An Advanced 2-Output DNN Model for Impulse Noise Mitigation in NOMA-Enabled Smart Energy Meters

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The next-generation power grid enables information exchange between consumers and suppliers through advanced metering infrastructure. However, the performance of the smart meter degrades due to impulse noise present in the power system. Besides conventional thresholding techniques, deep learning has been proposed in the literature for detecting noise in NOMA-enabled smart energy meters. This research introduces a novel deep neural network (DNN) capable of simultaneously detecting and classifying impulse noise as either high or low impulse. Combining the analysis of detected noise and its class has proven to be more effective in mitigating noise compared to previously proposed methods. The input feature vector to DNN is chosen based on its characteristics to detect impulse noise and its level in the data and includes ROAD characteristics, median differences, and probability of impulse arrival. The performance evaluation shows that the Bit Error Rate (BER) of the proposed DNN is lower than the BER of single output DNN which is proposed in the literature for mitigation only. It is also shown that besides simultaneous detection and mitigation, the second output of the proposed DNN i.e. classification of IN validates the first output which is IN identification.

Keywords: Smart Energy Meters (SM), Impulse Noise (IN), Deep Neural Network (DNN) and Non-orthogonal Multiple Access (NOMA).

Introduction:

A Smart Meter (SM) is a crucial component of an intelligent power grid, also known as a Smart Grid (SG). It is responsible for recording and exchanging information such as energy consumption, power factor, voltage levels, current, peak, off-peak hours, and associated costs. Power supply companies incorporate SMs in their infrastructure and run energy management systems by receiving consumer information such as usage during peak versus off-peak hours, power factor, line loss, and stealing electrical power. In terms of hardware logic, an SM consists of transducers, a display unit, and a communication unit as shown in Figure 1 [1]. The transducers are usually connected to the power line to measure energy parameters. These parameters measured by a transducer are shown to the user via an in-home display and simultaneously transmitted to power companies through the communication unit of SM. However, it's essential to note that the performance of smart meters can be adversely affected when electrical impulses occur within the system, impacting the communication unit and degrading its functionality [1].

With the rapidly growing demand for increased bandwidth in SG, Non-orthogonal Multiplex Access (NOMA) has emerged as a promising new technology for next-generation wireless communications. The NOMA technique offers high spectral efficiency by allocating the entire bandwidth to each user at the same frequency and time. This approach considers user location with respect to BS in order to allocate different power suitable for SM communication since most of the SMs are installed at different distances and exposed to different channel conditions [2][3]. Despite its high performance, NOMA is sensitive to noise, which can degrade its efficiency. This sensitivity is due to the non-orthogonal power allocation among users, especially in the presence of interference (IN). Some research studies [4][5][6][7] have considered impulsive noise, while studying the NOMA technique, most researchers have utilized AWGN as the standard model to present noise in a communication system. The distinctive characteristics of the NOMA scheme include power division multiple access of user's interference cancellation, and the incorporation of impulsive noise in the transmitted samples raising the requirement for complex mitigation solutions [5].

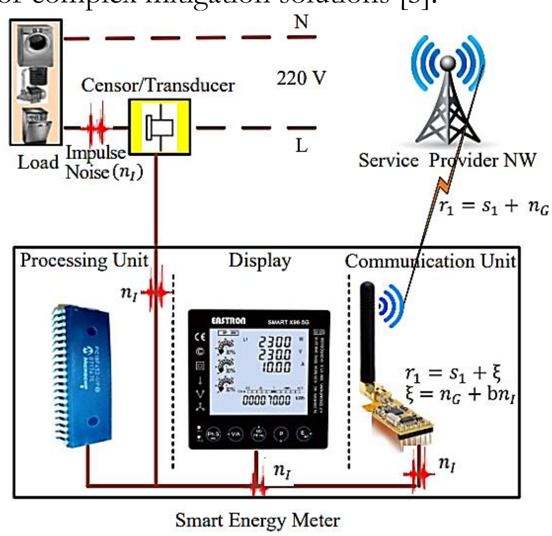

Figure 1: Working Principle of Smart Meter

Authors in [5] proposed a deep learning approach to determine the clipping/blanking threshold for NOMA users, given the impulsive noise parameters were already estimated. Since clipping/blanking cannot be optimized to simultaneously maximize the performance of all users, a multiple-stage clipping/ blanking receiver is tailored for NOMA. Deep learning has become an integral part of the data analysis of images as well as wireless signals. Authors in [8] have employed a Fuzzy SVM-based adaptive filter for impulse noise removal from color images. A research study in [9] implemented a convolutional neural network to successfully remove impulse noise from the images. Authors in a research study in [10] developed a deep recurrent neural network (RNN) for the reduction of transient sounds and analyzed the effect of transient sound reduction on listening capability and speech intelligence. Research work in [11] demonstrated suppression of impulse noise by developing deep learning-based receivers for Orthogonal Frequency Division Multiplexing (OFDM) systems. However, research work on noise mitigation using deep learning methods is still in its early stages, with promising developments though. The authors in [4] have successfully implemented deep learning for IN classification and mitigation in NOMA-based communication. Two different DNNs were proposed for IN suppression and IN classification respectively. However, an advanced deep learning network could be designed to simultaneously perform tasks of noise detection and classification to enhance the noise mitigation performance.

