A novel experimental-based tool for the design of LoRa networks

Susanna Spinsante*, Luca Gioacchini†, Lorenzo Scalise‡
*Dept. of Information Engineering
Polytechnic University of Marche, Ancona, Italy 60131
Email: s.spinsante@staff.univpm.it
†Dept. of Electronics and Telecommunications
Polytechnic of Turin, Torino, Italy 10129
Email: s257076@studenti.polito.it
‡Dept. of Industrial Engineering and Mathematical Sciences
Polytechnic University of Marche, Ancona, Italy 60131
Email: l.scalise@staff.univpm.it

***Abstract*—The use of Long Range (LoRa) technology in Internet of Things (IoT) deployments is exponentially increasing, as it allows to form one-hop networks linking tiny nodes to one (or more) gateways and ensuring a low power consumption. In dense networks, predicting the number of supported nodes in relation to their position and the propagation environment is essential to ensure a reliable and stable communication and limit costs. In this paper, after comparing different path loss models based on a field measurement campaign of LoRa Received Signal Strength Indicator (RSSI) values within our University campus, we implement two main modifications to the LoRa Simulator tool, in order to improve its accuracy in the prediction of the number of sustainable nodes, according to the target Data Extraction Rate. By an improved path loss evaluation, and using three gateways, the number of nodes could increase theoretically from about 100 to about 6000. Future work includes the possibility to validate the accuracy of the tool, by designing a dense network operating in real conditions (i.e. large industrial plant, small/medium size city area) and testing its performances.**

***Index Terms*—LoRa, scalability, LoRaSim, RSSI measurements, data extraction rate.**

I. Introduction

Industry 4.0 encompasses several key technological components and substantiates in the so-called smart factory, where computer-driven systems monitor physical processes, create a virtual copy of the physical world and make decentralised decisions based on self-organisation mechanisms. The Internet of Things (IoT) is considered an essential element of Industry 4.0, providing the connection of the different sub-systems and enabling both human-to-machine and machine-to-machine communications. As such, large-scale IoT deployments are expected to become widespread, not only within smart industrial plants, but also in similar scenarios, like multi-site production districts [1], smart construction sites and even mines [2].

Among the communication technologies enabling IoT, Low Power Wide Area Networks (LPWANs) are established as a good trade-off between performance and deployment costs [3]. In fact, widely distributed sensor networks relying on 3G/4G cellular infrastructures benefit from reserved frequencies (thus being free from interferences), network-based synchronization and a pervasive and reliable connectivity, but are associated with prohibitively high costs in the case of dense networks. On the other hand, LPWANs, such as the Long Range one (known as LoRa) [4], provide license-free long-range communication (possibly prone to interferences) with low power demand (essential for IoT sensors), but may need a dense deployment of gateways (GWs) to ensure adequate data transfer performance and limit data losses. In [5], the capability of low-cost LoRa transceivers to schedule the transmission of frames with a standard uncertainty less than 3 μs, and an acceptable long-term clock stability for applications such as process industry have been proved. LoRa is based on the Chirp Spread Spectrum (CSS) modulation technique, with sinusoidal signals whose frequency changes over the transmission time (chirp signals). This provides inherent robustness to interference, allowing the coexistence of several active nodes within the same frequency channel; the communication is robust even in the presence of high noise levels [6].

When the sensor network to be deployed needs to include a huge number of tiny devices, as it may happen in industrial or construction processes monitoring, the possibility to accurately predict the attainable Data Extraction Rate (DER) before setting up the real network may be critical. DER is the key criterion used to evaluate the scalability of a network: it is defined as the ratio of received messages to transmitted messages over a period of time. DER depends on position, number and behavior of nodes and sinks, and takes values between 0 and 1. In a perfect deployment, DER = 1. Once estimated, the predicted DER value can be checked against specific requirements, and, if the check fails, the network design can be modified (for example adopting a specific topology, as in [7]) before carrying out the final deployment, thus avoiding additional costs and delays associated to repeated test installations and failures.

