Towards Energy-Fairness in LoRa Networks

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***Abstract*—LoRa has become one of the most promising networking technologies for Internet-of-Things applications. Distant end devices have to use a low data rate to reach a LoRa gateway, causing long in-the-air transmission time and high energy consumption. Compared with the end devices using high data rates, they will drain the batteries much earlier and the network may be broken early. Such an energy unfairness can be mitigated by deploying more gateways. However, with more gateways, more end devices may choose small spreading factors to reach closer gateways, increasing the collision probability. In this paper, we propose a networking solution for LoRa networks, namely EF-LoRa, that can achieve energy fairness among end devices by carefully allocating network resources, including frequency channels, spreading factors and transmission power. We develop a LoRa network model to study the energy consumption of the end devices, considering the unique features of LoRa networks such as the LoRaWAN MAC protocol and capacity limitation of a gateway. We formulate the energy fairness allocation as an optimization problem and propose a greedy allocation algorithm to achieve max-min fairness of energy efficiency. Extensive simulation results show that EF-LoRa can improve the energy fairness by 177.8%, compared to the state-of-the-art solutions.**

***Index Terms*—Internet-of-Things, wireless networks, LoRa, 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 [2] and smart farming [3]. Recently, several LPWANs technologies have been develped and deployed, such as LoRa and SigFox operating on the unlicensed ISM bands, and NB-IoT operating on the licensed band supported by 3GPP cellular infrastructure. Among them, LoRa is one of the most promising technologies due to its low complexity, open link standard and scalability to IoT devices. According to the LoRa specifications [4], a gateway can cover a large area up to several square miles with thousands of end devices that are expected to work for several years without changing the battery.

LoRa physical layer adopts Chirp Spread Spectrum (CSS) modulation for reliable and low-power transmissions. Data in LoRa is carried in different chirps, and the spreading factor (SF) represents the number of bits per chirp. A large SF results in low data rate and long communication range [4]. For example, by setting the spreading factor to 7 or 12, the data rate of 125kHz bandwidth links is 5.47 kbps or 0.25 kbps, respectively. As a result, to transmit a 100-byte packet, it takes 146 ms or 3200 ms using a high or low data rate, respectively, indicating a large gap of 22 times difference. However, some end devices can only use large SFs so that they can send packets to the gateways through a long distance. As a result, these end devices have to transmit the packets with more time and more energy than those using smaller SFs.

The large gap in energy consumption can lead to unfairness in lifetime of end devices, and can affect the network lifetime which is an important design consideration in LPWANs. The authors in [5] have evaluated the energy consumption with spreading factor 7 and 12 (the difference could be as large as 22x). Even end devices sleep for most of the time, the gap of overall energy consumption between different spreading factors can reach four times difference, which is large enough to cause energy unfairness and affect network lifetime. For example, a LoRa network consists of end devices using spreading factor 7 and 12. As a result, end devices with spreading factor 7 consumes four times less energy than those with spreading factor 12, and they would have different lifetime (e.g., one month for spreading factor 12 while four months for spreading factor 7). If we define that the network would be broken if the first end device has run out of its battery [6], the network lifetime is only one month, while a lot of end devices (i.e., spreading factor 7) can still work for another three months. This indicates large potential improvement of network lifetime.

With the relatively low cost of LoRa gateways (e.g., $345.69 for TTN-gateway-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, both their signals can be decoded by the gateway simultaneously. As a result, with more gateways, more end devices will use low spreading factors, increasing collision probability and requiring multiple re-transmissions, and thus increasing the energy consumption. Compared with those end devices that have less collisions (when fewer con-

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tending nodes share the same SF), energy unfairness still exists. Spreading factors and frequency channels can affect collision probability and energy consumption, so they need to be carefully allocated to achieve fair energy consumption in multi-gateway LoRa networks.

The existing work on resource allocation in LoRa networks mainly focuses on a single gateway scenario, aiming at the fairness of collision probability [1], [9]–[11]. However, resource allocation in multi-gateway LoRa networks is challenging. First, a network model is required to reveal the relationship between resource allocation and energy fairness. 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 are broadcast and can be received by multiple gateways, so the packet reception ratio in multi-gateway LoRa networks differs from the single gateway scenario. Second, power control is more complex. LoRa packets are broadcast from end devices, and all the surrounding gateways can receive them so that packet reception ratio can be improved. Unlike the power control in cellular networks, if a LoRa end device uses a small transmission power to save energy, it will reach fewer gateways and miss the improvement due to multiple 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. Third, a typical LoRa gateway can simultaneously demodulate up to eight packets, which limits the capability of packet reception [12]. However, due to the randomness of packet arrival time, we cannot determine whether there are eight packets arriving at a gateway concurrently before the resources are allocated. Therefore, considering this limitation on gateways is difficult for resource allocation in LoRa networks.

In this paper, we propose a network solution EF-LoRa that allocates resources in multi-gateway 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 lowest energy efficiency in LoRa networks. Therefore, this max-min optimization problem considers both energy consumption and packet reception ratio. We develop a network model for multi-gateway LoRa networks. Our network model takes the distribution of end devices and gateways (i.e., the distance between them) as input. We first investigate the unique properties of spreading factor, i.e., data rates and multiplexing, which are indicated by transmission air time and interference in our network model. Besides, both transmission time and packet collision probability are included in the energy consumption model for each end device. We also formulate the impact of frequency channels and transmission powers in the scenarios of multiple gateways.

Moreover, 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 eight 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 propose a heuristic allocation algorithm that significantly improves the fairness of energy efficiency.

We implement our proposed solution on the simulation platform NS-3 and conduct large-scale simulation experiments where 5000 end devices and 25 gateways are involved. We represent energy fairness by the minimum energy efficiency in a LoRa network. The results show that EF-LoRa can outperform the state-of-the-art work by 177.8% on average with 3 gateways and 3000 end devices. We evaluate the network lifetime of EF-LoRa, and the experimental results show that the network lifetime can be improved by 64% compared with default legacy LoRa [13]. To further analyze the performance gain of EF-LoRa, we also decompose EF-LoRa and evaluate the benefits of the network model sensitivity to environment changing and transmission power allocation.

In summary, this paper makes the following contributions.

1) To the best of our knowledge, this work is the first to investigate the energy fairness problem in LoRa networks. The work is important for achieving the promising goal of LoRa technology, i.e., large coverage and long network lifetime.
2) We solve the energy fairness problem by proposing EF-LoRa, which optimizes the resource allocation based on a novel network model of multi-gateway LoRa networks.
3) We prove that the resource allocation problem is NP-hard and then develop a greedy algorithm to obtain a sub-optimal resource allocation solution.
4) We conduct extensive simulation experiments on NS-3 to evaluate the performance of EF-LoRa. The experimental results show that EF-LoRa can improve the energy fairness by 177.8%.

