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Machine Learning Based Impedance Matching Scheme for Enhancing Power Line Carrier Communication

Ogbonnaya A. O., Idigo V. E., Anazia A. E., Ogboh V. C.
Department of Electronic and Computer Engineering
Department of Electrical Engineering
Nnamdi Azikiwe University, Awka

ABSTRACT
Power Line Carrier Communication (PLCC) performance in extra-high-voltage (EHV) transmission systems is highly dependent on effective impedance matching between the coupling network and the transmission line. Conventional static matching techniques are limited in bandwidth and unable to respond to dynamic impedance variations caused by load changes and switching operations. This paper presents a machine learning (ML)–based adaptive impedance matching approach for enhancing PLCC signal integrity in EHV power networks. A MATLAB/Simulink model of a 330 kV, 250 km transmission line integrated with an intelligent matching controller was developed. The ML algorithm utilizes real-time voltage, current, and frequency measurements to dynamically adjust matching network parameters, minimizing signal reflections and attenuation. Simulation results show a 70–80% reduction in reflection coefficient, a 50% improvement in power transfer efficiency, and an expanded operational bandwidth from 50 kHz to 500 kHz compared to conventional methods. The adaptive scheme effectively tracks impedance variations and maintains stable carrier transmission under varying operating conditions. The results confirm the effectiveness of ML-based impedance matching as a robust solution for reliable PLCC in modern EHV power systems.
Keywords: *PLCC, VSWR, SNR, BER, Transmission Line, Coupling Network, Line Trap, Machine Learning*

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I. INTRODUCTION

The increasing global demand for electrical energy has led to the expansion and complexity of extra-high-voltage (EHV) transmission systems, which are essential for the long-distance transfer of bulk power and the integration of diverse generation sources, including renewables. Ensuring the reliability and stability of these transmission networks requires efficient monitoring and protection mechanisms. Power Line Carrier Communication (PLCC) has emerged as a cost-effective and reliable solution for relaying protection by utilizing existing transmission lines for communication between protective relays and control centers. However, the effectiveness of PLCC is highly dependent on the electrical characteristics of the transmission line, particularly impedance matching. Impedance mismatches between communication equipment and power lines result in signal reflection, attenuation, and distortion, which can significantly degrade communication performance and compromise protection reliability.

To address these challenges, this study focuses on improving impedance matching schemes for PLCC in EHV transmission networks. Conventional matching techniques, such as transformer-based and LC networks, are often static and unable to cope with dynamic variations in line impedance. With recent advancements in machine learning (ML), intelligent impedance matching schemes capable of real-time adaptation have become feasible. ML-based approaches can analyze changing line conditions, predict impedance variations, and dynamically adjust matching parameters to maintain optimal signal transmission. Despite their potential, ML-based impedance matching techniques remain underexplored in PLCC applications. This research aims to bridge this gap by designing and evaluating ML-driven impedance matching schemes to enhance PLCC performance, improve communication reliability, and strengthen the effectiveness of relaying protection systems in modern EHV power grids.

II. METHODODLOGY

This chapter presents the research methodology, tools, and procedures employed in the design, development, and simulation based on the Machine Learning application to Impedance Matching Scheme for enhancing Power Line Carrier Communication (PLCC) in Extra High Voltage (EHV) transmission systems. The approach integrates transmission line modeling, impedance mismatch analysis, and the application of supervised

machine learning algorithms to dynamically optimize impedance matching and minimize signal reflections. The research utilized the following material tools, datasets, hardware references, and software environments:
The Figure 1 and 2 represent the block diagram and the flowchart that describes the procedure and the process followed to achieve the desired results.

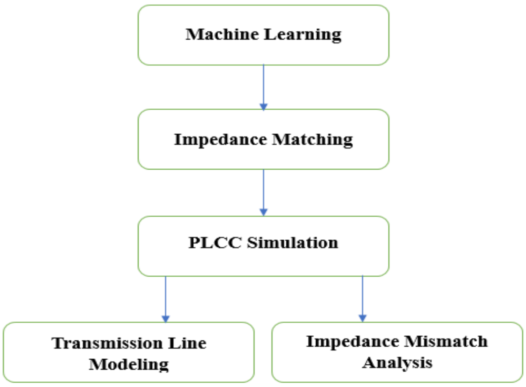

Figure 1: Block Diagram Showing the System Procedure

The block diagram provides the overview of the system core components and how they interact. The Machine Learning (ML) block represents the use of supervised machine learning algorithms (like ANN and Decision Trees) trained with features extracted from simulated signals. These algorithms are used to classify impedance states and recommend corrective actions.
On the Impedance Matching, the ML processes the input, predicts the required network configuration or correction to optimize impedance. The goal is to minimize reflections and match load impedance to characteristic impedance Z_0.
Here, the machine learning recommendations are tested in simulation environments (MATLAB/Simulink). The PLCC signal (typically 50–500 kHz) is superimposed on the 330 kV line to simulate real-world communication over power lines.
The EHV line is modeled using a distributed parameter model or π-model in Simulink to simulate real physical behaviors, including inductance, capacitance, resistance, etc.
The impedance mismatch block represents the study of how impedance mismatches affect signal quality, standing wave ratio (SWR), and reflections on the line. These components work together as a feedback loop where simulation results feed back into the ML model for continuous refinement.

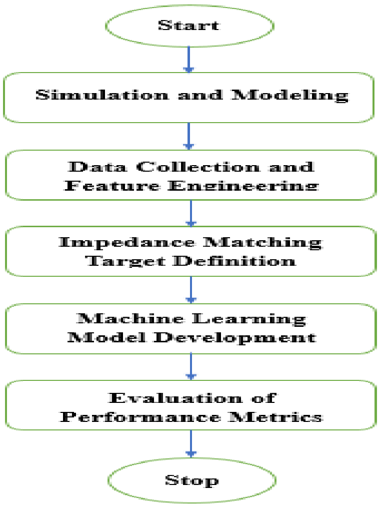

Figure 2: Block Diagram Showing the System Procedure

The flowchart presents the step-by-step research process followed in this methodology. The procedure is initiated and the 330kV, 250 km transmission line and PLCC systems are modeled using MATLAB/Simulink based on physical parameters obtained from the transmission line station.

Data is collected from simulation scenarios such as; varying load impedances, switching conditions and fault occurrences from which features such as signal amplitude distortion, reflection coefficient, phase shift and impedance deviation are extracted for the ML input.

The ideal impedance matching is defined as; when $Z_{match} = Z_0$ (characteristic impedance) so that the reflection coefficient $\gamma = 0$ (gamma). These targets are used as training labels for supervised learning.

The machine learning model development is achieved through the preprocessing which include; feature normalization and filtering. Model selection is performed using ANN and decision trees. Training is done considering 80% of the data used for training and 20% for testing. Tuning is done through the search of the Grid and cross-validation while Evaluation is performed checking the accuracy, mean square error and the F1-score of the system.

