Resource Management in Energy Harvesting Powered LoRa Wireless Networks

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***Abstract*—Long Range (LoRa) wireless networks, which is made up of low-powered connected devices, is a key technology for next generation wireless networks that support internet of things applications. Specifically, LoRa devices (LDs) may be powered by energy harvesting sources for greening wireless communications systems. Furthermore, LoRa modulation is based on the chirp spreading modulation (CSM) which consists of assigning various orthogonal spreading factors (SFs) among the LDs in the network. Hence, this paper investigates energy-efficient resource allocation in LoRa wireless networks, where the LDs are powered by independent energy harvesting sources. First, the problem of maximizing the number of scheduled LDs under quality of service constraints and making use of the available harvested energy, is formulated. Next, the relationship between the assigned SF, the instantaneous channel coefficients and the available energy at the batteries is analytically established. Hence, the optimal energy management, device scheduling, and SF assignment algorithm is proposed. Simulations results shows that the proposed resource allocation approaches offer efficient use of renewable energy which allows to enhance the rate of successful transmissions.**

***Index Terms*—LoRa, energy harvesting, energy management, device scheduling, SF assignment.**

I. Introduction

LoRa wireless networks are based on the deployment of large number of low-powered connected devices. They represent a key technology for internet of things (IoT) wireless sensor networks that meets the requirement of supporting the exponential growth of connected devices [1]. Robust operations, wider coverage, and high energy efficiency are required to connect the IoT devices. Hence, LoRa networks are able to offer sustainable connectivity to low-powered devices distributed over very large geographical areas [2]. Moreover, LoRa networks provide adaptive transmission rates and coverage for low-powered devices specifically when operating in unlicensed bands [3]. In addition, a new approach is investigated in [4] to provide connectivity in IoT networks by investigating a long range transmission technology in the unlicensed sub-gigahertz frequency bands. The functional components of LoRa networks are analyzed in [5]. Specifically, the physical and data link layers performance is analyzed in-depth and evaluated by field tests and simulations. These systems enable long range transfer of information with a low transfer rate. The modulation scheme underlying LoRa networks, namely, the frequency shift chirp modulation is designed in [6]. This scheme is based on coding the information in the frequency shift at the beginning of the symbol. The chirp is assumed to be as a kind of carrier and the modulated signal is a chirp waveform whose behaviour depends on a parameter called the spreading factor. The performance of this modulation technique was theoretically investigated. Moreover, the error rate performance of digital chirp communication systems was investigated over various fading channels in [7]. In [8], the performance of LoRa was investigated in the presence of both noise and interference. An efficient detection algorithm was proposed in [9] for multipath LoRa fading channels. Since the number of devices connected to IoT systems is growing at an exponential rate, the scalability of LoRa networks is investigated in [10] using a stochastic geometry framework. LoRa signals with different spreading factors (SFs) are quasi-orthogonal and LoRa signals with the same SF exhibit cross-correlation properties that could make them vulnerable to interference.

The performance of LoRa networks may be enhanced by adequate resource allocation strategies. Hence, previous efforts have investigated this resource allocation issue under different LoRa network architectures and assumptions. Specifically, SF assignment, user scheduling, and power allocation in LoRa networks were the focus of [11]–[21]. A dynamic SF assignment scheme based on instantaneous channel realizations is developed in [11] to enhance the symbol error rate in LoRa networks. In [12], the authors tried to enhance the network throughput for LoRa systems by proposing a SF allocation strategy based on matching theory. Similarly, the authors of [13] formulate a capacity maximization problem and solved it numerically. A new SF allocation scheme is proposed in [14] based on the total number of connected devices. The authors in [15] investigated SF assignment and power allocation in LoRa networks with imperfect orthogonality to reduce energy consumption. In [16], the authors proposed an efficient user scheduling, SF assignment, and power allocation scheme that maximize the energy efficiency in LoRa networks. In [17], the capacity of a multi-hop LoRa network is improved by an efficient clustering algorithm. In [18], a sub-optimal SF allocation strategy is proposed in order to maximize the packet success probability. In [19], an efficient interference-aware SF allocation algorithm is proposed. Scheduling is incorporated to a multichannel LoRa network [20] in to improve the synchronization packet length. The authors of [21] studied the average number of decoded LoRa frames by taking into account physical layer and medium access control.

