



HAL
open science

Deep Learning-based Successive Interference Cancellation to Improve Uplink in LoRa Networks

Angesom Ataklity Tesfay, Eric Pierre Simon, Mohammed Mallik, Virginie Deniau, Laurent Clavier

► **To cite this version:**

Angesom Ataklity Tesfay, Eric Pierre Simon, Mohammed Mallik, Virginie Deniau, Laurent Clavier. Deep Learning-based Successive Interference Cancellation to Improve Uplink in LoRa Networks. Fourth IEEE International Mediterranean Conference on Communications and Networking (IEEE MEDITCOM 2024), 2024, Madrid, Spain. pp.179-183. hal-04618668

HAL Id: hal-04618668

<https://hal.science/hal-04618668v1>

Submitted on 20 Jun 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Deep Learning-based Successive Interference Cancellation to Improve Uplink in LoRa Networks

Angesom Ataklity Tesfay¹, Eric Pierre Simon², Mohammed Mallik³, Virginie Deniau¹, and Laurent Clavier^{2,3}

¹COSYS-LEOST, Univ Gustave Eiffel, IFSTTAR, Univ Lille Villeneuve d'Ascq, France (e-mail: firstname.name@univ-eiffel.fr)

²Univ. Lille, CNRS, UMR 8520 - IEMN, F-59000, Lille, France (e-mail: firstname.name@univ-lille.fr)

³IMT Nord Europe, France (e-mail: firstname.name@imt-nord-europe.fr)

Abstract—This paper presents a deep learning-based successive interference cancellation (SIC) scheme to improve the uplink in the LoRa Network. The proposed receiver can decode simultaneous transmissions from multiple users on the same frequency channel with the same spreading factor. The objective of the proposed approach is to reduce the error propagation issues of the classical SIC method. Each SIC step employs a specific convolutional neural network model to decode each user's signal directly. Simulation results show that the proposed receiver significantly reduces the error propagation and increases the number of connected devices in the network compared to the classical SIC scheme.

Index Terms—LoRa, Deep-learning, SIC, IoT, CSS

I. INTRODUCTION

The number of connected Internet of Things (IoT) devices is expected to grow significantly in the coming years, demanding the development of technologies that can handle connectivity. Low-Power Wide Area Network (LPWAN) solutions have been introduced to address this issue, particularly LoRa in the license-free frequency range. LoRa is based on the Chirp-Spread Spectrum (CSS) Modulation technique and achieves quasi-orthogonal transmissions using several spreading factors (SF) and bandwidth configurations. However, collisions occur at the receiver when two or more devices transmit simultaneously using the same SF on the same frequency range, typically leading to packet loss. One packet may sometimes be decoded despite the collision due to the capture effect. This is possible when the useful signal is significantly stronger than the interfering one.

In [1] capture effect decodes two superposed signals using timing information when the signals are synchronized or slightly desynchronized. However, ensuring synchronization is not realistic in the uplink. To deal with co-SF interference in LoRa, [2] implements an interleaved chirp spreading (ICS) modulation method. However, the modulation scheme is not directly backward compatible with the LoRaWAN standard. The authors in [3] propose successive interference cancellation (SIC) to decode symbols from all users. A synchronized reception is considered, which is not the case in the uplink. In [4], a SIC technique that enables a receiver to decode multiple signals simultaneously is proposed. A more general case is considered, where transmitters are asynchronous. In this work, all users' channel is estimated to decode the strongest user, then suppressed, and the second strongest can, in turn, be

decoded. However, the performance is limited by the error propagation due to the issue of the channel estimation error.

Alleviating the impact of error propagation requires a perfect channel estimation and reduction of the decoded signal from the composite received signal, which is not the case. To address the issue of error propagation, the convolutional neural network (CNN) algorithm emerges as a promising solution due to its adeptness at extracting input signal characteristics through convolutional layers. Additionally, its adaptable architecture allows for flexible adjustments to accommodate varying input signal attributes. Furthermore, the CNN algorithm demonstrates effectiveness in noise reduction through the pooling process, facilitating the extraction of consistent features.

