Energy-Efficient Mobile Charging for Wireless Power Transfer in Internet of Things Networks

Woongsoo Na, Junho Park, Cheol Lee, Kyoungjun Park, Joongheon Kim, and Sungrae Cho

***Abstract*—The Internet of Things (IoT) is expected to play an important role in the construction of next generation mobile communication services, and is currently used in various services. However, the power-hungry battery significantly limits the lifetime of IoT devices. Among the various lifetime extension techniques, this paper discusses mobile charging, which enables wireless power transfer based on radio frequency (RF) with mobile chargers (MCs). MCs function as traveling target IoT networks that provide energy to battery-operated IoT devices. However, MCs with an energy-constrained battery result in limitation of travel-time. This paper formulates a problem to minimize energy consumption for charging IoT devices by determining the path of motion of an MC and efficient charging points, and proves that the problem is NP-Hard. An efficient algorithm, named Best Charging Efficiency (BCE), is proposed to solve the problem and the upper bound of the BCE algorithm is guaranteed using the duality of linear programming. In addition, an improved BCE algorithm called Branching Second Best Efficiency (BSBE) algorithm with additional searching techniques is introduced. Finally, this paper analyzes the difference in performance among the proposed algorithms, optimal solutions, and the existing algorithm and concludes that the performance of the proposed algorithm is near optimal, within 1% of difference ratio in terms of charging efficiency and delay.**

***Index Terms*—mobile charging, wireless power transfer, Internet of Things, and wireless charging**

I. Introduction

INTERNET of things (IoT) has been applied in various research domains [1], [2], [3]. However, the lifetime of IoT devices is limited because they are powered by energy-constrained batteries. To address this, a large variety of solutions have been proposed for extending the lifetime of IoT devices in recent years including energy harvesting [4], [5], energy conservation [6], [7], energy-efficient routing [8], [9], and incremental deployment [10], [11]. However, these techniques cannot cope with the unpredictable availability of solar energy for solar cell-based harvesting. Incremental deployment involves expensive replacement of IoT devices located in hard-to-access areas such as underground, surfaces of bridges, and containers of hazard materials.

In this context, this paper consider a type of emerging technique named wireless power charging [12], [13], [14]. In the wireless power charging domain, network and system researchers consider a mobile charger (MC), a mobile vehicle combined with a wireless charging technique/module, as a suitable solution for extending the lifetime of IoT devices. The additional advantage of a MC is that the technique supports the charging of multiple IoT devices simultaneously. As presented in [15], intensive field experiments show that the charging efficiency increases linearly when multiple IoT devices are charged simultaneously. Therefore, the research proves that mobile charging is able to provide more stable and comprehensive performance than the aforementioned techniques.

Two types of wireless energy transfer, are used in wireless charging: (i) single charging and (ii) multiple charging. The single charging technique can only charge one node at a time, whereas multiple charging allows charging of multiple IoT devices nodes simultaneously. The charging efficiency per IoT device in multiple charging is less than the efficiency in single charging because of the distance between the IoT device and charging point. However, the total efficiency increases approximately linearly when the number of IoT devices being simultaneously charged at the charging point increases [15]. Moreover, there are two approaches to schedule the MC's travel route. One possible approach is a proactive method that intends to reach a predetermined goal, rather than just reacting to sudden changes. The other approach is a reactive method that responds immediately to a charging request.

In general, an MC equipped with an energy constrained battery limits the travel time. Recently, several studies have attempted to schedule the MC by considering its battery constraint and multi-charging efficiency [16], [17], [18], [19], [20], [21]. However, in all these schemes, charging points are predetermined and chargeable at the points. Thus, the MC determines an optimum routing path based on pre-determined charging points.

To overcome this problem, our scheme does not have a pre-determined charging point since it is not easy to establish charging points in advance. Instead, clustering is performed to select an efficient charging point for each IoT device using the Welzl algorithm. Then, the MC finds an optimal path to traverse to the corresponding candidate charging points. Moreover, as the hardness of the MC's travel scheduling problem is NP-hard (will be proved in Sec. III), simple but efficient algorithms should be designed whose performance is near optimal.

The contribution of this paper can be summarized as follows

- We classify the existing wireless energy transfer algorithms and identify their limitations (refer to Sec. II).
- According to our taxonomy, our proposed technology belongs to offline/multi-charging/centralized/flexible charging point classification. In particular, technologies belong-

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Taxonomy of mobile charger dispatch strategies							
Demand timeliness		*Number of charging devices*		*Control structure*		*Charging points*	
Offline	Online	Single charging	Multi-charging	Centralized	Distributed	Predetermined	Flexible charging points
Receive a charging request when MC is idle	MC receives charging request in real time	MC performs charging from one point to one target	Multiple MC performs charging from one point to multi-target	The central entity determines the path of the MC	Determine the path through collaboration between MCs	The MC performs charging at the designated charging point.	The MC can perform charging at various charging points.

Figure 1: Taxonomy of mobile charger dispatch strategies

ing to the flexible charge point classification of the RF charging method are very rarely studied.

- We formulate the radio frequency (RF) based *multi-charging (or point-to-multipoint charging)* problem and identify that this problem is NP-hard. In addition, to find efficient charging points, the problem incorporates the Welzl algorithm used for enclosing a smallest circle problem [22], [23]. This approach is the first in this research, to the best of our knowledge (refer to Sec. III).
- We propose two multi-charging moving-path planning algorithms, Best Charging Efficiency (BCE) and Branching Second Best Efficiency (BSBE), in terms of energy-efficiency (refer to Sec. IV).
- We present the evaluation results of our proposed algorithms in comparison with the optimal solution and existing algorithms for the problem. The performance evaluation results show that our technology is superior to other RF-based charging technologies in terms of delay and energy efficiency. For this purpose a mobile charger simulator named MCSim is implemented (refer to Sec. V).

II. Related Work

Traditionally, research into wireless energy charging technology has yielded a number of results [24]. However, research on charging sensor nodes by operating the mobile charger has been initiated recently. This section introduces related work and categorizes previous research results according to the energy transfer type and MC scheduling scheme.

Fig. 1 shows the taxonomy of mobile charger dispatch strategies [24]. The schemes can be divided into online/offline dispatch planning (reactive/proactive) in terms of demand timeliness, and into single charging/multi-charging plan depending on the number of charging devices at one point. Further, depending on the control of the mobile charger, the techniques can be divided into those with centralized/distributed manner. Lastly, it also can be divided into the predetermined/flexible charging points.

In single charging/offline approach, S. Zhang, *et. al.* [25] proposed a scheduling algorithm named PushWait. They investigated collaborative mobile charging scheduling problem in 1-D IoT networks. The algorithm is a single charging, proactive method that accounts for the energy constraint of multiple MC. In addition, it is optimal for 1-D IoT networks. However, it is not practical because of the unilateral consideration in 1-dimensional IoT networks. In [26], [27], the authors proposed a non-linear programming problem to optimize the travel path, charging duration, and data flow routing jointly. Additionally, in [28], they provided solutions to handle joint energy replenishment and data gathering.

In single charging/online approach, L. He, *et. al.* [29], [30] proposed and analyzed the DMC problem using the Nearest-Job-Next with Preemption (NJNP) algorithm which is a single charging, reactive method. The NJNP schedules the MC to select a spatially closer charging node when the node that sends the new requesting charging message is closer to the MC. In addition, the authors provided analytic results on the system throughput and charging latency and demonstrated their closeness to the global optimal solutions. However, although the NJNP scheme is a simple and efficient algorithm, it is less efficient when compared with other schemes that use multiple charging method [15].

On the other hand, in multi-charging/offline scheme, L. Fu, *et. al.* [16] proposed a heuristic algorithm that involved multiple charging, and a proactive method that minimized charging delay in IoT networks. They included the smallest enclosed disk in the space topology to narrow the search space and discretized the disk into a finite number of regions in continuous space. Then, they searched neighboring charging points for all nodes where the charging power difference is bounded by a threshold. Additionally, they proposed a charging point k-merging design to reduce the number of charging points.

L. Xie, *et. al.* [17], [18], [19] proposed a proactive wireless charging method by jointly optimizing the traveling path, flow routing, and charging time. They used a cellular structure that partitions the 2-dimensional plane into adjacent hexagonal cells, such that the MC visits the center of the cell to charge all IoT devices in a cell. In their technique, the MC only moves through the centers of the cells and needs sufficient transfer energy power to cover the entire cell for charging. Therefore, if IoT devices are distributed at cell boundaries, the MC must visit all cells, which is very inefficient in terms of energy efficiency. In [20], [21], the authors proposed a multi-charging scheme that finds the shortest Hamiltonian cycle for a MC's travel path to optimize charging duration. However, previous schemes assumed a specified charging point and did not compute the optimal charging point by taking into account the location of the IoT devices; they just found optimized paths with predetermined points (predetermined charging point category).

