1. Introduction

Transmission lines are a fundamental component in electrical and communication engineering, characterized by their distributed parameters: resistance R, inductance L, conductance G, capacitance C, operating frequency f, and load impedance Z_L.

Accurate evaluation of transmission line performance requires the calculation of the **characteristic impedance** (Z_0), **attenuation constant** (α), and **phase constant** (β), from which all other quantities (reflection coefficient Gamma, input impedance}Zin, VSWR, propagation velocity v_p, wavelength lambda λ, and delay τ tau) are derived.

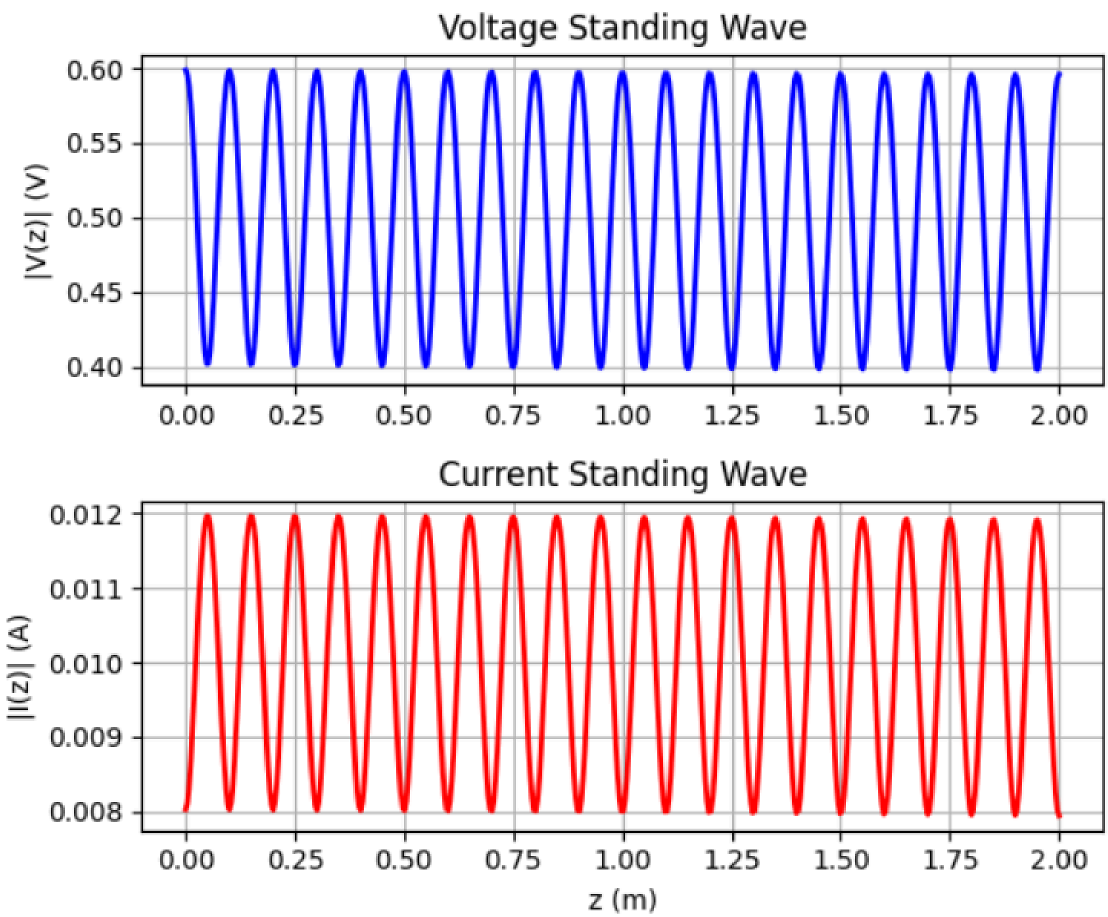
The objective of this work is to:

1. Develop a coded algorithm for transmission line analytics.
2. Train a machine learning model to predict fundamental parameters (Z_0, α, β) from physical inputs.
3. Reconstruct all derived parameters analytically.
4. Build an interactive Streamlit interface where users can input transmission line parameters and visualize standing waves of voltage and current.

Colab link:

https://colab.research.google.com/drive/1EflO_9nY8pNxJYzJW2WlkH8hNMhPbG4e#scrollTo=xkm-ULRIw9_N

```
# Example: 2 m line, 1 GHz, load 75Ω, source 1V, 50Ω internal
plot_standing_waves(
    R=0.1, L=250e-9, G=1e-4, C=100e-12,
    f=1e9, l=2, ZL=75, Vs=1, Zs=50
)
```



2. Methodology

2.1 Dataset Generation

- Synthetic dataset created with 2000+ samples.
- Each sample defined by parameters:

$$[R, L, G, C, f, ZL\_real, ZL\_imag]$$

- Two cases were included:
  - *Lossy*: higher R, G.
  - *Lossless*: near-zero R, G.