In this paper, we propose a CNN-based SIC for the uplink in LoRa networks that significantly improves the receiver's ability to decode multiple signals simultaneously and deals with the error propagation problem. In the literature, some works employ the deep learning approach for signal detection in LoRa networks [5]–[8]. To our knowledge, no works yet investigate deep learning-aided successive interference cancellation for LoRa Networks.

The main contributions of this paper involve designing deep learning-based SIC receivers for LoRa uplink communication that can decode multiple signals simultaneously while addressing the error propagation issue commonly observed in classical SIC techniques. The experimental results demonstrate a significant improvement in decoding performance compared to traditional SIC methods.

The paper is organized as follows. The system model is described in the following section. Section III presents the proposed deep learning-based SIC. The simulation results and discussions are shown in Section IV. In Section V, the conclusions are drawn.

II. SYSTEM MODEL

In LoRa, a symbol has SF bits that represent $M = 2^{\text{SF}}$ potential values. The symbol duration is $T_s = MT$, where $T = 1/B$ and B are the sampling period and signal bandwidth, respectively. The SF varies from 7 to 12. Each LoRa symbol includes a linear frequency change over T_s , known as a chirp.

It is generated from a raw chirp $s(t)$ with an instantaneous frequency of $\frac{B}{T_s}t$, giving the base-band equation [9]:

$$s(t) = \exp\left(2i\pi\frac{B}{2T_s}t^2\right) \quad t \in \left[-\frac{T_s}{2}, \frac{T_s}{2}\right]. \quad (1)$$

Let the number of LoRa symbols transmitted in a packet be Q . The j th user's transmitted symbol at time qT_s ($q = 0, \dots, Q-1$) is $m_j^{(q)} \in \{0, \dots, M-1\}$. This symbol is conveyed by shifting the raw chirp cyclically by $\delta_j^{(q)} = m_j^{(q)}T$, as shown in Fig. 1. Therefore, the coded chirp is:

$$s_j^{(q)}(t) = \begin{cases} \exp\left(2i\pi\left[\frac{B}{2T_s}t^2 + \frac{m_j^{(q)}}{T_s}t\right]\right), & t \in \left[-\frac{T_s}{2}, \frac{T_s}{2} - \delta_j^{(q)}\right), \\ \exp\left(2i\pi\left[\frac{B}{2T_s}t^2 + \left(\frac{m_j^{(q)}}{T_s} - B\right)t\right]\right), & t \in \left[\frac{T_s}{2} - \delta_j^{(q)}, \frac{T_s}{2}\right]. \end{cases} \quad (2)$$

User j 's transmitted signal $s_j(t)$, is then $s_j(t) = \sum_{q=0}^{Q-1} s_j^{(q)}(t - qT_s)$. The transmitted LoRa packet is obtained by prepending a preamble composed of raw chirps. We consider a circle radius of R with one gateway located

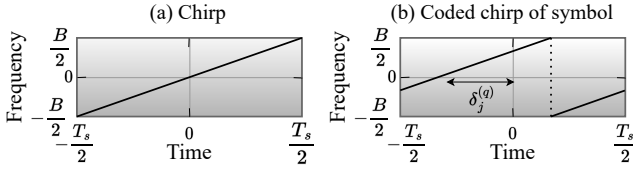


Fig. 1: (a) Raw chirp (b) Coded chirp of symbol $m_j^{(q)}$.

at the center is considered. We assume N users have the same SF uniformly distributed within the considered circle. Asynchronous transmission among the nodes is considered, and different devices operate autonomously. The distance between user i and the gateway is denoted by d_i . A set of users are considered to transmit their data through block fading channels during the time interval of interest. Path loss and Rayleigh multi-path fading χ_i are considered. The signal amplitude decays with distance by $d_i^{-\eta/2}$, where η is the path loss exponent. The channel attenuation coefficient (in amplitude) is then $h_i = d_i^{-\eta/2}\chi_i$.

