Wireless Environment Estimation with Directional Antennas using Radio Environment Database for Wireless Information and Power Transfer in Smart Factories

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***Abstract*—In the next-generation smart factories, not only wireless data transmission but also wireless power transfer is required to enable the continuous operation of wireless sensors. To achieve both wireless information transfer (WIT) and wireless power transfer (WPT) within the constraints of limited frequency resources, it is essential to accurately recognize the location-dependent characteristics of the wireless environment. In this paper, we propose a method for estimating the radio environment corresponding to various antenna directivity patterns by constructing a radio environment database based on limited measured data and incorporating antenna directivity information. We measured the received power of a wireless power transmitter with a fixed antenna pattern in a smart factory and constructed a database. Then, the radio environment for different antenna directivity patterns is estimated using the measurement data and the corresponding antenna directivity information. Using the proposed method, the estimation error of the received power at reception points for wireless power transfer can be reduced.**

I. Introdction

In recent years, the manufacturing industry has been required to establish flexible production systems in response to increasingly diversified market demands and shortened product life cycles. To address these challenges, the concept of the smart factory, based on Industry 4.0, has gained significant attention [1]. A smart factory connects production equipment, support devices, and various sensors via an Internet of Things (IoT) platform, enabling autonomous and efficient production through real-time dynamic control. In environments with frequent changeovers, such as high-mix low-volume production, cyber-physical systems (CPS) play a key role by reflecting physical-world data into cyber space, deriving optimal strategies, and feeding them back to physical systems [1]–[4]. CPS play a central role in enabling flexible and efficient control in smart factories by integrating advanced technologies such as control systems, wireless communication, IoT, digital twins, and artificial intelligence (AI).

To establish a CPS in factory environments, it is essential to deploy a large number of sensors throughout the physical space and to aggregate the data they generate into the cyber space with low latency and high reliability. In addition to sensors, automated guided vehicles (AGVs) also move throughout the factory while transmitting information. To ensure reliable and low-latency communication for these devices, it is crucial to accurately characterize the wireless environment—specifically, metrics such as latency, throughput, and received signal power—and to design communication systems accordingly.

In addition to wireless information transmission, the establishment of CPS requires a reliable power supply mechanism to ensure the stable operation of sensors and wireless devices. Providing wired power to every sensor significantly limits installation flexibility and increases wiring complexity, making it impractical for large-scale systems. On the other hand, achieving continuous operation solely with limited battery capacity is also infeasible in most cases.

As a promising solution to these challenges, wireless power transfer (WPT) has been proposed for supplying power to devices such as sensors and AGVs [5], [6]. In the design of WPT systems, it is essential to deliver power efficiently and dynamically to mobile nodes while mitigating the risk of human exposure to electromagnetic fields. To achieve this, adaptive antenna control is useful, as it enables flexible adjustment of the beam direction and coverage area according to the communication environment and the location of the intended receivers [7].

Moreover, WPT may interfere with wireless information transfer (WIT) from sensors and AGVs, potentially degrading sensor data aggregation and overall communication quality. To minimize interference between WIT and WPT—as well as among multiple information communication systems—it is crucial to accurately characterize the wireless environment and appropriately allocate frequency resources. In particular, given that the transmission characteristics of WPT vary depending on antenna directivity, it is essential to dynamically estimate the wireless environment while taking adaptive antenna control into account.

However, in indoor factory environments such as smart

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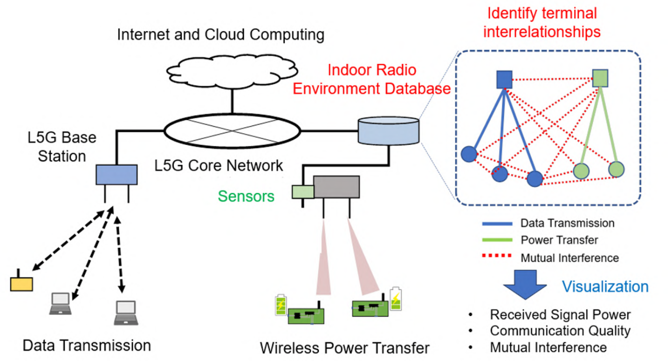

Fig. 1. Simultaneous transmission of data and power at the same frequency.

