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Published in:
IEEE Transactions on Industrial Informatics

DOI:
10.1109/TII.2020.2967123

Published: 01/12/2020

Document Version
Publisher's PDF, also known as Version of record

Please cite the original version:
Premsankar, G., Ghaddar, B., Slabicki, M., & Di Francesco, M. (2020). Optimal configuration of LoRa networks in smart cities. *IEEE Transactions on Industrial Informatics*, *16*(12), 7243-7254. Article 8998148. https://doi.org/10.1109/TII.2020.2967123

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2020.2967123, IEEE Transactions on Industrial Informatics

Optimal configuration of LoRa networks in smart cities

Gopika Premsankar, Bissan Ghaddar, Mariusz Slabicki, Mario Di Francesco

***Abstract*—Long Range (LoRa) is a wireless communication standard specifically targeted for resource-constrained Internet of Things (IoT) devices. LoRa is a promising solution for smart city applications as it can provide long-range connectivity with a low energy consumption. The number of LoRa-based networks is growing due to its operation in the unlicensed radio bands and the ease of network deployments. However, the scalability of such networks suffers as the number of deployed devices increases. In particular, the network performance drops due to increased contention and interference in the unlicensed LoRa radio bands. This results in an increased number of dropped messages and, therefore, unreliable network communications. Nevertheless, network performance can be improved by appropriately configuring the radio parameters of each node. To this end, we formulate integer linear programming models to configure LoRa nodes with the optimal parameters that allow all devices to reliably send data with a low energy consumption. We evaluate the performance of our solutions through extensive network simulations considering different types of realistic deployments. We find that our solution consistently achieves a higher delivery ratio (up to 8% higher) than the state of the art with minimal energy consumption. Moreover, the higher delivery ratio is achieved by a large percentage of nodes in each network, thereby resulting in a fair allocation of radio resources. Finally, the optimal network configurations are obtained within a short time, usually much faster than the state of the art. Thus, our solution can be readily used by network operators to determine optimal configurations for their IoT deployments, resulting in improved network reliability.**

***Keywords*—LoRa, LPWAN, LoRaWAN, optimization, integer programming, spreading factor, power control, scalability, IoT**

I. Introduction

Low Power Wide Area Networks (LPWANs) are a new class of communication networks primarily targeted for battery-powered and resource-constrained Internet of Things (IoT) devices [1]. LoRaWAN [2] is one such solution that relies on the LoRa physical layer [1] to provide long-range connectivity (in the order of kilometers) at low data rates and with low energy consumption. LoRaWAN is ideally suited to provide connectivity for industrial Internet [3–5] and smart city applications such as smart metering, smart street lights, smart waste collection and smart grids [1, 6–9]. The range of applications include both indoor [6, 10, 11] and outdoor scenarios [8, 12]. However, an important characteristic of such applications is that they do not have strict QoS requirements [7, 10]. Devices need to sporadically send only a small amount of data [13–15], which is appropriately supported by the data rates of LoRa. The low energy consumption ensures that the IoT devices do not need to be replaced for at least 10 years [3]. Moreover, LoRaWAN offers a scalable network architecture to support smart city applications [1, 9]. Specifically, devices communicate over unlicensed Industrial Scientific and Medical (ISM) bands over one-hop links with gateways and use a simple medium access control protocol that requires limited coordination [1].

Smart city application scenarios are characterized by massive densities of devices that need to communicate with very low energy over long distances [3, 4, 6]. However, the performance of LoRa networks reduces as the number of deployed devices increases, especially in urban areas where devices are typically located indoors [11]. As these devices share access to the unlicensed spectrum, radio bands become overloaded with increased collisions, thereby resulting in dropped messages. Poor network reliability is further exacerbated by regional restrictions on message frequency (and therefore retransmissions) [2] as well as the contention-based medium access in LoRaWAN [1]. Nevertheless, the performance of LoRa-based networks can be improved by appropriately configuring the radio parameters of each node, namely, their *spreading factor* (SF) and *transmission power* (TP). Dynamic adaptation of these parameters has been proposed to improve reliability and energy consumption through a standardized Adaptive Data Rate (ADR) [2] method. Unfortunately, this approach has several important limitations [16, 17]. In particular, ADR requires a long duration (hours to days) to converge to the ideal parameters for all nodes in a network [17]. Such a long convergence time could result in a significant amount of dropped messages, thereby severely reducing reliability in dense networks. Thus, it is essential that nodes already use the optimal parameters required to ensure reliable transmissions at the time of deployment.

In this article, we devise optimization problems that allow service providers of smart city applications to determine an optimal configuration of dense LoRa networks. In particular, our solutions determine the values of SFs and TPs at individual nodes to ensure that *all* of them send messages *reliably* while maintaining a *low energy consumption* right after their deployment. To this end, we formulate *novel and tractable integer linear programming models* to assign SFs and TPs. The optimization process is split into two stages. First, we propose models that assign SFs to each node such that (i) the collisions in the most overloaded SF is minimal, and (ii) the collisions

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in each SF is balanced for all gateways. As the considered problems are non-linear, they are transformed into tractable integer linear programming models. Second, we formulate an integer linear programming model to assign TPs such that the overall energy consumption in the network is minimized.

The novelty of our solutions is two-fold. First, the models are general, thereby allowing to configure networks with one or more gateways as well as with different spatial configurations of LoRa devices. In contrast, the state of the art [18, 19] has considered optimal assignments in small networks where all nodes can use all SFs and TPs. Such an assignment cannot work in real networks wherein certain nodes can use only a subset of the configuration parameters, depending on their distance from a gateway. Second, our optimization models can be solved by off-the-shelf solvers to obtain solutions within a short time for even large, dense networks with thousands of devices. We evaluate our solutions through extensive network simulations with different types of networks and radio environments. Additionally, we demonstrate the effectiveness of our proposed approach through simulations in a realistic smart city network in Dublin. We compare our solutions to state-of-the-art algorithms in terms of delivery ratio, energy consumed and whether *all* nodes can achieve a high delivery ratio. The results show that our proposed solutions consistently achieve a higher delivery ratio (up to 8% higher) than the state of the art with a low energy consumption. Moreover, the improved delivery ratio is shared by all the nodes in the network, thereby implying a fair allocation of radio resources to the nodes.

The rest of this article is organized as follows. Section II reviews the state of the art and Section III describes the relevant background. Section IV presents the integer linear programming models to assign SFs and TPs. Section V discusses the results from the network simulations to evaluate the performance of our solutions. Finally, Section VI provides concluding remarks and directions for future work.

II. Related Work

The scalability and reliability of LoRa-based networks is an active research topic, especially for smart city scenarios [6, 12]. Pasolini et al. [12] highlight the importance of setting LoRa parameters correctly to ensure low packet loss in smart city applications. Varsier and Schwoerer [6] describe the increase in packet loss in LoRa networks as the number of deployed smart meters increases. Bor et al. [11] analyze the impact of SF configurations through experimental evaluation in an urban built-up environment. They find that the scalability of networks increases when the parameters are configured to minimize the message airtime. Reynders et al. [18] present a heuristic to assign SFs and TPs to nodes in networks with a single gateway. The authors first calculate the optimal proportion of SFs based on the objective of minimizing the maximum probability of collisions in any one SF. Abdelfadeel et al. [19] use a similar approach based on the optimal proportion of SFs proposed in [18] under the assumption that each node can reach the gateway with any combination of SF and TP. Unfortunately, such an approach is feasible only for very small networks where all nodes are located close to the gateway. In contrast, our solution targets networks with any number of gateways and devices arranged in realistic spatial configurations, wherein the optimal proportion of SFs in [18, 19] cannot be employed. Cuomo et al. [20] propose EXPLoRa-AT, an algorithm to assign SFs for single-gateway scenarios. Such a solution balances the message airtimes in different SFs and also takes into account that only certain combinations of SFs and TPs are available for nodes. EXPLoRa-AT performs very well for networks with a single gateway, with results similar to those obtained by our approaches. However, it does not support networks with multiple gateways. EXPLoRa-AT is extended to networks with multiple gateways in a heuristic algorithm called AD-MAIORA [21], which iteratively determines the best SF for each node to balance the message airtimes. In contrast, we present an integer linear programming model to determine an optimal configuration that balances the weighted fraction of nodes in different SFs at once. Finally, a few articles evaluate the scalability of LoRa-based networks using stochastic geometry [9, 22, 23]. In particular, they evaluate the impact of capture effect as well as co-SF interference [22, 23] and inter-SF interference [9] on the delivery ratio in LoRa-based networks. However, such works consider networks with a single gateway wherein nodes are assigned SFs based on their distance to the gateway alone. In contrast, our goal is to assign SFs and TPs to the nodes such that they can all achieve a high delivery ratio.

