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Estimation Method of Electromagnetic Wave for Wireless Communication Applications in Small Modular Reactor

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1. Introduction

In the digitalized small modular reactor (SMR) that has plans to employ wireless communication, the influence of electromagnetic waves for wireless communication on nearby built equipment has been thoroughly examined from the perspective view of SMR safety [1]. Especially, electromagnetic interference (EMI) caused by wireless communication has obtained the focus on the regulatory side because the SMRs will be supported by various digital instrumentation and control (I&C) equipment sensitive to EMI. Regulatory guidance of KINS/RG-3.09, developed for achieving nuclear power plant (NPP) safety, requires building the exclusive zone to protect safe related digital equipment against EMI as shown in (1) [2].

$$(1)\ d = \sqrt{30 P_t G_t}\ /\ AE$$

where d, P_t, G_t, AE indicate the distance configuring exclusive zone, the input power, the gain of the transmitting (Tx) antenna, and the maximally allowable strength of the electric field (132 dBμV/m), respectively. Therefore, the exclusive zone implies the minimum separation distance from an EMI source to protect digital I&C equipment against an external electric field over 4 V/m (132 dBμV/m). As the target environment is to be larger and more complicated, the limitation would be considered more important in making the exclusive zone. Here we thus propose a convolutional neural network (CNN)-based EM environment prediction architecture to overcome the limitation of NPPs EM environment analysis [3].

2. Methods and Results

Figure 1 shows the configuration of the analyzed environment consisting of the I&C cabinet (5 m × 2 m × 3 m) at the origin in the rectangular room (11.6 m × 8.2 m × 3.25 m) with concrete walls (relative permittivity: 9.8, conductivity: 1.7×10^{-5} S/m). In addition, we suppose that the transmitting antenna of wireless communication can be located at Tx zones 1 and 2 illustrated in Fig. 1.

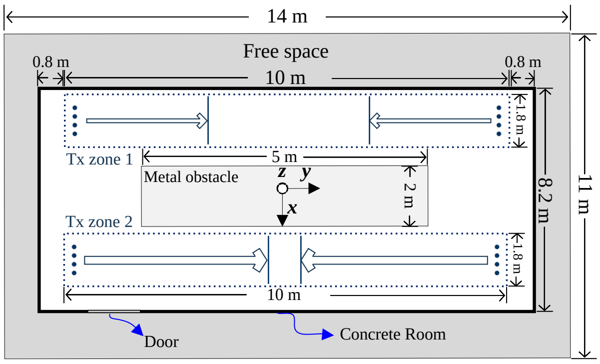


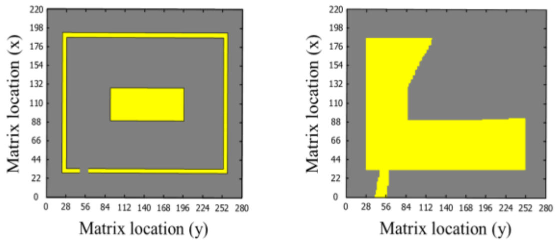
Fig. 1. Configuration of the analyzed environment.

To estimate electromagnetic field distribution efficiently in a variation of the location of the transmitting antenna, we employed the machine learning (ML) model based on the convolution neural network (CNN). Table I shows both input and output features as well as types of layers comprising the CNN-based ML model. As the input of the learning dataset, we utilized indoor structure, line of sight space, refraction points of placed objects, and Tx antenna location made of 280 × 220 pixels, respectively. We also used the path gain distribution (size of 70 × 55 pixels), computed by the ray tracing method, at a height of 1m in dBm corresponding to the input data. Figure 2 shows an example of the input data to express the indoor structure, the line of sight space, the refraction points of placed objects, and the Tx antenna location.