At the receiver end, the first step is to detect the preamble by sliding the preamble across the received signal and calculating the correlation at each position. Then the position with the highest correlation peak is detected and used to synchronize the received signal. The intended user to be decoded at a given time is indexed by j . The received signal associated with symbol q of user j sampled at $t = nT$, $n = -\frac{M}{2}, \dots, \frac{M}{2} - 1$ is:

$$r^{(q)}[n] = h_j s_j^{(q)}[n] + \sum_{i \in \mathcal{I}} h_i s_{j,i}^{\text{int},(q)}[n] + w^{(q)}[n], \quad (3)$$

where $s_j^{(q)}[n] = s_j^{(q)}(nT)$, \mathcal{I} is the set of interfering users and $w_q[n] \sim \mathcal{CN}(0, \sigma^2)$ is a circularly symmetrical complex Gaussian noise. h_j and h_i are the channel coefficients for users j and i , respectively.

Fig. 2 illustrates the collision between the q th symbol of the desired user j and two consecutive symbols of an interfering user i . The interfering part of user i is represented by $s_{j,i}^{\text{int},(q)}$ and $\delta_{j,i}$ is the delay between user j and user i (accounting for asynchronous transmissions between the nodes).

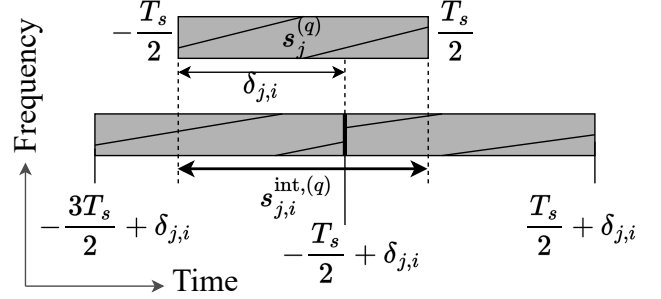


Fig. 2: Collision between a symbol of the desired user and two consecutive symbols of the interfering user.

The classical LoRa receiver first multiplies the samples of the received signal by the conjugate of the raw chirp to demodulate, giving $y^{(q)}[n] = r^{(q)}[n]s^*[n]$, where $s^*[n] = s^*(nT)$. Then, a Fast Fourier Transform (FFT) is applied:

$$Y^{(q)}[k] = \sum_{n=-M/2}^{M/2} y^{(q)}[n] e^{-2i\pi\frac{nk}{M}}, \quad k = 0, \dots, M-1. \quad (4)$$

The symbol $m_j^{(q)}$ is estimated by searching for the frequency index where the modulus of (4) is maximum in LoRa. However, collisions occur when multiple users transmit simultaneously using the same SF, yielding possible detection errors. In classical SIC, first, the strongest signal is decoded. Its contribution can then be reconstructed using an estimate of the channel and subtracted from the received signal. From the resulting residue, the second strongest signal can then be extracted. This results in an error propagation problem mainly due to the subtraction of the contribution of the decoded signal from the composite received signal.

III. PROPOSED DEEP LEARNING-BASED SIC

This section describes the proposed Convolutional Neural Network (CNN)-based SIC decoder for directly decoding multiple users' signals. The block diagram of the proposed decoder is illustrated in Fig 3. The problem is approached as a classification problem, with CNNs employed to associate received signals with transmitted symbols.

The decoding process is carried out sequentially, with a single user's signal decoded using a different CNN at each SIC step, as shown in Fig 3. Preamble detection is performed in a given window W , and N peaks are detected corresponding to the number of users that transmit during the considered window. Simultaneously, the timing information, or the delays δ between the users is extracted from the preamble.

