Efficient CNN-Based Time-Domain Denoising of Impulsive Noise in NB-PLC Systems

Wided Belhaj Sghaier, Fatma Rouissi, Héla Gassara, Fethi Tlili
GRESCOM Lab, Ecole Supérieure Des Communications De Tunis, University of Carthage, Tunisia

***Abstract*—In this study, a convolutional neural network (CNN)-based time-domain denoising approach is proposed to suppress impulsive noise which is considered as the most sever impairments in narrowband powerline communications (NB-PLC). Unlike conventional techniques, such as clipping and blanking, the proposed method does not require prior knowledge of noise statistics. The introduced CNN network is trained using synthetically generated OFDM signals corrupted by Middleton Class-A impulsive noise, calibrated from real NB-PLC measurement data. Extensive G3-PLC-compliant simulations demonstrate that the proposed method significantly outperforms classical blanking and clipping schemes. At an SNR of 10 dB, the proposed CNN achieves a mean squared error (MSE) of 1.2×10^{-4}, compared to 2.3×10^{-4} and 2.5×10^{-4} for blanking and clipping, respectively, under time-varying impulsive noise conditions. Moreover, the receiver incorporating the denoising method closely approaches the ideal AWGN reference under low impulsive noise density and for SNR values above 12 dB.**

Keywords*—*NB-PLC; Middleton Class-A; OFDM; impulsive noise; deep learning; CNN

I. Introduction

In recent years, significant research efforts have been devoted to smart grid applications based on narrowband power line communication (NB-PLC) [1], [2]. This technology enables data transmission over existing power distribution lines within a frequency band below 500 kHz, offering wide coverage at low deployment cost. NB-PLC systems facilitate communication expansion without the need for new infrastructure, as they leverage the already deployed electrical grid. However, the NB-PLC channel which not originally designed for data transmission is subject to several technical impairments. It is characterized by severe multipath propagation resulting from impedance mismatches and network topology variations in the power grid [3]. Moreover, NB-PLC channels are affected by various types of noise, among which impulsive noise is considered one of the most detrimental disturbances. Generated by electrical devices connected to the grid—such as motors, switching power supplies, lamps, and household appliances—impulsive noise can reach power levels up to 50 dB above the background noise [6]. It is widely recognized as a primary performance-limiting factor in NB-PLC systems. It is characterized by high amplitude, short duration, and random occurrence, and deviates significantly from the Gaussian noise assumption commonly used in communication theory. Unlike additive white Gaussian noise (AWGN), impulsive noise generates burst errors that conventional coding schemes struggle to correct, resulting in severe degradation of communication performance [7], [8]. This explains why OFDM modulation, used in NB-PLC systems and forming the basis of the PRIME [10], [11], [12] and G3-PLC [9] standards, is highly vulnerable to impulsive noise [13].

Over the years, various impulsive noise mitigation techniques have been proposed. Early research efforts mainly focused on traditional signal-processing-based solutions. Error-control-based techniques, including channel coding and interleaving, were employed to enhance robustness against channel impairments [14], [15], [16]. In parallel, nonlinear time-domain preprocessing methods such as blanking and clipping were introduced to suppress high-amplitude impulsive disturbances prior to OFDM demodulation [18]. In addition, statistical approaches relying on impulsive noise modeling and parameter estimation were widely investigated [19]. Although these methods are well established and relatively simple to implement, their performance is highly dependent on accurate noise statistics and fixed design parameters, which limits their robustness in practical NB-PLC environments characterized by non-stationary and appliance-dependent impulsive noise.

More recently, the emergence of deep learning (DL) has introduced a data-driven paradigm for impulsive noise mitigation in PLC systems. This capability has motivated extensive research efforts in PLC systems, where deep neural networks have been primarily employed to overcome the limited adaptability of conventional techniques. Early DL-based studies focused on estimating optimal parameters for nonlinear preprocessing methods, such as adaptive threshold selection for clipping and blanking, leading to significant SNR and BER improvements under time-varying impulsive noise conditions [25]. More advanced architectures, including CNN- and LSTM-based models, were subsequently proposed to exploit temporal and multi-domain features of impulsive noise [28], while recent self-supervised approaches have aimed at reducing the reliance on clean reference signals [26].

Despite recent advances in DL-based impulsive noise mitigation for PLC systems, direct end-to-end denoising solutions tailored to NB-PLC receivers remain largely unexplored. Existing studies mainly rely on adaptive parameter estimation for nonlinear preprocessing techniques, complex multi-branch architectures, or self-supervised models that require significant training and implementation effort. To the best of our knowledge, none of these approaches directly estimate the clean signal at the receiver.

In this study, we propose a time-domain CNN to directly suppress impulsive noise and produce a cleaned received signal. This approach is motivated by the proven effectiveness of CNNs in image and signal processing applications [29], [30]. Our CNN architecture is specifically designed for NB-PLC, aiming to enhance data transmission reliability under realistic NB-PLC noise conditions.

The remainder of this study is organized as follows: Section II presents the review of impulse noise cancellation methods. Section III describes the communication system model, details the statistical characteristics of impulsive noise in NB-PLC. Section IV introduces the proposed CNN-based impulsive noise mitigation framework, including the design of the CNN architecture and the dataset generation methodology. Section V reports and discusses the simulation results. Finally, Section VI summarizes the main contributions of this work and outlines potential directions for future research.

II. State-of-the-Art Approaches for Mitigating Impulsive Noise

A. Traditional Impulsive Noise Mitigation Techniques in PLC Systems

Over the years, various impulsive noise mitigation techniques have been proposed, which can be broadly classified into four categories: error-control-based methods, nonlinear preprocessing techniques, statistical model-based approaches, and learning-based methods [31].

Early studies focused primarily on error-control mechanisms at the physical layer. Channel coding techniques such as low-density parity-check (LDPC) codes [14], Turbo codes [15], polar codes [16], and bit-interleaved coded modulation (BICM) [17] were employed to enhance robustness against channel impairments. these techniques improve resilience to Gaussian noise, but are less effective against impulsive noise, as strong impulses cause long error bursts that exceed correction capabilities and reduce efficiency.

To directly suppress impulsive disturbances in the time domain, nonlinear preprocessing techniques such as blanking, clipping, and deep clipping were introduced at the receiver [18]. These methods are attractive due to their simplicity and low computational complexity. However, their performance is highly sensitive to fixed threshold parameters. Since impulsive noise statistics in PLC environments are time-varying and appliance-dependent, fixed-threshold methods lack adaptability and may either fail to suppress noise effectively or distort the useful signal.

Another class of approaches relies on statistical modeling and parameter estimation of impulsive noise. Techniques based on noise parameter estimation [19], cyclostationary noise mitigation [20], and frequency-domain minimum mean square error (MMSE) equalization [21] have been widely investigated. Although these methods are theoretically well-founded, they depend heavily on accurate noise models and precise parameter estimation. In practical NB-PLC scenarios, model mismatch and rapidly changing noise conditions often degrade their performance, while the associated computational complexity limits real-time applicability.

The sparse nature of impulsive noise has been exploited using compressed sensing techniques to estimate and cancel impulsive disturbances in OFDM-based PLC systems [22]. Sparse Bayesian learning (SBL) further improved robustness by providing probabilistic noise estimation [23], and advanced schemes such as sparse iterative covariance estimation were also proposed [24]. Despite their strong performance, these approaches typically require additional null subcarriers, strict sparsity assumptions, and high computational resources, which restrict their practical deployment in low-complexity NB-PLC receivers.

