Cognitive-LoRa: Adaptation-Aware of the Physical Layer in LoRa-Based Networks

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***Abstract*—Network technologies for large areas based on sub-GHz have emerged as a way to provide long-range communication with low cost and complexity. Among the various existing solutions, LoRa is arguably the most adopted and promising in this context. Its main application has been allowing the possibility of ubiquitous connectivity to IoT from a simple network and management structure. Some factors must be taken into account when proposing a LoRa network. The type of application directly affects the LoRa network communication, such as the center frequency, the spreading factor, the bandwidth, and the coding rates chosen by each node. We will observe in this work the characteristics of LoRa physical-layer and its automatic configuration based on the quality of the perceived signal-to-noise ratio (SNR). In this way, we propose an adaptable protocol for LoRa networks with low overhead and complexity. The results obtained by a real scenario show that only 23% of the observation time make changes in the configuration and has an average gain of 4.68% for SNR.**

***Index Terms*—LoRa, Wireless Cognitive Radio, Signal-to-Noise Ratio, IoT, Sub-GHz.**

I. Introduction

Support for communication technologies over long distances has aroused interest in the most diverse areas. From smart cities to Industry 4.0, they are adopting new technologies to help to solve their challenges. Some solution examples are health monitoring, safety monitoring, and intelligent transport systems (ITS - Intelligent Transport System) [1]. These services are linked to a growing concept, the Internet of Things (IoT) [1], [2]. The number of IoT devices connected by these technologies is expected to grow by 10 billion from 2015 to 2021 [2]–[5]. To connect these devices in large geographic areas, we have long-range networks (LoRa) and its protocol, LoRaWAN [1], [6]. LoRa is responsible for communication at the physical-layer level in this environment. Although it supports the open LoRaWAN protocol, this layer is like a black box. Thus, understanding the LoRa operation and applying its improvements is essential to adopt it.

This paper is proposing the use of a cognitive way to change/shift the frequency range and parameters of the LoRa modulation for wireless signal resilience over long distances. With a simple spectral analysis technique and adjustment of the LoRa configuration on the devices, it is possible to gain in signal quality and, consequently, in the network throughput. As a result, LoRa solutions tend to become easier to apply in the real world.

Based on the observation of the signal-to-noise ratio (SNR) of the nodes connected to the LoRa network, an adaptation algorithm in the physical-layer is proposed. The gains are, on average, 4.68% concerning the SNR, generating only 23% of shifts of configuration for 24 hours. The algorithm is efficient and straightforward to aware the LoRa network. In comparison to state-of-the-art, this work presents the first cognitive algorithm with adaptation-aware based on SNR in the physical-layer of LoRa-based networks.

The remainder of this paper is structured as follows: section II introduces the main concepts to understand the LoRa modulation; section III shows the related work comparing with our proposal; section IV introduces the adaptative algorithm for LoRa in two different frequencies; section V shows and discuss the results obtained on a real scenario; concluding this paper with section VI.

II. Overview of LoRa

The LoRa is a digital modulation scheme based on the spectral spreading technique called CSS (Chirp Spread Spectrum) to transmit messages, giving high communication rates for range and energy consumption. Another benefit of this modulation is the resistance to Doppler and multi-path effects. Its modulation consists of the representation of bits 0 and 1 as a linear variation of frequencies. Figure 1 contains a representation of bits 0 and 1, the corresponding symbol for each bit, and a representation of the frequency variation of the symbol. The shift rate of frequency is controlled by a parameter called SF (Spread Factor). The higher this value, the better is the signal's immunity against noise, and the lower is the data transmission capacity of the link.

$$C = B \times \log_2\left(1 + \frac{S}{N}\right) \rightarrow \frac{S}{N} \approx \frac{C}{B} \qquad (1)$$

The left of the equation 1 is the Shannon-Hartley theorem which represents a relationship between the communication capacity C expressed in $bits/s$ as a function of the bandwidth B (Hz) and the strengths of the signal S (mW) and noise N (mW). Simplifying the theorem, we have the equation on the right side, which shows that the higher the signal