The proposed model in research work carries out simultaneous detection and classification of IN using deep learning techniques to minimize the aforementioned challenges in existing systems using NOMA communication. The model's first output identifies IN and then smoothens it by identifying IN-contaminated data samples through the DNN and decoding them to eliminate IN. The second output classifies the present IN as high and low magnitude impulse, providing valuable information regarding the IN class to enhance the mitigation process carried out using the first output, thus ensuring better IN detection than the conventional as well as deep learning methods. The structure of the article is organized as follows: Section II examines the impact of IN in a NOMA-enabled communication system, as well as conventional mitigation approaches in the previous work and the contribution of research. Section III discusses the system model, whereas Section IV describes the structure of the proposed DNNs. Section V analyses the performance of the proposed approach for IN mitigation and classification, and Section VI draws conclusions.

Objectives:

- Exploring the challenges posed by impulsive noise (IN) in non-orthogonal multiple access (NOMA) communication systems, particularly in the context of IoT-based smart energy meters.
- Reviewing existing IN mitigation techniques, including traditional threshold-based methods and emerging deep learning approaches, highlighting their limitations and potential.
- Proposing a novel deep neural network (DNN) architecture for simultaneous IN detection and classification in NOMA-enabled smart energy meters, aiming to improve performance compared to conventional methods.
- Evaluating the effectiveness of the proposed DNN approach through simulations, analyzing its BER performance, and comparing it with existing mitigation techniques.
- Investigating the impact of user location and channel conditions on BER performance in NOMA systems, particularly in scenarios involving distant and nearby users.
- Validating the proposed DNN model's performance in different noise environments, such as Bernoulli-Gaussian (BG) and Laplacian-Gaussian (LG) models, to assess its robustness and versatility.

The novelty of this research lies in the development of a comprehensive approach to tackling impulsive noise (IN) challenges within non-orthogonal multiplex access (NOMA) communication systems, specifically tailored for IoT-based smart energy meters. By integrating traditional threshold and cutting-edge deep learning techniques, our proposed deep neural network (DNN) architecture offers simultaneous IN detection and classification, surpassing the limitations of conventional methods. Through extensive simulations and analysis, we demonstrate the superior performance of our approach in mitigating IN, thereby advancing the reliability and efficiency of NOMA-enabled smart energy metering systems. Additionally, our investigation into the influence of user location and channel conditions on bit error rate (BER) performance, as well as validation across diverse noise environments, underscores the robustness and versatility of our proposed solution.

Background:

Impulse Noise in NOMA-Enabled Smart Meters:

The impulse occurring in the power system eventually can introduce noise in the wireless transmission unit of SM, impacting the communication channel and potentially leading to transmission errors. In the presented work, the Bernoulli-Gaussian (BG) model and Laplacian-Gaussian (LG) model [12][13] are chosen models for IN representation for power line communication, these models were also utilized in [14][15] for wireless commutation analysis which validates our selection.

The literature extensively discusses various challenges associated with IN and its impact on the implementation of Non-Orthogonal Multiple Access (NOMA) systems, specifically in next-generation networks such as the Internet of Things (IoT) or Smart Grids (SGs). Research studies have explored the effects of IN on both NOMA uplink [5] and downlink [7] systems. The evaluation of the outage of uplink NOMA in the presence of IN is demonstrated in [5]. Performance deterioration of the NOMA system due to IN occurrence was shown using analytical results and Monte-Carlo simulations. Authors studied the effect of IN on sum-rate capacity for NOMA downlink systems in [7], while in [6] they examined the performance of IoT networks with NOMA in the presence of IN and proposed a deep-learning-based IN suppression method to estimate IN parameter for received OFDM symbols originating from PD-NOMA.

Impulse Noise Mitigation Techniques:

The non-linear memory-less IN mitigation approach is categorized as a threshold-based IN mitigation technique. It incorporates schemes such as blanking [16], clipping [17], and clipping/blanking [18], which utilize preset threshold levels to detect IN, having high amplitude and small duration. Even though the appropriate selection of a preset threshold level is still a debatable and challenging issue, authors in [19] proposed a Neyman-Pearson criterion-based technique for the selection of an optimized threshold level. Researchers in [20] proposed an analytical solution approach to mitigate IN via clipping and blanking. A hybrid method comprises blanking/clipping clips and receives data level threshold when signal amplitude lies between prescribed threshold ranges [21]. A comparative study based on various analog domain processing approaches for IN mitigation affirms the significance of appropriate threshold level selection in improving the response of threshold-based non-linear mitigation techniques [22]. However, the dependency of threshold selection on channel parameters makes the model inconsistent in varying channel conditions. Consequently, all conventional threshold-based techniques experience performance deterioration under extensive impulsive environments. Deep learning has recently gained tremendous popularity among machine learning algorithms and has also been explored as a new alternative to mitigate IN in applications related to communication network power/bandwidth allocations [23], signals [24] images [25], etc. In this context, a deep learning-based IN elimination strategy is proposed for an OFDM communication model [26]. In [26], the authors formulated a deep neural network scheme for the identification of affected signal samples which are blanked or clipped in the next step. In the research work presented in [27], run-time sample values were processed by DNN using a median filter output that serves as an input parameter for IN detection. Another study in [28] employed a statistical technique that used absolute differences of sample value from neighboring samples to assess the effect of IN on runtime samples. Table 1 summarizes the comparison of the proposed DNN technique with other modern IN mitigation methods.

