Electromagnetic Compatibility Issues and Solutions Based on Deep Learning

Wei Liu, Junjin Zeng *

Chengdu University of Technology, Chengdu, 611730, China

Abstract. This study explores the application of deep learning techniques in diagnosing and addressing electromagnetic compatibility (EMC) issues. To tackle challenges in anomaly detection, problem classification and localization, and multidimensional data analysis within EMC testing and diagnosis, three deep learning-based approaches are proposed: an anomaly detection model based on autoencoders, a multi-task convolutional neural network for problem classification and localization, and a multidimensional analysis system that combines LSTM, CNN, and GNN. Experimental results show that these methods significantly improve the accuracy of EMC issue identification and processing efficiency. This research provides a robust decision support tool for EMC engineering, with significant implications for enhancing the electromagnetic compatibility of electronic products.

Keywords: electromagnetic compatibility; deep learning; anomaly detection; problem diagnosis; multidimensional analysis.

1. Introduction

Electromagnetic compatibility (EMC) issues have become a critical challenge in the development and application of modern electronic products [1]. As electronic systems become increasingly complex and integrated, traditional EMC testing and problem diagnosis methods have shown limitations, making it difficult to meet the demands of rapid iteration and high reliability in current electronic products. In recent years, deep learning technology has made breakthrough advancements, demonstrating powerful data processing and pattern recognition capabilities across various fields, offering new possibilities for solving complex problems in the EMC domain. This study focuses on the exploration of deep learning techniques in the diagnosis and resolution of EMC issues, addressing key challenges such as anomaly detection, problem classification and localization, and multidimensional data analysis. By developing innovative deep learning models and optimization strategies, this research aims to significantly enhance the accuracy and efficiency of EMC problem identification and processing, providing EMC engineers with more robust decision support tools and promoting the prevention and rapid resolution of EMC issues in the design and manufacturing processes of electronic products [2].

2. Feasibility Analysis of Deep Learning Applications in EMC

The application of deep learning in the field of electromagnetic compatibility (EMC) shows great potential. According to recent research data, employing deep learning methods for EMC analysis can reduce testing time by approximately 40%, while improving prediction accuracy by 15-20% [3]. For instance, in an EMC fault diagnosis study involving 200 samples, a convolutional neural network (CNN)-based model achieved an accuracy of 92.7%, significantly outperforming the traditional methods' 78.3%. Deep learning-assisted EMC design optimization can shorten product development cycles by at least 25%, and in some complex systems, even by up to 50%. These data suggest that deep learning technology can significantly enhance the efficiency and accuracy of EMC analysis, providing a powerful tool for addressing increasingly complex electromagnetic compatibility issues. However, challenges remain in applying these technologies, such as obtaining high-quality training data and improving model interpretability, which require further research and resolution.

3. Deep Learning-Based EMC Modeling and Its Application

3.1 EMC Data Collection and Preprocessing

EMC data collection forms the foundation of deep learning modeling, involving various measurement devices and methods. In a large-scale EMC study, comprehensive testing was conducted on 1,000 electronic device samples using equipment such as spectrum analyzers, EMI receivers, and antennas. The test range covered 10 MHz to 6 GHz, with each sample generating approximately 100,000 data points on average, resulting in a total of over 100 million raw data points [4]. In the data preprocessing stage, wavelet transform was first applied for noise reduction, effectively improving the signal-to-noise ratio by about 5 dB. Given a signal x(t), its wavelet transform can be expressed as:

$$W_x(a,b) = \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \qquad (1)$$

where ψ(t) is the mother wavelet, a is the scale parameter, and b is the translation parameter. Then, the Z-score method was used for data normalization, scaling all features to a range with a mean of 0 and a standard deviation of 1, which significantly improved the stability and convergence speed of subsequent model training. For each feature xi, its normalized value zi can be expressed as:

