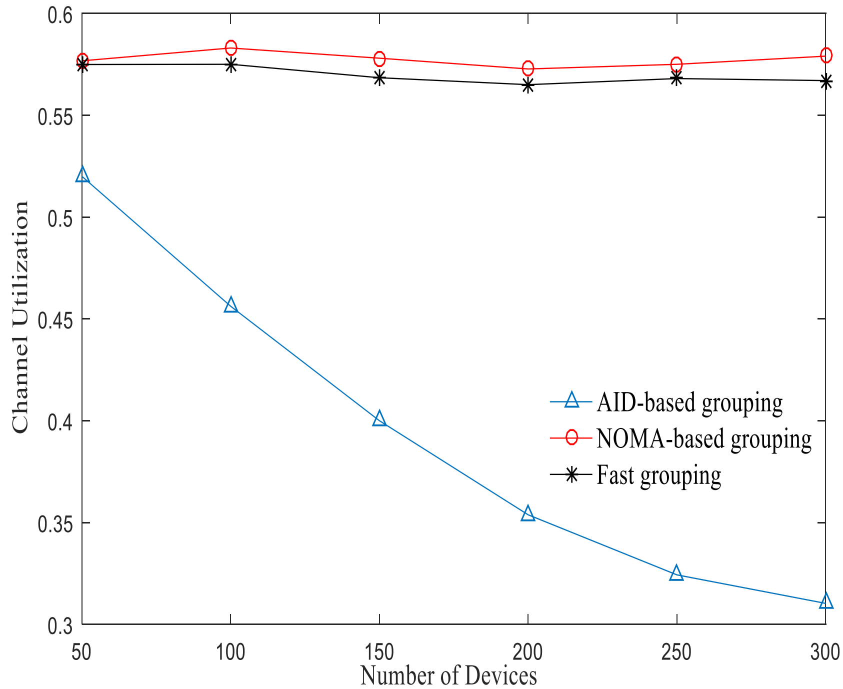
5.1 Network Performance

We compare the scalability performance of the network when the proposed and AID-based grouping methods are deployed. Our metrics are the throughput, transmission power, channel utilization, and collision reduction versus the number of IoT-Ds and number of groups.

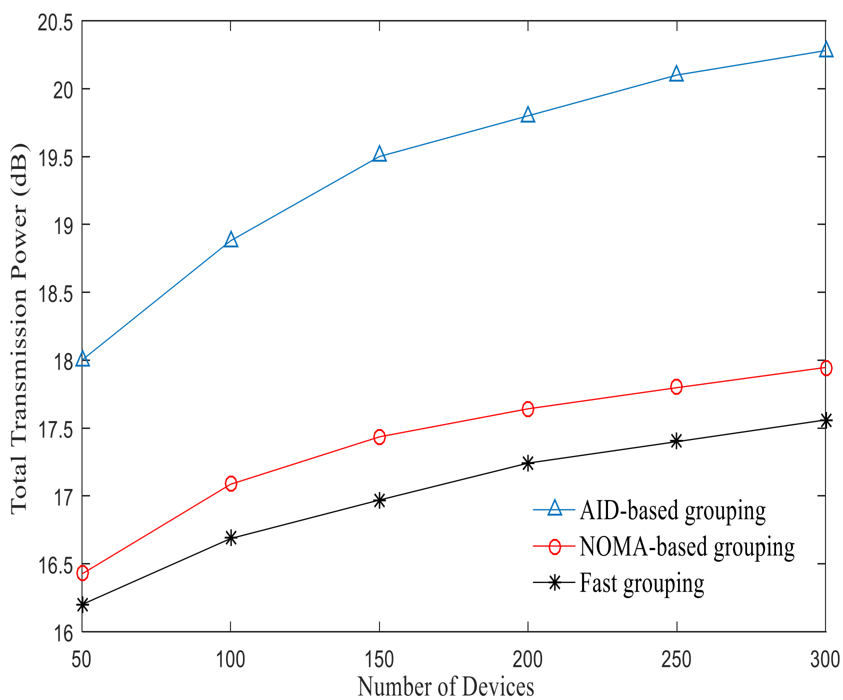
Fig. 2 shows the network performance against increasing number of IoT-Ds. The throughput of the network grows by NOMA-based and fast grouping methods, while the throughput degrades by AID-based grouping. The outperformance of the proposed grouping methods is because they can let several IoT-Ds to transmit simultaneously without collision. After each collision, the back-off counter of the involved IoT-Ds is doubled which increases the waiting time to access the channel and reduces the throughput. By reducing the collisions, the proposed grouping methods benefit from more transmission opportunities, so they enhance the throughput of the network. For the same reason, the performance of the network in terms of channel utilization enhances for the proposed methods, as Fig. 2(b) shows. Channel utilization is defined as the ratio of channel time used for transmitting to total channel access time. Fig. 2(c) shows the performance of the proposed grouping methods in terms of the total transmission power. In AID-based method, IoT-Ds send with maximum transmission power $p_{\max}$. In all three grouping methods, by increasing the number of IoT-Ds, the number of attempts to access the channel increases, resulting in more power consumption. However, the proposed grouping methods consume much less power than AID-based grouping method since transmission power of the IoT-Ds is determined according to the channel condition of each device. NOMA-based grouping method has higher throughput and total transmission power than fast grouping method. This is due to the optimization gap raised by decomposing the resource allocation problem in fast grouping method.