B. Deep Learning Approaches for Impulsive Noise Denoising in PLC Systems

Recently, DL-based approaches have emerged as a promising alternative to overcome the limited adaptability of traditional threshold-based and model-driven techniques. Classical methods such as clipping, blanking, or statistical filtering rely on fixed parameters or strong assumptions about noise distributions, which are often violated in real PLC environments characterized by non-stationary and appliance-dependent impulsive noise. In contrast, DL-based methods learn noise characteristics directly from received data, enabling adaptive and robust suppression under dynamic conditions [25], [26].

Early DL-based works in PLC primarily focused on adaptive parameter estimation rather than direct end-to-end denoising. For example, in [25], convolutional neural network (CNN)-based approaches were proposed to estimate optimal clipping and blanking thresholds for time-domain impulsive noise mitigation in OFDM-PLC systems. These methods approximate optimal signal-to-interference-plus-noise ratio (SINR)-driven thresholds under clustered impulsive noise from household appliances. Simulation results demonstrated SNR gains of approximately 3–5 dB compared to fixed-threshold methods, leading to improved BER performance in time-varying noise environments.

To further enhance robustness and remove the need for handcrafted preprocessing, end-to-end DL architectures were introduced. In [27], the Multi-Feature Space Domain Fusion Network (MFSDF-Net) was proposed for impulsive noise suppression in MIMO-PLC systems. This CNN-based model extracts and fuses features from parallel convolution kernels operating in different spatial domains, enabling effective mitigation of asynchronous impulsive noise without requiring null subcarriers. Compared to traditional clipping/blanking and earlier DL models, MFSDF-Net significantly reduces BER floors and achieves an SNR of 18 dB at a BER of 10^{-5}, compared to 26 dB or higher for other models, corresponding to an 8 dB improvement in highly dynamic environments.

In another study [28], LSTM-based adaptive mitigation schemes were introduced to track impulsive noise states over time and dynamically adjust clipping decisions using sliding windows. These methods were combined with peak-to-average power ratio (PAPR) reduction techniques, such as accelerated proximal gradient methods and differential phase time encoding, to protect useful OFDM signals. Simulation results showed clear BER improvements over conventional nonlinear methods, particularly under rapidly changing impulsive noise conditions.

More recently, self-supervised models such as UNet-INSN have marked a shift toward label-free training. In [26], the authors proposed UNet-INSN, a 1D UNet-based architecture trained without clean reference signals. The model employs a global mask mapper and a reproducibility loss to prevent identity mapping, allowing training directly on noisy PLC signals. In simulations, UNet-INSN achieves a BER of 10^{-6} at approximately 12 dB SNR with ideal channel estimation and

26 dB with non-ideal estimation. It outperforms Noise2Void by about 3 dB, Zero-Shot Noise2Noise by 4 dB, and Deep-Clipping by nearly 7 dB, while maintaining less than 1 dB degradation when the impulsive noise probability varies from 0.01 to 0.05. These results demonstrate strong robustness in coded MIMO-PLC systems.

C. Blanking and Clipping-Based Time-Domain Noise Mitigation Approaches

Traditional time-domain impulsive noise suppression methods are memoryless nonlinear techniques that adjust the signal amplitude based on predefined thresholds while preserving its phase [31], [25]. Applied to the received signal prior to FFT demodulation in OFDM systems, the most used in the literature are blanking and clipping [31].

In the blanking technique, the received signal sample y_s is set to zero whenever its amplitude exceeds a predefined blanking threshold T_b, and remains unchanged otherwise [see Eq. (1)]:

$$y_s = \begin{cases} y_s, & |y_s| < T_b, \\ 0, & |y_s| \geq T_b. \end{cases} \tag{1}$$

The clipping method limits the signal amplitude to a clipping threshold T_c while preserving the phase, and is defined as Eq. (2):

$$y_s = \begin{cases} y_s, & |y_s| < T_c, \\ T_c \cdot e^{j\arg(y_s)}, & |y_s| \geq T_c. \end{cases} \tag{2}$$

Blanking and clipping scheme performances are highly dependent on the choice of the threshold. An inadequately selected threshold can either remove useful signal samples (over-blanking/clipping) or fail to suppress impulsive noise effectively (under-blanking/clipping), leading to significant BER degradation. Many classical approaches determine the threshold through exhaustive offline optimization for each SNR level, providing near-optimal performance but being computationally prohibitive for real-time implementation. Other works set the threshold as a multiple of the noise standard deviation; however, such fixed thresholds are highly sensitive to variations in noise statistics and are not robust in dynamic NB-PLC environments. More analytical approaches derive optimal thresholds based on closed-form SNR expressions, yet they generally assume prior knowledge of SINR/SNR, which is difficult to estimate accurately in practice [31], [32], [25].

Consequently, the practical applicability of thresold-based methods remains limited, motivating the development of data-driven deep learning approaches. These methods either aim to estimate optimal threshold or to detect the temporal positions of impulsive noise events prior to applying classical nonlinear mitigation techniques.

In this work, a CNN-based deep learning framework is proposed to directly estimate the clean signal without explicitly inferring the nonlinear processing parameters or requiring prior estimation of SINR or SNR at the receiver.

III. System Architecture

We investigate an NB-PLC OFDM communication system compliant with the G3-PLC specification, operating in the FCC frequency band ranging from 154.6875 kHz to 487.5 kHz, as defined by the ITU-T G.9903 standard [9]. Each physical frame contains $N_s = 12$ OFDM symbols. The system employs 128 subcarriers with an IFFT size of 256, resulting in a subcarrier spacing of 4.6875 kHz is performed over $N_d = 72$ active subcarriers using BPSK modulation. The cyclic prefix (CP) is added to each OFDM symbol to mitigate inter-symbol interference. The G3-PLC parameters for FCC band are detailed in Table I [9] and the block diagram of the G3-PLC OFDM is depicted in Fig. 1.

TABLE I. Key Parameters of G3-PLC in FCC Band Configuration [9]

Parameters	Value
Active subcarrier (N_d)	72
IFFT size	256
Subcarrier spacing	4.6875 kHz
OFDM symbols (N_s)	12
CP duration	30
Modulation type	BPSK
Operating frequency range	154.7–487.5 kHz

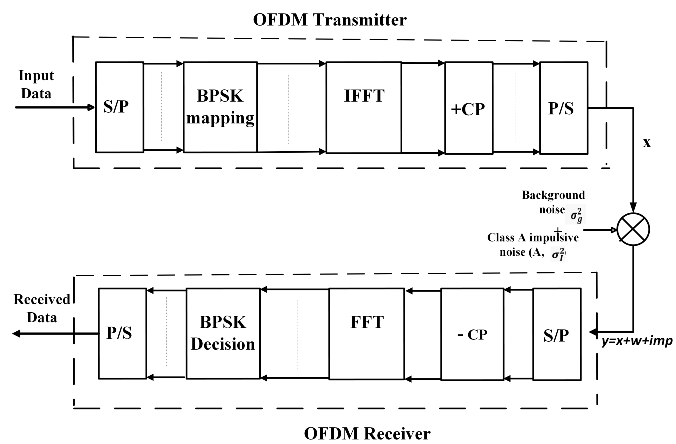

Fig. 1. Block diagram of G3-PLC OFDM system transceiver.

At the transmission side, coherent BPSK is employed for modulation.

The received signal $y(t)$ affected by impulsive noise, is expressed as Eq. (3):

$$y(t) = x(t) + w(t) + imp(t), \tag{3}$$

where, $x(t)$, $w(t)$ and $imp(t)$ denote transmistted signal, the additive white Gaussian noise (AWGN) and impulsive noise, respectively. After cyclic prefix removal and FFT blocks are applied, decision making for BPSK demodulation is performed.

