Predicting Power Density of Array Antenna in mmWave Applications With Deep Learning

JINKYU BANG, (Member, IEEE), AND JAE HEE KIM, (Senior Member, IEEE)

1Department of Electrical and Electronic Engineering, Youngsan University, Yangsan 50510, South Korea
2School of Electrical, Electronics and Communication Engineering, Korea University of Technology and Education, Cheonan 31253, South Korea

Corresponding author: Jae Hee Kim (jaehee@koreatech.ac.kr)

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ABSTRACT In this paper, we present a method for obtaining the power density value, which is the standard for radio frequency (RF) electromagnetic field (EMF) human exposure from mmWave mobile devices, using a deep learning network. An mmWave mobile communication device that uses an array antenna requires a large number of phase conditions for covering a wide communication range. However, the power density values must be repeatedly obtained every time the phase conditions are changed, which incurs a lot of time and cost. For implementing the process seamlessly, we present a deep learning network that can input the phase conditions of the mmWave array antenna and simultaneously obtain the power density results for the phase conditions of the array antenna as an output. For a $4 \times 1$ array patch antenna, which is commonly used in 5G mobile communication devices, the phases of the antenna were changed, and 5,832 electric and magnetic field data were acquired, which were then converted to power density values and learned thereafter. We examined whether appropriate power density values were output when inputting arbitrary phase sets of array antennas for the learned deep learning network. With the learned deep learning network, it was confirmed that when inputting unlearned phases for a $4 \times 1$ array antenna, the power density values similar to the actual simulation were quickly obtained as output.

INDEX TERMS Antenna, mmWave, power density, deep learning, neural network.

I. INTRODUCTION Mobile communication systems have evolved from 2G to 5G communication, making a considerable leap every 10 years [1], [2]. The increasing attention on new generation is attributable to the increasing number of mobile communication users and the subsequent need for markets that continuously demand high-quality communication services [3]. It is necessary to expand the frequency bandwidth for increasing the total amount of mobile traffic. Because the frequency band below 6GHz is very congested, in the 5G mobile communication system, a new frequency utilization method that included the mmWave spectrum was introduced along with a method of re-farming the existing frequency spectrum below 6 GHz [4]. In the future, 6G mobile communication systems will also consider the introduction of the mmWave spectrum over 100 GHz for larger mobile traffic capacity and higher data rates [2], [5].

The mmWave frequency spectrum is different from the propagation characteristics of frequencies less than 6 GHz which are used by the existing 2G, 3G, 4G, and some of 5G mobile communications [6], [7]. Since mobile devices emitting electromagnetic fields for radio communication must be designed to meet regulatory levels for radio frequency (RF) electromagnetic fields (EMF) human exposure, several organizations such as the International Commission on Non-Ionizing Radiation Protection (ICNIRP), the Institute of Electrical and Electronics Engineers (IEEE), and the U.S. Federal Communications Commission (FCC) have conducted research on RF EMF human exposure standards for mmWave spectrum [8]–[12]. The requirements for the mobile communication device supporting the frequency spectrum of less than 6 GHz use the specific absorption rate (SAR), and for a frequency spectrum of 6GHz or higher, such as mmWave, a new physical quantity called power density is used [8], [9], [11]. This is because the distance of the transmission of EMF to the human body varies depending on the frequency, and EMF energy is mostly...
absorbed by the subcutaneous tissue inside the human body below 6 GHz, but is mainly absorbed from the skin surface at 6–300 GHz [8], [13]–[15]. Various studies have been conducted on the power density RF EMF human exposure requirements of the ICNIRP, IEEE, and FCC for the mmWave mobile devices [16], [17].

In order to use mmWave spectrum, newer systems such as the beamforming technology was introduced [6], [7], with the aim of improving coverage and loss at high frequencies. It is necessary to implement an array antenna system for configuring mobile communication services. The array antennas generate various beam patterns according to the phase change, and the phase conditions can be selected on the basis of the application [7], [18]. Commercialized mmWave 5G mobile communication devices can cover a wide range of communication networks through a beam book composed of a plurality of phase conditions. To configure the beam book, the communication coverage should be simultaneously considered along with the EMF human exposure performance, which means that the power density for all phase conditions in the beam book must be measured or simulated [19], [20]. In addition, because the EMF human exposure considers both the phase conditions of the beam book and the usage case, power density tests on six surfaces around the device must be considered, and the total number of power density test cases is increased [19]. However, in the development stage of a mmWave mobile device, the beam book is frequently changed, and as a result, the process of obtaining power density results for all phase conditions and surfaces around the device must be repeated, which is time consuming and costly.