In each SIC step, the received signal is synchronized on the peak associated with the user intended to be decoded. The received signal is synchronized on the first strongest peak in

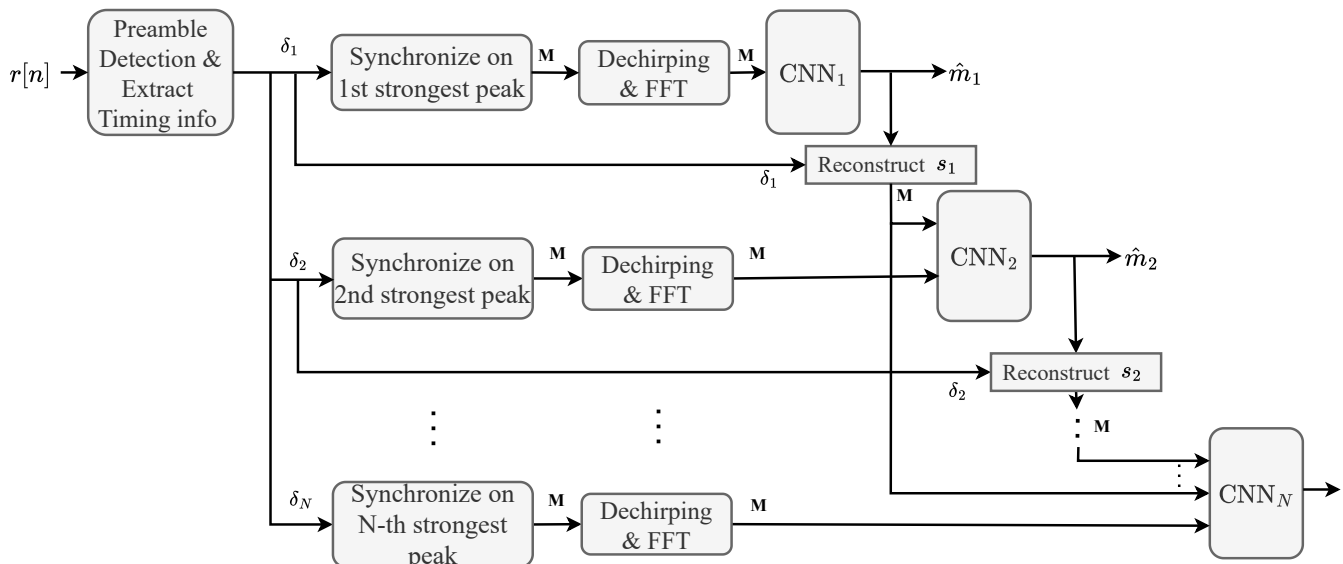


Fig. 3: Block diagram of the proposed CNN-based SIC.

the first SIC step, the second strongest peak in the second SIC step, and so on. Then, the dechirped received samples after the FFT are the input of the CNN models. Moreover, reconstructed signals of the previously decoded users after dechirping and FFT processes, along with their corresponding delays extracted in the preamble detection step, are used as additional inputs of the CNN models, except for the first CNN. The output of each SIC step is the index of the transmitted symbols.

As illustrated in Fig. 4, the proposed CNN model's structure contains several convolutional layers with a pooling layer and a series of fully connected layers. The parameters of the model, such as the number of convolutional layers (nCL), the number of fully connected layers (nFC), the number of kernels (nk), the size of kernels (sk), and the size of each fully connected layer (sFC) are fixed by Bayesian optimization. The input size of each CNN varies at each step, expanding with the number of detected users. Consequently, Hyperparameter tuning is conducted separately for each CNN model. Table I presents the optimized architecture of the CNN models, with subscripts indicating the corresponding layer numbers.

TABLE I: Tuned hyperparameters of the CNN models for $N = 7$.