A. Impulsive Noise Model

Numerous statistical models have been proposed in the literature to describe the impulsive noise [4], [5]. Among them the Middleton Class-A model is the most commonly used and has been extensively validated for NB-PLC environments.

The probability density function (PDF) of the Middleton Class-A noise is given by Eq. (4) [5]:

$$f_A(x_k) = \sum_{m=0}^{\infty} \frac{A^m e^{-A}}{m!} N(x_k, 0, \sigma_m^2), \tag{4}$$

where, x_k denotes the noise sample observed at discrete time index k, and A is the impulsive index, which controls the average density of impulsive events within a given observation interval. The term $N(x_k, 0, \sigma_m^2)$ represents a zero-mean Gaussian probability density function with variance σ_m^2, defined as Eq. (5):

$$\sigma_m^2 = \frac{\sigma_i^2}{A} m + \sigma_g^2 = \sigma_g^2 \left(\frac{m}{\tau} + 1 \right), \tag{5}$$

where, σ_i^2 denotes the variance of the impulsive noise component, σ_g^2 is the variance of the background gaussian noise, and $\tau = \sigma_g^2/\sigma_i^2$ represents the impulsive-to-Gaussian noise power ratio.

The magnitude of the impulse and the moment at which it occurs are key parameters of impulsive noise, as they fully characterize its behavior in the time domain, which are sufficient to describe its impact on the received signal. In NB-PLC channels, a single impulsive event typically corrupts one or a few signal samples, however, due to the FFT operation, its energy is spread over all subcarriers, leading to significant performance degradation if not properly mitigated.

IV. Proposed DL-Based Approach for Impulsive Noise Mitigation in NB-PLC Systems

CNNs are well suited for impulsive noise mitigation due to their ability to capture local patterns and abrupt signal variations caused by sparse, high-amplitude noise events.

Next, details of the CNN-based approach to suppress the impulsive noise are given, including the network architecture and the dataset generation process.

A. CNN-Based Impulsive Noise Mitigation In NB-PLC Receivers

The proposed CNN-based PLC signal denoising architecture is integrated into the OFDM receiver processing block, as illustrated in Fig. 2. It is placed before the serial-to-parallel conversion, CP removal, and FFT block within the OFDM receiver. The network input consists of time-domain samples arranged as a tensor of size $[1 \times 3432 \times 2]$, and the model is trained to estimate the corresponding clean signal.

The design of the CNN architecture, including the number of convolutional layers and kernel dimensions, is not based on heuristic assumptions, but is derived from a systematic experimental optimization performed during the offline training stage. The resulting architectural parameters are discussed in detail in Section V-A.

B. CNN Structure

The choice of CNNs model is motivated by prior work in wireless communication systems, which has consistently shown their superior effectiveness in denoising tasks. CNNs employ multiple learnable filters across successive layers to capture and refine complex structures in noisy observations enables [33], [34]. Moreover, their hierarchical architecture multiscale feature learning, a which is essential for effectively separating noise components from the underlying useful signal [33].

The proposed CNN architecture, depicted in Fig. 3, is formulated as a regression model. It is composed of five convolutional blocks, where the third and fifth blocks are replicated to reinforce feature learning capabilities, in addition to the input and output layers. The network input consists of a three-dimensional tensor of size $[1 \times 3432 \times 2]$, obtained after applying Z-score normalization to the received noisy OFDM samples.

Each convolutional block comprises a convolutional layer, followed by Batch Normalization and a Leaky ReLU activation function. The convolutional layers employ learnable kernels with *same* padding in order to maintain the spatial dimensions of the feature maps. Batch Normalization is used to reduce internal covariate shift and improve training stability, while the Leaky ReLU activation alleviates neuron saturation and facilitates faster convergence [33], [34]. The output stage consists of a final convolutional layer followed by a regression layer that produces the estimated clean signal with dimensions $[1 \times 3432 \times 2]$.

The convolutional layers are denoted using the format `conv | ` $K_s \times K_s$ ` | Num | same`, where `conv` represents a convolutional operation, K_s (9, 5, 3) indicates the kernel size, *Num* specifies the number of filters, and `same` denotes dimension-preserving padding. Employing convolutional kernels of varying sizes enables the network to effectively model impulsive noise patterns while retaining essential signal structures [37].

The proposed DL-network is trained using a dedicated dataset that reproduces the impulsive noise characteristics typical of NB-PLC channels. This training strategy allows the model to effectively cope with the temporal variability of the impulsive noise, thereby enabling accurate estimation of the clean OFDM signal under realistic NB-PLC operating conditions.

C. Dataset Generation

A diversified dataset is constructed to train the proposed OFDM-based model, considering exclusively the effect of the impulse noise presence in the NB-PLC channel. The noise is modeled using the Middleton Class-A distribution [5]. This synthetic data generation strategy ensures sufficient variability for robust network training while excluding channel effects such as multipath fading or attenuation. The modeled noise is directly added to the transmitted OFDM signals to construct the noisy dataset, providing realistic training samples for the proposed impulsive noise mitigation approach.

The training dataset for the CNN is constructed as follows: A total of 72 000 observations, each corresponding to

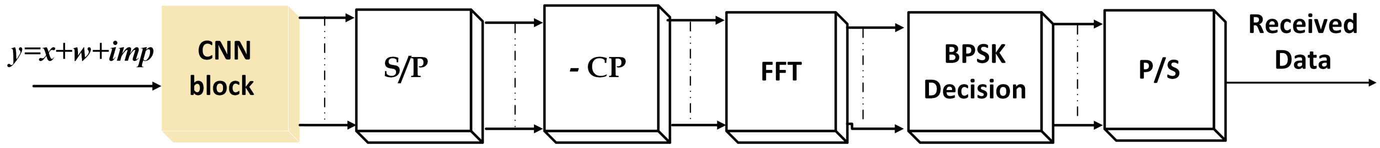

Fig. 2. Block diagram of the OFDM receiver incorporating the CNN model for impulsive noise mitigation.