For greening and improving energy efficiency of LoRa networks, the devices may be powered by renewable energy sources. The existing works did not consider the energy harvesting. hence, this work proposes to incorporate energy harvesting to LoRa networks by considering that each device is powered by its own energy harvesting source. The design of energy-efficient LoRa networks powered by energy harvesting is challenging due to the intermittency of renewable energy sources. The main contribution of this work are summarized as follows:

- The problem of maximizing the number of scheduled users in LoRa networks while the devices are powered by independent energy harvesting sources, is formulated.
- The relationship between assigned SF, energy level at the battery and fading channel coefficient is analytically established.
- Based on this relationship, the optimal online energy management algorithm, SF assignment, and device scheduling, is developed.
- Simulations results illustrate the performance of the proposed SF assignment algorithm in terms of number of scheduled devices.

The remainder of the paper is organized as follows. The system model is presented in Section II. The SF assignment and energy management problem is formulated in Section III. The online resource allocation algorithm is developed in Section IV. The computational complexity of the proposed solution is investigated in Section V. The numerical results are presented and discussed in Section VI. Finally, conclusions are provided in Section VII.

II. System Model

A. Channel and Signal Model

In this work, a typical LoRa wireless network as shown in Fig. 1 is considered that includes a gateway serving K arbitrarily distributed LDs. A given time interval is partitioned into L frames with duration T_{out}. The channel coefficients between the gateway and LD k at frame i is given by $g_k(i) = \beta_k(i) h_k(i)$, where $\beta_k(i)$ represents the path loss and $h_k(i)$ represents a quasi-static Gaussian independent and identically distributed (i.i.d.) slow fading channel.

The LoRa modulation technique is based on the chirp spreading modulation (CSM) [6], which is described as follows. Each LD k sends a symbol $s_k(i)$ at frame i with duration $2^{\alpha_k(i)} \cdot T$, where $\alpha_k(i)$ is the SF taking values in $\Gamma = \{7, 8, 9, 10, 11, 12\}$ and $T = \frac{T_{out}}{2^{12}}$ is the duration of a sample transmission. LD k transmits $\alpha_k(i)$ bits at each frame. The symbol $s_k(i)$ takes values in $\{0, 1, 2, \ldots, 2^{\alpha_k(i)} - 1\}$. The LDs adopt different spreading factor for transmission in order to ensure orthogonality and enable multi user detection at the receiver. Hence, the transmitted waveform vector for LD k at frame i is given by:

$$\mathbf{x}_k(i) = \begin{bmatrix} \left[\frac{1}{\sqrt{2^{\alpha_k(i)}}} e^{\jmath 2\pi \left[(s_k(i)+f) \mod 2^{\alpha_k(i)} \right] \frac{f}{2^{\alpha_k(i)}}} \right]_{f=0..2^{\alpha_k(i)}-1} \\ \mathbf{0}_{2^{12}-2^{\alpha_k(i)}} \end{bmatrix} \quad (1)$$

A zero padding with length $2^{12} - 2^{\alpha_k(i)}$ is added for each vector in order to ensure the same vector length for all LDs. The vector of received signals at the gateway at frame i is expressed as:

$$\mathbf{y}(i) = \sum_{k=1}^{K} p_k(i)\ g_k(i) \cdot \mathbf{x}_k(i) + \mathbf{w}(i), \quad (2)$$

where $p_k(i)$ is the transmitted power of LD k at frame i and $\mathbf{w}(i)$ is assumed to be additive white Gaussian noise (AWGN) with zero mean and variance σ^2. Hence, the signal-to-noise ratio (SNR) of LD k at frame i is expressed as:

$$\gamma_k(i) = \frac{p_k(i) \mid \mathbf{g}_k(i) \mid^2}{\sigma^2}. \quad (3)$$

The possible waveforms of CSM systems are shown to be orthogonal [7]. Hence, the inner product receiver may be applied. It consists of projecting the received vector $\mathbf{y}(i)$ onto the different signals of each LD $\mathbf{c}_{|s_k(i)} = \left[g_k^*(i) \frac{1}{\sqrt{2^{\alpha_k(i)}}} e^{\jmath 2\pi \left[(s_k(i)+f) \mod 2^{\alpha_k(i)} \right] \frac{f}{2^{\alpha_k(i)}}} \right]^T_{f=0..2^{\alpha_k(i)}-1}$ and choosing the one with maximal square modulus projection. Hence, the best estimate of the transmitted signal $\hat{s}_k(i)$ by LD k at frame i is given by:

$$\hat{s}_k(i) = \underset{0..2^{\alpha_k(i)}-1}{\text{argmax}} \ |\langle \mathbf{y}(i), \mathbf{c}_{|s_k(i)} \rangle|^2. \quad (4)$$