In this paper, moving from [8] and the LoRaSim simulation tool presented in [9], we implement some modifications, based on real measurements, aimed at improving the capability of the tool to predict the scalability performance of LoRa networks. Such modifications enable a more realistic modelling of the propagation losses and positioning of the nodes, to determine in a more accurate fashion the number of nodes that allows acceptably reliable and stable communications, and the network configuration that better adapts to different propagation scenarios.

The paper is organized as follows: in Section II, the original LoRaSim tool and the applied changes are briefly introduced. Section III describes the experimental tests performed and the results obtained. Section IV concludes the paper.

II. The LoRa Simulator and Applied Modifications

LoRaSim, a discrete-event simulator based on SimPy, is implemented according to the technical specification of the SX1272 LoRa module provided by Semtech [10]. The software operations also apply to later modules, like the recent SX1276 that features additional frequency bands of operation (169 MHz and 433 MHz, in addition to the 850 MHz - 1 GHz already supported by SX1272), more options for the programmable bandwidth, and a better receiver sensitivity (down to -148 dB$_m$ versus -137 dB$_m$ of the SX1272 module).

The software tool can be used to model the communications between randomly placed nodes and GWs, the number of which can be selected by the user. One of the tool's main features is the possibility to choose different configurations of the LoRa module, by a combination of settings such as transmission power (*TP*), carrier frequency (*CF*), spreading factor (*SF*), bandwidth (*BW*) and coding rate (*CR*). For each data transmission occurring over a node-to-GW link, LoRaSim estimates the path loss using an embedded model, and simulates collisions among data packets in terms of signal power (through the so-called *capture effect*), carrier frequency, spreading factor and received power. In order to obtain a more realistic evaluation of the network scalability, first of all we implemented additional path loss models to let LoRaSim adapt to different environmental scenarios. Then, a function enabling the insertion of nodes and GW positions from a file has been added, to analyze how DER performance changes, with respect to the default random node positioning assumption.

A. Path loss models

A path loss model is an equation describing the decrease of signal power density due to its propagation, in different environments. We focused on three main models, those that reasonably apply to the scenarios mentioned in Section I and that are valid in the frequency range used by LoRa.

1) Log-Distance: According to [8], the log-distance path loss model refers to built-up and densely populated areas. It expresses the signal attenuation as a function of the distance d between node and GW (given in km):

$$Pl(d) = \bar{P}l(d_0) + 10\gamma \log(\frac{d}{d_0}) + X_\sigma \tag{1}$$

where $Pl(d)$ is the path loss in dB, $\bar{P}l(d_0)$ is the mean path loss at the reference distance d_0, γ is the path loss exponent and $X_\sigma \sim N(0, \sigma^2)$ is the normal distribution with zero mean and σ^2 variance, to account for shadowing.

2) Okumura-Hata: The main enhancement introduced by the Okumura-Hata model [11] is the dependence of the path loss on the carrier frequency which characterizes the transmission, and on the terminals' (node and GW) height. This way, we can model in more details a wider range of nodes' distribution, accounting also for the height of the antennas, in four different scenarios:

$$Pl(d) = A + B\log(d) + C \tag{2}$$

where A, B and C are frequency- and antenna height-dependent terms. Factor A increases with carrier frequency and decreases with increasing height of the GW and the node. Also, the path loss exponent (proportional to B) decreases with increasing height of the GW: $A = 69.55 + 26.16\log(f_c) - 13.82\log(h_b) - a(h_m)$, and $B = 44.9 - 13.82\log(h_b)$ being f_c the carrier frequency in MHz, d the distance between node and GW in km, h_b and h_m the GW and node height, respectively, in m. The model is only intended for large areas, with the GW placed higher than the surrounding rooftops. Values assigned to the different terms have been obtained by interpolating the results of extensive measurement campaigns carried out in propagation scenarios corresponding to the model requirements (see [11], Appendix 7.A). Different expressions of the term C and the $a(h_m)$ function refer to four different scenarios or propagation environments:

- Small and medium size cities:

$$\begin{gathered} a(h_m) = (1.1\log(f_c) - 0.7)h_m - (1.56\log(f_c) - 0.8) \\ C = 0 \end{gathered} \tag{3}$$