The rest of the paper is organized as follows. We discuss the motivation of EF-LoRa with two illustrative examples in Section II. Next, we present the design of EF-LoRa in Section III. Section IV presents our experimental evaluation. Section V discusses the related work on energy fairness and resource allocation of LoRa networks. Section VI concludes this work.

II. Motivation

In this section, we use two illustrative examples to discuss the impact of SF allocation and transmission power allocation.

Spreading factor allocation. Figure 1(a) shows an example with one gateway and five end devices, uplink transmissions (i.e., from end devices to gateways) with 125 kHz bandwidth are illustrated. We use one channel and two SFs 7 and 8. The solid lines represent the links with SF 7, and the dashed lines denote links with SF 8. The time for transmitting a 10-byte packet is 14 ms and 26 ms for SF 7 and 8, respectively. For simplicity, we represent the energy consumption by the transmission time. With two to four end devices using the same spreading factor for transmission, their packet reception ratio are assumed to be 67%, 54% and 45%, respectively. In this example, two end devices (i.e., end device 1 and 4) can only use SF 8, while other end devices choose SF 7 to increase the data rate. We can calculate the average time for an end device to transmit a packet, and we use the min-max transmission time among the end devices to indicate the fairness of the allocation. The results are shown in the second

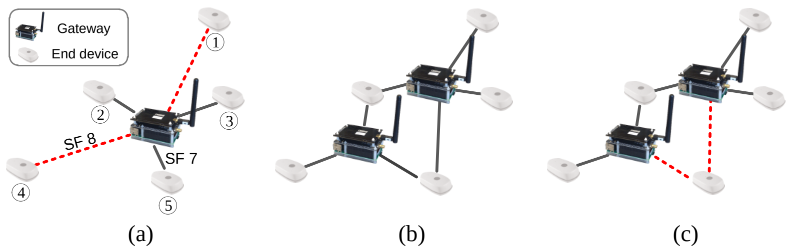


Fig. 1. Spreading factor allocation.

Fig. 2. Transmission power allocation.

TABLE I
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
Max(transmission time)	39	31	26

TABLE II
TRANSMISSION POWER ALLOCATION.

End Device ID	Total transmission time (ms)	
	Smallest TP	Adjusted TP
1	14	20.3
2	26	20.3
Average	20	20.3
Max(transmission time)	26	20.3

column in Table I. A large difference in the total transmission time among these end devices can be observed, which implies the significantly different energy consumption and the lifetime of end devices.

This energy unfairness can be mitigated by using two gateways as shown in Figure 1(b). The locations of end devices do not change, while the original gateway is replaced by two gateways. In this scenario, all the end devices can connect to gateways with the smallest spreading factor, i.e., SF 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 fairness is improved. However, we argue that this allocation still faces unfairness as end devices tend to use smaller spreading factors.

As seen in Figure 1(c), if we re-assign the spreading factors of end devices on end device #5 from 7 to 8, the collisions can be reduced and the fairness is further improved. The results in Table I demonstrate that the fairness is improved by 21.5% and 33.3% compared to the single gateway scenario and two gateways scenario where end devices choose the smallest spreading factor. As a result, the new spreading factor allocation can reduce collisions.

We can also calculate the network lifetime in the above examples based on the energy consumption (transmission time) of end devices. In this example, we define the network lifetime as the time that the first end device has run out of its battery. Assuming batteries of end devices have the same initial power, we estimate the network lifetime with the transmission time (used as the energy consumption) in Table I. The lifetime of the network in Figure 1(c) is longer than the single gateway scenario and two gateway scenario using the smallest spreading factor (i.e., Figure 1(a) and (b)) by 25.8% and 50.1%, respectively.

Transmission power allocation. In LoRa networks, as end devices do not associate with a pre-defined gateway, the packets from a certain end device can be received by all the surrounding gateways. As a result, using low transmission power may miss the chance from multiple gateways to improve the transmission reliability. In Figure 2(a), there are three end devices and two gateways. The lines denote the connections between end devices and gateways, and the end devices have the same resource allocation except transmission power. Spreading factor 7 is selected in this example. Every end device uses the lowest transmission power as long as it can reach one gateway. The packet reception ratio of the three end devices is 100%, 54% and 54%, respectively, and the transmission time is 14 ms, 26 ms and 26 ms, respectively. In this case, if we increase the transmission power of the end device on the right as shown in Figure 2(b), it can reach both gateways, where the connections are shown by the bold lines. As a result, the new transmission time turns to be 17 ms, 26 ms and 17 ms, respectively, which can improve the energy fairness by 24.2%. The results are illustrated in Table II.

It can be inferred from the above examples that the spreading factor and transmission power should be carefully allocated so that they can contribute positively to the energy fairness. Neither allocating small SFs (transmission power) nor only using large SFs (transmission power) for end devices can guarantee the fairness.

III. DESIGN

In this section, we describe EF-LoRa, the LoRa network solution that achieves 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 end devices are spatially distributed around the gateways within an area, with the total number of end devices N. Following some practical systems with mart city, smart building, environmental monitoring [14]–[17], we assume that the positions of end devices are known. Every end device broadcasts its packets with the unslotted Aloha protocol periodically with interval T_g, 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, the transmission of end devices also satisfies the duty cycle which is usually set below 1% according to ETSI [4]. According to the practical LoRaWAN systems [18]–[20], the overall transmission rate of each end device is the same.

There are five configurable parameters of LoRa which may have impact on the performance of LoRa signal transmissions such as energy consumption and transmission efficiency:

1) Spreading factor (SF), which impacts the communication range and data rate;
2) Transmission power (TP), which impacts the communication range and energy consumption;
3) Frequency channel (FC), which multiplexes the transmissions to reduce interference;
4) Bandwidth (BD), which can also impact the communication range and data rate;
5) Coding rate (CR), which represents the bit error correction capability.

The set of all the available SFs is denoted by $SF = \{7, 8, 9, 10, 11, 12\}$, implying the number of information bits that are encoded in one chirp. The available TP in the Europe can be set from 2dBm to 14dBm, with 2dBm per step. $\boldsymbol{S} = \{s_1, s_2, ..., s_N\}$ and $\boldsymbol{P} = \{p_1, p_2, ..., p_N\}$ denote the spreading factor and transmission power allocation for the N end devices, respectively.

