Broadband-Based IoT Communication Solutions for Agribusiness and High-Speed Industrial Internet of Things (IIoT): Advanced Machine Learning Approach

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***Abstract*—The Internet of Things (IoT) has transformed various sectors, including agriculture and industrial automation, by enhancing efficiency and productivity, including data-informed decision-making. Innovative communication solutions play a crucial role in the success of IoT applications in rural and remote areas, where connectivity/broadband is limited or unavailable. Agriculture and industrial IoT (IIoT) in this region will not thrive because of poor network coverage or unreliable broadband connectivity. This paper introduces a comprehensive strategy for implementing broadband-based IoT (B-IoT) communication solution for agribusiness and IIoT by leveraging an advanced machine learning (AML) framework known as the parameterized analytical modeling-based deep neural network-enhanced parametric rectified linear unit (PDNN-ePReLU) model. This approach incorporates a novel parameterized-based DNN algorithm and a new activation function F_A to enhance Cognitive Radio (CR) on TV White Spaces (TVWS) for backhauling and last-mile connectivity, along with the use of fifth-generation (5G) reduced-capability (RedCap) devices on sub-7GHz unlicensed or private frequency bands for IoT access networks. The proposed solution consists of an input layer comprising specific network parameters, hidden layers, and an output layer focusing on coverage, throughput, latency, and energy efficiency (EE), which the PDNN-ePReLU model aims to optimize. This model employs CR to utilize unused TVWS frequencies dynamically and improves the network performance by predicting optimal transmission and adaptively allocating resources. This paper outlines a detailed implementation framework showcasing the PDNN-ePReLU model's training, validation, and test phases while presenting the potential benefits for agribusiness and IIoT in underserved areas. MATLAB simulation results indicate that the optimized CR significantly enhances the coverage, throughput, latency, and EE over long distances, outperforming legacy CR and traditional networks (Wi-Fi, LTE, etc.). Furthermore, the optimized 5G RedCap surpasses its legacy (non-optimized) counterparts, offering a robust and scalable solution for B-IoT in agribusiness and IIoT applications.**

This work was partially funded by project XGM-AFCCT-2024-2-15-1 funded by xGMobile – EMBRAPII-Inatel Competence Center on 5G and 6G Networks, with financial resources from the PPI IoT/Manufatura 4.0 from MCTI grant number 052/2023, signed with EMBRAPII; by the SEMEAR Project funded by FAPESP (Grant No. 22/09319-9); by FAPEMIG under the contract No PPE-00124-23; and by CNPq-Brasil.

***Index Terms*—5G Reduced Capability (RedCap), Agribusiness, Advanced Machine Learning, Broadband-based IoT (B-IoT),Deep Neural Network (DNN), Enhanced parametric rectified linear unit (ePReLU)**

I. Introduction

Integrating B-IoT communication solutions in agribusiness and advanced AML techniques will help transform the landscape of agriculture and IIoT. This synergy enhances efficiency, productivity, and sustainability, addressing critical challenges in modern farming that require high throughput over long distances to support computational vision in precision agriculture (PA) and industrial automation (IA). The significance of IoT-driven solutions in the enhancement of PA and IA, particularly on the connectivity challenges and requirements prevalent in rural and remote regions, cannot be overstated, as effective connectivity in these areas possesses the potential to revolutionize the PA and IIoT landscapes through the utilization of real-time data acquisition, analysis, and application. Connectivity solutions such as fifth generation (5G) networks offer high throughput internet, which is essential for high data rate IoT applications within the agribusiness and IA sectors [1]. However, they may not be extensively extended to remote and rural areas due to the high cost of deployment and the low return on investment (ROI). Hence, cost-effective connectivity solutions that afford broader coverage, as well as high data rates, emerge as the most favorable options for rural agricultural contexts. These solutions will help in supporting certain IoT-enabled agricultural applications, including crop health monitoring and livestock video imaging, necessitating the transmission of substantial data volumes. The provision of suitable IoT connectivity characterized by high data rates over long distances or ranges is crucial in facilitating adequate throughput in agribusiness and IA. This necessitates the idea of developing a hybrid solution that will jointly address the coverage and throughput challenges over long distances concurrently leveraging an innovative AML technique called the PDNN-ePReLU model. Furthermore, understanding the concept of agribusiness and IA is important. On one hand, agribusiness encompasses the commercial activities related to the production, processing, and distribution of agricultural products. It covers the entire supply chain, from farming operations like crop cultivation and animal husbandry to the transformation of raw agricultural materials such as seedlings into food or other products, as well as the transportation and marketing of these goods. The scope of agribusiness extends to include the provision of inputs such as seeds and machinery, various services, marketing efforts, and trade operations. The primary focus of this sector is on enhancing agricultural efficiency, profitability, and long-term sustainability. On the other hand, IA refers to the implementation of control systems, including computers, robots, and information technology, to manage industrial processes with minimal human involvement. This approach involves automating various tasks in manufacturing, quality assurance, and materials handling to boost efficiency, precision, and output. The field of IA incorporates technologies such as robotics, programmable logic controllers (PLCs), ML, and artificial intelligence (AI). These tools are used to optimize operations, minimize errors, reduce expenses, and enhance overall production results across various industries. Hence, the contemporary IoT application use cases in agribusiness and IA requiring high data rates over long distances are:

- Computational Vision for crop and cattle monitoring: B-IoT facilitates computational visions leveraging high-resolution cameras mounted on fixed structures to capture images of crops across large fields [2].
- Real-time Remote Control of Drones and Machinery: B-IoT facilitates real-time remote control of drones and machinery by equipping drones with high-definition cameras, multispectral sensors, and GPS receivers deployed over large agricultural fields [3].
- Navigation and Platooning for DA: B-IoT is instrumental in revolutionizing DA by enabling advanced functionalities like navigation and platooning of agricultural machinery. For example, tractors and other agricultural machinery equipped with GPS receivers and B-IoT sensors navigate precisely across large agricultural fields, following predetermined paths that optimize the coverage and minimize overlap or gaps [4].
- Big Data for Agribusiness: B-IoT facilitates the harnessing of big data to drive agribusiness innovations and decision-making processes. This setup allows for collecting, transmitting, analyzing, and utilizing vast amounts of data from various sources, transforming traditional farming into a data-driven industry [5].
- Collaborative Robots: B-IoT facilitates fast data transfer for real-time processing, motion control, and sensor feedback [6].
- Real-time Monitoring and Control: Systems like Supervisory Control and Data Acquisition (SCADA) need high-speed data to monitor and control operations in manufacturing, energy, and utilities [7].
- Computer Numerical Control (CNC) Machines: B-IoT facilitates fast data transfer for precise control of machining operations [8].
- Augmented Reality (AR)/Visual Reality (VR) for Maintenance: B-IoT facilitates AR/VR including extended reality (XR) systems used in industrial settings for real-time diagnostics and remote assistance to render detailed images and information [9].

Hence, it is obvious that B-IoT is important in supporting agribusiness and IA/IIoT applications. This paper is motivated by solutions that will address both coverage and throughput challenges over long distances. Consequently, this paper's contributions are enumerated below.

- To develop a hybrid solution that will jointly address the coverage and throughput over long distances challenges using CR/TVWS for backhauling and 5G RedCap for the B-IoT access network.
- To develop a novel AML technique called the PDNN-ePReLU model.
- To implement a new activation function (ePReLU) for optimizing output parameters (coverage, throughput, latency, and EE of the CR and 5G RedCap network leveraging PDNN-ePReLU training and validation.
- To implement the PDNN-ePReLU algorithm and demonstrate the effectiveness of the solution, for example, showcasing the viability of CR maintaining appreciable coverage at increasing distances unlike legacy CR and traditional networks (Wi-Fi, LTE, etc.) that maintain coverage only at shorter distances because their coverage diminishes rapidly as distance increases.
- To incorporate a generalized frequency division multiplexing-based adaptive quadrature amplitude modulation and coding scheme (GFDM-AQAMCS) in the PDNN-ePReLU framework as a viable parameterization network component for optimal solution.
- To provide cost-effective communication solutions that significantly benefit agribusiness and IA industries over long distances without spectrum license procurement.

Hence, the remainder of this paper is structured as follows: Section II discusses related works. Section III presents the parameterized analytical modeling. In section IV, we present the network architecture and PDNN-ePReLU model framework. In section V, we demonstrate the PDNN-ePReLU implementation and simulation. In section VI, we present the results and discussion. Finally, we conclude the paper in section VII.

II. RELATED WORKS

In recent years, significant research has been conducted on utilizing TVWS for rural broadband connectivity. TVWS's ability to provide long-range communication at lower frequencies makes it an ideal solution for underserved rural areas.

Numerous studies have highlighted the potential of CR in exploiting TVWS efficiently. However, the studies have not experimented with network performance improvement over long distances. For instance, the authors in [10] present a medium access control protocol for a CR network, providing deterministic medium access for heterogeneous traffic and dynamic spectrum allocation to guarantee timely treatment of hard real-time traffic in industrial settings. This addresses only latency without considering long distances. The authors in [11] present an energy-efficient spectrum access (EESA) model for multi-channel mobile CR-WSN, and the experiment outcome shows EESA attains significant performance over the existing model in terms of throughput and energy efficiency though not in long-distance scenarios. The authors in [12] presented an outline of Cognitive-based IoT frameworks. They discussed the possible uses of Cognitive-based IoT frameworks, the EE, and the throughput of cognitive-based IoT frameworks. Still, they did not consider performance over long-distance scenarios or ML techniques for network performance improvement.

On the other hand, 5G RedCap devices have been identified as key enablers of massive IoT applications, especially in industrial environments. These devices are projected for low-cost, low-power consumption, making them suitable for IoT devices that require moderate data rates (up to 300 Mbps) [13]. Some of the works that investigated network performance improvement include the work in [14], which suggests optimizing beam management and energy consumption for RedCap devices but does not specifically address ML techniques for improving coverage, throughput, latency, and energy efficiency, and did not consider performance over long distances. The study in [15] highlights coarse-grained channel quality prediction as a viable method to enhance efficiency in 5G-RedCap devices, optimizing resource utilization without increasing computational complexity in diverse scenarios but does not consider performance over long distances in the work. The authors in [16] present a genetic algorithm-based neural network (GA-NN) model that enhances 5G RedCap devices by improving coverage, energy efficiency, and throughput, making them suitable for long-distance applications in agribusiness and IIoT but did not consider the integration of CR, and 5G RedCap for a unified IoT communication solution, so that the CR can support long distances as backhauling. The study in [17] demonstrated energy consumption modeling for RedCap devices in 5G networks but does not specifically address improving coverage, throughput, latency, or energy efficiency using ML techniques, and does not consider performance over long distances. Uplink performance enhancement of RedCap devices using existing 5G solutions is investigated in [18] but does not specifically address ML techniques for coverage and EE in rural and underserved areas. The work in [19], focuses on coverage evaluation of RedCap without specifically improving throughput, latency, and energy efficiency in NR-RedCap devices using ML techniques for agribusiness and IIoT in rural and remote areas. The study in [20], emphasizes enhancing throughput and latency in smart farming through a 5G-enabled pest and disease detection and response system (PDDRS) but does not specifically address RedCap devices or their EE in underserved areas.

From the literature, it is obvious that the integration of CR and 5G RedCap for a unified IoT communication solution, and the network performance metrics such as coverage, throughput, latency, and energy efficiency improvements over long distances for agribusiness and IIoT in underserved/rural areas using ML algorithms have not been holistically investigated. This paper builds on the existing research by introducing an AML-based solution that enhances the performance of these technologies and optimizes network resources in real-time while addressing the identified limitations holistically.

