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Automated and Optimized Sensor Deployment Using Building Models and Electromagnetic Simulation

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ABSTRACT

With the advent of wireless sensing technology and interest in tracking resources, researchers have developed advanced tracking algorithms by using one or more sensor systems for improved accuracy and reliability of tracking. The objective of this research lies in another aspect—deployment——of tracking that has received only little attention until now. The research explores a method for sensor deployment particularly designed for the building in which the sensors are used. To tailor our solution to a specific building, we integrate a building information model with an electromagnetic energy analysis. By using such a model, the system extracts the properties of building materials, which are used as parameters of sensor deployment optimization. Then, we find a method of optimizing the deployment of a received signal strength indication (RSSI)-based

tracking sensors for reducing wireless energy dissipation during the operation of the tracking system. For the numerical validation of the proposed method, the high-frequency structural simulator (HFSS) runs an electromagnetic simulation to generate comparison data of electromagnetic energy flow from optimized sensor deployment and random sensor deployment. The results indicate that the proposed method could produce results that are correlated to the HFSS results. In addition, the method shows clear evidence of a reduction in signal power loss. Finally, optimized sensor deployment through the proposed framework can use signals of electromagnetic energy more effectively and potentially improve the efficiency of the RSSI-based tracking system.

Keywords: building information model; electromagnetic simulation; indoor localization; sensing; optimization; sensor deployment;

1. INTRODUCTION

Researchers have devoted considerable attention to information and sensing technologies for more advanced construction operation and management. Over the past several decades, the demand for improved safety, efficient material and asset management, and effective communication has prompted substantial interest in the development of specific construction applications through the use of these technologies. Areas of the most active research efforts involve the development and evaluation of sensing technologies and/or models and the design of sensing systems for preventing collisions between ground workers and equipment (Marks and Teizer 2012; Park et al. 2017b; Wang and Razavi 2016). Other types of sensing technologies that researchers have extensively explored are motion sensors because of their ability to directly measure data representing motion-related information about objects (Li et al. 2016b; Pradhananga

and Teizer 2013). In addition, vision-related research studies have explored the potential of such technologies in safety, security, progress, and management for construction (Escorcia et al. 2012; Golparvar-Fard et al. 2011; Park and Kim 2013). Previous research has successfully proven the applicability and the performance of various sensing technologies in certain applications of construction. Despite this success, many of the sensing technologies discussed so far have not yet been able to realize the localization of construction assets.

Tracking has been a focus of research in various domains such as computer science, electrical engineering, and construction. With the advent of wireless sensor technology, construction research has explored a major area of interest in the field of sensing technology, localization, and its potential applications using tracking technologies. Using such technologies, a number of researchers have investigated various algorithmic approaches from theoretical points of view (Cai et al. 2014; Li et al. 2014a; b; Park and Cho 2017; Su et al. 2014; Taneja et al. 2016b), the development of hybrid-tracking systems (Park et al. 2016a; Taneja et al. 2016a) and their potential applications in construction management and operation (Carbonari et al. 2011; Kim et al. 2016; Park et al. 2011; Wang 2008).

Most algorithmic studies and other studies in construction related to accuracy (Costin and Teizer 2015; Li and Becerik-Gerber 2011; Montaser and Moselhi 2014) are also associated with developments/applications of tracking methods and the evaluation of system performance. Although these studies have revealed the potential of utilizing tracking systems on construction sites, the tested systems may be yet impractical because of their limitations and assumptions made in the presented research. For example, ultra-wideband (UWB), a sensor that offers mille-to-centimeter accuracy, is cost prohibitive and entails time-consuming calibration and complex system deployment (Shahi et al. 2012; Torrent and Caldas 2009). A recent study (Park et al. 2015)

reported that when radio frequency identification (RFID) was used in dynamic situations, its RFID signals underwent large fluctuations, compared with those of Bluetooth low-energy and magnetic field sensors. Such problems become more significant when the site presents complexity in geometry, workers interactions, and environmental changes. Results found by Shahi et al. (2012), who investigated the performance of a UWB system in various conditions and building materials, support the same issues. To improve the accuracy of a tracking algorithm that captured errors introduced by wall components in a building, Li et al. (2014b) developed a method of offsetting the negative impact from wall-induced signal attenuation. Their method extracts wall elements from a BIM model and iteratively performs maximum likelihood estimation for tracking. Although these studies expanded beyond the testing of the accuracy of tracking systems, they are still limited.

While the practicality of a system is the key to its widespread adoption in industry, the practical aspects of tracking systems applying to construction have not been adequately addressed, perhaps because such application involve a number of factors beyond accuracy and cost, including deployment, system coordination, system management, and form factor, all of which are thoroughly reviewed in an article by Li et al. (2016a). Recent research in various domains including electrical engineering and computer science explored a number of theoretical approaches for sensor deployment, such as multi-objective optimization (Domingo-Perez et al. 2016), convex optimization with estimation theory (Moreno-Salinas et al. 2013), signal energy loss (Cho et al. 2018) and the Fisher information matrix-based optimization (Nguyen and Dogancay 2015). These studies present advanced mathematical algorithmic approaches to solving the complex phenomena between signals and the environment and demonstrate the performance through computer simulation. The previously discussed factors (e.g., accuracy, cost, deployment, system

coordination) and the signal phenomena are all co-related, making all factors critical for a practical tracking system. Despite the importance of these factors, unfortunately, they have not been studied and are absent from most tracking research in construction. In addition, the nature of construction sites entails difficulty in applying such methods derived from other research fields. Tracking conditions required by construction include both dynamic and static conditions, which make solutions designed for static environments ineffective in many cases. As a result of this, construction researchers explored separate tracking studies as stated above, still limiting their application to algorithm and/or accuracy studies.