Recently, deep learning technology has been applied to various electromagnetics such as radiation and scattering problems as shown in Table 1 [21]–[28]. Especially in the field of antenna design and analysis, deep learning technology has been widely applied. In general, a 3D full electromagnetic (EM) simulation is required for antenna design, but it consumes a lot of time for higher frequencies as well as complex structures. The array antenna is based on a number of phase conditions, and it is necessary to acquire a radiation pattern according to each phase condition. To improve the efficiency of this system, various studies that are based on neural networks have been conducted. In particular, various methods for synthesizing the radiation pattern of the array antenna using a convolutional neural network (CNN) have been proposed [22]–[24], and an efficient method for outputting the phase condition of the array antenna to derive the desired radiation pattern using a deep neural network (DNN) is also presented [25]. In addition, when an element of the array antenna is defective, a method for diagnosing faults through a neural network and a method for efficient antenna design and optimization using the K-nearest neighbor (KNN) algorithm were also proposed [26], [27]. In the field of antenna design and analysis, deep learning technology has been widely applied to far-field conditions such as radiation pattern synthesis. However, there are areas that require research on near-field applications, such as power density analysis of mmWave mobile devices using the deep learning approach.

In this study, a deep learning method that can efficiently obtain the most similar power density results is presented for systems wherein a beam book composed of multiple phase conditions of an array antenna is input. The power density results for various phase conditions were obtained by implementing the learned neural network. The proposed method can quickly determine the possibility of a change in phase condition and construct a beam book without measuring or simulating the power density. This method can be used to predict EMF human exposure requirements beforehand, without any measurement and simulation, when the overall phase of the array antenna needs to be changed according to the communication coverage adjustments in a mmWave mobile communication device.

The definition and calculation method of power density, and the structure of the array antenna are described in Section II. Section III explains the method for extracting big data of the electric and magnetic fields, in order to derive the power density. Section IV describes the deep neural network (DNN) structure applied in this study. Section V shows the analysis and utilization of deep learning results, and finally, the conclusion is provided in Section VI.

### II. POWER DENSITY SIMULATION OF ARRAY ANTENNA

#### A. POWER DENSITY DEFINITION

The RF EMF human exposure requirements for the mmWave spectrum proposed by the FCC, ICNIRP and IEEE are expressed as the maximum value of the spatial-averaged power density for a specific area [8]–[10]. In order to obtain the spatial-average power density, the time-averaged power density must first be defined, as shown in (1) [20], [29].

\[
\overline{S}(x, y, z) = (1/2)\text{Re}\{\overline{E}(x, y, z) \times \overline{H}^*(x, y, z)\}
\]  

#### TABLE 1. Deep learning approaches in electromagnetics.

| Ref. | Approach | Architecture | Application |
|------|----------|--------------|-------------|
| [22] | 2D pattern synthesis | 8-layer CNN based on AlexNet | Reflectarray |
| [24] | 2D pattern synthesis | 4-layer CNN with multiple regression layers | Beamforming |
| [25] | 1D pattern synthesis | 5-layer DNN | Phased array antenna |
| [26] | Ant. failure detection | 6-layer CNN | Phased array antenna |
| [27] | Antenna optimization | Modified-KNN | Bragg reflector Microstrip ant |
| [28] | Inverse scattering | 6-layer CNN | Fracture imaging |
where $\text{Re}$ is the real part, $\vec{E}$ is the electric field (E-field), and $\vec{H}^*$ is the complex conjugate magnetic field (H-field). The term $\overrightarrow{S}$ represents the time-averaged power density and is expressed as a Poynting vector.

The spatial-average power density used as the standard for RF EMF human exposure is given by Equation (2) [17], [20].

$$S_{av}(z = d) = \max\left[\left\{\frac{1}{A}\int_{A} \overrightarrow{S}(x, y, z) \cdot \hat{z} \, dx \, dy \right\}\right]$$  \hspace{1cm} (2)

where $A$ is the area for averaging the time average power density, and $d$ is the separation distance between the areas to measure the spatial average power density from the antenna. The term $S_{av}$ represents the spatial-average power density and is expressed as the sum of the fluxes of power passing through area $A$ at a specific distance ($z = d$). In this study, the time-average power density ($\overrightarrow{S}$) is referred to as the Poynting vector, and the spatial-average power density ($S_{av}$) is referred to as the power density to distinguish between two physical quantities.

