On Wireless Network Infrastructure Optimization for Cyber-Physical Systems in Future Smart Buildings

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Abstract. Today, most cyber-physical systems (CPS) in smart buildings require a wireless-based network infrastructure for sensing, communication, and actuation. In such CPSs, the energy expenditure and hence battery lifetime of the wireless network infrastructure depend heavily upon the placement of the base stations (BS). However, in indoor environments, BS placement is particularly challenging due to the impact of building structures and floors/walls separations. In this paper, we study the problem of jointly optimizing BS placement and power control in buildings to prolong the battery lifetime of sensors in the CPS network infrastructure. We first show that the joint BS placement and power control problem can be formulated as a mixed-integer non-convex program (MINCP), which is NP-hard and difficult to solve especially when the network size is large. To address this difficulty, we propose a novel efficient algorithm called ECPC that targets at large-sized network infrastructures in buildings. Our theoretical analysis and numerical results show that ECPC achieves competitive solutions compared to the true optimal solutions obtained by the branch-and-bound method.

1 Introduction

Today, most cyber-physical systems (CPS) in smart buildings require a wireless network infrastructure for sensing, communication, and actuation. However, studies show that the poor battery lifetime performance of current wireless sensors is becoming a critical factor that affects the future prospect of these emerging CPSs in smart buildings. To prolong battery lifetime, there are two complementary approaches. The first one is to increase battery capacity, which had proved to be difficult over the years. The second approach is to reduce the energy expenditure. Since a wireless sensor's energy expenditure depends heavily on the distance from its associated base station (BS), BS placement optimization has become one of the most effective methods to address the battery lifetime issue.

In the literature, BS placement optimization has been studied for various types of wireless networks (see, e.g., cellular networks [1,2], sensor networks [3–5], and references therein). However, the focus of these existing work is *not* on CPS in building environments. Indeed, when the unique physical features of building

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environments are taken into consideration, BS placement optimization becomes much more challenging. In addition to the obvious change from 2-D planes to 3-D spaces, building environments have a complex impact on wireless channels: Different interior spaces (e.g., atrium, office, hallway, or basement) with different wall/floor separations yield different signal path losses and fading patterns. Also, building safety codes may impose further physical restrictions to the BS locations, which is unseen in the conventional BS placement literature. So far, it is unclear how to construct good mathematical models and optimization algorithms to capture these unique physical factors for CPS network infrastructure.

In this paper, we address the above challenges by studying the joint optimization of BS placement and power control to minimize the *uplink* transmission power of wireless sensors for CPSs in building environments. The main results of this work are as follows: i) we show that the joint BS placement and power optimization is a challenging *mixed-integer non-convex* optimization problem (MINCP), which is NP-hard and no off-the-shelf optimization methods can be readily applied; ii) to address this difficulty, we propose an efficient algorithm called ECPC (abbreviation for expansion-clustering-projection-contraction) that incorporates several novel ideas specifically designed for CPSs in buildings; and iii) we perform complexity and approximation ratio analysis for the proposed ECPC algorithm. Both our theoretical and numerical results indicate that ECPC yields competitive solutions compared to the global optimal solutions.

The remainder of this paper is organized as follows. In Section 2, we review the related work reported in the literature, putting our work in a comparative perspective. We then present our network model and problem formulation in Section 3. The proposed ECPC solution procedures, along with their numerical results, are presented in Section 4. Section 5 concludes this paper.