Let $\chi_k(i)$ be a Boolean parameter that is set to 1 if LD k at frame i is scheduled and to 0 otherwise.

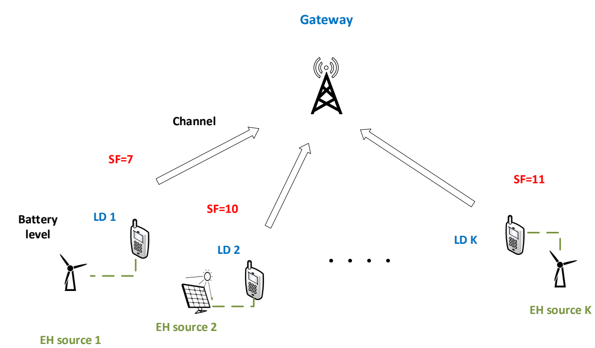

Fig. 1: Energy Harvesting Powered LoRa Wireless Networks.

B. Energy Model

Each LD is assumed to be powered by its own energy harvesting source. The harvested energy at each LD is first stored in a battery with maximal capacity B_{max}. It is modeled by a compound Poisson stochastic process [22]. Let $E_k(i)$ and $B_k(i)$ denote respectively the amount of harvested energy the battery level of LD k at frame i. The consumed energy from the energy harvesting source cannot exceed the battery level. Hence, the energy causality constraint is given by:

$$E_c + p_k(i) \cdot 2^{\alpha_k(i)} T \leq B_k(i), \tag{5}$$

where E_c is a fixed energy consumed by the circuit. The battery level update is expressed as:

$$\begin{aligned} B_k(i+1) = &\min(B_{max}, B_k(i) - \chi_k(i)(E_c + p_k(i) \cdot 2^{\alpha_k(i)} T) \\ &+ E_k(i)). \end{aligned} \tag{6}$$

III. Problem Formulation

The aim of this work is to maximize the number of scheduled LDs making use of the available harvested energy and ensuring a minimum SNR to each scheduled LD. Moreover, the various orthogonal SFs have to be allocated dynamically among the LDs based on the instantaneous channel coefficients and the available energy at the batteries. A SF could be assigned to only one LD at each frame. Hence, the join energy management, device scheduling, and SF assignment problem can be formulated as follows:

$$\begin{aligned}
&\underset{\substack{\{\chi_k(i), \alpha_k(i), p_k(i)\} \\ k=1..K, i=1..L}}{\text{maximize}} \sum_{k=1}^{K} \sum_{i=1}^{L} \chi_k(i) \\
&\text{subject to} \\
&(7.a): \gamma_k(i) \geq \chi_k(i) \cdot \gamma_{th}, \ k = 1..K, \ i = 1..L, \\
&(7.b): \sum_{i=1}^{l} \chi_k(i) \left(E_c + p_k(i) \cdot 2^{\alpha_k(i)} T\right) \leq \sum_{i=1}^{l} E_k(i), \\
&\qquad k = 1..K, \ l = 1..L, \\
&(7.c): \sum_{i=1}^{l} E_k(i) - \sum_{i=1}^{l-1} \chi_k(i) \left(E_c + p_k(i) \cdot 2^{\alpha_k(i)} T\right) \\
&\qquad \leq B_{max}, \ k = 1..K, \ l = 2..L, \\
&(7.d): \alpha_k(i) \in \Gamma, \ k = 1..K, \ i = 1..L \\
&(7.e): \alpha_k(i) \neq \alpha_p(i), \ \forall k \neq p, \ i = 1..L, \\
&(7.f): p_k(i) \geq 0, \ k = 1..K, \ i = 1..L, \\
&(7.g): \chi_k(i) \in \{0, 1\}, \ k = 1..K, \ i = 1..L.
\end{aligned} \tag{7}$$

Constraints $(7.a)$ ensure a minimum received SNR, denoted γ_{th}, to each LD. Constraints $(7.b)$ are related to the energy causality, i.e. the consumed harvested energy cannot exceed the energy harvested at each LD. Constraints $(7.c)$ specify that the harvested energy at the current frame cannot exceed the maximal battery capacity.

