Journal of Industrial and Management Optimization

JIMO, 22(10): 4676–4695.
DOI:10.3934/jimo.2026162
Received: 27 March 2026
Revised: 19 July 2026
Accepted: 20 July 2026
Published: 02 September 2026

https://www.aimspress.com/journal/jimo

Research article

Rechargeable wireless sensor network deployment optimization considering road traffic equilibrium and charging vehicle routing

Minghua Zeng[1], Danye Wang[2], Rong Zhang[3], Wei Xu[1] and Ni Dong[4,*]

[1] School of Automotive and Transportation Engineering, Guangdong Polytechnic Normal University, Guangzhou 510665, China
[2] School of Traffic and Transportation Engineering, East China Jiao Tong University, Nanchang 330013, China
[3] Xinjiang Vocational & Technical College of Communications, Urumqi, Xinjiang 831400, China
[4] School of Transportation and Logistics, Southwest Jiaotong University, Chengdu 611756, China

***Corresponding author:** Email: dongni@home.swjtu.edu.cn.

Abstract: Fully rechargeable wireless sensor networks (WSNs) serve as crucial infrastructure for the reliable collection and transmission of real-time road traffic information in emerging smart transportation systems. We study the optimization of rechargeable WSN layout, where sensors are recharged by mobile charging vehicles (MCVs). We propose a bi-level programming model for WSN layout optimization. The upper level minimizes sensor energy consumption subject to constraints including data flow balance and a sensor number budget. The lower level comprises two parallel models (MCV routing for sensor recharging and automated vehicle traffic flow equilibrium) that significantly affect optimal WSN deployment. A heuristic solution method is designed by integrating particle swarm optimization, depth-first search, and the Frank–Wolfe algorithm. Numerical experiments verify the model and method's effectiveness, yielding optimal deployment schemes for WSNs and meaningful results, such as a lower initial state of charge, a bigger recharging threshold; recharging priorities reduce optimal WSN energy consumption but increase MCV energy consumption.

Keywords: Deployment optimization; rechargeable WSN; MCV routing; bi-level programming; particle swarm optimization; traffic assignment

Mathematics Subject Classification: 90B50, 90B20, 90B06

1. Introduction

In urban intelligent transportation systems, sensors are widely used to collect real-time traffic data (speed, volume, occupancy) and transmit it to roadside base stations or a cloud network for processing.

Wireless sensor network (WSN) deployment has been extensively studied [1–3], but most have overlooked the pivotal influence of data flow dynamics [4,5]. Given the profound impact of data transmission patterns on energy utilization and sensor layout in a WSN, it is imperative to incorporate sophisticated data flow modeling into WSN deployment optimization.

More importantly, research on WSN layout optimization for urban intelligent transportation systems has rarely carried out intensive study on the influence of road traffic flow. Road traffic flow, governed by real-time information, serves as a primary data source for WSNs. Conversely, a WSN plays a pivotal role in facilitating real-time information transmission and supports intelligent transportation systems that are crucial for modern traffic mobility. However, the impact of traffic flow patterns on WSN layout optimization is underexplored.

Wireless energy transfer technology has emerged as a promising solution via dedicated mobile charging vehicles (MCVs) to address sensor power limitations [6–8], yet existing research has ignored heterogeneous sensor energy consumption [9], MCV travel energy consumption [10], and the impact of road traffic flow on charging planning and WSN deployment optimization.

To ensure the continuous and stable operation of a rechargeable WSN during data collection and transmission, this study focuses on two core aspects: (1) intensively characterizing the urban road traffic flow's impact on sensor energy consumption and layout; (2) using MCVs to provide priority-based charging services in a timely and effective manner to low-battery sensors. This research supports the sustainable development of urban intelligent transport systems.

2. Related work

Previous research on WSN deployment aims to achieve optimal performance metrics such as coverage, connectivity, and lifetime of WSNs with different sensor characteristics (radius, type, etc.) mainly through modeling [11–13], algorithm design [14–16], or both [17–19]. For example, Nene et al. [16] proposed an uncovered region exploration algorithm to maximize the coverage of a wireless camera sensor network, and Ababneh [17] studied error- and energy-aware sensor deployment for received signal strength localization. Contrary to most existing research focusing on rectangular regions, Cheng and Hsu [20] proposed a deterministic sensor deployment model and algorithm for the barrier coverage problem in WSNs with irregularly shaped areas.

The aforementioned studies have seldom modeled the impact of data flow on sensor deployment. Because data flow transmission affects the energy consumption and layout scheme of a WSN, modeling data flow in WSN deployment optimization is of practical significance. However, such investigations are few [4,5]. Güney et al. [4] formulated the integrated problem of sensor deployment, sink location, and data routing as mixed-integer linear programming models and proposed a tabu search heuristic to find optimal sensor locations meeting coverage requirements. Alfieri et al. [5] leveraged sensor spatial redundancy to maximize network lifetime. However, they assumed that the number of deployed sensors is sufficiently large. To achieve energy efficiency, many routing protocols have been proposed.