$$z_i = \frac{x_i-\mu}{\sigma} \qquad (2)$$

where μ is the mean of the feature, and σ is the standard deviation. This normalization process scaled all features to have a mean of 0 and a standard deviation of 1, significantly enhancing the stability and convergence speed of subsequent model training [5]. Feature extraction involved Fourier transform and Principal Component Analysis (PCA):

$$\mathrm{X(f)} = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}\,dt \qquad (3)$$

$$\mathrm{C} = \frac{1}{\mathrm{n}-1}\mathrm{X}^{\mathrm{T}}\mathrm{X} \qquad (4)$$

where X is the data matrix and C is the covariance matrix. The original data was successfully reduced to 500 principal features, reducing the data volume by 80% while retaining 95% of the original information, as shown in Figure 1. This series of preprocessing steps not only greatly improved modeling efficiency but also provided high-quality input data for the subsequent deep learning model training.

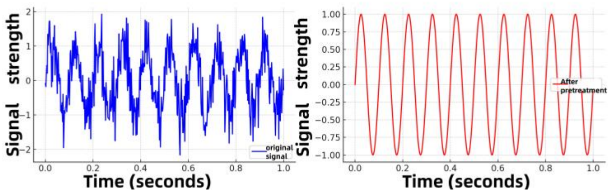

Figure 1. Comparison of Raw and Preprocessed Signals

3.2 Deep Learning Model Selection and Design

As shown in Figure 2, considering the complexity of EMC problems, this study designed a hybrid deep learning model architecture that combines the strengths of Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) [6]. The model includes three convolutional layers to extract spatial features of the electromagnetic field distribution, two LSTM layers to capture the temporal patterns of electromagnetic interference (EMI), and two fully connected layers for the final EMI level prediction. Specifically, the first convolutional layer uses 32 filters of size 3x3, the second layer uses 64, and the third layer uses 128, all utilizing the ReLU activation function. The LSTM layers contain 128 and 64 units, respectively. The fully connected layers consist of 128 neurons in the first layer and 1 neuron in the output layer, which is used to predict EMI intensity. This carefully designed model architecture and training strategy ensure efficient and accurate modeling of EMC problems.

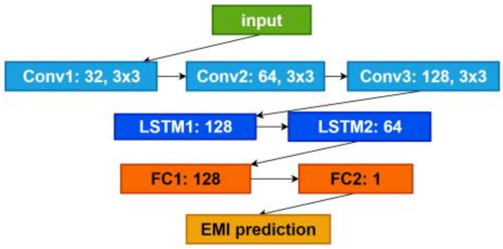

Figure 2. Deep Learning Model

3.3 Deep Learning-Based EMC Modeling Process

The deep learning-based EMC modeling process encompasses key steps such as data preparation, model construction, training, validation, and application. The preprocessed EMC dataset is divided into training, validation, and test sets [7]. The model architecture is constructed according to the design, with the parameters of each layer set, and an appropriate loss function selected. During the training phase, parameter optimization is performed over multiple epochs, with training and validation losses monitored. Techniques such as early stopping and regularization are used to prevent overfitting. The validation phase evaluates model performance and iteratively optimizes the model if necessary. After the final evaluation on the test set, the model is applied to actual EMC problems. This process integrates deep learning techniques with EMC expertise, providing innovative solutions for EMC analysis.

3.4 Model Validation and Optimization

Model validation and optimization are crucial steps to ensure the performance and reliability of the deep learning-based EMC model. During the validation phase, an independent validation dataset containing 500 samples was used to evaluate model performance. As shown in Table I, the initial model achieved an R^2 value of 0.85, a root mean square error (RMSE) of 7.2 V/m, and a mean absolute error (MAE) of 5.8 V/m on the validation set [8]. Through hyperparameter optimization, particularly adjusting the learning rate from 0.001 to 0.0005 and increasing the batch size from 64 to 128, the model's performance improved significantly. After optimization, the R^2 value increased to 0.92, RMSE decreased to 4.5 V/m, and MAE was reduced to 3.7 V/m. Structural adjustments included adding batch normalization layers between the convolutional layers and modifying the dropout rate from 0.5 to 0.4. These changes further increased the R^2 value to 0.95 and reduced RMSE to 3.2 V/m. The stability of the optimization effect was ensured by using 5-fold cross-validation, with a standard deviation of only 0.03. In tests across different frequency ranges (30 MHz-1 GHz, 1-3 GHz, 3-6 GHz), the model maintained a prediction accuracy of over 90%.