III. Overview of LoRaWAN and LoRa

The LoRaWAN specification defines the architecture of a LoRa network as well as the medium access control (MAC) and network layers [2]. A LoRa network comprises low-cost battery-powered end-devices (or *nodes*) that communicate to *gateways* over the LoRa physical layer. The nodes send packets to the gateways whenever there is data to communicate, i.e., they rely on an ALOHA-based MAC protocol [24]. Such a protocol allows to keep the complexity of the nodes low. LoRa nodes are not associated with a particular gateway – a message sent by a device is received by all gateways within its communication range. The gateways simply forward all received messages to a central *network server*, where the main intelligence of the network resides. The network server manages the network and filters out duplicate packets received by gateways. It also communicates with *application servers*, which provide the actual business logic to process device-generated data.

The end-devices communicate to gateways over the LoRa physical layer, which is a proprietary technology developed by Semtech [1]. LoRa relies on *chirp spread spectrum* modulation that allows long distance communication with low energy consumption. Such a modulation technique encodes the transmitted signal into *chirps* that vary their frequency over time and are spread over a wide spectrum [1]. The encoded chirp pulses can vary from a low-to-high (up-chirp) or from a high-to-low (down-chirp) frequency over time. This modulation technique makes the signal robust to interference [1], which is beneficial as LoRa operates in the unlicensed sub-GHz ISM band. LoRa transmissions can occur over different *spreading*

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factors (SFs), which correspond to different data rates [1, 2]. Choosing a particular SF represents a trade-off between data rate and communication range. At higher SFs, the data rate is lower whereas the communication range is longer, and vice-versa at lower SFs. The available SFs and thus the maximum achievable data rate depend on the region where the LoRa devices operate [25]. For instance, the European region allow SFs 7 to 12 corresponding to a data rate from 0.3 to 5 kbps. Another important aspect of LoRa communications is the *transmission power* (TP), which also affects the achievable distance in addition to the energy consumed. Thus, configuring the SFs and TPs appropriately can increase the network capacity and lower its energy consumption [2, 16].

IV. Optimal assignment of LoRa transmission parameters

A. System model

The target network to be configured consists of one or more LoRa gateways (denoted by set $\mathcal{J}$) and LoRa nodes (denoted by set $\mathcal{I}$). All nodes are stationary and d_{ij} denotes the distance between node i ($i \in \mathcal{I}$) and gateway j ($j \in \mathcal{J}$). Each node can use an SF from a set of SFs ($\mathcal{S}$) and a TP from a set of TPs ($\mathcal{P}$). The elements in $\mathcal{S}$ and $\mathcal{P}$ are discrete integer values that depend on the region of operation. Nodes can be in the range of one or more gateways; we assume that all nodes can reach at least one gateway with the highest TP. The path loss (in dB) between node i and gateway j is represented using the log distance path loss model [26]:

$$PL_{ij} = \overline{PL}(d_0) + 10n\log\left(\frac{d_{ij}}{d_0}\right) + X_\sigma, \tag{1}$$

where $\overline{PL}(d_0)$ is the mean path loss for distance d_0, n is the path loss exponent, and X_σ is a zero-mean Gaussian distributed random variable with standard deviation σ. A gateway receives messages sent with SF s if the received power is above the receiver sensitivity (tol_s) for that particular SF.

The probability of collisions in SF s follows from the ALOHA channel model, wherein nodes transmit data based on random access [18]. Equation (2) represents the probability of collisions in a network with a single gateway j and in a particular SF s:

$$\mathbb{P}(s,j) = 1 - e^{-\frac{2^{s+1}}{s}\frac{L}{B}f_{js}\lambda}, \tag{2}$$

where λ represents the traffic per unit time, f_{js} is the fraction of nodes transmitting with SF s in the range of gateway j, B is the bandwidth (in Hz) and L is the length of the packet (in bits). The probability of collisions affects the delivery ratio in the network; i.e., if $\mathbb{P}(s,j)$ increases, fewer packets are delivered successfully and thus the *delivery ratio* of the network reduces. We model the probability of collisions according to the pure ALOHA model to obtain a tractable formulation. We have verified through preliminary experiments[1] that the ALOHA model adequately estimates the delivery ratio in LoRa networks when devices send sporadic, unsynchronized traffic – typical of smart city applications such as smart metering – to respect the duty cycle restrictions in the unlicensed bands [9, 11].

[1]In practice, the delivery ratio might be higher due to the *capture effect* exhibited by LoRa transmissions, wherein overlapping signals can be decoded successfully if the signal to interference ratio of the desired signal is above a certain threshold [9]. We incorporate such a model in the network simulations (Section V) for better evaluation accuracy.

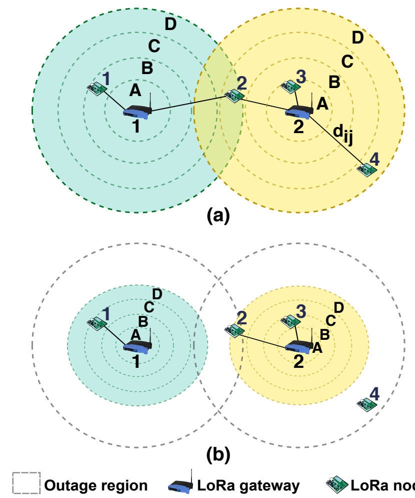

Fig. 1: Sample scenario with all nodes assigned to (a) the highest TP and (b) the lowest TP.

B. Problem description

We aim to optimally assign SFs and TPs to all nodes such that the network can reliably transfer messages with a high delivery ratio while keeping the energy consumption low. However, the assignment of SFs and TPs to nodes presents certain challenges and some unique trade-offs. To illustrate this, Figure 1 presents a simplified scenario with four nodes ($|\mathcal{I}| = 4$), two gateways ($|\mathcal{J}| = 2$), two TPs ($|\mathcal{P}| = 2$) and four SFs ($|\mathcal{S}| = 4$). The dotted rings represent the range up to which an SF can be used at a given power level p.

A node can be configured with SFs based on the region (A-D) in which it is located. The nodes have to use higher SFs as the distance from the gateway increases. For instance, in Figure 1, region A allows the use of any SF in $\{7, 8, 9, 10\}$, region B allows $\{8, 9, 10\}$ and so on. Moreover, the region (and thus availability of SFs) depends on the TP p. For instance, in Figure 1a, node 1 can use $s \in \{8, 9, 10\}$ at the highest TP, whereas the same node can only use $s \in \{9, 10\}$ to reach gateway 1 when configured with a lower TP (Figure 1b). Furthermore, a node is not associated with a particular gateway; this implies that transmissions by a node with certain SFs can be received by multiple gateways. For instance, in Figure 1a, node 2 can be configured with SF 9 or 10. In the first case (with SF 9), its transmissions are received only by gateway 2, whereas both gateways can receive its transmissions with SF 10. Thus, the effect of the node's transmission on multiple gateways needs to be taken into account. Finally, there are trade-offs in the assignment of SFs and TPs. Transmissions at a high SF occur at a low data rate, which implies that the time taken to send a packet is higher. This increases the energy consumption as the radio stays in the transmitting state (or high energy state) for a longer time. However, the lower SFs may be available only at high TPs which, in turn, increases energy consumption.