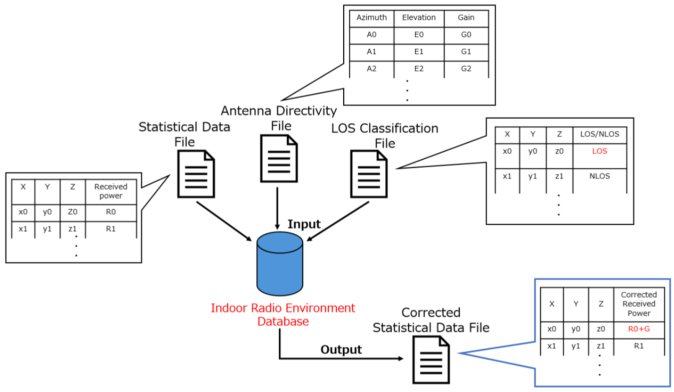

Fig. 2. System overview of the proposed method.

factories, radio wave propagation becomes extremely complex due to significant effects from multipath reflections and obstructions caused by walls and machinery. As a result, it is difficult to accurately predict the propagation characteristics using conventional physics-based models [8].

To address this issue, a spectrum database that accumulates and statistically analyzes received power and communication quality observed at terminals has been investigated [9]–[11]. One notable application of such databases is the construction of a radio environment map (REM), in which measured received power is statistically associated with location information to visualize the spatial distribution of the wireless environment.

In this paper, we propose a wireless environment estimation method that leverages an indoor spectrum database while taking antenna directivity control into account. In particular, the focus of this study is not on WIT, but rather on constructing REM for WPT. The proposed method builds directional REMs by applying antenna gain characteristics corresponding to arbitrary beam patterns onto a radio environment map (base map), which is initially generated using an omnidirectional antenna.

To verify the effectiveness of the proposed method, we conducted received power measurements using an omnidirectional antenna in an actual factory environment. Based on the collected data, we estimated REMs corresponding to multiple beam patterns. The proposed method enables the construction of flexible REMs that can support frequency resource management and interference evaluation, taking into account the coexistence of WPT and WIT.

II. Indoor Spectrum Database

In smart factory environments, achieving both wireless information transmission and wireless power delivery requires minimizing interference from WPT on communication links while ensuring reliable data transfer. This becomes especially critical when both systems operate in the same frequency band, necessitating accurate understanding of the radio propagation characteristics within the factory. However, indoor environments such as factories present complex propagation conditions due to multipath reflections and obstructions caused by walls and machinery, making theoretical modeling alone insufficient for accurate prediction [8].

To address this, wireless environment databases have been proposed. These databases statistically aggregate received power and communication quality data from distributed monitoring terminals, associating them with spatial information to visualize communication performance and interference patterns throughout the factory [9]–[11].

Figure 1 illustrates the architecture of the wireless environment database in a smart factory, along with an overview of a system that enables the coexistence of wireless information transmission and wireless power delivery. In this system, various devices—such as sensors, terminals, and AGVs—transmit data over a wireless network, while some sensing devices also receive power wirelessly via WPT.

The wireless environment database is connected to the P5G (Private 5G) core network and wireless power transmitters, and it collects and stores radio environment data—such as received power and communication quality—observed by these devices. P5G refers to a system that allows enterprises and local governments to build and operate their own 5G networks. In Fig. 1, it is labeled as "L5G (Local 5G)," which is the term commonly used for P5G in Japan.

By linking this data with spatial information, the database enables visualization of the communication status, interference relationships, and power distribution within the factory. This allows for the design of wireless systems that support simultaneous WIT and WPT, and for optimized interference management strategies to facilitate efficient frequency sharing.