In distributed control approach [31], [32], [33], the authors investigate distributed control with local information. In this technique, MCs exchange information among themselves by considering the surrounding MCs to find the optimal charging route route. However, since network information is exchanged frequently, control packet overhead is large and actual implementation is difficult.

Therefore, to recharge multiple IoT devices efficiently, it is important *to know where the mobile charger has to move and stop to replenish the IoT devices' consumed energy*. In this paper, we find the optimal charging point according to the arrangement of IoT devices, not the predefined charging points as in previous studies. Then, we consider a scheme for optimizing the total charging cost for the MC and search the locations to optimize the efficiency of multi-charging method (flexible charging points category).

In [34], *anchor* was used to determine the charging point in a manner similar to ours. The scheme used a magnetic resonance model as a multi-charging model, which is very inefficient with distance. To overcome this, they tried to maximize efficiency by using repeater and multi-hop transmission, but this is dependent on the arrangement of the sensor nodes and has a drawback in terms of charge delay.

Based on this fundamental concept of the proposed algorithms, we can state the novelties of the proposed algorithms (offline/multi-charging/centralized/flexible charging points) as follows: (i) cost reduction with minimization of moving paths using multi-charging, (ii) first proposal that defines trade-off between charging efficiency and the number of chargers (single-charging vs. multi-charging), and (iii) numerical verification of the performance improvement using our proposed algorithms when compared with other representative related work such as NJNP [29], [30]. For this purpose, a mobile charger simulator named MCSim has been implemented.

III. Problem Statement

A. Multi-Charging

We assume radio frequency (RF) based charging as a multi-charging model. Given that the MCs are capable of wireless energy transfer, it is possible to charge multiple IoT devices simultaneously as long as they are within the MC's charging range [14]. Note that the distance D from one MC to an IoT device varies from 0 to a certain threshold T. If $D = 0$, it means the MC and IoT devices are at the same position. In addition, the threshold T is determined by the distance at which the failure of wireless charging occurs and it is an indication factor of whether the IoT device is outside the MC's charging range or not.

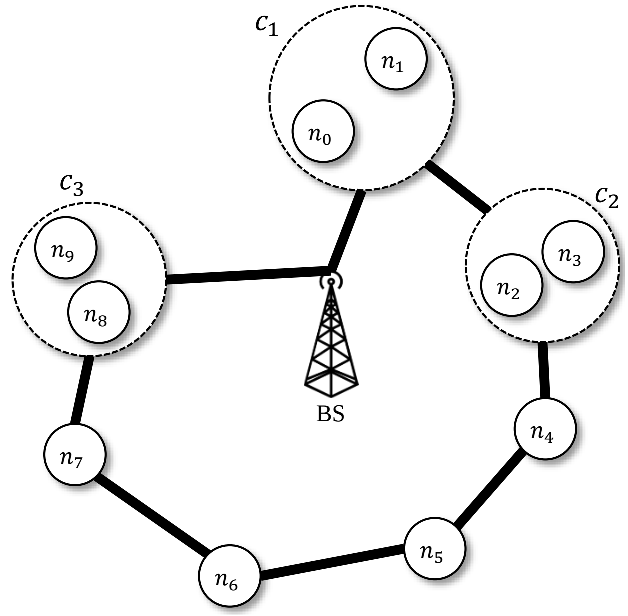


Figure 2: System model composed of a BS, $N = 10$ IoT devices, and one MC, which moves along the Hamiltonian cycle as the solid line. c_1, c_2, and c_3 are clusters performing multiple charging for groups of IoT devices $\{n_0, n_1\}$, $\{n_2, n_3\}$, and $\{n_8, n_9\}$, respectively.

The empirical model of wireless charging based on the well-known Friis free- space path-loss model was firstly formulated in [35]. According to this, the received power p_r at an IoT device is described as

$$p_r = \frac{G_t G_r \gamma}{L_p} \left(\frac{\lambda}{4\pi(D+\beta)} \right)^{\alpha} p_t, \tag{1}$$

where λ, γ, β, L_p G_t, G_r, α, p_t represent the wavelength, rectifier efficiency, parameter to adjust the Friis' free space equation for short-distance transmission, polarization loss, transmit antenna gain, receive antenna gain, path-loss coefficient, and transmit power, respectively. Note that these parameters are all constants. In general, the path-loss coefficient is between 2 and 4 (i.e., $2 \leq \alpha \leq 4$), and this paper assumes $\alpha = 2$.

In addition, when multiple IoT devices are charged together, the sum of the charged power increases more than that stated in field experiments, as observed in [11], [35]. Furthermore, it has been demonstrated that the relative gap between the sum of the individual charged power and simultaneous charged power is small [35]. From these experiments, it can be observed that the sum of simultaneous charged power increases linearly when the number of nodes that are charged together increases[1].

[1]If the number of IoT devices charged by a MC increases, the devices will be located closer. However, these devices will cause more interferences among them, which results in lower charging efficiency. Therefore, the sum of the received energy cannot exceed the transmitted energy from the MC [11], [21].

Table I: Notation of Symbols

n_i	i^{th} node
N, $\mathbb{N}$	The number of IoT devices, the set of IoT devices
c_j	j^{th} cluster
C, $\mathbb{C}$	The number of clusters, the set of clusters
n_{ij}	A Boolean variable if i^{th} node is in j^{th} cluster, $n_{ij} = 1$ otherwise, $n_{ij} = 0$
e_i	The amount of consumed energy at i^{th} IoT device
E_j	The maximum consumed energy in j^{th} cluster
x_j	A Boolean variable if j^{th} cluster is selected, $x_j = 1$ otherwise, $x_j = 0$
$\eta(c_j)$	Charging efficiency at j^{th} cluster
η_{ij}	Charging efficiency of i^{th} node at j^{th} cluster

B. System Model

The proposed algorithms in this paper are designed with two assumptions. First, the IoT devices are distributed according to a Poisson Point Process (PPP) in a 2-dimensional area consisting of one base station (BS) and N IoT devices, i.e., $\{n_i \mid i = 1, 2, 3, \cdots, N\}$. Note that all notation in this paper are summarized in Table I. The nodes transmit related information about their surrounding environment to the BS. Second, the positions of IoT devices are globally known and the position can be represented as follows:

$$\texttt{pos}\,(n_i) = (x_i, y_i)\,. \tag{2}$$

where n_i, x_i, and y_i denote node i, x-axis location of n_i, and y-axis location of n_i, respectively.

Fig. 2 shows an example topology and clustering. In the figure, there are three clusters c_1, c_2, and c_3 that are to be charged simultaneously. The bold line is moving along the path of the MC, and it follows the Hamiltonian Cycle (HC), as introduced in [36].

C. Energy Consumption Model

In this paper, each IoT device generates sensing data, which is transferred to a fixed base station. To transfer the sensed data to the base station, we assume that multi-hop data routing is employed for all IoT devices. To model multi-hop data routing, let f_i^j and f_i^B the flow rates from IoT device i to IoT device j and to the base station B, respectively. In this paper, we use the following energy consumption model at each IoT device [9]. To transmit a flow rate of f_i^j from node i to node j, the transmission power is $C_i^j \cdot f_i^j$, where C_i^j is the rate of energy consumption for transmitting one unit of data from node i to node j. Then, the aggregate energy consumption rate for transmission at node i is $\sum_{j\in\mathbb{N}}^{j\neq i} C_i^j \cdot f_i^j + C_i^B \cdot f_i^B$.

The energy consumption rate for reception at node i is modeled as $\rho \sum_{k\in\mathbb{N}}^{k\neq i} f_k^i$, where ρ is the rate of energy consumption for receiving one unit of data.

Let r_i denote the energy consumption rate at IoT device i, which includes energy consumption for transmission and reception. We have

$$r_i = \rho \sum_{k\in\mathbb{N}}^{k\neq i} f_k^i + \sum_{j\in\mathbb{N}}^{j\neq i} C_i^j \cdot f_i^j + C_i^B \cdot f_i^B \tag{3}$$

D. Discretizing a Continuous Charging Point

Determining the moving path of an MC to charge an IoT device is an important part of our proposed scheme for minimizing wireless transfer power consumption. However, the candidates for charging points are located continuously in a 2-dimensional area. Therefore, the Welzl algorithm is used for enclosing a smallest circle problem [22], [23] to discretize a continuous area and reduce the number of candidate points. By adopting the Welzl algorithm, the problem can be modeled as a clustering problem to find a good cluster for charging multiple IoT devices. The IoT devices can be grouped as a set of clusters $\mathbb{C} = \{c_i \mid i = 1, 2, 3, \cdots, C\}$ in polynomial-time $O\left(\frac{(n+1)(n-1)(n-2)(2n-3)}{6} + \frac{(n+1)(n-1)(n-2)}{2}\right)$. Each cluster has the centroid position information, which can be represented as $\texttt{pos}(c_i) = (x_i, y_i)$. Moreover, there is a constraint on the set of clusters that $\mathbb{C} = c_1 \cup c_2 \cup \cdots \cup c_C$ covers all IoT devices where $c_i \neq \emptyset \quad \forall c_i \in \mathbb{C}, \{c_i \cap c_j = \emptyset \mid i \neq j,\ c_i, c_j \in \mathbb{C}\}$.