According to [12], LoRa networks in the 868 MHz frequency band and have 10 channels in Europe. Eight of them are used for uplinks from end devices to gateways with 125 KHz bandwidth, and the other two channels are used for downlinks transmissions with 500 KHz bandwidth. Although there are more than sixty frequency channels in the U.S. specification [12], in a LoRa network, only eight of them are selected for gateways receiving packets to make sure that end devices can be heard by all the surrounding gateways to increase transmission reliability. LoRa uses Hamming code for error correction with coding rate from 4/5 to 4/8, where 4/x means four information bits and (x-4) redundant bits. However, Hamming coding rates 4/5 and 4/6 are not capable of correcting bit errors while coding rates 4/7 and 4/8 are both used for correcting only one single bit error [21]. We use coding rate 4/7 so that a bit error can be corrected without unnecessary redundant bits (i.e., coding rate 4/8). It is worth noting that, bandwidth is often fixed for a given LoRa network. We assume that the parameter settings follow the regional regulations [12] and assume bandwidth is fixed for the same network. However, it is also reasonable to assume the two parameters can be tuned in experimental scenarios. In this case, for different bandwidths, we can treat all nodes with the same bandwidth as a new subnet and then apply our model (section III-A) to all subnets. Similarly, for different coding rates, we can consider its impact in the calculation of PDR and energy consumption presented in Section III-B. In this paper, we consider them as fixed for a given network.

TABLE III
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
$\mathcal{N}$	Set of end devices
$\mathcal{G}$	Set of gateways
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

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. However, larger SF means more robustness to interference and noise, leading to a larger communication range. According to [5], two packets with the same SF 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 III.

B. Energy-Fairness Problem Formulation

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

EF-LoRa aims at balancing the energy efficiency of all of the end devices in LoRa networks to realize fairness. We promote the fairness of energy efficiency by achieving max-min fairness, which intends to maximize the minimum energy efficiency among the end devices. Let us denote the energy efficiency of end device i as EE_i, the problem can be formulated as Equation (1) to attain the max-min fairness for multi-gateway LoRa networks.

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

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. The objective of the problem is to maximize the energy efficiency of the worst case end device. The constraints C_1, C_2 and C_3 limit lower and upper bounds for the available transmission power, spreading factors and channels for end devices.

According to the definition, we can calculate $EE_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})$ 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 end device i, E_s^i represents the energy consumption for transmitting one single packet, and PRR_i represents the packet reception ratio of end device 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. The term $\frac{1}{PRR_i(S,P,C)}$ calculates the expected number of transmissions (ETX), including the packet retransimissions. For LoRa classes/applications without retransmissions, the ETX calculation becomes constant for each cycle as a fixed number of attempts will be used.

Energy consumption model. To calculate the energy consumption E_s^i, we analyze the energy consumption model in LoRa networks. According to Casals *et al.* [22], the energy consumption for a single transmission can be divided into several actions, accounting for end device waking up, radio preparation, signal transmission, radio off and postprocessing, respectively. These actions, except the signal transmission, accounts for a little portion of the total energy consumption and is slightly or not related to the resource allocation such as SF, so they are considered identical for every end device in the proposed model. The consumed energy for signal transmission E_{tx} is dependent on both transmission power and the different transmission time caused by SF, and E_{tx}^i is defined as:

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

where e_{p_i} denotes the energy consumption of transmission in a time unit with power p_i. T_i denotes the transmission time for end device 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} representing 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, coding rate is set to 4/7 thus CR equals 7.

Packet reception ratio modeling. Since an end device transmits a packet in a broadcast manner, all the surrounding gateways 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 [23]. The transmission from an end device is considered successful as long as it is received by one gateway. To get $PRR_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})$, we refer to the calculation of packet delivery ratio (PDR), which is the PDR of end device i sending packets to a single gateway. If end device i transmits at time t, the packet reception ratio can be calculated as follows:

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

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

$$\forall i \in \mathcal{N},\ k \in \mathcal{G},\ \sum_i \chi_{i,k}^t \leq 8, \tag{6}$$

According to [24], an uplink packet from end device i can be successfully decoded by a gateway when satisfying two conditions. First, the received signal-to-noise-ratio (SNR) is higher than a relative threshold th_{s_i}. The second one is that the received signal power p_r should exceed the receiver (gateway) sensitivity ss_k. So the PDR of end device i to gateway k can be calculated as the probability that SNR is above the threshold while signal power is above the sensitivity [25]:

$$\begin{aligned} PDR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) &= P\{SNR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) \geq th_{s_i}\}\\ &\cdot P\{p_r(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) \geq ss_k\} \end{aligned} \tag{7}$$

It is also worth noting that some well established models [26], [27] can effectively calculate the throughput under ALOHA access protocol in LoRaWAN, which could potentially enhance our model when we further study the throughput fairness in our future work.

Interference model. The received SNR of end device i is affected by the transmission power p_i and transmissions from all the other end devices which uses the same spreading factor and channel as it. It can be modeled as follows,

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

where $g_{i,k}$ is Rayleigh fading channel between end device i and gateway 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 end device j transmits at the same time t as end device 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:

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

which follows the fact that $g \sim exp(1)$. The value of the SNR threshold and receiver sensitivity depends on the spreading factor and bandwidth selected by the end device. For example, according to [25], the minimum received SNR required is -20dBm when using SF=12 and BW=125kHz. The sensitivity threshold is calculated as [4]:

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

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.

Impact of transmission power. The above equations can imply the significant impact of transmission power allocation on packet delivery ratio. In Equation (10), with a larger transmission power, the SNR and thus the packet reception ratio of an end device PRR_i can be improved, so that the packets can be received by gateways with fewer retransmissions, avoiding unnecessary energy consumption. However, according to Equation (3), the increased transmission power will also increase the energy consumption for a single transmission E_s^i, which will negatively impact the energy efficiency. Besides, this will also behave as a stronger interference to other end devices and affect their energy efficiency. This trade-off will make the energy fairness resource allocation in LoRa networks complex. Our proposed model aims to find the best transmission power allocation to deal with the above trade-off by realizing the max-min fairness of energy efficiency.

To make the proposed model more practical, we consider the properties of LoRa networks such as its limitation on gateway reception capacity and randomness of the LoRaWANs MAC protocol, as described in the following.

Capacity of LoRa gateways. LoRa gateways are based on chips called SX1301, which can only decode eight LoRa signals concurrently. This limits the capacity of LoRa gateways: although spreading factors allow for multiplexing, and theoretically at most 48 LoRa signals (eight channels and six spreading factors) can be decoded without interference, a LoRa gateway can receive only at most eight concurrent packets at a time.