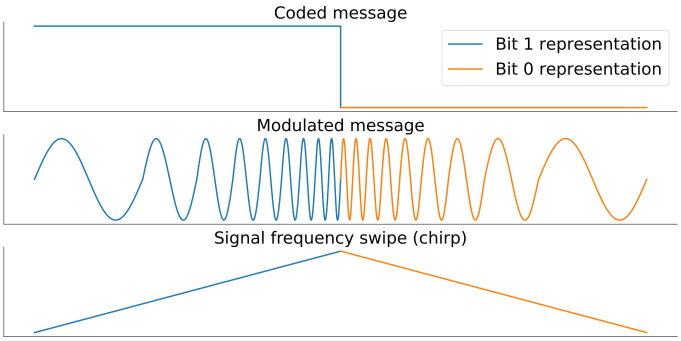

Fig. 1. Bit representation for LoRa-based networks.

bandwidth, the lower the signal-to-noise ratio (SNR) of the communication.

LoRaWAN is a wireless communication protocol that provides long-range connectivity with a low bit-rate based on LoRa modulation (physical-layer). Consequently, it supports the spreading spectrum of the LoRa spectrum over factors 7 to 12 [6].

Several parameters are available for customizing LoRa modulation: bandwidth (BW), spreading factor (SF), and code rate (CR). LoRa uses an unconventional definition of propagation factor as the base two logarithms of the number of chirps per symbol. Such parameters influence the effective bit rate of the modulation, its resistance to noise interference, and its decoding. Bandwidth is the most important parameter of LoRa modulation. A LoRa symbol consists of 2^{SF} chirps, which covers the entire frequency band. Since there is 2^{SF} chirps in a symbol, a symbol can effectively encode SF bits of information.

In LoRa, the chirp rate depends only on the bandwidth: it is equal to the bandwidth (*i.e.*, $\frac{chirp\ per\ second}{BW\ in\ Hz}$). The chirp has several consequences on modulation, including concerning signal strength and adequate bandwidth achieved. The symbol rate and bit rate at a given spread factor are proportional to the frequency bandwidth - so that doubling the bandwidth effectively doubles the transmission rate. It is possible to see in Equation 2, which correlates the duration of a symbol (TS) to the bandwidth and the spreading factor.

$$T_S = \frac{2^{SF}}{BW} \tag{2}$$

In addition, LoRa includes a FEC (Forward Error Correction) code, where the code rate (CR) is equal to $4/(4+n)$, with $n \in 1, 2, 3, 4$. Considering this, as well as the fact that SF bits of information are transmitted by symbol, Equation 3 allows us to calculate the useful bit rate (Rb). For example, for a configuration with $BW = 125kHz$, $SF = 7$, $CR = 4/5$, there is a bit rate of $Rb = 5.5kbps$. Following the Equation 3, for all CR values supported, the three biggest bandwidths and the available spreading factors, the Table I shows the bit rate for each configuration.

$$Rb = SF \times \frac{BW}{2^{SF}} \times CR \tag{3}$$

III. Related Work

LoRa-based networks is an active research topic, exploring its characteristics from scalability to reliability, especially for smart city scenarios [7], [8].

Pasolini et al. [8] highlight the importance of setting LoRa parameters correctly to ensure low packet loss in smart city applications. The authors show the benefits of using the correct configuration of parameters to obtain gain in throughput. However, the authors show the way to change the configuration only offline, without any intelligence to proceed it automatically.

Bor et al. [9] 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. With this simple experiment, the authors show the possibility of performance enhancement occupying less the spectrum. This kind of technique is useful to increase the scalability and can be used to configure the LoRa parameters automatically. Unfortunately, the authors did not propose it, verifying only its benefits to configure it offline without any adaptation online, as we propose in this paper.