Our goal is to optimize the assignment of SFs and TPs to each node in a LoRa network such that both the probability of collisions and the energy consumption are low. Given the interdependence between the choice of SFs and TPs, as well as the large problem space with dense networks, the optimization problem to assign the LoRa parameters is divided into two stages. First, the assignment of SFs is optimized based on all nodes using the highest TP (Section IV-C). The objective is to increase the delivery ratio following from Equation (2). Once the SFs are assigned, a second optimization problem determines the actual TP for each node so as to minimize the overall energy consumption in the network (Section IV-D).

C. Assignment of spreading factors

We propose two integer linear programming models, OPT-MAX and OPT-DELTA, to configure the SFs. The problems both return an assignment of SF s to each node i, but have different objective functions. The nodes are assumed to use the highest TP, which is then optimized separately (Section IV-D). Table I summarizes the notations used in the models.

1) Robust problem (OPT-MAX): The objective of OPT-MAX is to minimize the maximum probability of collisions in a single SF, similar to [18]. For a network with a single gateway $j \in \mathcal{J}$, Equation (3) defines the objective function. Since this function is not linear, it is linearized by introducing a new variable θ_j in Equation (4) and a corresponding constraint in Equation (5).

$$\min \quad \max_s \quad (1 - e^{-\frac{2^{s+1}}{s}\frac{L}{B}f_{js}\lambda}) \tag{3}$$

$$\Leftrightarrow \quad \min \quad \min_s \quad e^{-\frac{2^{s+1}}{s}\frac{L}{B}f_{js}\lambda}$$

$$\Leftrightarrow \quad \min \quad \max_s \quad \frac{2^{s+1}}{s}\frac{L}{B}f_{js}\lambda$$

$$\Leftrightarrow \quad \min \quad \theta_j \tag{4}$$

$$\text{s.t.} \quad \theta_j \geq \frac{2^{s+1}}{s}\frac{L}{B}f_{js}\lambda, \qquad \forall s. \tag{5}$$

OPT-MAX is then defined as follows:

$$\min \quad \sum_j \theta_j \tag{6a}$$

$$\text{s.t. } \theta_j \geq \frac{2^{s+1}}{s}f_{js}, \qquad \forall j, s \tag{6b}$$

$$P_{max} - PL_{ij} \geq \sum_s \text{tol}_s x_{is} - M(1 - \sum_s y_{ijs}), \quad \forall i, j \tag{6c}$$

$$\sum_s x_{is} = 1, \qquad \forall i \tag{6d}$$

$$x_{is} \leq \sum_j y_{ijs}, \qquad \forall i, s \tag{6e}$$

$$\sum_j y_{ijs} \leq |\mathcal{J}| x_{is}, \qquad \forall i, s \tag{6f}$$

$$y_{ijs} \geq x_{is}, \qquad \forall j, s, i \in N_{js} \tag{6g}$$

$$f_{js} = \frac{\sum_i y_{ijs}}{|N_j|}, \qquad \forall j, s \tag{6h}$$

$$\sum_s s x_{is} \leq \sum_s s x_{i+1,s}, \qquad \forall j, i \in K_j \tag{6i}$$

$$y_{ijs} \in \{0,1\}, \quad x_{is} \in \{0,1\} \tag{6j}$$

$$f_{js} \geq 0, \quad \theta_j \geq 0 \tag{6k}$$

Equation (6a) defines the objective of the optimization problem and Equation (6b), the associated constraint. They follow from Equations (4) and (5) for multiple gateways, i.e., the objective function is to minimize the maximum probability of collisions for each gateway in $\mathcal{J}$. The terms L, B and λ in Equation (6b) are omitted as we assume they are constant for a particular network. The remaining constraints are as follows. Equation (6c) sets both x_{is} and y_{ijs} to 1 (using a large constant M) if node i can reach gateway j with SF s. Specifically, it ensures that node i can reach gateway j with SF s at the maximum transmission power P_{max}. Equation (6d) ensures that each node is assigned only one SF. Equations (6e)–(6g) together ensure that the binary variable y_{ijs} is set when a node i is assigned SF s and is in the range of gateway j. The remaining constraints only apply to certain subsets of nodes in the target network[2]. Equation (6g) is required to set y_{ijs} to 1 if a node i is in the range of multiple gateways with SF s. Equation (6h) calculates the fraction of nodes in each SF s and in the range of gateway j; this term is required in Equation (6b). Equation (6i) ensures that nodes are assigned SFs based on the distance to the gateway (assuming that K_j is a priori sorted by increasing distance to its nearest gateway). A node closer to the gateway can use both low and high SFs to achieve connectivity. However, it is preferred that the node uses a lower SF so that the time taken to transmit is lower. Thus, Equation (6i) ensures that nodes are assigned higher SFs as their distance to the nearest gateway increases. Equation (6j) signifies that the decision variables y_{ijs} and x_{is} are binary integer variables. Finally, Equation (6k) sets the appropriate range for the variables.

2) Balanced problem (OPT-DELTA): The previous problem OPT-MAX minimizes the largest probability of collisions in any particular SF. On the other hand, OPT-DELTA considers the probability of collisions in other SFs as well. It aims to *balance* the probability of collisions in *all* SFs by taking into

[2]Given the distances (d_{ij}) and power level P_{max}, it is possible to estimate beforehand whether a node can reach a gateway with SF s from Equation (1). Accordingly, the set of nodes $\mathcal{I}$ can be partitioned into the following: N_j comprising of all nodes that can reach gateway j with any SF, N_{js} ($\subseteq N_j$) comprising of nodes that can reach gateway j with SF s, and K_j ($\subseteq N_j$) comprising of nodes in the range of *only* gateway j. Node indices in K_j are sorted by increasing order of distance from gateway j. For instance, in the sample scenario depicted in Figure 1a, we can partition set $\mathcal{I}$ into:

- N_1=$\{1,2\}$, N_2=$\{2,3,4\}$
- $N_{1,7}$=$\{\}$, $N_{1,8}$=$\{1\}$, $N_{1,9}$=$\{1\}$, $N_{1,10}$=$\{1,2\}$
- $N_{2,7}$=$\{3\}$, $N_{2,8}$=$\{3\}$, $N_{2,9}$=$\{3,2\}$, $N_{2,10}$=$\{3,2,4\}$
- K_1=$\{1\}$, K_2=$\{3,4\}$

Sym.	Description
$\mathcal{S}$	Set of spreading factors (SFs)
$\mathcal{P}$	Set of transmission powers (TPs)
$\mathcal{J}$	Set of gateways
$\mathcal{I}$	Set of nodes
P_{max}	Maximum TP
PL_{ij}	Path loss between node i and gateway j according to Equation (1)
tol_s	Sensitivity of the gateway for SF s
f_{js}	Fraction of nodes in range of gateway j with SF s
c_p	Instantaneous supply current for a node transmitting at TP p
M	Large constant; big-M
N_j	Nodes in the range of gateway j with any SF and TP set to P_{max}, $N_j \subseteq \mathcal{I}$
N_{js}	Nodes in the range of gateway j with SF s and TP set to P_{max}, $N_{js} \subseteq N_j$
K_j	Nodes in the range of a single gateway j with TP set to P_{max}, $K_j \subseteq N_j$
x_{is}	Binary variable for node i assigned SF s
y_{ijs}	Binary variable for node i in range of gateway j with SF s
u_{ip}	Binary variable for node i assigned TP p

TABLE I: Summary of notations in the optimization problems.

account the *weighted fraction* of nodes assigned to the same SF. Specifically, the objective of OPT-DELTA is to minimize the difference in the weighted fraction of the nodes assigned to an SF between every pair of SFs. Table II presents the weights used in the European region according to [20]. The values are obtained by normalizing each term $\frac{2^{s+1}}{s}$ by the value of 36.57, i.e., $\frac{2^{s+1}}{s}$ with the lowest SF, $s = 7$. We adjust the value of w_7 slightly from 1.0 to 1.06 without which the lowest SF would not be assigned because of its very low weight. A term δ_{jk} is introduced to represent the absolute difference in the probability of collisions between each pair of SFs ($[\mathcal{S}]^2 = \{\{a,b\}|a,b \in \mathcal{S}, a \neq b\}$) for each gateway j. The term k represents the index of the pair of SFs, i.e., $k \in 1, 2, ...\binom{|\mathcal{S}|}{2}$).

