Towards Energy-Fairness in LoRa Networks

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***Abstract*—LoRa has recently become one of the most promising networking technologies for the Internet of Things applications. Distant end devices have to use a low data rate to reach a LoRa gateway, which can cause long in-the-air transmission time and high energy consumption. Compared with the end devices using high data rate, they will drain the batteries much earlier and the network may be broken. Such an energy unfairness can be mitigated by deploying more gateways, since it allows end devices to reach closer gateways with higher data rates. However, multiple gateways may not solve the energy unfairness problem efficiently due to the collision problem caused by the chirp spread spectrum modulation of LoRa networks. Spreading factors of LoRa links can determine both data rate and multiplexing of different transmissions. With more gateways, more end devices may choose low spreading factors and reach closer gateways, which increase the collision probability. In this paper, we propose a networking solution for LoRa networks named EF-LoRa that can achieve fair energy consumption among end devices by carefully allocating different network resources, including frequency channels, spreading factors and transmission power, to achieve fair energy consumption among end devices in LoRa networks. We develop a LoRa network model to study the energy consumption of all the end devices in a network by considering the unique features of LoRa networks, such as LoRaWAN MAC protocol, spreading factors, interference, and the capacity limitation of a LoRa gateway. We formulate the energy fairness problem as an optimization problem and finally propose a greedy resource allocation algorithm to achieve the max-min fairness of energy efficiency in the LoRa networks. Simulation results show that the proposed solution EF-LoRa can improve the energy fairness of legacy LoRa networks by 177.8%.**

***Index Terms*—The Internet of Things, wireless networking, LoRa networks, energy fairness, resource allocation**

I. Introduction

Low Power Wide Area Networks (LPWANs) have been widely adopted to build autonomous wireless networks for a variety of Internet-of-Things (IoT) applications, such as smart city [1] and smart farming [2]. Several LPWANs technologies have attracted investment and spawned deployments these years such as LoRa [3] and SigFox [4] which operate on the unlicensed ISM bands, and NB-IoT [5] operating on the licensed band supported by 3GPP cellular infrastructure. Among them, LoRa is one of the most promising technologies due to its open standard that allows us to build our autonomous LPWANs. According to the LoRa standard [6], a gateway can cover up to several miles with thousands of end devices, and end devices are expected to work for several years without changing the battery. The LoRa physical layer adopts Chirp Spread Spectrum (CSS) modulation for interference resilience and low-power transmissions. Spreading factor represents the number of bits per chirp. A large spread factor results in low data rate and long communication range, e.g., for 125kHz uplinks, by setting the spreading factor to 7 or 12, the data rate is 5.47 kbps or 0.25 kbps, respectively. As a result, to transmit a 100 bytes packet, it takes 146 ms or 3200 ms using a high or low data rate respectively. However, some end devices can only use a large spreading factor due to its long distance to the gateway, so these end devices have to transmit packets consuming much more time and energy than those with smaller spreading factors. The large gap on transmission time can lead to the severe energy unfairness of end devices. If some end devices die much faster than the others, it may cause application failures and break the network due to the absence of some fatal data. As a consequence, the unfairness hinders the promising goal of LoRa networks (e.g., large coverage and long network lifetime).

With the relatively low cost of LoRa gateways (e.g., $345.69 for TTN-GW-915 [7] or $315 for MultiConnect Conduit Gateway [8]), improving the fairness of energy consumption by deploying more gateways becomes feasible, since end devices can choose smaller spreading factors to reach a closer gateway. However, besides data rates, spreading factors are also used to multiplex different transmissions in LoRa networks. If two end devices use two different spreading factors on the same channel, their signals can both be decoded by the gateway simultaneously. As a result, with more gateways, as the number of end devices using low spreading factors increases, the collision probability also increases. Spreading factors and frequency channels can affect packet reception and energy consumption since they need to be carefully allocated to achieve high transmission performance and fair energy consumption in multi-gateway LoRa networks.

The existing works on resource allocation of LoRa networks mainly focus on a single gateway. They aim at the fairness of collision probability for different spreading factors by considering their diverse in-the-air transmission time [9], [10]. While resource allocation in multi-gateway LoRa networks is challenging. First, to allocate spreading factors to end devices, we need to estimate the packet reception of each end device when different spreading factors are used. The network model of multi-gateway LoRa networks is more complex than single-gateway LoRa networks. Since a LoRa end device does not associate with a specific gateway, its packets can be received by multiple gateways, so the packet reception ratio in multi-gateway LoRa networks differs from the case that only one gateway is considered. Second, we also need to consider the transmission power allocation in multi-gateway LoRa networks. Unlike the power control in cellular networks, if a LoRa end-device uses a small transmission power to reduce the energy consumption and interference from other end devices, it will reach fewer gateways, which may lead to lower packet reception ratio. We show the impact of spreading factor and transmission power on energy fairness by two illustrative examples in Section II.

In this paper, we propose a network solution EF-LoRa that allocating resources in multi-gateway uplinks LoRa networks to realize fairness in energy efficiency among end devices. The resource allocation is formulated as a max-min optimization problem which intends to maximize the worst case regarding the energy efficiency among end devices. Therefore, our max-min optimization problem considers both energy consumption and transmission performance. We develop a network model for multi-gateway LoRa networks. Our network model takes as input the distribution of end devices and gateways (i.e., the distance between them). We first investigate the unique properties of spreading factor, i.e., data rates and multiplexing. We consider these two properties by in-the-air transmission time and interference in our network model. Both transmission time and packet collision probability are included in the calculation of the energy consumption model for each end device. We also formulate the impact of frequency channels and transmission powers in multiple gateways scenarios.

Moreover, in order to make the proposed network model more practical, we consider the capacity limitation of LoRaWANs gateways (i.e., one gateway can only receive up to 8 simultaneous packets using different channels or spreading factors) and the randomness of Aloha-based LoRaWAN MAC protocol. We analyze the complexity of the proposed optimization problem and its NP-completeness, Finally, we propose a greedy heuristics algorithm to obtain the fair resource allocation solution that significantly improves the fairness of end device energy efficiency.

We implement our proposed solution on the simulation platform NS-3 and conduct large-scale simulations. We change the number of end devices from 500 to 5000, and the number of gateways from 1 to 25. We compare the energy fairness by the minimum energy efficiency of each end device. The results show that EF-LoRa can outperform the legacy LoRa by 177.8% on average with 3 gateways and 3000 end devices.