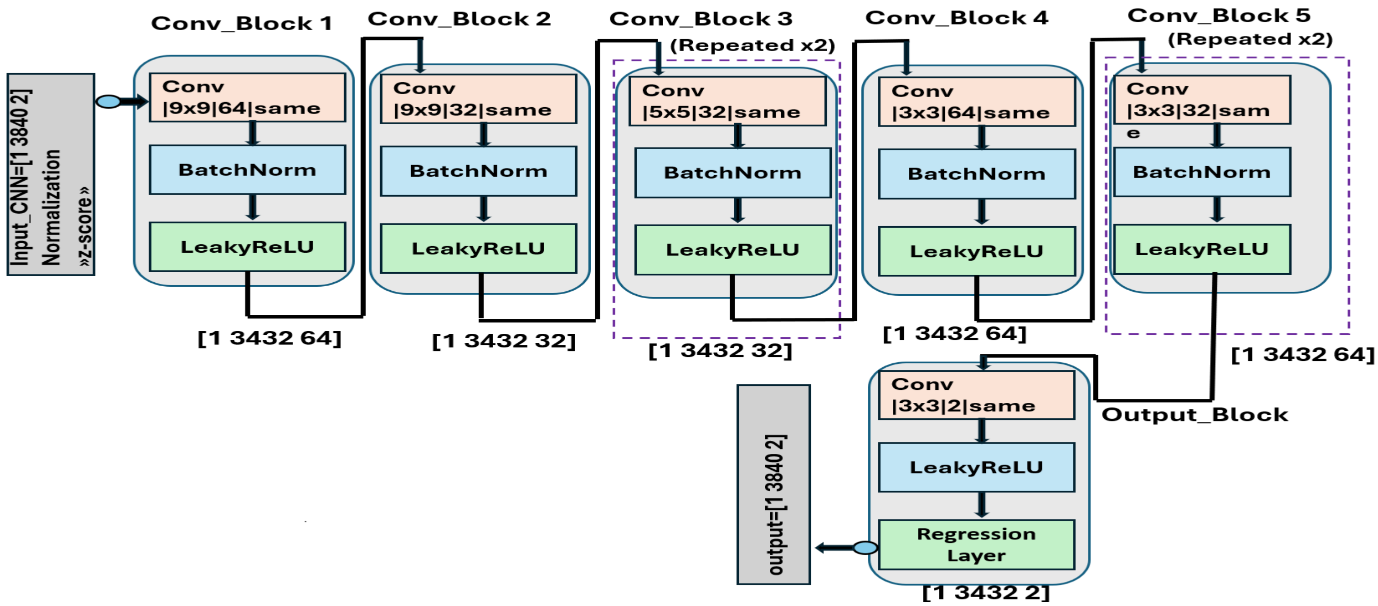

Fig. 3. CNN model architecture for impulsive noise suppression.

one OFDM frame, are generated. The dataset is organized into three blocks corresponding to different impulsive noise densities, with the Middleton Class-A parameter A set to 0.01, 0.1, and 0.5, respectively.

For each value of A, a total of 3 000 OFDM frames are generated and distributed across the SNR range from 0 to 30 dB in increments of 4 dB. This construction ensures a balanced representation of SNR conditions for each impulsive noise density and allows the network to jointly learn the variability of both A and SNR.

The impulsive noise is modeled according to the Middleton Class-A distribution with fixed parameters $\sigma_I^2 = 7.28 \times 10^{-4}$, $\Gamma = 0.01$, and $\sigma_G^2 = 7.28 \times 10^{-7}$, which were extracted from experimental measurements conducted by our research group using a Tektronix TDS3000C oscilloscope [5]. In addition, AWGN noise is added according to the target SNR.

The received noisy signals y, as defined in Eq. (3), serve as the input data. These complex-valued time-domain signals are preprocessed and represented as tensors of size $[1 \times 3432 \times 2]$. The first dimension corresponds to a single OFDM frame, the second dimension (3432) denotes the total number samples per OFDM frame including the CP, and the third dimension represents the complex signal components, with separate channels for the real and imaginary parts.

The label data consist of clean OFDM frames transmitted in the absence of impulsive noise. These reference signals are represented using the same tensor dimensions $[1 \times 3432 \times 2]$.

Consequently, the complete dataset is organized as 4D tensors of size $[1, 3432, 2, N_1]$, where $N_1 = 72000$ denotes the total number of training samples. Z-score normalization is applied to the input tensors to enhance numerical stability and accelerate network convergence.

V. Simulation Results and Discussion

To evaluate the performance of the proposed estimation approach in an OFDM-based NB-PLC system affected by impulsive noise, an extensive simulation campaign was conducted using a BPSK-OFDM transceiver compliant with the G3-PLC standard, as described in Section III. The impulsive noise samples are synthetically generated according to the Middleton Class-A model with fixed parameters $\sigma_i^2 = 7.28 \times 10^{-4}$,$\sigma_g^2 = 7.28 \times 10^{-7}$, and $\tau = 0.01$. The system performance is evaluated under various SNR conditions ranging from 0 to 30 dB and different levels of impulsive noise density.

For comparison purposes, conventional blanking and clipping schemes, were also evaluated, with optimal thresholds determined through an exhaustive search over the normalized threshold range $Th \in [0, 5]$ using a step size of $\Delta T = 0.01$. For each set of impulsive noise parameters, the threshold that minimizes the output BER is selected [25], [36].

All simulation scenarios were run on a Dell G15 5530 notebook featuring a 13th-generation Intel Core i7-13650HX CPU (14 cores, 20 logical threads, base frequency of 2.6 GHz), 32

GB of memory, and the 64-bit version of Microsoft Windows 11 Home.

A. Offline Training and Online Deployment of the Proposed CNN-Based Denoising Model

1) Offline training phase: The constructed dataset is randomly partitioned into training, validation, and testing sets with proportions of 80%, 10%, and 10%, respectively. The validation subset is solely employed to track the learning process and mitigate overfitting during training. Prior to network training, the time-domain input frames are standardized using Z-score normalization, which enforces zero mean and unit variance, thereby improving numerical stability and accelerating convergence of the CNN.

To identify the optimal CNN architecture, a tuning study is conducted by monitoring the mean squared error (MSE) loss function L_{MSE} defined in Eq. (6). The goal is to select a model configuration that achieves the lowest L_{MSE} while keeping the computational complexity within reasonable limits.

$$L_{\text{MSE}}(\Phi) = \frac{1}{K_T} \left\| \mathbf{O}_T - \mathbf{O}_T^* \right\|_2^2, \tag{6}$$

where, $\mathbf{O}_T \in \mathbb{R}^{K_T}$ denotes the complete set of target values in the training dataset, $\mathbf{O}_T^* \in \mathbb{R}^{K_T}$ represents the network's estimates, K_T is the total number of training samples, and $\Phi = \{\Phi_1, \Phi_2, \ldots, \Phi_L\}$ contains all trainable parameters of the network, with L being the total number of layers.

The CNN incorporates convolution kernels of different sizes (9×9, 5×5, and 3×3) to effectively capture impulsive noise characteristics while preserving the underlying signal.

The final optimized hyperparameters, summarized in Table II, are selected to minimize the loss function and provide considerably improved training stability and generalization performance of the CNN.

TABLE II. Optimized Set of Training Hyperparameters for the CNN-Based NB-PLC Denoising Model

Hyperparameter	CNN Model
Optimizer	Adam
Max Epochs	20
Initial Learning Rate	10^{-3}
L2 Regularization	10^{-4}
Mini-Batch Size	32
Input Size	Tensor $[1, 3432, 2]$
Output Size	Tensor $[1, 3432, 2]$

To assess the performance of the trained CNN, the coefficient of determination R^2 and the MSE are computed on the testing dataset, as defined in Eq. (7) and Eq. (8) [35]:

$$R^2_{\text{Testing}} = 1 - \frac{\sum_{i=1}^{K_{\text{Test}}} \left(TO_i - TO_i^*\right)^2}{\sum_{i=1}^{K_{\text{Test}}} \left(TO_i - \overline{TO}_i\right)^2}, \tag{7}$$

$$MSE_{\text{Testing}} = \frac{1}{K_{\text{Test}}} \sum_{i=1}^{K_{\text{Test}}} \left(TO_i - TO_i^*\right)^2, \tag{8}$$

where, TO_i denotes the actual target value of the i-th testing sample, TO_i^* represents the value estimated by the CNN model, $\overline{O}_{Test}$ is the mean of the target values in the testing set, and K_{Test} is the total number of testing samples.

The results show that the CNN model close to very low MSE value (7.0159×10^{-5}) and an R^2 value approaching 1 (≈ 0.91), indicating a highly accurate estimation.

Fig. 4 shows the training and validation loss evolution over 20 epochs. A rapid decrease is observed during the first epochs, indicating efficient learning of the underlying data representation. Both losses converge smoothly and remain closely aligned throughout training, demonstrating good generalization capability and the absence of overfitting. After approximately 14 epochs, the loss stabilizes around 0.15, suggesting that the model has reached convergence and additional training provides limited improvement.