We use $\chi_{i,k}$ to denote this capacity limitation in Equation (5). However, it is difficult to determine the value of $\chi_{i,k}$ due to the lossy nature of wireless communication and random starting time of end devices. We cannot determine whether a gateway has received the maximum concurrent packets at a time, thus it is impossible to determine the value of $\chi_{i,k}$ in advance. On this occasion, we replace $\chi_{i,k}^t$ with $\theta_{k,i}^t$, which denotes the probability that the number of packets which gateway k successfully receives is less than 8.

$$\begin{aligned}
\theta_{k,i}^t &= P\{N^t \leq 7\} \\
&= \frac{T_i}{T_c - T_i} \sum_{m=1}^{7} \sum_{S} \prod_{\substack{n\in S'\\ S'\subset S,\\ |S'|=m}} PDR_{n,k} \prod_{u\in S-S'} (1 - PDR_{u,k}),
\end{aligned} \quad (12)$$

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:

$$PRR_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = 1 - \prod_{k\in\mathcal{G}} (1 - \theta_{i,k}^t \cdot PDR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})), \quad (13)$$

Combining Equation (1) with Equation (12) to (13), we can eliminate $\chi_{i,k}^t$ by replacing the binary indicator into the probability.

Considering contending end devices. LoRaWANs constitute the MAC and network layers of LoRa networks and are proposed by the LoRa Alliance [4]. Due to the low power and low duty cycle of LoRaWANs, the transmissions work according to Aloha protocol. As a result, interference does not happen from all the end devices using the same spreading factor. It is 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 end device i and other end devices with the same SF and channel, it also means there is a proportion of h_i end devices interfering with end device i at the time when i transmits.

The packet transmissions for each node are periodic, and the time points of the transmission attempts within each cycle follow Poisson distribution [28]. Defining $N_{s,c}$ and T_c as the total number of end devices using SF s and channel c, and the size of contention window, given the number of end devices trying to transmit packets according to a Poisson distribution in the unslotted Aloha, h_i is calculated as:

$$h_i = 1 - e^{-\alpha N_{s,c}}, \tag{14}$$

where α is the duty cycle and $N_{s,c}$ is the number of end devices that using the same SF and channel as end device i.

Note that end devices with different SFs follow different duty cycles, because their transmission time is different while end devices transmit packets periodically every T_g time. Duty cycle of end device i, α_i can be calculated as follows:

$$\alpha_i = \frac{T_i}{T_g}, \tag{15}$$

where T_i is the time-on-air of a packet on end device i, and T_g denotes the packet transmission interval. As a result, the SNR of end device i to gateway k can be rewritten by replacing b_j^t to h_i:

$$SNR_{i,k}(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) = \frac{p_i \cdot g_{i,k} \cdot a(d_{i,k})}{h_i \sum\limits_{\substack{s_j=s_i,\\ c_j=c_i,\\ j\neq i}}^{\mathcal{N}} p_j \cdot g_{j,k} \cdot a(d_{j,k}) + N_0}, \tag{16}$$

Reducing computational overhead. From the above analysis, we formulate energy efficiency as:

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

where I_i is the cumulative interference on end device i from other end devices using the same spreading factor and channel.

Note that obtaining I_i is extremely difficult as all the interfering end devices have to be considered for every end device 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 end device 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 [29]. With the Poisson Point Process distribution of end devices, we denote the Laplace transform of the cumulative interference as $\mathcal{L}_{I_i}(s)$, then the energy efficiency can be expressed as follows,

$$\begin{aligned} EE_i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}) &= \frac{L}{E_s^i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C}))} - L\cdot \\ &\frac{\prod\limits_{k\in\mathcal{G}}\left(1 - \mathcal{L}_{I_i}(\frac{th_{s_i}h_i}{p_i\cdot a(d_{i,k})})exp(-\frac{N_0+ss_k}{p_i\cdot a(d_{i,k})})\theta_{i,k}^t\right)}{E_s^i(\boldsymbol{S},\boldsymbol{P},\boldsymbol{C})}, \end{aligned} \tag{18}$$

Taking the Rayleigh fading model and probability generating functional of PPP into account, we can calculate the Laplace transform $\mathcal{L}_{I_i}(s)$ according to [30]:

$$\mathcal{L}_{I_i}(s) = exp(-2\pi\lambda_{s_i,c_i}(s\cdot p_i)^{\frac{2}{\beta}}\int_0^\infty r\int_0^\infty e^{-t(1+r^\beta)}\,dt\,dr), \tag{19}$$

where λ_{s_i,c_i} is the density of end devices using SF s_i and channel c_i and can be expressed by:

$$\lambda_{s_i,c_i} = \lambda\frac{N_{s,c}}{N}. \tag{20}$$

In this way, the impact of other end devices on end device i can be reduced from the cumulative interference to $N_{s,c}$. The packet delivery ratio of all the other end devices can be estimated using Equation (19), 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 end devices are statically deployed. The server has the knowledge of the distances between end devices and gateways, which can be obtained 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. The optimization problem can be expressed with a function of power allocation $\boldsymbol{P}$.

$$\begin{aligned} &\max\min_{i\in\mathcal{N}}\frac{L}{E_p^i(\boldsymbol{P})} \\ &= \frac{L\cdot PDR_i(\boldsymbol{P})}{E_s^i(\boldsymbol{P})} \\ &= \frac{L\cdot f(SNR_i(\boldsymbol{P}))}{E_s^i(\boldsymbol{P})} \end{aligned} \tag{21}$$

where $f(.)$ is a function for calculating the PDR. According to [31], the problem of max-min SNR is non-convex and can be reduced to the Partition Problem which is known to be NP-complete. Therefore, the problem of Equation (21) is also NP-complete because it is a problem of max-min a function of SNR. The NP-completeness of the problem of multi-gateway resource allocation in Equation (1) can be inferred because it is more complex to solve.

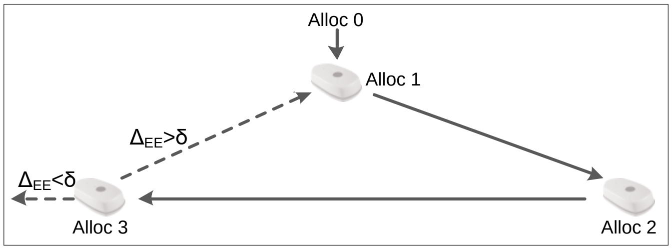


Fig. 3. Allocation algorithm example.

