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Wireless Charging for Indoor Drones: An Optimal Placement Strategy.

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Abstract

Today, we can easily utilize drones to perform a wide range of tasks, whether by employing semi or fully autonomous flight modes or controlling them remotely. However, a significant drawback of current drone deployment methods is the limited operational time due to battery constraints. To address the battery limitations of indoor drones, a solution is proposed wherein wireless chargers are strategically placed within the coverage area of the drones' flight paths. This research paper presents an optimization algorithm that determines the ideal number of wireless charging stations needed to cover the entire area to ensure continuous charging capability throughout the flight. This work proposes an optimization framework that effectively solves this non-deterministic polynomial-time hardness problem. The algorithm is assessed by comparing its results with those of other algorithms. To evaluate the performance of our proposed approach, we compared several recent algorithms. Our algorithm has demonstrated superior speed compared to other algorithms.

Keywords: Wireless Charging, Optimization, Drones.

1 | Introduction

Uncrewed Aerial Vehicles (i.e., drones), which can perform tasks without human intervention, are used in a wide range of applications, from manufacturing and logistics [1,2] to healthcare [3] and exploration [4]. Drones are used in logistics and warehousing to move goods around the facility, pick and pack orders, and track inventory [5,6]. They can also be used for tasks such as palletizing and depalletizing, loading and unloading trucks, and sorting packages [7,8]. The use of drones in warehouses is still relatively new but proliferates in warehouses, offering numerous benefits such as increased efficiency, cost savings, and improved safety.

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Like any other battery-powered device, drones are limited by their battery life [9]. Depending on the drone's size, weight, and battery capacity [10], its flight time can range from a few minutes to a few hours. The limited battery life can be a significant challenge, particularly for commercial or industrial applications [11], where drones must fly for extended periods to cover large areas or complete tasks [12]. One solution to the short battery life problem is to use multiple batteries or to swap out depleted batteries with fully charged ones [13]. This method can help extend the drone's flight time without waiting for the battery to recharge. Another solution is using a charging system to charge the drone's battery in the field. These charging systems can be solar-powered, portable, or vehicle-mounted, allowing the drone to recharge its battery while operating [14]. This solution is beneficial when the drone needs to operate in remote areas where access to power sources is limited. However, there are some limitations to these solutions. Using multiple batteries or swapping out batteries can add weight and cost to the drone, reducing its payload capacity and increasing its overall cost.

Wireless charging is a promising solution for nonstop indoor drone flying. [15]. With wireless charging, the drone can continuously fly and recharge its batteries simultaneously without requiring a manual battery swap or docking [16]. The principle behind wireless charging is that a power source generates an electromagnetic field [17], which a receiver coil receives in the drone. The received energy is used in magnetic resonance or inductive charging to charge the drone's batteries. One of the challenges of wireless charging is limited coverage [18,19], which can be a significant obstacle for indoor drone applications. The range of wireless charging is limited by various factors, such as the distance between the transmitter and receiver, the power of the transmitter, and the efficiency of the charging process [20,21]. Also, wireless charging technologies can be expensive, so optimizing their use is important to minimize costs. One way to do this is to ensure that the wireless charging capabilities are available at the necessary points in the environment without wasting resources on areas where they are not needed.

Determining the minimum number of wireless chargers needed in an indoor warehouse requires considering various factors, including the size of the area to be covered, the number of drones to be charged, the desired charging speed, and the wireless charging technology being used [22,23]. In general, the optimal placement of anchor sensors in two dimensions in a way that a single static target has access to at least one of the sensors is thoroughly studied [24,25]. Furthermore, determining an optimal anchor location configuration for a three-dimensional indoor space is a well-known Non-deterministic Polynomial-time Hardness (NP-Hard) problem [26,27,28].

This paper aims to determine the optimal number of wireless charger nodes needed to ensure comprehensive coverage of the indoor space. In other words, the objective is to ensure that a drone always has access to at least one wireless charger while in flight. All being said, the contribution of this work is twofold: this is a work that proposes a distributed wireless chargers' placement to enable recharging capability for drones at any point in the indoor environment, but also, this is a work that considers the minimization of the number of these wireless chargers and manages to find optimal solutions in an efficient and timely manner.

2 | Literature Review

Wireless charging placement optimization shares similarities with the Wireless Mesh Network (WMN) problem and Gateway Node Placement (GNP) problem. WMN [29] and GNP [30] have been proven to be in the class of NP-hard problems. Consequently, previous work has focused on providing efficient heuristic-based and meta-heuristics-based algorithms to find near-optimal solutions to the problem. Typically, the GNP problem is defined in terms of an Integer Linear Program (ILP) defined to find a minimum number of gateway nodes for a given WNM backbone network that satisfies a given set of Quality-of-Service (QoS) constraints [31,32]. Three QoS constraints that influence network performance are commonly considered. These include the communication delay, relay load, and gateway throughput.