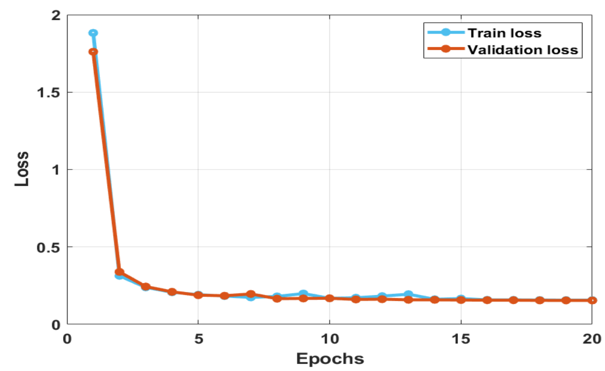

Fig. 4. Training and validation loss curves of the proposed CNN.

2) Online deployment phase: During the online testing phase, 10000 OFDM frames are transmitted under SNR conditions ranging from 0 to 30 dB with a 4 dB step. The frames are corrupted by impulsive noise realizations not used during training enabling a rigorous evaluation of the model's generalization capability under unseen noise conditions. Each transmission consists of a single OFDM frame containing 12 OFDM symbols.

B. Performance Evaluation and Analysis

The performance of the proposed CNN-based mitigation technique is evaluated in terms of MSE and BER, with results averaged over 10000 transmitted OFDM frames for each SNR value. Three distinct simulation scenarios are considered to benchmark this approach against reference schemes:

- A fixed impulsive index parameter A=0.1;
- A fixed impulsive index parameter A=0.5;
- A time-varying parameter A randomly drawn for each OFDM frame from a uniform distribution in the range [0.01, 0.5] to emulate dynamically varying impulsive noise conditions in realistic NB-PLC environments.

The performance of the proposed CNN-based denoising approach is finally compared with conventional blanking and clipping methods, where their thresholds are set to optimal values to maximize noise mitigation performance.

Fig. 5 shows the BER versus SNR for different impulsive noise mitigation methods, with the impulsive index parameter set to $A = 0.1$, the system without any mitigation suffers severe degradation, with a BER around 10^{-2} even at SNRs above 20 dB. This error floor highlights the dominant effect of unmitigated impulsive noise, which persists even when AWGN becomes negligible.

Classical methods such as Clipping and Blanking significantly improve performance. At SNR = 10 dB, Clipping reduces the BER to approximately 2×10^{-3}, while Blanking achieves 1×10^{-3}. A gain of 13 dB at a BER of 10^{-2} is observed compared to the untreated system. At SNR = 20 dB, Clipping and Blanking reach 1.2×10^{-5} and 2.31×10^{-6}, respectively. These methods show a consistent slope, demonstrating good adaptation to increasing SNR and confirming their effectiveness for attenuating impulsive noise in NB-PLC channels, at the cost of an additional processing step to determine the optimal threshold.

The proposed CNN method exhibits outstanding performance and outperforms classical techniques. At SNR = 10 dB, the CNN achieves a BER of 3×10^{-4}, corresponding to additional gain of approximately 3 dB over Clipping and 2 dB over Blanking. This demonstrates the CNN's ability to effectively learn the complex spatio-temporal features of impulsive noise and improve the performances of the system.

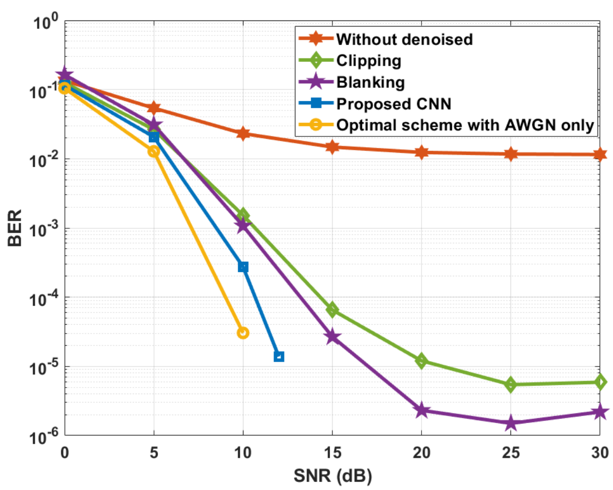

Fig. 5. BER versus SNR for different impulsive noise mitigation techniques under fixed noise density A=0.1.

Fig. 6 illustrates the average MSE versus SNR for the different tested noise mitigation approaches. The Clipping method exhibits the poorest performance, with an MSE stabilizing around 1.5×10^{-4} for SNR $\geq$ 10 dB. The Blanking technique performs better, starting at 1.2×10^{-3} at SNR = 0 dB and decreasing to approximately 1×10^{-4} for SNR $\geq$ 15 dB. However, both conventional methods exhibit an error floor, limiting their effectiveness at high SNR.

In contrast, the proposed CNN-based method demonstrates superior performance across the entire SNR range. Its MSE decreases monotonically from 2×10^{-4} at SNR = 0 dB to 2×10^{-5} at 30 dB, corresponding to an order-of-magnitude improvement. At SNR = 10 dB, the CNN achieves an MSE

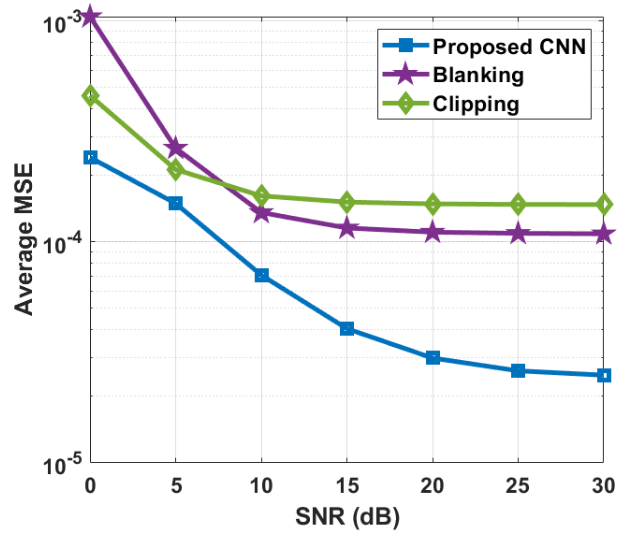

Fig. 6. Average MSE versus SNR for different impulsive noise mitigation techniques at a fixed impulsive index A=0.1.

of approximately 7×10^{-5}, outperforming the Blanking and Clipping methods, which yield MSE values of 1.3×10^{-4} and 1.6×10^{-4}, respectively. Notably, the absence of an error floor indicates that the CNN continues to benefit from increasing SNR for improved signal reconstruction, unlike conventional threshold-based methods, whose performance tends to saturate at high SNR.

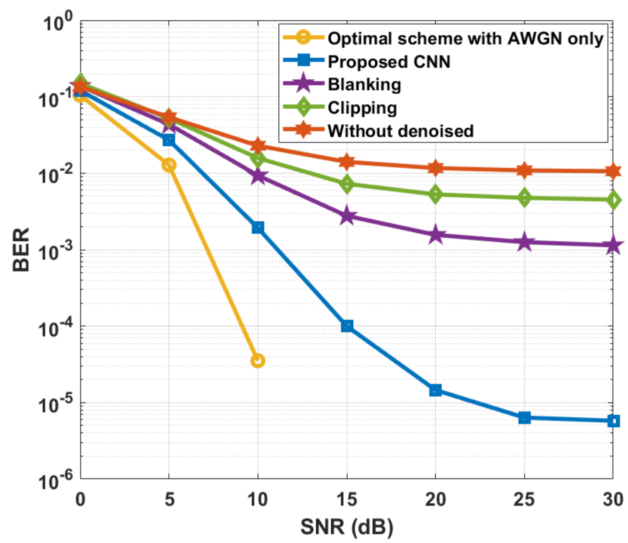

Fig. 7. BER versus SNR for different impulsive noise mitigation techniques at a fixed impulsive index A=0.5.