Thus, the objective function is to minimize the difference of the weighted fraction of nodes assigned to the same SF between each pair of SFs for each gateway. The absolute value in the objective function is linearized as given below.

$$\min \sum_j \sum_{\{a,b\}\in[\mathcal{S}]^2} |w_a f_{ja} - w_b f_{jb}| \tag{7}$$

$$\Leftrightarrow \quad \min \sum_j \sum_k \delta_{jk} \tag{8}$$

$$\text{s.t.} \quad w_a f_{ja} - w_b f_{jb} \leq \delta_{jk} \tag{9}$$

$$w_b f_{jb} - w_a f_{ja} \leq \delta_{jk}. \tag{10}$$

OPT-DELTA is then defined as follows:

$$\min \sum_j \sum_k \delta_{jk} \tag{11a}$$

$$\text{s.t. } w_a f_{ja} - w_b f_{jb} \leq \delta_{jk}, \qquad \forall j, \{a,b\} \in [\mathcal{S}]^2, k \tag{11b}$$

$$w_b f_{jb} - w_a f_{ja} \leq \delta_{jk}, \qquad \forall j, \{a,b\} \in [\mathcal{S}]^2, k \tag{11c}$$

$$P_{max} - PL_{ij} \geq \sum_s \text{tol}_s x_{is} - M(1 - \sum_s y_{ijs}), \quad \forall i, j \tag{11d}$$

$$\sum_s x_{is} = 1, \qquad \forall i \tag{11e}$$

$$f_{js} = \frac{\sum_i y_{ijs}}{|N_j|}, \qquad \forall j, s \tag{11f}$$

$$x_{is} \leq \sum_j y_{ijs}, \qquad \forall i, s \tag{11g}$$

$$\sum_j y_{ijs} \leq |\mathcal{J}| x_{is}, \qquad \forall i, s \tag{11h}$$

$$y_{ijs} \geq x_{is}, \qquad \forall j, s, i \in N_{js} \tag{11i}$$

$$\sum_s s x_{is} \leq \sum_s s x_{i+1,s}, \qquad \forall j, i \in K_j \tag{11j}$$

$$y_{ijs} \in \{0,1\}, \quad x_{is} \in \{0,1\} \tag{11k}$$

$$f_{js} \geq 0. \tag{11l}$$

Equation (11a) minimizes δ_{jk} for every pair of SFs. Equations (11b) and (11c) together represent the absolute difference between the weighted fractional values for each pair of SFs in $[\mathcal{S}]^2$ and for each gateway. The remaining constraints are the same as those described in OPT-MAX, i.e., Eq. (6c)–(6j).

D. Assignment of transmission powers

Next, the TPs for each node have to be assigned once the assignment of SFs is known. To this end, a simple integer linear programming model OPT-TP is proposed. The optimal value of the decision variables (y_{ijs} and x_{is}) from either OPT-MAX or OPT-DELTA determine the SF assigned to a node. We define (y^*_{ijs} and x^*_{is}) as the optimal solution of OPT-MAX or OPT-DELTA; these variables are used to assign the TPs to each node in OPT-TP:

$$\min \sum_p \sum_i u_{ip} c_p \tag{12a}$$

$$\text{s.t. } \sum_p p u_{ip} - PL_{ij} \geq \sum_s \text{tol}_s x^*_{is}, \qquad \forall i, j, s \mid y^*_{ijs} = 1 \tag{12b}$$

$$\sum_{p=1}^{|\mathcal{P}|} u_{ip} = 1, \qquad \forall i \tag{12c}$$

$$u_{ip} \in \{0,1\}. \tag{12d}$$

The objective in Equation (12a) is to minimize the overall energy consumption of all nodes. The term c_p denotes the instantaneous supply current required by a node when transmitting with power level p. The values for c_p in the European region are obtained from [11] and listed in Table III. The decision variable u_{ip} specifies whether node i is assigned TP p. Equation (12b) ensures that node i can reach gateway j with SF s at a given TP p if that node is assigned to that SF for the given gateway (i.e., $y^*_{ijs} = 1$) from OPT-MAX or OPT-DELTA. Equation (12c) ensures that each node is assigned only one TP. Finally, Equation (12d) defines the decision variable u_{ip} as a binary integer variable.

V. Evaluation

A. Methodology and Experimental Setup

The optimization problems OPT-MAX, OPT-DELTA and OPT-TP are solved with IBM ILOG CPLEX (version 12.7.1)

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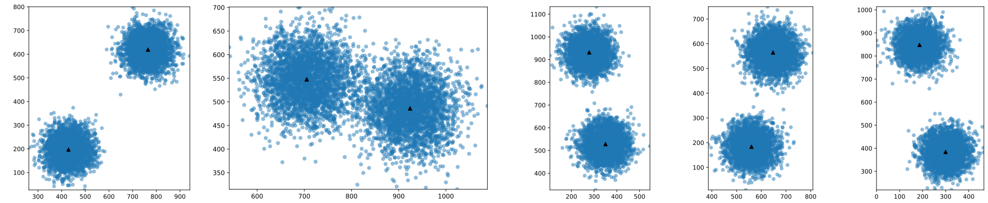
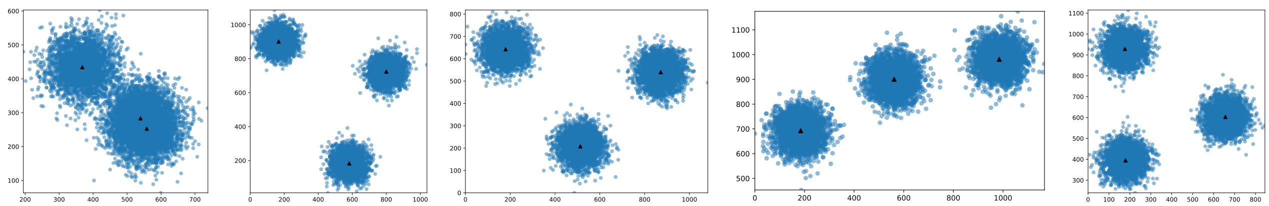


(a) Network 1 (b) Network 2 (c) Network 3 (d) Network 4 (e) Network 5

Fig. 2: Clustered networks with two gateways.



(a) Network 1 (b) Network 2 (c) Network 3 (d) Network 4 (e) Network 5

Fig. 3: Clustered networks with three gateways.

SF s	7	8	9	10	11	12
$\frac{2^{s+1}}{s}$	36.57	64	113.78	204.8	372.36	682.67
w_s	1.06	1.75	3.11	5.6	10.18	18.67

TABLE II: Weights (w_s) for each SF in OPT-DELTA.