Fig. 1 shows the distance ($d$) and area ($A$) from the antenna expressed in (2) [17]. The separation distance may be used to consider the distance between the human body and the antenna mounted inside the mobile communication device. The averaging area is represented by a square, it is generally 4 cm$^2$ for the 28 GHz frequency spectrum, which is used for 5G mobile communication [8], [9].

**B. ANTENNA STRUCTURE FOR POWER DENSITY SIMULATION**

For the power density simulation in the mmWave frequency band, the structure of the array antenna was designed as shown in Fig. 2. The structure is a 4$\times$1 array antenna, and a single antenna element is designed as a patch antenna. The 5G mobile device is in contact with the human body the most and because it requires a small space, a 4$\times$1 array antenna is generally used [19]. The dielectric constant and thickness of the device were set as 3.5 and 0.5 mm, respectively. The single-patch antenna was designed in a circular shape with a diameter of 3.1 mm, and the antenna feeding was placed at a distance of 0.7 mm from the center of the patch antenna in the vertical direction.

The operating frequency of a single antenna is 28 GHz, which is a commercial 5G mmWave operating frequency. To reduce the coupling between antennas, the distance between antennas, the distance between the centers of the antennas was set to 0.59 $\lambda$ (6.4 mm). Fig. 3 shows $S_{11}$ and radiation patterns for a single-patch antenna and a 4$\times$1 array antenna in Fig. 2, respectively. At $\Phi = 90$ degrees, a single-patch antenna has a 3dB beamwidth of 79 degrees and a gain of 6.9dBi, and a 4$\times$1 array antenna has a 3dB beamwidth of 21 degrees and a gain of 12.8dBi.

**C. POWER DENSITY ANALYSIS**

Fig. 4 shows the power density simulation result when an in-phase signal is applied to the feed of each antenna for the
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FIGURE 4. Poynting vector and power density distributions of 4×1 array antenna (phase conditions: 0°, 0°, 0°, 0°).

4×1 array antenna designed in Fig. 2. The Ansys HFSS, a commercial analysis software based on the finite element method (FEM), was used for 3D electromagnetic numerical simulations [30]. Fig. 4(a) shows the Poynting vector distribution. Because the Poynting vector is calculated for each x and y coordinate of the Cartesian coordinate system, the area around the antenna element appears to be the strongest, and a power image, with a shape similar to that of a 4×1 patch antenna, can be obtained. Fig. 4(b) shows the power density distribution, which is the result of averaging the distribution of the Poynting vector, as shown in Fig. 4(a), with an area of 4 cm². The maximum value of the power density distribution, which is the physical quantity that can be requested as the RF EMF human exposure, is 56.5 W/m². In this study, the maximum value of the power density distribution was used for the deep learning network.

The distributions in Fig. 4 are the results for a single-phase condition (0°, 0°, 0°, 0°). For multiple phases, the distributions of the power density and the maximum values for all phase conditions must be determined. In general, for 5G mmWave mobile communication devices, a set of approximately 50 phase conditions per array antenna is required to increase the communication coverage, and this phase condition set is also referred to as a beam book. In the development stage for mmWave mobile devices, when the beam book is changed to improve communication coverage, the power density values must be obtained again through measurement or simulation of the changed phase conditions. This can pose as a major risk factor for complying with the mobile device development schedule. To solve this problem efficiently, a deep learning technique was used to predict the power density results according to the phase changes of the array antenna.

