Dynamic LoRa Wireless Networks Powered by Hybrid Energy

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***Abstract*—In this paper, we investigate an energy-efficient Long Range (LoRa) wireless network powered by hybrid energy which consists of an energy harvesting source and the grid. The grid allows to compensate for the randomness and intermittency of the harvested energy. The aim is to propose a dynamic energy-efficient resource management scheme for LoRa wireless networks that enables green Internet of Things (IoT). Hence, we formulate a grid energy cost minimization problem subject to minimum received signal-to-noise ratio (SNR), and channel, spreading factor (SF) and energy availability constraints. The formulated problem is simplified and decoupled into two sub-problems which allows to derive the optimal resource management solution but with high computational complexity. Then, we propose a low complexity heuristic channel and SF assignment, and energy management algorithm for dynamic LoRa wireless networks. Numerical results shows the efficient use of renewable energy in green dynamic LoRa wireless networks.**

***Index Terms*—LoRa, energy harvesting, resource management.**

I. Introduction

The design and development of IoT is very challenging specifically when interconnecting large number of heterogeneous and distant devices. LoRa becomes a key technology for wireless sensor network (WSN) that enables the connectivity of a large number of low-powered wireless devices. This technology is suitable for IoT systems in terms of connectivity, energy efficiency, scalability, and complexity [1]. Indeed, LoRa ensures a long range transfer of the information for the IoT devices with a low transfer rate [2]. Moreover, LoRa offers a bidirectional communication on unlicensed bands [3]. LoRa operates based on the star network topology [4]. LoRa uses chirp spreading modulation (CSM) as a modulation technique [5]. The transmitted signal is modulated based on a chirp signal which varies with the frequency and depends on the SF. LoRa signals with different SFs are orthogonal which allows to reduce the complexity of the decoding at the receiver by removing multi-user interference [6]. Indeed, this spreading technique which encodes the symbol into a longer sequence of bits, allows to reduce the signal-to-noise-plus-interference ratio (SINR) [7]. Hence, it enhances the network coverage, link robustness, and energy consumption [8].

Several resource management techniques were the focus of [9]–[16] to enhance the efficiency of LoRa wireless networks for various assumptions and network architectures. In [9], a low complexity SF assignment algorithm was devised to optimize the symbol error rate. The throughput was optimized in [10] by proposing a novel SF assignment scheme based on matching theory. Another scheme was also proposed in [11] to optimize the number of connected devices. The authors of [12] designed a joint power allocation and SF assignment technique to reduce the consumed energy. In [13], the authors proposed a resource management algorithm to enhance the energy efficiency of LoRa. In [14], adequate SF allocation strategies were developed to maximize the packet success probability. An efficient interference-aware SF assignment is also developed in [15]. The convergence period of LoRa was reduced in [16] by proposing an efficient SF assignment technique.

Energy harvesting represents a key technology for greening next generation IoT wireless networks [17], that allows to reduce the network operation cost. LoRa could be powered by renewable energy sources [18], which allows it to continuously acquire clean energy from sustainable sources (e.g., solar, wind, and electromagnetic) and to improve its energy efficiency. Thus, we propose in this work to power the LoRa wireless network by an hybrid source. Hence, we formulate a grid energy cost minimization problem subject to minimum received SNR, and channel, SF and energy availability constraints. The optimal resource management scheme is devised after deriving analytically an optimal SF assignment solution. Moreover, we develop an efficient heuristic resource management scheme to reduce the computational complexity. Simulation results illustrate the performance of the proposed resource management scheme in terms of grid energy cost. We investigated an extended system model in [19] by considering correlated channels and proposing resource management algorithms based on deep reinforcement learning.

II. System Model

A. Channel and Signal Model

In this work, downlink LoRa wireless networks are investigated, as illustrated in Fig. 1. Our LoRa network is composed of one LoRa Gateway (LG) that serves K arbitrarily distributed LoRa devices (LDs) through M channels. We define B_m as the bandwidth of channel m. We also partition the studied time interval into L frames with duration T_{out}. Let $g_{k,m}(i)$ denote the channel coefficient between the LG and the LoRa device k through channel m at the time frame i. This coefficient is given by $g_{k,m}(i) = \beta_k(i)h_{k,m}(i)$, where $\beta_k(i)$ denotes the path loss and $h_{k,m}(i)$ presents the small-scale fading of a quasi-static Gaussian independent and identically distributed (i.i.d.) channel.

