

Generalizable Physics-Guided CNN Propagation Model in Tunnels Based on Frequency Conversion

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Abstract—Parabolic equation (PE) methods have been widely utilized for modeling radio wave propagation in tunnels due to their notable efficiency and fidelity. However, as emerging wireless communication systems in railway environments shift to higher-frequency bands, the computational costs associated with PE methods become prohibitively high. To that end, this project proposes a convolutional neural network (CNN)-based propagation model that provides predictions of radio wave propagation at high frequencies by leveraging data obtained by the PE method at a lower frequency. The proposed model significantly enhances the efficiency of wave propagation modeling in tunnels. Meanwhile, by explicitly incorporating prior knowledge from PE simulations and carefully designing the input, output, and structure of the CNN, the proposed model is more generalizable and robust compared to existing data-driven machine learning models. Numerical results are compared with predictions from conventional PE methods for various tunnel geometries, and the proposed model is also validated against experimental measurements in a realistic tunnel scenario. The principal outcome of this project was published in *IEEE Transactions on Antennas and Propagation* [1].

Index Terms—Electromagnetic wave propagation, parabolic wave equation, machine learning.

I. MOTIVATION

Radio wave propagation modeling in tunnel environments is critical for the effective deployment of wireless communication systems along railways. Deterministic propagation models based on parabolic equation (PE) methods [2] have been widely applied because of their high computational efficiency and accuracy in handling long guiding structures such as tunnels. In PE-based modeling, finite-difference schemes are commonly used to approximate the partial derivatives in the Helmholtz wave equation. To maintain accuracy, the discretization steps must remain a small fraction of the wavelength and are therefore closely related to the operating frequency. As wireless communication systems shift to higher-frequency bands, increasingly finer discretizations are required, leading to prohibitively high computational costs. Therefore, research on techniques that can significantly accelerate the propagation modeling process at high frequencies remains both valuable and timely.

In recent years, machine learning (ML) techniques have demonstrated great potential in the field of radio wave propagation. However, most existing ML models suffer from a major limitation in that they attempt to establish a direct mapping from scenario parameters to field distributions without fully

exploiting the prior knowledge provided by deterministic channel models. This strategy requires ML models to learn the underlying principles of electromagnetic wave propagation from scratch. Since the complex interactions between waves and environments depend strongly on the specific characteristics of the propagation scenario, it is extremely challenging to construct a universally applicable model. Therefore, this project aimed to develop a more physically grounded framework in which PE captures the environment-dependent propagation physics, whereas the neural network learns only the cross-frequency correlation within the same environment.

II. METHODOLOGY

The deterministic backbone of the proposed framework is based on the parabolic equation (PE) method, which can be formulated as

$$\frac{\partial u}{\partial z} = \frac{1}{2jk_0} \left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \right) u \quad (1)$$

where u denotes the reduced plane-wave solution and k_0 is the free-space wavenumber. Solved using an alternating-direction-implicit (ADI) marching scheme, this equation can be cast into the following update equations:

$$\left(1 - \frac{r_x}{4jk_0} \delta_x \right) \tilde{u}_{i,j}^{k+\frac{1}{2}} = \left(1 + \frac{r_y}{4jk_0} \delta_y \right) u_{i,j}^k \quad (2a)$$

$$\left(1 - \frac{r_y}{4jk_0} \delta_y \right) u_{i,j}^{k+1} = \left(1 + \frac{r_x}{4jk_0} \delta_x \right) \tilde{u}_{i,j}^{k+\frac{1}{2}} \quad (2b)$$

where

$$\delta_x u_{i,j}^k = u_{i+1,j}^k - 2u_{i,j}^k + u_{i-1,j}^k \quad (3)$$

$$\delta_y u_{i,j}^k = u_{i,j+1}^k - 2u_{i,j}^k + u_{i,j-1}^k \quad (4)$$

and $r_x = \Delta z / \Delta x^2$ and $r_y = \Delta z / \Delta y^2$. Here, $u_{i,j}^k$ denotes the field at location (i, j, k) , whereas Δx , Δy , and Δz denote the spatial discretization steps along the x -, y -, and z -directions, respectively.

As shown in Fig. 1, rather than applying this solver directly at the target frequency, the proposed framework first computes an anchor-frequency received signal strength (RSS) distribution. This anchor-frequency response already embeds the tunnel geometry, wall material properties, and the dominant wave-environment interaction patterns. Consequently, the learning task is reformulated as a conditional frequency-translation problem, rather than a direct regression from scenario parameters to field distributions.