Next evaluation deals with the scenario of the impulsive noise with a fixed parameter $A = 0.5$, which result a severely disturbed NB-PLC environment. Fig. 7 illustrates the BER versus SNR for the different tested noise mitigation approaches. First, the system without any denoising method to BER higher than 10^{-2} across the entire SNR range. The Clipping method reduces the BER to approximately 4×10^{-3} at 30 dB, a gain of

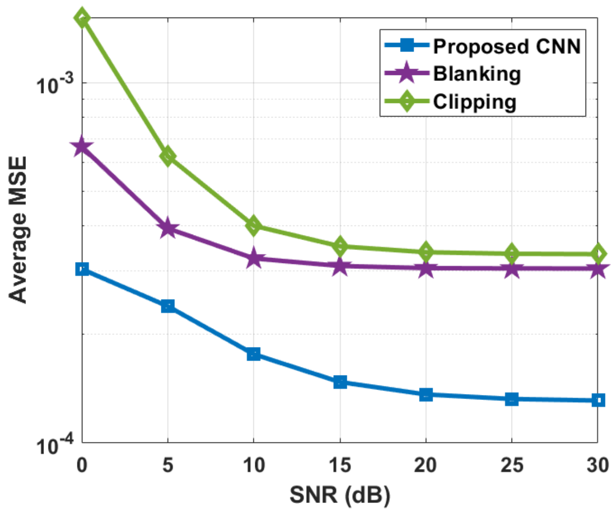

Fig. 8. Average MSE versus SNR for different impulsive noise mitigation techniques at a fixed impulsive index A=0.5.

approximately 6 dB is observed at a BER of 10^{-2}. Blanking provides greater improvement, with a BER of 1×10^{-2} at 10 dB and 1×10^{-3} at 30 dB, for a BER of 10^{-2}, provides an improvement of nearly 10 dB compared to the untreated system.

In contrast, the proposed CNN-based method achieves significantly lower BER than conventional techniques. At a target BER of 10^{-3}, a performance gain of nearly 18 dB is observed compared to the blanking method. Moreover, at a BER of 10^{-2}, the proposed approach provides a gain of approximately 23 dB relative to the untreated system, about 7 dB compared to clipping, and nearly 3 dB compared to blanking. At SNR = 20 dB, the CNN BER decreases to 10^{-5}. These results indicate that the CNN is able to exploit the complex temporal and statistical correlations of impulsive noise, unlike simple threshold-based methods.

In terms of MSE, the CNN-based technique clearly surpasses the benchmark methods, as illustrated in Fig. 8. It achieves an MSE of 1.7×10^{-4} at 10 dB decreasing to 1.2×10^{-4} at 30 dB, without any saturation. Alternatively, the Clipping method shows an MSE floor around 3.5×10^{-4} for SNR ≥ 15 dB, while Blanking reaches 3.2×10^{-4} at 10 dB and stabilizes near 3.0×10^{-4} for SNR ≥ 15 dB.

Fig. 9 presents the BER under a realistic NB-PLC scenario, where the parameter A varies dynamically from frame to frame, randomly drawn from a uniform distribution over the set $0.01, 0.5$.

In time-varying noise scenario, the CNN-based mitigation technique shows its advantage and demonstrates high robustness to fluctuations in impulsive index A. At SNR $= 10$ dB, the BER reaches 2.5×10^{-3}, corresponding to an SNR gain of approximately 5 dB compared to the Blanking method and 77 dB compared to Clipping. Moreover, the BER decreases monotonically to approximately 10^{-7} at SNR $= 30$ dB, while Blanking and Clipping saturate at around 2×10^{-4} and 3×10^{-3}, respectively. This result highlights the adaptability of the CNN, which learns to distinguish and effectively handle different levels of impulsive noise.

Finally, Fig. 10 presents the comparison of different methods in terms of average MSE. Similarly to previous results, the CNN-based methods outperforms the other noise mitigation techniques. It maintains a continuous MSE reduction from 2.8×10^{-4} at SNR = 0 dB to 6.5×10^{-5} at SNR = 30 dB. At high SNR, the proposed technique exhibits an MSE floor of 1.2×10^{-4}, whereas Blanking and Clipping do not decrease below 3×10^{-4} and 3.5×10^{-4}, respectively.

To further position the proposed approach with respect to existing DL–based impulsive noise mitigation techniques, Table III summarizes representative studies from recent years discussed above.

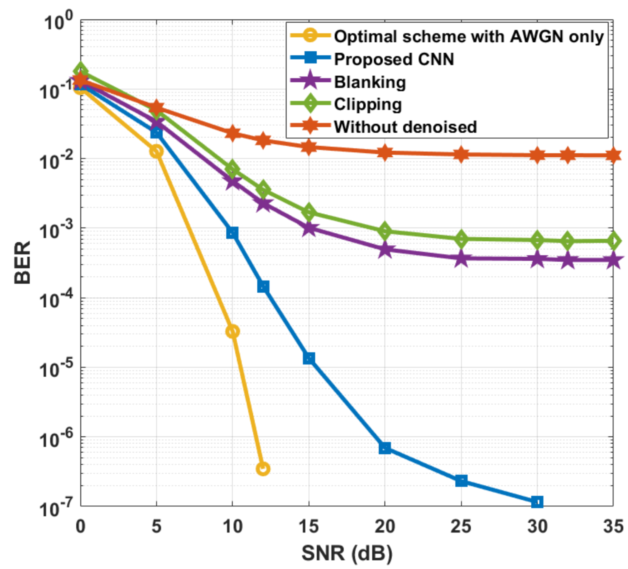

Fig. 9. BER versus SNR for different impulsive noise mitigation techniques with random noise density.

From the comparison presented in Table III, it can be observed that end-to-end time-domain denoising approaches offer an attractive trade-off between performance and computational efficiency. In this context, the proposed method avoids intermediate parameter estimation stages by directly learning the mapping between noisy and clean signals, while preserving robust generalization across varying impulsive noise densities. Moreover, the supervised learning framework relies on synthetic Middleton Class-A noise samples calibrated using experimental measurements, which facilitates a practical and reproducible implementation.