Authors in [5] introduced the LoRa modulation known as CSM, where the modulated signal is a chirp waveform and the frequency increases linearly with the time index. At time frame i of a duration $2^{\alpha_k(i)}T$, each LD k receives a symbol $s_k(i)$ sent by the LoRa gateway, where $\alpha_k(i)$ represents the SF taking values in $\Gamma = \{7, 8, 9, 10, 11, 12\}$ and $s_k(i)$ is in the range of $\{0, 1, 2, \ldots, 2^{\alpha_k(i)} - 1\}$. T is equal to $\frac{T_{out}}{2^{12}}$, which is defined as the duration of a sample transmission. Furthermore, $\alpha_k(i)$ is the number of bits sent by the LG to the LD k at frame i. In order to guarantee orthogonality and enable multi-user transmission, the devices use different SFs. Therefore, the transmitted waveform vector for device k at frame i is given by:

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

To ensure that all devices have the same vector length, a zero padding of length $2^{12} - 2^{\alpha_k(i)}$ is affixed to each vector. The possible waveforms of CSM modulation are proved to be orthogonal [6]. Hence, we can apply the inner product receiver, which consists of projecting the received vector $\mathbf{y}(i)$ onto the different signals given by:

$$\mathbf{c}_{|s_k(i)} = \left[g^*_{k,m}(i) \frac{1}{\sqrt{2^{\alpha_k(i)}}} e^{\jmath 2\pi \left[(s_k(i)+f) \bmod 2^{\alpha_k(i)}\right] \frac{f}{2^{\alpha_k(i)}}}\right]^T_{f=0..2^{\alpha_k(i)}-1} \quad (2)$$

and choosing the one with maximal square modulus projection. Hence, the best estimate of the transmitted signal $\hat{s}_k(i)$ by device k at frame i is given by:

$$\hat{s}_k(i) = \underset{0..2^{\alpha_k(i)}-1}{\operatorname{argmax}} \ |\langle \mathbf{y}(i), \mathbf{c}_{|s_k(i)} \rangle|^2. \quad (3)$$

It is worth to note that, for each channel, the gateway can only serve 6 LDs simultaneously, since only 6 SFs are available which are ranged from 7 to 12. Moreover, each LD can only use one transmission channel at most. Let $\chi_{k,m}(i)$ be a binary variable that is equal to 1 if the channel m is assigned to the LD k at a time frame i, and 0 otherwise. The set of devices related to the channel m at the frame i is denoted by $\psi_m(i)$. The vector of received signals through channel m at frame i is expressed as:

$$\mathbf{y}_m(i) = \sum_{k=1}^{K} \chi_{k,m}(i) p_k(i) g_{k,m}(i) \mathbf{x}_k(i) + \mathbf{w}_m(i), \quad (4)$$

where $p_k(i)$ is the power allocated for LD k at frame i and $\mathbf{w}_m(i)$ is assumed to be additive white Gaussian noise (AWGN) with zero mean and variance σ_m^2. Hence, the down-

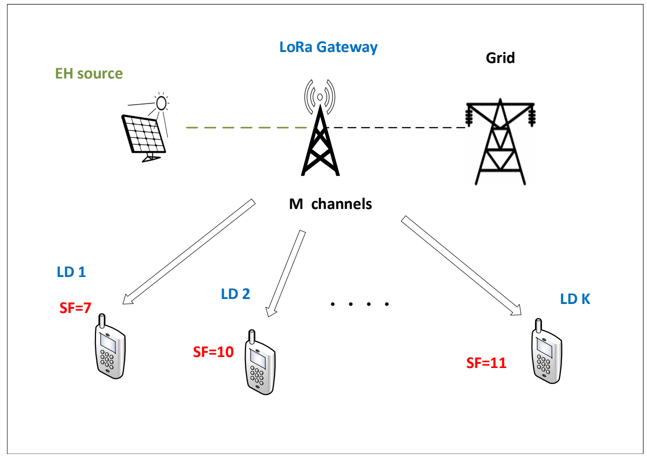

Fig. 1: Energy Harvesting Powered LoRa Wireless Networks.