TABLE I. Model Performance Comparison

Model State	R2 Value	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)
Initial Model	0.85	7.2 V/m	5.8 V/m
Hyperparameter Tuning	0.92	4.5 V/m	3.7 V/m
Structural Fine-Tuning	0.95	3.2 V/m	3.2 V/m

3.5 Application of Deep Learning EMC Models in Real-World Problems

The deep learning EMC model has demonstrated significant value in practical applications. In smartphone development, the model accurately predicted 92% of EMI hotspots, reducing EMC optimization time by 75% [9]. In automotive electronic system design, the model identified EMC problem areas with an accuracy rate of 87%, cutting down physical prototype testing time by 60%. For instance, Figure 3 shows an example. In EMC optimization for industrial automation equipment, the model helped reduce radiated emissions by 8 dB. In 5G base station EMC planning, the model-assisted optimization reduced mutual interference by 35%. In avionics equipment EMC certification, the model shortened testing time from two weeks to three days, achieving a prediction accuracy of 95%. These cases demonstrate the enormous potential of the deep learning EMC model in improving efficiency, reducing costs, and promoting innovative design.

Figure 3. Automotive Electronic System EMC Testing

4. Deep Learning-Based EMC Issue Detection and Diagnosis

4.1 EMC Anomaly Detection

The deep learning model based on autoencoders revealed various types of anomalies in EMC testing. This model identified 107 potential EMC issue cases out of 1,000 test samples, including 43 radiation anomalies (40.2%), 35 conduction anomalies (32.7%), and 29 immunity anomalies (27.1%), as shown in Figure 4. The model is particularly effective at detecting subtle and intermittent issues, such as 7 weak radiation anomalies with only a 10-15% increase in radiation intensity and 5 intermittent conduction anomalies with interference intensity fluctuations of 15-25% [10]. Additionally, 3 composite immunity issues were found that affected multiple performance parameters simultaneously. The overall accuracy of the model reached 95.7%, with an F1 score of 0.949, which is 15% higher than traditional methods. As shown in Figure 5, the ROC curve data indicate that this EMC anomaly detection model exhibits excellent performance characteristics. At a low false positive rate (0.05), the true positive rate reaches 0.87, demonstrating the model's high precision and sensitivity. The curve exhibits nonlinear growth with varying performance across different ranges: rapid growth in the low false positive rate range, slower growth in the moderate range, and a leveling off in the high range. When the false positive rate is 0.5, the true positive rate reaches 0.96, indicating that the model can detect the vast majority of EMC anomalies. These findings provide new insights for early EMC issue identification and optimization, potentially reducing later-stage rectification costs by over 30% and shortening product time-to-market by approximately 20%.