(a)



(b)



(c)

Fig. 2 Performance comparison of the proposed grouping and AID-based grouping methods in terms of **a** Throughput, **b** Channel Utilization, **c** Total Transmission power, K=25

To investigate more deeply on the scalability enhancement of the proposed NOMA-based grouping methods, we define accident resolution rate as the ratio of decoded transmissions by NOMA to the total transmissions. Fig. 3 shows that by increasing the number of IoT-Ds and hence the number of simultaneous transmissions, the number of transmissions decoded by NOMA is increased. Moreover, Fig. 3 presents the effect of contention window minimum size, CW_{min}, on the proposed grouping methods. Accident resolution rate increases as CW_{min} decreases. The reason is the probability of selecting the same back-off counter rises and the number of simultaneous transmissions decoded by SIC technique improves. Therefore, using NOMA-based grouping methods, enhances the scalability of the network by resolving more accidents and reducing the overhead of choosing large contention windows.

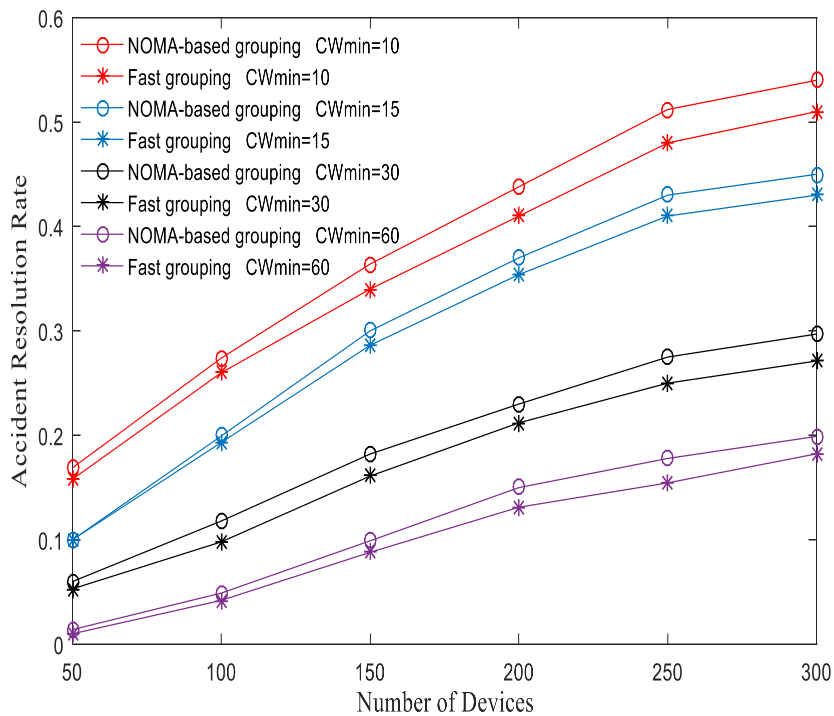
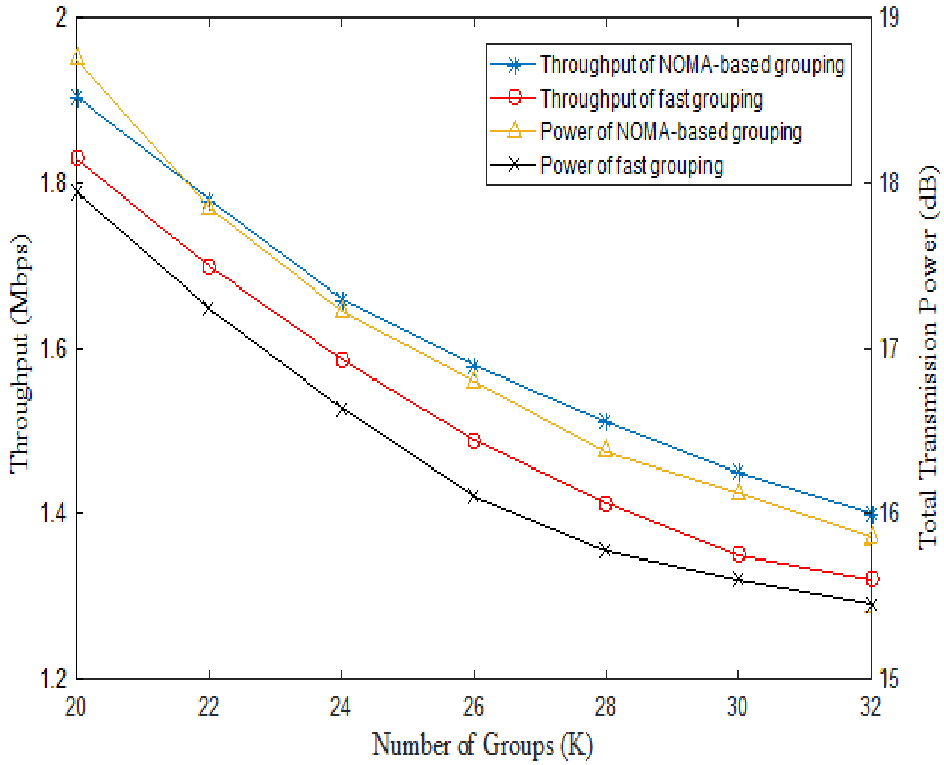
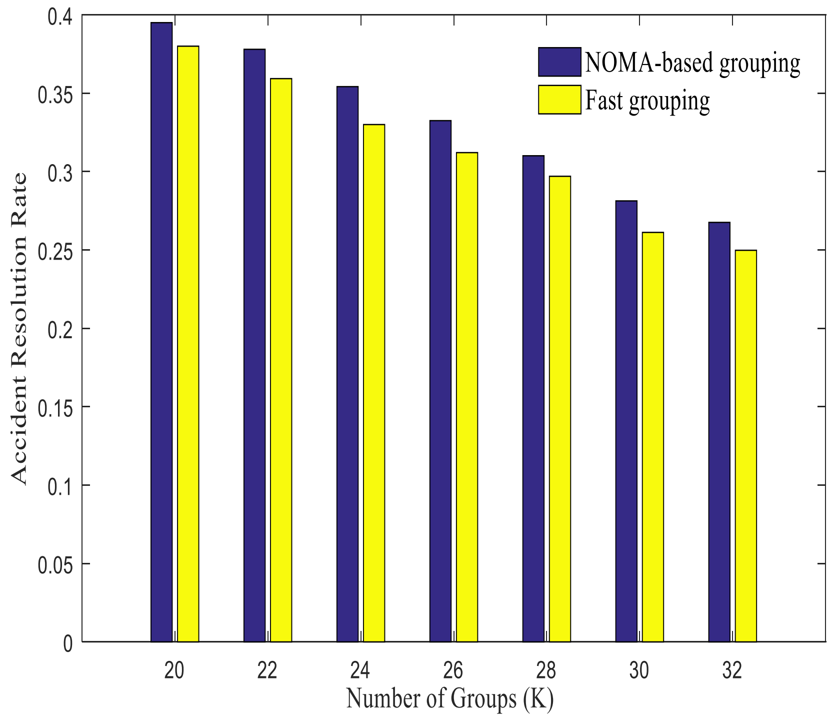