III. Construction of REM Considering Antenna Adaptive Control

This section presents the proposed method for flexibly estimating REM by leveraging an indoor wireless environment database while taking antenna directivity into account.

A. Overview of the Proposed Method

Figure 2 illustrates the overall architecture of the proposed method. In this method, the positions of observation terminals and their received power measurements are stored in a database, and statistically processed to generate a data file representing the spatial distribution of received power. This statistical data forms the basis of a REM, where directional corrections are subsequently applied to incorporate antenna gain and line-of-sight (LOS) conditions. The next subsection describes the procedure for constructing this statistical data file, which serves as the base map for REM generation.

B. Construction of the Statistical Data File

In the proposed method, an indoor wireless environment database designed in [11], [12] is employed as the foundation. Following its data format, the measurement results at each location are statistically processed to generate the statistical data file, which serves as the base map for the subsequent directional correction process. In the remainder of this subsection, we describe the method for constructing the statistical data file utilizing the database.

In constructing the statistical data file, the measurement results collected by the observation terminals are organized according to their location information, and a representative received power value is calculated for each position. This process enables the generation of data that represents the spatial distribution of received power.

At the observation point located at position $\mathbf{p}_i = (x_i, y_i, z_i)$, multiple received power measurements $\{R_{i,1}, R_{i,2}, \ldots, R_{i,N_i}\}$, expressed in dBm, are stored in the database. The representative value $\bar{R}_i$, which indicates the average received power at position $\mathbf{p}_i$, is obtained by averaging the measured values and is expressed as

$$\bar{R}_i = 10 \log_{10} \left(\frac{1}{N_i} \sum_{j=1}^{N_i} 10^{R_{i,j}/10} \right), \tag{1}$$

where N_i denotes the number of measurements taken at position $\mathbf{p}_i$, and $R_{i,j}$ represents the j-th received power measurement at that position. The resulting pairs $(\mathbf{p}_i, \bar{R}_i)$ are output in a unified format and saved as the statistical data file.

In this study, each entry of the database is defined as the observation position and the corresponding received power in dBm, with supplementary information such as frequency and transmitter ID also included. These additional attributes can serve as useful design references for future frequency sharing and interference management strategies.

Since constructing this statistical data file requires associating received power measurements with their corresponding locations, the proposed method assumes that the positions of observation terminals are known in advance. However, accurate indoor positioning is generally challenging due to the difficulty of receiving satellite signals in enclosed environments. To overcome this limitation, reference [12] proposes an indoor positioning method based on access points and beacons, which enables high-accuracy position estimation in indoor factory settings.

C. Directional Gain Correction Process

As illustrated in Fig. 2, this process takes the statistical data file constructed in the previous section, along with the antenna directivity file and LOS classification file, as inputs, and outputs the corrected statistical data file.

The antenna directivity file represents the antenna's directional characteristics and contains the directional gain values $G(\theta_i, \phi_i)$ corresponding to the azimuth angle in the horizontal plane and the elevation angle in the vertical plane. In the database used in this study, the definitions of azimuth and elevation angles—including the reference directions and sign conventions—are clearly specified. Based on these definitions, the azimuth and elevation angles relative to the antenna's main axis can be computed and used as input parameters for directional gain correction. This enables flexible statistical processing that reflects the actual transmitter placement and antenna design specifications.

The LOS classification file indicates the line-of-sight (LOS) condition between each coordinate and the transmitter. A binary flag is used to indicate the LOS condition: a value of "1" represents a line-of-sight (LOS) condition between the position and the transmitter, whereas a value of "0" indicates a non-line-of-sight (NLOS) condition due to obstructions such as walls or machinery.

In the correction process, for each position $\mathbf{p}_i$ in the statistical data file, the azimuth and elevation angles relative to the transmitter are calculated, and the corresponding antenna directivity gain is retrieved. In referencing the gain, the two closest angle data points are selected from the antenna directivity file, and the gain for the relevant direction is approximated by linearly interpolating between them. This interpolation based on neighboring data points enables the representation of continuous variations in antenna gain. This gain is then used to correct the received power, with the specific correction method depending on whether each point is classified as LOS or NLOS.