As discussed previously, many researchers have asserted that tracking solutions suffer from deployment issues, especially when they are applied to an indoor construction site. A system that uses sensors, which operate on the principle of signal propagation, experiences signal loss as the signals travel through a medium (Friis 1946). The loss of signal power is an indication of energy loss. If a significant loss occurs during signal communication, the system is deemed inefficient (Pozar 2009). Many experimental studies have overlooked the efficiency of sensor deployment as they used uniform sensor distribution or a specific sensor setup for testing scenarios without fully recognizing the complex phenomena of signal power loss. One of good resources that are available to the construction industry is BIM, which can help to automatically extract and account for complex signal behaviors caused by building elements. With the BIM model, we can now quantify the complex behavior of signal power and loss of signal power. With this capability, we can develop an integral strategy for sensor distribution that offers a solution to minimizing energy loss (signal power loss).

The contribution of this research is as follows:

- We make the first effort to address the problem of sensor deployment in an integrated method
- We proposed a method that offers an additional value to the algorithmic studies conducted by researchers in the domain of sensor experts (electrical engineering and computer science)
- Our method integrates knowledge in construction (by using construction resources) and in electrical engineering (by using the technique of electromagnetics) to solve the complex problem of signal phenomena.

2. OBJECTIVE AND SCOPE

The objective of this research is to address the issue of deploying the received signal strength indication (RSSI)-based sensor on a construction site. By creating a new approach for addressing this issue, this work presents a framework for optimizing a sensor deployment plan by using an electromagnetic (EM) analysis technique and BIM. The optimization of the sensor deployment plan is to find, for any given number of sensors, a deployment layout that offers minimized signal loss. We adopt the technique of BIM information extraction (Park et al. 2016b) and use BIM in the as-built geometric properties of a site for quantitatively assessing the effect of signal reflection and attenuation caused by various building elements; and we use EM to perform computational analysis by simulating a commercial software package, the high-frequency structural simulator (HFSS). The methodology for a sensor deployment strategy could provide a solution for sensor deployment that minimizes the loss of signal power, which in turn, maximizes the use of energy emitted from a sensing/tracking system.

The scope of this study includes the development of the framework, extraction of dynamic information from the BIM, the design of optimized sensor deployment, and numerical validation of the proposed method. Based on the theory of energy loss, the research relies on the assumption that minimized energy loss in signal communication indicates the most effective form of signal communication. In other words, minimal energy loss during sensor communication can provide an efficient deployment plan for the sensors of a tracking system. In addition to optimization, the findings of the research may eliminate the tedious process of designing sensor layouts for deploying sensors in a dynamically changing construction site.

3. MECHANISM OF AUTOMATED SENSOR DEPLOYMENT

To achieve the research objective, we create a mechanism for realizing a system of automated sensor deployment planning, illustrated in Figure 1. This automated planning requires several steps for optimizing sensor deployment that minimizes the loss of signal power. The first procedure of automated sensor deployment extracts information about geometry elements and materials from a BIM model of a construction site. Each construction site is unique and presents complex environmental conditions that affect EM waves in various ways such as reflection and distortion. Because of these effects, we model the precise environmental condition, which is a significant factor contributing to the problem of sensor deployment. Then, we define the wireless energy-flow relationship between a RSSI-based sensor and a worker's reader, which is based on the modeled environmental conditions at a construction site. After confirming the number of RSSI-based sensors deployed for tracking, we formulate an optimization problem that effectively distributes the sensors. Finally, HFSS conducts a full-wave EM simulation that validates the proposed sensor-deploy approach.

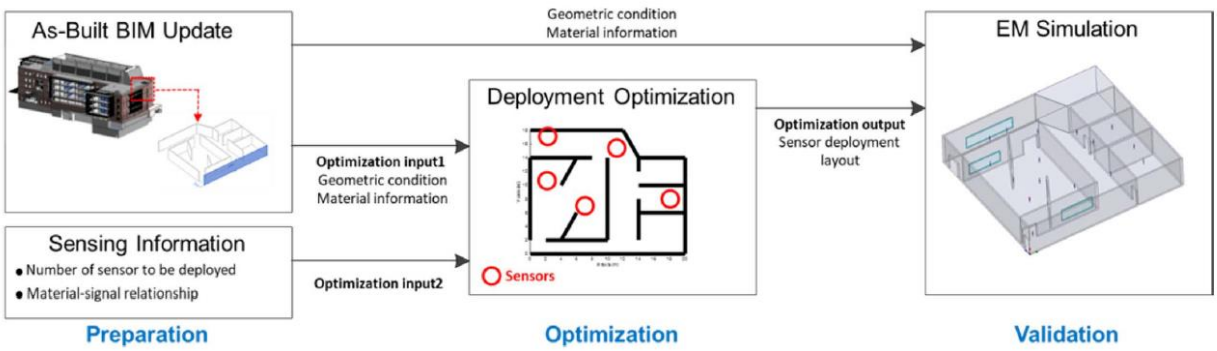

Figure 1. Illustration of the Framework for Automated Sensor Deployment

3.1 BIM Model Extraction for Planning Sensor Deployment

As discussed, the system of automated sensor deployment proposed in this research uses geometric and material information about a construction site where the RSSI-based tracking system is deployed. BIM, which has been developed specifically for construction projects and updated throughout the project life cycle, is one of the most appropriate repositories for project information that allows the extraction of the specific data needed for planning sensor deployment through signal loss minimization.

The as-built BIM model generates both geometric and material information. With the application programming interface of BIM software packages, the framework automatically extracts these two types of information. Even though manual information extraction is possible through the graphical user interface, automated information extraction using the application programming interface can produce input for sensor deployment optimization and reduce manual effort associated with the continuous sensor deployment planning proposed in this research. Figure 2 presents the conceptual flow of data extraction from a BIM model with an example of a wall element. The following lists extracted information:

- Material information: material layers, thicknesses of various materials

- Geometric information: location (coordinates) and shape of wall elements

For any given layout of sensor deployment, each of the sensors is uniquely coordinated with respect to the information extracted from a BIM model. The analysis of signal loss associated with coordination information exposes the effects of their relative coordination in relation to the geometric elements of the surroundings on signal optimization. The BIM extraction module is an integral part of the framework for automated tracking sensor deployment.