Overall, the PDNN-ePReLU offers several advantages over prior work, especially in terms of faster convergence/generalization, improved adaptability in diverse environments, and non-linearity handling as well as the simplification of the nonlinearity to linearity for further analysis with a better understanding of the trend. However, it also introduces challenges related to the sensitivity to hyperparameter tuning because PDNN-ePReLU requires careful tuning of its learnable parameters (α and τ) threshold. Improper tuning can lead to poor performance, particularly if the learning rate or initialization values are not properly set. For example, in scenarios involving large and highly dynamic systems like smart grid networks or autonomous systems, improper tuning may result in increased experimentation time and computational cost to achieve optimal performance. Another weakness is selectivity to application requirements, in which the PDNN-ePReLU benefits the most in high-complexity environment scenarios because of its flexible and adaptive nature, while simpler applications might not justify its potential maximally for high-complexity.

III. Parameterized Analytical Modeling

During data transmission, the transmitted signal is affected by channel fading. Hence, a strong signal strength, appropriate modulation technique, reliable encoder/decoder, and appreciable energy/SNR are needed to maintain a minimal error probability or block error rate (BLER) on the receiver side. Consequently, key parameters are parameterized by the analytical model. GFDM-AQAMCS is considered in the parameterized modeling for minimal error.

The GFDM system employs a shorter cyclic prefix (CP) compared to orthogonal frequency division multiplexing (OFDM), which makes it exhibit minimal out-of-band (OOB) emissions [21]. It facilitates fragmented spectrum utilization including mitigation of significant interference to coexisting users, thereby making it spectral efficient. GFDM has been advocated as an attractive option for applications that require low latency and minimal interference, such as real-time IoT applications [22].

Hence, modeling the BLER of GFDM-AQAMCS involves key network parameters. The analytic parameterized model is defined in the PDNN-ePReLU framework before the dataset generation for PDNN-ePReLU model training, validation, and testing.

The BLER for GFDM-AQAMCS is based on a QAM Modulator. GFDM is a flexible and spectrally efficient modulation scheme that allows the use of non-orthogonal subcarriers, QAM is used for its modulation. In this situation, the QAM is employed to be adaptive with a coding scheme (CS) giving rise to the term AQAMCS. The BLER is the probability of a block of data being received with at least one error, and it is obtained from the symbol error rate (SER) and the block size. The result of analytical expressions to evaluate the SER or bit error rate (BER) of a GFDM system conforms with that of a simulation result as demonstrated in [23].

Furthermore, considering the analytical modeling approach, the SER for the MQAM signal under Additive white Gaussian noise (AWGN) channel condition is given as

$$SER_{MQAM} = 1 - \left(1 - \frac{2(1-1/\sqrt{M})}{\log_2(M)}\right) \times Q\left(\sqrt{\frac{3\cdot\log_2(M)}{M-1} \times \frac{\gamma}{2}}\right)^2 \tag{1}$$

Where M is the QAM modulation order, Q is the Q-function, representing the tail probability of the Gaussian distribution, γ is the SNR.

SER for GFDM

In GFDM, the overall SER depends on the number of subcarriers K and the number of sub-symbols M. Then, using QAM on each subcarrier, the SER for GFDM with K subcarriers and MQAM modulation is given by:

$$SER_{GFDM} = SER_{MQAM} \tag{2}$$

Each subcarrier in GFDM experiences the same SER as the MQAM-modulated signal.

BLER from SER: If the block contains N symbols, the SER is the probability that any individual symbol is received in error, then the BLER can be computed as:

$$BLER_{GFDM-AQAMCS} = 1 - (1 - SER_{GFDM})^N \tag{3}$$

Where SER_{GFDM} is the symbol error rate for GFDM, N is the number of symbols in the block.

To obtain SER for MQAM signal under a Rayleigh fading channel, the average SER will be integrated over the Rayleigh fading probability density function (PDF).

Hence, the SNR PDF Distribution for the Rayleigh Fading is given by

$$p_\gamma(\gamma) = \frac{1}{\bar{\gamma}} e^{-\gamma/\bar{\gamma}}, \quad \gamma \geq 0 \tag{4}$$

Where γ is the instantaneous SNR, $\bar{\gamma}$ is the average SNR.

Then to compute the average SER under Rayleigh fading, we integrate the average SER on the AWGN condition over the Rayleigh fading PDF SNR. Hence,

$$SER_{MQAM-Rayleigh} = \int_0^\infty SER_{MQAM}(\gamma)\cdot p_\gamma(\gamma)\, d\gamma \tag{5}$$

Substituting the expressions for $SER_{MQAM}(\gamma)$ and $p_\gamma(\gamma)$, we have

$$SER_{MQAM-Rayleigh} = \int_0^\infty \left(1 - \left(1 - \frac{4}{\log_2(M)}\right)\left(1 - \frac{1}{\sqrt{M}}\right) Q\left(\sqrt{\frac{3\log_2(M)}{M-1}\gamma}\right)^2 \cdot \frac{1}{\bar{\gamma}} e^{-\gamma/\bar{\gamma}}\, d\gamma \tag{6}$$

Therefore, the analytical approximation for the average SER of MQAM under Rayleigh fading gives

$$SER_{MQAM-Rayleigh} \approx \left(\frac{4}{\log_2(M)}\right) \times \left(1 - \frac{1}{\sqrt{M}}\right) \times \left(\frac{1}{1 + \frac{3}{M-1}\cdot\bar{\gamma}}\right) \tag{7}$$

Similarly,

$$SER_{GFDM-Rayleigh} = SER_{MQAM-Rayleigh} \tag{8}$$

Likewise,

$$BLER_{GFDM-AQAMCS} = 1 - (1 - SER_{GFDM-Rayleigh})^N \tag{9}$$

Therefore, by substituting (7) in (9), we have,

$$BLER_{GFDM-AQAMCS} = 1 - \left(1 - \frac{4}{\log_2(M)}\right)\left(1 - \frac{1}{\sqrt{M}}\right)\left(\frac{1}{1 + \frac{3}{M-1}\cdot\bar{\gamma}}\right)^N \tag{10}$$

IV. NETWORK ARCHITECTURE AND PDNN-EPRELU MODEL

A. Network Architecture

The PDNN-ePReLU network architecture has two segments: the CR network for last-mile/backhaul connectivity and the 5G RedCap network for IoT access networks. The CR network helps to connect the network to a distant location or underserved remote areas where the farms and industries are situated. The 5G RedCap network will then leverage the extended network services for the IIoT networks in the farms/industrial settings.