CNN	nCL	nk ₁	nk ₂	sk ₁	sk ₂	nFC	sFC ₁	sFC ₂
1	2	52	162	2 × 2	3 × 3	2	695	256
2	2	67	174	3 × 3	4 × 4	2	531	256
3	2	85	192	4 × 4	4 × 4	2	479	256
4	2	72	188	3 × 3	5 × 5	2	591	256
5	2	96	212	4 × 4	4 × 4	2	715	256
6	2	94	198	3 × 3	4 × 4	2	692	256
7	2	98	184	3 × 3	3 × 3	2	521	256

The ReLU function is used as the activation function, and batch normalization is applied. The softmax function is employed for the output classification layer. The CNN model is trained to minimize the cross-entropy loss between the output and the transmitted symbols for 50 epochs with

a mini-batch size of 300 samples. The adaptive moment estimation (ADAM) algorithm with an initial learning rate of 0.001 is used to optimize the learnable parameters of CNN architectures, such as weights and biases.

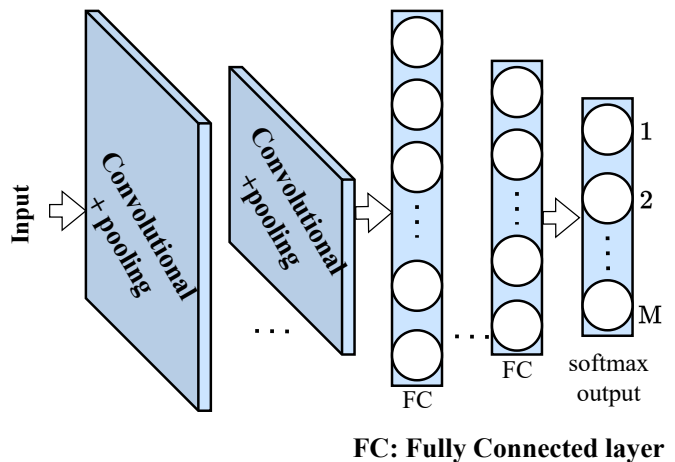


Fig. 4: The proposed CNN architecture.

IV. RESULTS

In this section, we present simulation results to evaluate the performance of the proposed CNN-based SIC. A Bayesian optimization technique is used to set all of the neural network parameters. Training is done offline, with training data generated from simulation for each SNR value.

A. Simulation setup

For the considered LoRa transmission, the bandwidth $B = 250$ kHz, $SF = 8$, resulting in $M = 256$. The noise level of a receiver at room temperature is $-174 + 10 \log_{10}(B) + NF = -114$ dBm, where NF is the receiver noise figure and a

classic 6 dB is considered [10]. The signal amplitude decays with distance according to $d_i^{-\eta/2}$, where η is the path loss exponent, $\eta = 3.5$ is considered here. The number of users N in a given time interval is uniformly distributed in the considered circle with a maximum radius of $R = 5$ km. All users use CSS modulation with the same SF, and the same power is utilized for transmission. Asynchronous transmission is considered, and different devices operate autonomously.

The symbol error rate (SER) as a function of SNR is used to compare the performance of the proposed CNN-based SIC with the classical SIC in [4]. A window $W = 3T_f$ is considered, where T_f is the frame length. We consider a set of N users that will collide in this window as they transmit during the vulnerability period of the pure ALOHA protocol that LoRa uses. The vulnerability period is $2T_f$, and to ensure that all complete packets are received $3T_f$ window is used. Asynchronicity is ensured through a random variable δ_j , uniformly distributed over $[0, 2T_f]$. The proposed CNN-based SIC is compared with classical SIC in [4], and for a fair comparison, all the considerations in this work are consistent with [4]. For the performance analysis, $N = 7$ and 10 interfering users are considered to provide insights into LoRa network robustness and scalability.