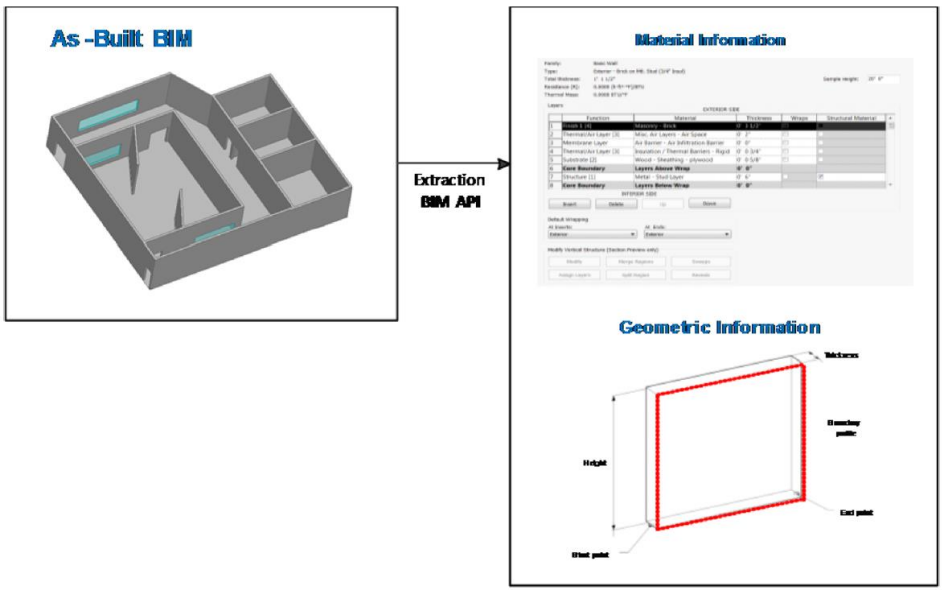

Figure 2. Conceptual Module for BIM Data Extraction

3.2 Theoretically Received Power Measurement for Estimating Distance

In the RSSI-based tracking system, each sensor radiates constant EM power uniformly to all azimuthal directions since omnidirectional antennas (e.g., dipole antennas) are installed. When workers move around deployed sensors, their readers capture modulated EM signals from each sensor and measure received power levels. Figure 3 shows that even when the transmitted power levels of two sensors are the same, the received power from sensor 1 is higher than that from sensor

2 because of electromagnetic energy dissipation in the air (wireless energy loss in the air). As a result, the tracking system indicates that the worker's location is closer to sensor 1 than it is to sensor 2. Therefore, the received power level from each sensor is an important index for back-estimating the distance between the worker and sensors.

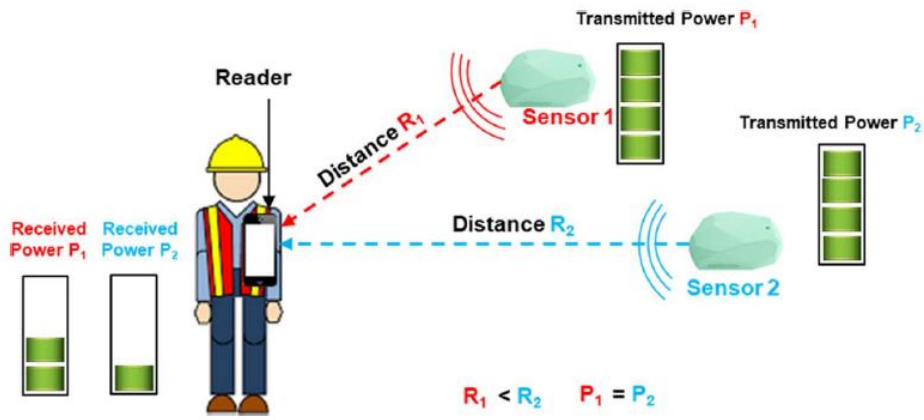

Figure 3. Illustration of a RSSI-based Tracking System

To calculate the distance between a transmitter and a receiver, several researchers have attempted to formulate equations by using received power levels (Chintalapudi et al. 2010; Li et al. 2014b). Although the equations are applicable to the RSSI-based tracking system, they are mainly empirical approaches that over-simplify the Friis transmission equation (Friis 1946). To more accurately measure electromagnetic performance such as antenna gain and patterns, this study adopts the basic form of the Friis transmission equation (Eq. (1)), which follows:

$$P_r = G_r G_t \left(\frac{\lambda}{4\pi R}\right)^2 P_t, \tag{1}$$

where G_t and G_r are the antenna gains of a sensor and a worker's reader; λ is the wavelength; R is the distance between a RSSI-based tracking sensor and a worker's reader; P_t is the transmitted power level from the tracking sensor; and P_r is the received power.

Since construction sites are subject to very complicated EM environmental conditions, Eq. (1) would not work properly in many applications. Therefore, the research group modifies Eq. (1) by adding an environmental factor.

$$P_r = G_r G_t \left(\frac{\lambda}{4\pi R}\right)^2 P_t w, \tag{2}$$

where w is the environmental factor that enables us to describe EM attenuation, distortion, reflection, and so on. This factor can be estimated by field measurements. Li et al. (2014b) assumed the value of this factor as -2 dB (0.6310 in a real scale) when they accounted for signal attenuation per wall. To estimate the distance between the reader and the tracking sensor, we rewrote Eq. (2) as follows:

$$R = \sqrt{\frac{P_t w G_r G_t}{P_r}} \frac{\lambda}{4\pi}. \tag{3}$$

3.3 Formulation of Automated Sensor Deployment

Figure 4, a schematic view of a tracking approach for the RSSI-based tracking system, depicts a construction site with eight randomly deployed tracking sensors and three worker locations. To identify a worker's location, the worker's reader measures received power levels from the tracking sensors and classifies three (or four) sensors whose received powers are higher than others. Then, Eq. (3) converts the received power levels from the classified sensors into distances between the worker and three (or four) sensors. Figure 4 shows the estimated distances, indicated as radii for

each circle (2D) or sphere (3D). By calculating the intersection of the circles or spheres, the RSSI-based tracking system identifies the worker's location.