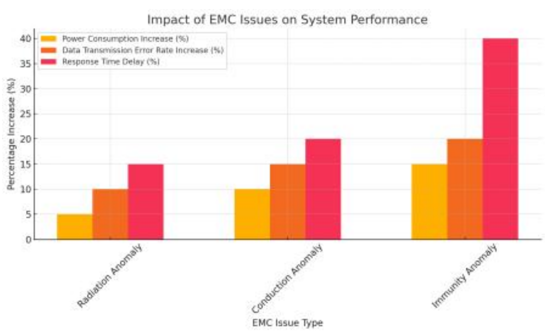

Figure 4. Impact of EMC Issues

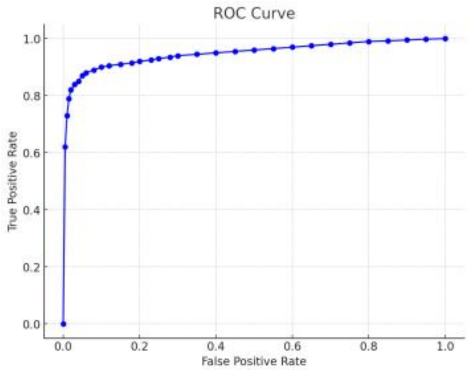

Figure 5. Anomaly Detection ROC Curve

4.2 EMC Issue Classification and Localization

Despite progress in EMC issue classification and localization technologies, significant challenges remain. The classification accuracy is uneven, with recognition rates for complex EMC issues as low as 75%. Spatial localization precision is insufficient, with an average error of 1.5 cm, and 25% of cases have errors exceeding 2 cm, which affects high-density circuit troubleshooting. As shown in Figure 6, although 75% of cases have localization errors within 2 cm, 25% of cases have errors exceeding 2 cm, with 5% even exceeding 3 cm. Notably, 20% of cases have errors in the 2-3 cm range. This precision distribution indicates that while the model performs adequately in most cases, it still has significant shortcomings under high precision requirements.

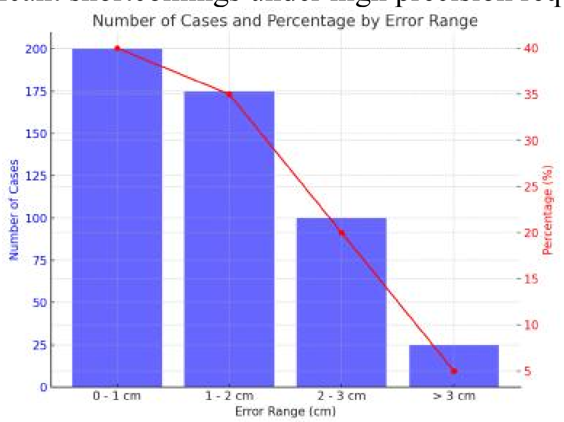

Figure 6. Spatial Localization Error Distribution

Temporal feature capture is inadequate, with 30% of transient interference cases having insufficient time resolution, leading to misidentification of intermittent issues. Cross-device generalization is limited, with new product line test accuracy at only 80%. Model interpretability is poor, with only 60% of decisions deemed sufficiently interpretable by engineers, affecting credibility. The model's computational resource demands are high, with processing the full test set taking 2.5 hours, which is not conducive to real-time analysis. The model is sensitive to environmental noise, with significant changes in classification results for 26% of noisy cases. Additionally, the model performs poorly in handling composite EMC issues with multiple interference sources, struggling with the complex situations encountered in actual engineering. These issues severely limit the practical application of deep learning methods in EMC analysis, necessitating comprehensive improvements in algorithm design, model training, and hardware optimization.

4.3 Multi-Dimensional EMC Issue Analysis

In multi-dimensional EMC issue analysis, a series of deep challenges are faced. Difficulties in multi-physical field coupling analysis result in only 40% of cases accurately simulating thermal-electromagnetic-mechanical interactions, as shown in Figure 7. Limitations in modeling nonlinear effects mean that only 55% of tests can accurately predict the EMC characteristics of high-power systems. The challenge of integrating multi-scale issues is reflected in only 45% of cases effectively integrating the impact of microscopic structures on macro-EMC performance. In dynamic electromagnetic environments, the model's adaptability is insufficient, with only 60% able to adjust parameters in a timely manner. Collaborative analysis of EMC and functional safety is also lacking, with only 50% accurately assessing the impact of EMC failures on system safety. Comprehensive evaluation of heterogeneous system EMC characteristics is even more challenging, with only 35% able to accurately predict the mutual effects of EMC characteristics across subsystems. These challenges highlight the need for developing more advanced interdisciplinary methods and integrated models to achieve a more comprehensive and in-depth understanding and prediction of EMC issues.