D. Allocation Algorithm of EF-LoRa.

A lightweight algorithm is necessary because: 1) LoRa's coverage is large, yet each node can still cover only one interesting location spot. Therefore, the network size could be very large in a star topology (e.g., 6000 nodes in [5] and 10,000 nodes in [32]). 2) In many practical systems [33], [34], addition and removal of LoRa end devices are frequent (mis-placement, additional interesting spots, etc.), which requires adjusting the parameters of LoRa end devices. With N end devices, n_s spreading factors, n_c frequency channels and n_t available transmission power levels, there are totally $(n_c \cdot n_s \cdot n_t)^N$ possible allocations and it is very difficult to traverse all of them to find the optimal solution. We propose an greedy solution to achieve an energy-fairness resource allocation with low complexity, and Figure 3 gives an illustrative example of the algorithm.

Assuming there are three end devices in a LoRa network, we allocate the resources for end devices iteratively. An initial resource allocation $Alloc_0$ is first generated for all the end devices. Starting from the end device with the most neighboring/contending end devices (density-first selection), we assign the minimum available SF to it according to the device-gateway distance. EF-LoRa then calculates energy efficiency for all the possible resource allocation for this end device. The reason is that such devices affect more devices, if we deal with them in the first place, the decision space for other devices will be limited. As a result, the algorithm can be boosted. We conduct simulations to confirm the impact of density-first selection of the starting device. Compared with random selection of the starting device, the execution delay of the algorithm is reduced by 10.3% on average with a network size of 1000 nodes.

On the premise that the allocations of other end devices keep constant. As a result, the allocation that can maximize the energy fairness $Alloc_1$ is obtained. We only change the allocation of one end device, so the complexity of this step is low. After the allocation of the first end device is updated, and EF-LoRa goes to the second end device and allocates optimal resources $Alloc_2$ for it. Similarly, the optimal allocation for the last end device $Alloc_3$ is calculated. With the above iterative allocation, we can calculate the improvement of energy fairness Δ_{EE} through the allocation of all the end devices. If δ_{EE} is larger than a threshold δ, it means that we have improved the energy fairness a lot, and it is highly possible the energy fairness can be further improved by a new iteration. So the algorithm repeats the above procedure and continues to find better resource allocation to improve energy fairness. Otherwise, it is considered that there is little improvement space and the iteration stops, and the new allocation is output. δ can be set by the operators as the expected accuracy of allocation. The detailed description of the resource allocation process is shown in Algorithm 1.

Algorithm 1: Energy-fairness resource allocation

Alloc = *DensityFirst*($\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{C}$);
EE = *Min*(Alloc);
$\delta = 0.01$;
do
    $EE_0 = EE$;
    for $each\ k \in \mathcal{N}$ **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) = $(s_{i,k}, p_{i,k}, c_{i,k})$
while($EE - EE_0 > \delta$)
Function *Min*(Alloc)#Minimum energy efficiency
{
    temp = 999;
    for $eachk \in \mathcal{N}$ **do**
        EE = $Calculate_{EE}$(k);
        if $EE < temp$ **then**
            temp = EE;
    Return temp;
}

It is worth noting that we assume that the positions of all nodes are known [15]–[17]. If the positions are unknown in the first place, we can also collect the positions in the initial stage after deployment. However, for the cases where the end devices are not even equipped with GPS/other localizing sensors, our algorithm cannot work. We may consider solving this problem by inferring the pairwise collision probabilities according to the packet reception traces. We will continue to work on parameter optimization without the pre-knowledge of end device positions.

E. Discussions

Different transmission rates of end devices. In this work, we assume that the same transmission rate (transmissions per time unit) for all end devices following the practical system settings [18], [19], [35]. However, in experimental scenarios with practical developments, it is also feasible to use different transmission rates for different LoRa EDs. In this case, the calculation of collision probability will be affected. To incorporate the impact of the different transmission rates, we need to change the modeling and calculation of interference model (the potential number of contending end devices). Instead of using distribution-based probabilities, we need to employ the transmission rates of all end devices in the model. Another feasible way is to find out an accurate distribution by curve fitting with the transmission rates from all end devices.

TABLE IV
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

Incremental algorithms for device additions/removals. Following our current algorithm design, every time when there are device additions/removals, all parameters will be re-assigned, which may lead to interruptions to the network operations. Therefore, in our future work, we will study incremental algorithms to adjust the parameters of LoRa end device with the minimum change on the existing parameter settings. Besides, as the problem can be reduced as a partition problem, we will study the optimum of the proposed algorithms following the derivations of the similar greedy algorithm [36] in our future work.

Inter-SF interference. Some studies have identified inter-SF interference exist due to the imperfect orthogonality in LoRa communications [27], [37], [38]. Such interference will affect our fairness models. Specifically, in the calculation of contending end devices, we need to additionally consider the nodes with different SF and use the inter-SF interference models to evaluate its impact on the SNR estimation in Eq. (14-16). We plan to incorporate the inter-SF interference in our future work.

IV. EVALUATION

We conducted a series of large scale experiments on the simulation platform NS-3. Up to 25 gateways and 5000 end devices are deployed within a disc of 5 kilometers radius. The simulation with NS-3 is based on the LoRa network module proposed by [13], which supports the packet transmission in multiple gateway scenarios. Each simulation with a given set of parameters is repeated 100 times. All the gateways and end devices 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 [5], the sleep duration of end devices includes MCU sleep duration and radio sleep duration.

The region was meshed and gateways were deployed on the cross positions of these meshes according to the number of gateways. If we deployed one gateway, it was set at the center of the region. If multiple gateways were used, they were uniformly deployed inside the coverage, and 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 [4]. Table IV illustrates them with different spreading factors.

Benchmarks. In our experiments, we compared EF-LoRa with legacy LoRa [13] and RS-LoRa [6] which introduces the state-of-the-art resource allocation works. Legacy LoRa [13] chooses the smallest available spreading factors for end devices, which are calculated according to the estimated SNR while not considering the interference from other end devices in the networks. RS-LoRa considered the collision probability of end devices that use the same spreading factor. It tries to realize the fairness of collision probability among all the SFs. The percentage of end devices using different SFs is calculated by the following equation,