2 Related Work

In the literature, there has been a large body of work on BS placement for cellular networks (see e.g., [1,2]) and sensor networks (see, e.g., [3–5]). In contrast, results on BS placement in buildings remains limited and most work in this area considered performance metrics different from ours (e.g., minimum number of BSs to ensure network coverage [6–11], channel assignment/load balancing [12, 13], bit error rate minimization [14, 15], and throughput maximization [16–18]). Most of these efforts, except [18], considered problems in 2-D planes (i.e., single floor). The focus of [18], however, was on indoor propagation model evaluations and little effort was made in developing optimization algorithms to optimize BS placement. Moreover, a common problem formulation approach in [8–11, 19] is to discretize the coverage region into a set of finite candidate locations. As a result, BS placement problems were usually modeled as a mixed-integer linear programming problem (MILP), which can be readily solved by off-the-shelf integer programming solvers (e.g., CPLEX). In contrast, our model allows the region to be continuous. This leads to a much more challenging problem because there are an infinite number of BS candidate locations, implying that off-line path loss

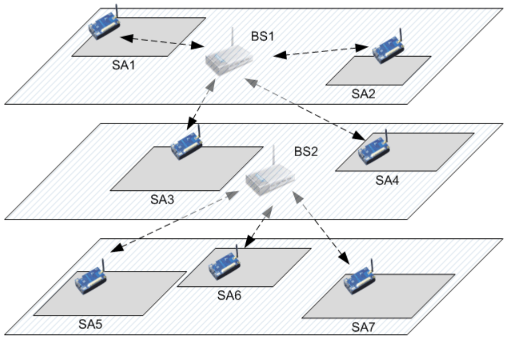

Fig. 1. An illustration of a CPS wireless infrastructure with multiple BSs and SAs in a multi-floor building

computation is no longer feasible. In our previous related works [20,21], we have proposed two non-trivial reformulation approaches to transform the problem into a mixed-integer convex program (MICP) and a mixed-integer linear program (MILP), respectively, thus enabling the use of branch-and-bound method (BB) to find a global optimal solution. However, due to the NP complexity nature of BB, the global optimization algorithms in [20,21] do not scale well as the network size increases.

3 Network Model and Problem Formulation

1) Indoor Wireless Channel Modeling. We consider a wireless CPS network infrastructure in a multi-floor building with M BSs and N sensing areas (SA), as shown in Figure 1. We use $\mathcal{N}$ to denote the set of all SAs. Here, an SA could be any subregion in the building where wireless sensors of the CPS are installed. For simplicity, we assume in this paper that M is large enough to ensure network coverage. We denote the BSs and SAs as BS1, ..., BSM and SA1,..., SAN, respectively. We further assume that co-channel interference among all BSs is negligible under a proper channel assignment and reuse scheme. The case where co-channel interference exists will be left for our future study. We use (u_i, v_i, w_i), $i = 1, \ldots, N$, to denote coordinates of the center of SA i. The length and width of SA i are denoted as L_i and W_i, respectively. Similarly, (x_m, y_m, z_m), $m = 1, \ldots, M$, denotes the coordinates of BS m, which are to be determined. Due to the practical use of building space, the BSs of a CPS network infrastructure are usually required to be mounted on the ceiling of each floor. Also, in buildings, a wireless sensor could be installed on each floor. As a result, the vertical coordinates w_i and z_m cannot be arbitrary and can only take on integer values: $1, 2, \ldots, F$, where F is the maximum number of floors.

To ensure that BS m can cover every point in SA i, we define the distance as the straight line between BS m and the point in SA i that is *furthest* away from BS m. We let h and ρ_i denote the height of each floor and the average installation height of the sensors in SA i, respectively. Then, it is not difficult to show that the distance between BS m and SA i, denoted as d_{im}, can be computed as:

$$d_{im} = [(|x_m - u_i| + \frac{1}{2}L_i)^2 + (|y_m - v_i| + \frac{1}{2}W_i)^2 + |(z_m - w_i + 1)h - \rho_i|^2]^{\frac{1}{2}}. \quad (1)$$