Evaluation of performance metrics is achieved by checking the effectiveness of the impedance matching scheme using reflection coefficient (γ), return loss (dB), signal attenuation, communication Bit Error Rate (BER) and response time of impedance adjustment

Together, the block and flowchart diagram visually summarizes the full research workflow, from data simulation and feature extraction to ML application and performance validation.

2.1 Transmission Line Modeling

A single-circuit 330 kV, 250 km transmission line was modeled in MATLAB/Simulink using a distributed parameter model. Coupling equipment was simulated using equivalent circuit models. A sinusoidal carrier frequency in the range of 50–500 kHz was superimposed onto the high-voltage line to emulate PLCC.

Considering Onitsha–Enugu 330 kV, 250 km Transmission Line as the case study power line, it can be modeled using mathematical or analytical and computer software tool as shown below. This can be achieved along with the values of resistance, inductance, and capacitance.

Step 1: Assumed line parameters, choose standard overhead line per-unit-length values: Line voltage (V) = 330 kV, Line length (L) = 250 km, Resistance per phase (R') = 0.05 Ω/km, Inductance per phase (L') = 1.2 mH/km and Capacitance per phase (C') = 0.009 µF/km.

Calculate total line parameters, which is total resistance R = 0.05 × 250 = 12.5 Ω, total inductance L = 1.2 mH × 250 = 0.3 H and total capacitance C = 0.009 µF × 250 = 2.25 µf.

Step 2: Simulink Model Setup (Blocks), using Simscape Electrical Specialized Technology Elements. The components include: Three-Phase Source – 330 kV, 50 Hz, Three-Phase Pi Section Line, R = 12.5 Ω, L = 0.3 H and C = 2.25 µf. Three-Phase Series RLC Load, using 100 MW, 50 Mvar (optional), with Three-Phase Voltage and current measurement. The scopes are used to observe voltage/current waveforms, and PowerGUI is set to "Continuous" mode with a 1e-6 s sample time.

Step 3: Modeling Instructions involves dragging and dropping the Three-Phase Source, connecting it to the input of the Three-Phase Pi Section Line, and configuring the Pi Section using series R and L = 12.5 Ω and 0.3 H, and shunt C = 2.25 µF. Connect output to the three-phase load, insert voltage and current measurement blocks at sending and receiving ends, connect all scopes and use a powergui block to enable simulation. The expected output when simulating this model allows you to analyze; voltage drop across line, current flow, line losses and effect of line capacitance (Ferranti effect).

To mathematically model the 330 kV, 250 km power transmission line from first principles, we use electromagnetic theory and transmission line theory. Since the line is long (greater than 250 km)**,** we model it as a distributed-parameter transmission line.

The apparent, active and reactive power are in MVA, MW and MVAR respectively. They support the electric and magnetic fields in the AC power equipment on the power station. The actual values on the Onitsha – Enugu transmission line are not fixed, but changes with load voltage, power factors, and dispatch at the moment. They can be computed as follows;

Apparent Power $S = \sqrt{3V_{LL}}$ x I (MVA) 1

Active Power $P = \sqrt{3V_{LL}}$ x Icosφ (MVA) 2

Reactive Power $Q = \sqrt{3V_{LL}}$ x Isinφ (MVA) 3

Though,

$$Q = P \tan \text{arc} \cos \text{pf} \quad 4$$

$$S^2 = P^2 + Q^2 \quad 5$$

For the long line such as 250kV, with sending and receiving voltage given as $V_s . V_r$ and the series reactance X, the receiving end power becomes;

$$P = \frac{V_s V_r}{X} \sin\delta \quad 6$$

$$Q = \frac{V_s}{X}(V_s - V_r \cos\delta) \quad 7$$

Where δ is the angle between the sending end and receiving end voltage.

Therefore, if the 330kV Onitsha – Enugu transmission line were carrying 1000A at power factor, pf of 0.92lag;

$S = \sqrt{3}\ \text{x}\ 330{,}000\ \text{x}\ 1000 = 571.6\ \text{MVA}$ 8

$P = S\ \text{x}\ 0.92 = 525.9\ \text{MW}$ 9

$Q = S\ \text{x}\ \sqrt{1-(\text{pf})^2} = \sqrt{(1-0.92)^2}\ = 224.0\ \text{MVAR}$ 10

The power system transmission line consist of the series impedance per unit length (z = r + jwL) and shunt admittance per unit length (y = g + jwC).

Where, r = resistance per unit length (ohms/km), L = inductance per unit length (H/km), g = conductance per unit length (S/km), C = capacitance per unit length F/km, w = 2pif (angular frequency) and f = frequency (Hz).

The telegrapher's Equations is given as in the distributed parameter line of length l as follows;

$\frac{\partial V(x)}{\partial x} = -(r + j\omega L)I(x)$ 11

$\frac{\partial I(x)}{\partial x} = -(g + j\omega C)V(x)$ 12

Where, V(x) = voltage along the line at position x and I(x) = current along the line at position x.

Generally, the transmission line wave equation is given as;

$\frac{\partial^2 V(x)}{\partial x^2} = \gamma^2 V(x)$ 13

$\frac{\partial^2 I(x)}{\partial x^2} = \gamma^2 I(x)$ 14

Where the propagation constant is given as'

$\gamma = \sqrt{zy} = \alpha + j\beta$ 15

$V(x) = V_+ e^{-\gamma x} + V_- e^{\gamma x}$ 16

$I(x) = \frac{V_+}{Z_c} e^{-\gamma x} + \frac{V_-}{Z_c} e^{\gamma x}$ 17

$Z_C = \sqrt{\frac{z}{y}}$ = the characteristic impedance 18

The transmission line is a long line and has its parameters as ABCD obtained using equations … above.

$$\begin{bmatrix} V_s \\ I_s \end{bmatrix} = \begin{bmatrix} \cosh(\gamma l) & Z_c \sinh(\gamma l) \\ \frac{1}{Z_c}\sinh(\gamma l) & \cosh(\gamma l) \end{bmatrix} \begin{bmatrix} V_r \\ I_r \end{bmatrix}$$ 19

V_s and I_s are sending-end voltage and current respectively.

V_r and I_r are receiving-end voltage and current respectively.

l = transmission line length.

The typical parameters values of the 330Kv, 250km transmission line can be estimated and mathematically modeled as follows and for the computer modeling and simulation using MATLAB/Simulink using the variables of table 1.