1) CR for Backhauling/Last-Mile Connectivity: CR leverages dynamic spectrum access (DSA) capability to access TVWS frequencies dynamically. CR network represents the secondary users (SUs) users or unlicensed users without a spectrum license. The CR uses the existing spectrum through opportunistic access without causing harmful interference to the primary users (PUs) or licensed users [24]. CR base station (BS) or gateway searches for the available portion of the spectrum that is not in use called a spectrum hole or white space. Available channels are then used for long-distance transmission as backhauling or last-mile connectivity with other CR users in remote areas. The PDNN-ePReLU framework predicts traffic patterns and adjusts spectrum allocation based on real-time demand, and optimal coverage and throughput. The CR gateway at the remote location has a dual interface (CR and RedCap) to offload broadband data stream to the RedCap interface. The PDNN-ePReLU network architecture is depicted in figure 1.

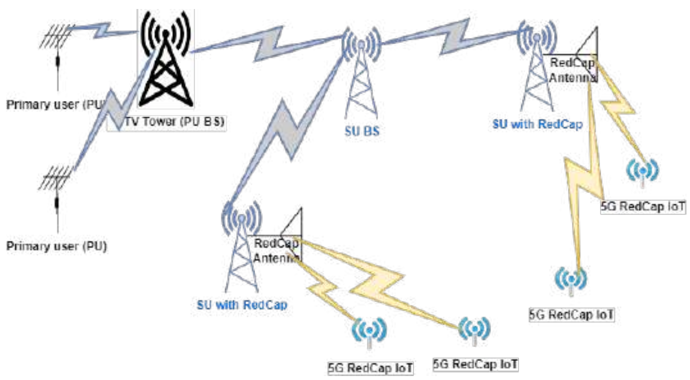

Fig. 1. PDNN-ePReLU network architecture.

2) 5G RedCap for IoT Access Networks: 5G RedCap devices are meant to support medium-to-high data rate IoT applications that are presently not supported by IoT connectivity devices like low power wide area networks (LPWANs) devices: LoRaWAN, Sigfox, NB-IoT, etc [16]. The 5G RedCap devices are deployed as access points for IoT access networks. The RedCap devices operate on a lower complexity 5G standard, providing adequate throughput for most IoT applications while minimizing power consumption. These devices leverage sub-7 Ghz free-spectrum or 5G private network shared spectrum for their connectivity, thus making it a cost-effective solution. The PDNN-ePReLU model is applied to optimize the GFDM-AQAMCS and improve the overall throughput and EE of the RedCap.

B. The PDNN-ePReLU Model Framework

The PDNN-ePReLU is a framework for handling optimization tasks emphasizing prediction. It leverages DNN and a new activation function called ePReLU to provide accurate predictions. In this paper, the PDNN-ePReLU model is implemented to optimize and predict measurable output parameters of networks. The PDNN-ePReLU model framework consists of an input layer with eleven parameters, two hidden layers (22 neurons in hidden layer 1, and 11 neurons in hidden layer 2) with four network parameters, and an output layer with four parameters. Figure 2 shows the PDNN-ePReLU model framework. The hidden layer parameters depend on the input parameters. Hence, for each input parameter, there is a corresponding hidden layer parameter, which is computed from a given expression. Similarly, the output parameters depend on the input and hidden layer parameters, which are obtained from a given expression. The details for these expressions are provided in the algorithm section.

- Input layer: The input dataset includes SNR, Receiver sensitivity, Path loss, Transmit power, Channel bandwidth, Carrier frequency, Modulation order, Channel quality indicator (CQI), Coding rate, Spectrum sensing channels (SSC) information, and Distance.
- Hidden layers: This comprises two layers with four parameters, which include block error rate (BLER), Maximum coupling loss (MCL), signal strength, and received signal power (RSP).
- Output layer: This includes Coverage, Throughput, Latency, and EE.

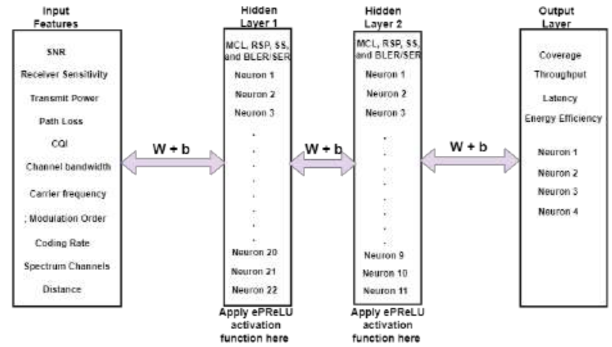

Fig. 2. PDNN-ePReLU architectural framework.

1) PDNN-ePReLU Model Representation: The definition of the PDNN-ePReLU model framework follows an algorithmic process. First, the model is built layer-wise and includes the necessary operations, such as weight (W) and bias (b) computation, followed by the activation function.