In summary, this paper makes the following contributions.

1) To the best of our knowledge, we are the first to investigate the energy fairness problem in LoRa networks.
2) We propose EF-LoRa to solve the energy fairness problem, which optimizes the resource allocation on a novel network model of multi-gateway LoRa networks.
3) We prove the resource allocation problem is NP-hard and develop a greedy algorithm to obtain a sub-optimal resource allocation solution.
4) We conduct extensive simulations on NS-3 to evaluate the performance of EF-LoRa.

II. Motivation

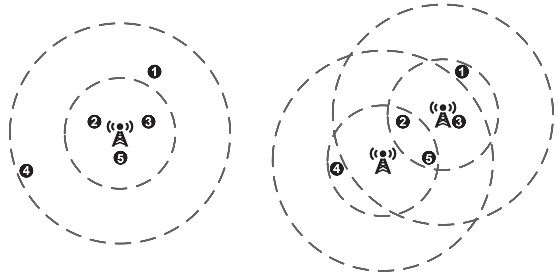
In this section, we use two illustrative examples to discuss the impact of spreading factor allocation and transmission power allocation. Despite end devices can use smaller spreading factors or large transmission power, there will be inefficiency and unfairness in energy efficiency and thus on the lifetime of the networks.

Spreading factor allocation. Figure 1 (a) shows an example with one gateway (GW) and six end devices (EDs). For simplicity, there are one channel and two available spreading factors 7 and 8, where the dashed circles represent the coverage of these two spreading factors. Duty cycle is set to 20%, according to the randomness of Aloha protocol from LoRaWANs, with the assumption of 100% link quality of a single link, the packet reception ratio of two to three end devices using the same spreading factor is to 67%, 54% and 45%. The time for transmitting a 10 bytes packet is 14 ms and 26 ms for spreading factor 7 and 8, respectively. Here the consumed energy is reflected by the transmission time. In this case, there are two EDs that can only use spreading factor 8, while other EDs choose spreading factor 7 to reduce the data rate. We can calculate the average time for an ED to transmit a packet, as well as the standard deviation of transmission time indicating the fairness of the allocation. The results are shown in the second column in Table I.

A large difference in total transmission time among these EDs can be observed, which implies the significantly different energy consumption and the lifetime of EDs. This can be mitigated by using two GWs as shown in Figure 1 (b). The locations of EDs do not change, while the original GW is replaced by two GWs. In this scenario, all the EDs can connect to GWs with the smallest spreading factor, i.e., spreading factor 7. The new total transmission time and fairness can be calculated and the results are shown in the third column in Table I. We can see that the average transmission time and fairness is improved due to the increased data rate that the end devices choose. However, we argue that this allocation may induce unnecessary collisions and unfairness as EDs tend to use smaller spreading factors.

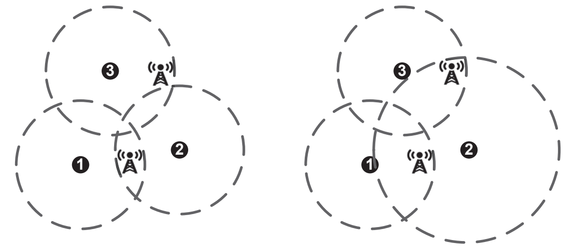
If we re-assign the spreading factor of ED 3 from 7 to 8, the collisions can be reduced and fairness is further improved. The results in Table I demonstrate that the fairness is improved by 47% and 74% compared with single gateway scenario and multi-gateway scenario while end devices choose the smallest spreading factor, as a result of allocating spreading factors to reduce collisions. With the definition of lifetime above, the lifetime of this network can be improved by 50% and 20% for a single gateway and two gateway scenario that chooses the smallest spreading factor.

Transmission power allocation. The transmission power of a transceiver is highly related to the communication range of the ED. Low transmission power is usually set to reduce



(a) (b)

Fig. 1. Spreading factor allocation with different number of gateways.



(a) (b)

Fig. 2. Transmission power allocation.

the interference to other nodes in wireless networks [11]. In LoRa networks, however, EDs do not associate with a predefined GW, so using low transmission power may degrade reliability resulting from multiple GWs. In Figure 2 (a), there are three EDs and two GWs in a given area. The dashed circles now denote the communication range of EDs, and spreading factor 7 is selected in this example. Every ED uses the lowest transmission power as long as it can reach one of the GWs. The packet reception ratio of the three EDs is 100%, 54% and 54%, respectively, and the transmission time is thus 14 ms, 26 ms and 26 ms, respectively. In this case, if we increase the transmission powers of ED on the right as shown in Figure 2 (b), it can reach both two GWs, which is shown by the bold lines. Thus the new transmission time turns to be 17 ms, 26 ms and 17 ms, respectively, which can improve the standard deviation by 33%.

It can be inferred from the above examples that the spreading factor and transmission power should be carefully allocated such that the resulted reliability and energy consumption can contribute positively to the fairness of energy efficiency.

III. Design

In this section, we describe EF-LoRa, the LoRa network solution that achieve fair energy consumption among end devices. We first develop the system model of the multi-gateway LoRa networks. We formulate the resource allocation problem to achieve the max-min fairness of energy efficiency, taking the impact of spreading factor, transmission power and channels into account. Analyzing the difficulty of solving the developed model, we propose a heuristic algorithm to calculate fair resource allocation in LoRa networks.

A. System Model

We focus on the uplink LoRa networks where multiple gateways are deployed and EDs are spatially distributed in a Euclidean plane through an inhomogeneous Poisson point process (PPP) ϕ of intensity λ [12], with the total number of EDs N. Every ED broadcasts its packets with the unslotted Aloha protocol, and all gateways within reach of a device will receive its packets and forward them to remote servers. The remote server then filters the redundant received packets with de-duplication operation. Due to the low power property,

TABLE I
IMPACT OF SPREADING FACTOR ALLOCATION.

End Device ID	Total transmission time (ms)		
	Single GW	Two GWs	
		Smallest SF	Ajusted SF
1	39	31	26
2	26	19	17
3	26	31	26
4	39	26	21
5	26	19	26
Average	31.2	25.2	23.2
Standard deviation	7.12	6.02	4.09

the transmission of EDs also satisfies the duty cycle which is usually set below 1% according to ETSI [3].