Table 1: An overview of noise mitigation state-of-the-art techniques

Ref	Objective	Solution Approach	Technique	Performance
[16]	Evaluate the performance of the blanking method for IN mitigation in OFDM signals.	Combination of adaptive blanking threshold and iterative interference cancellation scheme.	Iterative Blanking	The best results were achieved through an assigned blanking threshold in three iterations.
[17]	Evaluate the performance of the clipping method by applying threshold with a priori knowledge.	Computation of clipping threshold by estimating the arrival probability for OFDM transmission.	Stochastic Clipping	Performance was better than the conventional method using a turbo decoder coupling.
[18]	Improvement of SNR at OFDMA receiver by suppression of IN.	Nonlinear estimators based on the multiple thresholding with associated piece-wise attenuation.	Multiple Threshold Blanking/Clipping	The proposed clipping and attenuating estimators attain nearly the same performance as the optimal Bayesian estimator with only five thresholds.
[20]	Threshold Calculation of blanking and clipping.	Estimation of a threshold for blanking and soft limiting.	Blanking/Clipping	Well, is suited for soft limiting in moderately noisy environments and for blanking in strong noisy environments.
[21]	Elimination of IN from PLC-based systems utilizing OFDM symbols.	A time and frequency domain combined method for suppressing the IN in PLC systems employing OFDMA.	Blanking, Clipping, and Blanking/Clipping	The combined TD/FD technique performs Better than the conventional techniques in IN reduction.
[29]	Interference reduction for small-sized BS in high-density network.	Distributed power allocation algorithm based on multi-agent Q-learning.	Machine Learning	The proposed technique is well suited for comparatively small-sized BS.
[26]	Elimination of IN in received symbols for an OFDM system.	A two-step DNN-based technique for identification and suppression of IN.	DNN	Better performance than blanking and clipping.
[6]	Finding the optimal threshold for IN reduction	Deep learning applied for threshold estimation of IN parameters in	DNN	Performance maximized by using DNN for threshold estimation.

	of a PD-NOMA User.	symbols on OFDM-based PD-NOMA systems.		
[4]	IN mitigation in PD-NOMA-based system.	Deep learning approach using statistical properties to model randomness.	DNN	IN mitigation and classification is better than traditional techniques.

Contribution:

In this research study, the performance of deep learning-based IN mitigation [4][5] has been improvised by designing a novel multiple-input dual-output deep neural network. The developed DNN model with two outputs can detect and classify IN at the same time for a NOMA-enabled SM communication model. Earlier, a deep learning model presented in [5] predicted signal threshold for noise detection and mitigation for highly impulsive data of 1 Mbps with 0-5 dB SNR in a NOMA-based IoT network. Another Deep Learning (DL) model described in [4] detected the noise for the aforementioned network scenario and noise parameters which were then mitigated by setting a threshold parameter. In contrast to the above DL techniques, this research work proposes a deep learning model that can efficiently detect as well as classify the noise. This dual functionality enables better noise mitigation for a 2-user scenario i.e. two users are allocated different power levels based on their distance from the base station using the same time/frequency resource blocks. While BER values of 0.35 and 0.5 were obtained for two user scenarios tested on the DL model in [5], the DNN proposed in [4] accomplished BER values of 0.04 and 0.15 for the same given scenario. Comparatively, the proposed dual output DNN has successfully reduced the BER values up to 0.03 and 0.1 for a two-user scenario in NOMA-enabled smart energy meters. The comparison of recent deep learning-based IN mitigation techniques with the proposed method is illustrated in Table 2.

Table 2: Critical analysis and comparison of the recent DNN-based IN mitigation techniques

Title	Data set	Method	Performance
[5] NOMA-Based IoT Networks: Impulsive Noise Effects and Mitigation (2020).	1 Mbits data sample affected by highly impulsive of 0-5 dB.	Deep learning	DNN-based optimum threshold achieves 0.5 BER for user 1 and 0.35 BER for user 2 at an SNR of 10 dB.
[4] Deep Learning Approaches for Impulse Noise Mitigation and Classification in NOMA-Based Systems (2021).	1 Mbits data sample affected by highly impulsive noise of 0-5 dB.	Deep learning	DNN-based detection achieved 0.04 BER for user 1 and 0.15 BER for user 2 at an SNR of 10 dB.
[Proposed] An Advanced 2-Output DNN Model for Impulse Noise Mitigation in NOMA-Enabled Smart Energy Meters.	1 Mbits data sample affected by highly impulsive of 0-5 dB.	Deep learning	Improved DNN-based mitigation achieves 0.03 BER for user 1 and 0.1 BER for user 2 at an SNR of 10 dB.