The charging efficiency of the cluster c_j is denoted by $\eta(c_j)$. The efficiency is defined by the ratio of the minimum power received by all nodes in the cluster to the transmitted power from the MC.

$$\begin{aligned}\eta(c_j) &= \frac{p_r}{p_t} = \frac{\frac{G_t G_r \gamma}{L_p}\left(\frac{\lambda}{4\pi(D_j+\beta)}\right)^2 p_t}{p_t} \\ &= \frac{G_t G_r \gamma}{L_p}\left(\frac{\lambda}{4\pi(D_j+\beta)}\right)^2\end{aligned} \tag{4}$$

where D_j is defined by $\arg\max_{n_i \in c_j}(\texttt{dist}(p_j, n_i))$, where $\texttt{dist}(a, b)$ represents the Euclidean distance between a and b, p_j is the center point of cluster c_j, and n_i is an element of cluster set c_j.

The charging efficiency of node n_i in cluster c_j is defined as η_{ij},

$$\eta_{ij} = \frac{G_t G_r \gamma}{L_p}\left(\frac{\lambda}{4\pi(\texttt{dist}(p_j, n_i)+\beta)}\right)^2. \tag{5}$$

The energy required for charging batteries in IoT devices depends on the battery in each IoT device. The consumed energy of an IoT device n_i is denoted by e_i. Then, the amount of energy in MC that is used for charging multiple nodes in cluster should also be considered. For inducing the maximum energy demand for cluster c_j, described as E_j, e_i in cluster c_j considered along with the distance between the centroid point of the cluster and each node contained in the cluster owing to charging efficiency. Therefore, the maximum demand energy E_j to charge all nodes included in cluster c_j is defined as follows:

$$E_j = \arg\max_{n_i \in c_j} \left(\frac{e_i n_{ij}}{\arg\min_{n_k \in c_j} \eta_{kj}} \right). \quad (6)$$

In this paper, a solution set of clusters is denoted as $\mathbb{S}$. In addition, no element of the solution set is intersected. Therefore, it is true that $S \leq N$ where S, denotes the number of elements in $\mathbb{S}$. Then, the objective function $f(\mathbb{S})$ can be described as follows:

$$\text{minimize} \qquad f(\mathbb{S}) = G(\mathbb{S}) \cdot E_d + \sum_{c_j \in \mathbb{S}} \left(\frac{E_j}{\eta(c_j)} \right) \quad (7)$$

where E_d, E_j, and $G(\mathbb{S})$ stand for energy consumption in the Hamiltonian Cycle (HC) tour (constant), requirement energy of cluster (constant), and total distance of the HC tour, respectively. Note that E_j denotes the energy requirement for full charge of the least efficient node in cluster c_j according to (7). Therefore, $\frac{E_j}{\eta(c_j)}$ indicates the amount of energy consumed to completely charge all IoT devices in cluster c_j. In the objective function, we should find a cluster set having minimum energy requirement and maximum energy charging efficiency ($\sum_{c_j \in \mathbb{S}}(\frac{E_j}{\eta(c_j)})$). Additionally, the objective function should be minimized in order to minimize the energy spent by a mobile charger.

However, the number of grouping cases follows a bell number B_n which can be described as:

$$B_n = \sum_{k=0}^{n-1} B_k \begin{pmatrix} n-1 \\ k \end{pmatrix} \quad (8)$$

which is not a linear function (for example, $B_{10} = 115975$, $B_{20} = 51724158235372$). Because of the complexity of the problem, it is hard to find an optimal solution. Therefore, a fast and efficient two-stage framework is proposed in this paper. First, clustering is performed to select an optimal charging point for each device. Second, we find the optimal path to traverse the corresponding charging points. Since all IoT devices that need energy charging must be charged, it is necessary to perform clustering first In the next section, we describe the proposed grouping problem referred to as the Minimum Mobile Charger Energy Problem (MMCEP).

E. Complexity of the MMCEP

The MMCEP is not NP because, for a number of given IoT devices, the solution cannot be verified as being optimized in polynomial time. Therefore, the MMCEP should be reduced from a minimum exact cover problem to a well-known NP-hard problem.

To formally prove the hardness of the MMCEP problem, a restricted version of the MMCEP problem (RMMCEP) is defined. After that, the RMMCEP reduced from the minimum exact cover problem [37].

Definition 1 (MMCEP):

Given a set of clusters, a set of IoT devices, and relevant charging efficiency, the goal is to find the minimum-energy consumption plan of an MC. The input to the MMCEP consists of following items:

- A set of nodes $\mathbb{N} = \{n_1, ..., n_N\}$ that must be charged by the MC,
- A set of clusters $\mathbb{C} = \{c_1, c_2, ..., c_C\}$ for charging IoT devices,
- A value of efficiency $\eta(c_j)$ for each $c_j \in \mathbb{C}$. This is the efficiency resulting from the farthest distance between the charging point in c_j and the nodes charged by the MC,
- A value of distance $G(\mathbb{S})$, which is the distance value along the HC tour of potential clusters,
- A constant E_d that is the energy requirement per distance to tour HC, and
- A constant E_j that is the maximum consumed energy to charge in the j^{th} cluster.

This problem involves selecting a subset $\mathbb{K}$ where $\mathbb{K} \subseteq \mathbb{C}$ of potential clusters to charge IoT devices at these clusters and to assign each node to exactly one cluster such that the MC's consuming charging-energy is minimized. The number of clusters to be selected, K, where K is the number of elements in $\mathbb{K}$, is not pre-specified; rather, it is determined by an optimal solution. The efficiency $\eta(c_j)$ usually depends on several aforementioned factors of the model of received power.

The restricted version of the MMCEP problem (RMMCEP) assumes that not all the values and factors are considered. Therefore, all values and factors of MMCEP are considered to be 1.

Theorem 1: The Minimum Mobile Charger Energy Problem (MMCEP) is NP-hard.

Before proving the NP-hardness of MMCEP, the minimum exact cover problem is introduced.

Definition 2 (Minimum Exact Cover Problem): Given a (finite) collection $\mathbb{S}$ of subsets of set $\mathbb{X}$ find a subcollection $\mathbb{S}^* \subseteq \mathbb{S}$ that covers $\mathbb{S}$ and minimizes the sum of cardinalities of the sets in $\mathbb{S}^*$.

Definition 3 (RMMCEP): Restricted MMCEP problem, which is an instance of our problem is able to be restricted for RMMCEP, where all of $\frac{E_j}{\eta(c_j)}$ are assumed (restricted) to be 1.

Proof 1: Given the instance of the minimum exact covering problem, an instance of the MMCEP can be constructed such that an optimal solution also provides an optimal solution for the exact covering problem. First, a bipartite graph can be constructed based on the exact cover instance: for each element x_i, there is node x_i in the "left part" of the bipartite graph, and for each set $\mathbb{S}_j$ where $\mathbb{S}_j \subseteq x_1, x_2, ..., x_N$, there is node $\mathbb{S}_j$ in the "right part" of the bipartite graph. There is an edge $x_i S_j$ if and only if node x_i belongs to set S_j.

An example of the MMCEP problem is as follows: the set of IoT devices is $\{x_1, x_2, \cdots, x_N\}$, the set of charging clusters is $\{S_1, S_2, \cdots, S_M\}$, then n_{ij} is taken to be either 1 if edge $x_i S_j$ is present or 0 otherwise, and the maximum energy for charging $\frac{E_j}{\eta(c_j)}$ (for each $j = 1, \cdots, n$) is taken to be 1. Therefore, the problem is to select the minimum number of clusters such that each node (element) x_i can be assigned to a cluster (set) S_j that includes x_i (that contains x_i). It can be easily seen that a solution of the MMCEP instance is optimal if and only if (iff) the corresponding solution of the exact cover instance is optimal.

F. Problem Formulation

We start with the integer programming formulation of the problem. For each potential cluster $c_j \in \mathbb{C}$, a Boolean indicator variable x_j exists. The intention is that cluster is selected as cluster c_j iff $x_j = 1$. For each node $n_i \in \mathbb{N}$ and cluster $c_j \in \mathbb{C}$, an indicator value n_{ij} exists. The intention is that node n_i is served by MC at cluster c_j iff $n_{ij} = 1$. The first constraint essentially states that n_j is the number of nodes in the j^{th} cluster defined by $\sum_{n_i \in c_j} n_{ij}$ for each node included by only one cluster. This can be formulated as an integer programming as shown in the following section.

