

A Benchmark TEAM Problem of Second-Scale Prediction of Magnetic Thermal Fields in Wireless Power Transfer Based on Diffusion Model

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Computationally accurate and reliable finite element methods are the mainstream approach for solving magnetic thermal field calculations. However, they are subject to certain limitations, the most significant of which is the required computational resources. The rapid development of artificial intelligence has made it possible to use data-driven methods to overcome the limitations in magnetic thermal field computations. Wireless power transmission, as a novel electrical energy transmission technology, has found applications in multiple fields. To meet practical needs, this paper conducts finite element simulations of the magnetic thermal fields in wireless power transfer systems under various conditions such as different voltages, currents, loads, coil parameters, and relative positions. A diffusion model-based magnetic thermal field calculation method is trained to achieve high-precision physical field computations at the second scale. The results demonstrate that the error compared to finite element calculations can be below 3%. This provides a new approach for field computations in wireless power transfer systems and offers an effective computational method for design and optimization.

Index Terms—Wireless Power Transfer, magnetic thermal fields, deep learning, diffusion model

I. INTRODUCTION

Wireless power transfer (WPT) technology, known for its convenience, has attracted extensive attention from both academia and industry. The distribution of its physical fields influences the performance of wireless power transfer. Numerical simulation methods provide more accurate field calculation results; however, they are constrained by issues such as long computation times, high resource demands, and limited reusability, particularly when dealing with complex geometries, precise models, and varying parameters. These limitations make it difficult to meet the needs of design and optimization, so numerical simulations are generally used as posterior methods to validate design accuracy.

The rise of deep learning has brought new opportunities for the calculation of physical fields. Early studies focused on validating the feasibility of CNN models for field prediction using simple geometries. Subsequently, more scholars have introduced methods such as U-Net, Transformer, residual networks, LSTM, and attention mechanisms to improve the predictive capabilities for physical field distributions [1]. In the field of wireless power transfer, these methods have primarily focused on predicting parameters such as current, voltage, and circuit parameters [2], with less attention given to physical field calculations. Considering the potential advantages of diffusion models in feature extraction and physical interpretation, this paper proposes a diffusion model-based method for magnetic thermal field calculation and compares it with finite element analysis results.

II. DIFFUSION MODEL-BASED MAGNETIC THERMAL FIELD CALCULATION METHOD

The diffusion model-based physical field calculation framework is shown in Fig. 1. First, data pairs consisting of current i , voltage u , magnetic permeability μ , load resistance r ,

vertical distance d , and position offsets (x, y) are formed as $\{i, u, \mu, r, d, x, y\}$ and serve as conditional inputs. These are used along with physical field data to train the model. During the process of minimizing the loss function, the model continuously learns the mapping relationship between the inputs and the target physical field distribution, finally outputting the field distribution in the form of a cloud plot.

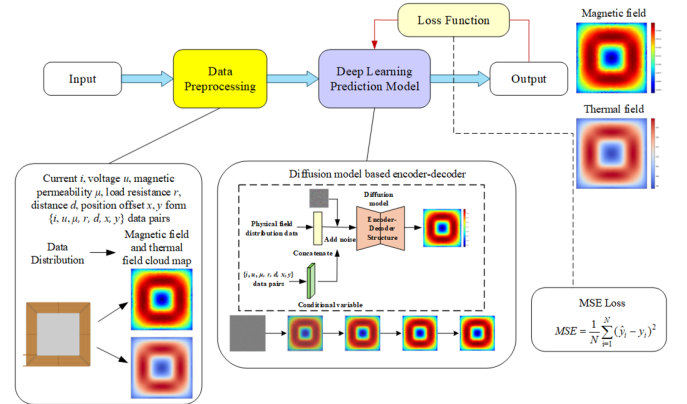


Fig. 1. Neural network computing framework.

In order to obtain training data, finite element method was used to simulate the receiving coil, and a total of 400 sets of magnetic and thermal field distributions were obtained. Subsequently, the data was converted into magnetic and thermal field cloud maps. Max-min normalization and standardization were applied, and the dataset was finally split into training and testing sets in an 8:2 ratio.

The Denoising Diffusion Probabilistic Model (DDPM) [3] originates from the study of molecular diffusion in nonequilibrium thermodynamics and consists of two Markov chains: forward noise addition and reverse denoising. The core idea is to progressively corrupt the structure of the original data using Gaussian noise, and then gradually eliminate the noise in the reverse process to recover the initial data. The model structure is shown in Fig. 2.

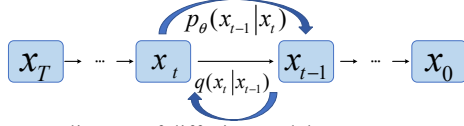


Fig. 2. Structure diagram of diffusion model.