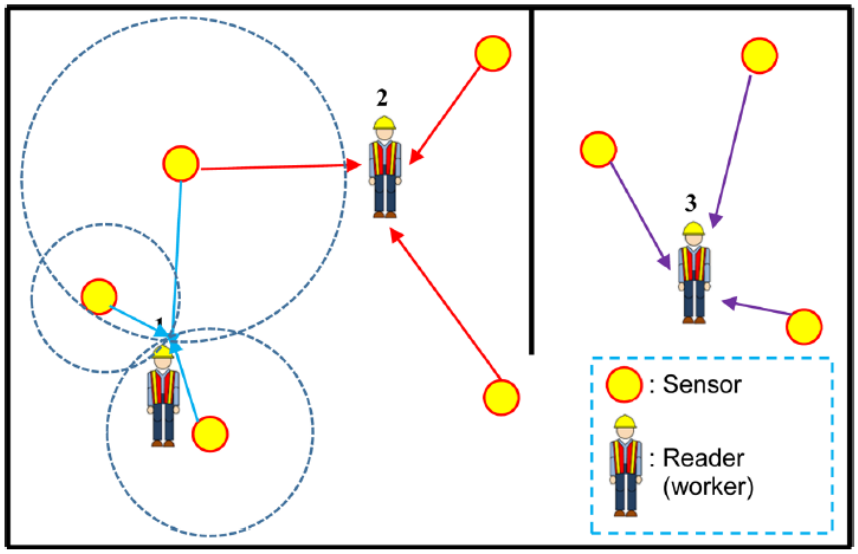

Figure 4. Tracking Method for the RSSI-based Tracking System

To ensure optimal sensor deployment, this study suggests three steps. In the first, we calculate the received power level corresponding to the location of the sensors and the worker. To account for the locations of multiple workers and sensors, we modify Eq. (2) as follows:

$$P_r(x_i, y_j) = G_r G_t \left(\frac{\lambda}{4\pi R(x_i, y_j)}\right)^2 P_t(x_i) w(x_i, y_j), \tag{4}$$

where x_i is a vector in the three-dimensional Cartesian coordinate system that presents the ith sensor location, y_j is a Cartesian coordinate vector that shows the jth location of a worker, $R(x_i, y_j)$ is the distance between x_i and y_j, $P_t(x_i)$ is the transmitted power of the ith sensor, and $w(x_i, y_j)$ is an extracted environmental factor between x_i and y_j from a BIM model.

Based on Poynting's theorem (Poynting 1884) , $w(x_i, y_j)$ is formulated as:

$$w(x_i, y_j) = \frac{1}{\eta} e^{-2\left[\frac{2\pi f}{c}\sqrt{\frac{\mu_r \varepsilon_r^{'}}{2}}\left(\sqrt{1+\left(\frac{\varepsilon_r^{''}}{\varepsilon_r^{'}}\right)^2}-1\right)^{1/2}\right]\sqrt{\left(x_i^1-y_j^1\right)^2+\left(x_i^2-y_j^2\right)^2+\left(x_i^3-y_j^3\right)^2}} \tag{5}$$

where η is the intrinsic impedance in the propagating medium; f is the operating frequency (2.4GHz in the BLE application); c is the speed of light (3×10^8 m/s); μ_r is relative permeability; $\varepsilon_r^{'}$ and $\varepsilon_r^{''}$ refer to the relative real permittivity and relative complex permittivity, respectively; x_i^1, x_i^2, and x_i^3 are vector components for x_i based on Cartesian coordinate; y_j^1, y_j^2, and y_j^3 are vector components for y_j.

In the second step, we identify the three highest signal strengths:

$$\begin{aligned} P(\mathbf{X}, y_j) = {} & max1\{P_r(x_1, y_j), P_r(x_2, y_j) \dots P_r(x_n, y_j)\} \\ & + max2\{P_r(x_1, y_j), P_r(x_2, y_j) \dots P_r(x_n, y_j)\} \\ & + max3\{P_r(x_1, y_j), P_r(x_2, y_j) \dots P_r(x_n, y_j)\}, \end{aligned} \tag{6}$$

where $max1\{\bullet\}$, $max2\{\bullet\}$, and $max3\{\bullet\}$ are functions for calculating the first, the second, and the third highest values, respectively, n is the number of sensors, and $\mathbf{X}$ is a matrix that contains sensor location vectors ($\mathbf{X} = [x_1, x_2, \dots x_n]$). In the last step, we formulate automated sensor deployment as

$$\begin{aligned} & \underset{\mathbf{X}}{\text{maximize}} \ \sum_{j=1}^{m} P(\mathbf{X}, y_j) \\ & \text{subject to } \mathbf{X}_{\mathrm{L}} \leq \mathbf{X} \leq \mathbf{X}_{\mathrm{U}}, \end{aligned} \tag{7}$$

where m is the number of locations for workers and $\mathbf{X}_{\mathrm{L}}$ and $\mathbf{X}_{\mathrm{U}}$ are lower and upper bounds for optimization parameter $\mathbf{X}$. It is noteworthy that maximizing received power is the same process as minimizing energy loss.