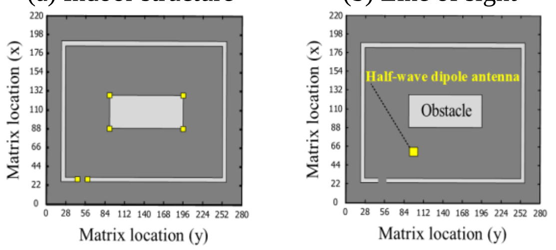
In the training process of the ML model, the performance of the trained ML model dominantly depends on the amount of learning dataset reflecting various learning cases. However, a small amount of learning datasets can be available in our study due to limited resources for EM simulation. Thus, we employed the k-fold cross-validation to overcome the aforementioned limitation and improve the performance of the ML model [4].

Table I. Machine Learning Configuration

Input	CNN-based ML composition	Output
- Indoor structure - line of sight - Refraction points - TX antenna location	- 2 Convolution layers - 2 poling layers	Path gain distribution



(a) Indoor structure (b) Line of sight



(c) Refraction points (d) Antenna location

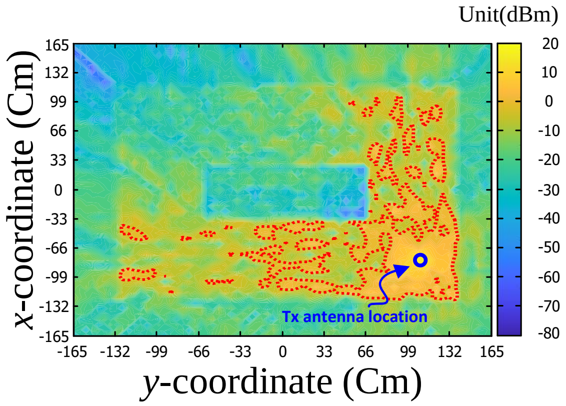
Fig.2. Input features for machine learning.

We evaluate quantitively the maturity of the trained ML model by using the mean square error (MSE) as a loss function. After checking the resulting MSE as the training process proceeds, we found that the MSE converges to zero. This result reveals that the CNN-based ML model was sufficiently mature for predicting the path gain distribution in the target environment.

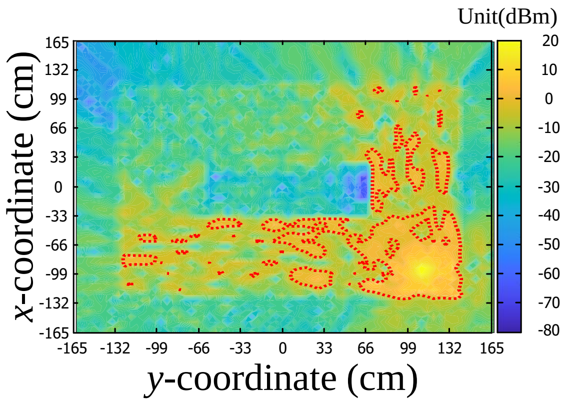
Next, we then applied the trained ML model to the estimation of the path gain distribution inside the room to validate the performance of the trained ML model. Figure 3 shows the predicted results derived from the trained ML model compared with the EM-simulated results computed by the ray tracing method. In comparison between Figs. 3 (a) and (b), we confirm that the predicted path gain distribution of the proposed CNN-based ML model exhibits only the maximum difference of 6.7 dBm with that of the EM-simulation. Consequently, we conclude that the proposed CNN-based ML model applied by k-fold cross-validation can apply to the estimation of EM distribution in the environment of NPPs to enhance nuclear safety.

3. Conclusions

In this paper, we propose an ML-based methodology for protecting the digital I&C equipment affected by EMI sources caused by wireless communication. To overcome the limited availability of the learning dataset, we employed k-fold cross validation. After confirming that the proposed CNN-based ML model is well-trained, we validated the performance of the CNN-based ML model by comparing the path gain distribution obtained from the lay tracing method of the sample EM environment. We consider that the proposed methodology to predict path gain distribution can contribute to efficiently finding the exclusive zone.



(a) Path gain distribution derived from an EM simulator.



(b) Path gain distribution predicted by trained model.

Fig.3. Estimated and simulated EM analysis results for target environment.

4. Acknowledgement

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