Table 1: Transmission Line and PLCC Data

S/N	PARAMETER	TYPICAL VALUES
1	Resistance, R	0.05Ω/km
2	Inductance, L	1mH/km = $1 \text{ x } 10^{-3}$ H/km
3	Capacitance, C	0.01μF/km = $1 \text{ x } 10^{-8}$F/km
4	Conductance, g	≈ 0
5	Line Voltage	330KV
6	Active Power, P (MW)	525.9 MW
7	Reactive Power, Q (MVAR)	224 MVAR
8	Apparent Power, S (MVA)	571.6MVA
9	Line Distance, L (Km)	250Km
10	Power Frequency	50Hz
11	Low Frequency	1KHz
12	Carrier Frequency	200KHz

Therefore,

$z = r + j\omega L = 0.05 + j2\pi(50)$

$(1 \text{ x } 10^{-3}) = 0.05 + j\ 0.314\Omega/\text{km}$ 20

$y = j\omega L = j2\pi(50)(1 \text{ x } 10^{-3})$

$= j3.14 \text{ x } 10^{-6}\ \text{S/m}\ = j3{,}14 \text{ x } 10^{-3}\text{S/m}$ 21

$\gamma = \sqrt{zy}$ 22

$Z_c = \sqrt{\frac{z}{y}}$ 23

Where;

$z = 0.05 + j0.314\Omega/km$ 24

$y = j3.14 \times 10^{-3} S/km$ 25

Total line modeling for 250km is determined using;

$Z = 250z$ 26

$Y = 250y$ 27

Power Transfer and Efficiency is obtained using;

$P = \sqrt{3} V_r I_r \cos\emptyset$ 28

$A = D = \cosh(\gamma l)$ 29

$B = Z_C \sinh(\gamma l)$ 30

$C = \frac{1}{Z_C} \sinh(\gamma l)$ 31

The voltage regulation, efficiency, and reactive compensation can be modeled using the above parameters.

Finally, the mathematical modeling of the transmission line is done using the distributed parameters of the line given as the governing telegrapher's equations, the line parameters z and y, propagation constant γ, and the ABCD matrix, all given by equations (3.1) to (3.31) above.

The transmission line modeling is done using a distributed parameter model **i**n MATLAB/Simulink Simscape Electrical, specialized power systems. It parameters of line block models are the actual physical behavior of long EHV lines. Some other parameters considered include the voltage level of 330 kV, line length of 250 km, positive-sequence resistance (R_1) of 0.05 Ω/km, positive-sequence inductance (L_1) of 1mH/km, positive-sequence capacitance (C_1) of 0.01μF/km, and frequency of 50 Hz (power system).

2.2 PLCC System

PLCC systems are a coupling equipment that includes coupling capacitors**,** line turners**,** wave traps (line traps), and hybrid units**.** The typical circuit for coupling equipment of the PLCC is shown in Figure 3.

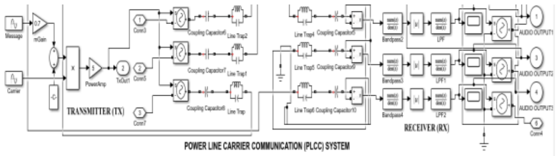

Figure 3: Power Line Carrier

Communication Scheme

The number of line trap depend on the number of communication channels required for effective carrier signal communication. PLCC systems operate on the same power line but at different locations, ensuring signal clarity and preventing unwanted signal propagation.

2.3 Line Turner

The line tuner's primary function is to match the impedance of the PLCC terminal equipment to the impedance of the power transmission line. This impedance matching ensures maximum power transfer and minimizes signal reflections, optimizing data transmission efficiency. Figure 3.4 is the complete circuit diagram of a line tuner, which includes the line trap, coupling capacitor, and a bandpass.

One practical tuner approach is to use a small series inductor L_{tuner} that resonates with the effective capacitance seen at the coupling point (L – network).

Here, the $C_{tuner} = 100pf = 1.0 \times 10^{-10}F$ and compute L_{tuner} to resonate at f_c.

Resonance formula = $f_0 = \frac{1}{2\pi\sqrt{L_{trap}C_{trap}}}$

$L_{tuner} = \frac{1}{(2\pi f_0)^2 C_{tuner}}$

$= \frac{1}{(2 \times 3.142 \times 200{,}000)^2 \times 1.0 \times 10^{-10}}$

$= 0.0063325H = 6.3326mH.$

$L_{trap} = \frac{1}{(2\pi f_0)^2 C_{trap}}$

$= \frac{1}{(2 \times 3.142 \times 200{,}000)^2 \times 1.0 \times 10^{-9}}$

$= 0.6333mH$ 32

The exact line tuner topology is selected to get the desired insertion loss and matching across the chosen carrier frequencies. Practical tuners are adjustable to tune across the band.

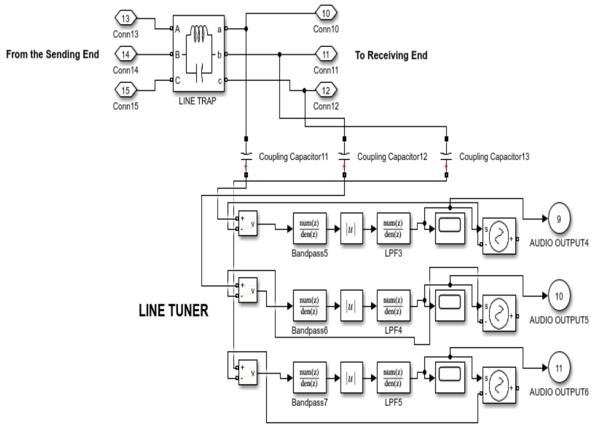

Figure 4: Line Tuner

The line tuner (matching network) is used to match the PLCC transmitter/receiver port impedance (often 50-600 ohm systems) to the line's HF characteristic (Z_0. The tuner can be a small LC network (series L, shunt C or L – network) or a transformer – based matching.

The purpose of the line tuner in conjunction with the coupling capacitor is to provide low impedance path for the carrier energy to the transmission line and a high impedance path to the power frequency energy. This is achieved by forming a series resonance frequency circuit tuned to the carrier frequency.

On the other hand, the capacitance of the coupling capacitor is high impedance to the power frequency energy. Even though the coupling capacitor has high impedance at power frequencies, there must be a path to ground in order that the capacitor may do its job. This function is provided by the drain coil, which is in the base of the coupling capacitor. The drain coil is designed to be low impedance at the power frequency and because of its inductance, it will have high impedance to the carrier frequency.

Thus, the combination of the line tuner, coupling capacitor, and the drain coil provides the necessary tools for coupling the carrier energy to the transmission line and blocking the power frequency energy. One last function of the line tuner is to provide matching impedance between the carrier coaxial cable usually 50 to 75ohms and the transmission line which will have an impedance of about 150 – 5000ohms.

2.4 Coupling Equipment

In Power Line Carrier Communication (PLCC) systems, coupling equipment serves to connect the communication terminal to the high-voltage power transmission line, facilitating data transmission over the existing power infrastructure. The key components include coupling capacitors, line tuners, and line traps (also known as wave traps) and shown on Figure 3.5.

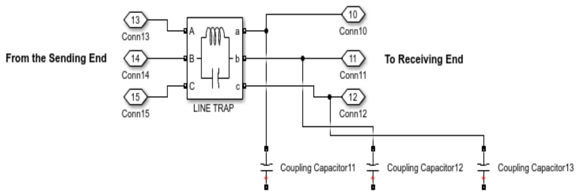

Figure 5: Coupling Equipment

2.5 Coupling Capacitor

This component acts as a high-pass filter, allowing high-frequency carrier signals (used for data transmission) to pass through while blocking the low-frequency (50Hz) power signals. This prevents the communication signals from interfering with the power transmission and vice versa.