link signal-to-noise ratio (SNR) of LD k through channel m at frame i is expressed as:

$$\gamma_{k,m}(i) = \frac{\chi_{k,m}(i) p_k(i) \mid \mathbf{g}_{k,m}(i) \mid^2}{\sigma_m^2}. \quad (5)$$

The rate for LD k through channel m at frame i is given by:

$$R_{k,m}(i) = B_m \log_2 \left(1 + \frac{\chi_{k,m}(i) p_k(i) \mid \mathbf{g}_{k,m}(i) \mid^2}{\sigma_m^2}\right). \quad (6)$$

An LD k is scheduled at frame i, if it is assigned to one of the channels $\sum_{m=1}^{M} \chi_{k,m}(i) = 1$, otherwise it is not scheduled and $\sum_{m=1}^{M} \chi_{k,m}(i) = 0$.

B. Energy Model

The LoRa gateway is assumed to be powered by two sources of energy, which are the energy harvesting and the grid. More specifically, since the harvested energy is characterised by its randomness and intermittency, the grid energy source serves as a supply in case of green energy shortage. This harvested energy is stored in a battery with maximal capacity B_{max} and it is modeled as a correlated time process. The amount of harvested energy during the frame i is denoted by $E(i)$, while the battery level is presented by $B(i)$. The required energy consumed at frame i is given by:

$$\begin{aligned} X(i) &= X^h(i) + X^g(i) \\ &= E_c + \sum_{k=1}^{K} p_k(i) 2^{\alpha_k(i)} T, \end{aligned} \quad (7)$$

where E_c presents the fixed energy consumed by the circuit, while $X^h(i)$ and $X^g(i)$ present the energies supplied by the energy harvesting and the grid sources, respectively. We note that the consumed energy from the energy harvesting source should be constrained by the battery level, as given by:

$$X^h(i) \leq B(i). \quad (8)$$

The battery level update is expressed as:

$$B(i+1) = \min\left(B_{\max}, B(i) - X^h(i) + E(i)\right). \quad (9)$$

We consider that the consumed grid energy at frame i is weighted by a factor θ_i [20]. Hence, the grid energy cost is expressed as:

$$\Delta = \sum_{i=1}^{L} \theta_i X^g(i). \tag{10}$$

III. Problem Formulation

In this section, we formulate our resource management in hybrid energy LoRa wireless networks as an optimization problem. The objective function aims at minimizing the grid energy cost while exploiting the available harvested energy and achieving a minimum received SNR by each scheduled LD. The energy management strategy should be able to benefit from the grid power's weight variations. More specifically, when this weight is low, more grid power should be consumed while saving the harvested energy for future use. If the grid weight is high, the usage of grid power should be minimized. Additionally, the channels and SFs should be optimally assigned to different LDs while respecting the requirements of the system, particularly, each channel can only serve 6 LDs per frame. The main problem can be formulated as:

$$\begin{aligned}
&\min_{\substack{\{\chi_{k,m}(i),\alpha_k(i),p_k(i)\}\\ k=1,\dots,K, m=1,\dots,M, i=1,\dots,L}} \sum_{i=1}^{L} \theta_i X^g(i)\\
&\text{subject to}\\
&(11.a): \gamma_{k,m}(i) \geq \chi_{k,m}(i)\gamma_{th},\ \forall k=1,\dots,K, i=1,\dots,L,\\
&(11.b): \sum_{i=1}^{l} X^h(i) \leq \sum_{i=1}^{l} E(i),\ \forall l=1,\dots,L\\
&(11.c): \sum_{i=1}^{l} E(i) - \sum_{i=1}^{l-1} X^h(i) \leq B_{max},\ \forall l=2,\dots,L,\\
&(11.d): X^g(i) + X^h(i) = E_c + \sum_{k=1}^{K} p_k(i) 2^{\alpha_k(i)} T,\\
&\qquad \forall i=,\dots,L,\\
&(11.e): \sum_{m=1}^{M} \chi_{k,m}(i) \leq 1,\ \forall k=1,\dots,K, i=1\dots L,\\
&(11.f): \sum_{k=1}^{K} \chi_{k,m}(i) = 6,\ \forall m=1,\dots,M, i=1\dots L,\\
&(11.g): \alpha_k(i) \neq \alpha_p(i),\ \forall k,p \in \psi_m(i), k \neq p,\\
&\qquad m=1,\dots,M, i=1,\dots,L,\\
&(11.h): p_k(i) \geq 0,\ \forall k=1,\dots,K, i=1,\dots,L,\\
&(11.i): \alpha_k(i) \in \Gamma,\ \forall k=1,\dots,K, i=1,\dots,L\\
&(11.j): \chi_{k,m}(i) \in \{0,1\},\ \forall k=1,\dots,K, m=1,\dots,M,\\
&\qquad i=1,\dots,L.
\end{aligned} \tag{11}$$