B. Performance of a selected link

Fig. 5 shows the performance of a specific link as a function of its SNR when $N = 7$ and 10 interfering users are present. The performance curve shows that the proposed CNN-based SIC performs better than the classical SIC. In the presence of 7 and 10 interfering users, the proposed CNN-based SIC is more efficient than the classical SIC in [4], with at least 2 dB gain for a target SER of 10^{-4} .

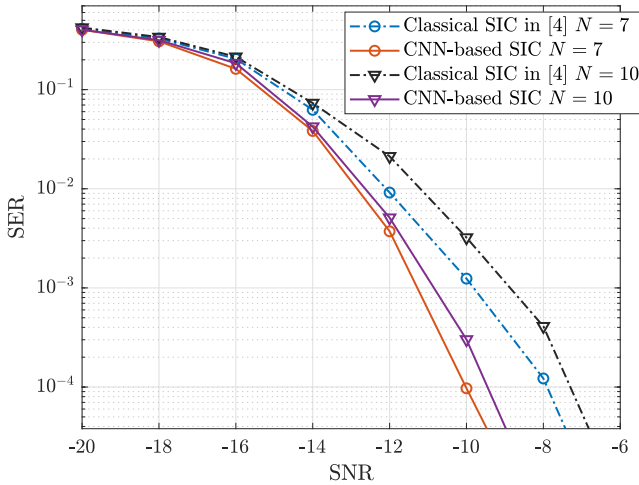


Fig. 5: SER vs SNR for $N = 7$ and $N = 10$.

C. Error propagation

Due to the successive decoding, reconstruction, and suppression process, a SIC receiver can be affected by error

propagation. This affects the performance of decoding the users with lower received power.

The SER of each user when $N = 7$ and 10 is shown in Figs. 6 and 7, respectively. The users are ordered according to their received power, from the highest (1) to the lowest (7) for $N = 7$ and (10) for $N = 10$. User one, for instance, is the one with the better channel, so the one with the highest received power. As Figs. 6 and 7 illustrate the classical SIC receiver encounters a significant performance gap between the first (with the highest received power) and the last decoded users. The error propagates from the first to the last decoded users. On the contrary, the proposed CNN-based SIC receiver offers a fair performance between users, slightly increasing the SER for the last decoded user (with the lowest received power) but keeping a more constant SER and significantly improving performance in comparison to the classical SIC in [4] for the last users.

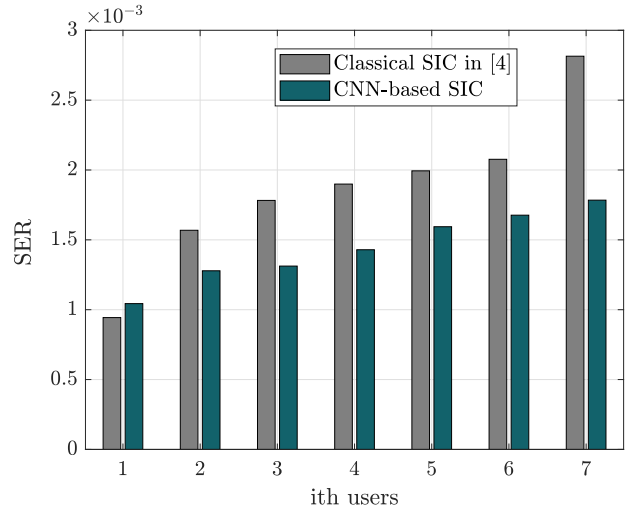


Fig. 6: SER of each users for $N = 7$.