VI. Conclusion

This study presented a CNN-based approach for direct time-domain impulsive noise mitigation in NB-PLC OFDM systems compliant with the G3-PLC standard. The proposed method eliminates the need for threshold optimization, noise parameter estimation, or additional null subcarriers, as required by conventional cancellation techniques. Trained on synthetic data generated using Middleton Class-A model calibrated with experimental measurements, the CNN effectively suppresses

TABLE III. SUMMARY OF DEEP LEARNING ARCHITECTURES AND THEIR ROLES FOR IMPULSIVE NOISE MITIGATION IN OFDM-BASED PLC SYSTEMS

Reference	Year	DL Architecture and Role	System Description and Noise Model	Key Performance Results
Barazideh et al.[38]	2019	DNN (Fully Connected, 2 hidden layers: 20+10 neurons, ReLU activations; Sigmoid output) Detects impulsive samples using statistical features (ROAD, median deviation) for subsequent blanking.	OFDM-based systems; Noise: Bernoulli–Gaussian and Middleton Class-A ($\epsilon, A \in [0.04, 0.2]$)	Up to 2 dB SNR gain over blanking/clipping at BER 10^{-3}
He et al.[25]	2023	MaxPoolCNN (CNN with Max-Pooling layers) Extracts local features and adaptively estimates the optimal threshold values for the Deep Clipping method.	OFDM-based broadcasting and PLC system; Noise: Middleton Class-A ($A = 0.1$), Poisson arrival	Average interference reduction 15.1 dB (up to 19.6 dB); improved BER vs fixed threshold for blanking/clipping
Yang et al.[27]	2024	LSTM architecture Models temporal dependencies in impulsive noise to dynamically adjust thresholds.	OFDM-based smart grid PLC system; Noise: Bernoulli–Gaussian ($p = 0.1, 0.2$)	BER reduction 87.85% ($p = 0.1$) and 89.72% ($p = 0.2$) at 8 dB SNR vs blanking
Ouyang et al.[28]	2024	MFSDF-Net (CNN multi-feature fusion, parallel convolutions 1×1,1×3,1×5,1×7) Uses parallel convolutional kernels to extract and fuse features from multiple signal domains, effectively suppressing impulsive noise.	OFDM-based PLC; Noise: Bernoulli–Gaussian (p), dataset generated at SINR = -15 dB	BER 10^{-5} at 18 dB SNR, 8 dB improvement over Adaptive Parameter / GMM
Zhu et al.[26]	2025	1D-UNet (CNN encoder-decoder) Self-supervised denoising; learns signal reconstruction from noisy input only via global mask mapper.	OFDM-based MIMO-PLC system; Noise: Bernoulli–Gaussian ($p = 0.01, 0.05$)	At BER 10^{-6}, gains of 3 dB over Noise2Void, 4 dB over Zero-Shot Noise2Noise, 7 dB over DeepClipping
This work	**2026**	Multi-layer CNN (5 convolutional blocks: Conv + BatchNorm + Leaky ReLU) Direct end-to-end regression of clean signal from noisy input; robust to dense impulsive noise	NB-PLC OFDM system according to G3-PLC standard; Noise: Middleton Class-A ($A = \{0.01, 0.1, 0.5\}$)	Up to 18 dB SNR gain over blanking at BER 10^{-3} for $A = 0.5$; additional 3 dB over clipping and 2 dB over blanking at 10 dB SNR for $A = 0.1$; MSE = 7.01×10^{-5}

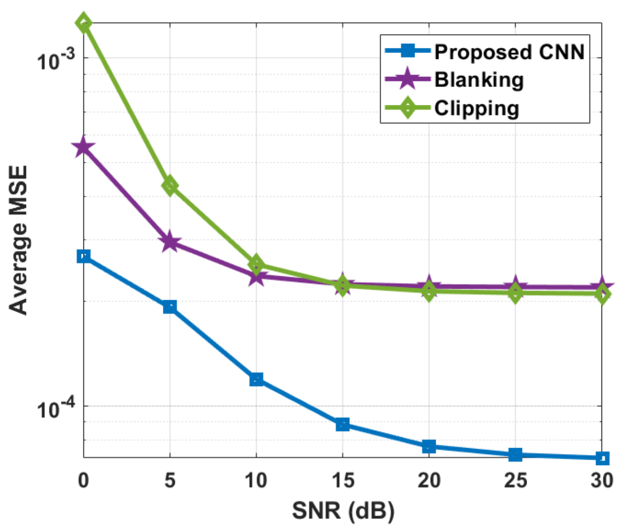

Fig. 10. Average MSE versus SNR for different impulsive noise mitigation techniques with random noise density.

impulsive noise while preserving useful signal components under varying noise densities.

Simulation results demonstrate that the proposed approach achieves significant improvements in BER and MSE over SNR range and under various impulsive noise conditions compared to conventional methods. These findings confirm that data-driven learning-based approaches consitutues a promising alternative to classical impulsive noise mitigation techniques for NB-PLC systems.

Future work will focus on integrating channel estimation and equalization within the proposed architecture for joint optimization, as well as investigating hybrid schemes that combine the CNN with channel coding techniques such as LDPC or polar codes to further enhance reliability.

REFERENCES

[1] G. López, J. Matanza, D. Vega, M. Castro, A. Arrinda, J. Moreno, and A. Sendin, "The Role of Power Line Communications in the Smart Grid Revisited: Applications, Challenges, and Research Initiatives," *IEEE Access*, vol. pp. 1–1, Jul. 2019. doi: 10.1109/GLOCOM.2014.7037191.

[2] M. Luka, S. Pallam, I. Thuku, and U. Uyoata, "Narrowband Power Line Communication for Smart Grid," *International Journal of Scientific and Engineering Research*, vol. 6, no. 8, pp. 876–880, Aug. 2015. [Online]. Available: https://www.ijser.org

[3] H. Gassara, F. Rouissi, and A. Ghazel, "Statistical characterization of the indoor low-voltage narrowband power line communication channel," *IEEE Trans. Electromagn. Compat.*, vol. 56, no. 1, pp. 123–131, Feb. 2014, doi: 10.1109/TEMC.2013.2272759.

[4] F. Rouissi, A. J. H. Vinck, H. Gassara, and A. Ghazel, "Statistical characterization and modelling of impulse noise on indoor narrowband PLC environment," in *Proc. IEEE Int. Symp. Power Line Communications and its Applications (ISPLC)*, Madrid, Spain, 2017, pp. 1–6. [Online]. Available: doi:10.1109/ISPLC.2017.7897119.

[5] F. Rouissi, A. J. H. Vinck, H. Gassara, and A. Ghazel, "Improved Impulse Noise Modeling for Indoor Narrow-Band Power Line Communication," *AEU – International Journal of Electronics and Communications*, vol. 103, Mar. 2019. doi: 10.1016/j.aeue.2019.02.019.

[6] M. Zimmermann and K. Dostert, "An analysis of broadband noise scenario in powerline networks," in *Proc. IEEE International Symposium on Power Line Communications and Applications (ISPLC)*, 2000.

[7] M. Marey and H. Steendam, "Analysis of the Narrowband Interference Effect on OFDM Timing Synchronization," *IEEE Transactions on Signal Processing*, vol. 55, no. 9, pp. 4558–4566, Sep. 2007. doi: 10.1109/TSP.2007.896020.

[8] A. Mehboob, L. Zhang, and J. Khangosstar, "Adaptive impulsive noise mitigation using Multi Mode Compressive Sensing for powerline communications," in *Proc. IEEE International Symposium on Power Line*

Communications and Its Applications (ISPLC), 2012, pp. 368–373. doi: 10.1109/ISPLC.2012.6201304.

[9] International Telecommunication Union (ITU), “Narrowband orthogonal frequency division multiplexing power line communication transceivers for G3-PLC networks,” *ITU-T Recommendation G.9903*, 2017. [Online]. Available: https://www.itu.int/rec/T-REC-G.9903-201708-I/en

[10] A. Sanz, “I3: ITU-T G.9904 (PRIME 1.4) evolution of implementation and certification of NB-PLC,” in *Proc. IEEE International Symposium on Power Line Communications and Its Applications (ISPLC)*, 2016.

[11] J. Matanza, S. Alexandres, and C. Rodriguez-Morcillo, “Performance evaluation of two narrowband PLC systems: PRIME and G3,” *Computer Standards & Interfaces*, vol. 36, no. 1, pp. 198–208, 2013. doi: 10.1016/j.csi.2013.05.001.