The optimization problem has the following constraints. Constraint $(11.a)$ ensures a minimum received SNR, namely γ_{th}, by each LD. Constraint $(11.b)$ ensures that the energy consumed from the harvested source cannot exceed the energy available at the battery. Equation $(11.c)$ guarantees that the harvested energy ate the current frame is constrained by the maximal battery capacity. Constraint $(11.d)$ implies that the required consumed energy is supplied from the energy harvesting and the grid sources. Constraint $(11.e)$ ensures that each LD can use one channel at most for transmission at each frame. Constraint $(11.f)$ indicates that the number of LDs transmitting on the same channel cannot exceed the number of SFs. Constraint $(11.g)$ specifies that LDs using the same channel should be assigned to different SFs. Constraint $(11.h)$ guarantees that the allocated amounts of power are non-negative. Constraints $(11.i)$ and $(11.j)$ specify the set of available SFs and the channel assignment index, respectively.

IV. Optimal Resource Management

In this section, we investigate the optimal channel and SF assignment and the energy management in LoRa wireless networks. The problem formulated in (11) is a mixed integer non-linear program because of its combinatorial nature and the non-linearity of the constraints. To solve (11), we propose to decouple the problem into two sub-problems. First, the channels and SFs should be optimally assigned to different LDs at each frame, in order to minimize the total consumed energy. Using the optimal total required consumed energy derived in the first optimization, the optimal energy drawn from the energy harvesting source over time can be determined in the second optimization based on the grid's weight.
The required transmit power to meet the SNR constraint of LD k using channel m at frame i following (5) is given by:

$$p_k(i) = \chi_{k,m}(i) \frac{\gamma_{th}\sigma_m^2}{\mid \mathbf{g}_{k,m}(i) \mid^2}. \tag{12}$$

Hence, the required consumed energy at frame i is given by:

$$X(i) = E_c + \sum_{k=1}^{K} \left(\sum_{m=1}^{M} \frac{\gamma_{th}\sigma_m^2}{\mid \mathbf{g}_{k,m}(i) \mid^2} \chi_{k,m}(i) \right) 2^{\alpha_k(i)} T. \tag{13}$$

Hence, substituting $p_k(i)$ and $X(i)$ by their expression in (12) and (13), the channel and SF assignment problem at frame i can be formulated as

$$\begin{aligned}
&\min_{\substack{\{\chi_{k,m}(i),\alpha_k(i)\}\\ k=1,\dots,K, m=1,\dots,M}} \sum_{k=1}^{K} \left(\sum_{m=1}^{M} \frac{\gamma_{th}\sigma_m^2}{\mid \mathbf{g}_{k,m}(i) \mid^2} \chi_{k,m}(i) \right) 2^{\alpha_k(i)}\\
&\text{subject to}\\
&(14.a): \sum_{m=1}^{M} \chi_{k,m}(i) \leq 1,\ \forall k=1,\dots,K,\\
&(14.b): \sum_{k=1}^{K} \chi_{k,m}(i) = 6,\ \forall m=1,\dots,M,\\
&(14.c): \alpha_k(i) \neq \alpha_p(i),\ \forall k,p \in \psi_m(i), k \neq p, m=1,\dots,M,\\
&(14.d): \alpha_k(i) \in \Gamma,\ \forall k=1,\dots,K,\\
&(14.e): \chi_{k,m}(i) \in \{0,1\},\ \forall k=1,\dots,K, m=1,\dots,M.
\end{aligned} \tag{14}$$

The problem (14) is combinatorial and non-linear; and thus is a non-linear integer problem. Consequently, the problem is

NP-hard [21] and could be solved by brute-force search with exponential complexity growth.