1) Integer Programming (IP): The formulation with integer programming (IP) for our given problem is as follows:

$$\text{minimize} \quad z_{\text{IP}} = \sum_{c_j \in \mathbb{C}} \frac{E_j x_j}{\eta(c_j) - I_{c_j}} \tag{9}$$

subject to

$$\sum_{c_j \in \mathbb{C}} x_j n_{ij} = 1, \qquad \forall n_i \in \mathbb{N}, \tag{10}$$

$$x_j \in \{0,1\}, \qquad \forall c_j \in \mathbb{C}, \tag{11}$$

$$\sum_{n_i \in c_j} p_{r,i} \le p_t, \qquad \forall c_j \in \mathbb{C} \tag{12}$$

where $p_{r,i}$ denotes the received power of i^{th} IoT device and I_{c_j} denotes the charging efficiency attenuation factor due to interference between sensor nodes[2].

Before transforming the integer program to a linear program, the objective function z_{IP} is induced.

$$z_{\text{IP}} = \sum_{c_j \in \mathbb{C}} \frac{E_j x_j}{\eta(c_j)} = \sum_{c_j \in \mathbb{C}} \sum_{n_i \in \mathbb{N}} \frac{n_{ij} E_j x_j}{\eta(c_j) \sum_{n_i \in \mathbb{N}} n_{ij}} \tag{13}$$

In addition, a new indicator variable y_{ij} in defined. The intention is that cluster c_j is selected and node n_i is in c_j iff $y_{ij} = 1$. y_{ij} is also defined as $y_{ij} = n_{ij} x_j$. Moreover, $y_{ij} \le x_j$ because $y_{ij} = n_{ij} x_j$. If $x_j = 0$, y_{ij} should be 0. On the other hand, if $x_j = 1$, y_{ij} are 1 or depending on 0 whether n_{ij} is 1 or not.

In general, charging efficiency is linearly proportional to the number of nodes since the charging efficiency is extremely low in the RF-based charging technique (the distance between IoT device and charger is more than 20cm, the charging efficiency is 1% [11], [21].), charging efficiency is linearly increased as number of nodes increases. Therefore, if more than 100 IoT devices in a cluster receive energy without any interference each other, the sum of received energy by IoT device will exceed the transmitted energy. However, it is practically impossible to ideally deploy more than 100 nodes (even if only 6 nodes are arranged in one cluster, the charging efficiency/node is reduced due to the interference effect [11], [21].). Therefore, we assume that the charging efficiency increases with the number of receiving nodes and the objective function can be expressed as a relaxed form without constraint (12).

Finally, the integer program is defined as follows:

$$\text{minimize} \quad z_{\text{IP}} = \sum_{n_i \in \mathbb{N}} \sum_{c_j \in \mathbb{C}} \frac{y_{ij} E_j}{\eta(c_j) \sum_{n_i \in \mathbb{N}} n_{ij}} \tag{14}$$

subject to

$$\sum_{c_j \in \mathbb{C}} y_{ij} = 1, \qquad \forall n_i \in \mathbb{N}, \tag{15}$$

$$y_{ij} \le x_j, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{16}$$

$$y_{ij} \in \{0,1\}, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{17}$$

$$x_j \in \{0,1\}, \qquad \forall c_j \in \mathbb{C}. \tag{18}$$

Even if the integer constraints on y_{ij} are relaxed, i.e., even if the above constraints (17) are replaced by

$$y_{ij} \ge 0, \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{19}$$

the resulting mixed integer program is equivalent to the integer programming above. Suppose that $c_k \in \mathbb{C}$, then $x_k = 1$.

Then, the constraint $\sum_{c_j \in \mathbb{C}} y_{ij} = 1, \forall n_i \in \mathbb{N}$ ensures that each y_{ik} is at most 1. Otherwise, if $x_k = 0$, $y_{ik} = 0, \forall n_i \in \mathbb{N}$. Therefore, all constraints of the resulting mixed integer program are satisfied.

To obtain a linear program, the constraints (18) are relaxed as follows:

$$0 \le x_j \le 1, \forall c_j \in \mathbb{C}. \tag{20}$$

The linear programming relaxation of the integer programming is called the strong LP relaxation (SLRP); more details are provided in the following section.

2) Strong Linear Relaxation Programming (SLRP): As stated in previous section, SLRP can be formulated as follows:

$$\text{minimize} \quad z_{\text{LP}} = \sum_{n_i \in \mathbb{N}} \sum_{c_j \in \mathbb{C}} \frac{y_{ij} E_j}{\eta(c_j) \sum_{n_i \in \mathbb{N}} n_{ij}} \tag{21}$$

subject to

$$\sum_{c_j \in \mathbb{C}} y_{ij} = 1, \qquad \forall n_i \in \mathbb{N}, \tag{22}$$

$$y_{ij} \le x_j, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{23}$$

$$x_j \le 1, \qquad \forall c_j \in \mathbb{C}, \tag{24}$$

$$x_j \ge 0, \qquad \forall c_j \in \mathbb{C}. \tag{25}$$

To determine the lower bound of the SLRP, the SLRP is converted to an equivalent standard form as follows.

3) Equivalent Standard Linear Relaxation Programming (ESLRP): The SLRP problem from (21) to (25), can be rewritten as follows:

$$\text{maximize} \quad -z_{\text{LP}} = -\sum_{n_i \in \mathbb{N}} \sum_{c_j \in \mathbb{C}} \frac{y_{ij} E_j}{\eta(c_j) \sum_{n_i \in \mathbb{N}} n_{ij}}, \tag{26}$$

subject to (22), (23), (24), and (25).

In this SLRP formulation, dual variables are additionally

[2]As mentioned in subsection III-A, as the number of nodes increases, the charging efficiency also decreases. However, since the value of the charging efficiency is very small in the RF-based wireless charging method, I_{c_j} can be ignored in this paper [38].

introduced,

$$u_i, \qquad \forall n_i \in \mathbb{N}, \tag{27}$$
$$w_{ij}, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{28}$$
$$z_j, \qquad \forall c_j \in \mathbb{C}, \tag{29}$$

corresponding to the Equivalent Standard Linear Relaxation Programming (ESLRP) constraints

$$\sum_{c_j \in \mathbb{C}} y_{ij} = 1, \qquad \forall n_i \in \mathbb{N}, \tag{30}$$
$$y_{ij} - x_j \leq 0, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{31}$$
$$x_j \leq 1, \qquad \forall c_j \in \mathbb{C}, \tag{32}$$

respectively.

4) Dual ESLRP: The dual Equivalent Standard Linear Relaxation Programming (Dual ESLRP) formulation of the given problem is represented as follows:

$$\text{minimize} \quad w = \sum_{n_i \in \mathbb{N}} u_i + \sum_{c_j \in \mathbb{C}} t_j \tag{33}$$

subject to

$$t_j - \sum_{n_i \in \mathbb{N}} w_{ij} \geq 0, \qquad \forall c_j \in \mathbb{C}, \tag{34}$$
$$u_i + w_{ij} \geq -\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}}, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{35}$$
$$w_{ij} \geq 0, \qquad \forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}, \tag{36}$$
$$t_j \geq 0, \qquad \forall c_j \in \mathbb{C}. \tag{37}$$

Suppose that all variables u_i have fixed values. Therefore, to minimize the objective function, we have to assign each w_{ij} the minimum value, where constraints

$$w_{ij} \quad \geq \quad 0, \tag{38}$$
$$\sum_{n_i \in \mathbb{N}} n_{ij} y_i + z_j \quad \geq \quad \sum_{n_i \in \mathbb{N}} -\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}}, \tag{39}$$

where $\forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{C}$ are satisfied. This gives the following equation:

$$w_{ij} = \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i \right)^+ \tag{40}$$

where for an expression θ, $(\theta)^+$ denotes $\max\{\theta, 0\}$. Now, consider the variables $t_j, \forall c_j \in \mathbb{C}$. To minimize the objective function, we must assign each t_j the minimum value such that the constraints $t_j - \sum\limits_{n_i \in \mathbb{N}} w_{ij} \geq 0$, where $\forall c_j \in \mathbb{C}$; and $t_j \geq 0$, where $\forall c_j \in \mathbb{C}$ are satisfied. Therefore,

$$t_j = \left(\sum_{n_i \in \mathbb{N}} w_{ij} \right)^+, \forall c_j \in \mathbb{C}. \tag{41}$$

Substituting the formula for w_{ij} above, following the equation can be obtained:

$$t_j \quad = \quad \left(\sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i \right)^+ \right)^+ \tag{42}$$
$$\quad = \quad \sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i \right)^+ \tag{43}$$

where $\forall c_j \in \mathbb{C}$. This formulation gives the condensed dual as follows:

$$\text{minimize} \quad w = \sum_{n_i \in \mathbb{N}} u_i + \sum_{c_j \in \mathbb{C}} \left(\sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i \right)^+ \right) \tag{44}$$

IV. Proposed Algorithms

In this section, efficient algorithms are proposed for solving the MMCEP, namely, (i) Best Charging Efficiency (BCE) algorithm and (ii) Branch Second Best Efficiency (BSBE) algorithm. These two algorithms find a candidate solution $x_j \in \{0, 1\}$, where $\forall c_j \in \mathbb{C}$, to the MMCEP instance as well as a feasible solution for the dual of the ESLRP. Based on the duality of linear programming, the objective value of every feasible solution of (Dual SLPR) gives an upper bound on the optimal value of ESLRP; therefore, it provides an upper bound on the optimal value of the MMCEP instance.