There are five configurable parameters of LoRa which may impact the performance of LoRa signal transmissions such as energy consumption and transmission efficiency: spreading factor (SF), transmission power (TP), carrier frequency (CF), bandwidth (BW) and coding rate (CR). The set of all the available spreading factors is denoted by $SF = \{7, 8, 9, 10, 11, 12\}$, implying the number of information bits that are encoded in one chirp. The available transmission power TP in the US can be set between 10dBm to 30dBm with 2dBm per step.

Different SFs induce significantly different time-on-air for transmitting a symbol. With $SF = n$, a symbol can encode n information bits into a chirp, and the bit rate is given by $R_b^n = n \cdot \frac{1}{2^n/BW}$, so the symbol period is calculated by $T_{symbol} = \frac{2^n}{BW}$. When $SF = n+1$, the symbol period of one symbol equals to $\frac{2^{n+1}}{BW}$, which doubles the transmission time by sending only one more bit. But larger SF means more robustness to interference and noise, thus leading to a larger communication range.

According to [13], LoRa networks operate in the 902MHz to 928MHz frequency band in the United States, and the band for uplinks is divided into eight sub-bands such that each sub-band has 8×125kHz channels and a 500kHz channel. Although there are more than sixty channels can be configured, a LoRa network GW can listen to up to eight channels. Usually, one of the eight sub-bands is chosen by LoRa network GWs, such that every ED can send packets to all the surrounding GWs without setting the available channel set in advance. Different LoRa networks can choose different sub-bands for gateways, in this way, their transmission can avoid interference from other LoRa networks due to the unlicensed spectrum. In this way, the reliability can be greatly improved by the reception of multiple gateways [14].

Bandwidth of 125 KHz is used in this paper for uplinks. Coding rate aims at correcting bit errors inside a packet, since we analyze the link reliability based on the packet level SNR model, coding rate is set to be default value 4/5 to avoid the impact of bit error correction. According to [15], two packets with the same spreading factor and channel will collide once their transmissions overlap with each other regardless of the size of overlapping. The notations used throughout this paper are summarized in Table II.

TABLE II
NOTATIONS USED IN THIS PAPER

Symbols	Notations
s_i, p_i, c_i	Spreading factor, transmission power and channel of end-device i
EE_i	Energy efficiency of end-device i
PL	Payload size of a packet
E_p^i	Energy consumption for a successful transmission
E_s^i	Energy consumption for single transmission
λ	Density of end-devices
e_{pi}	Energy consumption with power p_i within a time unit
T_i	Time for single transmission of end-device i
n_{pr}, n_{pl}	Number of symbols of packet preamble and payload
T_{symbol}	Time for transmitting a symbol
χ_k^t	Binary indicating whether gateway k is available at time t
D	Maximum available simultaneously received packets for gateways
th_{SF}	SNR threshold of spreading factor SF
ss_k	receicver sensitivity of gateway k
$SNR_{i,k}$	SNR of link from end-device i to gateway k
p_{rx}	Received power strength
$d_{i,k}$	Distance between end-device i to gateway k
b_j^t	Binary indicating whether end-device j transmits at time t
$N_{s,c}$	Number of end-devices using spreading factor s and channel c
T_c	Size of contention window
N^t	Number of successful packets at time t

B. Problem Formulation

We consider the problem of realizing energy fairness by allocating resources including spreading factors, transmission powers and channels to EDs within the coverage of multiple GWs. We are interested in the energy efficiency of EDs which refers to the total number of delivered data bits per energy consumption unit for an ED.

We promote the fairness of energy efficiency by achieving max-min fairness [16], which intends to maximize the minimum energy efficiency among the EDs. Let us denote the energy efficiency of ED i as EE_i. The problem can be formulated as Equation 1:

$$\begin{aligned} &\max \min_{i \in EDs} EE_i(\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C}), \\ s.t. \quad & \forall i \in EDs,\ 10 \le p_i \le 30 \qquad (C_1) \\ & \forall i \in EDs,\ 7 \le s_i \le 12 \qquad (C_2) \\ & \forall i \in EDs,\ 1 \le c_i \le 8 \qquad (C_3) \end{aligned} \tag{1}$$

where $\boldsymbol{S} = \{s_1, s_2, ...\}, \boldsymbol{P} = \{p_1, p_2, ...\}, \boldsymbol{C} = \{c_1, c_2, ...\}$ denote the allocation of spreading factor, transmission power and channel, respectively, p_i, s_i and c_i denote the transmission power, spreading factor and channel that ED i uses. The objective of the problem is to maximize the energy efficiency of the worst case ED. The constraints C_1, C_2 and C_3 limit lower and upper bounds for the available transmission power, spreading factors and channels for EDs.

Specifically, we can calculate $EE_i(\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C})$ according to the definition above as follows:

$$\begin{aligned} EE_i(\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C}) &= \frac{L}{E_p^i(\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C})} \\ &= \frac{L}{E_s^i \cdot \frac{1}{PRR_i(\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C})}}, \end{aligned} \tag{2}$$

where L denotes the payload size of a packet, E_p^i denotes the energy consumption for successfully transmitting this packet from ED i, E_s^i represents the energy consumption for transmitting one single packet, and PRR_i represents the packet reception ratio of ED i. The second line in Equation 2 comes from the existence of interference, because a packet may be retransmitted several times causing extra energy consumption.

Energy consumption model. To describe the energy consumption E_s^i, we analyze the energy consumption model in LoRa networks. According to Casals *et al.* [17], the energy consumption for transmitting a LoRa packet can be divided into several parts of actions, accounting for ED waking up, radio preparation, signal transmission, radio off and postprocessing, respectively. The energy consumption of all of these actions except the signal transmission is slightly or not related to the resource allocation, so they are considered identical for every ED in the proposed model. The consumed energy for signal transmission E_{tx} is dependent on the transmission power and the different transmission time caused by spreading factor, and we define the E_{tx}^i as:

$$E_{tx}^i = e_{p_i} \cdot T_i, \tag{3}$$

where e_{p_i} denotes the energy consumed of transmission process in a time unit with power p_i. T_i denotes the transmission time for ED i to transmit a packet and can be calculated by:

$$\begin{aligned} T_i &= (n_{pr} + n_{pl}) \cdot T_{symbol} \\ &= (20.25 + \max(\lceil \frac{8L - 4s_i + 28 + 16}{4(s_i - 2DE)} \rceil CR, 0)) \times \frac{2^{s_i}}{BW}, \end{aligned} \tag{4}$$

with n_{pr} and n_{pl} the number of symbols of packet preamble and payload, and DE = 1 when the low data rate optimization is enabled, otherwise DE = 0, CR is the coding rate ranging from 5 to 8, as described before, the coding rate is set to 4/5 thus CR equals to 5.