TP	2	5	8	11	14
c_p	0.24	0.25	0.25	0.32	0.44

TABLE III: Weights (c_p) for each TP in OPT-TP.

through its Python API on a machine with an Intel Core i5-5300U CPU and 16 GB of RAM. In CPLEX, the absolute gap is set to 0.05 and the time limit to 1 hour. The remaining CPLEX parameters are set to their default values. In the optimization problems, the values for $\mathcal{S}$, $\mathcal{P}$, tol_s and PL_{ij} are the same as used later in the network simulations (Table IV) and M is set to 1,000. We evaluate the efficiency of our formulation in terms of the time taken to solve each target network instance. Each network is configured first with either OPT-MAX or OPT-DELTA to decide SFs and then with OPT-TP to decide the TPs.

Once the optimal configuration is obtained, we evaluate the performance through network simulations. To this end, we use FLoRa [16], an open source software based on OMNeT++, to simulate end-to-end LoRa networks. The simulator includes a realistic model of LoRa transmissions including both co-SF and inter-SF interference [9]. Specifically, transmissions that overlap in time in a single channel can be successfully decoded at the receiver if the *capture effect* occurs, i.e., if the signal to interference ratio (SIR) of the desired signal is above a certain threshold. The threshold for determining whether the capture effect occurs depends on both the SF of the main signal as well as the SF of the interfering transmission. Accordingly, the thresholds for both co-SF and inter-SF interferences are obtained from the SIR matrix [9, 27] in Equation (13). Finally, the successful reception of overlapping transmissions also requires that at least the last 5 preamble symbols of the frame to be decoded remain intact [11].

$$\begin{array}{c c} & \begin{array}{cccccc} SF_7 & SF_8 & SF_9 & SF_{10} & SF_{11} & SF_{12} \end{array} \\ \begin{array}{c} SF_7 \\ SF_8 \\ SF_9 \\ SF_{10} \\ SF_{11} \\ SF_{12} \end{array} & \begin{bmatrix} 1 & -8 & -9 & -9 & -9 & -9 \\ -11 & 1 & -11 & -12 & -13 & -13 \\ -15 & -13 & 1 & -13 & -14 & -15 \\ -19 & -18 & -17 & 1 & -17 & -18 \\ -22 & -22 & -21 & -20 & 1 & -20 \\ -25 & -25 & -25 & -24 & -23 & 1 \end{bmatrix} \end{array} \tag{13}$$

The path loss parameters are obtained from [11] and correspond to a dense urban environment with LoRa devices deployed indoors. We first evaluate our solution in an environment with no variation in path loss by setting the standard deviation σ to 0 in Equation (1), similar to [11, 16, 17, 21]. This allows us to compare our solution to other state-of-the-art algorithms evaluated in such an environment [21]. We then evaluate the performance of our solution in a radio environment with shadowing by setting σ to 3.57, according to measurement results from [11]. Table IV lists the simulation parameters.

We carry out extensive simulations with different types of networks to evaluate the performance of the optimized configuration. The networks consist of LoRa nodes, gateways and a network server. We consider two different classes of networks, described as follows.

1) *Clustered networks*. Such networks are representative of IoT devices densely clustered in “hotspots” such as

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Parameter	Value
Spreading factors ($\mathcal{S}$)	{7, 8, 9, 10, 11, 12}
Transmission powers ($\mathcal{P}$)	{2, 5, 8, 11, 14} dBm
Path loss (PL_{ij})	Eq. (1) with $\overline{PL}(d_0)$ = 127.41, d_0 = 40, n = 2.08, σ = {0, 3.57}
Receiver sensitivity (tol$_s$)	{7: -124, 8: -127, 9: -130, 10: -133, 11: -135, 12: -137} dBm
Carrier frequency	868 MHz
Bandwidth	125 kHz
Coding rate	4/8
Duty cycle	1%
Message size	20 bytes
Message inter-arrival time	Exponential distribution with mean of 1,000 s

TABLE IV: Simulation parameters.

buildings and shopping centers [28]. To this end, the gateways and nodes are deployed using a spatial Poisson Cluster Process [29] following the Thomas Cluster Process. The cluster process consists of a parent Poisson point process that forms the gateway locations and the offspring points (LoRa nodes) spatially distributed around the parent points. Specifically, the gateways are deployed using a parent Poisson point process with density λ set to $3{\cdot}10^{-6}$ m^{-2}. The nodes follow a Gaussian distribution, with an average of 3,000 nodes per gateway and σ set to 50. We consider two configurations (of five instances each) having either (i) *two gateways* (Figure 2), or (ii) *three gateways* (Figure 3). All nodes are within the coverage area of at least one gateway. Each network instance has a different number and layout of nodes clustered around the gateways and different levels of overlap between gateways. The density of the clustered nodes can reach up to 12,000 nodes/km^2.

2) *Smart city network*. We consider a realistic network in Dublin, Ireland wherein LoRa nodes and gateways are placed in a dense urban area. A map of 500 m by 500 m containing the outlines of buildings and roads (Figure 4a) is obtained from OpenStreetMap[3]. Ten sensors are deployed in each building[4] and one sensor is deployed at each public waste bin location[5]. Thus, a total of 5,859 nodes are located in the considered area. The gateways are deployed with a distance of at least 250 m between them and such that all nodes are within the range of at least one gateway. The density of such a network is 23,436 nodes/km^2 which is within the range of estimated densities in dense urban areas. For instance, Li et al. [30] evaluate the average number of LoRa nodes to be 109,460 nodes/km^2, whereas Varsier and Schwoerer [6] estimate a density of 18,000 nodes/km^2 for electricity meters alone.

Each individual simulation run lasts for one day of simulated time, during which each node sends a 20-byte packet[6] at time intervals drawn from an exponential distribution with a mean of 1,000 s (16.7 minutes), similar to [11]. This represents a typical smart metering application wherein measurements are reported infrequently with a small payload up to four times an hour [13–15].

We compare the performance of our solution to the following algorithms.

(a) *Minimum-SF*: This baseline algorithm comprises of two steps. First, a node is assigned the lowest SF required to achieve connectivity to the nearest gateway at the highest TP (14 dBm), similar to [22, 23]. Next, the TP for each node is reduced to the lowest value at which connectivity to the nearest gateway is still possible with the SF from the previous step.

(b) *AD-MAIORA* [21]: The AD-MAIORA algorithm balances the message airtimes of nodes to achieve fairness between the different SFs. AD-MAIORA assumes that initially all nodes are configured with the minimum SF required to reach the nearest gateway. The algorithm then calculates the load on each gateway (in terms of message airtime) for each SF based on the number of nodes using a particular SF. The nodes are then assigned new SFs so as to balance the message airtime at the gateways. To this end, a node is assigned a higher SF if such a change does not increase the maximum message airtime for the gateway(s) in range of the considered node. However, the algorithm does not configure TPs. For a fair comparison, we minimize the TP assigned to each node such that it can still reach a gateway with the assigned SF.

The performance of the considered networks is compared on the basis of the following metrics:

(a) the *delivery ratio*, as the number of messages correctly received by the network server divided by the total number of messages sent by the nodes, expressed as a percentage;

(b) the *energy consumed per successful transmission*, as the total energy (in mJ) used by all LoRa nodes divided by the total number of messages correctly received by the network server;

(c) the *standard deviation* of the delivery ratio achieved by individual nodes, to represent the variation between them, expressed as a percentage. A lower standard deviation indicates a more fair distribution of the delivery ratio between nodes.

B. Comparison with state of the art

1) Clustered networks: Tables V and VI present the results for the clustered networks with two and three gateways respectively. First, we recognize that the optimization problems are able to configure the networks within a reasonable time and faster than AD-MAIORA in most cases. We do not present the time taken to configure networks with the minimum-SF heuristic as this is very small[7]. Next, we observe that the networks configured by OPT-MAX and OPT-DELTA outperform the

[3]https://www.openstreetmap.org

[4]An average of 10 sensors are deployed per house in dense urban areas according to [30].