Another paper that verifies the scalability of LoRa-based networks is Varsier and Schwoerer [7]. This paper describes the increase in packet loss in LoRa networks as the number of deployed smart meters increases. This work presents a theoretical evaluation of LoRa scalability based on interference and overlap spectrum. However, any evaluation or consideration about change the configuration of LoRa parameters online was investigated.

In the theoretical field, it is possible to cite other works. Reynders et al. [10] present a heuristic to assign SFs and transmission power (TPs) to nodes in networks with a single gateway calculating an optimal proportion of SFs based on the objective of minimizing the maximum probability of collisions in any SF. Abdelfadeel et al. [11] use a similar approach based on the optimal proportion of SFs proposed [10] under the assumption that each node can reach the gateway with any combination of SF and TP. Different from others, Jeon et al. [12] are unique to propose an adaptation of the LoRa parameters. It was conducted based on the uplink data rate, and not of any other metric. In this way, our paper is the first to verify the impact and benefits of observing the SNR values in a real LoRa-based network in order to obtain the maximum link resilience. The Cognitive-LoRa is a physical/spectrum-level strategy to optimize the network throughput, showing be a considerable candidate to be incorporated on high-level frameworks as Cognitive-LPWAN [13]. The next section introduces our proposal.

IV. Cognitive LoRa

The decision to choose the wireless spectrum concern several metrics. For example, decisions can be made considering

TABLE I
RELATION BETWEEN SF, BW, AND MAXIMUM THROUGHPUT VALUES IN KBPS.

		Bandwidth (kHz)												
		125				250				500				
		CR												
		4/5	**4/6**	**4/7**	**4/8**	**4/5**	**4/6**	**4/7**	**4/8**	**4/5**	**4/6**	**4/7**	**4/8**	
SF	**7**	5.5	4.6	3.9	3.4	10.9	9.1	7.8	6.8	21.9	18.2	15.6	13.7	***kbps***
	8	3.1	2.6	2.2	2.0	6.3	5.2	4.5	3.9	12.5	10.4	8.9	7.8	
	9	1.8	1.5	1.3	1.1	3.5	2.9	2.5	2.2	7.0	5.9	5.0	4.4	
	10	1.0	0.8	0.7	0.6	2.0	1.6	1.4	1.2	3.9	3.3	2.8	2.4	
	11	0.5	0.4	0.4	0.3	1.1	0.9	0.8	0.7	2.1	1.8	1.5	1.3	
	12	0.3	0.2	0.2	0.2	0.6	0.5	0.4	0.4	1.2	1.0	0.8	0.7	

Algorithm 1: Cognitive LoRa for Two Frequencies

```
// range of frequencies
F = {433, 915};
// range of spread spectrum
SF = {10, 11, 12};
// range of bandwidth
BW = {125, 250, 500};
// number of control packet to send
γ ⟵ 9;
// only a loop control
control ⟵ 0;
/* function responsible to get the best
configuration parameters based on packets' SNR
listened                                          */
Function SNR_Packet(f, sf, bw):
    SNR ⟵ snr.packet[f][sf][bw];
    if SNR > Φ then
        Φ ⟵ {f, sf, bw};
    end if
    return Φ;
/* function responsible to receive the
parameters combination                            */
Function Request_SNR(F, SF, BW):
    foreach f in F do
        foreach s in SF do
            foreach bw in BW do
                Φ ⟵ SNR_Packet(f, sf, bw);
            end foreach
        end foreach
    end foreach
    return Φ;
// the main code.
// first request of the best configuration
α ⟵ Request_SNR(F, SF, BW);
/* send data packets gamma times and verify
again the best parameters configuration          */
while exist packet to be send do
    Send one packet using α values;
    if control < γ then
        control = control + 1;
    else
        // update the best configuration
        α ⟵ Request_SNR(F, SF, BW);
    end if
end while
```

the SNR and received signal power, regarding handover and QoS (Quality of Service) [14]. In IEEE 802.11 and LTE networks, the SNR and RSSI (Received Signal Strength Indication) are the main parameters supported for decision making regarding proceed with a handover, the bandwidth selected, and the channel configuration to be used [15].