A. Best Charging Efficiency (BCE) Algorithm

We start with an empty set $\mathbb{S}$ of clusters, and at each step we add to the $\mathbb{S}$ cluster $c_j \in \mathbb{C} \backslash \mathbb{S}$ that yields the maximum improvement in the objective value, where $\mathbb{C} \backslash \mathbb{S} = \{c_j \mid c_j \cap s_i \neq \emptyset, \ \forall c_j \in \mathbb{C}, \forall c_i \in \mathbb{S}\}$. For a set $\mathbb{S}$ where $\mathbb{S} \subset \mathbb{J}$, of clusters, the objective value is given as follows:

$$-z(\mathbb{S}) = \sum_{n_i \in \mathbb{N}} \max_{c_j \in \mathbb{S}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} \right). \tag{45}$$

For the currently selected set of clusters $\mathbb{S}$ and for each node $n_i \in \mathbb{N}$, define $u_i(\mathbb{S})$ to be as follows:

$$u_i(\mathbb{S}) = \max_{c_j \in \mathbb{S}} \left(-\frac{1}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} \right), \tag{46}$$

where $u_i(\mathbb{S})$ is the maximum profit obtained from serving node n_i using only the clusters in $\mathbb{S}$. Then,

$$-z(\mathbb{S}) = \sum_{n_i \in \mathbb{N}} u_i(\mathbb{S}). \tag{47}$$

In addition, for cluster $c_j \in \mathbb{C} \backslash \mathbb{S}$, suppose that $p_j(\mathbb{S}) = -z((\mathbb{S} \backslash \{c_j\}) \cup c_j) - (-z(\mathbb{S}))$ denotes the change in the objective value when a new cluster is selected at c_j:

$$\begin{aligned} p_j(\mathbb{S}) &= -z((\mathbb{S}\backslash\{c_j\}) \cup c_j) - (-z(\mathbb{S})) \\ &= \sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i(\mathbb{S}) \right)^+ . \end{aligned} \quad (48)$$

Moreover, in order to choose the best $c_j \in \mathbb{C}\backslash\mathbb{S}$, the evaluation function $e_j(\mathbb{S})$ is defined as follows:

$$e_j(\mathbb{S}) = \max_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i(\mathbb{S}) \right)^+ . \quad (49)$$

In each iteration of the BCE algorithm, $e_j(\mathbb{S})$ is calculated for each $c_j \in \mathbb{C}\backslash\mathbb{S}$. If either $\mathbb{C}\backslash\mathbb{S}$ is empty or $e_j(\mathbb{S}) = 0$ for each $c_j \in \mathbb{C}\backslash\mathbb{S}$, the algorithm will be terminated. Otherwise, a $c_j \in \mathbb{C}\backslash\mathbb{S}$ will be added to $\mathbb{S}$ whose incremental value $e_j(\mathbb{S})$ is maximum.

Consider the first condensed dual of ESLRP; for each $n_i \in \mathbb{N}$, let the i^{th} dual variable u_i be assigned the value $u_i(\mathbb{S})$ defined above. Then, the dual objective value corresponding to $\mathbb{S}$ is as follows:

$$\begin{aligned} w(u(\mathbb{S})) &= \sum_{n_i \in \mathbb{N}} u_i(\mathbb{S}) + \sum_{c_j \in \mathbb{C}} t_j(\mathbb{S}) \\ &= \sum_{n_i \in \mathbb{N}} u_i(\mathbb{S}) + \\ &\quad \sum_{c_j \in \mathbb{C}} \left(\sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i(\mathbb{S}) \right)^+ \right) \\ &= \sum_{n_i \in \mathbb{N}} u_i(\mathbb{S}) + \sum_{c_j \in \mathbb{C}} p_j(\mathbb{S}) \\ &= \sum_{n_i \in \mathbb{N}} u_i(\mathbb{S}) + \sum_{c_j \notin \mathbb{S}} p_j(\mathbb{S}), \end{aligned} \quad (50)$$

since each $c_j \in \mathbb{C}$ has

$$\sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i(\mathbb{S}) \right)^+ = p_j(\mathbb{S}) \quad (51)$$

and

$$\sum_{n_i \in \mathbb{N}} \left(-\frac{E_j}{\eta(c_j) \sum\limits_{n_i \in \mathbb{N}} n_{ij}} - u_i(\mathbb{S}) \right) = 0 \quad (52)$$

where $\forall n_i \in \mathbb{N}, \forall c_j \in \mathbb{S}$.

For the final solution $\mathbb{S}^G$ found by the BCE algorithm, each $c_j \in \mathbb{C}$ has $p_j(\mathbb{S}^G) = 0$. Therefore, the dual objective value is as follows:

$$w\left(u(\mathbb{S}^G)\right) = \sum_{n_i \in \mathbb{N}} u_i(\mathbb{S}^G). \quad (53)$$

The BCE algorithm actually computes the dual objective value $w(u(\mathbb{S}))$ for the set $\mathbb{S}$ in each iteration and takes the smallest of these values to be the upper bound $W^G = w(u(\mathbb{S}^G))$ that is returned at the end, since this value is the lowest upper bound computed on the optimal value of ESLRP.

Algorithm 1 BCE Algorithm

Input:
Node set $\mathbb{N} = \{n_1, ..., n_N\}$
Cluster set $\mathbb{C} = \{c_1, ..., c_C\}$
$n_{ij} = \{0,\ 1\} \quad \forall n_i \in \mathbb{N},\ \forall c_j \in \mathbb{C}$
Solution Cluster set $\mathbb{S}$ is a set of single charging clusters
$\mathbb{C} = \mathbb{C} - \mathbb{S}$
calculate $n(c_j),\ E_j \quad \forall c_j \in \mathbb{C}$

repeat
  choose the best charging efficiency $\frac{E_q}{\eta(c_q) \sum_{n_i \in \mathbb{N}} n_{ij}}, \forall c_q \in \mathbb{C}$
  $best \leftarrow c_q$
  if $p_j(\mathbb{S}) > 0$ **then**
    $\mathbb{S} = (\mathbb{S} \setminus \{best\}) \cup \{best\}$
    $\mathbb{C} = \mathbb{C} \setminus best$
  else
    $\mathbb{C} = \mathbb{C} - best$
  end if
until $\mathbb{C} = \emptyset$ or $e_j(\mathbb{S}) = 0, \quad \forall c_j \in \mathbb{C}$
return $\mathbb{S}$

When choosing the best evaluation value $E_j/\eta(c_q) \times \sum_{n_i \in \mathbb{N}} n_{ij}$, we exclude intersected clusters with the best cluster from the set of clusters. In our algorithm, this is reasonable because we do not approve intersection of clusters of the solution. Therefore, the proposed BCE algorithm can be expressed as shown in the pseudo-code in Algorithm 1.

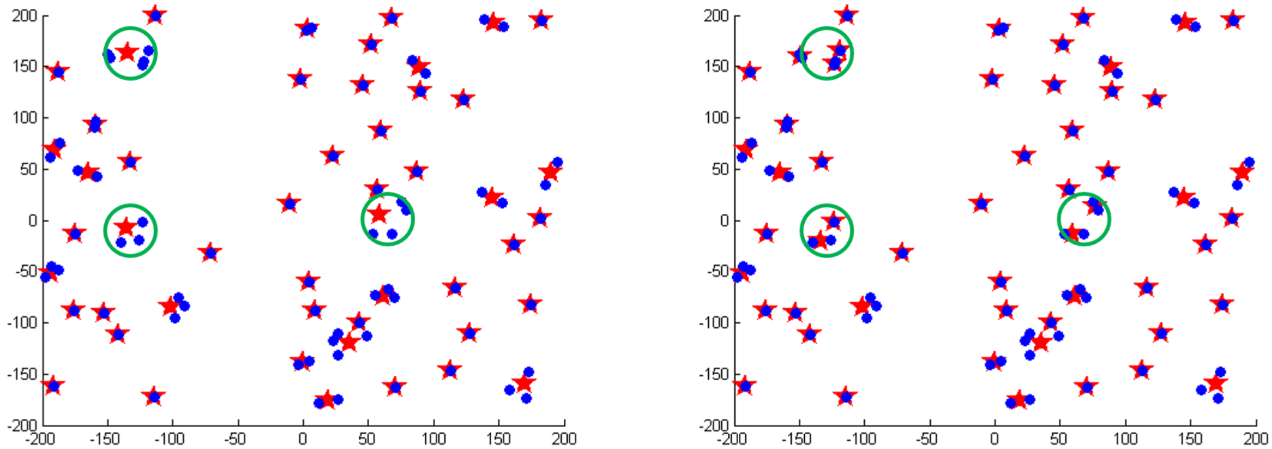
Table II: The difference between the optimal solution and BCE solution focusing on charging cost regardless of tour distance

# of nodes	Optimal (J)	BCE (J)	Different ratio (Optimal/BCE)
40	6095.758	6113.116	99.7%
50	7513.137	7543.295	99.6%
60	8888.718	8930.665	99.5%
70	10196.3	10256.08	99.4%
80	11462.77	11551.08	99.3%

B. Drawback of the BCE Algorithm

The proposed BCE algorithm has relatively good performance when compared with the optimal solutions. The gap between the total charging cost of BCE and that of the optimal solution is almost within 1% (see Table II). However, the gap between BCE and the optimal solution increases when more IoT devices are added.