Material and Methods:

Impulse Noise Analysis in NOMA-Based Smart Energy Meters:

The SG field comprises large IN segments that degrade the received signal leading to a communication failure. Therefore, key parameters such as SG noise parameter ξ for SM have been used to analyze the effect of IN in the proposed model. The developed mitigation method incorporates BG and MC representation models for IN. In the BG model, the sum of background and impulse noise can be represented as follows: $\xi = n_G + n_I$. Here, n_I and n_G our representation of AWGN for Bernoulli and Gaussian random sequences respectively with zero mean and variance σ_G^2 and σ_I^2 [12][14]. Here, for the Bernoulli random sequence, b is known as the impulse arrival rate with the probability p which is independent of n_I and n_G. The noise is considered an independent and identically distributed (i.i.d.) random variable whose Probability Density Function (PDF) is given by:

$$P_n(x) = (1-p)\boldsymbol{G}(x, 0, \sigma_G^2) + p\boldsymbol{G}(x, 0, \sigma_G^2, \sigma_1^2) \tag{1}$$

Here, $\boldsymbol{G}(x, 0, \sigma_G^2)$ is a Gaussian PDF with a mean μ_x and variance σ_x^2 . The average noise power ξ_0 of BG model is given as follows: $\xi_0 = E[n^2] = E[n_G^2] + E[b^2]E[n_1^2] = \sigma_G^2 + p\sigma_1^2$ [12]. The PDF of Laplacian noise with zero mean and variance $2c^2$ is heavy-tailed and approaches slowly to zero [13][15]. The average noise power in the Laplacian-Gaussian noise model can be expressed as: $\xi_0 = E[n^2] = E[n_G^2] + E[r^2]E[n_1^2] = \sigma_G^2 + p2^2$. Where Bernoulli's random variable r is known as the impulse arrival rate for the Laplacian-Gaussian (LG) model. Although the LG model can be a good candidate to represent IN with a large number of impulses occurring with a short amplitude, the BG model is more suitable otherwise and hence it is chosen for noise representation in our work.

The Middleton Class-A (MCA) noise model is a form of the Poisson noise model which is an extension of Bernoulli distribution to the continuous space but with the impulse width taken into account. The parameter $A = \frac{\eta\tau}{T_0}$ here, represents the density of impulses (of a certain width) in an observation period [30] where η is the average number of impulses per second and T_0 is unit time. The parameter τ, is the average duration of each impulse, with each impulse occurring for the same duration. The PDF MCA noise can be written as:

$$P_n(x) = \sum_{m=0}^{\infty} \frac{A^m \boldsymbol{e}^- \boldsymbol{A}}{\boldsymbol{m}!} \boldsymbol{G}(x, 0, \sigma_M^2) \tag{2}$$

$\boldsymbol{G}(x, 0, \sigma_M^2)$ represents a Gaussian PDF with mean μ and variance σ_M^2. The MCA noise model is a sum of different zero mean Gaussian PDFs with different variances σ_M^2 , where PDFs are expressed as weighted Poisson PDF $P_m = \frac{A^m e^- A}{m!}$. The average noise power in the MCA noise model can be expressed as: $\xi_0 = \sigma_G^2 + \frac{m}{A}\sigma_1^2$. Here, the parameter A is the density of impulses (of a certain width). By utilizing the NOMA system, multiple SMs can share the same frequency bandwidth since each SM only uses a portion of the total power. They can be identified by the power level allotted by the BS. Successive interference cancellation (SIC) allows the decoder to identify an SM's signals while treating the other SMs as noise [31][32]. For two SM models, which are placed apart from each other, the symbol received by SM 1 (nearby SM) with IN added can be written as:

$$SM_1 = s_1\sqrt{\alpha_1 P h_1} + s_2\sqrt{\alpha_2 P h_1} + \xi \tag{3}$$

A symbol received by SM 2 (distant SM) with IN added can be written as:

$$SM_2 = s_2\sqrt{\alpha_2 P h_2} + s_1\sqrt{\alpha_1 P h_2} + \xi \tag{4}$$

Here, s_1 and s_2 are transmitted symbols, α_1 and α_2 are power allocation coefficients, h_1 and h_2 are channel gains for SM 1 and SM 2 respectively. Subsequently, received a symbol for an k_{th} SM, with IN contamination can be mathematically represented as:

$$SM_k = s_k\sqrt{\alpha_k P h_k} + \sum_{l=1, l\neq k}^{k-1} s_1\sqrt{\alpha_s P h_k} + \xi \tag{5}$$