In the scenario of long-range networks, there are several sources of signal that can generate interference, deteriorate quality, and make communication between two points more difficult. In this work, we propose a study of the signals collected in a real LoRa network. These data are used to improve a cognitive protocol and identify the best configuration and frequency range in a given moment. The SNR is a good physical-layer metric for the received signal quality. Therefore, in this proposal, SNR is the metric used to make the configuration changes of LoRa nodes.

The Algorithm 1 is responsible for performing the configuration based on network-aware, changing the parameters of frequency, spread spectrum, and bandwidth. As a result, there is a change of configurations in the nodes in order to maximize the SNR. The algorithm is responsible for sending LoRa data packets/datagrams γ times using the frequency, spread spectrum, and bandwidth (F, SF, BW) settings determined as the best configuration, represented for α. Once the number of data packets to be sent is reached, a new evaluation is carried out. For this, a control packet is generated for each configuration of F, SF, BW, using the function $Request\_SNR$. This function sends a control packet and measures the SNR through the function SNR_Packet, which evaluates the best configuration, and returns it to the main code, where the algorithm decides to make or not a shift on the α parameters.

V. RESULTS

The evaluation of the algorithm on the LoRa was supported in a real environment with a ESP32 client and gateway with the SEMTECH SX1276 and SX1278 chips, which implement LoRa physical layer and a Raspberry Pi 3 server. Communication was carried out between one client node and the gateway operating on $433MHz$ and $915MHz$ frequencies (2 separate antennas). The SF values considered for the evaluation are 10, 11, and 12[1]. Regarding the bandwidth (BW), the values of $125kHz$, $250kHz$, and $500kHz$ were adopted, which are the same bands used by LoRaWAN. The coding rate (CR - Coding Rate) was maintained in all experiments as $4/5$. Table II summarizes the values described, and Figure 2 shows the evaluation environment. The SNR values were correlated for distances between 1 and 800 meters and it was found that in the evaluated outdoor environment, measures of approximately

[1]The SF values of 7, 8, and 9 were ignored due to previous measurements and the correlation between lower SF values implying worse transmitter sensitivities [6].

10 meters of distance between the nodes were sufficient to demonstrate the necessity for node aware and parameters changing to improve SNR. The Figures 3 to 11 shows the change/shift points made and the biggest three SNR percentage improvements are assign on each figure with an arrow.

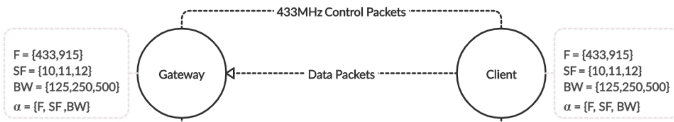

Fig. 2. Evaluation scenario.

TABLE II
SUMMARIZED SETTINGS AND RESULTS.

Configuration #	SF	BW	CR	Percentage of shifts
1	10	125kHz	4/5	28.45%
2	10	250kHz	4/5	32.48%
3	10	500kHz	4/5	12.93%
4	11	125kHz	4/5	27.59%
5	11	250kHz	4/5	31.90%
6	11	500kHz	4/5	11.50%
7	12	125kHz	4/5	28.83%
8	12	250kHz	4/5	22.64%
9	12	500kHz	4/5	20.95%

Figures 3 to 5 correspond to the spreading factor (SF) equals to 10, and we can see that the lowest level of the number of configuration shifts occurred for the frequency of $500kHz$, showing 12.93% of frequency changes of the total evaluations performed. However, the one with the highest number of frequency shifts was the $250kHz$ bandwidth, with a total shift rate equals to 32.48%. Finally, the frequency of $125kHz$ presented a median level of shifts in configurations, with 28.45% of the total evaluations.