Bacanli et al. [33] aim to tackle the issue of positioning charging stations in a UAV-assisted opportunistic network by utilizing three distinct clustering techniques: K-means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and random clustering. It was observed that employing K-means clustering with three clusters to determine the charging station locations yielded superior results compared to randomly selecting the locations regardless of the routing strategy used between nodes. Wang et al. [34] propose beacon placement algorithms that leverage the floor plan geometry with provable theoretical guarantees. Firstly, a greedy algorithm is presented, utilizing the properties of sub-modular functions. Additionally, a random sampling algorithm is proposed, strategically placing beacons to ensure all targets' localization. Wang et al. [35] focus on addressing the problem within a constraint network model, where the traffic demand is distributed non-uniformly, and the potential positions for mesh routers (MRs) are predetermined. After formulating the MR placement problem, the authors conduct theoretical analysis to validate the traffic demand and identify the optimal position for the Internet gateway. Li et al. [36] explore the challenge of cooperatively deploying chargers and sink stations in wireless sensor networks while minimizing their number. The authors propose a near-optimal algorithm that tackles this problem by breaking it down into two subproblems and optimizing the deployment of chargers and sink stations iteratively.

Ding et al. [28] investigate the problem of determining the optimal placement of wireless chargers considering deployment costs. The authors approach the problem from two perspectives: the first focuses on minimizing costs in charger placement, while the second aims to maximize the charging level in charger placement. He et al. [37] examine the deployment of wireless chargers in a network to minimize their number while ensuring that any static node positioned in the network can receive enough wireless energy to operate continuously. Li et al. [38] examine the problem of minimal charger placement to deploy the fewest chargers while ensuring sufficient recharge power for battery-free nodes to sustain their operation. To tackle this challenge, the network area is divided into grids, and the researchers develop both greedy and efficient heuristics to address this problem effectively.

Having considered the existing literature, it is evident that certain gaps persist in the current body of knowledge. As a result, this research endeavors to address these deficiencies, and the primary objective of this study is to ascertain the ideal quantity of wireless charger nodes essential for achieving complete coverage throughout the indoor environment.

3 | Optimization Formulation

To solve this Mixed Integer Programming (MIP) problem, we modified the MIP problem to incorporate all the constraints. A modified WMN planning problem presented in [39] can be defined where let $S = \{1, 2, ..., n\}$ denotes the set of possible positions where to install charger devices and $I = \{1,2, ..., m\}$ is the set of positions in the warehouse for drones that can fly (i.e., receiving positions in the warehouse). The cost associated with installing an MR in $s_j \in S$ is denoted by c_j, while the additional cost required to install a (Mesh Access Points) MAP in $s_j \in S$ is denoted by p_j. Therefore, the total cost for installing a MAP in S is given by $c_j + p_j$. The connectivity parameters define which network elements can be connected through wireless links. They depend on $i \in I$ and $s \in S$ locations and can be determined by using proper propagation prediction tools. For each pair $i \in I$; $j \in S$, the coverage parameters are considered a_{ij}.

$$a_{ij} = \begin{cases} 1 & if\ a\ MAP\ or\ MR\ in\ S_j\ covers\ i \\ 0 & otherwise \end{cases}$$

the wireless connectivity parameters b_{ij}:

$$b_{ij} = \begin{cases} 1 & if\ S_j\ and\ i\ can\ be\ connected\ with\ a\ link \\ 0 & otherwise \end{cases}$$

the decision variables of the problem include i assignment variables x_{ij},

$$x_{ij} = \begin{cases} 1 & if\ i\ is\ assigned\ to\ s_j \\ 0 & otherwise \end{cases}$$

installation variables z_j:

$$z_j = \begin{cases} 1 & if\ a\ MAP\ or\ a\ MR\ is\ installed\ in\ S_j \\ 0 & otherwise \end{cases}$$

wireless connection variables y_{jl}, $\forall j, l \in S$:

$$y_{jl} = \begin{cases} 1 & if\ there\ is\ a\ wireless\ link\ between\ S_j\ and\ l \\ 0 & otherwise \end{cases}$$

and finally, flow variables f_{jl} which denotes the traffic flow routed on a link j, l), where the special variable f_{jN} denotes the traffic flow on the wired link between MAP_j and the backbone network. Accordingly, the problem can be formulated as follows in this case, and wired backbone connection variable w_{jN} will be ignored.

$$min \sum_{j \in S} c_j z_j + p_j w_{jN}$$

Here, $\forall i \in I$ & $\forall j, l \in S$, Subject to:

$$\sum_{j \in S} x_{ij} \tag{1}$$

$$x_{ij} \le z_i a_{ij} \tag{2}$$

$$y_{jl} \le z_j, y_{jl} \le z_I, y_{jl} \le b_{jl} \tag{3}$$

$$x_{ij}; z_j; y_{jl} \in \{0,1\} \tag{4}$$

The objective function accounts for the total cost of the network including installation costs c_j and costs p_j.