4. NUMERICAL VALIDATION

To validate the proposed framework, we conduct a numerical analysis for several reasons: 1) The use of an actual site test in which the loss of signal power is measured is impractical and extremely challenging; 2) because of the requirement of site coordination for field tests, frequent changes in the deployment layout are impossible; and 3) the numerical analysis will allow for the validation of the proposed framework against a greater variety of test scenarios (e.g., various deployment layouts). The proposed framework for automated deployment of an RSSI-based tracking system is validated through an example model in this section. First, the framework extracts materials and geometric information from a BIM model. Then, the proposed method determines the optimal sensor deployment, and then compares the optimized results by HFSS EM simulation, which produce accurate descriptions of electromagnetic properties in 3D space. It is noteworthy that we select a Bluetooth Low Energy (BLE) technology for numerical validation. The BLE system is one of the most recent RSSI-based technologies.

4.1 Model Description

To validate the automation approach for BLE sensor deployment, we selected a portion of a real-world BIM model, shown in Figure 5. The selected portion, whose dimensions are 20m (length) by 18m (width) by 4m (height), consists of concrete walls and openings. Concrete walls significantly influence electromagnetic waves by reflection and attenuation. To quantify their negative influence through the modeling process, the system uses BIM to extract geometric and material information about individual elements that are then used as input for simulation and optimization. The developed custom application transfers the extracted information to the analysis

module of the proposed system for modeling of the HFSS simulation without excessive manual input. To investigate effectiveness of the proposed method in a more extensive manner, we introduce two more variated models from the original portion of the BIM model associated with complex geometries such as concrete walls and openings (Figure 5).

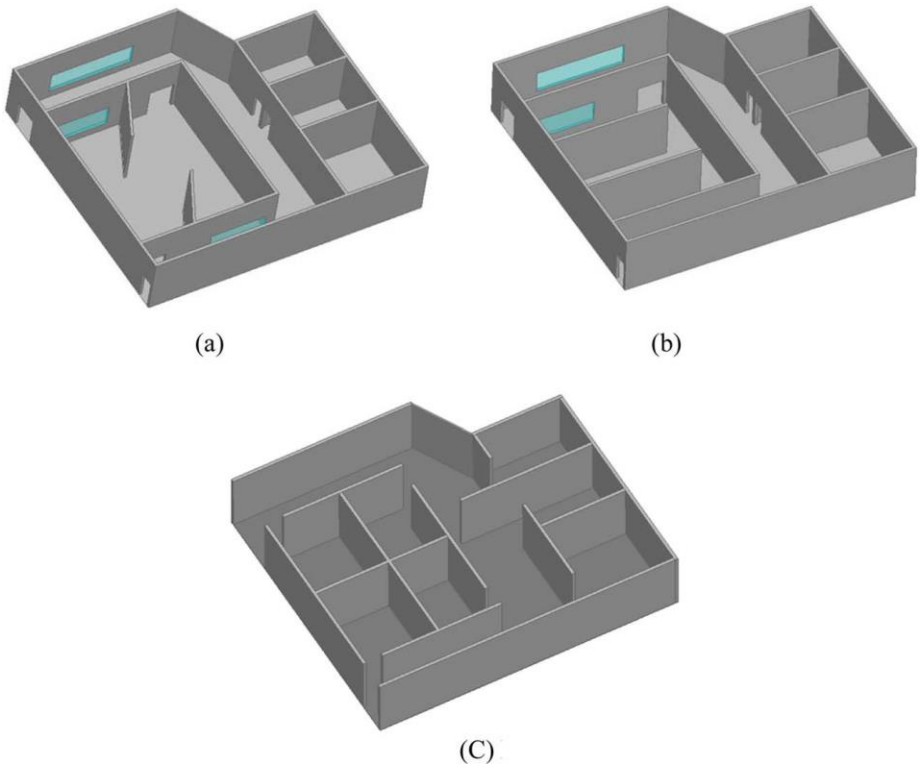

Figure 5. Perspective Views of BIM Models: (a) Model 1 (original model), (b) Model 2 (the first model variation), (c) Model 3 (the second model variation)

4.2 Optimal Sensor Deployment

Previous research has tested BLE tracking systems with certain ranges of sensor density from 25 to 57 m^2 per sensor (Park et al. 2017a). In this study, we consider three scenarios of senor density for each model by setting the sensing density to 22, 25, and 36 m^2 per sensor, respectively. As shown in Figure 6, the numbers of deployed sensors for each scenario are 15, 13, and 9, respectively. The applied operating frequency and the wavelength for the BLE sensor system are 2.4GHz and 0.125m.