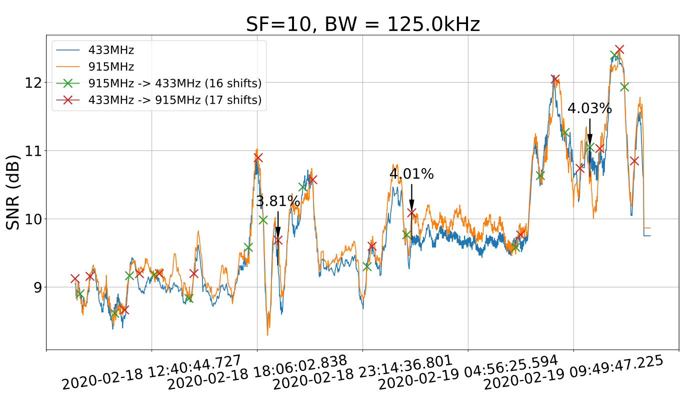

Fig. 3. LoRa settings: $SF = 10$, $BW = 125kHz$ for both frequencies ($433MHz$ and $915MHz$).

The Figures 6 to 8, correspond to the SF equals to 11, the least number of shifts in configurations also occurred for the frequency of $500kHz$, presenting 11.50% of frequency shifts of the total evaluations performed. In contrast, the one with the highest number of frequency shift was the $250kHz$ bandwidth,

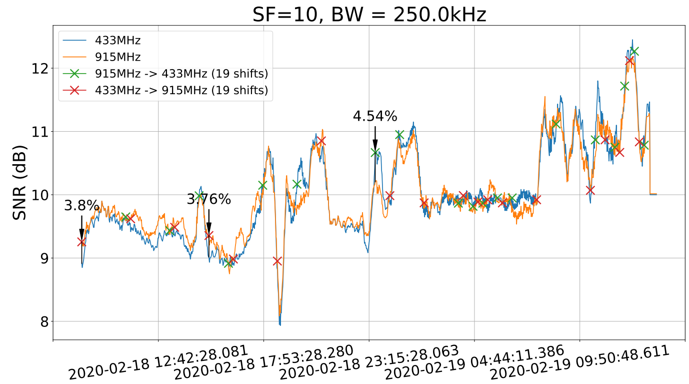

Fig. 4. LoRa settings: $SF = 10$, $BW = 250kHz$ for both frequencies ($433MHz$ and $915MHz$).

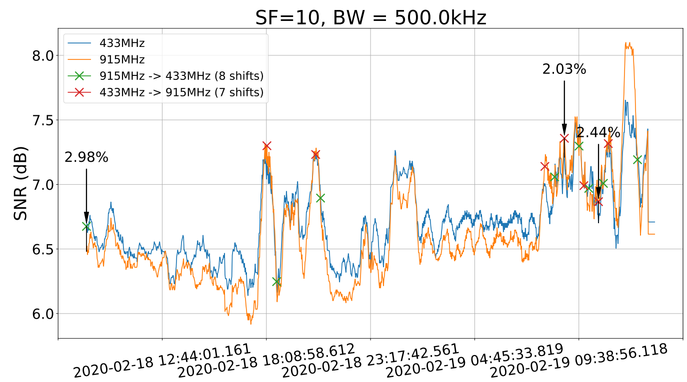

Fig. 5. LoRa settings: $SF = 10$, $BW = 500kHz$ for both frequencies ($433MHz$ and $915MHz$).

with a shift rate of 31.90%. Finally, the frequency of $125kHz$ again presented a median level of shifts in configurations, with 27.59% of the total evaluations.

Finally, analyzing the Figures 9 to 11, correspond to the SF equals to 12, the least number of setting shifts occurred again for the frequency of $500kHz$, presenting 20.95% of frequency shifts of the total evaluations performed. The bandwidth that presented the highest percentage of shifts was $125kHz$, with a rate of 28.83%. Finally, the $250kHz$ bandwidth showed a shift rate equals to 22.64%. Table II summarizes the change percentages for each investigated configuration.