For a single fully connected layer with n inputs and m neurons, the weighted sum for each neuron i is computed as

$$z_i = \sum_{j=1}^{n} w_{ij} x_j + b_i \tag{11}$$

Where $\mathbf{x} = [x_1, x_2, \ldots, x_n]$ is the input vector. $\mathbf{w}_i = [w_{i1}, w_{i2}, \ldots, w_{in}]$ is the weight vector for the i-th neuron. b_i is the bias term for the i-th neuron.
Using vector notation for all neurons in the layer, we can express the weighted sum for the entire layer as

$$\mathbf{z} = \mathbf{W}\mathbf{x} + \mathbf{b} \tag{12}$$

Where $\mathbf{W} \in \mathbb{R}^{m \times n}$ is the weight matrix (size $m \times n$, where m is the number of neurons in this layer). $\mathbf{b} \in \mathbb{R}^m$ is the bias vector (size m).

Applying the ePReLU activation function After computing the weighted sum z_i for each neuron, we apply the ePReLU activation function to introduce non-linearity.

The ePReLU function is an enhancement of the traditional ReLU function and is defined as

$$y_i = \begin{cases} z_i, & \text{if } z_i > 0, \tau_i \\ \alpha_i z_i, & \text{if } z_i \leq 0, \tau_i \end{cases} \tag{13}$$

Where z_i is the weighted sum (pre-activation value) for the i-th neuron. y_i is the output after applying ePReLU to the i-th neuron [16], α_i is a learnable parameter that adjusts the slope for negative values. τ_i is the learnable threshold for the i-th neuron.

In nonzero with negative slope conditions, ePReLU becomes

$$\text{ePReLU}(y_i) = \begin{cases} z_i, & \text{if } z_i \geq \tau_i \\ \alpha \cdot (z_i - \tau_i), & \text{if } x < \tau_i \end{cases} \tag{14}$$

In vector notation, for all neurons in the layer, the ePReLU activation function is applied element-wise as

$$\mathbf{y} = ePReLU(\mathbf{z}) = \begin{cases} \mathbf{z}, & \text{if } \mathbf{z} > \tau \\ \alpha \odot (\mathbf{z} - \tau), & \text{if } \mathbf{z} \leq \tau \end{cases} \tag{15}$$

Where α is the vector of α_i values for all neurons. τ is the vector of τ_i values for all neurons. $\odot$ represents element-wise multiplication.

If we extend this to multiple layers, the general expression for the l-th layer becomes

$$\mathbf{z}^{(l)} = \mathbf{W}^{(l)}\mathbf{y}^{(l-1)} + \mathbf{b}^{(l)} \tag{16}$$

Where $\mathbf{z}^{(l)}$ is the weighted sum (pre-activation) for layer l. $\mathbf{W}^{(l)}$ and $\mathbf{b}^{(l)}$ are the weights and biases for layer l. $\mathbf{y}^{(l-1)}$ is the output from the previous layer (or the input to the network if it's the first layer).

The output after applying the ePReLU activation function at layer l is

$$\mathbf{y}^{(l)} = ePReLU(\mathbf{z}^{(l)}) = \begin{cases} \mathbf{z}^{(l)}, & \text{if } \mathbf{z}^{(l)} > \tau^{(l)} \\ \alpha^{(l)} \odot (\mathbf{z} - \tau)^{(l)}, & \text{if } \mathbf{z}^{(l)} \leq \tau^{(l)} \end{cases} \tag{17}$$

2) PDNN-ePReLU Algorithm: ‘

1 Initialized input features: Input number of samples % $num_{Samples_Stage1}$ = 1500;% $num_{Samples_Stage2}$ = 500;

2 Define Parameterized model: equation (7) & (10);

3 Generate Input $num_{Samples_Stage1}$: SNR: random values $> 0\& \leq 30$ dB; Receiver Sensitivity: random values > -90 & $\leq -80dBm$; Path Loss: random values $> 80\&$ $\leq 130dB$; Transmit Power: random values between 20 and 30 dBm; Channel quality indicator (CQI): random integer values between 1 and 15; Channel bandwidth: set to 20 MHz & 8 MHz; Carrier frequency: set to 5 GHz & 470-890 MHz; Modulation order: randomly choose between 16-QAM & 64-QAM; Coding rate: randomly choose between 0.5 & 0.75; SSC: random integer values representing spectrum channel information; Distance over 100 km;

4 Compute BLER/SER: use the Parameterized GFDM-AQAMCS BLER/SER model and the $Samples_Stage1$ generated parameters to compute the BLER or symbol error rate for each sample;

5 store first 1000 samples that are within BLER threshold into the input data matrix & store the remainder into the $num_{Samples_Stage2}$;

6 Compute the hidden layer parameters: MCL: $MCL = PathLoss + 10 \cdot \log_{10}(CarrierFrequency) - TransmitPower$; RSP: $RSP = TransmitPower - PathLoss + SNR$; Signal strength: $SignalStrength = TransmitPower - PathLoss$; BLER: computed for each corresponding input leveraging the parameterized GFDM-AQAMCS BLER model.

7 Prepare Input and Output Datasets
(i) Input Data Matrix: concatenate the stored input data matrix: [SNR, Receiver sensitivity, Path loss, Transmit power, CQI, Channel bandwidth, Carrier frequency, Modulation Order, Coding rate, SSC, Distance]. These are stored as parameterized input datasets which will be generated for training the model.
(ii) Output Data Matrix: Define the 4 output parameters to predict: Coverage, Throughput, Latency, and EE. These are computed based on the inputs and hidden layer parameters:

$$\text{Coverage} = C_0 \cdot \frac{MCL}{Path_{\text{loss}}}$$

where C_0 is the constant that depends on the network traffic conditions.

$$\text{Throughput} = B \cdot \log_2(1 + SNR) \cdot (1 - \text{BLER})$$

B is the channel bandwidth (Hz)

$$\text{Latency} = C_0 \cdot \frac{Path_{\text{loss}}}{CQI}$$

$$\text{EE} = \frac{B \cdot \log_2(1 + SNR)}{\text{Transmit power}}$$

8 Split Data for Training, Validation, and Testing Split the Dataset: split the dataset into 70% for Training, 15% for Validation, and 15% for Testing.