Transmission reliability. For $PRR_i(\boldsymbol{S}, \boldsymbol{P})$, we refer to the calculation of packet delivery ratio (PDR), which is the reception probability of ED i connecting to a single gateway. Since an ED transmits a packet in a broadcast manner, all the surrounding GWs can receive this packet and then send them to the remote server. The impact of redundant packet reception at multiple gateways in LoRaWANs is studied by [18]. The transmission from an end device is considered successful as long as it is received by one gateway. If ED i transmits at time t, the packet reception ratio can be calculated as follows:

$$PRR_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = 1 - \prod_{k \in GWs} (1 - \chi_{i,k}^t \cdot PDR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})), \quad (5)$$

where $PDR_{i,k}$ represents the PDR of node i transmitting to GW k, $\chi_{i,k}^t$ is a binary variable indicating if GW k is available to receive packets from ED i at time t. $\chi_{i,k}^t$ is set necessarily because GWs are limited to simultaneously receive up to 8 packets, which is related to the hardware of GWs. The constraint of this capacity limitation can be written by:

$$\forall i \in EDs,\ k \in GWs,\ \sum_i \chi_{i,k}^t \le 8, \quad (6)$$

According to [19], an uplink packet from ED i can be successfully decoded by a GW when satisfying two conditions. First, the received signal-to-noise-ratio (SNR) is higher than a relative threshold th_{SF_i}. The second is that the received signal power should exceed the receiver (GW) sensitivity ss_k. So the PDR of ED i to GW k is calculated as:

$$\begin{aligned} PDR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = P\{SNR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) \ge th_{s_i}\} \\ \cdot P\{p_{rx}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) \ge ss_k\} \end{aligned} \quad (7)$$

Interference model. The received SNR of ED i is affected by the TP i and transmissions from all the other EDs which uses the same spreading factor and channel. It can be modeled as

$$SNR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = \frac{p_i \cdot g_{i,k} \cdot a(d_{i,k})}{\sum\limits_{\substack{s_j=s_i,\\ c_j=c_i,\\ j\neq i}}^{EDs} b_j^t \cdot p_j \cdot g_{j,k} \cdot a(d_{j,k}) + N_0}, \quad (8)$$

where $g_{i,k}$ is Rayleigh fading channel between ED_i and GW_k, and can be modeled as a zero mean and independent circularly-symmetric complex Gaussian random variable. b_j^t is a binary indicating whether ED_j transmits at the same time t as ED_i, and N_0 denotes the power of additive white Gaussian noise (AWGN) with zero-mean. $a(d_{i,k})$ denotes the path loss attenuation function which follows from the Friis transmission equation and can be defined as

$$a(d_{i,k}) = (\frac{c}{4\pi f d_{i,k}})^{\beta}, \quad (9)$$

where c is the velocity of electromagnetic wave, f is the carrier frequency and β is the path loss exponent.

With $SNR_{i,k}$ and received signal power $r_i = p_i \cdot g_{i,k} \cdot a(d_{i,k})$, we have:

$$\begin{aligned} PDR_{i,k}&(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = P\{SNR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) \ge th_{s_i}\} \\ &\cdot P\{tp_{rx}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) \ge ss_k\} \\ = P\{g_{i,k} &\ge \frac{th_{s_i}\left[\sum\limits_{\substack{s_j=s_i,\\ c_j=c_i,\\ j\neq i}}^{EDs} b_j^t \cdot p_j \cdot g_{j,k} \cdot a(d_{j,k}) + N_0\right]}{p_i \cdot a(d_{i,k})}\} \\ \times P\{g_{i,k} &\ge \frac{ss_k}{p_i \cdot a(d_{i,k})}\}, \\ = exp(&- \frac{th_{s_i}\left[\sum\limits_{\substack{s_j=s_i,\\ c_j=c_i,\\ j\neq i}}^{EDs} b_j^t \cdot p_j \cdot g_{j,k} \cdot a(d_{j,k}) + N_0\right] + ss_k}{p_i \cdot a(d_{i,k})}), \end{aligned} \quad (10)$$

which is followed by the fact that $g \sim exp(1)$. The value of the SNR threshold and receiver sensitivity depends on the spreading factor and bandwidth the ED select. For example, according to [20], the minimum received SNR required is -20dBm when using SF=12 and BW=125kHz. The sensitivity threshold is calculated as [21]:

$$ss_k = -174 + 10log_{10}(BW) + NF + th_{s_i}, \quad (11)$$

where the first term describes thermal noise in 1Hz of bandwidth and is constant without changing the temperature of the receiver. NF is the receiver noise figure and is fixed for given hardware implementation.

Considering randomness of LoRa MAC protocol. LoRaWANs constitute the MAC and network layers of LoRa networks and are proposed by the LoRa Alliance [22]. Due to the low power and low duty cycle of LoRaWANs, the transmissions work in the manner of Aloha protocol. As a result, interference does not happen from all the EDs using the same spreading factor. It's hard to determine whether any node transmits at time t under a random access protocol, so we propose a variable h_i to represent the overlap probability between ED_i and other EDs with the same SF and channel, it also means there is a proportion of h_i EDs interfering with ED i at the time when i transmits. Defining $N_{s,c}$ and T_c as the total number of EDs using spreading factor s and channel c, and the size of contention window, given the number of EDs trying to transmit packets according to a Poisson distribution in the unslotted Aloha, h_i is calculated as:

$$h_i = 1 - e^{-\alpha N_{s,c}}, \quad (12)$$

where α is duty cycle and $N_{s,c}$ is the number of EDs that using the same SF and channel as ED_i. The SNR of ED i to GW k can be rewritten by replacing b_j^t to h_i:

$$SNR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = \frac{p_i \cdot g_{i,k} \cdot a(d_{i,k})}{h_i \sum\limits_{\substack{s_j=s_i,\\ c_j=c_i,\\ j\neq i}}^{EDs} p_j \cdot g_{j,k} \cdot a(d_{j,k}) + N_0}, \quad (13)$$