In this paper, we adopt the following path loss model in building environments [22]: $P_{R_m} = P_{T_i} - L_{d_0} - 10\alpha \log_{10}(d_{im}/d_0) - L_{FAF}$, where α is the path loss index and L_{FAF} denotes the path loss caused by floor attenuation factor (FAF). Moreover, numerous field tests had indicated that FAF approximately follows the following relationship [22, Table 4.4]:

$$L_{FAF} = \begin{cases} \Lambda_1 + (\varphi - 1)\Lambda_a, & \text{if } \varphi \geq 1, \\ 0, & \text{if } \varphi = 0, \end{cases} \quad (2)$$

where Λ_1 represents the FAF for a single floor separation, Λ_a represents the FAF for each additional floor, and φ denotes the number of separating floors. Combining all the earlier discussions and after converting P_{R_m}, P_{T_i}, and L_{d_0} from dB scale to a linear scale, it is not difficult to derive the following result for path loss modeling in building environments:

$$P_{R_m} = \frac{P_{T_i}}{H(z_m, w_i)\Lambda^{|z_m - w_i|} d_{im}^{\alpha}}, \quad \forall i, m. \quad (3)$$

Here, $H(z_m, w_i)$ is a step function that depends on z_m and w_i and has the following structure:

$$H(z_m, w_i) = \begin{cases} H_0, & \text{if } z_m = w_i, \\ H_1, & \text{if } z_m \neq w_i, \end{cases}$$

where $H_0 = L_{d_0} d_0^{-\alpha}$, $H_1 = L_{d_0} d_0^{-\alpha} 10^{(\Lambda_1 - \Lambda_a)/10}$, and $\Lambda = 10^{\Lambda_a/10}$.

2) QoS Requirement Constraints. To maintain the transmission data rate that satisfies a sensor's QoS requirement, a necessary condition is that the received power at the BS should be greater than a certain threshold value. We let $P_{\min}$ denote the minimum threshold value. According to (3), we have: $\frac{P_{T_i}}{H(z_m, w_i)\Lambda^{|z_m - w_i|} d_{im}^{\alpha}} \geq P_{\min}, \forall i, m$. After rearranging and letting $B_i(z_m, w_i) = H_0 P_{\min}$ if $z_m = w_i$ or $H_1 P_{\min}$ if $z_m \neq w_i$, we have

$$B_i(z_m, w_i)\Lambda^{|z_m - w_i|} d_{im}^{\alpha} - P_{T_i} \leq 0, \forall i, m. \quad (4)$$

3) BS Association Modeling. Unlike conventional wireless networks, in building environments, the channel to the nearest BS may not be the best because the nearest BS could be separated by floors, which leads to an inferior channel due to FAF. Rather than specifying a BS association rule, we model BS association as a part of the overall joint BS placement and power control optimization. For this purpose, we define the following set of binary variables:

$$\gamma_{im} = \begin{cases} 1 & \text{if SA } i \text{ is associated with BS } m, \\ 0 & \text{otherwise.} \end{cases}$$

Then, the BS association can be modeled as:

$$\sum_{m=1}^{M} \gamma_{im} = 1, \quad \forall i = 1, \ldots, N. \tag{5}$$

Considering BS association, we modify the QoS constraint in (4) as:

$$B_i(z_m, w_i)\gamma_{im} \Lambda^{|z_i - w_i|} d_{im}^{\alpha} - P_{T_i} \leq 0, \quad \forall i, m. \tag{6}$$

4) Problem Formulation. To prolong the sensor battery lifetime and ensure fairness among all SAs, we can minimize the total transmission power from all SAs. Incorporating all constraints, the joint BS placement and power optimization (BSPO) can be formulated as:

$$\textbf{BSPO:}\ \text{Minimize} \sum_{\forall i} P_{T_i}$$
$$\text{subject to Constraints in (1), (5), and (6).}$$

Since (1) and (6) are non-convex and involve integer variables, BSPO is a *mixed-integer non-convex program* (MINCP), which is NP-hard in general [23]. Further, since Problem BSPO is highly unstructured, no off-the-shelf optimization method can be readily applied. As mentioned earlier, in [20,21], we have proposed two novel reformulation strategies to transform BSPO into a mixed-integer convex program (MICP) and a mixed-integer linear program (MILP), respectively, both of which enabled the use of branch-and-bound (BB) approach to solve the problem to global optimality. The major benefit of using BB is that, upon its convergence, it *guarantees* finding a global optimal solution to the BSPO problem. However, we note that due to the NP nature of the mixed-integer problems, the convergence time of BB increases exponentially as the network size gets large. Therefore, in this paper, we focus on designing an efficient algorithm that offers competitive solutions for large-sized building networks.