IV. Online Resource Management

In this section, the online resource management problem is investigated by considering the channel coefficient and the batteries levels are known only for the current frame. Hence, the main could be decomposed into sub-problems. The sub-problem at frame i is given by:

$$\begin{aligned}
&\underset{\substack{\{\chi_k(i), \alpha_k(i), p_k(i)\} \\ k=1..K}}{\text{maximize}} \sum_{k=1}^{K} \chi_k(i) \\
&\text{subject to} \\
&(8.a): \gamma_k(i) \geq \chi_k(i) \cdot \gamma_{th}, \ k = 1..K, \\
&(8.b): \chi_k(i) \left(E_c + p_k(i) \cdot 2^{\alpha_k(i)} T\right) \leq B_k(i), \ k = 1..K, \\
&(8.c): B_k(i) + E_k(i) - \chi_k(i) \left(E_c + p_k(i) \cdot 2^{\alpha_k(i)} T\right) \\
&\qquad \leq B_{max}, \ k = 1..K, \\
&(8.d): \alpha_k(i) \in \Gamma, \ k = 1..K, \\
&(8.e): \alpha_k(i) \neq \alpha_p(i), \ \forall k \neq p, \\
&(8.f): p_k(i) \geq 0, \ k = 1..K, \\
&(8.g): \chi_k(i) \in \{0, 1\}, \ k = 1..K.
\end{aligned} \tag{8}$$

The aim is to select the best LDs at the current frame and to assign a dynamic SF to each one based on the channel coefficients and the batteries levels. Also, a power allocation scheme is required. The required transmit power to meet the SNR constraints for user k at frame i is given by:

$$p_k(i) = \frac{\gamma_{th} \sigma^2}{\mid \mathbf{g}_k(i) \mid^2}. \tag{9}$$

Hence, the amount of transmit power given by equation (9) could be replaced in problem (8) and it is simplified as:

$$\begin{aligned}
&\underset{\substack{\{\chi_k(i), \alpha_k(i)\} \\ k=1..K}}{\text{maximize}} \sum_{k=1}^{K} \chi_k(i) \\
&\text{subject to} \\
&(10.a): \chi_k(i) \left(E_c + \frac{\gamma_{th} \sigma^2}{\mid \mathbf{g}_k(i) \mid^2} \cdot 2^{\alpha_k(i)} T\right) \leq B_k(i), \\
&\qquad k = 1..K, \\
&(10.b): B_k(i) + E_k(i) - \chi_k(i) \left(E_c + \frac{\gamma_{th} \sigma^2}{\mid \mathbf{g}_k(i) \mid^2} \cdot 2^{\alpha_k(i)} T\right) \\
&\qquad \leq B_{max}, \ k = 1..K, \\
&(10.c): \alpha_k(i) \in \Gamma, \ k = 1..K, \\
&(10.d): \alpha_k(i) \neq \alpha_p(i), \ \forall k \neq p, \\
&(10.e): \chi_k(i) \in \{0, 1\}, \ k = 1..K.
\end{aligned} \tag{10}$$

The selected LD k at frame i with an assigned SF $\alpha_k(i)$ may satisfy the following two inequalities:

$$\alpha_k(i) \leq \log_2 \left(\frac{\mid \mathbf{g}_k(i) \mid^2 (B_k(i) - E_c)}{\gamma_{th} \sigma^2 T} \right) \tag{11}$$

and

$$\alpha_k(i) \geq \log_2 \left(\frac{\mid \mathbf{g}_k(i) \mid^2 (B_k(i) + E_k(i) - B_{max} - E_c)}{\gamma_{th} \sigma^2 T} \right). \tag{12}$$