[5]https://data.smartdublin.ie/dataset/dcc-public-bin-locations

[6]This is in line with an average packet size of 18 bytes reported by [31] in a live LoRaWAN network.

[7]The minimum-SF heuristic only checks whether the distance between a node and nearest gateway falls within a certain range and assigns the SF accordingly.

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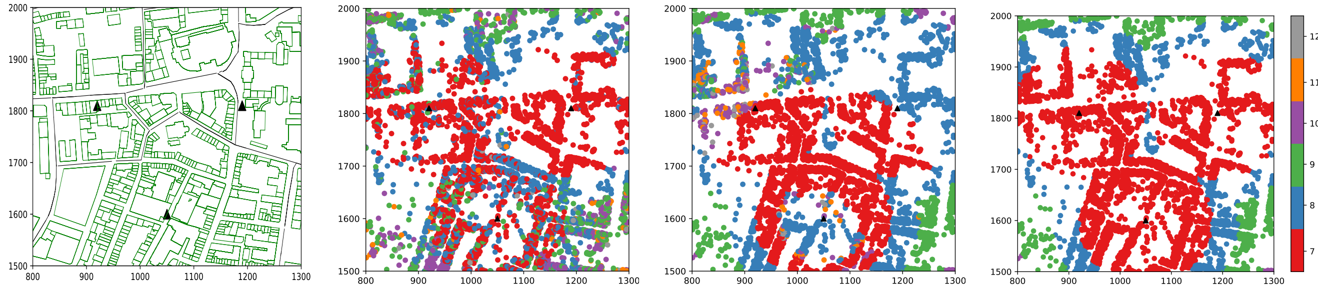


(a) (b) (c) (d)

Fig. 4: (a) Map of the considered area in Dublin, Ireland with the gateways marked as black triangles. Configuration of SFs with different approaches: (b) OPT-DELTA, (c) AD-MAIORA, and (d) minimum-SF in a radio environment with no channel variation.

Method	**Configuration time (s)**	**Delivery ratio (%)**	**Standard deviation (%)**	**Energy consumed (mJ)**
Network 1				
OPT-DELTA	68.50	84.74	7.71	104.12
OPT-MAX	283.20	84.94	7.55	103.19
AD-MAIORA	29.62	73.10	13.54	110.11
minimum-SF	-	76.61	11.93	97.42
Network 2				
OPT-DELTA	1.16	83.14	9.96	104.12
OPT-MAX	1.70	84.40	8.25	99.96
AD-MAIORA	162.78	79.72	11.93	100.09
minimum-SF	-	76.49	12.00	97.83
Network 3				
OPT-DELTA	7.38	84.34	7.96	104.71
OPT-MAX	1.53	84.75	7.57	103.68
AD-MAIORA	357.50	81.25	11.12	112.37
minimum-SF	-	76.44	11.73	98.03
Network 4				
OPT-DELTA	1.15	83.88	8.24	105.23
OPT-MAX	1.37	84.72	7.62	103.52
AD-MAIORA	141.75	78.25	12.42	117.05
minimum-SF	-	76.16	12.02	98.27
Network 5				
OPT-DELTA	16.68	84.82	7.91	104.27
OPT-MAX	20.02	84.88	7.75	103.45
AD-MAIORA	101.43	77.17	12.03	113.27
minimum-SF	-	75.81	12.19	98.61

TABLE V: Summary of results for clustered networks with two gateways.

Method	**Configuration time (s)**	**Delivery ratio (%)**	**Standard deviation (%)**	**Energy consumed (mJ)**
Network 1				
OPT-DELTA	13.23	81.82	12.79	104.39
OPT-MAX	8.84	83.33	11.46	101.88
AD-MAIORA	1067.17	73.64	18.08	114.56
minimum-SF	-	71.65	16.80	105.73
Network 2				
OPT-DELTA	3600.20	82.39	9.13	96.39
OPT-MAX	3600.32	79.94	10.69	96.80
AD-MAIORA	145.74	80.54	10.37	99.11
minimum-SF	-	77.26	11.70	97.29
Network 3				
OPT-DELTA	277.83	85.40	7.52	103.26
OPT-MAX	284.31	85.46	7.35	102.97
AD-MAIORA	556.77	83.77	9.66	104.12
minimum-SF	-	77.08	11.69	97.85
Network 4				
OPT-DELTA	10.44	84.17	8.08	105.17
OPT-MAX	13.68	84.34	7.84	104.73
AD-MAIORA	850.91	81.19	10.56	106.62
minimum-SF	-	77.02	11.64	98.16
Network 5				
OPT-DELTA	244.81	84.04	8.02	105.44
OPT-MAX	463.58	84.93	7.79	104.95
AD-MAIORA	35.38	76.92	11.61	103.08
minimum-SF	-	76.90	11.83	98.17

TABLE VI: Summary of results for clustered networks with three gateways.

other approaches in terms of delivery ratio. The improvement in delivery ratio when compared to the minimum-SF heuristic can be up to 8%. We observe that the improvement in delivery ratio is greater in networks with two gateways than in networks with three gateways. This is because the networks with three gateways consist of many nodes in the coverage area of all three gateways, which can all receive a node's transmission. However, it is important to note that even a 1% improvement in delivery ratio represents 7,722 fewer messages lost per day in networks with three gateways.

The minimum-SF heuristic does not diversify the SFs that can be used and simply assigns the lowest possible SF to the node. This results in a poor network delivery ratio when the number of nodes using the same SF increases. Furthermore, the standard deviation in the delivery ratio achieved by individual nodes is higher when configured with minimum-SF. However, the energy consumption in networks configured by minimum-SF is the lowest because most nodes use the lower SFs. The networks configured by OPT-DELTA and OPT-DELTA outperform AD-MAIORA despite the latter aiming to achieve the same objective. This is partly because AD-MAIORA does not assign SFs to a node based on its distance to the gateway. Thus, in certain networks, the nodes closer to the gateway are assigned a higher SF. Furthermore, several nodes are configured with SF 7, although an improvement can be obtained by moving these nodes to a higher SF. In fact, the performance of AD-MAIORA can sometimes be lower than

Method	Configuration time (s)	Delivery ratio (%)	Standard deviation (%)	Energy consumed (mJ)
OPT-DELTA	7.08	89.20	6.95	102.63
OPT-MAX	3.28	89.31	6.91	103.08
AD-MAIORA	177.18	88.20	7.27	103.73
minimum-SF	-	87.15	7.63	94.63

TABLE VII: Summary of results for smart city network.

minimum-SF (as for network 1 in Table V). Finally, we observe that OPT-MAX does not perform as well as OPT-DELTA in certain networks where a large number of nodes have to use SF 12 to reach a gateway. This is because the objective of OPT-MAX is to minimize the probability of collisions in the SF that performs the worst. As the objective function depends only on this SF, some nodes are not assigned lower SFs. However, this effect is seen only in networks with a large number of nodes requiring SF 12, which does not occur in more realistic networks (discussed later).

Next, we examine the distribution of the delivery ratio for each node in two networks where the delivery ratio is similar when configured by our approach and AD-MAIORA: network 3 from both Table V and Table VI. Figure 5a shows that several nodes achieve a delivery ratio lower than 50% with AD-MAIORA. On the other hand, OPT-MAX and OPT-DELTA ensure that all nodes achieve a delivery ratio of at least 60%. Next, in the network with three gateways, Figure 5b shows that close to 70% of the nodes are able to achieve a better delivery ratio when configured by OPT-DELTA or OPT-MAX. Moreover, the OPT-DELTA configuration allows all nodes to achieve a delivery ratio of 60%, whereas the delivery ratio of some nodes configured by AD-MAIORA drop to below 50%. Thus, OPT-DELTA and OPT-MAX are able to achieve a more fair allocation of SFs to ensure that all nodes reach a gateway with a reasonably high success.