III. BIG DATA EXTRACTION IN E-FIELD/H-FIELD

To increase the coverage of the array antenna, the phase of each input signal of the array antenna must be changed, and the distribution of the power density varies according to the phase changes. The E-field and H-field data were obtained while changing the phase of the antenna input signal for evaluating the power density values for each phase. The relative phase difference is more significant for the phase of the array antenna than the absolute value of the phase of each antenna. Therefore, for deep learning, the phase of antenna #1 was fixed at 0°, and the phase of the other antenna was compared with this and subsequently increased by 20° to obtain the E-field and H-field data. As seen in Table 2, because the number of phase change cases made per antenna element is 18, the total number of E-fields and H-fields is $1 \times 18 \times 18 \times 18 = 5,832$. Based on the obtained E-field and H-field data, the distributions of 5,832 Poynting vectors can be obtained using (1), and the distributions of 5,832 power densities can be obtained through (2). Finally, the maximum values which are obtained from the power density distributions can be converted into big data. For the DNN to learn efficiently, the validation data that do not overlap with the training data are required. In this study, 5,832 power density data were randomly split, wherein 80% was used as training data, and 20% was used as validation data.

| Antenna phase conditions to make E/H-field big data. |
| --- | --- | --- |
| Antenna #1 | 6.3 | 0° | 1 |
| Antenna #2 | 6.3 | 0°, 20°, 40°, 60°, 80°, ...320°, 340° | 18 |
| Antenna #3 | 6.3 | 0°, 20°, 40°, 60°, 80°, ...320°, 340° | 18 |
| Antenna #4 | 6.3 | 0°, 20°, 40°, 60°, 80°, ...320°, 340° | 18 |
| Total | 5,832 |

The HFSS automation using MATLAB from Mathworks was implemented to efficiently obtain big data for the E-field and H-field [31]. An antenna analysis result simulated with HFSS was executed, and these fields were extracted by
post-processing for inputting the amplitude and phase variables of the antenna signal to the HFSS. The extracted fields were converted into the Poynting vector and the power density distributions, and the maximum values of the power density distributions were extracted. The big data yielded four phase values for each antenna as input values and one power density value as an output value.

IV. NEURAL NETWORK

A neural network with four phases of a $4 \times 1$ array antenna as the input and a power density value as an output is constructed, as shown in Fig. 5. For training a neural network, the power densities, which are the output data, were standardized using the mean ($\mu$) and standard deviation ($\sigma$), as shown in Equation (3), to make the data distribution even.

$$Z = \frac{(X - \mu)}{\sigma}$$  (3)

The deep neural network (DNN) consists of five layers, among which four layers, excluding the output layer, used the “Sigmoid” function as an activation function. The output layer used the “Linear” function. Each layer uses the “Dense” layer which connects both the input and output. Tensor Flow 2.0 was used for network analysis for deep learning, and the application conditions are as follows. The loss for each layer analysis was mean square error (mse), and the optimizer used “adam.” As mentioned above, 5,832 data were separated and 80% of 4,665 data were used as training data and 20% of 1167 data were used as validation data. Each data was shuffled to eliminate regularity. For data training, epoch was set to 2,000, and the loss according to the increase in epochs is shown in Fig. 6. As seen in Fig. 6, as the epoch value increases, both the training and validation losses converge. The final training and validation losses were 0.11 and 0.12, respectively.

Table 3 shows the result of the comparison of the loss of the neural network while changing the number of layers and the hidden layer condition to construct the neural network shown in Table 3. In Table 3, N1 and N2 are three layers networks that consists of one input layer, one hidden layer, and one output layer, and the number of nodes inside each layer is expressed as L1, L2, and L3, respectively.
The 4-layer network is N3–N7, and it consists of one input layer, two hidden layers, and one output layer, and the internal nodes of each layer are L1, L2, L3, and L4, respectively. N8–N14 is a 5-layer network consisting of one input layer, three hidden layers, and one output layer, and the internal nodes of each layer are L1, L2, L3, L4, and L5, respectively. To check the trend, the L2 was changed for each layer condition. Fig. 7 indicates that the validation loss improves as the number of hidden layers increases. As the number of layers increased in three layers, the loss improved by 0.05, and the overall loss of five layers improved by more than 0.1, compared to the loss of three layers. When L2 is eight under the five-layer condition, it shows the lowest loss, and thus, it was selected as the network condition in this study.

**V. SIMULATION RESULTS AND DISCUSSION**

When an arbitrary phase is input to the deep learning network for a 4×1 array antenna, the deep learning data and the actual simulation result were compared to check whether an appropriate antenna power density value was output. For verification, 10 phase sets, as shown in Table 4, were selected as conditions that did not overlap with the big data used in training and validation.

Table 5 shows the simulated power densities and predicted power densities through the DNN for the 10 test cases mentioned in Table 4. After comparing the simulated and the predicted results, it was observed that the relative percent error is at a maximum level of 4.68%, indicating that the power density value derived by deep learning is similar.