$$p_s = \frac{s/2^s}{\sum_{i \in SF} i/2^i} \tag{22}$$

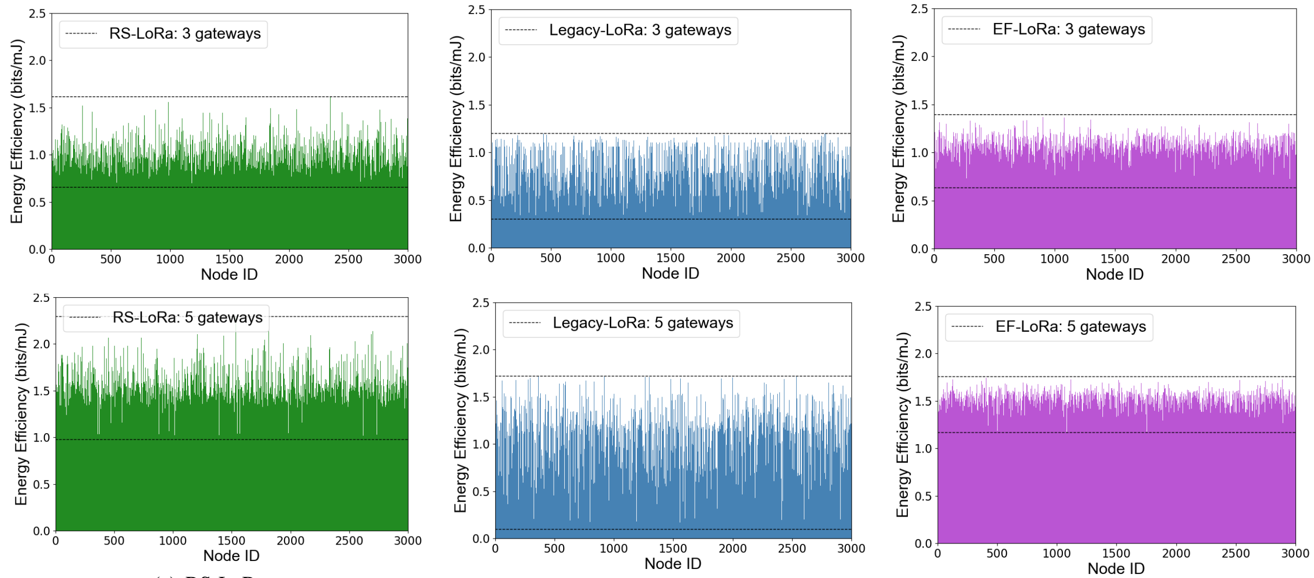
where s denotes a certain spreading factor, and SF represents the set of all the available spreading factors. This indicates that every end device is possible to choose the largest SF, which can lead to energy unfairness.

A. Energy fairness in the networks

Energy efficiency among end devices. We first investigate the energy efficiency in LoRa networks in Figure 4. 3000 end devices along with three gateways and five gateways are picked as examples of network deployment. The energy efficiency of all the end devices in the networks is collected and calculated, and different methods (i.e., RS-LoRa, Legacy-LoRa and EF-LoRa) are depicted with different colors. As can be observed, the great fluctuation in Figure 4(a) and (b) indicates that the energy efficiency of legacy LoRa and RS-LoRa is not well balanced. As a result, the batteries of some end devices in RS-LoRa and Legacy-LoRa drain much faster than others, reducing the lifetime of the networks. Although the overall energy efficiency is improved in legacy LoRa and RS-LoRa with more gateways, the unfairness problem among end devices still exists and is even worse. Besides, the average energy efficiency of all the three methods is improved when the number of gateways increases from three to five. However, the fluctuation of energy efficiency (energy unfairness) is exacerbated. The reason is that with more gateways, packets have more chances to be received and packet reception ratio is improved, but the difference of reception ratio among end devices also increases since different end devices can be received by different number of gateways and use different spreading factors. In that case, the allocation induces more fluctuations and unfairness in energy efficiency.

It can be also observed in Figure 4 that the average energy efficiency of RS-LoRa and EF-LoRa is similar. This is because EF-LoRa tries to achieve the fairness of both packet reception ratio and transmission time, while RS-LoRa aims at only the fairness of packet reception ratio, the energy efficiency in RS-LoRa is then differentiated by transmission time (spreading factor). As a result, the average energy efficiency between RS-LoRa and EF-LoRa is similar but the stability is different.

CDF of energy efficiency. To further analyze the three methods, Figure 5 depicts the CDF (cumulative distribution function) of energy efficiency for the three methods according to Figure 4. As expected, the energy efficiency of EF-LoRa distributes within a narrow interval for both three gateways and five gateways scenarios (3GW and 5GW in the figure), and their cumulative probability increases with similar speed. On the contrary, energy efficiency in RS-LoRa spreads over a wide region from 0.69 bits/mJ to 1.61 bits/mJ and 0.98



(a) RS-LoRa (b) Legacy-LoRa (c) EF-LoRa

Fig. 4. Energy efficiency for different allocations.

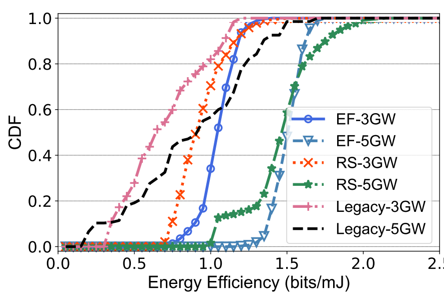


Fig. 5. CDF of Energy Efficiency.

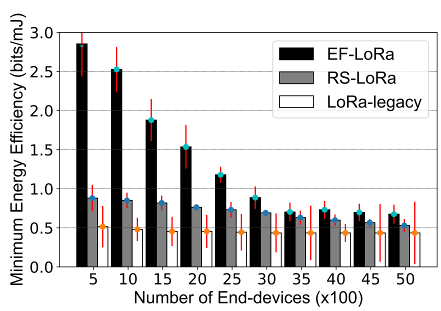


Fig. 6. Minimum energy efficiency.

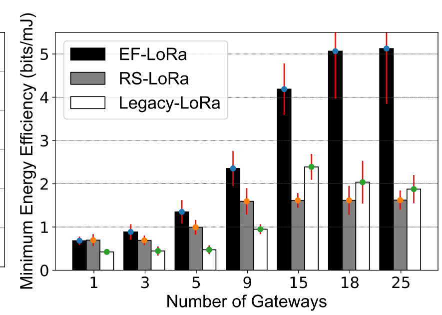


Fig. 7. Minimum energy efficiency.

bits/mJ to 2.29 bits/mJ. Besides, a small portion of end devices suffers from relatively low energy efficiency. Note that for RS-LoRa with five gateways, there is a relatively fast increasing of cumulative probability when the energy efficiency is small, due to the choice of large spreading factors. End devices in RS-LoRa are possible to choose large spreading factors regardless of the network deployment, leading to a long transmission time. As the packet reception ratio can be greatly improved by multiple gateways, a larger spreading factor will result in lower energy efficiency as illustrated in Figure 5. Similarly, legacy LoRa also shows wide distribution in energy efficiency (i.e., 0.3 bits/mJ to 1.2 bits/mJ for three gateways and 0.1 bits/mJ to 1.6 bits/mJ for five gateways). The reason is that all the end devices intend to use small spreading factors, as a result, end devices that use large spreading factors do not face as severe interference as end devices using small spreading factors, and the spreading factors of some end devices are not very large (e.g., SF9), the energy efficiency will be very high compared with those end devices using small spreading factors.