After determining the optimal channel and SF assignment, the required consumed energy can be calculated for each frame. Based on these derived energies, the optimal energy drawn from the harvesting source to minimize the grid energy cost over time frames can be found using the following energy management problem:

$$
\begin{aligned}
&\min_{\substack{\{X^h(i)\}\\ i=1,\dots,L}} -\sum_{i=1}^{L}\theta_i X^h(i)\\
&\text{subject to}\\
&(15.a): \sum_{i=1}^{l} X^h(i) \leq \sum_{i=1}^{l} E(i),\ \forall l = 1,\dots,L\\
&(15.b): \sum_{i=1}^{l} E(i) - \sum_{i=1}^{l-1} X^h(i) \leq B_{max},\ \forall l = 2,\dots,L,\\
&(15.c): X^h(i) \leq X(i),\ \forall i = 1,\dots,L,\\
&(15.d): X^h(i) \geq 0,\ \forall i = 1,\dots,L.
\end{aligned}
\tag{15}
$$

We can see, in the problem (15), that the objective function and the constraints are linear. Therefore, the interior-point method can be used to solve our linear program and obtain the optimal energy management strategy. This method can be implemented on a numerical tools such as CVX.

After assigning all the channels, the optimal SF allocation can be obtained using the following theorem.

Theorem 1. Let consider K LDs where their coefficients v_k verify $v_1 < v_2 < \dots < v_K$. The optimal SF assignment that minimizes the objective function $\sum_{k=1}^{K} v_k 2^{\alpha_k}$ is given by start assigning the lowest SF $\alpha^{\min}$ to the LD with biggest coefficient v_k until assigning the biggest SF $\alpha^{\max}$ to the LD with lowest coefficient v_k.

Proof. Let us consider two LDs with $v_1 < v_2$. We have

$$
\begin{aligned}
v_1 2^7 + v_2 2^8 - (v_1 2^8 + v_2 2^7) &= -v_1 2^7 + v_2 2^7\\
&= 2^7(v_2 - v_1) > 0.
\end{aligned}
\tag{16}
$$

Hence, the optimal SF assignment is given by assigning 8 to LD 1 and 7 to LD 2. This relation can be extended recursively to the case of K LDs.

□

V. Online Resource Management

In this section, we propose a low complexity heuristic to handle real-time resource management. In this heuristic, we assume that the LG has a full knowledge about the channel coefficients, the grid's weight, and the harvested energy only at the current frame i. Only NM LDs can be scheduled at each frame. Our algorithm starts by assigning channel coefficients to different LDs one by one. More specifically, in order to reduce the required consumed energy, the best channel is allocated to the LD with the highest channel coefficient modulus. This resource allocation procedure is repeated until using all the available channels.

Next, following **Theorem 1**, the lowest SF $\alpha^{\min}$ is assigned to the LD with the biggest coefficient p_k, until assigning the biggest SF $\alpha^{\max}$ to the LD with lowest coefficient p_k. Finally, when all channels and SFs are fully allocated, the required consumed energy can be determined and the maximum available harvested energy at the battery at each frame can be used. The proposed Heuristic Resource Management Algorithm (HRMA) is described in **Algorithm 1**.

The computational complexity of HRMA is derived as follows. The channel assignment in the **while** loop has a complexity order equal to $O(MN\log(MN))$, since it is similar to sorting an array with MN elements. For the SF assignment in the **for** loop, an array with N elements is sorted M times. Hence, the computational complexity of HRMA is given by:

$$C^{\text{HRMA}} = O(MN\log(MN)). \tag{17}$$

On these bases, the proposed low complexity algorithm can be executed in polynomial time.