4 ECPC: An Efficient Solution Approach

In this section, we propose an algorithm called ECPC (abbreviation for "expansion–clustering–projection–contraction") for large-sized building networks. In what follows, we will first present the basic idea of ECPC. Then, from Section 4.1 to Section 4.3, we present the details of each component in ECPC.

Basic Idea of ECPC: The basic idea of ECPC is motivated by the observation that the main difficulty in solving BSPO stems from: i) the FAF effect, and ii) the integrality constraints on the vertical coordinates. This observation leads us to the following idea: First, suppose that we can expand the network from the original space to an *equivalent virtual 3-D space* without floors and yet the path loss effect after expansion is equivalent, then the problem becomes much easier. This is because we can partition the SAs into M clusters in the virtual space, where SAs in each cluster are "close" to each other. Since there is no FAF effect within each cluster, it is easy to determine the optimal BS placement for each cluster. Next, we project the BS placement to the locations corresponding to the nearest floor in the virtual space and then shrink the virtual space back to the original one. As a result, we arrive at a solution to the original problem.

Clearly, the solution quality of the ECPC approach hinges heavily on the details in carrying out the expansion, clustering, projection, and contraction. As will be seen later, the expansion subtask is non-trivial and care must be taken to obtain a satisfactory performance. In the remainder of this section, we will develop these key components of ECPC.

4.1 Expansion

Let $\mathcal{S}$ and $\hat{\mathcal{S}}$ represent the original space and the expanded space, respectively. We let $e(p_i) \in \hat{\mathcal{S}}$ denote the image of the expansion mapping of point $p_i \in \mathcal{S}$. The concept of *equivalent distance* is defined as follows:

Definition 1. *For two points $p_i, p_j \in \mathcal{S}$, if the path loss effect between $e(p_i) \in \hat{\mathcal{S}}$ and $e(p_j) \in \hat{\mathcal{S}}$ is the same as that between p_i and p_j, then we call the distance $\hat{d}_{ij}$ between points $e(p_i)$ and $e(p_j)$ the equivalent distance for p_i and p_j.*

For ease of algebraic manipulations, we consider $s_{ij} \triangleq d_{ij}^2$ and $\hat{s}_{ij} \triangleq \hat{d}_{ij}^2$ rather than d_{ij} and $\hat{d}_{ij}$ directly. Under Definition 1 and the discussions in Section 3, it is not difficult to derive the following expression (details are omitted here due to space limitation):

$$\hat{s}_{ij} = \begin{cases} s_{ij}, & \text{if } w_i = w_j, \\ s_{ij} G(w_i, w_j), & \text{if } w_i \neq w_j, \end{cases} \tag{7}$$

where the term $G(w_i, w_j)$ is defined as $G(w_i, w_j) \triangleq 10^{\frac{\Lambda_1 + (|w_i - w_j| - 1)\Lambda_a}{20\alpha}}$.

Next, we need to determine the new coordinates of the SAs in $\hat{\mathcal{S}}$. A natural choice is to find a new set of coordinates $(\tilde{u}_i, \tilde{v}_i, \tilde{w}_i) \in \hat{\mathcal{S}}$, $i = 1, \ldots, N$, such that the pair-wise distance $\tilde{d}_{ij}$ is as close to $\hat{d}_{ij}$ as possible. Notice that $\tilde{w}_i$ is no longer integer-valued in $\hat{\mathcal{S}}$. This problem is closest in spirit to the classical multidimensional scaling (MDS) problem that often arises in statistics and information visualization [24]. However, we point out that classical MDS techniques cannot be applied here due to the "arbitrariness" of the MDS solutions. That is, for an optimal MDS solution, any rotation or reflection is also a valid optimal solution. This poses a problem to our ECPC approach since we not only need to determine the optimal BSs locations in $\hat{\mathcal{S}}$, but also need to recover the corresponding locations in $\mathcal{S}$. The arbitrariness of an MDS solution makes such a reversed mapping difficult. In this paper, we propose the following approach to circumvent the above MDS limitations.