Here, s_k and s_1 are the symbols transmitted from BS for k_{th} and l_{th} SMs respectively, and h_k represents channel gain for k_{th} SM. Nearer users' signals are considered to be interference and distant ones as the noise. The term $\sum_{l=1,l\neq k}^{l-1} s_1\sqrt{\alpha_1 P h_k} \;= x$, in (5) represents level inter-cell interference symbols for UE_k. Also, $\sum_{=1,l\neq k}^{l-1} \alpha_j P|h_k|^2$ is the total power of inter-cell users' interference which is considered as a noise component. Whereas, α is the power allocation coefficient such that $\alpha_1 + \alpha_2 + \alpha_3 + \cdots + \alpha_k = 1$ and h is the Rayleigh fading coefficient for the wireless channel. The above equation can be re-written as:

$$SM_k = s_k h_k + x + \xi \tag{6}$$

System Model:

An SG infrastructure is shown in Figure 2 in which GS (Grid Station) controls the power transfer through information exchange between consumers and utility using smart metering, hence performing the function of BS as well. To accommodate a large number of users, NOMA is implemented for information transmission and reception through the transceiver unit of SM. However, disruptions in the power system can cause disturbances in the wireless transmission unit of SMs, leading to the introduction of IN at SMs. The NOMA scheme, on the other hand, suffers from inter-user interference due to power division multiple user access which increases the complexity of noise representation in wireless links. To reduce IN effect, an advanced 2-output DNN model is introduced at the receiving end. On the first output, DNN identifies the IN-affected signal and then mitigation is applied to remove the identified noisy signal. The mitigation process is supported by DNN second output which classifies the noise as low level and high-level impulse.

Proposed DNN for IN Detection and Classification:

A deep feed-forward neural network with backpropagation is proposed for the simultaneous detection and classification of IN in the incoming signal samples that are contaminated/corrupted by IN. The hidden layers are an integral part of a neural network and provide an appropriate mapping of input to the outputs. Several experiments were performed to obtain minimum training losses which led to an optimal number of layers and connected neurons for the proposed setup. The presented DNN comprised four hidden layers $H^{[1]}, H^{[2]}, H^{[3]}, and\ H^{[4]}$.

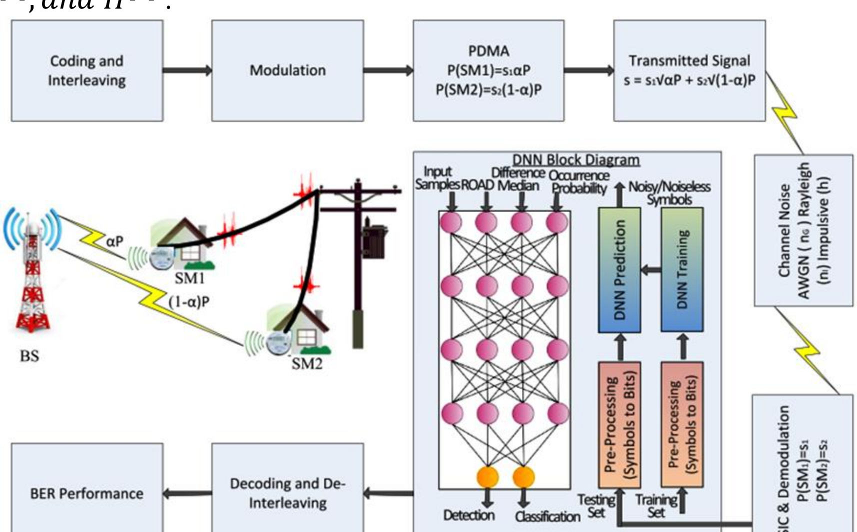

Figure 2: System Model

Each layer is constituted of n neurons. The input to the proposed DNN includes three features in addition to the input sample and is represented as $F = [f_1, f_2, f_3, f_4]^T$ (The next subsection discusses the features in detail). The output of DNN is represented as $[O_1, O_2]$ and comprised of a single layer with two nodes which yield (i) a binary sequence of '1' and '0' representing IN or no IN respectively, (ii) IN classification of each bit. The connection between each preceding and subsequent hidden layer and between the last layer to the output layer is created by an activation function C, multiplying hidden layers with parameter matrix P and adding a bias vector b. The association of different layers in the network can be mathematically expressed as:

$$H^{[1-4]} = C^{[1]}\left(P^{[1]}F + b^{[1]}\right) \dots C^{[4]}\left(P^{[3]}H^{[3]} + b^{[3]}\right) \tag{7}$$

$$O = [O_1, O_2] = C^{[4]}\left(P^{[4]}U^{[4]} + b^{[4]}\right) \tag{8}$$

Here, Rectified Linear Unit $ReLU(F) = max(F, 0)$ is used as an activation function in the hidden layers and gives 0 for input value F less than 0 and gives an output equal to F for all values otherwise. The sigmoid function is used as the activation function at the output layer represented by $Sgmd\ (F) = \frac{1}{1+e^{-F}}$. This function gives either 0 or 1 as output after rounding off the result. The training accuracy of the proposed deep neural network for a training dataset is evaluated through a cost function that determines the mean error present in the output predicted value. The magnitude of evaluated error using a cost function has a direct relationship with the difference between predicted O' and actual output O values and is expressed as [33]:

$$Error(P, b) = -\frac{1}{m}\left[\sum_{j=1}^{m} O_j \log\left(\hat{O}_j\right) + \left(1 - O_j\right) \log\left(1 - \hat{O}_j\right)\right] + \frac{\lambda}{2m}\sum_{r=1}^{R-1}\sum_{p=1}^{n_r}\sum_{q=1}^{n_r+1} P_{pq}^2 \tag{9}$$

Where k is the number of samples used for training, λ is the scalar regularization rate for fine-tuning the network, n_r represents the number of neurons in R^{th} layer. The training of DNN is done with Adam's optimizer as the proposed DNN works on a backward propagation algorithm [34]. Since the Error parameter is a function of P and b, DNN needs to calculate these values during training to minimize the value of $Error\ (P, b)$.