Algorithm 1 Heuristic Resource Management Algorithm (HRMA)

$B(1) \leftarrow E(1)$
for $i = 1 : L$ **do**
  $\chi_{k,m}(i) \leftarrow 0$
  $\boldsymbol{c} \leftarrow \boldsymbol{0}_{K\times 1}$
  $\boldsymbol{c}_f \leftarrow \boldsymbol{0}_{M\times 1}$
  while $\sum_{m=1}^{M} \boldsymbol{c}_f[m] \neq MN$ **do**
    $(k_{\max}, m_{\max}) \leftarrow \operatorname{argmax} \boldsymbol{V}$
    if $\boldsymbol{c}_f[m_{\max}] < N$ **then**
      $\boldsymbol{c}[k_{\max}] \leftarrow m_{\max}$
      $\boldsymbol{c}_f[m_{\max}] \leftarrow \boldsymbol{c}_f[m_{\max}] + 1$
      $\chi_{k_{\max},m_{\max}}(i) \leftarrow 1$
      $\boldsymbol{V}[k_{\max}, :] \leftarrow \boldsymbol{0}_{1\times M}$
    else
      $\boldsymbol{V}[:, m_{\max}] \leftarrow \boldsymbol{0}_{K\times 1}$
    end if
  end while
  for $m = 1 : M$ **do**
    $\boldsymbol{d}_m \leftarrow$ indices of LDs assigned to m
    $v_n \leftarrow \frac{\sigma_m^2}{|\mathbf{g}_{\boldsymbol{d}_m(n),m}(i)|^2}, n = 1,\dots,N$
    $\boldsymbol{s}_m \leftarrow \boldsymbol{d}_m$ sorted in ascending order based on p_n
    $\alpha_{\boldsymbol{s}_m(n)}(i) \leftarrow 13 - n, n = 1,\dots,N$
  end for
  $X(i) \leftarrow E_c + \sum_{k=1}^{K}\left(\sum_{m=1}^{M} \frac{\gamma_{th}\sigma_m^2}{|\mathbf{g}_{k,m}(i)|^2}\chi_{k,m}(i)\right) 2^{\alpha_k(i)} T$
  if $X(i) \leq B(i)$ **then**
    $X^h(i) \leftarrow X(i)$
    $X^g(i) \leftarrow 0$
  else
    $X^h(i) \leftarrow B(i)$
    $X^g(i) \leftarrow X(i) - X^h(i)$
  end if
  $B(i) \leftarrow \min\left(B_{\max}, B(i) - X^h(i) + E(i)\right)$
end for

VI. Numerical Results

We evaluate the performance of the proposed resource management strategy for hybrid energy LoRa wireless networks via Monte Carlo simulations. We consider that devices are uniformly distributed within a circular cell. The grid energy consumption's weights θ_i are randomly generated according to a standard uniform distribution. Unless otherwise mentioned, the following values are used in the simulations $B_{\max} = 200$ J, $\nu = 3.7$, $M = 5$, $K = 40$, $L = 50$, the coverage radius is 500 and the noise PSD is -174 dBm/Hz.

In Fig. 2, we show the performance of the different resource management schemes in terms of grid energy cost as a function of the SNR. The optimal resource management solution is derived with high computational complexity. It is clear that the proposed algorithm HRMA outperforms the random scheme thanks to its adequate SF and channel assignment method. Indeed, the performance gap with the optimal is tight specifically in low SNR region in which LoRa operates.

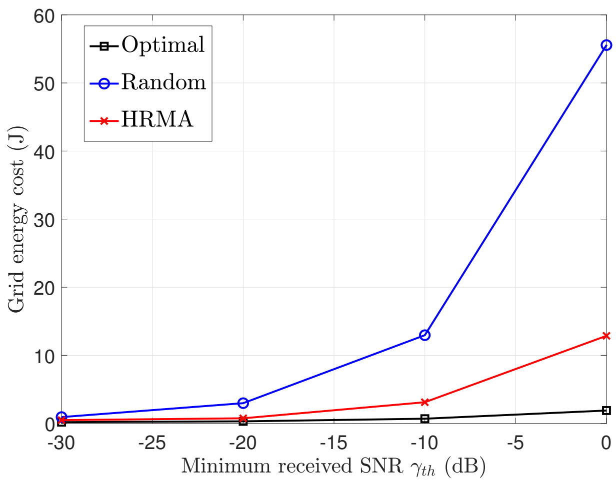

Fig. 2: Optimal grid energy cost versus SNR target ($M = 2, K = 6, B_{max} = 10$ J$, \Gamma = \{7, 8, 9\}$).