We first note that in $\mathcal{S}$, there is no floor separation between SAs on the same floor. As a result, $\hat{s}_{ij} = s_{ij}$ for any two SAs i and j on the same floor. From this observation, a natural approach is to retain the horizontal coordinates of

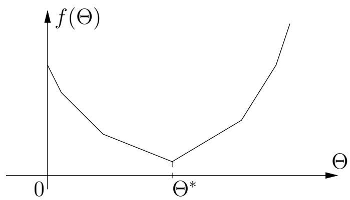

Fig. 2. An illustration of the structure of the objective function in Problem (9).

all SAs to preserve the distances between same-floor SAs. This also means that the expansion will *only* occur along the vertical direction. However, due to the nonlinear FAF effect, it is difficult to precisely model the appropriate expansion along the vertical direction. To simplify the problem, we propose to use the following linear expansion rule:

$$(\tilde{u}_i, \tilde{v}_i, \tilde{w}_i) = (u_i, v_i, w_i h\theta), \tag{8}$$

where $\theta > 1$ is a linear vertical scaling factor. Under this rule, we have $\tilde{d}_{ij}^2 = (u_i - u_j)^2 + (v_i - v_j)^2 + (w_i - w_j)^2 h^2 \theta^2$, $\forall i, j \in \{1, \ldots, N\}, w_i \neq w_j$. Next, we want to find the optimal θ such that the total difference between $\tilde{d}_{ij}^2$ and the equivalent squared distance $\hat{s}_{ij}$ is minimized. This can be formulated as the following minimization problem after some algebraic manipulations (details are omitted due to space limitation):

$$\underset{\Theta \geq 0}{\text{Minimize}} \sum_{i,j \in \Omega} |a_{ij}\Theta + b_{ij}|, \tag{9}$$

where $a_{ij} \triangleq (w_i - w_j)^2 h^2$, $b_{ij} \triangleq (u_i - u_j)^2 + (v_i - v_j)^2 - \hat{s}_{ij}$, $\Theta \triangleq \theta^2$, and $\Omega \triangleq \{i, j \in \{1, \ldots, F\} : i < j, w_i \neq w_j\}$. In (9), Θ is the decision variable.

For convenience, let $f(\Theta)$ denote the objective function of Problem (9). Since $f(\Theta)$ is convex and piece-wise linear, $f(\Theta)$ has a structure as depicted in Figure 2. Due to this special structure, we can devise a *polynomial-time* line search algorithm. First, it is easy to see that the minimizer of Problem (9) must be located at the non-differentiable points of $f(\Theta)$ because all other points have non-zero derivatives. The non-differentiable points of $f(\Theta)$, denoted as Θ_{ij}^{ND}, can be easily computed as $\Theta_{ij}^{\text{ND}} = -b_{ij}/a_{ij}$, for all $(i, j) \in \Omega$. Also, noting that $\Theta \geq 0$, we only need to consider the set of non-negative Θ_{ij}^{ND}. Let the set Ω_+ be defined as $\Omega_+ = \{(i, j) \in \Omega : \Theta_{ij}^{\text{ND}} \geq 0\}$. For convenience, we re-index the elements in Ω_+ such that $\Theta_1 \leq \ldots \leq \Theta_{|\Omega_+|}$. Then, solving Problem (9) becomes finding the optimal index, denoted as I^*, from Ω_+. Let $\mathcal{I} = \{I_1, \ldots, I_2\}$ be the initial index set, where $I_1 = 1$ and $I_2 = |\Omega_+|$. Then, our algorithm is based on the following result:

Proposition 2. *Let I_1' and I_2' be two indices with $I_1 \leq I_1' < I_2' \leq I_2$. If $f(\Theta_{I_1'}^{\text{ND}}) > f(\Theta_{I_2'}^{\text{ND}})$, then $I_1' \leq I^* \leq I_2$. On the other hand, if $f(\Theta_{I_1'}^{\text{ND}}) < f(\Theta_{I_2'}^{\text{ND}})$, then $I_1 \leq I^* \leq I_2'$.*

Proof. By contradiction, suppose that when $f(\Theta_{I_1'}^{\mathrm{ND}}) > f(\Theta_{I_2'}^{\mathrm{ND}})$, we have $I_1 \leq I^* < I_1'$. Since I^* is the optimal index, we have $f(\Theta_{I^*}^{\mathrm{ND}}) < f(\Theta_{I_2'}^{\mathrm{ND}})$. Also, since $\Theta_{I^*}^{\mathrm{ND}} \leq \Theta_{I_1'}^{\mathrm{ND}} < \Theta_{I_2'}^{\mathrm{ND}}$, we have that $\Theta_{I_1'}^{\mathrm{ND}}$ can be represented as a convex combination of $\Theta_{I^*}^{\mathrm{ND}}$ and $\Theta_{I_2'}^{\mathrm{ND}}$. By the convexity of $f(\cdot)$, we have $f(\Theta_{I_1'}^{\mathrm{ND}}) < \max\{f(\Theta_{I^*}^{\mathrm{ND}}), f(\Theta_{I_2'}^{\mathrm{ND}})\} = f(\Theta_{I_2'}^{\mathrm{ND}})$, contradicting the assumption that $f(\Theta_{I_1'}^{\mathrm{ND}}) > f(\Theta_{I_2'}^{\mathrm{ND}})$. This completes the proof of the first half of the lemma. The other half of the lemma can also be proved similarly. □

Proposition 2 implies that we can reduce the index set by ignoring either the indices that are larger than I_2' or smaller than I_1', depending on the comparison between $f(\Theta_{I_1'}^{\mathrm{ND}})$ and $f(\Theta_{I_2'}^{\mathrm{ND}})$. Thus, we can choose I_1' and I_2' in the following *dichotomous* way: for $\mathcal{I} = \{I_1, \ldots, I_2\}$, we let $I_1' = \lfloor \frac{I_1+I_2}{2} \rfloor$ and $I_2' = \lfloor \frac{I_1+I_2}{2} \rfloor + 1$. This process continues until there are only two elements left in the index set. Then, the optimal index I^* can be found by simply comparing the objective values at these two indices. In finding I^*, the computation complexity is dominated by the evaluation of $f(\cdot)$. Since we reduce the size of the index set by approximately half in each iteration, we only need $O(\log_2(|\Omega_+|))$ objective value evaluations, which is evidently polynomial-time.

4.2 Clustering

To perform clustering, we first construct a matrix $\tilde{\mathbf{D}}$ in $\hat{\mathcal{S}}$, where the entry $[\tilde{\mathbf{D}}]_{ij}$ in the i-th row and the j-th column represents the distance between SA i and SA j. Initially, we treat each SA in $\mathcal{S}$ as an individual cluster. Then, the clustering proceeds in the following "bottom-up greedy" fashion. In each iteration, we merge two closest clusters (could be two SAs, two clusters, or a cluster and an SA) into a new cluster. Next, update the new distances of the remaining clusters to the new cluster. In the next iteration, we repeat the merging based on the updated $\tilde{\mathbf{D}}$. After each iteration, the number of clusters in $\hat{\mathcal{S}}$ is reduced by 1. This process continues until there are M clusters remaining.