Constrains (1) guarantee full coverage of all $\forall i \in I$, while constraints (2) are coherence constraints assuring respectively that $i \in I$ can be assigned to S_j only if a device is installed in j and if i is within the coverage set of j. Constraints (3) defines the existence of a wireless link between S_j and S_l, depending on the installation of nodes in j and l and wireless connectivity parameters b_{jl}. Constraints force the assignment of a i to the best j in which a MAP or MR is installed, while constraints (4) restrict the decision variables to take binary values. The resulting model includes the set of $s^* \in S$ which covers $\forall i \in I$.

Also, a modified GNP problem presented in [31,40] can be defined without considering QoS constraints. For each WMN generated, a network topology graph, $G = (V, E)$, can be constructed and used for analysis. The topography network is inconsequential in our specific case since the warehouse is a straightforward cube shape. In the literature for RNPs [24, 27], the set of vertices (V) in a graph consists of mesh clients and mesh routers. The edges (E) represent connectivity, where: 1) for two router nodes to be connected, they must be in their communication range, and 2) the client/router edge is added when the client is in the communication range of a router.

In this case, a WMN for the RNP problem [30] is defined as a set of interconnected devices in a universe $U = S \cup I$, where $S = \{1,2,\dots,n\}$ is a set of n mesh router nodes and $I = \{1,2,\dots,m\}$ is a set of m

mesh clients. The r_i represents the i^{th} mesh router and consists of a tuple $(r_i, \gamma_i, \Upsilon_i)$ where $r_i = (x_i, y_i) \in$

S, is the position of the router node, γ_i is its nominal communication range, and Υ_i is the circle representing its radio coverage centered at the r_i position with radius γ_i for $i \in \{1,2,\dots,n\}$. A binary variable a_i is used to indicate if a corresponding mesh router $s_i \in S$ has been selected as a gateway. For $i \in I$ and $s \in S$:

$$x_i = \begin{cases} 1 & if\ node\ s_i \in\ S\ is\ selected\ as\ a\ gateway \\ & 0\ \ otherwise \end{cases}$$

In order to represent a router node assignment to a gateway, a binary variable $b_{i,j}$ is used. Data traffic generated by each router node will be served by a single gateway.

$$b_{i,j} = \begin{cases} 1 & if\ node\ i_j\ is\ assigned\ to\ gateway\ s_i \\ & 0\ \ otherwise \end{cases}$$

Finally, the objective function for the GNP problem is defined as:

$$min \sum_{i}^{n} x_i$$

Subject to:

$$\| r_i - r_j \| < min\ \gamma_i, \gamma_j \quad (1)$$

$$\forall v_j \in V, \forall v_i \in I: \sum_{v_i \in I} b_{i,j} = 1 \quad (2)$$

$$\forall v_j \in V, v_i \in I: \ bi, j \ \leq xi \quad (3)$$

$$\forall v_j \in V \ \& \ \forall v_i \in I: \ x_i; \ b_{i,j} \in \{0,1\} \quad (4)$$

The ILP searches for the optimal value for gateway assignment, minimizing their number. The condition defined in Eq. (2) ensures that each router node is only assigned to one gateway. The inequality specified in Eq. (3) guarantees that a node i_j is only assigned to a node that has been selected as a gateway. The constraints defined in Eq. (4) indicate that x_i and $b_{i,j}$ are binary variables. This ILP formulation for the GNP problem is NP-hard since it can be reduced to the minimum set cover problem [25,41].