In summary, the studies on WSN layout optimization, whether considering data flow or not, have hardly considered the role of road traffic flow that is a direct source of sensor data flow and is distributed under the influence of real-time information. Therefore, we intensively explore the impact of traffic flow patterns (a principal characteristic of a transport system) on the layout optimization of WSNs (serving as a transportation infrastructure). This valuable problem is rarely addressed. Furthermore, existing WSN layout research fails to construct a bi-level programming optimization model with upper-level decision-making for sensor deployment and a lower-level road traffic flow model or a lower-level MCV charging routing.

Wireless charging research includes single-vehicle charging [6,7], multivehicle charging [10], multiple-charger charging [9,21], demand-responsive charging schemes [8–10], and other interesting methods [22–24]. Lin et al. [25] proposed a method of double warning thresholds with a double preemption charging scheme, and Priyadarshani et al. [9] proposed an on-demand multinode partial charging scheme with multiple MCVs.

In summary, most existing literature on wireless sensor charging ignores the heterogeneous energy consumption rates of sensors [9] and the energy consumed by charging vehicles during travel [10]. Furthermore, these studies rarely consider the impact of road traffic flow on charging planning and WSN layout. No prior studies integrate traffic flow characteristics, data flow dynamics, heterogeneous sensor power consumption, MCV travel energy loss, and priority charging rules into one unified optimization model as our work does.

3. Contributions

As the literature review indicates, few investigations have focused on the deployment optimization of wireless sensor networks with heterogeneous sensor energy consumption induced by heterogeneous road traffic flow distribution. Therefore, we elaborate on this unresolved problem to obtain the optimal placement of a rechargeable wireless sensor network for collecting and disseminating real-time information about automated vehicles that are monitored road vehicles. The contributions are fourfold.

(1) A priority- and multi-MCV-based on-demand charging scheme considering road traffic distribution is integrated into WSN deployment.

(2) A novel bi-level programming model for the WSN layout problem: The lower level includes the MCV optimal routing and road traffic assignment model with link capacity adjusted by active sensors.

(3) A new sensor recharging priority index combining its current state of charge (SOC) and road traffic volume (higher traffic or lower current SOC indicates higher charging priority).

(4) An adjusted Bureau of Public Roads function for link travel time, incorporating link capacity using an exponential function modified by the number of active sensors per unit road link length.

The remainder of this paper is arranged as follows. Section 4 describes the rechargeable wireless sensor network deployment problem. Section 5 formulates a bi-level model for the problem. Section 6 proposes solution algorithms for the bi-level model. Section 7 presents example analyses, followed by conclusions in Section 8.

4. Problem description

A road network is composed of a set of nodes and links. Sensor candidate locations V include nodes and selected locations on links. The actual deployed sensors are denoted by $N \subseteq V$. Sensors are homogeneous in communication radius, initial SOC, and recharging threshold, but heterogeneous in energy consumption rate and recharging priority. $|K|$ homogeneous MCVs are arranged to charge sensors via wireless technology (no energy loss and constant charging rate), where K represents the MCV set. An MCV runs on an optimal path determined by a vehicle routing scheme [26], and its energy consumption is linear with travel distance. It may be difficult for one MCV to recharge all sensors in one trip starting from and back to the garage (the charging station is located here). Multiple MCVs (returning to the garage for recharging) complete the charging task. Figure 1 illustrates the process in which MCVs travel in the road network to recharge WSN. It is worthwhile to point out that the assumptions of zero energy loss in wireless charging, constant charging rate, linear relationship between vehicle energy consumption and travel distance, and the absence of traffic lights are adopted to focus on core routing and charging arrangement problems and reduce computational complexity.

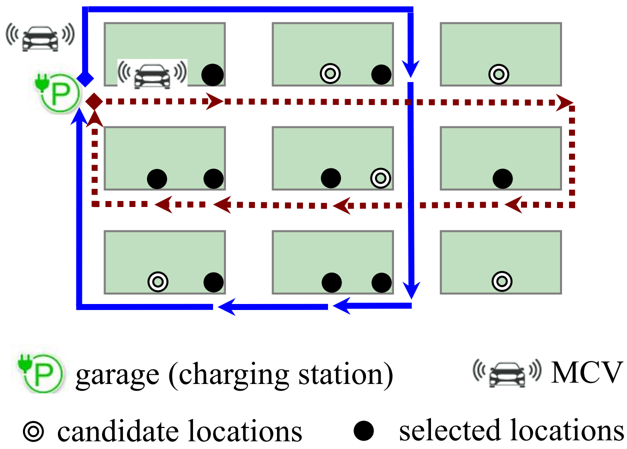

Figure 1. The WSN recharging process by MCVs.