- Metropolitan areas:

$$\begin{gathered} a(h_m) = \begin{cases} 8.29(\log(1.54h_m))^2 - 1.1; & f_c \leq 200\text{MHz} \\ 3.2(\log(11.75h_m))^2 - 4.97; & f_c \geq 400\text{MHz} \end{cases} \\ C = 0 \end{gathered} \tag{4}$$

- Suburban environments:

$$C = -2[\log(\frac{f_c}{28})]^2 - 5.4 \tag{5}$$

- Rural areas:

$$C = -4.78[\log(f_c)]^2 + 18.33\log(f_c) - 40.98 \tag{6}$$

The function $a(h_m)$ in suburban and rural areas is the same as for urban (small and medium-sized cities) areas.

3) 3GPP: Both 3GPP and 3GPP2 developed a path loss model to evaluate the performance of cellular systems. Here again, the equation considers the carrier frequency and antennas' height:

$$\begin{gathered} P_l = (44.9 - 6.55\log(h_b))\log(d) + 45.5 + (35.46 - 1.1h_m)\cdot \\ \cdot\log(f_c) - 13.82\log(h_m) + 0.7h_m + C \end{gathered} \tag{7}$$

where h_b and h_m are the base station (GW) and mobile station (node) antennas' height, respectively. The distance d

is expressed in m in contrast to the previous two models. According to the value of the constant term C, a suburban macrocell system (C = 0 dB) or a urban macrocell one (C = 3 dB) is assumed. These models have been implemented in LoRaSim, starting with the Log-Distance one, as the following lines show:

```
#Log-Distance Model
Pl = Pld0+10*gamma*math.log10(distance/d0)
```

The variables used in the code have the same meaning as those in Eq. (1). The `distance` variable represents the distance between the GW and each node: considering that models *2)* and *3)* include the antennas' height, turning the 2D spatial representation of the Log-Distance model into a 3D one, we changed the variable definition by applying the Pythagorean theorem.

The following lines are used to implement the Okumura-Hata and the 3GPP models, respectively. The user can select them through a simple **`if...elif`** control that here we left out for convenience.

```
#Okumura-Hata Model
#small and medium-size cities
ahm = (1.1*(math.log10(self.freq)-math.log10
    (10**6))-0.7)*hm-(1.56*(math.log10(self.
    freq)-math.log10(10**6))-0.8)
C = 0
#metropolitan areas
if (self.freq <= 2*10**8):
   ahm = 8.29*((math.log10(1.54*hm))**2)-1.1
elif (self.freq >= 4*10**8):
   ahm = 3.2*((math.log10(11.75*hm))**2)-4.97
C = 0
#suburban enviroments
ahm = (1.1*(math.log10(self.freq)-math.log10
    (10**6))-0.7)*hm-(1.56*(math.log10(self.
    freq)-math.log10(10**6))-0.8)
C = -2*((math.log10(self.freq)-math.log10
    (2.8*10**7))**2) - 5.4
#rural area
ahm = (1.1*(math.log10(self.freq)-math.log10
    (10**6))-0.7)*hm-(1.56*(math.log10(self.
    freq)-math.log10(10**6))-0.8)
C = -4.78*((math.log10(self.freq)-math.log10
    (10*6))**2)+18.33*(math.log10(self.freq)-
    math.log10(10*6))-40.98

A = 69.55+26.16*(math.log10(self.freq)-math.
    log10(10**6))-13.82*math.log(hb)-ahm
B = 44.9-6.55*math.log10(hb)

#3GPP Model
#suburban Macro
C = 0
#urban Macro
C = 3
```

where `self.freq` is the carrier frequency, `hb` and `hm` are the base station (GW) and node height, respectively. All the equations are the same of Section II-A. The result of the path loss computation is passed to the `Pl` variable by the following line of code for the Okumura-Hata model:

TABLE I
CONFIGURATIONS SETTINGS

Parameter	SN_1	SN_5
Transmission Power (dBm)	14	14
Carrier Frequency (MHz)	860	860
Spreading Factor	12	best of 7-12
Bandwidth (kHz)	125	best of 125/250/500
Coding Rate	4/8	4/5

```
Pl = A+B*(math.log10(distance)-math.log10
    (1000))+C
```

and by the following one for the 3GPP model:

```
Pl = (44.9-6.55*math.log10(hb))*math.log10(
    distance/1000)+45.5+(35.46-1.1*hm)*(math.
    log10(self.freq)-math.log10(10**6))-13.82*
    math.log10(hm)+0.7*hm+C
```

B. Nodes placement

The second relevant change applied to the LoRaSim tool enables to specify the placement of nodes. In fact, the original tool only allows a random distribution of nodes, according to which the GW is positioned at the center of a circular area, and the nodes are randomly placed inside it, based on a simplified Poisson Point Process (PPP) [12]. We modified the simulator to feed it with the positions of *hot spots* recorded as GPS coordinates in a file. Then, in order to account for possible misplacements of the LoRa nodes around these hot spots (due for example to physical obstacles or constraints met during the installation), each hot spot is assumed as the center of a circular area in which an evenly distributed number of nodes is randomly placed, with a minimum distance between nodes equal to 10 m and their height between 1 m and 2 m.

III. Experimental Results

A. Measurements campaign

Before adding the different path loss models into the LoRaSim software tool, an extensive measurements campaign aimed at evaluating the validity of the models has been carried out within our University campus. LoRa RSSI measurement values (in dBm) were collected over 1-hour long intervals at each position, and GPS-referenced, by using a transmission module (LoRa node) based on the Adafruit Feather M0 with RFM95 LoRa Radio - 900 MHz, equipped with a GPS receiver (ITEAD RoyalTek REB-4216/REB-5216 GPS Shield Breakout Board For Arduino MEGA) and connected to a laptop, as shown in Fig. 1. The multi-channel LoRa GW located on top the campus tower was implemented by using a Raspberry Pi and an iC880A board, that integrates two Semtech SX1257 transceivers and an SX1301 baseband processor, thus allowing to simultaneously receive up to 8 LoRa packets transmitted with different SF values, and on different channels.

As shown in Fig. 2, the single GW was positioned on top the highest tower in the campus (200 m a.s.l.), and 37 different outdoor measurement positions were planned, moving approximately along eight different directions, at a

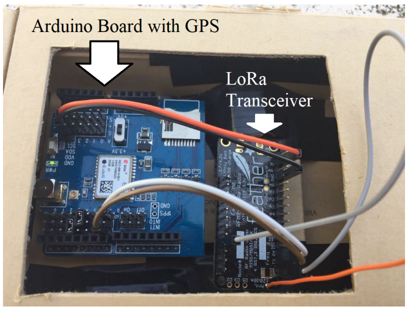

Fig. 1. The hardware used to implement the LoRa node equipped with a GPS receiver.

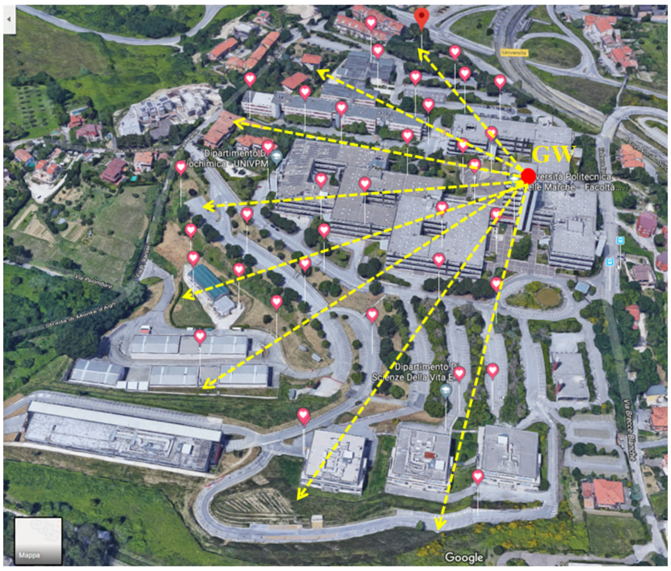

Fig. 2. The 37 planned LoRa RSSI measurement positions within the University campus.