- **At position classified as LOS**: The received power is corrected by incorporating the antenna directivity gain $G(\theta_i, \phi_i)$ as follows:
$$R_i^{\text{corr}} = \bar{R}_i + G(\theta_i, \phi_i). \tag{2}$$
- **At position classified as NLOS**: Assuming that the influence of directivity is negligible, no correction is applied, and the received power is set as follows:
$$R_i^{\text{corr}} = \bar{R}_i. \tag{3}$$

Here, θ_i and ϕ_i represent the azimuth and elevation angles, respectively, from the transmitter toward the position $\mathbf{p}_i$. In this way, a statistical data file that reflects the corrected received power at all positions is generated, enabling the estimation of a REM corresponding to arbitrary antenna directivity patterns.

Since the proposed method constructs the base map using measured data, it inherently captures propagation characteristics specific to the actual environment, such as obstructions and reflections within the factory. Therefore, it is expected to provide more accurate estimations compared to model-based approaches.

IV. Measurement Campaign

To construct the indoor wireless environment database and generate the REM, a received power measurement campaign

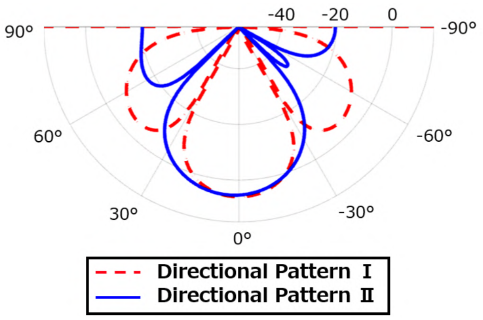

Fig. 3. Two types of beam patterns.

TABLE I
MEASUREMENT SPECIFICATION.

Observation points	76
Directional antenna elements	4
Directional Transmitter: Power	9.73 [dBm]
Omnidirectional Transmitter: Power	9 [dBm]
Omnidirectional Transmitter: Antenna Gain	2 [dBi]
Center Frequency	5750 [MHz]
Measurement equipment	Spectrum analyzer (Tektronix RSA513A)
Installation Height of Receiver and WPT transmitter	0.80 [m]

was conducted by installing a WPT transmitter within a smart factory. This experiment considers a single WPT transmitter, while practical scenarios may involve multiple transmitters.

An observation experiment was carried out in the learning factory (LF) of the Okayama Research and Development Center of Yamamoto Metal Technos. The LF is a facility designed for demonstration experiments aimed at realizing smart factories, providing a real-world environment that assumes the coexistence of WPT and WIT. In fact, a P5G base station is installed within the LF. As directional patterns for the WPT transmitter, two beam patterns are used, as illustrated in Fig. 3. Directional Pattern I features a single-lobe configuration that concentrates the main beam in a specific direction, while Directional Pattern II is designed to include null—directions with suppressed radiation. The measurement environment, as shown in Fig. 6, contains numerous machines and devices, resulting in the presence of many metal obstacles. The observation layout is illustrated in Fig. 4.

The LF observation area was divided into 1[m]×[m] meshes, and predefined coordinates were assigned to each point. At each point, the received power from the WPT transmitter was measured using a device placed on a container, as illustrated in Fig. 5, and stored in the database together with the corresponding coordinates. In this measurement, RSSI (Received Signal Strength Indicator) is employed as an indicator of the received power level. Table I summarizes the observation parameters.

At each observation point, the received power was continuously recorded over a 30-second interval, focusing on the strongest signal component—namely the peak frequency—within the frequency band used by the WPT transmitter.

In this experiment, the receiver and the wireless power transmitter were installed at the same height, so the radio environment mapping was performed in a two-dimensional horizontal plane. Therefore, in the directivity gain correction, only the azimuth angle was considered for angle calculation.