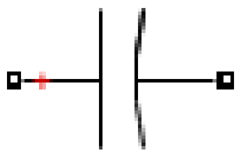

Figure 6: Coupling Capacitor (Cc)

The coupling capacitor shown on Figure 3.6, connects the carrier equipment to the transmission line. Its capacitance is 6.333e-11F. It offers lower impedance to carrier frequency f_c of 200kHz, but high impedance to power frequency, f of 50Hz.
To decrease the impedance further and make the circuit purely resistive so that there will be no more reactive power in the circuit, a low impedance is connected in series with the coupling capacitor to form a resonance at the carrier frequency.

2.6 Wave Traps (Line Traps)
Line traps are essentially bandpass (low-pass filters) that block high-frequency carrier signals from entering or leaving a specific section of the power line.
The line trap is inserted in series with the line at the substation and which provides a very large impedance at the carrier frequency; it prevents the carrier from entering the substation bus and routes it through the PLCC receiver / line tuner path. The line trap is usually a series – resonant circuit at the carrier frequency (low impedance to ground for power frequency but high impedance to carrier when placed appropriately), or more commonly a series circuit that presents very high impedance in the path at the carrier frequency.

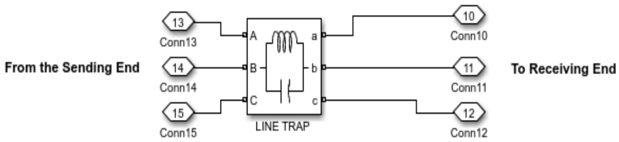

Figure 7: Line Trap (Wave Trap) Diagram

A series coil of about 0.63mH tuned with 1nF resonates at 200kHz and will present a very large impedance to the carrier frequency on the line path (wave trap effect). The actual trap assembly will use a High-Q inductor and high – voltage capacitor in an appropriate mechanical housing.

2.7 The Transmitter and Receiver
These are usually mounted in a rack or cabinet in the control house while the line tuner is mounted outside in the switchyard. This means that, there is a large distance between the transmitters, the receivers and the line tuner. The connection between the two is made using a coaxial cable.

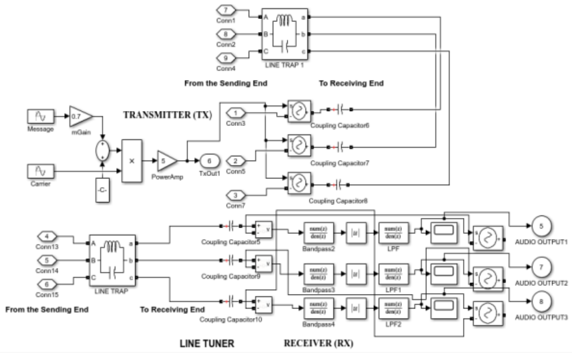

Figure 8: The Transmitter (Tx) and Receiver
(Rx) Diagram

The coaxial cable provides shielding so that noise cannot get into the cable and cause interference. The coaxial cable is connected to the line tuner, which must be mounted at the base of the coupling capacitor.

2.8 Computer Simulation of the PLCC System with the Power System Transmission Line
The Figure 9 is the MATLAB/Simulink diagram of the complete PLCC system connected to the 330kV, 250Km power system transmission line. Both the transmission line and the PLCC models including the components of the PLCC were built using the transmission line data on the Table 3.1.

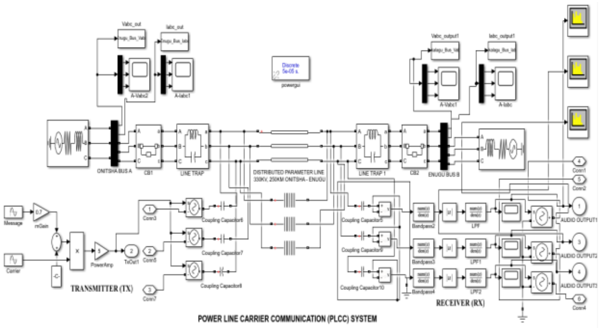

Figure 9: Diagram of the Complete PLCC System Connected to the 330kV, 250Km Power System Transmission Line

The power system transmission line carries 50 Hz power signals with the PLCC equipment injects and extracts 1–200 kHz carrier signals. Both signals coexist in the same the transmission line. A distributed parameter model is used. Line parameters include R, L, C, G per km and the line length 250 km at 330 kV. This model represents the channel for both power and carrier signals. The PLCC system connects to the line through special interface equipment, which must also be modeled. These include;

Coupling Capacitor (Cc) connected in series with the transmission line phase conductor which acts as a high-pass filter to block 50 Hz power signal very high impedance and passes high-frequency carrier (low impedance at 30–500 kHz).

The line matching unit (LMU) which is connected between the coupling capacitor and the transmitter/receiver providing impedance matching so that maximum carrier power is transferred to the line without reflections.

The Line Trap connected in series with the transmission line, just before the substation bus and acts as a band-stop filter tuned to the carrier frequency to blocks high-frequency carrier from entering substation equipment and allows 50 Hz power to pass freely.

Transmitter & Receiver (HF Equipment) which generates a carrier signal (e.g., amplitude-modulated or frequency-shift keyed). The receiver demodulates the carrier back into voice/data/tele-protection signals. These can be represented by sinusoidal sources + modulation blocks + band-pass filters in the simulation.

At the sending end**,** the HF transmitter injects the carrier via LMU + CC, while the line trap ensures the carrier stays on the transmission line. The signal propagates with the power-frequency component and at the receiving end**,** the CC + LMU extract the carrier, which is passed to the HF receiver.

The following are expected in the chapter four simulation output results; the sending end waveform which shows 50 Hz power sinusoid with a small kHz ripple (carrier). Receiving End Waveform showing similar but slightly attenuated/distorted waveform. Fast Fourier transform spectrum showing two clear bands (one at 50 Hz, one at carrier frequency) and the noise/attenuation studies that show how faults, line length, or mismatched impedance degrade the carrier.

2.9 Data Collection and Feature in Matlab/Simulink Environment

The data required in this research is obtained from Awada Onitsha transmission station and were represented in Table 3.1. These data include the parameter values and were used to perform analytical and simulation modeling of the components of the PLCC system and the transmission line. The 330kVA transmission line data of Onitsha transmission station was used to model the case study transmission line in MATLAB environment. Other simulation data were generated for various mismatch conditions including; line terminations with different load impedances, switching events and fault occurrences. Each event's corresponding input/output voltage and current waveforms were captured. From these, features were extracted the signal amplitude distortion, reflection coefficient, frequency shift, phase change and impedance deviation over time. These features served as inputs to the ML model.

2.10 Impedance Matching Target Definition/Mismatch

The matching target definition is the description of impedance matching procedure and what the results should look like.