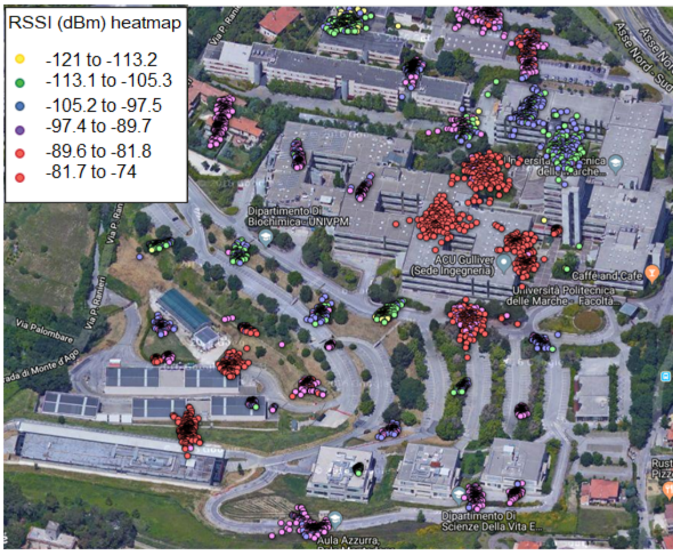

Fig. 3. GPS-referenced LoRa RSSI measurements in the real positions chosen.

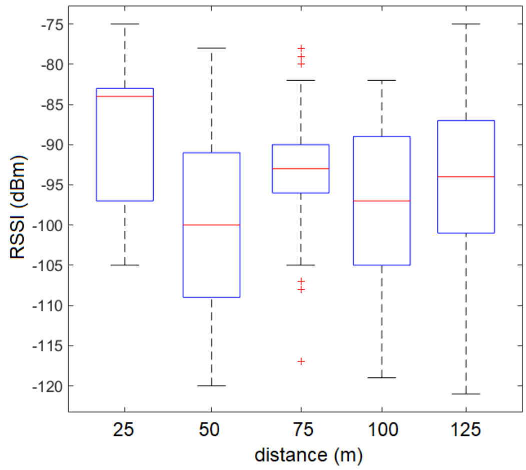

Fig. 4. LoRa RSSI measurements at different distances from the GW.

distance of 25 m, 50 m, 75 m, 100 m, and 125 m from the tower where the GW was positioned, along each direction, and collecting more than 7000 measures in total. The measurement positions identified in this preliminary step, based on the observation of the University campus planimetry, were respected as much as possible during the measurement campaign. When the identified measurement position fell indoor, the nearest possible outdoor position was actually chosen to collect the RSSI measurement values, because we were interested in checking the signal power distribution in outdoor conditions and referencing each measurement by GPS coordinates.

Fig. 3 shows in a pictorial fashion the distribution of RSSI values measured at each real position, encoded by colored dot clouds of different gradations, and associated to their GPS coordinates. It is necessary to point out that the LoRa node was kept fixed at each position during the 1-hour long collection of measurements, but the resulting GPS coordinates provided by the onboard receiver fluctuate around such a position, due to the GPS module horizontal position accuracy of 2.5 m [13].

The positions located in Line-of-Sight (LoS) to the GW experience the highest RSSI values (violet to red dots, from -97.4 dBm to -74 dBm) even if at a longer distance. Conversely, positions located near to the GW, but obstructed by buildings (yellow to light green dots, from -121 dBm to -97.5 dBm), may exhibit the lowest RSSI values. This is further evidenced by the box plots in Fig. 4 where the measured RSSI values are grouped based on the distance from the GW, so irrespective from the direction along which the measurement position is located. It is possible to see that the median RSSI (horizontal red line inside each box) does not always decrease with increasing distance, because of the propagation effects due to buildings and other surrounding obstacles.

Based on the experimental RSSI measurements carried out, the 3GPP path loss models (urban and suburban), and the Okumura-Hata suburban one provided the best approximation to predict the propagation behavior of the LoRa signals within the campus.