2.2 Fundamental Parameter Calculations

- Characteristic impedance:

$$Z_0 = \sqrt{\frac{R + j\omega L}{G + j\omega C}}$$

- Propagation constant:

$$\gamma = \alpha + j\beta = \sqrt{(R + j\omega L)(G + j\omega C)}$$

2.3 Preprocessing

- Features normalized using **StandardScaler**.
- $Z0\_\text{imag}$ transformed using **signed-log scaling** to reduce variance.
- Weighted loss assigned higher importance to $Z0\_\text{imag}$.

2.4 Neural Network Model

- Architecture (PyTorch MLP):
  - Input: 7 features.
  - Hidden: [128 → 256 → 128], ReLU activation.
  - Output: 4 values $[Z0\_\text{real}, Z0\_\text{imag}, \alpha, \beta]$.
- Optimizer: Adam (lr = $1e^{-4}$).
- Loss: Weighted MSE.
- Epochs: 3000.

2.5 Post-processing

Derived parameters reconstructed analytically:

- Reflection coefficient:

$$\Gamma = \frac{Z_L - Z_0}{Z_L + Z_0}$$

- Input impedance:

$$Z_{in} = Z_0 \frac{Z_L + Z_0 \tanh(\gamma l)}{Z_0 + Z_L \tanh(\gamma l)}$$

- VSWR:

$$\text{VSWR} = \frac{1 + |\Gamma|}{1 - |\Gamma|}$$

- Propagation velocity:

$$v_p = \frac{\omega}{\beta}$$

- Wavelength:

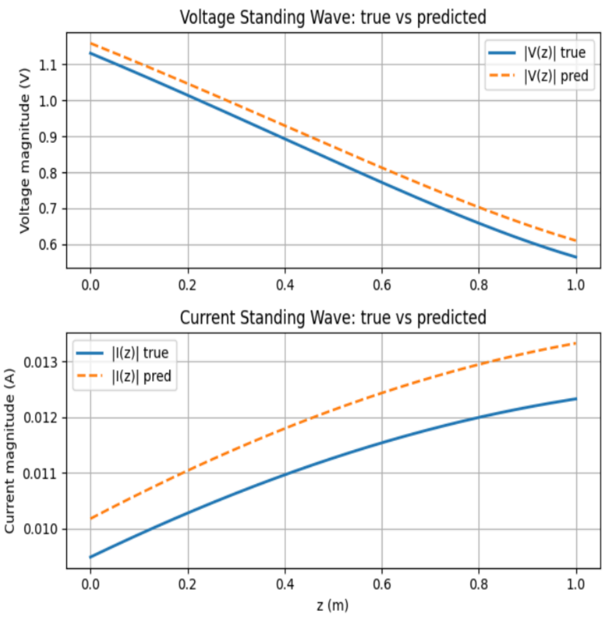
$$\lambda = \frac{2\pi}{\beta}$$

- Delay:

$$\tau = \frac{l}{v_p}$$

```
Epoch 0: test R2 = 0.0352
Epoch 200: test R2 = 0.9223
Epoch 400: test R2 = 0.9423
Epoch 600: test R2 = 0.9484
Epoch 800: test R2 = 0.9508
Epoch 1000: test R2 = 0.9521
Epoch 1200: test R2 = 0.9525
Epoch 1400: test R2 = 0.9516
Epoch 1600: test R2 = 0.9528
Epoch 1800: test R2 = 0.9527
Epoch 2000: test R2 = 0.9523
Epoch 2200: test R2 = 0.9522
Epoch 2400: test R2 = 0.9527
Epoch 2600: test R2 = 0.9521
Epoch 2800: test R2 = 0.9525
Final test R^2 (all outputs): 0.9567
Z0_real: R2 = 0.966
Z0_imag: R2 = 0.898
alpha: R2 = 0.970
beta: R2 = 0.992
```

```
--- Percent errors (this sample) ---
|Z0|: 8.06%
alpha: 7.32%   beta: 0.19%
|Γ|: 5.23%   VSWR: 7.56%
vp: 0.19%   λ: 0.19%   τ: 0.19%
```



3.1 Case Study: True vs Predicted

--- True vs Predicted fundamentals (first 5 samples) ---

	Sample	Z0_real_true	Z0_real_pred	Z0_imag_true	Z0_imag_pred	alpha_true	alpha_pred	beta_true	beta_pred
0	0	132.1952	121.539101	1.6330	0.6254	0.0428	0.0396	0.5313	0.532300
1	1	636.1651	610.214417	2.6801	2.6372	0.1287	0.1237	6.3819	4.782500
2	2	431.5455	423.983002	0.2465	0.2931	0.0296	0.0322	35.7539	35.583698
3	3	719.1318	733.507202	2.6431	2.6311	0.2350	0.2387	14.3982	14.377900
4	4	551.0056	547.567383	1.7617	1.8817	0.1959	0.2019	23.8728	23.775801