The forward process can be regarded as the diffusion of molecules in water, where noise with a variance of θ is gradually added to make the data approach a random Gaussian distribution, which is formalized as a Markov chain. Compared to GAN (Generative Adversarial Network), the generative process of diffusion models has a clearer probabilistic foundation and better interpretability. Let $q(x_t | x_0)$ represents the original data, following the distribution $x_0 \sim q(x_0)$, and $x_1, x_2, \dots, x_T$ represent the data after adding noise of varying intensities. According to the Markov property, the conditional distribution of $x_1, x_2, \dots, x_T$ given x_0 is $q(x_1, x_2, \dots, x_T | x_0)$, which can be decomposed as

$$q(x_1, \dots, x_T | x_0) = \prod_{t=1}^T q(x_t | x_{t-1}) \quad (1)$$

In the formula, T is the total number of time steps.

The diffusion model-based physical field calculation method is shown in the dotted box in Fig. 1. Further, the encoder-decoder structure of U-Net is combined with convolutional and Transformer modules to form CT-Unet as the denoising network, aiming to better balance local details and global information, as shown in Fig. 3. The CT layer uses convolution operations to extract features from the raw data, and the extracted tokens are used as inputs to the Transformer.

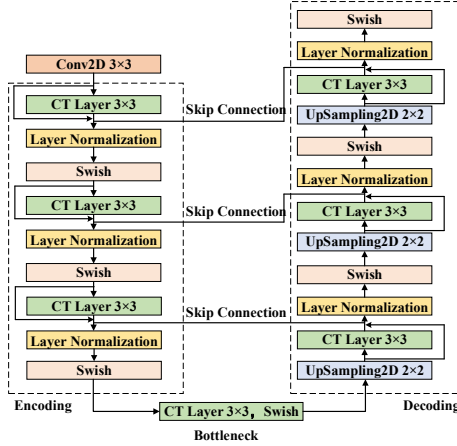


Fig. 3. CT-Unet structure diagram.

To optimize the model's performance, this paper uses the Optuna framework to automate the search for key hyperparameters, with the primary goal of minimizing the MSE loss on the test set.

III. EXPERIMENTAL RESULTS

In order to verify the progressiveness of the diffusion model proposed in this paper, it is compared with the following advanced deep learning models: U-net, CGAN with a transposed convolution network as the generator, Unet-CGAN with U-Net as the generator, and the ResUnet-Transformer model with short residuals and Transformer modules [4]. The

loss function uses MSE, and the other hyperparameters are set the same as the above model. The performance and generalization ability of each model are verified through the test dataset, and the results are shown in Table I.

TABLE I

PREDICTION ERROR AND TRAINING TIME OF DIFFERENT ALGORITHM MODELS

Evaluation indicators	MSE/ $\times 10^{-3}$		MAPE/%		Training time /h	
Physical fields	Magnetic field	Thermal field	Magnetic field	Thermal field	Magnetic field	Thermal field
Unet	1.52	1.68	9.4	9.7	0.68	0.63
CGAN	1.38	1.45	6.7	7.2	0.92	0.90
Unet-CGAN	1.05	1.15	5.3	6.0	1.66	1.58
ResUnet-Transformer	0.53	0.62	4.2	4.5	2.42	2.38
Diffusion model	0.27	0.30	2.5	2.7	3.56	3.52

The comparison reveals that the U-Net and CGAN structures are the simplest, resulting in relatively shorter training times but also lower prediction accuracy. Unet-CGAN improves accuracy by more effective feature extraction. ResUnet-Transformer further enhances accuracy by incorporating Transformer modules into the short residual structure. The proposed diffusion model, during training, simultaneously considers both local and global field strength gradients, and enhances physical interpretability and feature extraction capabilities through the noise addition and denoising mechanisms. Therefore, although training time is longer, the prediction accuracy is significantly improved.

IV. CONCLUSION

This paper achieves high-precision prediction of the magnetic thermal field in wireless power transfer systems based on the diffusion model. The results show that under various complex operating conditions, such as different voltages, currents, loads, coil parameters, and relative positions, the magnetic field prediction errors (MSE and MAPE) are 0.27×10^{-3} and 2.5%, respectively, while the thermal field prediction errors (MSE and MAPE) are 0.30×10^{-3} and 2.7%, respectively. The primary goal of using deep learning methods instead of traditional numerical methods is to reduce computation time. The analysis reveals that, compared to the finite element method, excluding training time, the average prediction time per instance is 0.4 seconds, and the acceleration of neural networks is improved by about 267 times.

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