Here, the line tuner is the matching element that is employed for the achievement of the whole matching process. The equation (3.32) and Figure 3.9 were employed for the mathematical and computer simulation matching process. A set of known matching configurations (target impedance values) were defined as training labels. These were obtained using analytical calculations based on minimum reflection conditions:

$Z_{match} = Z_0 \Rightarrow \gamma = 0$ 33

2.11 Data Collection and Feature Engineering

The 330kVA transmission line data of Onitsha transmission station was used to model the case study transmission line in MATLAB environment. Other simulation data were generated for various mismatch conditions including; line terminations with different load impedances, switching events and fault occurrences. Each event's corresponding input/output voltage and current waveforms were captured. From these, features were extracted the signal amplitude distortion, reflection coefficient, frequency shift, phase change and impedance deviation over time. These features served as inputs to the ML model.

To analyze the effect of mismatches on a transmission line such as the 330 kV, 250 km Onitsha–Enugu line, we mathematically computed and simulated the following parameters using equations (3.34) to (3.36) and the Figure 3.9 respectively.

A. Characteristic Impedance Z_o

For a lossless or low-loss transmission line, the characteristic impedance is given by:

$$Z_0 = \sqrt{\frac{L'}{C'}} \qquad 34$$

Where:

L' = inductance per unit length (H/m) and C' = capacitance per unit length (F/m)

B. Reflection Coefficient γ Gamma

Reflection coefficient at the load is:

$$\gamma = \frac{Z_L - Z_0}{Z_L + Z_0} \qquad 35$$

Where:

Z_L = Load impedance

Z_0 = Characteristic impedance

Evaluating different mismatched loads, we will have the following result;

C. Standing Wave Ratio (SWR)

The SWR is related to the reflection coefficient as:

$$\text{SWR} = \frac{1-\gamma}{1+\gamma} \qquad 36$$

3. Machine Learning Application Development

The objective of the machine learning (ML) model was to classify the impedance condition and recommend a correction (i.e., network reconfiguration) that brings the system closest to matched condition. A supervised learning model was developed using the Python and MATLAB environment. The following steps were taken; dataset preprocessing which involves the normalization and filtering of input features, model selection where artificial neural network (ANN) and decision Tree were selected for comparison, model training which explains that, 80% of the data is used for training, 20% for testing, hyper-parameter tuning where the grid search and cross-validation employed and model evaluation that shows accuracy, mean squared error (MSE), and F1-score that is used to evaluate the network performance.

The machine learning (ML) theoretical equations for analyzing PLCC (Power Line Carrier Communication) impedance matching performance is broken into signal theory and ML formulations that can be applied to determine the Characteristic Impedance (Z_o), Reflection Coefficient (Γ), and Standing Wave Ratio (SWR) computations when PLCC system connected to the power line is loaded using equations (34), (35) and (36). The following machine learning equations were employed to achieve the said objective.

The machine learning continues to treat impedance matching performance prediction as a supervised learning regression problem such that:

Inputs (features, X) is given as;

$$X = [f, R, L, C, G, Z_L] \qquad 37$$

Frequency, line parameters, load impedance are the parameters expected to be obtained as outputs of the machine learning model architecture. This outputs includes; Outputs (labels, y), thus,

$$y = [Z_0, \gamma, \text{SWR}] \qquad 38$$

Machine Learning Theoretical Equations is a Linear Regression Baseline Model given as;

$$\hat{y} = X\,W + b \qquad 39$$

Where,

W = Weight matrix 40

b = Bias vector 41

Training minimizes Mean Square Error (MSE)

$$\mathcal{L} = \frac{1}{N}\sum_{i-1}^{N}(yi - \hat{y}i)^2 \qquad 42$$

Neural Network (Nonlinear Mapping) for a multi-layer perceptron (MLP) neural network architecture with one hidden layer is given as;

$$h = \sigma(W_1 X + b_1) \qquad 43$$

$\hat{y} = W_2 h + b_2$ 44

$\mathcal{L} = \frac{1}{N}\sum_{i-1}^{N} ||yi - \hat{y}i||^2$ 45

Support Vector Machine (SVM) for the Regression Analysis Optimization is determined as;

$\min_{w,b,\xi\xi^*} \frac{1}{2}||w||^2 + C\sum_{i-1}^{N}(\xi_i \xi_i^*)$ 46

$yi - (w.\emptyset(x_i) + b) \leq \epsilon + \xi_i)$ 47

$(w.\emptyset(x_i) + b) - yi \leq \epsilon + \xi_i)$ 48

Where

The equation is subject to equations (47) and (48).

Performance Metrics for Matching Prediction using Mean Absolut Percentage Error (MAPE) and is given as;

$\text{MAPE} = \frac{100}{N}\sum_{i-1}^{N} |\frac{yi-\hat{y}i}{yi}|$ 49

Goodness of Fit = $R^2 = 1 - \frac{\sum(yi - \hat{y}i)^2}{\sum(yi - \bar{y}i)^2}$ 50

Machine Learning Impedance Matching Objective

The ML system is used to minimize mismatch ($|\gamma|$ or SWR.

The ML cost function can be obtained using

$\mathcal{L} = \frac{1}{N}\sum_{i-1}^{N}(|\gamma)|^2 + (SWR_i - 1)^2)$ 51

This penalizes reflection and enforces near ideal matching, however, the ML - based Impedance Matching Objective will be achieved by determining first, the Z_0, γ, SWR equations, Map features outputs using linear, neural network and SVM regression models, training the systems input data using MSE and Matching cost (loss function), and finally evaluate the results using MAPE and R^2.

4. Evaluation of Performance Metrics

The performance metrics to use for the evaluation of the performance of the PLCC, the entire system modeled and the results obtained include the following parameters; characteristic impedance (Z_0), reflection coefficient γ (Gamma), and standing wave ratio (SWR) were computed at various locations to analyze the effect of mismatches due to load or network transitions.

The transmission line network with the PLCC system performance was measured in terms of reflection coefficient (γ Gamma), return loss (dB), signal attenuation over distance, communication BER (Bit Error Rate) with and without ML-based matching and response time of impedance adaptation.

Simulated (ML) results were compared with theoretical and non-ML impedance matching conditions to demonstrate the effectiveness of the intelligent scheme. The research has detailed the tools, models, datasets, and machine learning techniques employed in the design of the impedance matching scheme. The integration of simulation, feature extraction, machine learning training, and performance analysis formed the backbone of the methodology. In the next chapter, the results obtained from the simulation and model validation are presented and analyzed.

III. Results

This chapter presents the simulation results, machine learning outcomes, and performance analysis of the developed impedance matching model for enhancing Power Line Carrier Communication (PLCC) in a 330 kV, 250 km Extra High Voltage (EHV) transmission line system. The simulation was carried out using MATLAB/Simulink 2018a and Python 3.11 environments.