In this study, to add realism to our study, we introduce the constraint that chargers cannot be installed on the floor. Furthermore, it is reasonable to make an assumption of a 4-meter height for the warehouse, considering the typical dimensions observed in real-world warehouses. Our analysis considers the ceiling and walls as the feasible locations *(S)* for the chargers. The designated drone space *(I)* represents the area within the environment where the drone can freely navigate. The optimization constraint is employed to ensure that the resulting charger configuration effectively covers all points within the set *I*, guaranteeing accessibility to at least one wireless charger for each point with a radius of γ. In this case, Python was employed to simulate and assess the performance of our proposed scheme. Algorithm 1 provides both pseudocode and an implementation for the algorithm. Initially, the code generates coordinate points for the warehouse area, computing the Euclidean distances (D_{ik}) between these points. Constraints are established for each node in the range of points outside the warehouse; it checks if the Euclidean distance between the point inside the warehouse *(I)* (indexed by i) and the point outside the warehouse *(S)* (indexed by k) is less than or equal to γ. If it is, the index k is appended to the list K. After checking all the points outside the warehouse, the function calculates the product of the binary variable x_k and the sum of the distances of the points in *K*. It ensures that the resulting sum is greater than or equal to 1, indicating that some points have a binary variable value of 1, ensuring the existence of a charger within a distance of γ from that specific node. This step effectively ensures that each point inside the warehouse is covered by at least one charger placed within a radius of γ positioned within a predefined radius. The subsequent step involves setting the binary variables corresponding to the designated points in the warehouse. In the next section, we will present the performance evaluation outcomes conducted on our optimization framework.

Algorithm 1. Placement Optimization Algorithm

Algorithm 1: Placement Optimization Algorithm

Input: Warehouse Dimensions (X, Y, Z), wireless charger range of operation (γ).
Output: Optimal Charger placement with coverage over the entire room (x).
Initialization;
Organize the lists of coordinates to differentiate between internal and external points.
Arrange possible charger positions set $(S \leftarrow n)$,
Arrange receiving positions set $(I \leftarrow m)$
while *x is being constructed* **do**
  Arrange *Obj Func*;
    return $\sum_{i=1}^{n} x_i$ for k in S;
  Arrange *Cons(i, k)*;
  for *s_k in S* **do**
    Compute the Euclidean distance between two points i and s_k, $\forall i \in I$;
    if $D(i, s_k) <= \gamma$ **then**
      keep k in K;
    end
    Compute the product of the binary variable x_k and the sum of the distances of the points in K.
    $ConsVar = (\sum_k \sum_i D(i, s_k) * x_k)$, $\forall i \in I$ & $\forall k \in K$;
    return $ConsVar >= 1$;
    It indicates that one (some) point(s) have a binary variable value of 1, ensuring the existence of a charger within a distance of 5 from that specific node.
  end
end

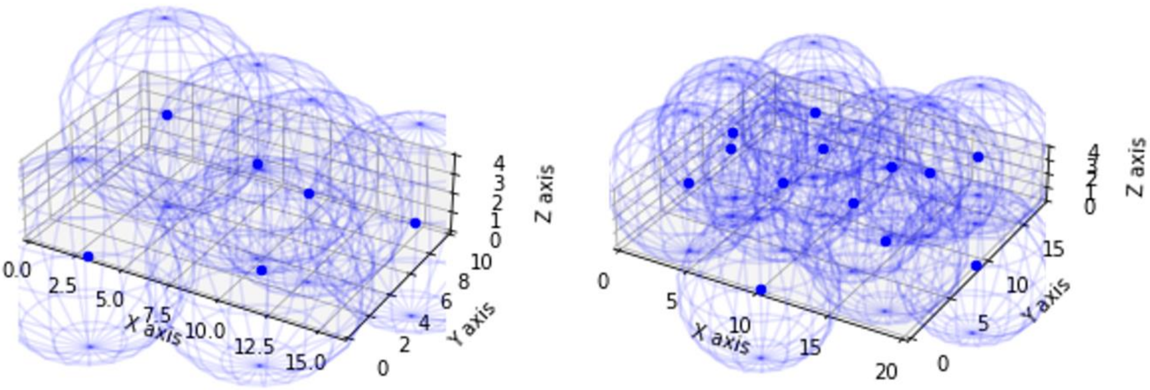
4 | Results and Evaluations

In this section, the performance evaluation results of the algorithm are presented. We conducted a comparison between our algorithm and the theoretical approach in scenarios with smaller room dimensions, where the theoretical approach, although capable of determining the optimal placement, exhibited slower performance. This finding reinforces the proposed algorithm's reliability, assuring its applicability to larger room dimensions and faster performance.

Table 1 displays the outcomes of the proposed algorithm across various room dimensions. It is crucial to recognize that the resolution to each problem may not be singular and can vary depending on the algorithm's combination and assortment of constraints. We present the outcomes for a selection of warehouse dimensions, considering large-scale scenarios. We determine the optimal number of wireless chargers for each room size needed to achieve complete coverage while acknowledging that multiple solutions may exist. Figure 1 illustrates the arrangement of wireless chargers in two different scenarios. In (a), we have a room with dimensions of 16×10×4, while in (b), the room has dimensions of 20×18×4. The figure visually represents the optimal placement strategy for the wireless chargers in each room configuration.