2) Smart city network: Table VII presents a summary of the results for the network in Dublin. The solutions to OPT-MAX and OPT-DELTA are obtained much faster than AD-MAIORA. We observe the overall delivery ratio improves (by about 1% as compared to AD-MAIORA and 2% to minimum-SF) when the network is configured by our solution. This improvement in delivery ratio represents about 9,900 fewer dropped packets in a day[8]. We observe that the improvement in the delivery ratio is lower than in the clustered networks. This is because the minimum-SF and AD-MAIORA heuristics are able to diversify the used SFs due to the spatial configuration of sensors (and buildings). This is unlike the previous scenario where nodes are more densely clustered in hotspots in the city. Figure 4 presents the allocation of SFs with the different approaches. We observe that AD-MAIORA (Figure 4c) diversifies the SFs only in certain sections around the gateways and also assigns some nodes closer to the gateways with higher SFs. Thus, it is not able to achieve the same performance as OPT-DELTA. Next, the energy consumed per successful transmission is similar for OPT-MAX, OPT-DELTA and AD-MAIORA, whereas minimum-SF achieves the lowest energy consumption due to the lower SFs used. Finally, Figure 5c shows the distribution of the delivery ratios for all the nodes in this network when configured by the different approaches. We observe that about 60% of the nodes achieve a better delivery ratio when configured by OPT-MAX or OPT-DELTA as compared to the other approaches. Thus, OPT-MAX and OPT-DELTA are able to ensure that more nodes achieve a high delivery ratio. We also evaluated the same network with higher densities of devices (by increasing the number of sensors per building) and observed a larger improvement in delivery ratio. We do not report these results here as the trends are similar.

[8]Namely, the duration of a simulation run.

Method	Configuration time (s)	Delivery ratio (%)	Standard deviation (%)	Energy consumed (mJ)
Network 1				
OPT-DELTA	742.01	87.08	4.55	110.81
OPT-MAX	427.68	87.09	4.48	110.12
minimum-SF	-	85.45	5.90	106.30
Network 2				
OPT-DELTA	21.02	88.12	4.64	108.17
OPT-MAX	108.54	88.29	4.52	107.17
minimum-SF	-	87.04	5.63	103.53
Network 3				
OPT-DELTA	661.35	87.27	4.54	110.60
OPT-MAX	442.64	87.32	4.43	109.92
minimum-SF	-	85.69	5.98	106.36
Network 4				
OPT-DELTA	1029.24	87.26	4.59	110.43
OPT-MAX	420.93	87.32	4.50	109.76
minimum-SF	-	85.80	5.79	105.66
Network 5				
OPT-DELTA	983.89	86.89	4.55	110.94
OPT-MAX	894.45	86.82	4.50	110.41
minimum-SF	-	85.24	5.99	106.21

TABLE VIII: Summary of results for clustered networks with two gateways in a radio environment with shadowing.

Method	Configuration time (s)	Delivery ratio (%)	Standard deviation (%)	Energy consumed (mJ)
Network 1				
OPT-DELTA	17.92	88.02	6.09	107.89
OPT-MAX	19.36	88.03	5.89	107.17
minimum-SF	-	86.22	7.03	103.39
Network 2				
OPT-DELTA	3600.45	86.98	4.58	111.64
OPT-MAX	1074.97	86.94	4.44	111.18
minimum-SF	-	84.99	6.22	108.02
Network 3				
OPT-DELTA	2710.14	87.08	4.54	112.02
OPT-MAX	700.49	87.07	4.47	111.52
minimum-SF	-	85.06	6.32	108.35
Network 4				
OPT-DELTA	1630.98	87.19	4.48	111.17
OPT-MAX	1529.18	87.25	4.46	110.54
minimum-SF	-	85.33	6.04	106.97
Network 5				
OPT-DELTA	1774.78	86.95	4.62	112.09
OPT-MAX	1157.56	86.92	4.55	111.74
minimum-SF	-	84.84	6.28	108.23

TABLE IX: Summary of results for clustered networks with three gateways in a radio environment with shadowing.

C. Impact of shadowing

Next, we evaluate the performance of OPT-MAX and OPT-DELTA in an environment with shadowing by setting σ to

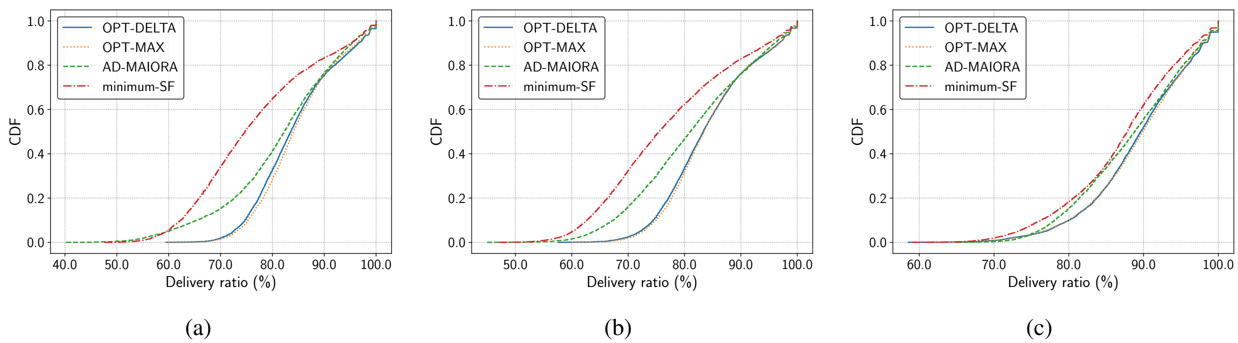


Fig. 5: Distribution of the delivery ratio achieved by each node in (a) clustered network 3 with two gateways, (b) clustered network 3 with three gateways and (c) smart city network.

3.57 in the zero-mean Gaussian distributed variable X_σ in Equation (1). This represents a more realistic environment where transmissions are affected by variations in the radio channel, for instance, due to mobility of obstacles. To this end, we add a parameterized value to constraints (6c), (11d) and (12b) in OPT-MAX, OPT-DELTA and OPT-TP respectively to account for the possible increase in path loss. Specifically, we again optimize for the worst scenario wherein the nodes transmissions' are negatively affected by channel variations by adding -2σ to PL_{ij} in constraints (6c), (11d) and (12b). This is based on the property that 95% of values drawn from a Gaussian distribution ($X_{\mu,\sigma}$) are within $\pm 2\sigma$ of the mean μ. We then evaluate the new SF and TP allocations by carrying out simulations with σ set to 3.57. We compare the performance of our solutions to that of the minimum-SF heuristic, which is also modified to include a margin of -2σ when estimating whether a node can reach a gateway with a particular SF s. We no longer include the AD-MAIORA algorithm as the authors do not describe how their algorithm could be adapted to networks with channel variation.