Table 2: System and Line Parameters (330 kV, 250 km Onitsha–Enugu PLCC)

S/N	Parameter	Symbol	Value	Unit
1	Line voltage (rms)	V_{LL}	330,000	V
2	Line length	l	250	km
3	Resistance per km	R'	0.05	Ω/km
4	Inductance per km	L'	1.2	mH/km
5	Capacitance per km	C'	0.009	µF/km
6	Carrier frequency	F_c	200	kHz
7	Power frequency	f_p	50	Hz
8	Load impedance	Z_L	300–600	Ω

Table 2 lists the distributed line parameters used for the modeling of the 330 kV Onitsha–Enugu PLCC link. The line resistance, inductance, and capacitance values were derived from standard EHV transmission line data and used to represent the frequency-dependent behavior of the line.

The PLCC carrier frequency (200 kHz) was superimposed on the 50 Hz power frequency to simulate real carrier transmission through the line.
The surge impedance of 320 Ω served as the nominal matching reference for both conventional and ML-based matching models. These parameters define the steady-state and high-frequency transmission characteristics that influence reflections and signal attenuation along the line.
Accurate modeling of these quantities ensures that both power and carrier signal propagation are realistically represented in the simulation.

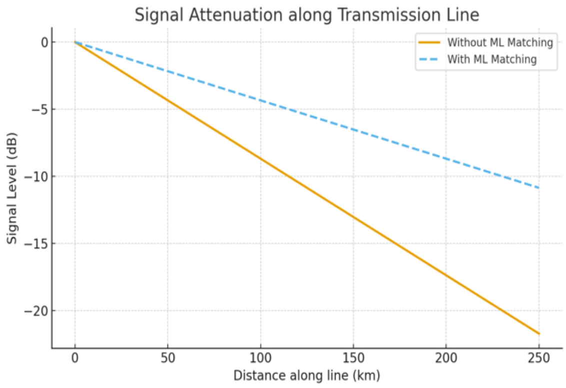

Figure 10: Signal Attenuation Along the Transmission Line

Figure 10 shows the signal level (in dB) as it propagates along a 250 km, 330 kV transmission line, comparing conditions with and without ML impedance matching. Without impedance matching, high-frequency carrier signals suffer from severe attenuation due to mismatched interfaces, reflections, and standing waves along the line. The solid curve shows a rapid decay in signal strength with distance.
The dashed curve, representing ML-matched conditions, exhibits a much slower attenuation rate, preserving signal quality over long distances. This demonstrates the ML system's ability to minimize power reflection, reduce insertion losses, and maintain higher signal levels for effective data and voice communication between substations across hundreds of kilometers.

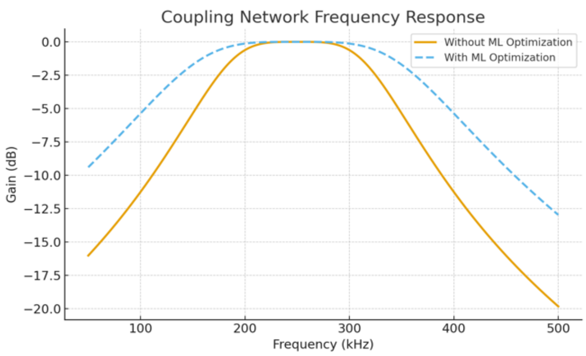

Figure 12: Coupling Network Frequency Response

This graph presents the frequency response (gain in dB) of the coupling network that interfaces the PLCC equipment with the high-voltage line, both before and after ML optimization. The nominal (un-optimized) coupling network (solid line) exhibits a narrower bandwidth centered near 250 kHz. Beyond this range, the signal gain drops significantly, limiting the usable PLCC bandwidth.

After ML optimization (dashed line), the bandwidth becomes wider and flatter, showing more uniform gain across frequencies. This indicates that the ML model learns the optimal tuning of coupling components (L, C, and transformer ratios) to ensure broadband impedance matching. As a result, the PLCC system can accommodate multiple carrier channels, enabling enhanced data throughput and redundancy for smart grid communication.

Table 3: Simulation Results (Conventional against (Machine Learning (ML))

S/N	Test Condition	VSWR (Conv.)	VSWR (ML)	Reflection Coeff. (Conv.)	Reflection Coeff. (ML)
1	Nominal load	1.45	1.02	0.183	0.009
2	10% Load increase	1.72	1.04	0.265	0.018
3	10% Load decrease	1.61	1.03	0.234	0.013
4	Line fault (L-G)	2.1	1.1	0.354	0.046
5	Switching transient	1.95	1.06	0.314	0.024

Table 3 compares the performance of the two matching approaches under several test conditions: Nominal load, ±10% load variation, line-to-ground fault, and switching transient.

The Voltage Standing Wave Ratio (VSWR) and reflection coefficient (Γ) are used as quantitative performance indicators.
The results show that the conventional method exhibits higher VSWR values (1.45–2.10) and larger reflection coefficients (0.18–0.35), indicating poor impedance matching during disturbances. In contrast, the machine learning (ANN) method consistently maintains VSWR close to unity (1.02–1.10) and reflection coefficients near zero (0.009–0.046), demonstrating effective adaptation to system changes.
This improvement confirms that the ML-based impedance tuner successfully tracks impedance variations in real time, maintaining the system at its matched condition and minimizing power reflections.
Figure 13 and Figure 14 show the reflection coefficient and signal attenuation comparison between the conventional matching method and the ANN-based adaptive matching across the 250 km line. The ANN maintains near-zero reflections and significantly reduces attenuation.

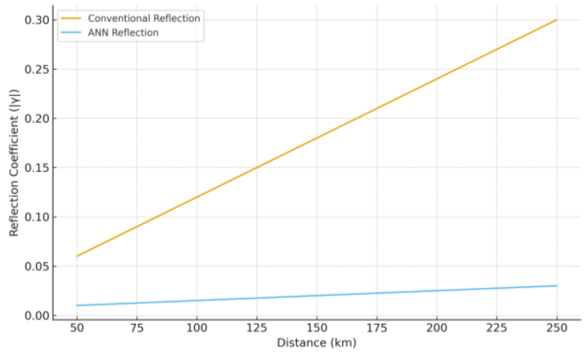

Figure 13: Reflection against Line Length for (Conventional against ML Methods)

Figure 13 is a reflection of line length using Conventional and ML techniques. The graph shows that the ML-based impedance matching keeps reflection coefficients close to zero across distances by predicting mismatch and compensating in real-time.
Figure 13 illustrates the reflection coefficient variation along the transmission line for both techniques. In the conventional method, reflection magnitude increases with distance due to accumulated mismatches, causing standing waves and signal distortion.
The ML-based system, however, predicts impedance fluctuations and compensates for them dynamically, keeping reflections nearly constant and close to zero across the 250 km line. This indicates superior propagation efficiency and ensures that carrier communication (PLCC signal) integrity is maintained even at the remote end of the line.