Considering capacity limitation of GWs. Besides b_j^t, it is difficult to determine the value of $\chi_{i,k}$ due to the lossy nature of wireless communication and random starting time of EDs. We cannot make sure whether a GW has received 8 packets at a certain time. On this occasion, we replace $\chi_{i,k}^t$ with $\theta_{k,i}^t$, which denotes the probability that the number of packets which GW k successfully receives is less than 8.

$$\begin{aligned}\theta_{k,i}^t &= P\{N^t \leq 7\} \\ &= \frac{T_i}{T_c - T_i}\sum_{m=1}^{7}\sum_{S}\prod_{\substack{n\in S' \\ S'\subset S, \\ |S'|=m}} PDR_{n,k}\prod_{u\in S-S'}(1-PDR_{u,k}),\end{aligned} \tag{14}$$

where N^t is the number of successfully received packets transmitted at time t, and $S = \{1, 2, ..., \left\lfloor N\frac{T_i}{T_c}\right\rfloor\}$. Thus PRR_i is approximated by:

$$PRR_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = 1 - \prod_{k\in GWs}(1-\theta_{i,k}^t\cdot PDR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})), \tag{15}$$

Combining Equation 1 with Equation 12 to 15, the proposed model is more practical and less complex.

Reducing computational overhead. From the analysis above, the energy efficiency is formulated as:

$$\begin{aligned}EE_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) &= \frac{L\left(1-\prod_{k\in GWs}(1-PDR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})\theta_{i,k}^t\right)}{E_s^i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})} \\ &= \frac{L - L\prod_{k\in GWs}\left(1-exp(-\frac{th_{s_i}I_ih_i+N_0+ss_k}{p_i\cdot a(d_{i,k})})\theta_{i,k}^t\right)}{E_s^i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})},\end{aligned} \tag{16}$$

where I_i is the cumulative interference of ED_i from all the other EDs using the same spreading factor and channel.

Note that obtaining I_i is extremely difficult as all the interfering EDs have to be considered for every ED i. Note that obtaining I_i needs the information and allocation of all the other end devices, while those end devices have to refer to the allocation of ED i, this deadlock will greatly hinder the calculation of resource allocation. To break it and reduce the computational overhead, Laplace transform is adopted to reduce the search space of the cumulative interference since Laplace transform can effectively convert a complex problem into an easier algebraic problem [23]. With the Poisson Point Process distribution of EDs, we denote the Laplace transform of the cumulative interference as $\mathcal{L}_{I_i}(s)$, then the energy efficiency can be expressed as follows,

$$\begin{aligned}EE_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) &= \frac{L}{E_s^i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}))} - L\cdot \\ &\frac{\prod_{k\in GWs}\left(1-\mathcal{L}_{I_i}(\frac{th_{s_i}h_i}{p_i\cdot a(d_{i,k})})exp(-\frac{N_0+ss_k}{p_i\cdot a(d_{i,k})})\theta_{i,k}^t\right)}{E_s^i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})},\end{aligned} \tag{17}$$

Taking the Rayleigh fading model and probability generating functional of PPP into account, we have $\mathcal{L}_{I_i}(s)$ according to [24]:

$$\mathcal{L}_{I_i}(s) = exp\left(-2\pi\lambda_{s_i,c_i}(s\cdot p_i)^{\frac{2}{\beta}}\int_0^\infty r\int_0^\infty e^{-t(1+r^\beta)}\,dt\,dr\right), \tag{18}$$

where λ_{s_i,c_i} is the density of EDs using spreading factor s_i and channel c_i and can be expressed by:

$$\lambda_{s_i,c_i} = \lambda\frac{N_{s,c}}{N}. \tag{19}$$

In this way, the impact of other EDs on ED_i can be reduced from the cumulative interference to $N_{s,c}$. The packet delivery ratio of all the other EDs can be estimated using Equation 18, so the gateway capacity factor θ can be obtained, which is calculated by these PDRs.

C. Complexity Analysis

Our problem is mainly based on the scenario that EDs are statically deployed. The server has the knowledge of the distances between end devices and gateways, which can be easily obtained in practice by collecting the location information of end devices when they join the networks.

To analyze the complexity of the proposed model, let us consider the scenario of a single gateway, so that the packet reception ratio equals to the probability that this packet is successfully received by this gateway. If We relax the allocation problem by making spreading factors and channels constant, in this way, the model is to achieve max-min fairness of energy efficiency by allocating transmission power based on the SNR model. And the optimization can be expressed with a function of power allocation $\boldsymbol{P}$.

$$\begin{aligned}&\max\min_{i\in EDs}\frac{L}{E_p^i(\boldsymbol{P})} \\ &= \frac{L\cdot PDR_i(\boldsymbol{P})}{E_s^i(\boldsymbol{P})} \\ &= \frac{L\cdot f(SNR_i(\boldsymbol{P}))}{E_s^i(\boldsymbol{P})}\end{aligned} \tag{20}$$

where $f(.)$ is a function for calculating the PDR. According to [25], the problem of max-min SNR is non-convex and equivalent up to scaling with the QoS beamforming problem. QoS beamforming problem aims at minimizing the power used on the antennas while guaranteeing the requirements of SNR. It can be reduced to the Partition Problem which is known to be NP-complete [26]. As a result, the problem of Equation 20 is also NP-complete. Furthermore, the NP-completeness of the original model of multi-gateway resource allocation problem can be inferred because it is much more complex and difficult to solve than Equation 20. So solving such a problem is prohibitively difficult.

D. Allocation Algorithm.

For N EDs, with the number of available channels, spreading factors and transmission power n_c, n_s and n_t, respectively,

Algorithm 1: Heuristics for resource allocation.

Alloc = *Random*($\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C}$);
EE = *Min*(Alloc);
$\delta \geq 0$;
do
  $EE_0 = EE$;
  for $each\ k \in EDs$ **do**
    for $each\ (s_{i,k}, p_{i,k}, c_{i,k}) \in (\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C})$ **do**
      minEE = *Min*($s_{i,k}, p_{i,k}, c_{i,k}$);
      if $minEE > EE$ **then**
        EE = minEE
        Alloc(k) = $(s_{i,k}, p_{i,k}, c_{i,k})$
      end
    end
  end
while($EE - EE_0 > \delta$)

#Calculate minimum energy efficiency
Function *Min*(Alloc)
{
  temp = 9999;
  for $eachk \in EDs$ **do**
    EE = $Calculate_{EE}$(k);
    if $EE < temp$ **then**
      temp = EE;
    end
  end
  Return temp;
}

there are totally $(n_c \cdot n_s \cdot n_t)^N$ possible allocations and it is impossibly difficult to traverse all of them to find the optimal solution. We thus propose a greedy algorithm to allocate the resources each ED which provides the most increase in the minimal energy efficiency.