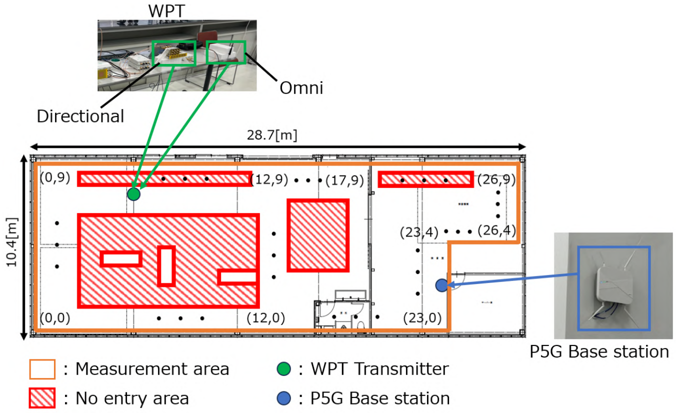

Fig. 4. Layout fo LF.

Fig. 5. Measuring instruments.

Fig. 6. Measurement environment.

V. ESTIMATION RESULTS AND ANALYSIS BASED ON MEASUREMENTS

This chapter analyzes the estimation accuracy of the REM for the WPT transmitter, which was constructed using the data obtained from the measurement campaign in the LF.

A. Overview of the Benchmark Method

This section describes the benchmark method used to evaluate the proposed approach. As a benchmark, the indoor path loss model (IPLM) defined in ITU-R Recommendation P.1238 is adopted. In this model, the basic path loss $L_b(d, f)$ is calculated based on the transmitter-receiver distance d [m] and the center frequency f [GHz] using the following equation:

$$L_b(d, f) = 10\alpha \log_{10}(d) + \beta + 10\gamma \log_{10}(f), \qquad (4)$$

where α is the distance loss exponent, β is the path loss offset, and γ is the frequency-dependent loss coefficient. To account for random fluctuations, Gaussian noise with zero mean and standard deviation σ is added.

The received power P_r [dBm] is then calculated using the transmit power P_t [dBm], the transmit antenna gain G_t [dBi], and the receive antenna gain G_r [dBi] as follows:

$$P_\mathrm{r} = P_\mathrm{t} + G_\mathrm{t} + G_\mathrm{r} - L. \qquad (5)$$

In this study, the receive antenna is assumed to be omnidirectional with no gain, i.e., $G_\mathrm{r} = 0$ [dBi]. The transmit antenna gain G_t is set in accordance with the proposed method, taking into account the directionality based on azimuth and elevation angles.

Furthermore, two benchmark scenarios are considered in the IPLM: with and without the ability to identify LOS or NLOS conditions. In the case where LOS or NLOS classification is available, each observation point is identified as either LOS or NLOS, and the corresponding parameter set (α, β, γ, σ) is used to calculate the path loss. Otherwise, a single parameter set is uniformly applied to all points.

B. Application of the Proposed Method

In this study, a directional REM was estimated based on a measured omnidirectional map, which serves as the base map. Specifically, Directional Patterns I and II were considered, and the measured omnidirectional REM, used as the base map, was corrected using the corresponding directivity gain files to construct directional REMs. Furthermore, the directional REM obtained using Directional Pattern I was treated as a new base map, from which the REM for Directional Pattern II was estimated. In this case, the directivity gain file contained the gain differences between Patterns I and II, which were used to perform the correction. In addition, since the transmit power differs between the omnidirectional and directional transmitters, the power difference was also taken into account during estimation by applying a transmit power correction.

For evaluation, the estimation error is calculated as the absolute difference between the estimated and measured received power, averaged over a 30-second interval at each observation point. In addition to evaluating the estimation accuracy across all observation points, this study also defines a virtual WIT area, which represents a region used for information communication purposes rather than power transfer. Specifically, the area around the P5G base station (with x ranging from 18 to 26) is designated as the WIT area. The estimation accuracy within this region is assessed to evaluate the suppression of power leakage, which is critical for the design of frequency-sharing systems.