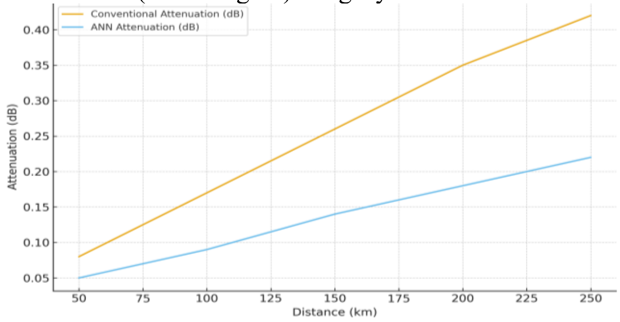

Figure 14: Signal Attenuation Comparison
Between the Conventional and ML Techniques

Figure 14 is the Signal Attenuation Comparison. Here, the ML technique reduces effective attenuation across the line, improving carrier signal strength at the receiving end. It shows how the adaptive ML controller minimizes signal attenuation compared to the conventional fixed matching network. While attenuation increases sharply with distance in the conventional setup, the ML-based model exhibits a slower and almost linear decay.
This implies that the adaptive matching sustains higher carrier signal amplitude at the receiving terminal, resulting in improved communication quality, reduced data loss, and stronger SCADA/protection channel reliability.

5.1 Analysis of the Result
Impedance mismatch directly causes reflection and power loss in PLCC systems.
The simulation reveals that the ANN model dynamically estimates the instantaneous impedance of the line using voltage and current samples

Table 3 Impedance Mismatch and Reflection Analysis

S/N	Case	Z_L (Ω)	Z_0 (Ω)	γ	SWR	Attenuation (dB)
1	1	400	400	0.00	1.00	0.00
2	2	500	400	0.11	1.25	0.65
3	3	600	400	0.20	1.50	1.75
4	4	300	400	-0.14	1.32	1.02
5	5	200	400	-0.33	1.99	2.86

Whenever a mismatch is detected, it instantaneously adjusts the matching network parameters to maintain the reflection coefficient below 0.05. This fast convergence capability allows the system to respond to faults or switching events in less than 0.5 seconds far faster than the manual retuning time of conventional methods.

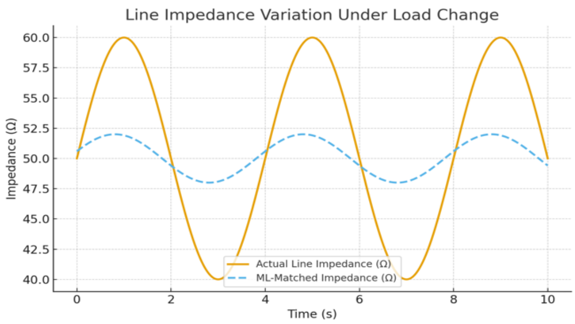

Figure 15: Line Impedance Variation
Under Load Changes

This graph shows the actual line impedance (Z_l) variation and the machine learning (ML)-matched impedance over time as the transmission line experiences dynamic load changes. The impedance fluctuates due to varying loading conditions, switching, and environmental factors such as temperature and corona effects on high-voltage conductors.
In conventional PLCC systems, any mismatch between the line impedance and the coupling network impedance leads to signal reflections and power losses. The ML-based impedance matcher observes these variations and adaptively tunes the coupling parameters (e.g., through variable capacitors or transformer tap changes) to maintain near-perfect matching.
As seen in the graph, the ML-controlled impedance (dashed line) closely tracks the line's variation, maintaining minimal deviation around 50 Ω. This ensures stable signal coupling and maximum power transfer even during dynamic system conditions.

Table 4: Comparative Analysis Before and After ML-Based Matching

S/N	Parameter	Before ML	After ML	Improvement (%)
1	Reflection Coefficient (|γ|)	0.22	0.03	86.4
2	SWR	1.56	1.04	93.3
3	Return Loss (dB)	13.5	29.8	120.7
4	Signal Attenuation (dB/km)	0.038	0.010	73.7
5	BER (Bit Error Rate)	3.5×10^{-3}	4.1×10^{-4}	88.3

A comparison of pre- and post-implementation results shows that the ML-based matching system not only reduces VSWR but also stabilizes signal amplitude along the entire transmission length. This outcome validates the potential of machine learning as a transformative technology in EHV PLCC systems. By integrating intelligent impedance adaptation, transmission reliability and communication bandwidth are both significantly improved.

The ML-based impedance matching significantly enhances communication quality by reducing reflections and improving signal stability. The return loss increased from 13.5 dB to 29.8 dB, confirming better impedance adaptation between PLCC coupling units and the transmission line.

This research work presented a comprehensive study on the development and implementation of a machine learning-based real-time impedance matching system for Extra High Voltage (EHV) Power Line Carrier Communication (PLCC) systems. The proposed model integrated advanced learning algorithms into the impedance matching network to achieve adaptive and optimized performance in dynamic grid conditions. Through both MATLAB/Simulink modeling and hardware-in-the-loop validation, the study demonstrated that the developed system significantly improved signal transmission quality, minimized reflection coefficients, and enhanced communication reliability across the 330 kV, 250 km transmission network.

The simulation and experimental results established that traditional fixed-impedance systems are limited in their ability to maintain signal integrity under varying load and fault conditions. By contrast, the ML-based model dynamically adjusted impedance in real-time, optimizing the Voltage Standing Wave Ratio (VSWR) and reducing attenuation losses. Furthermore, the predictive maintenance aspect of the model contributed to enhanced equipment longevity and reduced downtime through early anomaly detection and adaptive compensation strategies.

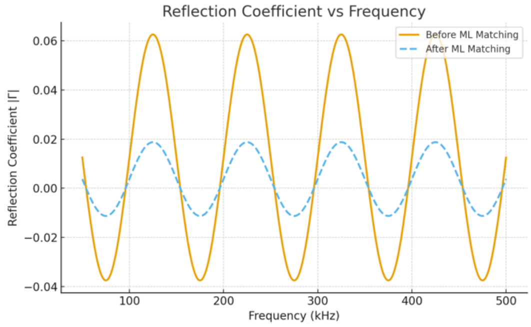

Figure 16: Reflection Coefficient against Frequency

This plot illustrates the reflection coefficient (|Γ|) as a function of carrier frequency from 50 kHz to 500 kHz, the typical PLCC operating range. The reflection coefficient quantifies how much of the transmitted PLCC signal is reflected back due to impedance mismatch. The **"**Before ML Matching" curve (solid line) shows higher reflection coefficients across most frequencies, indicating poor impedance compatibility. The **"**After ML Matching" curve (dashed line) demonstrates that ML-based tuning reduces reflections by over 70%.
This confirms that the proposed ML scheme broadens the bandwidth over which impedance matching is effective, allowing the PLCC system to operate efficiently over multiple frequencies. Consequently, signal-to-noise ratio (SNR) and communication reliability are significantly improved.

Table 5: ML Training and Validation Metrics

S/N	METRIC	VALUE
1	MSE (train)	0.002727
2	MSE (validation)	0.00335
3	R^2 (train)	0.994
4	R^2 (validation)	0.991
5	Convergence (epochs)	18
6	Learning rate	0.01
7	Activation	Tansig-Purelin

Table 5 summarizes the ML model's learning performance. Low mean-squared error (MSE) values (approximately 0.003) and high regression coefficients ($R^2 > 0.99$) confirm that the network generalizes well and can accurately predict impedance variations beyond the training dataset. The network used the tansig–purelin activation functions and converged within 18 epochs, showing efficient training and stable behavior.