9 Define the PDNN-ePReLU Model with ePReLU Activation Function; (i) Input Layer: Input size is 11 (number of input features);
(ii) First hidden layer: 22 neurons;
(iii) Apply the ePReLU activation function defined in eqn (15) or (17);
(iv) Second hidden layer: 11 neurons;
(v) Apply another ePReLU activation function;
(vi) Output Layer: neurons representing Coverage, Throughput, Latency, and EE;
(vii) Regression layer is used for continuous output;

10 Train the PDNN-ePReLU Model (i) Define Training Options: use the Adam optimizer; set the number of epochs = 100; set the mini-batch size = 64; use Root Mean Squared Error (RMSE)as the loss or error function;
(ii) Train the model using the training dataset;

11 Initialize Weights and Biases for all Layers: for each layer, initialize weights randomly; Initialize bias terms for each neuron;

12 Forward Propagation: for each epoch: pass input parameters through the input layer; for each hidden layer:
apply fully connected layer operation (Weighted sum + bias);

apply ePReLU activation function with slope parameter α and threshold τ
Output Layer: apply fully connected layer;
13 Predict network parameters (Coverage, Throughput, Latency, EE);
14 Loss Calculation: compute the loss using RMSE between predicted outputs and actual outputs;
15 Backpropagation: for each output neuron:
(i) Compute the gradient of loss concerning weights and biases;
(ii) Propagate gradients back through each layer using the chain rule;
(iii) Update weights and biases using the Adam optimizer;
16 Validation: after every 10 epochs, validate the model using the validation dataset; Compute validation loss and track performance for accurate model generalization;
17 Update ePReLU Parameters (α and τ): adjust ePReLU slope parameter α and threshold τ during training as part of backpropagation to minimize loss;
18 Repeat Steps 10 to 17 for all epochs;
19 Output: predicts optimized parameters for new unseen inputs after training of the model is complete;
Then, output predicted parameters: Coverage, Throughput, Latency, EE;
20 Test the Model: use the trained model to predict network performance for unseen test data from the test set or a new separate data.
21 repeat the process from step 4 leveraging $num_{Samples_{Stage2}}$ & step 5 to store any number samples within the BLER threshold for BLER computation into input matrix2;
22 Then, repeat steps 6 to 20 for extended and future model training, validation, and testing;
23 End;

V. IMPLEMENTATION AND SIMULATION

The PDNN-ePReLU model is a parameterized DNN that uses the ePReLU activation function, providing better flexibility and robustness in handling complex tasks like communication system optimization. The implementation follows the earlier presented PDNN-ePReLU framework and Algorithm. This involves an input layer comprising 11 input features; two hidden layers with four features comprising 22 neurons in hidden layer 1, and 11 neurons in hidden layer 2; an output layer with four features. This framework is implemented in MATLAB 2024a leveraging the DNN and Communication/5G toolbox. The input features are parameterized and stored in the input matrix after being used for the BLER/SER computations for the 1000 samples. These parameterized stored datasets are generated for the model training.

Let $\mathbf{x}$ be the input to the framework, and the forward pass through the two hidden layers and applying the ePReLU activation function are written as:

For Layer 1:

$$\mathbf{z}^{(1)} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \tag{18}$$

$$\mathbf{y}^{(1)} = ePReLU(\mathbf{z}^{(1)}) \tag{19}$$

For Layer 2:

$$\mathbf{z}^{(2)} = \mathbf{W}^{(2)}\mathbf{y}^{(1)} + \mathbf{b}^{(2)} \tag{20}$$

$$\mathbf{y}^{(2)} = ePReLU(\mathbf{z}^{(2)}) \tag{21}$$

To demonstrate the effectiveness of the PDNN-ePReLU model, a simulation model was developed in MATLAB 2024a that integrates: CR via TVWS: the CR dynamically selects available TVWS frequencies from the spectrum sensing channel feature in the dataset for backhauling over a 100 km distance, optimizing the use of available spectrum and predicting optimized coverage, throughput, latency, and EE over this distance.
5G RedCap Device Simulation: the RedCap device was simulated to provide IoT access over a 100 km distance and to optimize the modulation and coding rate and other input features from the input matrix to improve coverage, throughput, latency, and EE prediction over this distance. A first-order polynomial leveraging linear regression approach is incorporated in this simulation to transform the nonlinear PDNN-ePReLU output into a linear graph for a simplified further analysis. The simplified linearity still maintains a reasonable approximation of the original nonlinear behavior.

Table 1 shows the simulation parameters for PDNN-ePReLU model implementation and comparisons with legacy CR and RedCap (without model optimization). In the simulation setup, the traditional or legacy CR and 5G RedCap systems utilize a simplified wireless communication mechanism without deep learning optimizations. They use traditional MCS and other basic features/parameters as baseline models without dynamic adjustments based on network conditions. However, the PDNN-ePReLU model leverages the DNN and ePReLU parameters for dynamic adjustments based on network conditions to improve the performance of CR and 5G RedCap systems.

VI. RESULTS AND DISCUSSION

The MATLAB 2024a simulation results demonstrate the effectiveness of the PDNN-ePReLU model and show performance improvement better than the legacy CR and 5G RedCap in terms of coverage, throughput, latency, and EE over 100 km distance ranges as juxtaposed below. Considering Coverage performance over 100 km distances, the use of CR optimized with the PDNN-ePReLU model extends the coverage area by approximately 37% compared to legacy CR solutions in rural areas. This is because there is a slightly minimal decrease of optimized CR coverage as the distance increases, unlike the legacy CR in which the coverage decreases rapidly as shown in Figure 3. This estimate is obtained by considering the coverage at the 70 km distance. The CR with the PDNN-ePReLU model gives an 8.8% decrease in coverage while the legacy CR gives a 41.17% decrease in coverage.