C. Estimation Results

This section presents a quantitative comparison of the estimation accuracy of the REMs obtained using the proposed and benchmark methods described in the previous section.

Figures 7 and 8 show the distributions of absolute estimation error for the REMs constructed using each method. Figure 7 shows the estimation accuracy under Directional Pattern I, with the proposed method (top), and the benchmark method with LOS classification (bottom). Figure 8 shows the estimation accuracy under Directional Pattern II, with the proposed method using different base maps (top: omnidirectional, middle: Pattern I) and the benchmark method with LOS classification (bottom). Figure 9 shows the cumulative distribution function (CDF) of the absolute estimation error across all observation points. The results for the proposed database-based method (DB) and the benchmark method (IPLM) are presented with variations in base maps and LOS classification. Note that

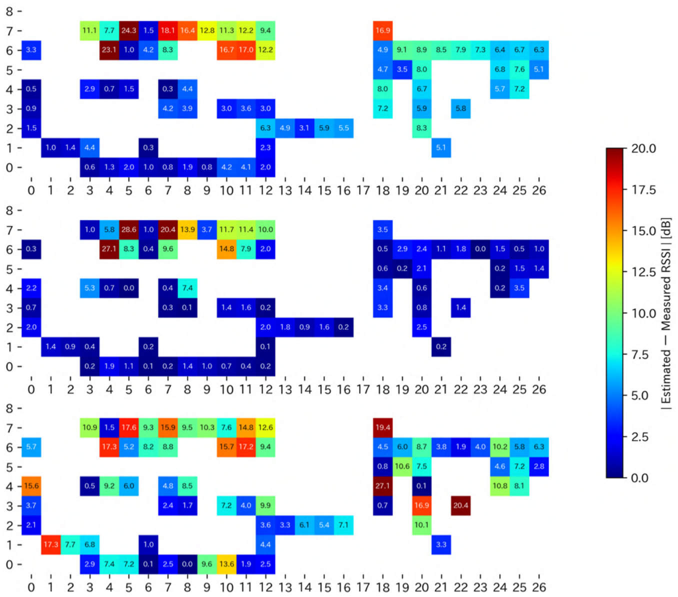

Fig. 7. Estimation error under directional pattern I: proposed method based on omnidirectional map (top), and IPLM (bottom).

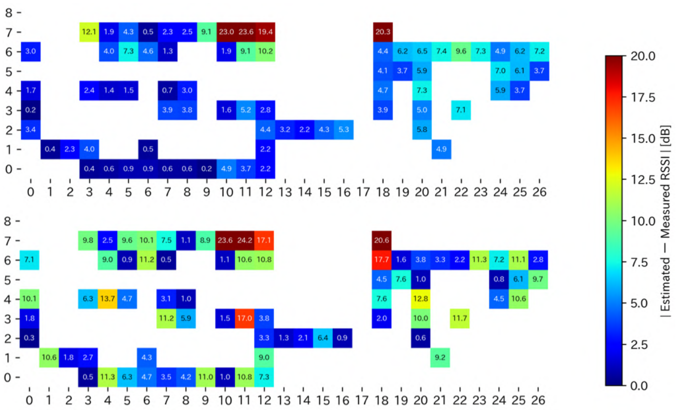

Fig. 8. Estimation error under directional pattern II: proposed method based on omnidirectional map (top), proposed method based on pattern I (middle), and IPLM (bottom).

"IPLM (all LOS)" and "IPLM (all NLOS)" represent the cases where LOS classification is not available, and the LOS or NLOS parameters are uniformly applied to all observation points, respectively. In contrast, "IPLM" refers to the case where LOS classification is performed at each observation point and the corresponding parameters are used for estimation. Table II summarizes the average absolute estimation error for all observation points and within the WIT area for each estimation method.

From CDF shown in Fig. 9, it can be observed that the proposed method yields lower estimation errors for both directional patterns. In particular, a large proportion of observation points fall within the range of 5–7 [dB], indicating that high estimation accuracy is achieved.