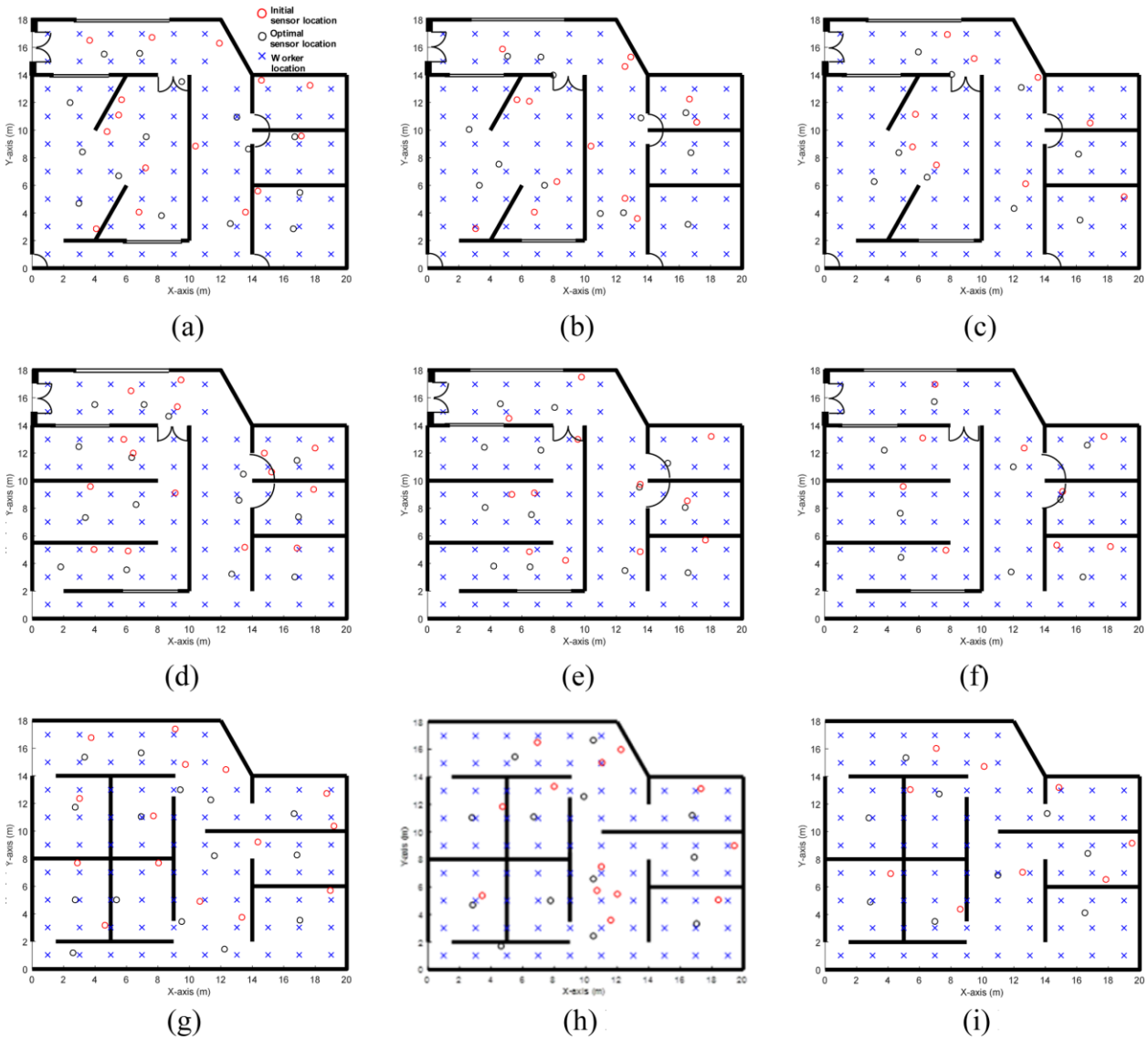

Figure 6. Optimal Sensor Deployment: (a) Model 1: Scenario 1 (Case 1-1), (b) Model 1: Scenario 2 (Case 1-2), (c) Model 1: Scenario 3 (Case 1-3), (d) Model 2: Scenario 1 (Case 2-1), (e) Model 2: Scenario 2 (Case 2-2), (f) Model 2: Scenario 3 (Case 2-3), (g) Model 3: Scenario 1 (Case 3-1), (h) Model 3: Scenario 2 (Case 3-2), (i) Model 3: Scenario 3 (Case 3-3)

In optimal sensor deployment with the solution of Eq. (7), the initial matrix $\mathbf{X}_0$ of the optimized variables is randomly generated within a lower bound $\mathbf{X}_\mathrm{L}$ and an upper bound $\mathbf{X}_\mathrm{U}$. Generating the location of workers, the system uses an equal distance of 2m between workers. These locations correspond to the y vectors in Eqs. (4), (6), and (7). Because the theoretical gain value of a half-wave dipole antenna is 2.15dB (real scale=1.64), G_r and G_t are set as the same number. To solve

the optimization problem of the sensor deployment, we adopt `MultiStart` in the MATLAB optimization toolbox as a global optimization solver. Using `MultiStart`, we randomly generate 100 trial starting points for optimizing variable matrix **X**. Starting from each of 100 points, the `fmincon` (nonlinear least-squares solver) with "sequential quadratic optimization" algorithm finds a local optimum. This process determines the optimal sensor locations and computes the objective function described in Eq. 6. In Model 1 with Scenario 1 (Case1-1), the detailed values of matrices $\mathbf{X}_0$, $\mathbf{X}^*$, $\mathbf{X}_\mathrm{L}$, and $\mathbf{X}_\mathrm{U}$ are summarized as

$$\mathbf{X_0^T} = \begin{bmatrix} 4.08, & 6.77, & 13.56, & 14.33, & 17.12, & 10.41, & 7.21, & 4.74, & 5.68, & 5.48, & 14.57, & 17.65, & 11.92, & 7.62, & 3.68 \\ 2.83, & 4.05, & 4.06, & 5.60, & 9.56, & 8.86, & 7.27, & 9.87, & 12.20, & 11.10, & 13.63, & 13.25, & 16.30, & 16.73, & 16.52 \end{bmatrix} \mathrm{m} \tag{8}$$

$$\mathbf{X^{*T}} = \begin{bmatrix} 2.96, & 8.22, & 12.58, & 16.63, & 17.04, & 13.74, & 5.50, & 3.19, & 2.42, & 7.25, & 13.04, & 16.69, & 9.50, & 6.82, & 4.56 \\ 4.72, & 3.78, & 3.25, & 2.85, & 5.50, & 8.61, & 6.67, & 8.41, & 12.01, & 9.50, & 10.96, & 9.50, & 13.50, & 15.58, & 15.52 \end{bmatrix} \mathrm{m} \tag{9}$$

$$\mathbf{X_L^T} = \begin{bmatrix} 1.0, & 5.0, & 9.0, & 13.0, & 13.0, & 9.0, & 5.0, & 1.0, & 1.0, & 5.0, & 9.0, & 13.0, & 9.0, & 5.0, & 1.0 \\ 1.0, & 1.0, & 1.0, & 1.0, & 5.0, & 5.0, & 5.0, & 5.0, & 9.0, & 9.0, & 9.0, & 9.0, & 13.0, & 13.0, & 13.0 \end{bmatrix} \mathrm{m} \tag{10}$$

$$\mathbf{X_U^T} = \begin{bmatrix} 7.0, & 11.0, & 15.0, & 19.0, & 19.0, & 15.0, & 11.0, & 7.0, & 7.0, & 11.0, & 15.0, & 19.0, & 15.0, & 11.0, & 7.0 \\ 7.0, & 7.0, & 7.0, & 7.0, & 11.0, & 11.0, & 11.0, & 11.0, & 15.0, & 15.0, & 15.0, & 15.0, & 19.0, & 19.0, & 19.0 \end{bmatrix} \mathrm{m} \tag{11}$$

The detailed values of all cases (3 models × 3 scenarios = 9 cases) are referred to Appendix.