The LD k unscheduled at frame i if:

$$\log 2\left(\frac{\mid \mathbf{g}_k(i)\mid^2 (B_k(i)-E_c)}{\gamma_{th}\sigma^2 T}\right) < 7, \quad (13)$$

or

$$\log 2\left(\frac{\mid \mathbf{g}_k(i)\mid^2 (B_k(i)+E_k(i)-B_{max}-E_c)}{\gamma_{th}\sigma^2 T}\right) > 12. \quad (14)$$

Let a LD k has a set of eligible SFs, i.e. satisfying the inequalities (11) and (12), denoted $\Lambda_k = \{\alpha_k^{min}, ..., \alpha_k^{max}\}$ with cardinal $\psi_k = |\Lambda_k|$. A LD k could be scheduled if it has at least one eligible SF.

The optimal SF assignment solution is given as follows. First, the set of eligible SFs at frame i for each LD are derived using (11) and (12). Then, the sets of LDs that don't have any eligible SF are removed. The LD with minimal Λ_k has the least probability to be selected. Hence, the optimal procedure starts by assigning the SFs among the remaining LDs one by one, by choosing the LD with minimal ψ_k and assigning it the minimal SF from its eligible set Λ_k. Next, the assigned SF is removed from the remaining sets of eligible SFs of others LDs. This iterative procedure ends when all SFs are assigned. Finally, the batteries of each LD are updated accordingly. The details of the algorithm are given in **Algorithm 1**.

Lemma 1: The maximal number of LDs that can be scheduled is upper bounded by the cardinal of $\underset{k\in\Delta}{\cup}\Lambda_k$. Δ denotes the set of LDs that can be scheduled.

Algorithm 1 Optimal Dynamic SF Assignment Algorithm

for $i = 1 : L$ **do**
  Compute the upper and lower bounds of $\alpha_k(i)$ using (11) and (12)
  Derive Δ
  Derive Λ_k for $k \in \Delta$
  while $|\Delta| \neq 0$ **do**
    $k^* \leftarrow \underset{k\in\Delta}{\text{argmin}}\ \psi_k$, find LD k^* with minimal number of eligibles SFs
    $\alpha_k^*(i) \leftarrow \min \Lambda_k^*$, assign the minimal remaining SF
    $\Delta \leftarrow \Delta\backslash\{k^*\}$
    $\Lambda_k \leftarrow \Lambda_k\backslash\{\alpha_k^*(i)\}, k \in \Lambda_k$, remove $\alpha_k^*(i)$ from all the remaining set of eligibles SFs
  end while
  Update the batteries levels using (6)
end for

V. Complexity Analysis

The computation of the upper and lower bounds of $\alpha_k(i)$ requires K operations. The computation of the set of LDs that can be scheduled Δ requires K operations. The computation of the sets Λ_k for $k \in \Delta$ requires $|\Delta|$ operations. When entering the while loop, it requires $|\Delta|$ to find the LD with a minimal number of eligible SFs and $|\Lambda_k|$ operations to assign the suitable SF. Hence, the computational complexity of the optimal SF assignment algorithm is given by:

$$\begin{aligned} C^{opt} &= O\left(L(K+|\Delta|+\sum_{k=1}^{|\Delta|}|\Delta|+|\Lambda_k|)\right) \\ &= O\left(L(K+|\Delta|^2)\right). \end{aligned} \quad (15)$$

Hence, the proposed low complexity SF assignment algorithm can be executed in polynomial time.

VI. Numerical Results

In this section, Monte Carlo simulations are used to evaluate the performance of the proposed resource management scheme in LoRa networks. The users are uniformly distributed within the circular cell of radius r_c. The simulation parameters used in this section are summarized in Table I.

TABLE I: Simulation Parameters.

Symbol	Description	Value
ν	path loss exponent	3.7
B_{max}	max battery capacity	200 J
K	number of LDs	10
L	number of frames	50
	noise PSD	-174 dBm/Hz
	circuit power per RF chain	30 dBm
r_c	cell radius	500 m

Fig. 2 plots the performance of the optimal SF assignment algorithm as a function of the SNR in terms of number of scheduled LDs. It is clear that proposed algorithm significantly outperforms the random SF assignment scheme in terms of number of scheduled LDs due to the efficient management of available energy at the batteries. The proposed algorithm allows to optimally schedules the best set of LDs and assign them suitable SFs. Moreover, the number of scheduled LDs decreases when the SNR target increases since higher amount of transmit power is required.