As shown in Table II, the proposed method reduces the estimation error compared to IPLM, achieving an improvement of approximately 10 [dB] over IPLM (all LOS), which assumes LOS without classification, and about 4.4 [dB] over IPLM with LOS classification for Directional PatternII. These

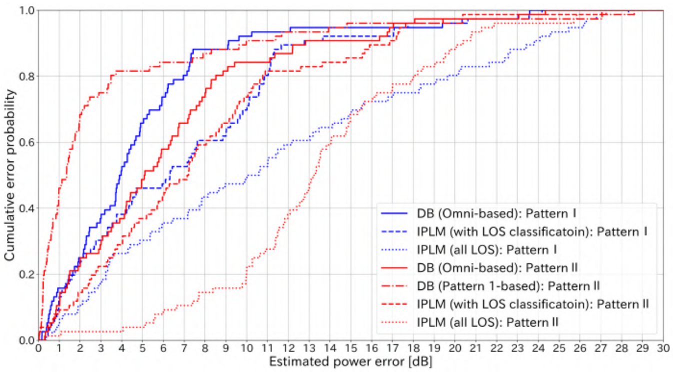

Fig. 9. CDF of estimation error.

TABLE II
THE AVERAGE ESTIMATION ERROR OVER ALL OBSERVATION POINTS AND THE WIT AREA.

Method	Target Directional Antenna	All Points Avg. [dB]	WIT Area Avg. [dB]
DB (Omni-based)	pattern I	4.93	6.37
IPLM (with LOS classification)	pattern I	6.97	7.21
IPLM (all LOS)	pattern I	11.29	18.58
IPLM (all NLOS)	pattern I	7.49	6.53
DB (Omni-based)	pattern II	6.23	7.14
DB (Pattern 1-based)	pattern II	3.34	1.48
IPLM (with LOS classification)	pattern II	7.70	8.06
IPLM (all LOS)	pattern II	13.54	14.44
IPLM (all NLOS)	pattern II	8.60	7.71

results demonstrate the effectiveness of using a database that incorporates LOS information. Furthermore, within the WIT area (x ranging from 18 to 26), the proposed method also shows lower estimation errors than the benchmark methods. In particular, for Directional Pattern II, the average error with IPLM (all LOS) was 14.44 [dB], whereas the proposed method achieved 1.48 [dB], resulting in a reduction of more than 12 [dB]. This confirms the effectiveness of the proposed method in frequency-sharing scenarios where suppressing power leakage into communication areas is required.

From the error maps shown in Figs. 7 and 8, it can be virsually confirmed that the proposed method forms a low-error distribution overall. In contrast, the IPLM method results in large estimation errors exceeding 8 [dB] at many observation points. On the other hand, relatively large errors are also observed near the transmitter, especially at observation points located directly to the side of the antenna (around an azimuth angle of 90°). This is attributed to the sharp attenuation and steep spatial gradient of antenna gain in that direction, which causes even slight directional errors to significantly affect the gain correction. As a result, errors in the direction vector calculation are amplified in the estimation output, leading to locally increased estimation errors.

Among the proposed methods, the highest estimation accuracy was achieved when Directional Pattern II was estimated using the Pattern I map as the base. This is considered to be due to the similarity between the beam patterns and the use of the same transmitter.

VI. CONCLUSIONS

In this paper, we proposed a method for constructing REMs that reflect antenna directivity, based on omnidirectional maps from a wireless environment database, assuming frequency sharing in smart factories. By integrating antenna radiation characteristics and LOS classification into the database, the method allows flexible reconstruction of REMs for various directivity patterns. Measurement experiments in a real environment showed that the proposed method achieved higher estimation accuracy than the benchmark, both across the entire area and within the WIT area. On the other hand, in lateral directions near the transmitter, the directional antenna exhibits steep variations in gain, making the estimation results highly sensitive to even slight directional deviations. To suppress estimation errors in such high-sensitivity regions, future work will consider improving the smoothness of the gain correction process and incorporating models that account for temporal variations.

VII. ACKNOWLEDGMENT

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