Input Features of Proposed DNN:

A DNN often experiences over-fitting problems during the training period which can be eliminated by accurate extraction of input features and devising their appropriate relationship with the output. The idea is to remove the redundancy in the DNN learning framework by carefully selecting the input features. This allows a fair sample classification of corrupted and true data. Furthermore, to understand the pattern of noise in data samples, the sample bit under test must be analyzed in conjunction with its adjacent sample data. To attain this, the following useful and relevant features are fed to the input layer along with input sample values.

ROAD Statistic Value: Rank Order Absolute Difference (ROAD) statistic is a well-known technique used in the detection of IN which is randomly generated in 2D images and serves as one of the inputs in the proposed DNN. The ROAD feature can identify a sample as noisy or true by returning a high value or low value respectively [26]. In the proposed work, the value of ROAD statistic is determined for data samples stored in a 1-D vector having a 1x2n dimension. To calculate the ROAD score, the following steps are executed:

The magnitude of variance between the sample data under test s_a and its adjacent data (both right and left side) is represented by Absvar(i) and is computed as:

$$Absvar(a) = | s_a - [s_{av\leftrightarrow n}, \dots, s_{av\leftrightarrow 1}, s_{a+1}, \dots, S_{a+n}\ ]|$$

(10)

Absvar (i) values are sorted in ascending order:

$$vector(a) = sort(Absvar(a)) \tag{11}$$

The first n values of vector(a) are summed up to obtain the ROAD feature:

$$ROAD = \sum_{a=1}^{n} vector(a) \tag{12}$$

Median Deviation feature: The Median Deviation feature of Med Dev is computed as follows:

$$MedDev = s_a - median([s_{a-n}, \dots, s_a, \dots, s_{a+n}]) \tag{13}$$

Here median is a standard moving average filter that calculates the median of 2n+1 samples.

Average Occurrence Probability feature (Avg Prob): This is the third input feature chosen for the proposed deep learning model and is a powerful index to classify low and high impulsivity. It is computed by averaging the occurrence probability P_a on 64 samples including the input sample under the test and subsequent 63 samples [26]. The low chance of high-noise happening often is confirmed by the low average occurrence probability at outputs. Similarly, the high chance of low noise happening often is confirmed by the high average occurrence probability at outputs. Avg Prob feature is computed as follows:

$$AvgProb = \frac{\sum_{a=1}^{64} P_a}{64} \tag{14}$$

Outputs of Proposed DNN:

As discussed earlier, inputs to the presented DNN for IN detection are the incoming sample, ROAD statistic, difference median, and average occurrence probability. Response of the first two input features appears to be high when an input sample is contaminated with IN and response is low when the true sample is received. Both outputs of DNN generate binary sequences of 0's and 1's. By learning the statistical characteristics of contaminated samples, DNN is trained such that a value of 1 at the first output indicates a noisy sample detection and a value of 0 as a true sample detection. The second output of the developed network classifies IN into high or low categories. However, this task is challenging due to randomly varying amplitude. The output is represented as a 0 or 1. A '0' output at location 'k' of sample data represents k_{th} the sample being contaminated by a low-intensity IN while a received '1' indicates the contamination from high-intensity IN.

Result and Discussion:

The presented DNN is integrated into the NOMA downlink to mitigate and classify IN coming from a Rayleigh fading channel. The proposed research work was done through the BPSK modulation technique for computational convenience. The tuning parameters used for network training are as follows: Learning Rate hyper-parameter $\eta = 0.02$; Regularization parameter $\lambda = 0.4$; Number of data bits taken at a time (n) = 5; Number of neurons in 4 hidden layers are chosen as $n_1 = 20$, $n_2 = 20$, $n_3 = 20$ and $n_4 = 10$ respectively. Power allocation coefficients for the NOMA system are α_1= 0.333 and α_2= 0.667. The parameter matrices $P^{[1]}$, $P^{[2]}$, $P^{[3]}$, $P^{[4]}$, and $P^{[5]}$ have dimensions of 20×4, 20×20, 20×20, 20×10 and 2×10 respectively. Whereas bias vectors $b^{[1]}$, $b^{[2]}$, $b^{[3]}$, $b^{[4]}$, and $b^{[5]}$ were selected to have dimensions of (20 × 1), (20 × 1), (20 × 1), (10 × 1) and (2 × 1) respectively. The initialization of chosen parameters in neural networks was done using Xavier initialization [35] which is known for its good random initialization. The number of BPSK symbols used in training of dual output DNN is 4×10^6. The symbols are mathematically defined in (3) and (4) and noise occurrence in these symbols is represented using the Gaussian-Bernoulli noise model. First, DNN identifies whether a bit is affected by IN or not which is reflected in the first output of DNN. In case of bits being unaffected by IN, conventional hard decoding is performed. If bits are affected by IN, the effect of IN is removed by implementing adaptive decoding in which the threshold is predicted by the second output of the proposed DNN.