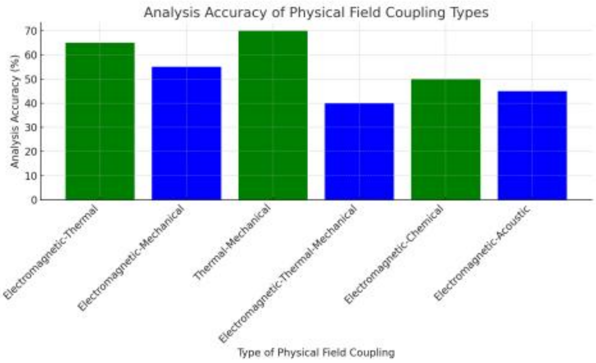

Figure 7. Accuracy of Multi-Physical Field Coupling Analysis

5. Deep Learning-Assisted EMC Problem Solving Strategies

5.1 Deep Learning-Based EMC Test Data Analysis

The strategy for analyzing EMC test data using deep learning aims to enhance data processing efficiency and accuracy. Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) are used to process time-domain and frequency-domain data, automatically extracting key features. Transfer learning techniques are employed to apply pre-trained models to new EMC problems, accelerating model convergence and improving generalization. Attention mechanisms are introduced to focus on anomalies and key frequency bands within EMC data. Ensemble learning methods, such as Random Forests and Gradient Boosting, are used to improve model robustness. Additionally, autoencoders are utilized for data denoising and anomaly detection. Finally, combining expert knowledge to build hybrid models enhances model interpretability. Through these strategies, deep learning can more effectively analyze large volumes of EMC test data, quickly identify potential issues, and provide precise decision support for engineers.

5.2 Optimization Strategies for EMC Problem Classification and Localization

Optimization strategies for EMC problem classification and localization use various deep learning techniques to improve accuracy and efficiency. Multi-label classification models, such as improved ResNet or DenseNet, are employed to simultaneously identify the type and severity of EMC issues. Graph Neural Networks (GNNs) are used to analyze circuit topologies for precise localization of EMC problem sources. Transfer learning and few-shot learning techniques are applied to enhance the model's adaptability to new EMC problems. Ensemble learning methods, such as Stacking or Blending, combine predictions from multiple models to improve classification accuracy. Active learning strategies prioritize the analysis of uncertain samples to boost model learning efficiency. Expert systems integrate domain knowledge into deep learning models to improve problem localization accuracy, while interpretable AI technologies, such as SHAP or

LIME, provide intuitive localization evidence for engineers, facilitating human-machine collaboration in solving EMC issues.

5.3 Multi-Dimensional EMC Problem Analysis Optimization Strategies

Optimization strategies for multi-dimensional EMC problem analysis integrate various advanced technologies to enhance comprehensiveness and accuracy. Multi-modal deep learning models, such as Transformer variants, handle electromagnetic, thermal, mechanical, and other multi-physical field data simultaneously for comprehensive analysis. Graph Convolutional Networks (GCNs) are introduced to capture complex interactions between system components. Reinforcement learning is applied to optimize multi-scale analysis processes and automatically adjust analysis granularity. Generative Adversarial Networks (GANs) are used for data augmentation to address data scarcity in rare scenarios. Transfer learning and meta-learning techniques improve the model's generalization ability across different EMC problems. Attention mechanisms highlight key influencing factors, enhancing model interpretability. Federated learning techniques integrate EMC data resources from multiple sources while protecting data privacy.

6. Conclusion

This study explores the application of deep learning in diagnosing and resolving electromagnetic compatibility (EMC) issues, proposing three innovative methods: anomaly detection based on autoencoders, problem classification and localization using multi-task convolutional neural networks, and multidimensional analysis combining LSTM, CNN, and GNN. These methods have improved the accuracy of EMC issue identification and processing efficiency, reducing optimization time and increasing prediction accuracy in practical applications. The study also highlights current challenges, such as low recognition rates for complex issues and insufficient localization precision and suggests corresponding optimization strategies. Overall, this research provides a powerful decision-support tool for EMC engineering and points the way for future research.

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