Specifically, the initial allocation $(\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C})$ is randomly generated for all the EDs. Then we have the following operations executing iteratively to reach the optimal allocation. In each iteration, we traverse every ED to greedily choose the preferred allocation for it. Specifically, for an ED, the energy efficiency of all the possible allocation are calculated on the premise of allocation of other EDs remaining constant. Thus the minimum energy efficiency min_r can be picked up. In this way, the resources with the largest min_r are allocated to this ED which local optimal allocation is on this ED. After traversing all the EDs in one loop, the algorithm will calculate the improvement of minimum energy efficiency compared with that before this iteration. If the improvement is larger than a threshold δ, it is considered that there may still be improvement space in the next iteration so next loop starts. If the improvement is smaller than δ, the iteration will stop. δ can be set by the operators as the expected accuracy of allocation. The detailed description of the processing is shown in Algorithm 1.

TABLE III
THRESHOLD FOR SNR AND SENSITIVITY.

Spreading factor	7	8	9	10	11	12
SNR threshold (dBm)	-6	-9	-12	-15	-17.5	-20
Sensitivity (dBm)	-123	-126	-129	-132	-134.5	-137

IV. EVALUATION

We conducted a series of large scale experiments on the simulation platform NS-3. Up to 25 GWs and 5000 EDs are deployed within a disc of 5 kilometers radius. The simulation with NS-3 is based on the LoRa network module proposed by [27], which supports the packet transmission in multiple gateway scenarios. All the GWs and EDs were configured to use the channel frequency from 902.3 MHz to 903.7 MHz with 125kHz bandwidth. Duty cycle was set to 1%, the uplink packets had an application payload of 8 bytes, which implied a PHY payload of 21 bytes. The energy is consumed by both active transmission and sleep, based on the experiments in [15], the sleep duration of EDs includes MCU sleep duration and radio sleep duration.

The region was meshed and GWs were deployed on the cross positions of these meshes according to the number of GWs. If we deployed one GW, it was set at the center of the region, if multiple GWs were used, they were uniformly deployed inside the coverage, end devices were also uniformly deployed. The trigger parameter of allocation algorithm iteration termination δ was set to 0.01.

SNR threshold and receiver sensitivity could be configured according to Semtech specification [21], Table III illustrates them with different spreading factors.

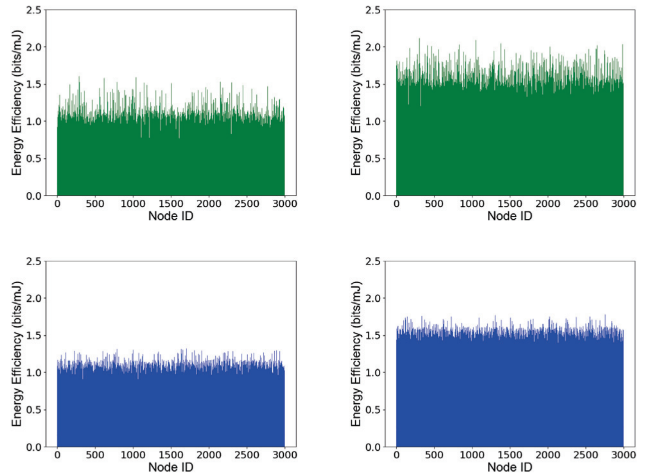
Benchmarks. In our experiments, we compared EF-LoRa with legacy LoRa [27] and RS-LoRa [10] which introduces the state-of-the-art resource allocation works. Legacy LoRa [27] chooses the smallest available spreading factors for end devices, which are calculated according to the estimated SNR while not considering the interference of other EDs. RS-LoRa considered the collision probability of EDs that use the same spreading factor. It tries to realize the fairness of collision probability among all the SFs. The percentage of EDs using different SFs is calculated by the following equation,

$$p_{sf} = \frac{sf/2^{sf}}{\sum_{i \in SF} i/2^i} \tag{21}$$

where sf denotes a certain spreading factor, SF represents the set of all the available spreading factors. This indicates that every end device is possible to choose the largest SF, which can lead to energy unfairness.

A. Performance comparison

Energy efficiency distribution. We ran the simulations with 500 to 5000 EDs and one to nine GWs to evaluate the performance of EF-LoRa. We first investigated the achieved fairness of energy efficiency in Figure 3. We picked the network topology of 3000 EDs along with three GWs and five GWs. The energy efficiency of all the EDs was collected and



(a) Energy efficiency with 3 GWs (b) Energy efficiency with 5 GWs

Fig. 3. Energy efficiency among EDs. Figures in green represent the energy efficiency of RS-LoRa, figures in blue represent the energy efficiency of EF-LoRa.

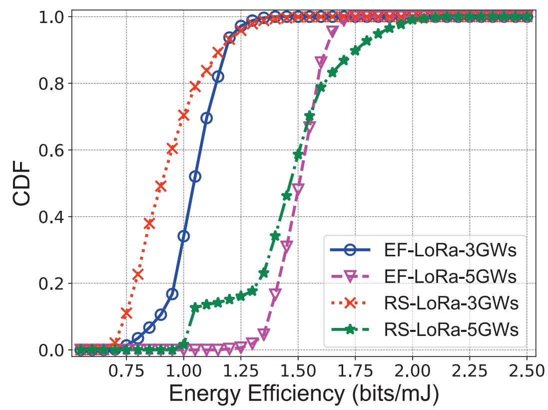


Fig. 4. CDF of Energy Efficiency.

illustrated. The two figures in green showed the distribution of energy efficiency of RS-LoRa and the figures in blue denoted that of EF-LoRa. As can be observed, the great fluctuation in the upper two figures meant the energy efficiency of RS-LoRa was not well balanced. Also, the difference between the maximum and minimum energy efficiency in RS-LoRa was up to 59.3% and 55.3%. The energy drains of certain EDs were much faster than others, which would potentially limit the lifetime of the network. Even if with an increased number of GWs, the overall energy efficiency was improved, but the unfairness was still obvious. While the lower two figures demonstrated a certain level of stability of EF-LoRa. Statistics showed that difference between the maximum and minimum energy efficiency in EF-LoRa were only 36.7% and 23.5% with three GWs and five GWs, respectively. The difference in energy efficiency distribution was due to the calculation of resource allocation. The allocation of RS-LoRa was calculated based on the single GW scenario, and it was assumed that the packet reception ratio with the same spreading factor was identical and equals the collision probability. However, the reception ratio in multi-gateway scenarios can significantly differ from each other because all the surrounding GWs can possibly receive packets from an ED. So it might lose some effectiveness under the multi-gateway scenarios.