4.3 HFSS (numerical) Comparison

The proposed method for optimal sensor deployment is formulated based on the theory of the Friis transmission, which enables the estimation of energy dissipation in far-field communication. However, the Friis transmission equation still shows limited accuracy at analyzing EM properties such as wave reflections and distortions. Thus, we adopt the HFSS simulation as a numerical validation method. HFSS, a powerful finite element method that serves as an electromagnetic solution, entails dividing a 3D construction site into small elements, and generates EM

environments. A number of microwave engineers have used the HFSS simulation tool to improve the accuracy of their antenna or radio frequency circuit designs (Kozlov and Turner 2010; Mirotznik and Prather 1997).

Figure 7(a) presents a dipole antenna model for a BLE sensor. Since a main purpose of this study is to investigate wireless energy flow in the construction site, dipole antenna models provide a sufficient means of describing EM phenomena in the BLE tracking system. In other words, the EM simulation requires only antenna models but no other components of BLE sensors. The electromagnetic radiation pattern of the dipole antenna is omni-directional; that is, the antenna radiates equal power in all azimuthal directions perpendicular to the wire axis, illustrated in Figure 7 (b). The maximum gain of the antenna is 2.01dB, which, although slightly lower than the theoretical value, is acceptable. Figure 7 (c), (d), and (e) illustrate 3D full wave models for the tracking system. BLE antennas are deployed according to Appendix, and the concrete walls are modeled with an exterior box—a simulation boundary—that truncates the EM domain. After this modeling, HFSS simulation is conducted as a numerical validation process for checking whether the proposed method produces similar results of improvement in optimizing the sensor locations for the tested conditions. The major drawback of HFSS is its high computational demand and efforts in setting up the analysis model. If the proposed method demonstrates its ability to provide comparable results with HFSS with respect to improvement in signal efficiency, it will be of significant value as the method can produce optimal (or close to optimal) results with significantly fewer resources.

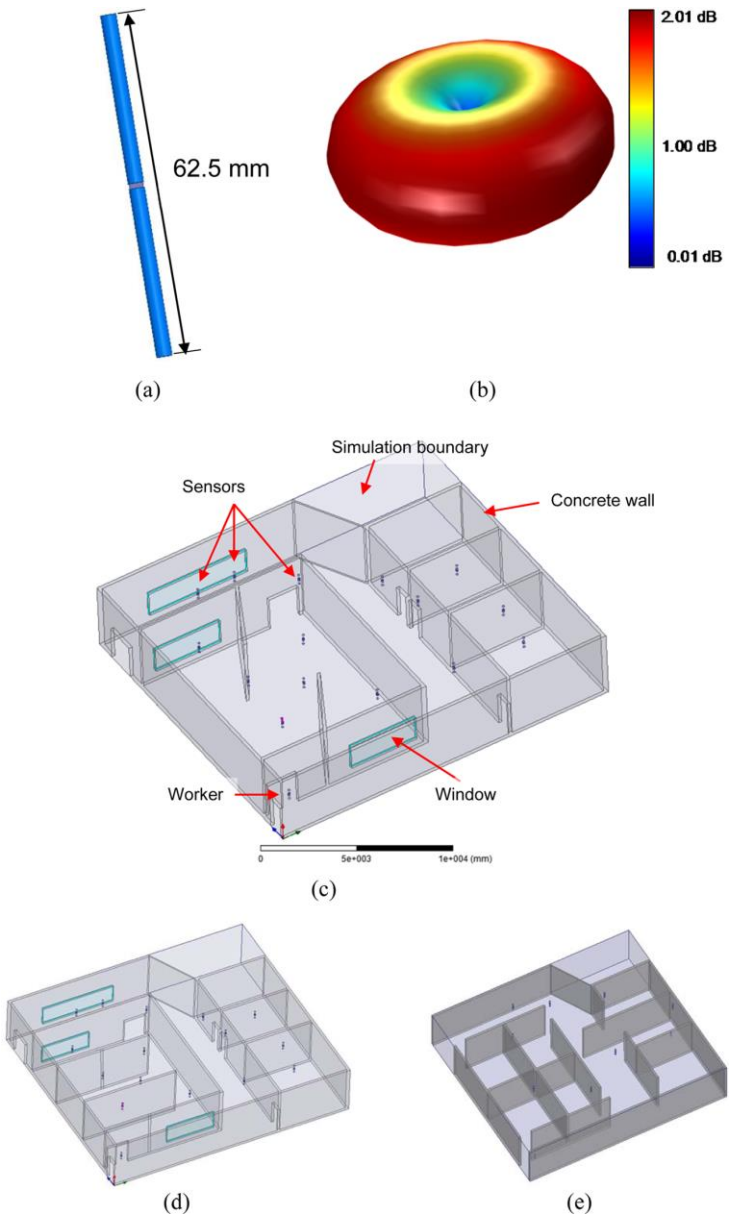

Figure 7. HFSS Simulation Model: (a) BLE Sensor Modeling (dipole antenna), (b) Antenna Radiation Pattern, (c) Full-wave Simulation Model for the Tracking System, (d) Full-wave Simulation Model 2, (e) Full-wave Simulation Model 3

4.4 Results

Based on the proposed method, the initial location matrix $\mathbf{X}_0$ is randomly generated and the optimal sensor location matrix $\mathbf{X}^*$ is determined by Eq. 7 as shown in Figure 6. By comparing the

two objective functions, which indicate the energy use for their sensor set-ups, we enable to estimate the effectiveness of the proposed method associated with sensor deployment.