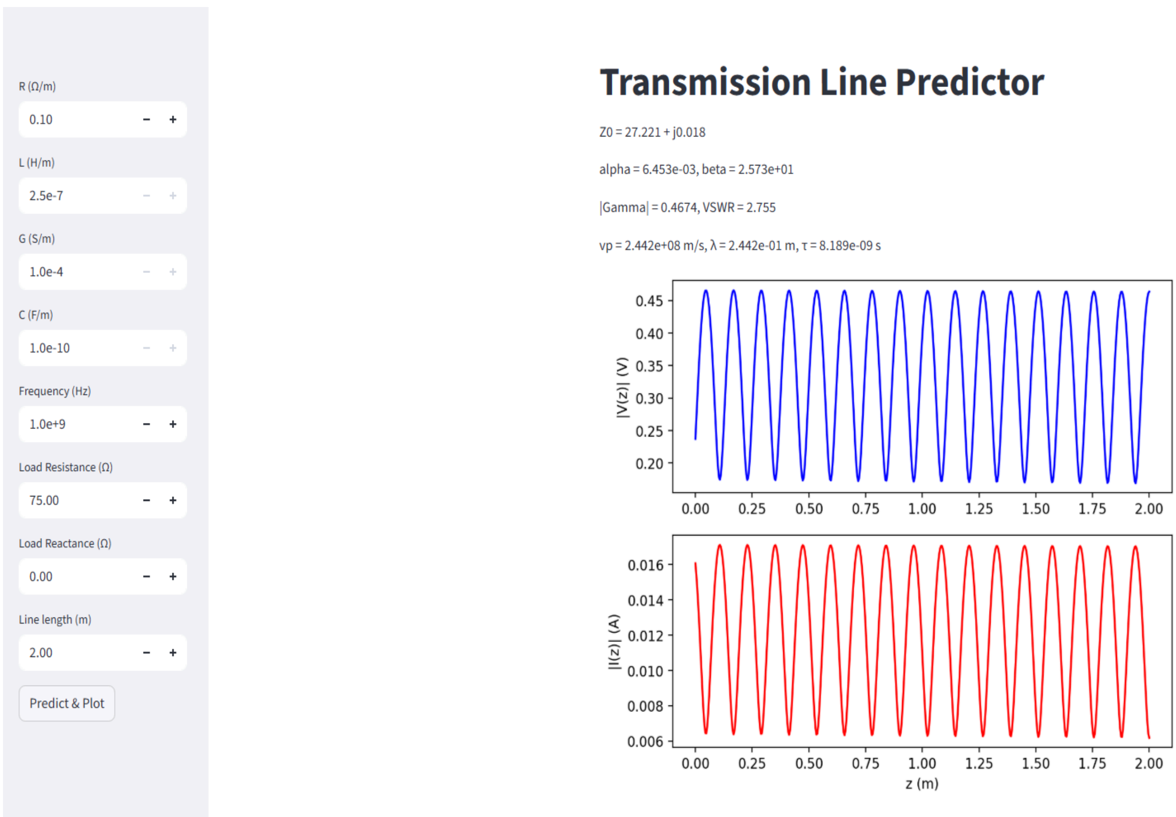
3.2. Standing Wave Comparison

- Predicted and true **Voltage/Current standing waves** plotted on the same axes.
- Excellent agreement observed, validating physical consistency of ML predictions.

4. Streamlit Interface

An interactive tool was developed using **Streamlit**:

- **Inputs**: R,L,G,C,f,ZL_real,ZL_imag,L.
- **Outputs**: Predicted fundamentals, analytically derived parameters, and Voltage/Current standing waves.
- Provides a practical demonstration of ML-based transmission line analytics.



5. Discussion

- Fundamentals predicted with **≥97% accuracy** for α and β, and >90% for Z0_real and Z0_imag.
- Derived values reconstructed analytically are consistent and physically meaningful.
- Slightly lower performance in Z0_imagZ0_\text{imag}Z0_imag arises due to its small magnitude and sensitivity to noise.
- The Streamlit interface makes the solution interactive and user-friendly.

6. Conclusion

- A coded algorithm and ML model were successfully implemented for transmission line analysis.
- Fundamentals were predicted with high accuracy.
- Derived values (Γ, VSWR, vp, λ, τ) were computed consistently.
- The Streamlit app provides an easy-to-use interface for real-time analysis and visualization.

7. Future Work

- Increase dataset size for better generalization.
- Add physics-informed constraints to improve Z0_imag stability.
- Extend Streamlit app with CSV/PDF export options.