Fig. 8 shows the result of expressing the correlation between the simulation result and the deep learning result of the power density in Table 5; the correlation coefficient is 0.962, indicating that the result derived by deep learning has a high correlation with the actual simulation result.

To further verify the feasibility of the proposed neural network, the power density simulation results for the phase conditions in Table 6 and the neural network prediction results were compared. For the phase conditions, 504 data were used, and the eight phase conditions used in the neural network learning were excluded. The correlation between the actual power density simulation results and the learned power density results was compared.

Fig. 9 shows the relative percent error between the simulated power density and the predicted power density by the DNN for the phase conditions mentioned in Table 6. Among the 504 data, 31 data with a percent error between simulated power densities and the predicted power densities using a DNN exceeding 5% were only 6% of the total data, and the highest error rate among the 31 data was 8%. The power densities of the prediction results show a tendency similar to that of the actual simulation results, and it can be effectively used to predict the power density results when the

| TABLE 4. Antenna input conditions for deep learning network verification 1. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Antenna #1 | Antenna #2 | Antenna #3 | Antenna #4 |
| Amplitude  | 6.3 [mW] |
| Phase #1   | 0°      | 59°      | 27°      | 342°      |
| Phase #2   | 0°      | 44°      | 157°     | 256°      |
| Phase #3   | 0°      | 82°      | 158°     | 2°        |
| Phase #4   | 0°      | 80°      | 37°      | 257°      |
| Phase #5   | 0°      | 209°     | 356°     | 127°      |
| Phase #6   | 0°      | 237°     | 298°     | 125°      |
| Phase #7   | 0°      | 167°     | 262°     | 256°      |
| Phase #8   | 0°      | 332°     | 315°     | 114°      |
| Phase #9   | 0°      | 54°      | 213°     | 207°      |
| Phase #10  | 0°      | 150°     | 31°      | 339°      |

| TABLE 5. Comparison of simulation and deep learning results of power densities for the conditions in Table 4. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Power density [W/m²] | Error |
| Simulation | Deep learning | Absolute error | Percent error [%] |
| Phase #1 | 54.354 | 53.539 | 0.815 | 1.52 |
| Phase #2 | 59.090 | 56.448 | 2.642 | 4.68 |
| Phase #3 | 52.947 | 51.295 | 1.652 | 3.22 |
| Phase #4 | 48.518 | 49.245 | 0.726 | 1.48 |
| Phase #5 | 44.893 | 44.725 | 0.168 | 0.38 |
| Phase #6 | 49.107 | 50.404 | 1.297 | 2.58 |
| Phase #7 | 48.899 | 49.745 | 0.846 | 1.70 |
| Phase #8 | 51.802 | 52.518 | 0.716 | 1.36 |
| Phase #9 | 56.427 | 55.863 | 0.564 | 1.01 |
| Phase #10 | 52.302 | 53.368 | 1.066 | 2.00 |
TABLE 6. Antenna input conditions for deep learning network verification 2.

| Antenna | Amplitude [mW] | Phase [degrees] | Num of cases |
|---------|----------------|----------------|--------------|
| #1      | 6.3            | 0°            | 1            |
| #2      | 6.3            | 0°, 45°, 90°, 135°, 180°, 225°, 270°, 315° | 8            |
| #3      | 6.3            | 0°, 45°, 90°, 135°, 180°, 225°, 270°, 315° | 8            |
| #4      | 6.3            | 0°, 45°, 90°, 135°, 180°, 225°, 270°, 315° | 8            |
| Total (Excluding 8 conditions that overlap with the deep learning data in Table II) | 504 |

Actual beam book is changed. Fig. 10 is a scatter plot of the data distribution and correlation between the simulated power densities and the predicted power densities using a DNN. The correlation coefficient between the simulation results and the prediction results was 0.941, and the two results were similar. The results in Fig. 9 and 10 indicate that the power density prediction method based on the DNN presented in this study is highly efficient.