TABLE I

SIMULATION PARAMETERS.

Parameters	Value
Simulation runs	100,000
Channel fading	Rayleigh
Modulation order	16-QAM, 64-QAM
SNR	0:3:30 (dB)
B	5 MHz, 6 MHz, 8 MHz, and 20 MHz
Tx	1
Rx	1
Encoder	polar code
Carrier frequency	470 to 890 MHz, and 5 to 7 GHz
Receiver Sensitivity	-90 to -70 dBm
Transmit power	15 to 25 dBm
Path loss	80 to 160 dB
Device type	CR, and 5G RedCap
CQI	1 - 15
Coding rate	0.5 - 0.75
Distance	0 - 100 km
SSC	20 - 50
MCL	0 - 180
Number of subcarriers (No)	52
Epoch	100
iteration	1000
Learning rate	0.001
W	0: 1000
ePReLU thresholds (α, τ)	0.1, 0.2, 0.9 and 2, 3, 5

Similarly, the coverage of the 5G RedCap optimized with the PDNN-ePReLU model outperforms the legacy 5G RedCap by 56% improvement as shown in Figure 4. This is because of a minimal decrease in optimized RedCap coverage as the distance increases, whereas the legacy RedCap decreases sharply with the increased distance.
Considering the throughput performance as distance increases, figures 5 and 6 show that the throughput of the CR and RedCap optimized with the PDNN-ePReLU model outperforms legacy CR and RedCap respectively.
Furthermore, figures 7 and 8 demonstrate that the latency of the CR and RedCap optimized with the PDNN-ePReLU model outperforms legacy CR and RedCap respectively. This is because the latency increases minimally for the optimized systems, however, it increases rapidly in the legacy systems.

Finally, figures 9 and 10 confirm that the EE of the CR and RedCap optimized with the PDNN-ePReLU model outperforms legacy CR and RedCap respectively. This is because the EE of the CR and RedCap optimized with the PDNN-ePReLU model decreases minimally as distance increases, and it maintains higher energy-efficient values with distance than the legacy systems which show a rapid decrease in EE and low energy-efficient values with distance.

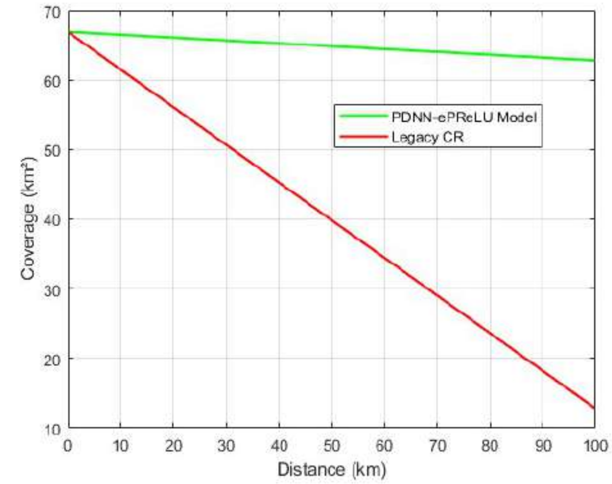

Fig. 3. Coverage performance comparison for CR.

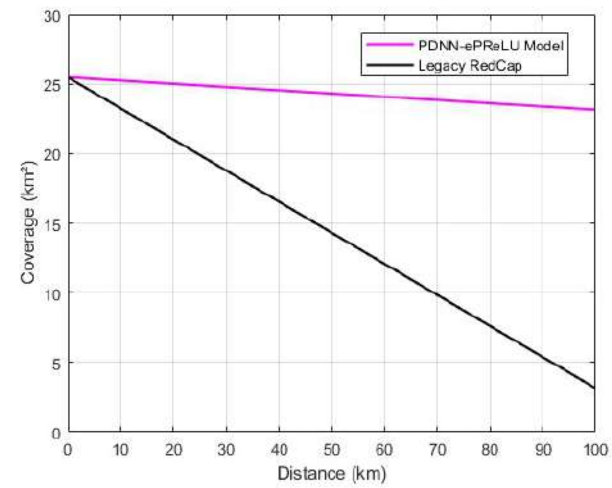

Fig. 4. Coverage performance comparison for 5G RedCap.

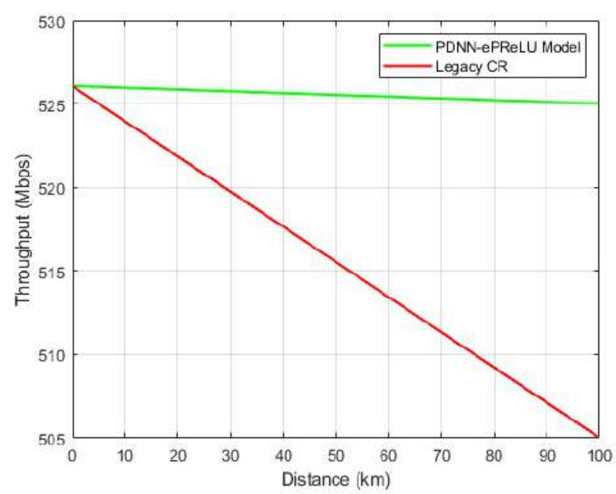

Fig. 5. Throughput performance comparison for CR.