B. Simulations with modified LoRaSim

The LoRaSim tool considers N LoRa end-nodes and M GWs, each of them featuring specific configurations of *TP*, *CF*, *SF*, *BW* and *CR* parameters. Together with the average rate of transmitted packets (λ) and the packet load (B), these parameters identify a so-called network setting $SN = \{TP, CF, SF, BW, CR, \lambda, B\}$. Following the modifications to the LoRaSim tool, a first simulation campaign aimed at evaluating how the network DER is affected by the selection of the path loss model. For a better comparison with previous studies we used the same settings chosen in [8], thus assuming: $N = 1000$, each LoRa node is able to send a packet of 20 bytes every 16.7 minutes to a single GW ($M = 1$), and the simulated transmission time is 1 hour. The signal carrier frequency is 860 MHz. For each path loss model, 100 simulation runs have been executed.

Path losses and collisions determine the communication behavior of LoRa nodes. In LoRaSim, the so-called *Simple Model* (*S.M.*) variant assumes an infinite communication range, and collisions happening whenever any two transmissions overlap in time at the receiver with the same *CF*, *SF* and *BW*, thus making both the transmissions lost. The $S.M.$ variant allows to establish a baseline which can be analytically described.

In a first experiment, the SN_1 parameters' configuration detailed in Table I was considered, but in two different simulation settings: the former, named SN_1^{PL} assumes the combination of selectable parameters which allows the strongest transmission (i.e. the most robust to channel quality degradation), with the longest possible airtime of 1712.13 ms (*SF* = 12), the selection of different path loss models, and collisions as defined above. The latter, named SN_1 $S.M.$, assumes the same node configuration of the *S.M.* variant, but with a fixed Log-Distance path loss model (default one).

The mean DER value obtained for N = 1000 nodes randomly placed around a single GW was evaluated. As visible in Fig. 5, the $S.M.$ variant provides DER values always smaller than 4%, due to the underestimation of the communication channel, making a good packets reception very improbable. On the other hand, the results of the SN_1^{PL} configuration show a dependence on the path loss model used. The Okumura-Hata model, which considers different terrains, provides the highest DER in the rural scenario (as expected), but still very low (around 12%).

Fig. 6 shows the expected mean DER trend with increasing number of nodes, for different path loss models. In line with the previous experiment, the generic SN_1 $S.M.$ configuration provides the lowest chances of receiving packets, while the configuration incorporating the 3GPP model is the most beneficial one. Assuming a DER ≥ 0.8 as an acceptable value for a realistic deployment, while the Log-Distance model predicts a number of 64 nodes supported, the other two models foresee about 100 nodes.

According to Section II-B, we then modeled a more realistic LoRa deployment by placing nodes in the same GPS-

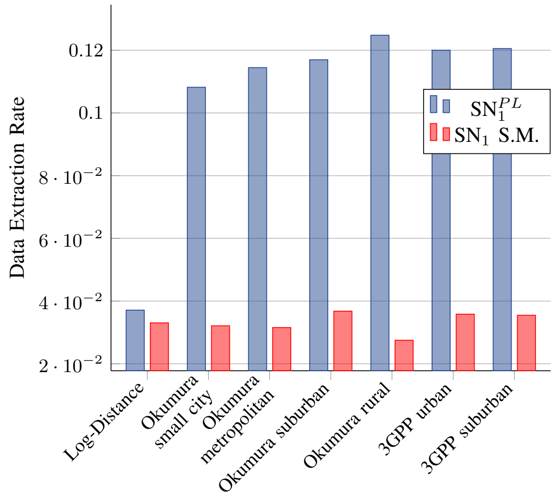

Fig. 5. Comparison of DER results obtained by setting different path loss models, in the two configurations SN_1 $S.M.$ and SN_1^{PL}, for N = 1000.