Table 1. Result of the proposed algorithm.

Room dimensions	Number of chargers	(x,y,z) of placement	# of variables	# of constraints
10,10,4	4	(2, 5, 4), (3, 0, 1), (5, 10, 1), (10, 5, 1)	282	91045
16,10,4	6	(3, 0, 0), (3, 7, 4), (9, 5, 4), (9, 10, 0), (12, 0, 2), (16, 7, 2)	396	213301
16,16,4	9	See Appendix	546	490501
20,18,4	13	See Appendix	704	908277
20,20,4	14	See Appendix	762	1098885
27,27,4	27	See Appendix	1217	3288065
30,24,4	26	See Appendix	1208	3220277



(a) (b)

Fig. 1. Optimal placement of the wireless chargers: (a) room with 16 × 10 × 4 dimension; (b) room with 20 × 18 × 4 dimension.

5 | Conclusion and Future Research

This article introduces a solution to address the limited battery life of drones, allowing for uninterrupted flights through the utilization of wireless charging technology. As this fall within the NP-Hard category of optimization problems, we have presented our algorithm, which efficiently and promptly finds a solution and has superior speed compared to other algorithms [42]. While the proposed system allows drones to recharge while in flight or while quickly hovering, without the need to deviate from their primary mission path, it has limitations due to certain real assumptions and needs more sensitivity analysis to understand the robustness of the solution.

For future research, conducting a site survey to identify areas of drone operation and wireless charging requirements would optimize the placement of wireless chargers. Based on the survey findings, the optimal placement of chargers and the required power output can be determined, ensuring that the drones can recharge their batteries as needed. To further improve the system, it is recommended to consider real assumptions such as capacity constraints of the hubs and apply QoS constraints in the sense of the strength of wireless charger signals to ensure a specific strength. This guarantees a continuous and uninterrupted charging process, minimizing any potential interruptions or disruptions. Incorporating a cost function into the optimization process is advisable for future investigations, considering the variations in installation costs across different warehouse areas. This cost function would enable the consideration of installation expenses when determining the optimal locations for charging stations, accounting for the differing costs associated with each specific location within the warehouse. Also, conducting sensitivity analysis could be an area for further exploration in future research endeavors, enabling a more comprehensive understanding of the solution's robustness and performance under various conditions.

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Appendix: Result of the proposed algorithm

Room Dimensions	Number of Chargers	(x,y,z) of Placement
16,16,4	9	(3, 3, 4),(3, 8, 4),(3, 13, 4),(8, 3, 4),(8, 8, 4),(8, 13, 4),(13, 3, 4),(13, 8, 4),(13, 13, 4)
20,18,4	13	(0, 13, 2),(3, 3, 4),(3, 8, 4),(5, 15, 4),(8, 6, 4),(8, 11, 4),(10, 0, 0) , (12, 18, 0), (13, 6, 4) , (13, 11, 4) , (17, 3, 4) , (17, 15, 4) , (20, 9, 0)
20,20,4	14	(3, 7, 4),(3, 12, 4),(3, 17, 4),(4, 0, 0),(8, 7, 4),(8, 12, 4),(8, 17, 4),(11, 0, 0), (13, 7, 4),(13, 12, 4),(13, 17, 4),(17, 3, 4),(20, 9, 0),(20, 16, 0)
27,27,4	27	(0, 10, 0),(0, 22, 0),(3, 3, 4),(3, 15, 4),(5, 27, 2),(6, 7, 4),(6, 19, 4),(7, 13, 4), (9, 0, 0),(10, 11, 4),(10, 22, 4),(11, 6, 4), (11, 16, 4),(14, 27, 0),(15, 9, 4), (15, 14, 4),(15, 19, 4),(16, 3, 4),(19, 7, 4),(19, 22, 4),(20, 12, 4),(20, 17, 4), (23, 0, 0), (23, 27, 0),(24, 7, 4),(24, 20, 4),(27, 13, 0)
30,24,4	26	(0, 4, 0),(0, 10, 0),(0, 17, 0),(4, 24, 2),(7, 3, 4),(7, 8, 4),(7, 13, 4),(7, 18, 4), (12, 0, 0),(12, 7, 4),(12, 12, 4),(12, 17, 4), (12, 24, 0),(17, 7, 4),(17, 12, 4), (17, 17, 4),(19, 0, 0),(19, 24, 0),(22, 7, 4),(22, 12, 4),(22, 17, 4),(26, 0, 0), (26, 24, 0),(27, 7, 4), (27, 12, 4),(27, 17, 4)