There are some cases when the BCE algorithm cannot arrive at the optimal solution. The major reason is that the BCE algorithm cannot find the combinations of the second best clusters owing to its capability to choose the best cluster containing the best value in each iteration. In Fig. 3a and Fig. 3b, there are 80 IoT devices (represented with blue dots)



(a) The optimal solution in the IoT networks, Different results for BCE the optimal solution ($N = 80$, blue dots = nodes, red stars = clusters)

(b) The solution of BCE algorithm in the IoT networks, Different result of BCE and optimal solution ($N = 80$, blue dots = nodes, red stars = clusters)

Figure 3: Comparison between the optimal solution and the BCE solution

and result clusters(represented with red stars) of algorithms. The green circle describes the difference between the optimal solution and the solution of the BCE algorithm. The BCE algorithms pick the best cluster of candidate clusters in the green circle. As such a result, the BCE algorithms have to pick more clusters than the optimal solution after the selection of the best cluster in the green circle. Consequently, the performance of the BCE algorithm is less than that of the optimal.

Thus, a new algorithm is additionally proposed to deal with this issue, i.e., Branch Second Best Efficiency (BSBE) algorithm.

C. Branching Second Best Efficiency (BSBE) Algorithm

In contrast to the BCE algorithm, the BSBE algorithm considers the combination of the second best clusters. The BEBE algorithm involves a trade-off between performance and computation time. In the initial stages, the BSBE algorithm works like the BCE algorithm. If the algorithm finds the best cluster, it searches for the second best cluster associated with the nodes of the best cluster. Furthermore, if the difference between the best cluster and the second best cluster is less than or equal to threshold γ, another solution set $\mathbb{S}'$ will be generated that is equal to the origin solution set $\mathbb{S}$ before selecting the second one. Finally, we select the best cluster as an element of $\mathbb{S}$ and the second best one as an element of $\mathbb{S}'$.

There is a further point that needs to be clarified. If the threshold γ is loose or the number of nodes increases, the number of multiplication operation in the BSBE algorithm increases exponentially. Therefore, an additional restriction is introduced on top of the BSBE algorithm via a constant T. The complexity of the BCE algorithm is $O(n \log n + n) = O(n \log n)$. Therefore, the complexity of the BSBE algorithm is determined as $O(Tn \log n)$. The detailed pseudo-code of the proposed BSBE algorithm is shown in Algorithm 2.

In addition, the proposed BSBE algorithm can produce some branched solutions smaller than the limit number. The solution of the BCE algorithm must be among these branched solutions because the first branch solution is the BCE solution. Thus, the performances of the BCE and BSBE algorithms always follow the below expression:

$$Z(\mathbb{S}^{\text{opt}}) \leq Z(\mathbb{S}^{\text{BSBE}}) \leq Z(\mathbb{S}^{\text{BCE}}), \tag{54}$$

where $Z(\mathbb{S}^{\text{opt}})$, $Z(\mathbb{S}^{\text{BSBE}})$, and $Z(\mathbb{S}^{\text{BCE}})$ stand for the evaluation function of the solutions of the optimal, BSBE algorithm, and BCE algorithm, respectively (see Table III).

D. Weighted Vertex based Travelling Path Selection Algorithm

After finding the optimal cluster set, the MC finds the optimal path based on the given set of clusters. In this paper, we choose the optimal path by considering the energy used by the MC as well as the remaining energy of the IoT devices in the cluster. To find the optimal path, we assume a complete graph in which weights are measured based on the distance between the cluster sets and remaining energy of the IoT devices in the cluster. The weight w_i^j between cluster i and j is calculated based on the average energy level of the nodes in each cluster and the distance between two clusters. Thus, w_i^j is calculated as

$$w_i^j = \frac{P_i^j}{P_{max}} + \epsilon_i + \epsilon_j \tag{55}$$

where P_i^j and ϵ_i denote the distance from cluster i to j and normalized consumed energy for cluster i defined by $\frac{N_j \cdot E_j}{\sum_{k \in j} e_j}$, respectively.

From (55), the weight increases as the distance between two clusters increases, and as the energy remaining in each cluster increases. For finding the globally optimal Hamiltonian cycle tour, Concorde solver and CPLEX Optimizer are

Algorithm 2 BSBE Algorithm

Input:

Node set $\mathbb{N} = \{n_1, ..., n_N\}$
Cluster set $\mathbb{C} = \{c_1, ..., c_C\}$
$n_{ij} = \{0,\ 1\} \quad \forall n_i \in \mathbb{N},\ \forall c_j \in \mathbb{C}$
Solution Cluster set $\mathbb{S}$ is a set of single charging clusters
$\mathbb{C} = \mathbb{C} - \mathbb{S}$
calculate $n(c_j),\ E_j \quad \forall c_j \in \mathbb{C}$
$limit \leftarrow T$

Procedure: BSBE PROCEDURE($\mathbb{C}, S$)

If the number of executed BSBE procedures is greater than limit, then exit
repeat
  choose the best charging cluster $\frac{E_q}{\eta(c_q)\sum_{n_i \in \mathbb{N}} n_{ij}}, \forall c_q \in \mathbb{C}$
  $best \leftarrow c_q$
  if $p_j(\mathbb{S}) > 0$ **then**
    second-Best $\leftarrow$ SEARCHSECONDCLUSTER($best$)
    if $second - Best$ is not null **then**
      $\mathbb{S}' = (\mathbb{S} \setminus \{best\}) \cup \{$second-Best$\}$
      $\mathbb{C}' = \mathbb{C} \setminus$ second-Best
      BSBE PROCEDURE($\mathbb{C}$',$\mathbb{S}$')
    end if
    $\mathbb{S} = (\mathbb{S} \setminus \{best\}) \cup \{best\}$
    $\mathbb{C} = \mathbb{C} \setminus best$
  else
    $\mathbb{C} = \mathbb{C} - best$
  end if
until $\mathbb{C} = \emptyset$ or $e_j(\mathbb{S}) = 0, \quad \forall c_j \in \mathbb{C}$
return $\mathbb{S}$

Procedure: SEARCHSECONDCLUSTER(cluster best)

find the second best c_j, $\forall c_j\ c_j \cap best \neq \emptyset$
if $(c_j.\text{Effi} - best.\text{Effi}) < \gamma)$ // γ: threshold **then**
  return c_j
end if
return Null
Choose a best solution of branched solutions after all of BSBE procedure are terminated

adopted corresponding to an open source TSP solver and an optimization software package implemented by IBM.

V. Performance Evaluation

This section analyzes the performance of our proposed algorithms in two ways. First, we compare the proposed algorithm with the optimal solution for small-scale networks. Then, the proposed algorithms are evaluated and compared with existing algorithms for MCs in large-scale networks using different system parameter settings.

We implemented the mobile charger simulator MCSim to conduct performance evaluation by simulating all algorithms to solve the mobile charger problem in C#.

Moreover, we additionally implemented the existing algorithm, NJNP [29], [30] (for comparing single charging method) and a k-merging design [16]. However, these algorithms are not perfectly suitable for our problem. Therefore, we modify the reactive algorithm NJNP into a proactive

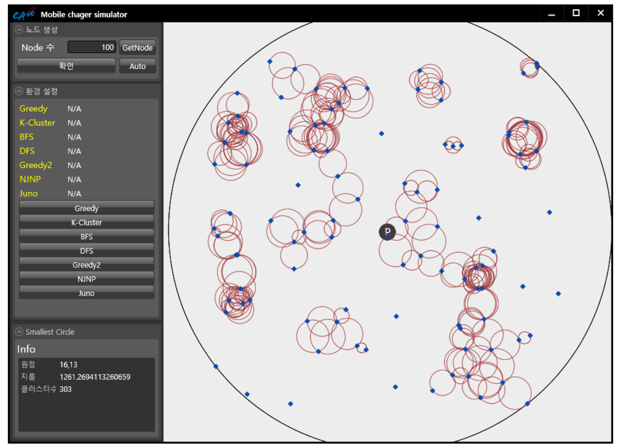


Figure 4: The mobile charger simulator, MCSim, describes all clusters as red circles that can be candidate clusters of a solution for the MC problem in a wireless IoT network with N nodes, and provides a solution for each algorithm we implemented

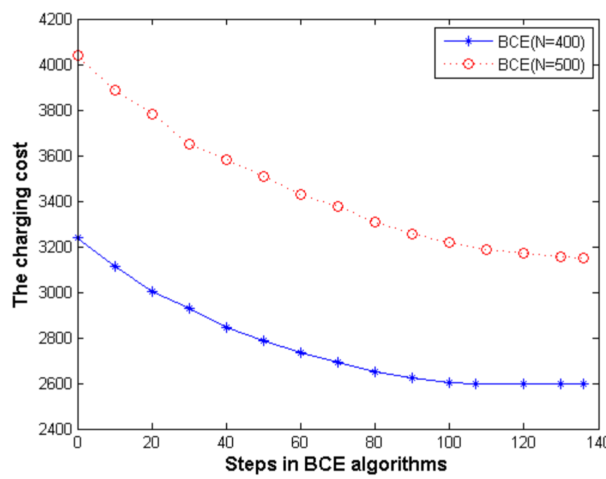


Figure 5: The charging cost decreases as the algorithm progresses ($N = 400$, $N = 500$)

algorithm and k-merging design to exclude the neighboring region phase to reduce complexity.