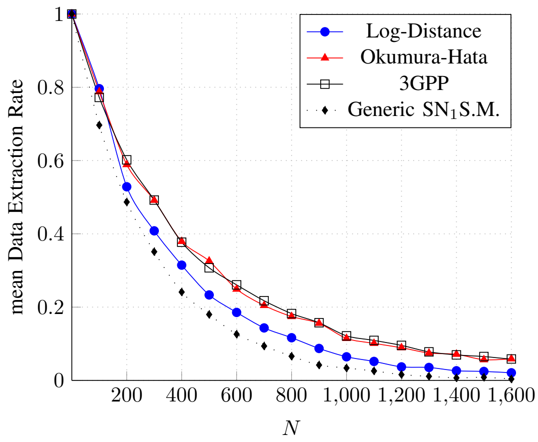

Fig. 6. Comparison of mean DER results obtained by setting different path loss models, for an increasing number of nodes.

referenced positions used for field RSSI measurements (hot spots). Given the poor DER results obtained from the simulations discussed above, and in order to increase the number of nodes supported by the network, we assumed a scenario including 3 GWs, one located on top the highest tower (as for the measurements campaign), and two additional GWs, both at 150 m a.s.l.. The new scenario is shown in Fig. 7.

We first tested the SN_1 configuration, comparing the DER results provided by the random positioning of the nodes (deafult option in LoRaSim), and the GPS-based positioning, in the two cases of 1 GW and 3 GWs serving the network. From Fig. 8 it is clear that with the GPS-based node placing method and 1 GW, a 34.6% increase of mean DER is obtainable, from about 0.11 to about 0.148. The network performances are further improved by using 3 GWs. This way (GPS-3GW) we can obtain a 91.94% increase of the DER compared to a single gateway (GPS-1GW), and a global 158.4% increase compared to the random placement method (Random-1GW),

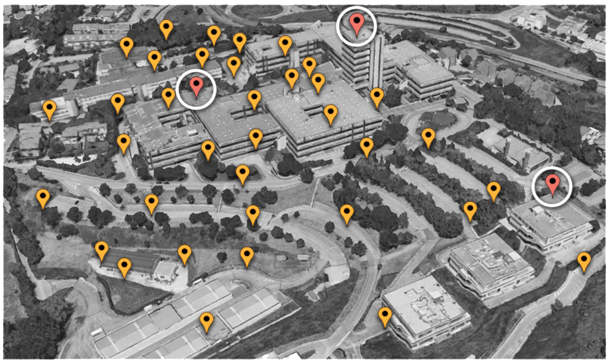

Fig. 7. The simulated scenario with 3 GWs located in the campus area: hot spots (yellow markers) and GWs (white circled red markers) placement.

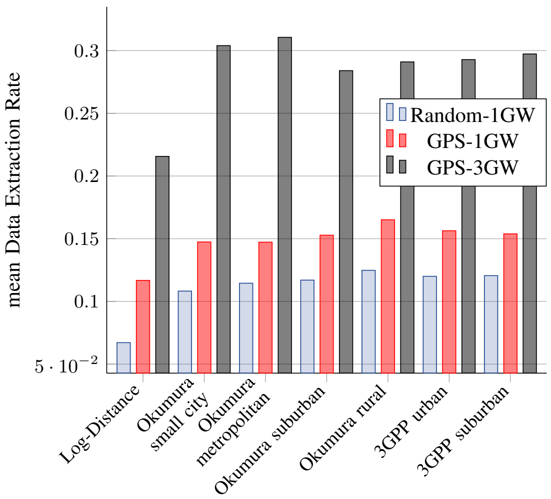

Fig. 8. Comparison of mean DER results obtained with different nodes placing methods, in the SN_1 configuration.

thus increasing the mean DER value from 0.11 to 0.285. The use of the GPS-based location of the nodes improves the simulated performance as it allows to fully exploit the results of the field RSSI measurements campaign, with a realistic distribution of the received signal power described by the propagation model used.

The last simulated configuration, named SN_5 in Table I, relies on dynamic parameters and allows to minimize both airtime and *TP*. As shown in Table II, this is the best choice to ensure a high reception rate, since the mean DER ranges between 0.97 and 0.99: from simulations, a DER $\geq$ 0.8 is obtainable with up to 6000 nodes deployed.