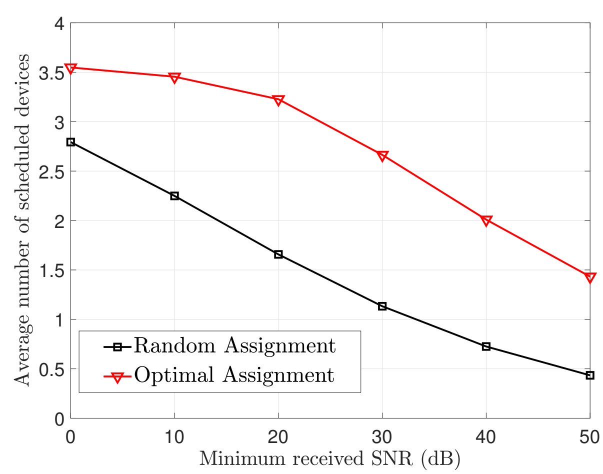

Fig. 2: Average number of scheduled LDs.

In Fig. 3, we investigate the performance of the optimal SF assignment algorithm as a function of the number of

LDs in the networks K. The proposed algorithm allows to efficiently schedules more users. In addition, the performance gap between the two schemes increases when the number of LDs K increases. However, the performance tends to saturate since the maximal number of scheduled LDs at each frame cannot exceed the number of available SFs which is 6 in LoRa.

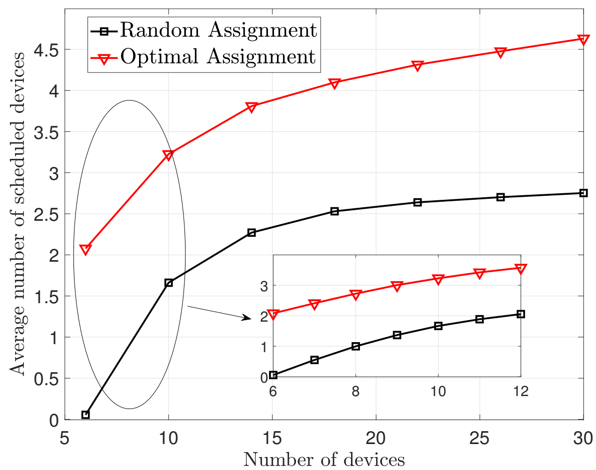

Fig. 3: Impact of the number of LDs in the network.

Fig. 4 shows the performance of the optimal SF assignment algorithm as a function of the enrgy arrival rate. It is can be seen that increasing the energy arrival rate allows to increase the number of scheduled LDs for both schemes. However, the performance tends to saturate.

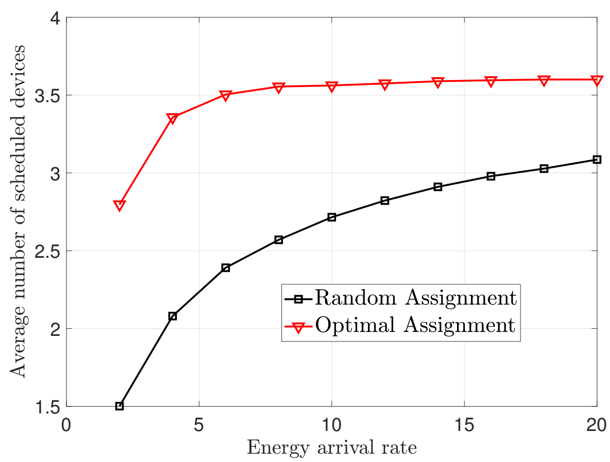

Fig. 4: Impact of the energy arrival rate.

VII. Conclusion

This paper investigates resource management in LoRa wireless networks based on the instantaneous channel coefficients and energy availabilities while the LDs are powered by energy harvesting sources. The relationship between various wireless parameters is analytically established. Hence, the optimal SF assignment, device scheduling, and power allocation algorithm that maximizes the number of scheduled LDs, is developed. Simulations results show that the proposed scheme can significantly enhance the system performance of LoRa networks.

Future works will focus on developing efficient bit allocation and deadline scheduling schemes for federated learning over LoRa wireless networks.

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