Besides, when the number of GWs increased from three to five, the average energy efficiency was improved and at the same time, the fluctuation of RS-LoRa was exacerbated. Although more GWs provided improved reliability, the difference of reception ratio among EDs also increased due to the different number of receiving GWs. In that case, the allocation induced more fluctuations and unfairness in energy efficiency.

CDF of energy efficiency. According to Figure 3, we further illustrated the CDF of energy efficiency for RS-LoRa and EF-LoRa as in Figure 4. As expected, the energy efficiency of EF-LoRa was distributed within a narrow interval for both three GWs and five GWs and the cumulative probability increased with similar speed. On the contrary, energy efficiency in Rs-LoRa spread over a wide region from 0.69 bits/mJ to 1.61 bits/mJ and 0.98 bits/mJ to 2.29 bits/mJ. A small portion of EDs suffered from relatively low energy efficiency. Note that for RS-LoRa with five GWs, there was a relatively fast increasing of cumulative probability in small energy efficiency, this was the result of choosing the large spreading factor. RS-LoRa was always possible to choose the large spreading factor, and this leads to a long transmission time. As the packet reception ratio could be greatly improved by multiple GWs, a larger spreading factor could result in lower energy efficiency as illustrated in Figure 4.

Minimum energy efficiency. Figure 5 showed the minimum energy efficiency of legacy LoRa, RS-LoRa and EF-LoRa with 500 to 5000 EDs and three GWs. As can be seen that the minimum energy efficiency decreased when more EDs were deployed, and EF-LoRa performed better on it than legacy LoRa and RS-LoRa. This was because the collision probability increased which resulted in lower reception ratio and lower energy efficiency with more EDs, while for legacy LoRa, the minimum energy efficiency kept low even with a small number of EDs due to the severe collisions.

Another important information delivered from Figure 5 is that the minimum energy efficiency of EF-LoRa was much larger than that of legacy LoRa and RS-LoRa with relatively few EDs, while this gap was reduced as the number of EDs increases. The reason was that when the number of EDs was small, the EDs in EF-LoRa could choose smaller spreading factors without too many collisions in the coverage of multiple GWs, which could lead to several times faster transmissions, thus, the energy efficiency of EF-LoRa was generally high. While for RS-LoRa, there would be always some EDs choosing large spreading factors such as 11 and 12 because it tried to balance the collision probability of all the spreading factors. Since the ToA of a transmission exponentially increased when larger spreading factors were used, the bottleneck of minimum energy efficiency was usually dependent on the EDs with large spreading factors. In this

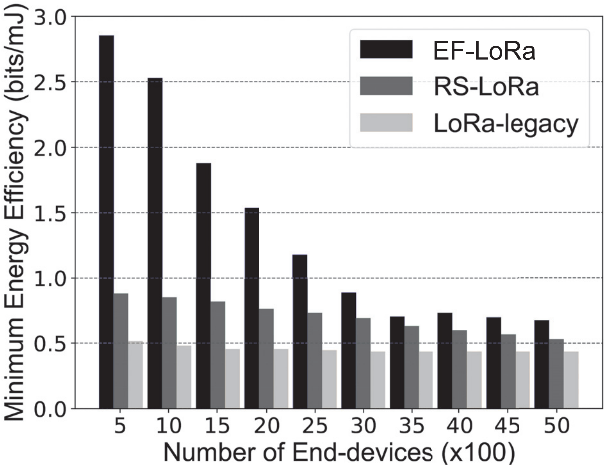


Fig. 5. Minimum energy efficiency.

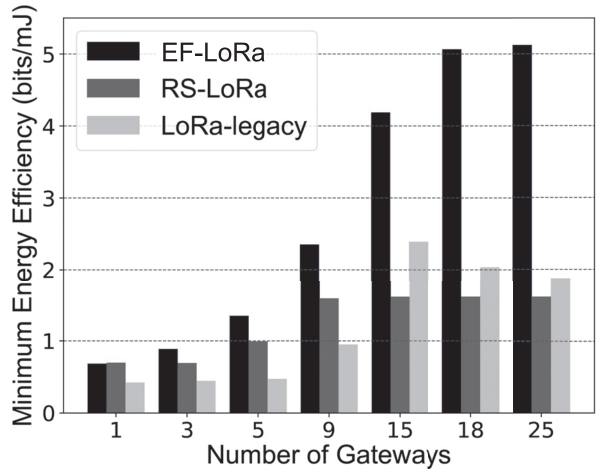


Fig. 6. Minimum energy efficiency.

case, a large gap of minimum energy efficiency appeared. But if there were too many EDs such as 5000 in Figure 5,both RS-LoRa and EF-LoRa had to use large spreading factors and low transmission power to balance the collisions among EDs, so the gap of minimum energy efficiency was greatly impacted by the reception probability and it showed the similarity between RS-LoRa and EF-LoRa. Figure 6 demonstrated the minimum energy efficiency with different number of GWs, and there were 3000 EDs in total. We can see that the minimum energy efficiency of EF-LoRa was larger than that of legacy LoRa and RS-LoRa, and the difference increased with more GWs. The reason behind this was similar to Figure 5. With one GW, EDs had to use large spreading factors to reach the GW, so the minimum energy efficiency was relatively high due to the low data rate, and both RS-LoRa and EF-LoRa could balance the collision probability. As the number of GWs increased, collisions could be greatly reduced, at the same time, EDs of EF-LoRa could choose smaller spreading factors to reach the GWs while RS-LoRa still experienced a low energy efficiency because it always had some EDs using large spreading factors, which would be the bottleneck of energy efficiency.