TABLE II
DER RESULTS FOR A 3 GWS DEPLOYMENT

Model	$SN_1 S.M.$	SN_1	SN_5
Log-Distance	0.07	0.21	0.97
Okum. small city, metropolitan	0.03	0.31	0.99
Okum. suburban	0.04	0.28	0.99
Okum. rural	0.03	0.29	0.98
3GPP urban, suburban	0.03	0.29	0.99

IV. CONCLUSION

In this paper, we presented two effective modifications to the LoRa simulator, aimed at improving the accuracy of the software tool in predicting the number of nodes that can be sustained by a dense LoRa network, given a target mean DER. The applied modifications consist of introducing the possibility of testing different path loss models, previously verified through an extensive field measurements campaign of LoRa RSSI values, and providing a GPS-based positioning of the nodes, instead of a random one, as natively available within the simulator. While the default *Simple Model* configuration tends to underestimate the link quality, the 3GPP path loss models are the most beneficial ones, allowing to place about 100 nodes in a metropolitan area, contrary to the 64 nodes supported by the deafult Log-Distance model. The Okumura-Hata model introduces an 83% increase of DER, compared to the Log-Distance one, in rural scenarios. The GPS-based location of nodes allows to simulate a more realistic network deployment that optimizes the estimation of the mean DER. This way, regardless of the path loss model applied, a 34.6% increase of the mean DER has been obtained. Future activities foresee the deployment of an adequate number of nodes to measure the simulator performance, and the introduction of additional capabilities, like accounting for imperfect orthogonality among nodes' transmissions.

REFERENCES

[1] C. Liu, S. Yan, and T. Lai, "The establishment of an integrated automation production line with multiple monitoring and control loops," in *2018 IEEE International Conference on Applied System Invention (ICASI)*, April 2018, pp. 968–971.

[2] H. Geng, *Modernizing the mining industry with the Internet of Things*. Wiley, 2017.

[3] G. Margelis, R. Piechocki, D. Kaleshi, and P. Thomas, "Low throughput networks for the IoT: Lessons learned from industrial implementations," in *2015 IEEE 2nd WF-IoT*, Dec 2015, pp. 181–186.

[4] LoRa Alliance. (2019) LoRa Alliance Website. [Online]. Available: https://lora-alliance.org/about-lorawan

[5] M. Rizzi, P. Ferrari, A. Flammini, and E. Sisinni, "Evaluation of the IoT LoRaWAN solution for distributed measurement applications," *IEEE Trans. Instr. & Meas.*, vol. 66, no. 12, pp. 3340–3349, Dec 2017.

[6] L. Angrisani, P. Arpaia, F. Bonavolontà, M. Conti, and A. Liccardo, "LoRa protocol performance assessment in critical noise conditions," in *2017 IEEE 3rd International Forum on Research and Technologies for Society and Industry (RTSI)*, Sep. 2017, pp. 1–5.

[7] H. Lee and K. Ke, "Monitoring of Large-Area IoT Sensors Using a LoRa Wireless Mesh Network System: Design and Evaluation," *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 9, pp. 2177–2187, Sep. 2018.

[8] M. C. Bor, U. Roedig, T. Voigt, and J. M. Alonso, "Do LoRa Low-Power Wide-Area Networks Scale?" in *Proceedings of 19th ACM MSWiM*. New York, NY, USA: ACM, 2016, pp. 59–67.

[9] University of Lancaster. (2019) LoRa Sim. [Online]. Available: https://www.lancaster.ac.uk/scc/sites/lora/lorasim.html

[10] Semtech, "SX 1272/3/6/7/8: LoRa Modem, Semtech, Designer's Guide," Tech. Rep. AN1200.13, rev 1, July 2013.

[11] A. Molisch, *Wireless Communications*. Wiley-IEEE Press, 2005.

[12] O. Georgiou and U. Raza, "Low Power Wide Area Network Analysis: Can LoRa Scale?" *IEEE Wireless Communications Letters*, vol. 6, no. 2, pp. 162–165, April 2017.

[13] U-Blox.com. (2019) NEO-6u-blox 6 GPS Modules Data Sheet. [Online]. Available: http://www.u-blox.com/images/downloads/Product_Docs/NEO-6_DataSheet_(GPS.G6-HW-09005).pdf