As we analyze the figures 3 to 11 there is a clear tendency to have fewer frequency shifts for the adopted algorithm when opting for $500kHz$ bandwidth. However, a more significant number of shifts occurs on the $250kHz$ bandwidth, not presenting a perspective of linear behavior. The algorithm does not appear to present a relationship between the spreading factor adopted and the number of frequency changes.

In conclusion, the configuration with $SF = 10$ and $BW = 250kHz$ had the biggest SNR improvement, of 4.54%. As for the $SF = 11$ and $BW = 250kHz$ configuration, the biggest SNR improvement was 4.77%. Finally, for the configuration of $SF = 12$ and $BW = 125kHz$, the biggest SNR improvement was 4.74%. Considering the results, an average of

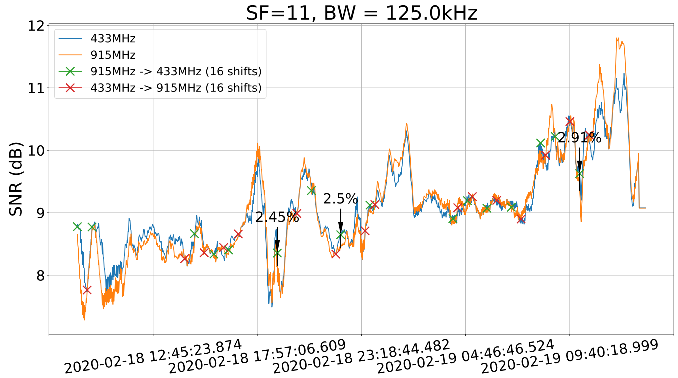

Fig. 6. LoRa settings: $SF = 11$, $BW = 125kHz$ for both frequencies ($433MHz$ and $915MHz$).

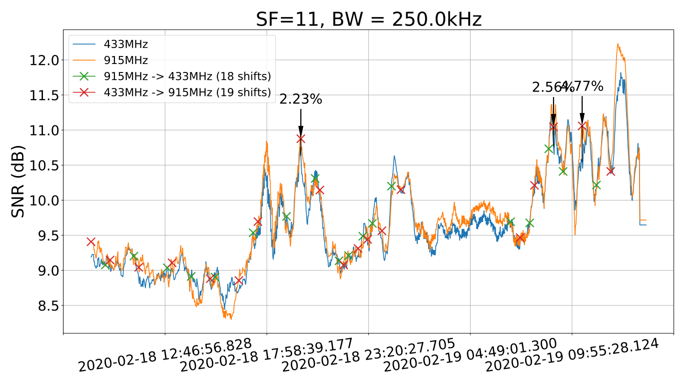

Fig. 7. LoRa settings: $SF = 11$, $BW = 250kHz$ for both frequencies ($433MHz$ and $915MHz$).

approximately 23% shifts is required regarding all measures. In our experiment, a total of 1160 measures were collected in each SF and BW configuration, with 116 possible shifts each. Even with a low value of shifts, the algorithm behaves well concerning SNR improvement, presenting an average of 4.68% even in a scenario with little interference. Thus, the presented algorithm, as well as the results, are relevant to the IoT field and motivate more studies about cognitive radio in LoRa.

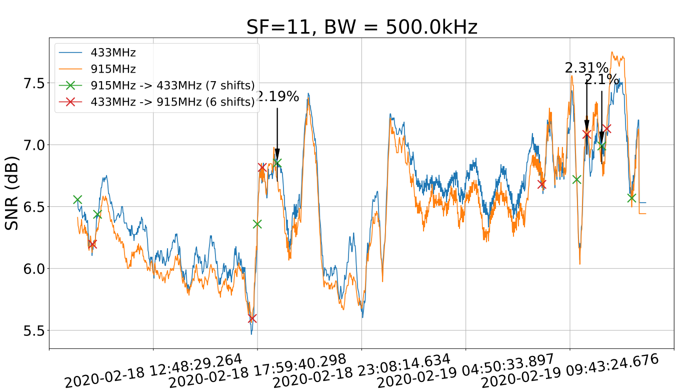

Fig. 8. LoRa settings: $SF = 11$, $BW = 500kHz$ for both frequencies ($433MHz$ and $915MHz$).