Comparison of energy fairness. We use the minimum energy efficiency in a network to represent the energy fairness. Figure 6 illustrates the minimum energy efficiency of the three methods with three gateways, and the network deployment changes by different number of end devices (i.e., from 500 to 5,000). It can be seen that the minimum energy efficiency decreases when more end devices were deployed, and EF-LoRa performs better than both RS-LoRa and legacy LoRa. This is because the collision probability increases, leading to the lower reception ratio and lower energy efficiency with more end devices, while for legacy LoRa, the minimum energy efficiency keeps low even with a small number of end devices due to the severe collisions.

Another important insight delivered from Figure 6 is that the minimum energy efficiency of EF-LoRa is larger than that of legacy LoRa and RS-LoRa when the number of end devices is small, while this gap is reduced as the number of end devices increases. This is because when the number of end devices is small, the end devices in EF-LoRa can choose smaller spreading factors without many collisions in the coverage of multiple gateways, leading to several times faster transmissions. As a result, the energy efficiency of EF-LoRa is generally high. While for RS-LoRa, there are always some end devices choosing large spreading factors such as

11 and 12 because it tries to balance the collision probability of all the spreading factors. Since the transmission time of a packet exponentially increases when larger spreading factors are used, the bottleneck of minimum energy efficiency is usually dependent on those end devices with large spreading factors. In this case, a large gap of minimum energy efficiency appears. However, if there are too many end devices such as 5000 in Figure 6, both RS-LoRa and EF-LoRa have to use large spreading factors and low transmission power to balance the collisions among end devices, so the gap of minimum energy efficiency is greatly impacted by the reception ratio and the energy fairness between RS-LoRa and EF-LoRa is similar.

In Figure 7, we consider energy fairness of the networks with 3000 end devices, and the deployment is changed by different number of gateways. Figure 7 demonstrates that the minimum energy efficiency of EF-LoRa is larger than that of both legacy LoRa and RS-LoRa, and this benefit increases as more gateways are deployed. The reason behind this is similar to Figure 6. With one gateway, end devices have to use large spreading factors to reach the gateway, so the minimum energy efficiency is relatively high due to the low data rate, and both RS-LoRa and EF-LoRa could balance the collision probability. As the number of gateways increases, collisions can be reduced, at the same time, end devices of EF-LoRa can choose smaller spreading factors to reach the gateways. However, RS-LoRa still experiences a low energy efficiency because it always has some end devices using large spreading factors, which can be the bottleneck of energy efficiency. For legacy LoRa, more gateways means that more end devices can use small spreading factors, and they still suffer from severe collisions. On the other hand, the minimum energy efficiency decreases after a certain number of gateways. The reason is that with a very dense gateway deployment, all the end devices use the smallest spreading factor, and the extremely low packet reception ratio will limit the minimum energy efficiency.

Network lifetime. Since energy inefficiency can affect network lifetime, which is a very important consideration for low power wireless networks, we evaluate the performance gain of network lifetime for EF-LoRa. The network lifetime is defined as the time that 10% of the end devices have run out of their batteries, Figure 8 depicts the comparison of network lifetime with different network deployment. 3GW and 5000ED denote the network deployment with three gateways and 5000 end devices, respectively. The results show that EF-LoRa can improve network lifetime of RS-LoRa and legacy LoRa by 15.3% and 41.5% on average, respectively. This benefit comes from the improved energy fairness in the network. Besides, network lifetime of RS-LoRa also outperforms legacy LoRa. This is because many end devices in legacy LoRa choose small spreading factors and the overall collision probability is higher than that in RS-LoRa. It can also be observed that the network lifetime of all the three methods increases as the deployment density decreases (we first reduce the number of end devices, and then increase the number of gateways), because the collision probability is reduced and the lifetime of individual end devices is improved.

B. Performance decomposition

Sensitivity to path loss exponent β. To further analyze the benefits of EF-LoRa, we decompose the performance gain of EF-LoRa. We first evaluate the performance gain from the network model. To obtain the path loss attenuation function $a(d_{i,k})$, not only the distances between end devices and gateways have to be considered, the path loss exponent β can also impact the final resource allocation by the calculation of $a(d_{i,k})$. In this paper, β is set to 2.7 for line-of-sight end devices and 4 for non-line-of-sight end devices, which are usually considered for suburban and urban scenarios [25]. However, the resource allocation may be different with different path loss exponent. To verify the sensitivity of EF-LoRa to the path loss exponent, we conducted experiments with different β with more path loss and less path loss. Figure 9 first shows the comparison of energy fairness between different path loss exponent. It can be seen that the energy efficiency and its fairness slightly changes with different β. Specifically, the energy fairness decreases by 25% with less path loss (β is 2.4 for line-of-sight and 3.7 for non-line-of-sight) and 3% with more path loss (β is 3 for line-of-sight and 4.3 for non-line-of-sight). The reduction implies that the testbed on the campus experiences high path loss which may be caused by the tall trees and buildings with many walls. Finally, the energy fairness of all the path loss exponent settings still outperforms the legacy LoRa and RS-LoRa, and EF-LoRa is robust to the change of path loss exponent β.

Transmission power allocation. LoRa networks have several configurable resources such as spreading factor and transmission power. The importance of spreading factor and channel allocation has been well studied in previous work for improving data rate or reducing interference. However, transmission power allocation can also significantly affect the energy fairness. Figure 9 also depicts the impact of transmission power allocation. For comparison, we set up a LoRa network that does not have transmission power allocation, where all the end devices use the largest transmission power, 14 dBm (EF-LoRa-14dBm in Figure 9).

Experimental results in Figure 9 depict that with identical transmission power on end devices, the energy fairness is reduced by 26%. The reason is that with the maximum transmission power, all the end devices have a long communication range. As a consequence, the interference increases significantly, and it is harder to achieve energy fairness than with the schemes that allocate different transmission power to end devices. Furthermore, it can be seen that even with identical transmission power, the minimum energy efficiency of EF-LoRa still outperforms that of legacy LoRa and RS-LoRa by 71% and 3%, respectively. This also reveals that the EF-LoRa can significantly improve the energy fairness of LoRa networks.