Figure 3 shows graphs of predicted values of threshold by proposed DNN using a red line against the amplitude of impulses accrued at that time. In the conventional/nonlinear mitigation method, a fixed threshold is used which is based on historical data. If there is any change in channel condition or sources of IN, the threshold becomes ineffective. The proposed DNN predicts threshold values close to the targeted amplitude of IN as shown in Figure 3 which is very useful in successfully removing the effect of IN in received bits. Moreover, if the channel condition or source of IN is altered by any means, DNN updates its threshold accordingly. BER performance of different mitigation techniques including blanking, clipping, clipping/blanking [16][17][18], DNN [4], and new DNN (proposed DNN) are compared in Figure 4. Although BER is observed to improve with increasing SNR, the proposed DNN demonstrates the best BER for all SNR values. The results obtained in Figure 4 show that traditional threshold-based mitigation techniques (blanking and clipping methods) are prone to noise for smaller SNR values. Therefore, computing an acceptable threshold value for discrimination between noisy and noiseless symbols is a challenging task for traditional mitigation techniques.

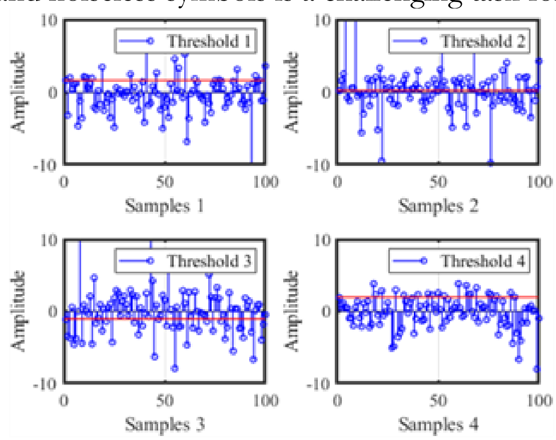

Figure 3: Predicted values of threshold by proposed DNN.

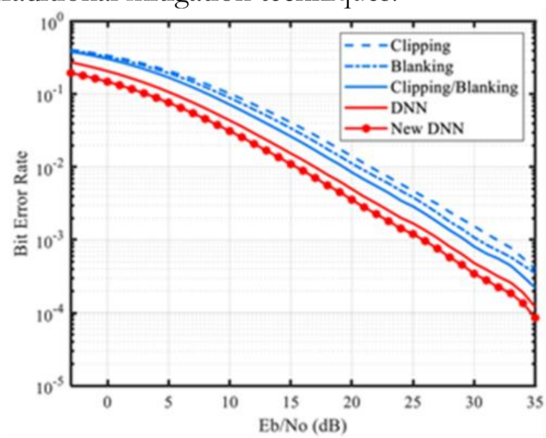

Figure 4: BER performance of mitigation models.

In contrast, new DNN can successfully detect IN for low as well as high levels of signal compared to DNN in [4]. For example, the proposed network has identified approximately 0.25 Mbits more true symbols within a stream of 1 Mbits at 5 dB SNR in comparison to nonlinear mitigation methods and 0.15 Mbits more true symbols in comparison to DNN in [4]. Moreover, DNN recognized 810 more true symbols at greater SNR values than the nonlinear mitigation methods. This is the result of better noise detection at high SNR. Overall, achieved results with the new DNN approach at different (high as well as low) SNRs are superior to DNN [4] and nonlinear mitigation methods.

The BER performance highly depends upon user location with respect to BS. Distant users receive more power than nearby users since they have to perform a smaller number of SIC operations as compared to nearby users. Consequently, they face interference from nearby users and have low BER performance. Theoretically, the transmitted power of a user is determined using the power coefficient α. For two user scenarios, if the nearby user (user 1) transmits signal power of α_1, then the transmitted power of the distant user (user 2) is expressed as $\alpha_2 = 1 - \alpha_1$ which shows the coefficient's sensitivity to noise/interference. In Figure 5, the performance of distant and nearer NOMA user pair has been demonstrated using the based IN mitigation approach in [4] and the proposed DNN approach. The BER performances of user 1 and user 2 are almost the same at less than 5 dB SNR, while at a higher SNR of 30 dB, the proposed DNN detected 200 more true symbols from the near user (user 1) and 500 more true symbols from the distant user (user 2) compared to DNN presented in [4]. Since the number of IN occurrences in user 2 signal is high, user 2 exhibits a poor BER performance than user 1. Consequently, noisy samples of user 2 are better mitigated by the proposed DNN. Furthermore, as shown in Figure 5, IN mitigation in user 1 samples has been performed more consistently than for user 2. However, user 1 still suffers from IN since it cancels inter-user interference using SIC.