To verify the efficiency, the computation time of the proposed method by the DNN and the conventional method was compared under the same conditions. The conventional method is to directly calculate power density values using E-fields and H-fields data for all phase conditions. Table 7 shows the comparison of computation time between the conventional method and the proposed method for 46,656 phase conditions in which the input phases of the 4 × 1 array antenna were divided by 10-degree intervals. The hardware specification of Intel(R) Xeon(R) CPU @ 2.30 GHz with a memory of 16 GB was used. After full 3D EM simulation using HFSS, the time of conventional simulation per single phase set by post-processing was 2.63 seconds.

In Table 7, to calculate power densities for 46,656 phases, the conventional method took 2,045.1 minutes, and the proposed method including the generation time of training data took 261.6 minutes. It shows that the computation time of the proposed method with DNN is reduced by almost 1/8 compared to the conventional method, and the proposed method...
has advantages in terms of efficiency. Since the phase values of the array antenna are known to be used up to 1st or 2nd
decimal places in a commercial mmWave application model,
more computation time is required to determine the final
phase set through the conventional method.

VI. CONCLUSION
In this study, a method for efficiently predicting power
density, which is a new physical quantity required for the
RF EMF human exposure, using deep learning for array
antennas used in mmWave mobile device, is proposed. After
designing a $4 \times 4$ array patch antenna, the E-field and
H-field were obtained for each input phase, and two field data
were synthesized to derive power density results and then
converted into big data. A deep learning network with one
power density output for four input phases was constructed.
After training the deep learning network by using 80% of the
5,832 data as training data sets and 20% data as validation
data sets, it was found that the validation loss converged
well to 0.12. In addition, it was confirmed that the results
derived from the deep learning network for 504 arbitrary
phase sets that were not learned, were similar to the actual
power density simulation results as the correlation coefficient
0.941. To verify the efficiency, the computation time of the
proposed method with the DNN and the conventional method
was compared under 46,656 phase sets and it was found that
the calculation time of the proposed method was reduced by
almost 1/8 compared to the conventional method. A mobile
device using the mmWave frequency requires many phase
sets to increase communication coverage, and it is necessary
to measure or simulate the power density for each phase
condition to check whether it meets the RF-EMF human exposure
requirements. A significant amount of time and effort is
required to obtain these power density results. In the mobile
device development stage, a beam book that composed of a
plurality of phase sets is frequently changed to improve com-
unication coverage. It is difficult and inefficient to simulate
or measure the power density results of all phase conditions
every time the beam book is changed. In addition, as the num-
er of antenna elements of the array antenna increases and the
phase conditions vary, more time may be required to obtain
the power density results. With the help of the proposed
method, it is possible to obtain a fast and relatively accurate
power density result for tighter phase conditions and a larger
number of antennas. As a future work, to further improve the
performance of the DNN methodology, the proposed method
can be extended to a measurement-based methodology that
constructs a network using the power density measurement
results, and furthermore, the methodology for the power
density analysis can be developed by using other estimation
algorithms with the deep learning.

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JINKYU BANG (Member, IEEE) received the B.S. degree in electrical engineering from Inha University, Incheon, South Korea, in 2000, and the M.S. degree in computer and communication engineering and the Ph.D. degree in electrical engineering from Pohang University of Science and Technology, Pohang, South Korea, in 2002 and 2007, respectively. In 2005, he was with the Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, as a Visiting Researcher. From 2007 to 2020, he was with the Mobile Communication Division, Samsung Electronics, as a Principal and Senior Engineer, participating with the development of RF/antenna solution for mobile devices. Since September 2020, he has been an Assistant Professor with the Department of Electrical and Electronic Engineering, Youngsan University, Yangsan, South Korea. His research interests include mobile antenna and RF component design, analysis of RF EMF human exposure of mobile devices, computational electromagnetics, and deep learning.

JAE HEE KIM (Senior Member, IEEE) received the B.S. degree in electrical engineering from Korea University, Seoul, South Korea, in 2005, and the Ph.D. degree in electrical engineering from Pohang University of Science and Technology, Pohang, South Korea, in 2010. From 2010 to 2012, he was a Senior Engineer with Samsung Electronics, Suwon, South Korea. From 2012 to 2020, he was a Senior Researcher with Korea Railroad Research Institute, Uiwang, South Korea. He is currently an Assistant Professor with the School of Electrical, Electronics and Communication Engineering, Korea University of Technology and Education, Cheonan, South Korea. His research interests include the design and analysis of antennas, microwave components, development of wireless power transfer systems for railways, and sensor fusion of autonomous vehicles.