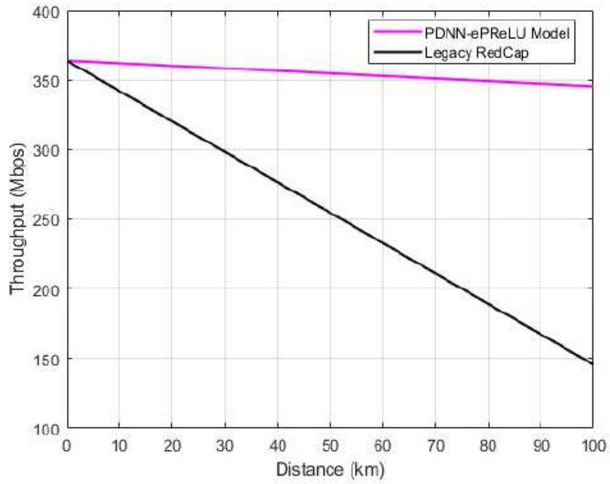

Fig. 6. Throughput performance comparison for 5G RedCap.

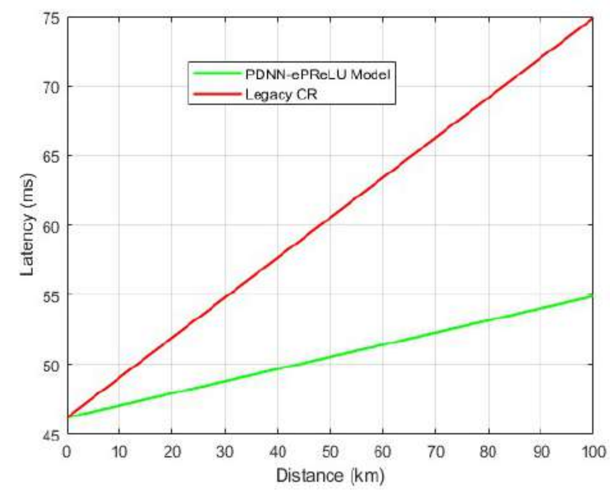

Fig. 7. Latency performance comparison for CR.

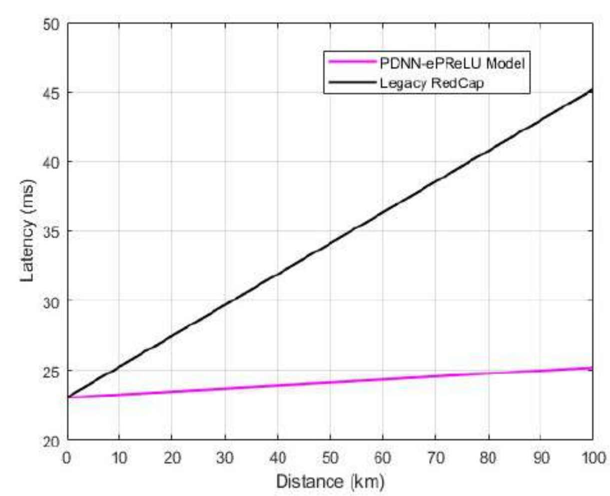

Fig. 8. Latency performance comparison for 5G RedCap.

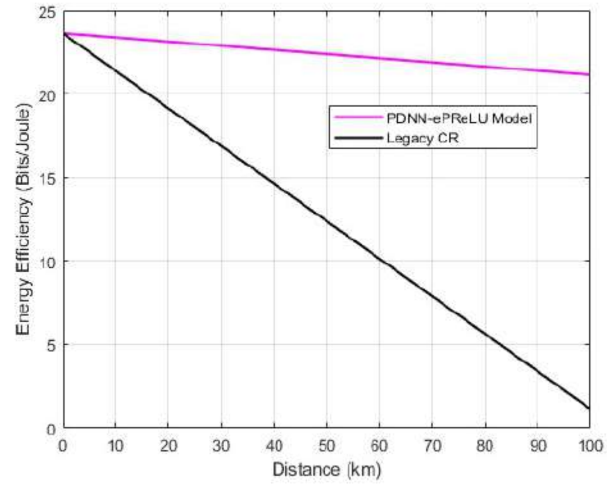

Fig. 9. EE performance comparison for CR.

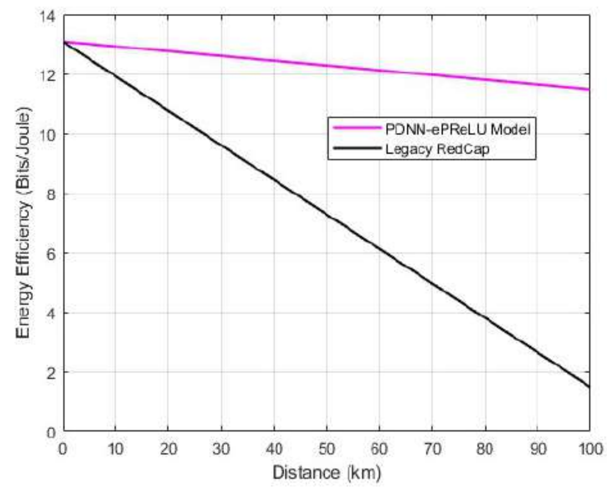

Fig. 10. EE performance comparison for 5G RedCap.

VII. CONCLUSION

This paper presents an innovative B-IoT communication solution for agribusiness and IIoT that leverages CR network for backhauling/last-mile connectivity and 5G RedCap devices for IoT access networks. Integration of the PDNN-ePReLU model enhances network performance, ensuring that coverage, throughput, latency, and energy efficiency are improved. This approach involves incorporating a new parameterized modeling into DNN and a new activation function called ePReLU which enables weight and bias adjustment of the model uniquely for optimal solution. It addresses the unique challenges of rural connectivity, offering a scalable and cost-effective solution for the deployment of IoT applications in remote areas. Considering the uniqueness of the features, the paper presents new algorithmic steps that enable accurate generalization of the model with the capability of supporting transfer/incremental learning. The MATLAB 2024a simulation results demonstrate that the PDNN-ePReLU model significantly outperforms the legacy CR and 5G RedCap in terms of coverage, throughput, latency, and EE over 100 km distance ranges. Hence, this communication solution is a cost-effective and viable solution for agribusiness and IA industries in underserved areas not presently covered by traditional networks.

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