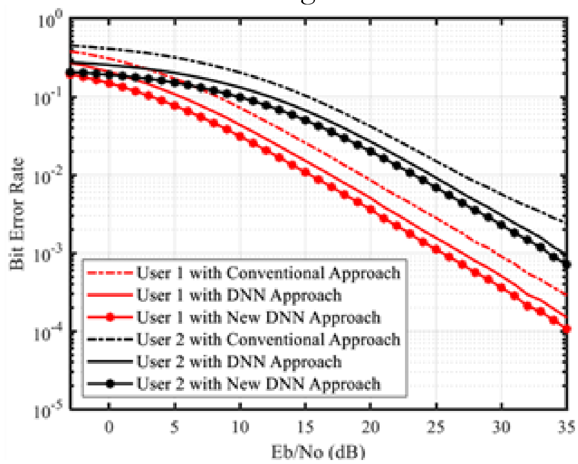

Figure 5: Performance of NOMA user pair with deep learning-based IN mitigation.

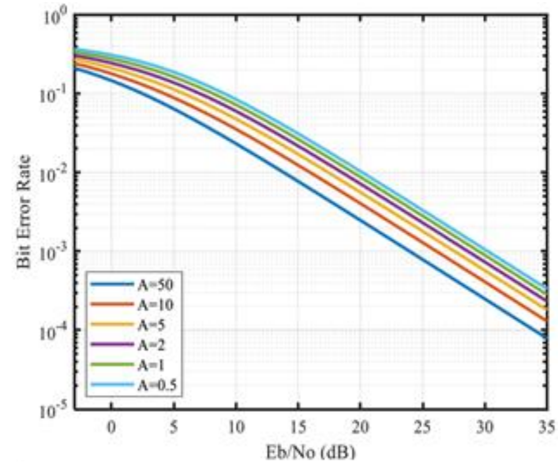

Figure 6: BER Performance in BG test environment.

Due to IN occurrence as well as inter-user interference, user 2 shows varying BER for different SNR values. Figure 6 and Figure 7 illustrate the BER performance evaluation of the proposed DNN-based IN mitigation technique in test environments of BG and MCA respectively. In Figure 6, parameter A represents the density value of impulse (of a certain width) for a particular observation period whereas, in Figure 7, parameter p represents the probability value of IN arrival rate which is independent of n_G and n_I.

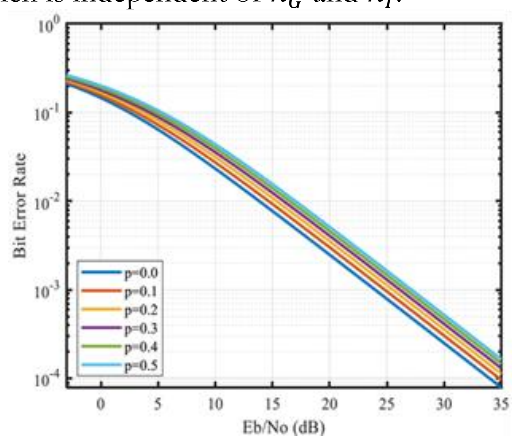

Figure 7: BER Performance in MCA test environment.

The MCA noise model is an infinite sum of different zero mean Gaussian PDFs with different variances with weighted PDFs weighted by Poisson PDF. Another important model is the BG model which is a mixture of two Gaussian PDFs with different variances. The parameters in the MCA model are linked to the physical channel but do not represent the bursty nature of the impulses observed. Figures 6 and 7 show that with an increase in frequency of IN occurrence as expected, BER performance is degraded in BG and MCA environments.

Conclusion:

In this research work, a multiple-input dual-output DNN is proposed for IN detection and classification generated in NOMA-enabled smart energy meters. The described work addresses the issues faced in conventional mitigation techniques and improvises the performance of the deep learning method proposed in the literature for noise mitigation. The two outputs of presented DNN in this research study efficiently detect as well as classify the IN. By investigating and incorporating new input features that can predict better thresholds for noise mitigation, the performance of the proposed deep neural network can be further improved.

The future work of this research will focus on enhancing the understanding of power system impulses' effects on wireless transmissions within NOMA-enabled smart grid communication systems. Additionally, future research will address NOMA challenges by developing optimization strategies tailored to effectively mitigate inter-user interference. Moreover, the research will continue to explore noise mitigation techniques and signal processing algorithms beyond deep learning to optimize reception quality in smart grid communication systems. Lastly, future research will investigate advanced optimization techniques such as power allocation and resource management to maximize spectral efficiency and system performance.

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Author's Contribution:

- Author 1 performed the experiment, and the experiment's calculations, and wrote the manuscript.
- Author 2 performed simulations, analyzed the data and contributed to the final version of the manuscript.
- Author 3 revised the manuscript and contributed to the final version of the manuscript.
- Author 4 prepared the rebuttal and contributed to the final version of the rebuttal.

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