EF-LoRa also showed stability when deploying more GWs, this was because with a certain number gateways, if the distance between EDs and GWs was short thus every ED could transmit with all the spreading factors and transmission power, thus the relationship between reception ratio and energy consumption turned stable with even more gateways. For legacy LoRa however, more GWs also meant more EDs can use small spreading factors which still suffered from severe collisions. But the minimum energy efficiency decreased after a certain number of GWs. The reason was that with a very dense gateway deployment, all the EDs would use the smallest spreading factor, in this case, the extremely low packet reception ratio would limit the minimum energy efficiency.

B. Convergence of the algorithm

Although the EF-LoRa algorithm reduce the computation overhead of the optimal allocation from an exponential level to the multiplication by introducing a termination parameter δ, the convergence for running the proposed algorithm could be greatly influenced by the scale of the network. Figure 7 showed the convergence time for calculating the allocation according to the EF-LoRa algorithm, by varying the number of EDs from 1000 to 3000 and GWs from three to nine, We measured the running time it takes for EF-LoRa to stabilize.

The hardware we used for calculation was a Lenovo ThinkPad X1 Carbon laptop with 2.2GHz i5-5200 CPU and 4GB RAM. The running time for EF-LoRa implemented with Python 3.4 represented the algorithm convergence for the computation overhead with the termination parameter. As shown in Figure 7, the convergence time of EF-LoRa algorithm increases as more EDs and GWs were deployed. Besides, the convergence time increasing resulting from both more EDs and more GWs showed a near-linear trend. Specifically, by using 1000 more EDs, the increased convergence time was similar to that by deploying 2 more GWs.

As a result, the convergence time of EF-LoRa would not unlimited increase as the scale of the network expands. Despite the long convergence time on the simulation laptop, the calculation for resource allocation only had to run once when setting up the networks, and it would be running on the high-performance LoRa application servers, which could greatly reduce the convergence time. In this case, EF-LoRa algorithm can be practically implemented and deployed on large scale LoRa networks and achieve energy fairness.

V. Related Work

Energy fairness in wireless sensor networks. Since wireless sensors work in low power manner, there have been considerable studies tailored for achieving energy fairness to prolong the network lifetime of wireless sensor networks. Given that the communication range of sensors is small, wireless sensor networks connect nodes and sink nodes in a multi-hop manner, so the works on energy fairness mainly focus on the routing and rate control [16], [28], [29]. A network model is proposed for 802.11 networks to study hidden terminal and exposed terminal problems [30], [31]. While in LoRa networks, there is single hop between end

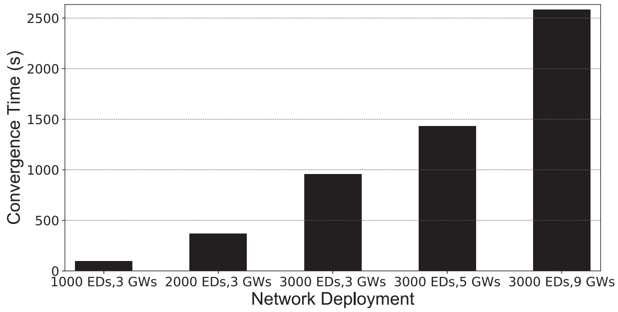


Fig. 7. Convergence time of EF-LoRa for different network deployment.

devices and gateways, to achieve energy fairness, the resources such as spreading factor have to be carefully allocated to them.

Resource allocation in LoRa networks Due to the extremely low power of LoRa end devices, the existing works on resource allocation in LoRa networks mainly aim at fairness. In [9], the authors realize fairness by minimizing the maximal collision probability of EDs with different spreading factors, and the results gave the percentage of EDs to use the spreading factors. Based on this, [10] proposed a MAC layer protocol using the above percentages to schedule EDs and their spreading factors. However, the above allocation is obtained with a single gateway, which does not consider the impact of other gateways due to the broadcast transmission of end devices, thus cannot efficiently reflect the performance of multi-gateway LoRa networks.

Resource allocation in cellular networks. Recently, multi-tier cellular networks which deploy femto-cells or pico-cells to balance the pressure of the base stations induce the need for designing an efficient resource allocation scheme such as spectrum assignment and power control to mitigate inter-cell interference. Usually, the base stations in cellular networks communicate with each other using wired communication and select different spectrum for mobile devices in the overlapped areas [32]–[34], so that the inter-cell interference is mitigated, which can be referred to techniques such as partial frequency reuse (PFR) [35] or soft frequency reuse (SFR) [36].

Furthermore, it has been shown that the inter-cell interference can be mitigated with the efficient power control scheme. Also, there have been quite a few research on power control approaches recently [11], [37]–[40], to reduce the interference and improve the sum of the data rate.

Resource allocation in WiFi networks. In WiFi networks, spectrum assignment and power control schemes can also help with improving the throughput or capacity of the networks. Mhatre *et al.* [37] proposed to mitigate interference in WiFi networks using power control, and a cross-layer approach was adopted to deal with the asymmetric starvation problem.

Data rate has been widely studied as another resource to be allocated in WiFi networks. The 802.11 specifications mandate multiple transmission rates at the physical layer (PHY) that use different modulation and coding schemes [41]. Higher data rate means higher transmission speed but induces smaller communication range, which can be deduced with Shanon's Principle. For mobile devices within the coverage of APs, their data rate are usually dynamically allocated or adjusted according to the unreliable wireless situation and distance between them [42].

Resource allocation problem in cellular and WiFi networks has been widely studied, while in multi-gateway LoRa networks, the spreading factors should be considered not only as channels due to the orthogonality but also data rates which mean different transmission time and coverage. This combination of the properties of channels and data rate makes it difficult to allocate spreading factors in LoRa networks. Thus, realizing energy fairness with resource allocation in LoRa networks is much more difficult than that in cellular networks or WiFi networks.

VI. Conclusion

In this paper, we propose EF-LoRa that achieves fair energy consumption among end devices and prolongs the network lifetime. We first investigated the problem of achieving energy fairness in LoRa networks. We proposed a mathematical model of energy efficiency in multi-gateway LoRa networks and formulated the resource allocation problem to achieve max-min fairness. The property of spreading factor as channel and data rate were considered in the formulation to make the optimization more efficient and practical. We also formulated the impact of channel and transmission power allocation. The interference and load of gateways were alleviated by controlling the transmission power of EDs. Finally, we proposed a greedy algorithm to solve the problem and get the allocation of all the resources. The simulation results showed that the allocation calculated by the proposed algorithm can achieve better fairness of energy efficiency than the state-of-the-art works in LoRa resource allocation.

VII. Acknowledgments

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