Table 1 summarizes the results of the nine compared cases with respect to their objective function values between the proposed method and HFSS simulation. In all cases, the proposed method shows clear improvement in energy efficiency, ranging from approximately 7.00 % to 30.00 %. This indicates that all optimized locations could offer improved wireless communication in the perspective of electromagnetic energy. It is also worthwhile to note that the total received powers (the objective function value) from the HFSS simulation are higher than those of the proposed method because of its additional ability to account for EM environmental reflections. Since the HFSS simulation accounts for EM environmental reflections, accordingly, the results of HFSS simulation showed that the range of improvement is from 13.79 % to 42.76 %. Given the similar trend in improvement and improved signal communication for all cases, the EM analysis suggests a high correlation between the two methods and thus validates the proposed method.

Our observations suggest an interesting finding as to the ability of the proposed method with respect to signal efficiency improvement. As the HFSS results are compared with those of the proposed method, the improvement ratio between the proposed method and the HFSS simulation is under a small range of perturbation from 0.5635 to 0.5985 as shown in Figure 8. This is strong evidence of correlation that the proposed method generates similar trends of improvement as the HFSS does and thus is capable of finding optimized sensor locations with reliable energy efficiency optimization.

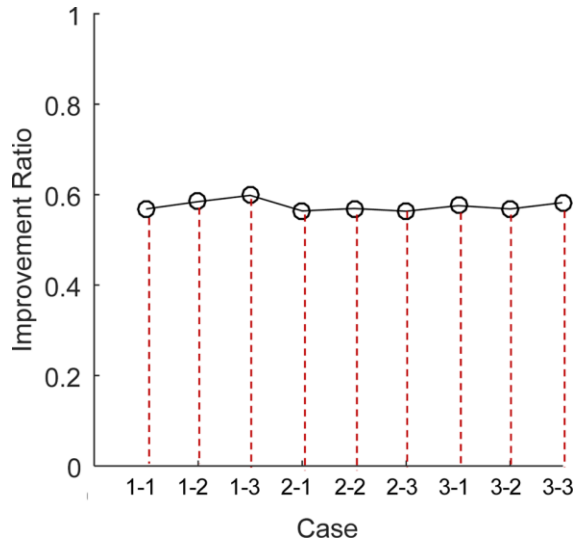

Figure 8. Improvement Ratio between HFSS Simulation and the Proposed Method

Table 1. Comparison between the Total Received Power Values of the Proposed Method and the HFSS Simulation.

	Proposed method		Improvement	HFSS simulation		Improvement
	Optimal deployment	Random deployment		Optimal deployment	Random deployment	
Case1-1	0.1893	0.1652	14.59 %	0.3534	0.2812	25.67 %
Case1-2	0.1723	0.1498	15.02 %	0.3121	0.2483	25.69 %
Case1-3	0.1341	0.1138	17.83 %	0.2766	0.2131	29.79 %
Case2-1	0.1851	0.1653	11.97 %	0.3432	0.2831	21.23 %
Case2-2	0.1690	0.1453	16.63 %	0.3012	0.2331	29.21 %
Case2-3	0.1290	0.1197	7.77 %	0.2632	0.2313	13.79 %
Case3-1	0.1769	0.1601	10.49 %	0.3134	0.2651	18.22 %
Case3-2	0.1585	0.1275	24.31 %	0.2991	0.2095	42.76 %
Case3-3	0.1249	0.1106	12.92 %	0.2511	0.2025	22.19 %

5. DISCUSSION

This study addressed the problem of sensor deployment, an issue that has been neglected in the construction industry. To address this problem, this research provided a framework for automated tracking sensor deployment. The framework integrates BIM with EM analysis: The role of BIM was to automatically extract construction site information—the parameters of sensor deployment optimization; and the role of the EM analysis was to provide solutions that validate

the proposed method. To minimize loss of signal power, we adopted a technique of maximizing the total received power as the method of analysis. The proposed method demonstrated its capability to improve power efficiency by finding the optimized sensor layout. To validate the proposed method, three BIM models were built (the portion of real-world BIM model and its two variations) and different sensing resolutions (22, 25, and 36 m^2 per sensor) were assigned for each scenario.

The proposed method formulated solutions for optimal sensor deployment that produced more received power than random sensor deployment. For the tested cases, the maximum improvement was 28.53% while the minimum improvement was 7.77%. In addition, the EM simulation results successfully confirmed the ability of the proposed method to improve signal efficiency with an optimized sensor layout. While the proposed method considered only energy dissipation under mediums, the HFSS simulation described all possible electromagnetics phenomena such as reflection and distortion. However, the effect of additional electromagnetics phenomena was not significant with respect to the outcome as the improvement ratios between the two simulation methods were consistent.

From the results of the experiments, we concluded that the proposed method could produce optimal sensor deployment as it produced comparable results to rigorous HFSS analysis. One of the most significant findings of this work is that we proposed mathematical equations in significantly compact format that could emulate the optimized effects that are obtained by HFSS. The advantage of the proposed method is its capabilities, which should facilitate the sensor deployment at sites using BIM without requiring complex and rigorous HFSS analysis for optimized sensor deployments. This study is of value to researchers because the developed method offers simplicity and remarkably improves computational speed while generating reliable results.

Although the numerical validation in this study is based on the BLE technology and its associated antenna characteristics, the same technique can be applied to other RSSI systems. For this application, the BIM-EM analysis needs to include the properties of antennas used by other systems. However, since the EM simulation requires more computing resources for analyzing a large construction site, the optimized deployment area is limited for numerical validation. In future research, we will explore a numerical technique for enhancing computing speed in the EM simulation. With faster computing, the EM simulation will become an integral part of the optimization framework.

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