C. Convergence of the algorithm

Although the EF-LoRa algorithm reduces 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

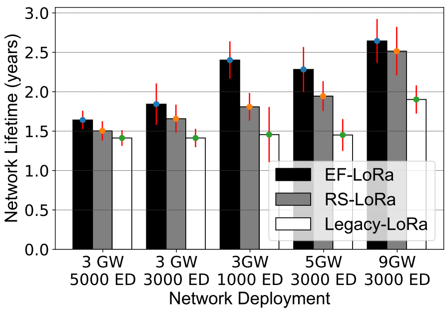


Fig. 8. Network lifetime.

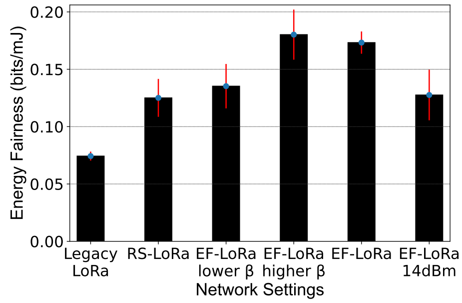


Fig. 9. Impact of transmission power.

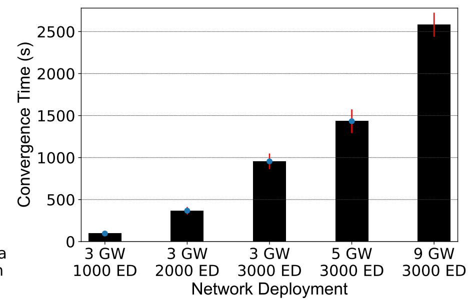


Fig. 10. Algorithm convergence time.

greatly influenced by the scale of the network. Figure 10 shows the convergence time for calculating the allocation according to the EF-LoRa algorithm, by varying the number of end devices from 1000 to 3000 and gateways from three to nine, we measure the running time it takes for EF-LoRa to stabilize.

The hardware we used for algorithm 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 represents the algorithm convergence for the computation overhead with the termination parameter. As shown in Figure 10, the convergence time of EF-LoRa algorithm increases as more end devices and gateways were deployed. Besides, the convergence time increasing resulting from both more end devices and more gateways shows a near-linear trend. Specifically, by using 1000 more end devices, the increased convergence time is similar to that by deploying two more gateways.

As a result, the convergence time of EF-LoRa will not increase unlimitedly as the scale of the network expands. Despite the long convergence time on the simulation laptop, the calculation for resource allocation only has to run once when setting up the networks, and it will be running on the high-performance LoRa application servers, which can 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

In this section, we study the existing work on energy fairness and resource allocation of LoRa networks and other networks, respectively.

Reducing energy consumption in LoRa networks. Network lifetime is one of the most important design considerations in low-power wireless networks. Prior work [39]–[42] mainly focuses on reducing the energy consumption on individual end devices through more efficient and reliable transmissions. For example, unnecessary re-transmissions can be avoided by Charm [40] (i.e., recovering weak LoRa signals from the copies received by multiple gateways) and Ftrack [41] (i.e., concurrently identifying and decoding multiple colliding LoRa signals). However, the energy fairness problem has not received sufficient attention.

Resource allocation in LoRa networks Due to the extremely low battery power of LoRa end devices, the existing works on resource allocation in LoRa networks also aim at fairness [6], [10], [43], [44]. In [10], Reyndder *et al.* achieve the fairness of collision probability of end devices in a single gateway scenario. Based on this allocation, [6] proposed a MAC layer protocol to schedule end devices and their spreading factors. However, they do not consider the energy consumption gap of different spreading factors, and the allocation is obtained assuming that end devices are deployed following a uniform distribution around the gateway. Besides, 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.

Energy fairness in wireless sensor networks. Wireless sensor networks (WSNs) consist of low-cost and energy-constrained sensors to monitor the environment such as fire alarming. 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 sensor nodes and sink nodes in a multi-hop manner, that is, sensor nodes collect data and send the data to sink nodes by multiple relaying from other nodes, so the prior work on energy fairness mainly focuses on the routing and rate control [45]–[48]. However, in LoRa networks, end devices broadcast their packets to gateways within a single hop, so there is no routing problem. Besides, spreading factor not only performs orthogonally but also indicates different data rates. These two properties should be jointly considered in resource allocation.

Adaptive Data Rate in LoRaWAN. The Adaptive Data Rate (ADR) protocol is one of the key techniques in LoRaWAN, which can adjust the parameters of end devices according to the network conditions. The topic of ADR has attracted increasing research attention in recent years.

Cuomo *et al.* [49] proposed *Explora*, which aims at ensuring equal time occupation for different SFs. Garlisi *et al.* [26] further extended the work by considering the multi-gateway scenarios and obtained further improvements by considering the channel capture effect. Abdelfadeel *et al.* [50] aimed at achieving fair ADR by assigning SF and transmission power. Marini *et al.* [51] proposed a collision-aware adaptive data rate algorithm for LoRaWAN, which aims at minimizing the collision probability when assigning data rates while keeping the link-level performance under control. Coutaud *et al.* [52] proposed an ADR proposal for multi-gateway LoRaWAN Networks. The work relies on the accurate estimation of the effective channel, dynamically adapts to the number of gateways and exploits the macro-diversity. Li *et al.* [53] analyzed the performance of ADR in terms of agility and identified that convergence is a bottleneck for the performance of ADR.

Compared with the above works, our work in this paper focuses more on modeling the max-min fairness (energy efficiency) of the whole network and tries to provide a global view of the fairness of LoRa networks.

Resource allocation in cellular/WiFi/Edge networks. Resource allocation problem in cellular networks such as spectrum assignment and power control has been widely studied [54]–[56]. For example, techniques like partial frequency reuse (PFR) [54] or soft frequency reuse (SFR) [56] are used to mitigate the inter-cell interference in cellular networks. In WiFi networks, spectrum assignment and power control schemes can also help with improving the throughput and capacity of the networks.

Different from cellular/WiFi networks, in multi-gateway LoRa networks, the spreading factors should be considered not only due to orthogonality but also due to 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 more difficult than that in cellular networks or WiFi networks.

VI. Conclusion

In this paper, we proposed EF-LoRa, a networking solution that achieves energy fairness among end devices and extends the network lifetime. Specifically, 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 properties of SFs, channels and data rates 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 end devices. Finally, we proposed a greedy algorithm to solve the problem and got the resource allocation. The simulation results show 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.

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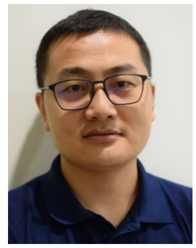

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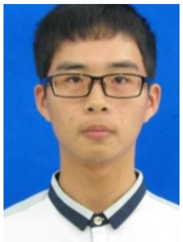

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