A. Simulation Setup

In the simulation, we assume that the IoT devices are deployed in a 2-dimensional environment. The base station from which the MC departs is assumed to be located at the origin $(0, 0)$. The evaluation metrics used here include *total charging cost and charging delay*, which are defined as the total energy replenished by the MC to compensate for the energy consumption of each node.

For the battery at the node, we set its nominal cell voltage and the quantity of electricity as 600mAh/1.5V. Then, the maximum energy of node battery is $B_{\max} = 600$mAh $\times 1.5$V $\times 3,600$ seconds = 3.24KW = $3,240$W. The energy consumption ratio of a battery from each node is randomly generated within $[40, 60]\%$, which is equal to the remaining capacity of the battery from each node $[1296, 1944]$W. We assume a wireless energy transfer rate from the MC P_t = 5W. The traveling speed of the MC is V = 5m/s, and the power consumption for traveling E_d is 5 J/m.

The following are the system parameters used in this simulation study. In the equation regarding the charging efficiency of cluster (i.e., Eq. (4)), the parameters are determined as suggested in [16].

B. Analysis of the Proposed Algorithms

As the proposed BCE algorithm is formulated by integer programming, we can verify that the charging cost decreases as the BCE algorithm is processing. It can also be observed that the BCE algorithm is able to find the optimal value even though it is not global, as shown in Fig. 5.

In addition, from the comparison results between the BCE and BSBE algorithms, it can be observed that the BCE algorithm has superior execution time and the BSBE algorithm has better performance. As shown in (54), the proposed BSBE algorithm always has a better solution than the BCE algorithm. However, the BSBE algorithm is influenced by threshold γ and limit. As the threshold and the limit increase, the execution time of the BSBE algorithm increases.

C. Measurement with Global Optimal Solutions in Small Examples

Owing to the NP-hardness of the MMCEP problem, it is infeasible to compute the optimal solutions for large-scale networks. Therefore, we compute the optimal solution for small-scale networks and compare the optimal solutions with the solutions obtained from existing and proposed BCE/BSBE algorithms. The results are the average of 50 times simulations with different numbers of nodes, namely, {40,50,60,70,80}. In order to determine the optimal solution to our problem, we exploit the Depth-First Search (DFS) algorithm and Divide& Conquer techniques to be tolerant of the high complexity of the problem.

In our simulation study, the size of the network is determined as a 400m $\times$ 400m square. We analyze two metrics, the total charging cost and the charging delay, from the experiment on a small-scale network. As seen from Fig. 6a and Fig. 6b, the total charging cost and charging delay for all algorithms increase when the number of IoT devices increases, since the total energy demand to charge increases. However, the gradient of lines in multi-charging algorithms decreases, since the charging efficiency increases as the probability of becoming a cluster containing multiple IoT devices increases, as shown in Fig. 6a. It can also be observed that the proposed algorithms achieve a performance close to the optimal solutions, within 1% of the total charging cost and the charging delay and better than k-merging design and NJNP. In the case of the NJNP scheme (single charging technique), the charger performs charging at a very short distance from the each IoT device to achieve good charging efficiency. Therefore, we observed that the NJNP technique has the greatest amount of charge energy due to the large travel distance. Furthermore, in the case of single charging, as can be seen in Fig. 8, as the enrgy consumption for traveling increases, the total charging cost increases with higher slope.

Basically, the MC will travel through the clustered paths and recharge all nodes with low battery power. Therefore, the reduction of the charging delay implies that IoT devices wait a short time to recharge, which means that they can prolong the network lifetime.

From Fig. 7a and Fig. 7b, it can be observed that the gradient of difference with the optimal solution in the proposed algorithms is slight, but the other algorithms have a steep gradient.

Table III: The execution time between fetch and end of the BCE and BSBE algorithms

# of nodes	BCE (ms)	BSBE ($limit = 10000$)	BSBE ($limit = 100000$)
100	1.345	1.8719	1.5346
150	1.4918	7.1515	7.5589
200	17.86	211.3124	5597.38
250	29.52	391.4864	35939.41
300	38.35	449.8657	41881.55

D. Performance Evaluation of the Proposed Algorithms in Large-Scale Networks

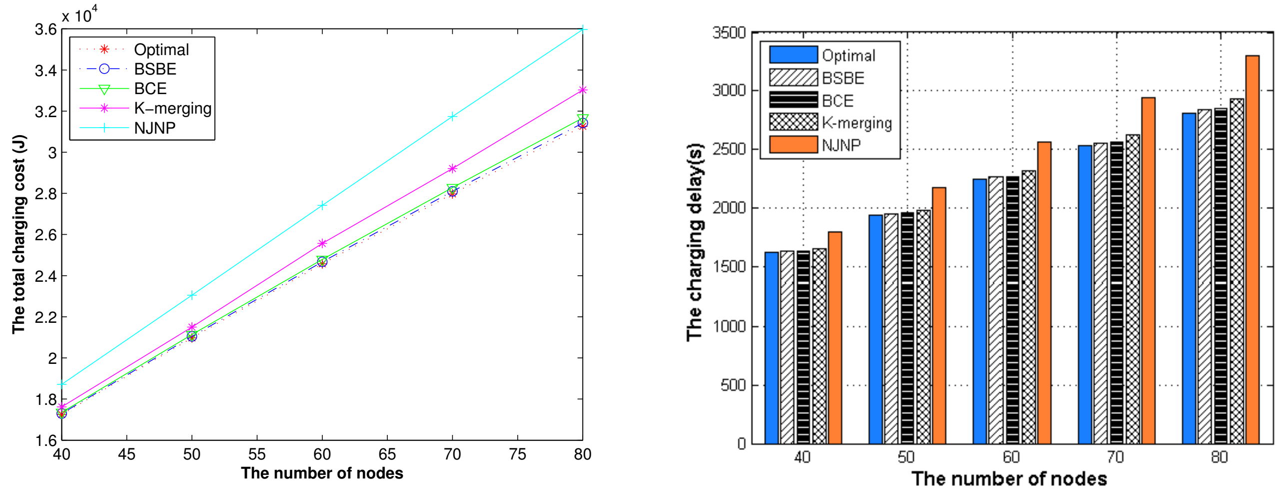
In this section, the performance of the proposed BCE and BSBE algorithms are evaluated in comparison with the existing algorithms in large scale networks. By assuming that the size of the network field is 700m $\times$ 700m, we evaluate the performance of total charging cost and charging delay. The number of nodes is varied among {100, 150, 200, 250, 300} and the simulation was conducted 50 times for each number N.

From Fig. 9a and Fig. 9b, it can be observed that the proposed BCE and BSBE algorithms outperform the k-merging design and NJNP for all numbers of IoT devices. As N becomes larger, the performance difference between the proposed BCE and BSBE algorithms and existing algorithms also becomes larger, as shown in Fig. 9a. For example, when the number of nodes $N = 100$, the difference in charging cost between the BSBE algorithm and existing algorithms is 1.3 x 10^4J and 2.0 x 10^4J corresponding to k-merging and NJNP, respectively, and when the number of nodes is $N = 300$, the difference is 4.7 x 10^4J and 8.3 x 10^4J. As the proposed BCE and BSBE algorithms provide clusters that have a higher charging efficiency, the total charging cost and delay can be reduced meaningfully.

In addition, it can also be observed that the performance of multi-charging algorithms improves when the number of nodes increases owing to the efficiency advancement of multi-charging, as shown in Fig. 10.