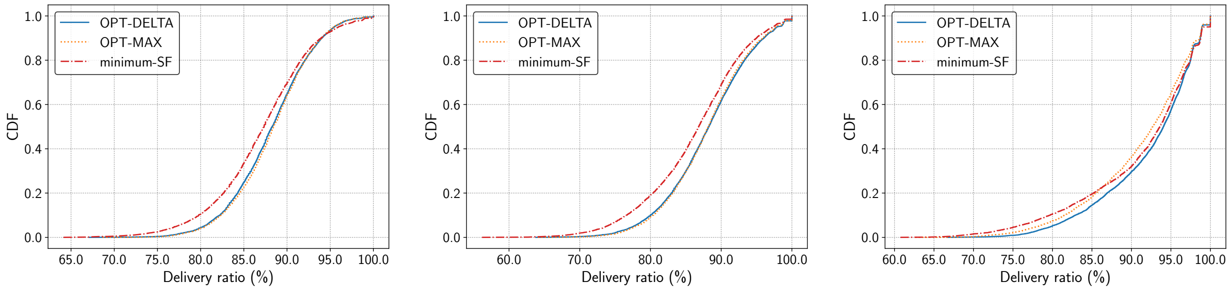
1) Clustered networks: Tables VIII and IX present the results for clustered networks with two and three gateways, respectively. We observe that the delivery ratios achieved by OPT-DELTA and OPT-MAX are still higher that of minimum-SF, although by a smaller margin than before. This is because minimum-SF now under-estimates the number of nodes that can reach a gateway with lower SFs (due to the added margin -2σ) and, thus, assigns more nodes with higher SFs. Thus, it is able to diversify the assigned SFs similar to CPLEX. However, as demonstrated earlier, the minimum-SF approach cannot work when the channel variation is low. On the other hand, OPT-DELTA and OPT-MAX are able to consistently achieve a higher overall delivery ratio even when the channel variation is high. Next, we observe that the overall delivery ratio in all networks with the new allocations are in fact higher than that reported earlier in Tables V and VI. This is due to the fact that optimizing for higher channel variation results in more nodes using higher SFs. For instance, we observe that OPT-DELTA and OPT-MAX assign more nodes to higher SFs, i.e., SFs 10 to 12. Thus, the nodes are able to achieve connectivity by using the higher SFs even when the channel is severely affected by shadowing. However, using the higher SFs comes at the expense of increased energy consumption as the minimum-SF heuristic achieves a slightly lower energy consumption. Finally, we observe that the time taken by OPT-MAX and OPT-DELTA to configure the networks increases as compared to Section V-B. This is because the updated path loss constraints reduce the distances up to which each SF can be used. Such an update results in a more restricted search space; in fact, a solution to the updated model is also a feasible solution to the original problem. Nevertheless, the updated problem requires more exploration to obtain an optimal solution due to the structure of the search space. Even so, we observe that the time taken to reach an optimal solution is within the configured time limit for almost all network instances.

Method	Configuration time (s)	Delivery ratio (%)	Standard deviation (%)	Energy consumed (mJ)
OPT-DELTA	1.86	92.32	6.09	136.77
OPT-MAX	3600.03	91.19	6.59	142.21
minimum-SF	-	91.27	7.48	130.98

TABLE X: Summary of results for smart city network in a radio environment with shadowing.

Finally, we examine the distribution of the individual node's delivery ratio in networks where the delivery ratio is very similar to minimum-SF: clustered network 2 with two gateways (Table VIII) and network 1 with three gateways (Table IX). Figure 6a shows that close to 90% of the nodes configured by OPT-DELTA and OPT-MAX are able to achieve a higher delivery ratio. Similarly, almost all nodes achieve a higher delivery ratio when configured by our solutions in network 1 with three gateways (Figure 6b). Furthermore, several nodes configured by minimum-SF achieve a delivery ratio below 70% in the network with two gateways and below 63% in the network with three gateways. This demonstrates that OPT-DELTA is able to achieve a more fair allocation of SFs by ensuring that all nodes can achieve a high delivery ratio.

2) Smart city network: Finally, we evaluate the performance of the network in Dublin with channel variation in the radio environment. We add an extra gateway in such a network (i.e., for a total of 4 gateways) as several nodes would be unable to reach a gateway when severely affected by shadowing. This



(a) (b) (c)

Fig. 6: Distribution of the delivery ratio achieved by each node in (a) clustered network 2 with two gateways, (b) clustered network 3 with three gateways and (c) smart city network evaluated in a radio environment with shadowing.

was not required in the previous environment without variation as the network was already able to achieve a delivery ratio of close to 90 % with three gateways. Table X presents a summary of the results. Here, we observe that the overall delivery ratio is higher when configured by OPT-DELTA. Again, the difference in the delivery ratio has reduced marginally as compared to the channel without variation (Section V-B). However, the distribution of the delivery ratios (Figure 6c) shows that close to 80% of the nodes achieve a higher delivery ratio when configured by OPT-DELTA. Some nodes in the minimum-SF allocation only achieve a delivery ratio between 60% and 65%. The performance of OPT-MAX drops to that similar to minimum-SF as several nodes need to be configured with SF 12. This is because the objective of OPT-MAX is to reduce the probability of collisions in the worst performing SF, i.e., SF 12. Thus, OPT-MAX stops assigning more nodes to SF 7 when several nodes in the network need to use SF 12 due to the high margin in constraint (6c). On the other hand, OPT-DELTA aims to balance the performance in different SFs.

D. Summary and discussion

The results show that OPT-DELTA and OPT-MAX consistently outperform other approaches by achieving a higher overall delivery ratio. Furthermore, our solutions result in a more fair performance by ensuring all nodes are able to achieve a high delivery ratio. The minimum-SF and AD-MAIORA heuristics come a close second but their performance is dependent on the spatial distribution of nodes and gateways in the network. We demonstrate the strength of our approach under different path loss conditions, i.e., with and without shadowing. On the other hand, minimum-SF and AD-MAIORA exhibit a high delivery ratio only in certain types of networks and environment.

The actual path loss parameters are highly dependent on the environment in which the network is deployed. For instance, we use the path loss parameters in [11] which describe a harsh indoor environment as compared to other measurement studies [16, 32]. It is important that the network operators accurately determine the path loss parameters of the environment where the network is deployed. However, the path loss parameters can change over time [33]. To this end, our proposed solution may also be extended to a dynamic algorithm as OPT-DELTA, OPT-MAX and OPT-TP are tractable and solve even large networks within a short time. The optimization problems may be run as needed (e.g., periodically) at the network server, which has a global view of the network. In particular, the network server may also estimate more accurate or up-to-date path loss parameters (for instance, through linear regression on measured data [33] and recently-proposed remote sensing techniques [32]) and re-run the optimization problems over time. However, in dynamic environments, the optimization problems need to determine the best allocation of SFs and TPs based on an existing configuration. This would also require a constraint for limiting the number of re-configurations so that the network is not flooded with re-configuration messages. We leave the configuration of networks in a dynamic environment to future work.

VI. Conclusion

This article addressed the optimal assignment of spreading factors (SFs) and transmission powers (TPs) to nodes in dense LoRa networks. Specifically, we introduced integer linear programming models to determine the optimal assignment of the parameters by taking into account the spatial configuration of nodes and the effect of other nodes' transmissions. The optimization is split into two stages: first, the SF is optimized to ensure reliable communications in the network; second, the TP is optimized to minimize the energy consumption in the network. Our solutions were evaluated through extensive simulations with different types of networks and compared to state-of-the-art algorithms. We also evaluated our solutions in different shadowing environments. The obtained results show that the optimized configuration performs consistently well, achieving a higher delivery ratio and a minimal energy consumption across different scenarios. The obtained configuration is able to ensure that a large percentage of nodes is able to communicate reliably with a high delivery ratio, thereby guaranteeing a fair allocation of radio resources to the nodes. The solutions to the optimization problems were obtained within a short time, and faster than the state of the art in almost all cases. Hence, our solution can be used by service providers to determine the optimal configuration of the LoRa parameters. As future work, we plan on extending the optimization problems to include the dynamic re-configuration of the LoRa parameters.

VII. Acknowledgments

This work was partially supported by the Academy of Finland under grants number 299222 and 319710 as well as the Polish National Center for Research and Development under grant number POIR.04.01.04-00-0005/17. Bissan Ghaddar was supported by NSERC Discovery Grant 2017-04185. We would like to thank the CSC – IT Center for Science for provisioning the computational resources used in the evaluation.

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