In Fig. 3, we plot the performance of HRMA for higher number of devices $K = 35$. Indeed, HRMA outperforms the random scheme in terms of grid energy cost for wide range of SNR thanks to its adequate SF and channel assignment method.

Finally, we show in Fig. 4 the performance of the proposed scheme HRMA as a function of the number of channels M. Considering higher number of channels in the network allows to increase the number of scheduled devices, which generates an increase of the total grid energy cost. HRMA performs very well in terms of grid energy cost and the performance gap with the random scheme keeps increasing when the number of channels increases.

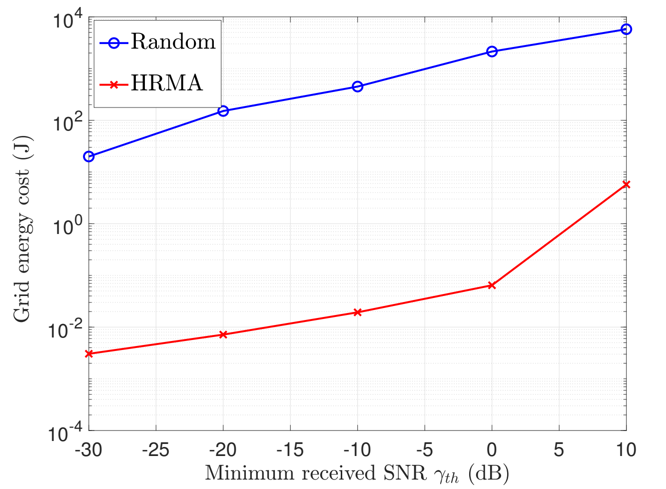

Fig. 3: Grid energy cost versus SNR target with heuristic resource management scheme ($M = 5, K = 35, B_{max} = 200$ J$, \Gamma = \{7, 8, 9, 10, 11, 12\}$).

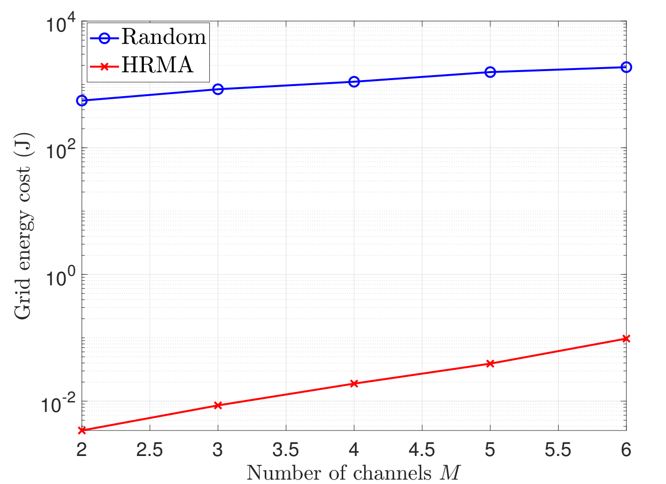

Fig. 4: Grid energy cost versus number of channels with heuristic resource management schemes ($K = 40, B_{max} = 200$ J$, \Gamma = \{7, 8, 9, 10, 11, 12\}, \gamma_{th} = 0$ dB).

VII. Conclusion

A green LoRa wireless network has been investigated in this work, where the LoRa gateway is powered by th grid and an energy harvesting source. A grid energy cost minimization problem subject to minimum received SNR constraints, has been formulated. Then, the optimal resource management problem has been simplified and solved. Next, to reduce the NP-hardness of the optimization problem, a low complexity heuristic online resource management algorithm, has been developed. Simulations results have shown that the proposed resource management approach allows efficient use of renewable energy in LoRa wireless networks.

Future works will focus on developing adaptable and intelligent resource management schemes for LoRa wireless networks based on Reinforcement Learning.

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