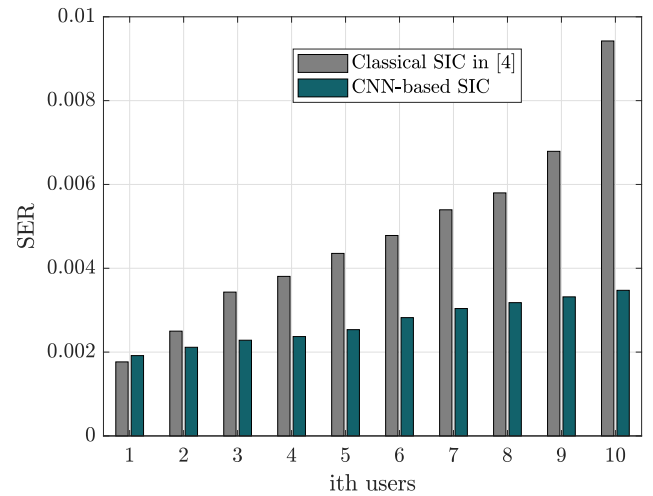


Fig. 7: SER of each users for $N = 10$.

V. CONCLUSION

This paper proposes a LoRa uplink transmission with a CNN-based SIC scheme where a gateway decodes signals of multiple users successively from the strongest to the weakest signal. CNN model with several convolutional and fully connected layers is utilized at each SIC step to decode the signal of the corresponding user. The problem is treated as a classification problem in which the CNN model takes inputs composed of the synchronized received signal and the previously decoded user's reconstructed signal, except for the first CNN, which uses only the synchronized received signal as input. The proposed scheme decodes the user's signal in a single without explicitly estimating channel coefficients and subtracting the decoded signal. This helps alleviate the issues related to error propagation in SIC. Simulation results reveal that the SER performance of our proposed scheme outperforms existing SIC schemes in [4] for different numbers of users. In the presence of 7 and 10 interfering users, the proposed CNN-based SIC is more efficient than the classical SIC in [4], with at least 2 dB gain for a target SER of 10^{-4} .

REFERENCES

- [1] N. E. Rachkidy, A. Guitton, and M. Kaneko, "Decoding superposed LoRa signals," in *2018 IEEE 43rd Conf. on Local Computer Networks (LCN)*, pp. 184–190, 2018.
- [2] P. Edward, S. Elzeiny, M. Ashour, and T. Elshabrawy, "On the coexistence of LoRa- and Interleaved Chirp Spreading LoRa-Based modulations," in *2019 International Conference on WiMob*, 2019.
- [3] U. Noreen, L. Clavier, and A. Bounceur, "Lora-like css-based phy layer, capture effect and serial interference cancellation," in *European Wireless 2018; 24th European Wireless Conference*, pp. 1–6, 2018.
- [4] A. A. Tesfay, E. P. Simon, G. Ferré, and L. Clavier, "Serial interference cancellation for improving uplink in LoRa-like networks," in *2020 IEEE 31st Annual International Symposium on PIMRC*, (London, UK), 2020.
- [5] A. A. Tesfay, E. P. Simon, S. Kharbech, and L. Clavier, "Deep learning-based signal detection for uplink in lora-like networks," in *2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pp. 617–621, 2021.
- [6] K. Dakic, B. Al Homssi, A. Al-Hourani, and M. Lech, "LoRa Signal Demodulation Using Deep Learning, a Time-Domain Approach," in *2021 IEEE 93rd Vehicular Technology Conference*, pp. 1–6, 2021.
- [7] A. A. Tesfay, E. P. Simon, S. Kharbech, and L. Clavier, "Deep learning-based receiver for uplink in lora networks with sigfox interference," in *18th Int. Conf. on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pp. 25–29, 2022.
- [8] A. A. Tesfay, S. Kharbech, E. P. Simon, and L. Clavier, "Signal denoising and detection for uplink in lora networks based on bayesian-optimized deep neural networks," *IEEE Communications Letters*, vol. 27, no. 1, pp. 214–218, 2023.
- [9] B. Reynders and S. Pollin, "Chirp spread spectrum as a modulation technique for long range communication," in *2016 Symposium on Communications and Vehicular Technologies (SCVT)*, pp. 1–5, 2016.
- [10] Semtech, "AN1200.22: LoRa Modulation Basics," tech. rep., Semtech Corporation, 2015.