The CNN adopts an asymmetric encoder-decoder architecture consistent with the approach reported in [1]. In the

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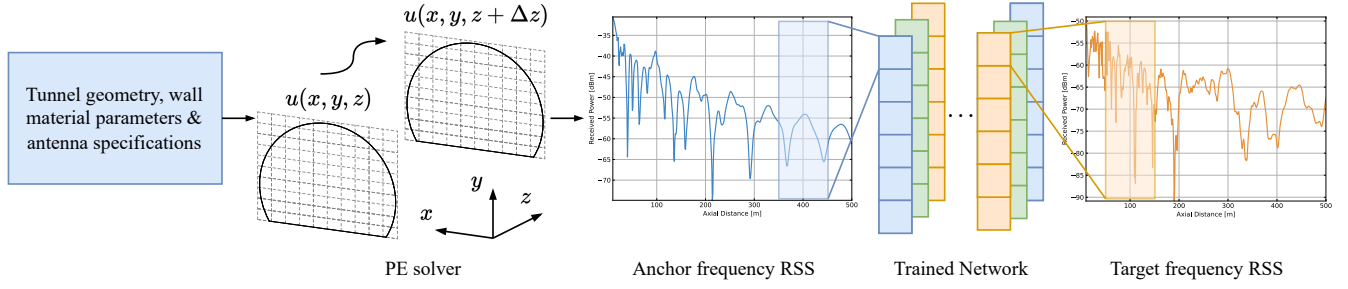


Fig. 1. Framework of the proposed PE-driven CNN propagation model. The PE solver generates the anchor-frequency response, and the CNN converts this physics-based anchor into the target-frequency RSS.

encoder, early downsampling and depthwise-separable convolutions are used to extract both low-level scene information and high-level electromagnetic interaction features from the anchor-frequency RSS. An atrous spatial pyramid pooling block is further introduced to enlarge the receptive field and capture the multiscale variations associated with frequency conversion, including changes in attenuation, reflection, scattering, and guided-wave behavior. The decoder then fuses these features with an embedding of the anchor- and target-frequency pair to reconstruct the target-frequency RSS. In this manner, the deterministic PE solver resolves the dominant propagation physics, whereas the CNN learns the remaining frequency-conversion operator.

III. RESULTS AND VALIDATION

As reported in [1], across representative rectangular, arched, and trapezoidal tunnels, the predicted received power is in close agreement with that obtained from direct target-frequency PE simulations. In terms of execution time, the proposed framework provides substantial savings, as shown in Table I.

TABLE I
RUNTIME COMPARISON BETWEEN PE AND THE PROPOSED FRAMEWORK.

Scenario	PE (s)	Proposed (s)	Speedup
1.8 GHz synthetic	112.2	14.0	$\sim 8\times$
2.4 GHz synthetic	307.4	14.0	$\sim 22\times$
3.0 GHz synthetic	676.0	14.0	$\sim 48\times$
Massif Central tunnel	10854.1	615.3	$\sim 17.6\times$

The framework was further validated in the Massif Central tunnel [3]. As shown in Fig. 2, the predicted received power closely follows both the measured data and the target-frequency PE reference, indicating that the learned mapping remains valid in a realistic tunnel environment. The runtime comparison in Table I further shows that the computational advantage of the PE-driven CNN is preserved in this realistic, measurement-backed case study.

IV. CONCLUSION

This project demonstrates that ML is most effective when embedded within a physics-guided computational framework to enhance computational efficiency, rather than used as an unconstrained black-box surrogate for deterministic solvers. By anchoring the network to a low-frequency PE solution, the

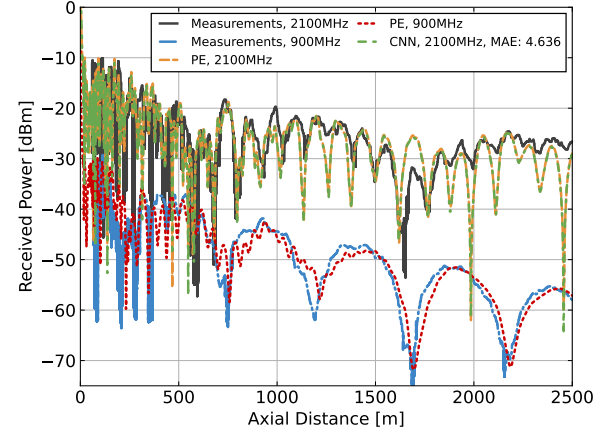


Fig. 2. Received power predictions in the Massif Central tunnel.

proposed framework preserves the dominant electromagnetic structure of tunnel propagation and learns only the residual cross-frequency mapping. The resulting model achieves high fidelity, robustness, and efficiency in high-frequency tunnel propagation analysis.

V. FUTURE DIRECTIONS AND FELLOWSHIP IMPACT

This work strengthened my interest in computational electromagnetics and scientific machine learning. I plan to continue my Ph.D. research on developing digital twins of the electromagnetic environment, aiming to enable real-time, high-fidelity forward modeling, seamless assimilation of real-world measurements, and high-precision inverse modeling. In the longer term, I hope to pursue a faculty career in microwave engineering and related areas of electromagnetics.

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