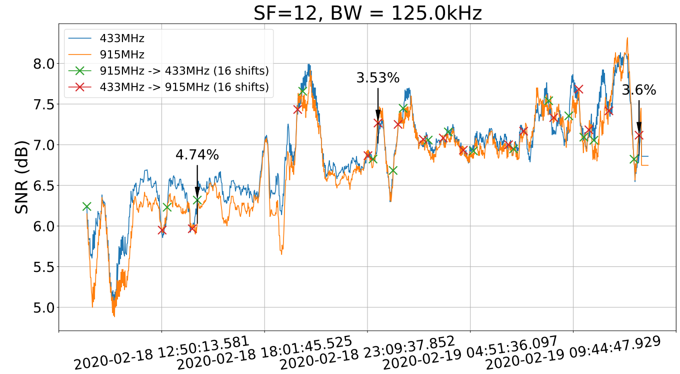

Fig. 9. LoRa settings: $SF = 12$, $BW = 125kHz$ for both frequencies ($433MHz$ and $915MHz$).

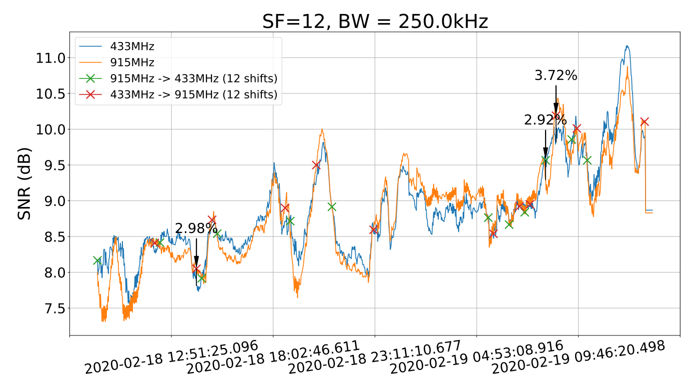

Fig. 10. LoRa settings: $SF = 12$, $BW = 250kHz$ for both frequencies ($433MHz$ and $915MHz$).

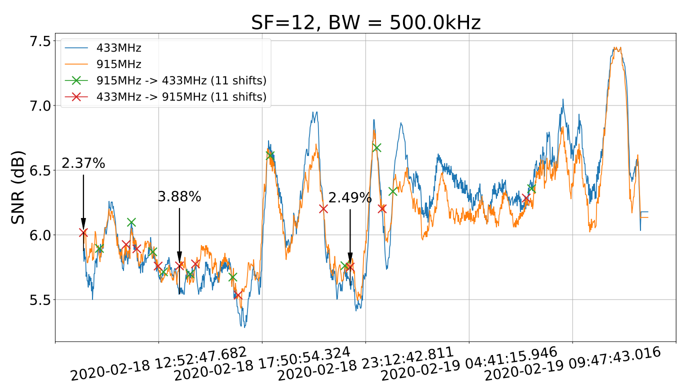

Fig. 11. LoRa settings: $SF = 12$, $BW = 500kHz$ for both frequencies ($433MHz$ and $915MHz$).

VI. Conclusion

The number of IoT devices connected is expected to grow by 10 billion from 2015 to 2021, and to connect them in large geographic areas, we have LoRa and its protocol, LoRaWAN. LoRa as the most promise to be used for extended areas based on wireless communication, but its behavior is not well-known. Based on the state-of-the-art and proposing an adaptative-aware protocol, we introduce a concept of LoRa-cognitive, where the nodes can listen and change their parameters' configuration. With this concept applied to the LoRa-based networks, it is possible to improve SNR and promote the IoT long-range solutions. Our results showed a SNR improvement of 4.68% on average.