Different strategies could be employed in updating $\tilde{\mathbf{D}}$ in each iteration. For example, the distance between an existing cluster E_1 and a new cluster E_2 could be computed using the maximum distance between the elements of each cluster, i.e., $d(E_1, E_2) = \max\{d(p_1, p_2) : p_1 \in E_1, p_2 \in E_2\}$, or the average distance between the elements of each cluster, i.e., $d(E_1, E_2) = \frac{1}{|E_1||E_2|} \sum_{p_1 \in E_1} \sum_{p_2 \in E_2} d(p_1, p_2)$. We refer to these two strategies as "updating with maximum distance" (UMD) and "updating with average distance" (UAD), respectively.

After clustering, we need to determine the optimal BS location for each cluster. Since there is no floor separation in $\hat{\mathcal{S}}$, each SA's power is solely determined by the distance to the BS in the cluster. Thus, we only need to find an optimal BS location to minimize a certain metric related to the distance from the BS to the SAs. Let $\mathcal{C}_m$ denote the m-th cluster. Let $(\tilde{x}_m, \tilde{y}_m, \tilde{z}_m) \in \hat{\mathcal{S}}$ denote the location of the m-th BS for the m-th cluster. Then, the optimal BS location can be formulated as the following optimization problem (details are omitted due to space limitation):

$$\begin{array}{ll} \text{Minimize} & \sum_{i=1}^{|\mathcal{C}_m|} s_{im}^{-\frac{\alpha}{2}} \\ \text{subject to} & s_{im} \geq (\tilde{x}_m - \tilde{u}_i)^2 + (\tilde{y}_m - \tilde{v}_i)^2 \\ & \quad +(\tilde{z}_m - \tilde{w}_i)^2, \ \forall (\tilde{u}_i, \tilde{v}_i, \tilde{w}_i) \in \mathcal{C}_m. \end{array} \tag{10}$$

The decision variables in (10) are $(\tilde{x}_m, \tilde{y}_m, \tilde{z}_m)$ and s_{im}. It can be easily verified that (10) is a standard second-order cone program (SOCP), which can be efficiently solved by standard convex programming solvers.

4.3 Projection and Contraction

Since the expansion in ECPC occurs only along the vertical direction, the projection of the m-th BS can be easily done by fixing $\tilde{x}_m$ and $\tilde{y}_m$ and changing the value of $\tilde{z}_m$ to the vertical coordinate of the nearest floor. Then, the contraction of the m-th BS location back to the $\mathcal{S}$ can be done by simply letting $x_m = \tilde{x}_m$, $y_m = \tilde{y}_m$, and $z_m = \tilde{z}_m / h\theta^*$. Here, θ^* is the optimal expansion factor obtained earlier by solving Problem (9).

4.4 Complexity and Approximation Ratio Analysis

In this section, we first analyze the computational complexity of the ECPC algorithm. As mentioned earlier, in ECPC, to determine the expansion ratio Θ, we need $O(\log_2(|\Omega_+|))$ times of objective function evaluations. Note that $|\Omega_+|$ is on the order of $O(N^2)$. For partitioning the N SAs into M clusters, exactly $N - M$ times of groupings and updates are needed. The complexity of solving M SOCP in the form of (10) is $O(M\sqrt{N/M}) = O(\sqrt{NM})$ [25]. Finally, we need exactly $2M$ iterations in performing projection and contraction. Thus, combining all the above discussions, we have the following result, which clearly shows that the ECPC scheme is a polynomial-time algorithm:

Proposition 3. *The computational complexity of the proposed ECPC scheme is* $O(2\log_2 N + 2M + \sqrt{NM})$.