Fig. 3 Scalability performance of the proposed NOMA-based grouping methods, K=25

Fig. 4 demonstrates the effect of the number of groups on the network performance. The number of simultaneous transmissions grows with reducing the number of groups, and SIC receiver is able to decode more transmissions as shown in Fig. 4(b). Hence, the throughput as well as the transmission power increase as illustrated in Fig. 4(a). When the number of groups is low, more power is required to create enough difference among IoT-Ds transmission power to satisfy NOMA constraints. Finding the minimum number of groups that all IoT-Ds be served is the point at which the maximum throughput exists. Some devices may not be considered in any group with values in Fig. 4, to serve 200 IoT-Ds, K = 20 groups are required.



(a)



(b)

Fig. 4 a Throughput and Total Transmission Power **b** Accident Resolution Rate versus Number of Groups

6 Conclusion

In this paper, having the scalability in mind, we have proposed NOMA-based grouping methods for large-scale IEEE 802.11ah networks deployed in IoT networks. In each beacon interval, we assign a group to each RAW slot and the IoT-Ds to groups according to their channel gain. The assignment problem has been formulated as a non-convex mixed-integer programming problem aiming at maximizing total throughput subject to the SIC and NOMA transmission power constraints. Using quadratic FP method, we reformulated the main problem into a convex problem and solved it using ALM. In addition, a fast grouping method based on decomposing the grouping and power allocation problems has been proposed to reduce computational complexity of the original problem. Simulation results demonstrate that the proposed NOMA-based grouping methods outperforms AID-based grouping in terms of the throughput, power consumption and channel utilization as the number of users increases. In other words, the scalability of the network improves as NOMA and SIC techniques allow more simultaneous transmissions in each group. Moreover, for a small reduction in network performance, the fast grouping method decreases the computational complexity greatly.

Statements & Declarations

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