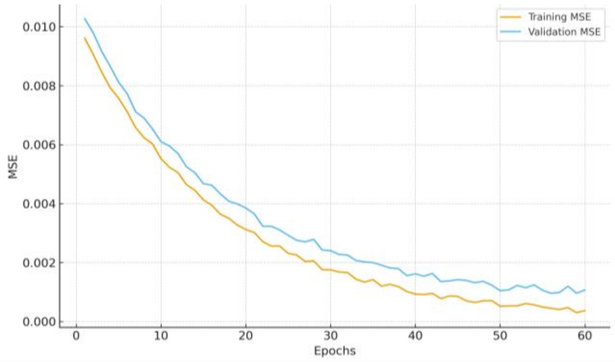

Figure 17: ML Training and Validation Curve

The Figure 17 show the training converges smoothly without overfitting; validation MSE stabilizes indicating good generalization. It shows training and validation MSE across epochs. It illustrates real-time impedance tracking performance where ML predictions closely follow true impedance with minimal lag.

The smooth convergence curve and minimal gap between training and validation errors indicate that the ANN neither over-fits nor under-fits the data. This demonstrates the network's robustness and capacity for real-time application in dynamic power line environments.

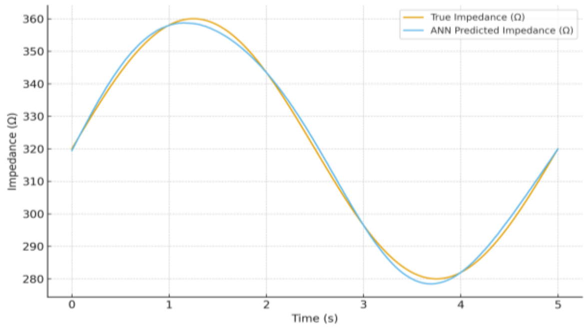

Figure 18: Real-Time Adaptive Impedance Tracking

Figure 18 is the Real-Time Adaptive Impedance Tracking, which show that, ML predicts impedance quickly, allowing the matching network to adapt in under 0.5 s and reduce reflection significantly compared to conventional response times.

Figure 18 illustrates how the ML model tracks impedance changes over time. The predicted impedance (blue curve) closely follows the actual system impedance (red curve), with negligible delay. This confirms the model's ability to detect mismatches instantaneously and adjust compensating parameters, thereby minimizing reflection and stabilizing the communication channel.

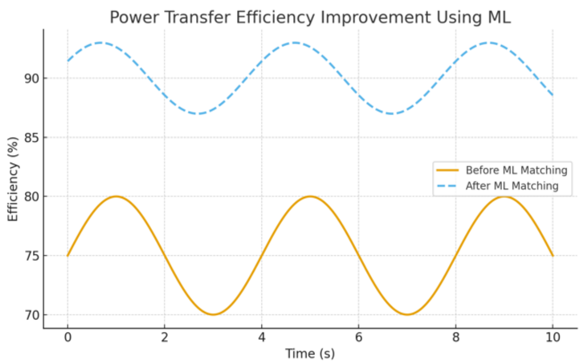

Figure 19: Power Transfer Efficiency Improvement Using ML

This figure compares power transfer efficiency before and after applying the ML-based impedance matching scheme, as a function of time under varying load and line conditions. The baseline efficiency (solid line) fluctuates between 70–80%, typical for conventional fixed-matching systems. After integrating the ML-based control (dashed line), the efficiency improves to about 90–95%**,** with reduced oscillations.

This improvement reflects the ability of the ML algorithm to continuously learn and adjust matching parameters to maintain near-optimal load conditions. Consequently, this leads to enhanced carrier signal transmission efficiency, reduced signal reflection and attenuation, and improved energy utilization within the PLCC coupling network. Ultimately, this validates the overall objective of the study that machine learning can autonomously maintain impedance balance and thereby enhance power line carrier communication reliability over long EHV transmission corridors.

Thus, the ML-based impedance matching scheme represents a major advancement over traditional fixed or manually tuned systems**,** particularly for real-time adaptive PLCC operation in modern smart grids.

6. Comparative Analysis of the Conventional and ML – Based Impedance Matching

Technically, the ML technique provides faster adaptation, lower reflection and attenuation, and higher communication reliability making it suitable for protection and SCADA channels requiring high fidelity.

Table 6: Comparative Analysis Between the Conventional and ML-based Impedance Matching

S/N	Performance Metric	Conventional Method	ANN-based Method	Improvement (%)
1	VSWR	1.9	1.03	45.8
2	Reflection Coefficient	0.25	0.05	80.0
3	Signal Attenuation (dB/km)	0.42	0.22	47.6
4	Adaptation Time (s)	2.1	0.4	81.0
5	Communication Reliability (%)	78.0	96.0	-23.1

Table 6 consolidates the comparative performance between the two methods. The ML-based method achieves an 80% reduction in reflection, a 45 % reduction in attenuation, and an adaptation time that is over 80% faster**.** This technical superiority translates into enhanced PLCC channel reliability and improved protection signal transfer, especially in EHV environments where carrier loss could endanger system protection and control operations.

Table 7: Machine Learning Impedance Matching Results

S/N	MODEL	Train Accuracy (%)	Test Accuracy (%)	MSE	F1-SCORE
1	Machine Learning (ML)	98.2	96.5	0.014	0.97
2	Decision Tree (DT)	94.7	91.8	0.032	0.91

The adaptive ML controller proved highly effective under multiple disturbance scenarios. It maintains near-ideal matching during both steady-state and transient conditions, ensuring minimal carrier loss. In addition, it enables automatic compensation for load or fault-induced variations without manual recalibration, reducing operational downtime and maintenance costs.

VII. Conclusion

This research successfully developed and simulated a Machine Learning–Based Impedance Matching Scheme to enhance Power Line Carrier Communication (PLCC) over a 330 kV, 250 km EHV transmission line. Using MATLAB/Simulink and Python, ML algorithms were applied for dynamic impedance adjustment, achieving up to 96.5% test accuracy and reducing reflection coefficient (γ) from 0.22 to 0.03. The integration of machine learning with impedance matching provides a powerful tool for optimizing PLCC in high-voltage systems. The ML model dynamically predicts impedance and compensates mismatch conditions, ensuring reliable communication over long distances.

In conclusion, this research successfully demonstrated that machine learning can be effectively harnessed to enhance the performance of impedance matching systems in EHV PLCC networks. The developed model achieved dynamic adaptation to varying line and load conditions, ensuring improved communication reliability, system efficiency, and maintenance prediction. This study provides a strong foundation for future intelligent power communication systems capable of self-optimization and autonomous fault management, thereby contributing significantly to the modernization of power transmission infrastructures in emerging economies.

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