[12] Š. Matějka and P. Hladík, “Initial tests of DVB-T receivers on tolerance to impulsive interference,” in *Proc. 21st International Conference Radioelektronika*, 2011, pp. 1–4. doi: 10.1109/RADIOELEK.2011.5936471.

[13] P. Torio and M. G. Sanchez, “Cell interleaving against impulsive noise in OFDM,” *IEEE Transactions on Consumer Electronics*, vol. 58, no. 2, pp. 269–273, 2012. doi: 10.1109/TCE.2012.6227422.

[14] R. G. Gallager, “Low-density parity-check codes,” *IEEE Transactions on Information Theory*, 1962. [Online]. Available: IEEE Xplore.

[15] C. Berrou, A. Glavieux, and P. Thitimajshima, “Near Shannon limit error-correcting coding and decoding: Turbo-codes,” in *Proc. IEEE International Conference on Communications (ICC)*, 1993. [Online]. Available: IEEE Xplore.

[16] E. Arıkan, “Channel polarization: A method for constructing capacity-achieving codes for symmetric binary-input memoryless channels,” *IEEE Transactions on Information Theory*, 2009. [Online]. Available: IEEE Xplore.

[17] G. Caire, G. Taricco, and E. Biglieri, “Bit-interleaved coded modulation,” *IEEE Transactions on Information Theory*, 1998. [Online]. Available: IEEE Xplore.

[18] F. H. Juwono, Q. Guo, D. Huang, and K. P. Wong, “Deep Clipping for Impulsive Noise Mitigation in OFDM-Based Power-Line Communications,” *IEEE Transactions on Power Delivery*, vol. 29, no. 3, pp. 1335–1343, 2014. doi: 10.1109/TPWRD.2013.2294858.

[19] M. Elgenedy, M. Sayed, M. Mokhtar, M. Abdallah, and N. Al-Dhahir, “Interference mitigation techniques for narrowband powerline smart grid communications,” in *Proc. IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2015, pp. 368–373. doi: 10.1109/SmartGridComm.2015.7436328.

[20] Y.-R. Chien, S. S.-D. Xu, and S.-H. Lu, “Cyclostationary impulsive noise mitigation algorithm for narrowband powerline communications,” *Journal of the Franklin Institute*, vol. 357, no. 1, pp. 687–703, 2020. doi: 10.1016/j.jfranklin.2019.10.026.

[21] Y. G. Yoo and J. H. Cho, “Asymptotic Analysis of CP-SC-FDE and UW-SC-FDE in Additive Cyclostationary Noise,” in *Proc. IEEE International Conference on Communications (ICC)*, 2008, pp. 1410–1414. doi: 10.1109/ICC.2008.273.

[22] G. Caire, T. Y. Al-Naffouri, and A. K. Narayanan, “Impulse noise cancellation in OFDM: an application of compressed sensing,” in *Proc. IEEE International Symposium on Information Theory (ISIT)*, 2008, pp. 1293–1297. doi: 10.1109/ISIT.2008.4595196.

[23] J. Lin, M. Nassar, and B. L. Evans, “Impulsive Noise Mitigation in Powerline Communications Using Sparse Bayesian Learning,” *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1172–1183, 2013. doi: 10.1109/JSAC.2013.130702.

[24] Z. Liu, Y. Li, and S. Shi, “Impulsive noise suppressing method in power line communication system using sparse iterative covariance estimation,” *Radio Science*, vol. 57, e2022RS007424, 2022. doi: 10.1029/2022RS007424.

[25] Y. He, C. Zou, D. Li, R. Yao, F. Yang, and J. Song, “Adaptive Impulsive Noise Suppression: A Deep Learning-Based Parameters Estimation Approach,” *IEEE Transactions on Broadcasting*, vol. 69, no. 2, pp. 505–515, 2023. doi: 10.1109/TBC.2022.3224249.

[26] E. Zhu, Y. Ren, R. Li, S. Ouyang, Y. Ma, X. Yang, and G. Liu, “UNet-INSN: Self-Supervised Algorithm for Impulsive Noise Suppression in Power Line Communication,” *Applied Sciences*, vol. 15, no. 16, art. no. 9101, 2025. doi: 10.3390/app15169101.

[27] S. Ouyang, G. Liu, T. Huang, Y. Liu, W. Xu, and Y. Wu, “Impulsive Noise Suppression Network for Power Line Communication,” *IEEE Communications Letters*, vol. PP, pp. 1–1, Nov. 2024. doi: 10.1109/LCOMM.2024.3466893.

[28] G. Yang, Y. Qian, Z. Wang, X. Zhou, and W. Wu, “An intelligent impulsive noise mitigation with deep learning method,” *International Journal of Mechanical System Dynamics*, 2024. [Online]. Available: Semantic Scholar.

[29] C. L. Fan, “Multiscale feature extraction by using convolutional neural network: Extraction of objects from multiresolution images of urban areas,” *ISPRS International Journal of Geo-Information*, vol. 13, no. 1, Art. no. 5, 2024. [Online]. Available: MDPI.

[30] S. Sadrizadeh, H. Otroshi, and F. Marvasti, “Impulsive noise removal via a blind CNN enhanced by an iterative post-processing,” *Signal Processing*, vol. 192, Art. no. 108378, 2021. [Online]. Available: doi:10.1016/j.sigpro.2021.108378.

[31] O. P. Aiyelabowo, C. K. Ng, and N. K. Noordin, “Power line communication (PLC) impulsive noise mitigation: A review,” *Journal of Information Engineering and Applications*, vol. 4, no. 10, 2014, ISSN 2224–5782.

[32] M. Hussain, H. Shakir, and H. Rasheed, “Deep learning approaches for impulse noise mitigation and classification in NOMA-based systems,” *IEEE Access*, vol. 9, pp. 143836–143846, 2021. doi: 10.1109/ACCESS.2021.3121533.

[33] C.-L. Fan, “Multiscale feature extraction by using convolutional neural network: Extraction of objects from multiresolution images of urban areas,” *ISPRS International Journal of Geo-Information*, vol. 13, no. 1, art. 5, 2024. [En ligne]. Disponible : https://www.mdpi.com/2220-9964/13/1/5

[34] S. Sadrizadeh, H. Otroshi, and F. Marvasti, “Impulsive noise removal via a blind CNN enhanced by an iterative post-processing,” *Signal Processing*, vol. 192, art. 108378, Nov. 2021. [En ligne]. Disponible : https://doi.org/10.1016/j.sigpro.2021.108378

[35] D. Chicco, M. J. Warrens, and G. Jurman, “The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation,” *PeerJ Computer Science*, vol. 7, p. e623, Jul. 2021. [En ligne]. Disponible : https://doi.org/10.7717/peerj-cs.623

[36] A. A. G. Liong, F. H. Juwono, L. Gopal, W. R. Chiong, and Y. Rong, “Multiple blanking preprocessors for impulsive noise mitigation in OFDM-based power-line communication systems,” *International Journal of Electrical Power & Energy Systems*, vol. 130, p. 106911, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061521001514

[37] N. Sadeghi and M. Azghani, “Deep learning based channel estimation in PLC systems,” *Annals of Telecommunications*, vol. 80, no. 7–8, pp. 581–590, 2024. doi: 10.1007/s12243-024-01051-3. :contentReference[oaicite:0]index=0

[38] R. Barazideh, S. Niknam, and B. Natarajan, “Impulsive Noise Detection in OFDM-based Systems: A Deep Learning Perspective,” arXiv:1901.00447v1 [eess.SP], 2 Jan. 2019.