VI. Concluding Remarks

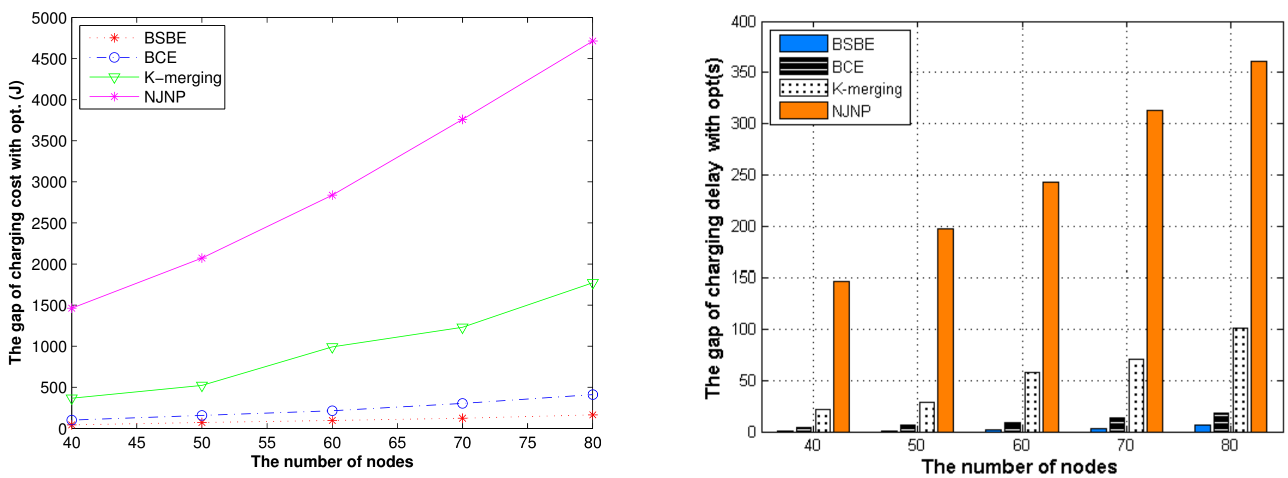
Recently, mobile wireless power transmission technology has attracted attention for charging battery-limited IoT devices.



(a) Comparison of the charging cost with the optimal solution in the IoT networks

(b) Comparison of the charging delay with the optimal solution in the IoT networks

Figure 6: Comparison between the algorithms and the optimal solution in small IoT networks



(a) Difference in charging cost with the optimal solution in the IoT networks

(b) Difference in charging delay with the optimal solution in the IoT networks

Figure 7: The difference between algorithms compared with the optimal solution in small IoT networks

In this paper, we formulated the mobile charging problem as a Minimum Mobile Charger Energy Problem (MMCEP), to minimize the recharging energy needed to replenish the consumed energy of all the IoT devices. In addition, the NP-hardness of the MMCEP was proved. Based on this, two efficient algorithms were proposed for the mobile charging problem, namely the Best Charging Efficiency (BCE) and Branching Second Best Efficiency (BSBE) algorithms. In order to make the BCE algorithm tractable we derived the lower bound of the algorithm using the duality of linear programming. Furthermore, this paper analyzed the reason for the degradation of the BCE algorithm when compared with the optimal solution. The BSBE algorithm was proposed to resolve the drawback and improve the performance of the BCE algorithm. Experimental results validate that the proposed BCE and BSBE algorithms outperform the existing algorithms; and the solution derived from our proposed algorithms was within 1% of the optimal solution in terms of charging cost and delay.

In the future work, we will compare single charging and multi-charging methods in the RF-based charging. Since the energy transfer efficiency decreases dramatically with the increase of the distance between a charger and a IoT device, charging efficiency is highly dependent on several factors, including how the IoT device is deployed, the amount of energy consumed by moving the vehicle, energy capacity and the transmission power. Therefore, the technique of recognizing the network situation and selectively applying the charging model will be a very interesting research topic, which is our future work.

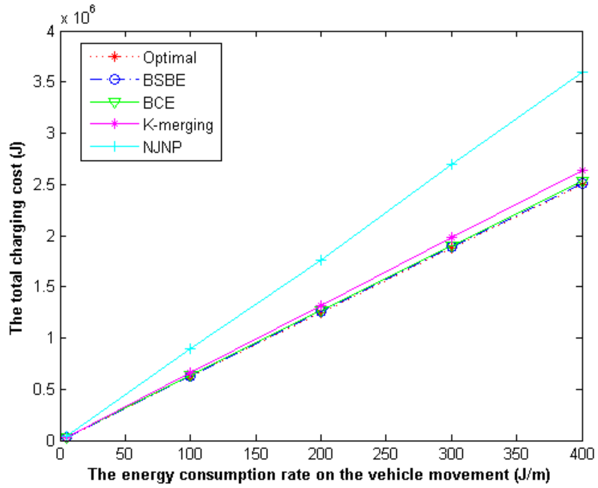


Figure 8: Total charging cost vs. the energy consumption rate on the vehicle movement ($N = 8$)

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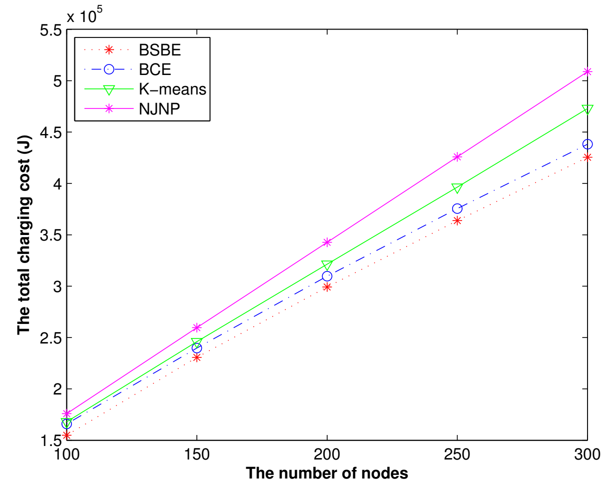
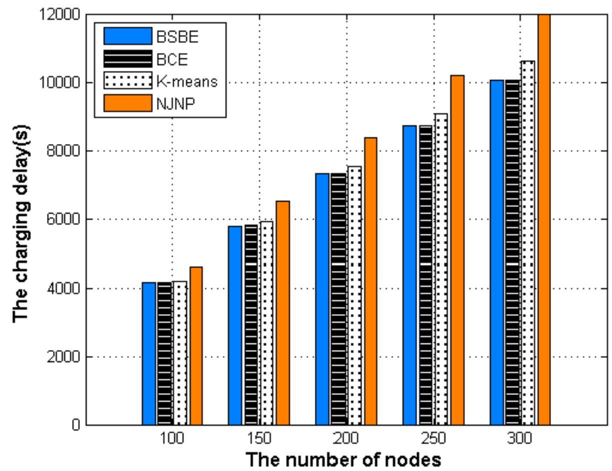
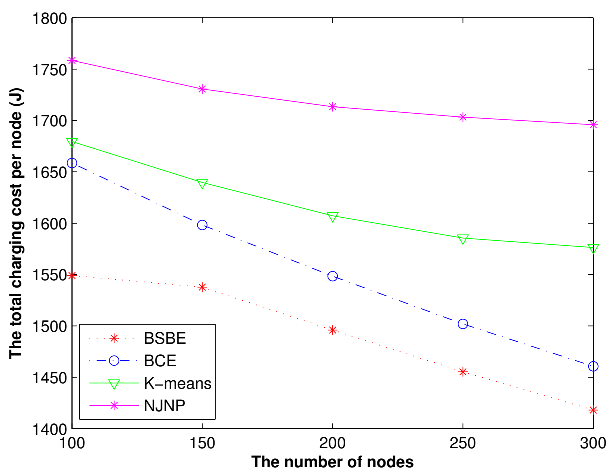


(a) Comparison of the total charging cost among the proposed and the existing algorithm in large-scale networks

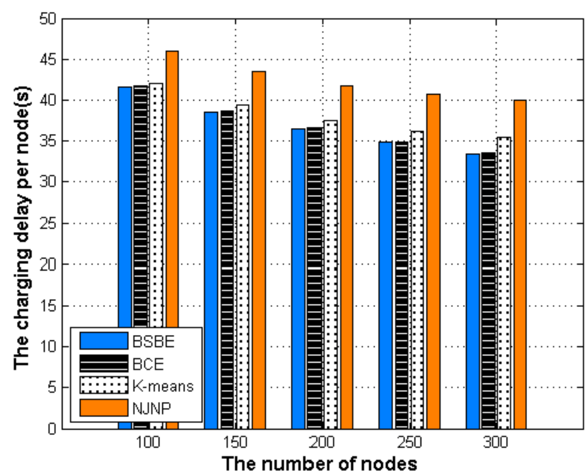


(b) Comparison of the charging delay among the proposed and the existing algorithm in large-scale networks

Figure 9: Comparison between the algorithms and the optimal solution in large IoT networks



(a) Comparison of the total charging cost per node among the proposed and the existing algorithms in large-scale networks



(b) Comparison of the charging delay per node among the proposed and the existing algorithm in large-scale networks

Figure 10: Algorithms compared with optimal solution in large IoT networks

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