Next, we analyze the approximation ratio of the ECPC algorithm. First, we note that the dominant source error comes from the expansion step, in which we only use a linear expansion factor to model the complex relationship in the equivalent space, which is obviously nonlinear. The inexact expansion will in turn lead to erroneous group in the clustering stage, which may associate an SA with a BS that has an inferior channel quality. However, a nice feature of the ECPC scheme is that all the inexact expansions only occur between SAs in different floors. Based on this insight, we can derive the following approximation ratio bound for the ECPC algorithm:

Theorem 4. *The approximation ratio of the proposed ECPC scheme is upper bounded by*

$$1 + \frac{|\Omega|}{N} \left(\frac{F^2 h^2 + x_{\max}^2 + y_{\max}^2}{\min_{(i,j)\in\mathcal{N}} d_{ij}} \right)^{\alpha}. \tag{11}$$

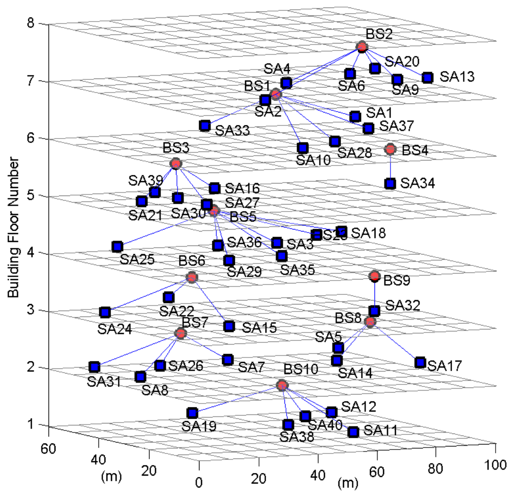

Fig. 3. The solution for a 40-SA 10-BS network under the ECPC approach

Due to space limitation, we relegate the proof details of Theorem 4 to [26]. It is worth pointing out that the approximation ratio bound in (11) is a worst case upper bound. In practice, the ECPC algorithm usually works much better than the bound in (11), as evidenced by the numerical examples presented in the next subsection.

4.5 Numerical Results

To see the efficiency of ECPC, we use a network with 40 SAs in a 7-story building as an example. The building's length, width, and per-floor height are 100, 60, and 3 meters, respectively. We use 10 BSs to serve the entire network. The maximum transmission power for each sensor is 1 W. The minimum received power threshold for each sensor is -90 dBm. The path loss exponent is 4. Note that the BB approach in [20, 21] is not a practical choice for such a large-sized network. Under ECPC, however, it only takes 9.98 seconds to find a solution, which shows the efficiency of ECPC. The BSs placement and the BS-SA associations are illustrated in Figure 3 (for better visibility, we only plot the centers of the SAs in Figure 3).

To compare the gap between ECPC solutions and the objective values obtained under the BB approach in [20, 21], we randomly generated 50 networks with 3 BSs, 10 SAs, in a 3-story building. As mentioned earlier, a major feature of BB is that it guarantees finding an optimal solution to the original problem. For these 50 examples, the mean objective value of ECPC and the mean of the true optimal values are 0.4181 W and 0.2073 W, respectively. The standard deviation are 0.3252 and 0.1313 W, respectively. Further, there are 36 (72%) examples where the ECPC objective value is less than twice of the true optimal objective value, including 8 examples (16%) where two solutions coincide . The mean of normalized objective values (ECPC divided by true optimum) is 1.995 (with a standard deviation of 0.7261). Thus, we can see that ECPC offers competitive results compared to true optimal solutions.

5 Conclusion

In this paper, we investigated the joint BS placement and power control optimization to prolong the sensor battery lifetime for cyber-physical systems (CPS) in building environments. We show that the joint BS placement and power control problem can be formulated as a mixed-integer non-convex program, which is difficult to solve to global optimality for large-sized networks even after convexification and linearization. To address this difficulty, we developed an efficient algorithm called ECPC that incorporates several novel ideas specifically designed for CPSs in building environments. We conducted both theoretical and numerical analysis for the ECPC scheme. Our numerical results showed that ECPC provides competitive solutions compared to the true optimal solutions obtained by the branch-and-bound based approach used in our previous work. We note that CPS network infrastructure in smart buildings is an important and yet under-explored area. Possible future directions include to study the trade-off between power and other performance metrics, such as throughput, delay, etc.

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