As future works, it is possible to observe other metrics from layers above, *e.g.*, delay and goodput to improve the algorithm. Besides that, implement a history to prevent the ping-pong effect on changing the parameters' configuration, as well as use the data collected as an input for forecast techniques.

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REFERENCES

[1] R. S. Sinha, Y. Wei, and S.-H. Hwang, "A survey on LPWA technology: LoRa and NB-IoT," *Ict Express*, vol. 3, no. 1, pp. 14–21, 2017.

[2] E. F. Silva, B. J. Dembogurski, A. B. Vieira, and F. H. C. Ferreira, "Ieee p21451-1-7: Providing more efficient network services over mqtt-sn," in *2019 IEEE Sensors Applications Symposium (SAS)*. IEEE, 2019, pp. 1–5.

[3] A. Abuarqoub, H. Abusaimeh, M. Hammoudeh, D. Uliyan, M. A. Abu-Hashem, S. Murad, M. Al-Jarrah, and F. Al-Fayez, "A survey on internet of things enabled smart campus applications," in *Proceedings of the International Conference on Future Networks and Distributed Systems*, 2017, pp. 1–7.

[4] L. R. Frank, Y. M. Ferreira, E. P. Julio, F. H. C. Ferreira, B. J. Dembogurski, and E. F. Silva, "Multilayer perceptron and particle swarm optimization applied to traffic flow prediction on smart cities," in *International Conference on Computational Science and Its Applications*. Springer, 2019, pp. 35–47.

[5] Y. M. Ferreira, L. R. Frank, E. P. Julio, F. H. C. Ferreira, B. J. Dembogurski, and E. F. Silva, "Applying a multilayer perceptron for traffic flow prediction to empower a smart ecosystem," in *International Conference on Computational Science and Its Applications*. Springer, 2019, pp. 633–648.

[6] *SX1272/3/6/7/8: LoRa Modem Designer Guide = AN1200.13*, Semtech Corporation, 7 2013, rev. 1.

[7] N. Varsier and J. Schwoerer, "Capacity limits of lorawan technology for smart metering applications," in *2017 IEEE international conference on communications (ICC)*. IEEE, 2017, pp. 1–6.

[8] G. Pasolini, C. Buratti, L. Feltrin, F. Zabini, C. De Castro, R. Verdone, and O. Andrisano, "Smart city pilot projects using lora and ieee802. 15.4 technologies," *Sensors*, vol. 18, no. 4, p. 1118, 2018.

[9] M. C. Bor, U. Roedig, T. Voigt, and J. M. Alonso, "Do lora low-power wide-area networks scale?" in *Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, 2016, pp. 59–67.

[10] B. Reynders, W. Meert, and S. Pollin, "Power and spreading factor control in low power wide area networks," in *2017 IEEE International Conference on Communications (ICC)*. IEEE, 2017, pp. 1–6.

[11] K. Q. Abdelfadeel, V. Cionca, and D. Pesch, "Fair adaptive data rate allocation and power control in lorawan," in *2018 IEEE 19th International Symposium on" A World of Wireless, Mobile and Multimedia Networks"(WoWMoM)*. IEEE, 2018, pp. 14–15.

[12] W. S. Jeon and D. G. Jeong, "Adaptive uplink rate control for confirmed class a transmission in lora networks," *IEEE Internet of Things Journal*, 2020.

[13] M. Chen, Y. Miao, X. Jian, X. Wang, and I. Humar, "Cognitive-lpwan: Towards intelligent wireless services in hybrid low power wide area networks," *IEEE Transactions on Green Communications and Networking*, vol. 3, no. 2, pp. 409–417, 2018.

[14] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE personal communications*, vol. 6, no. 4, pp. 13–18, 1999.

[15] F. Afroz, R. Subramanian, R. Heidary, K. Sandrasegaran, and S. Ahmed, "SINR, RSRP, RSSI and RSRQ measurements in long term evolution networks," *International Journal of Wireless & Mobile Networks*, 2015.