5. A bi-level model for WSN deployment

The bi-level model optimizes sensor deployment at the upper level and integrates MCV routing and traffic assignment at the lower level. By comprehensively considering communication radius, location, battery SOC, and data flow, the upper-level leader pursues the balance of energy consumption among sensors and prolongs the WSN lifetime through optimal sensor deployment. The lower-level followers exhibit two types of behavior: equilibrium route choice behavior described by the user equilibrium (UE) model of road network traffic flow, and charging routing behavior described by the mobile charging vehicle routing problem (MCVRP). The MCVRP provides the optimal paths for MCVs to recharge sensors. The UE model performs road automated vehicle traffic assignment based on the criterion that road users choose paths with the lowest travel time cost. The followers provide for the upper level with sensor battery SOCs, optimal recharging paths and energy consumption of MCVs, and assigned traffic flows.

5.1. Upper-level WSN deployment model

According to communication radius, deployed number, location, SOC, and data flow balance, we establish a mathematical model aiming to minimize sensor energy consumption.

The energy consumption E_j of sensor j is as follows [5]:

$$E_j = E^c \rho_j x_j + \sum_{i \in V} E^T f_{ji} x_{ji} + \sum_{i \in V} E^R f_{ij} x_{ij}, \forall j \in V, \tag{1}$$

where E^c, E^T, and E^R are the energy consumed by a sensor to sense and compress, transmit, and receive a unit of data flow, respectively; f_{ji} is the data flow from sensor j to sensor i; x_i is a binary variable indicating whether a sensor is deployed at location i ($x_i = 1$) or not ($x_i = 0$); and x_{ji} ($i \neq j$) is a binary variable indicating that $x_{ji} = 1$ if sensors i and j are connected and zero otherwise. x_{ji} can be expressed as $x_{ji} = x_j x_i p_{\bar{d}_{ji}}$ with the connectivity $p_{\bar{d}_{ji}}$ between sensors i and j defined as follows:

$$p_{\bar{d}_{ji}} = \begin{cases} 1, \bar{d}_{ji} \leq R \\ 0, \bar{d}_{ji} > R \end{cases}, \forall i, j \in V, \tag{2}$$

where $\bar{d}_{ij}$ is the crow-fly distance between sensors i and j; R is the communication radius of a sensor; and ρ_i represents the data flow into WSN from sensor i and is determined by the traffic flow on the link where sensor i locates and is covered by the WSN, that is, $\rho_i = B v_a \varsigma_{ai} \xi_i$. B is the data bits of information about a vehicle; v_a is the traffic flow on link $a \in A$; A is the set of road links; ς_{ai} is a binary variable indicating that sensor i is located on link a ($\varsigma_{ai} = 1$) or not ($\varsigma_{ai} = 0$); and ξ_i is a binary variable indicating that sensor i is covered by the WSN ($\xi_i = 1$) or not ($\xi_i = 0$), in which $\xi_i = 1$ means there exists $j' \in N$ such that $p_{\bar{d}_{j'i}} = 1$ or $p_{\bar{d}_{ij'}} = 1$.

The objective function is defined as the minimization of the maximum sensor energy consumption as follows:

$$\min_{x,f} Z_1(x, f, h, v) = E_{\max}, \tag{3}$$

where $E_{\max} = \max_{j \in V} E_j$; $x = (x_i), f = (f_{ij}), i, j \in V$ are the decision variables of the upper-level model; $h = (h_{ij}^k), i, j \in N_0, k \in K$, and $v = (v_a), a \in A$ are the decision variables of the lower level MCV routing problem and automated vehicle traffic flow assignment model, respectively; h_{ij}^k is a binary variable with $h_{ij}^k = 1$ indicating that MCV k travels on link (i, j) and 0 otherwise; and N_0 is the set of nodes visited by MCVs $N_0 = N \bigcup \{0\}$, in which 0 represents the garage.

The balance constraints of data flow between sensors are as follows:

$$\rho_j x_j + \sum_{i \in V} f_{ij} x_{ij} = \sum_{i \in V} f_{ji} x_{ji}, \forall j \in V. \tag{4}$$

The total number $|N|$ of sensors to be deployed is constrained as follows:

$$\sum_{i \in V} x_i = |N|. \tag{5}$$

The energy consumption cannot exceed the current SOC of sensor j, that is,

$$\sum_{i \in V} E^R f_{ij} x_{ij} + E^c \rho_j x_j + \sum_{i \in V} E^T f_{ji} x_{ji} \leq \hat{E}_j, \forall j \in V, \tag{6}$$

where the current SOC of sensor j ($\hat{E}_j$) is set as its initial SOC (E_j^0) at the beginning of the planning horizon (assumed fully charged) and is updated in the lower-level MCVRP during planning.

Finally, the definition constraints for sensor deployment and data flow are as follows:

$$x_i \in \{0,1\}, i \in V , \tag{7}$$

$$f_{ij} \geq 0, i, j \in V . \tag{8}$$

5.2. Mobile charging vehicle routing problem

Considering constraints on MCV SOCs, sensor SOCs, and routing, we propose an MCVRP to find optimal routes for MCVs to recharge all deployed sensors.

A sensor is powered by its rechargeable battery, which is recharged by MCVs via wireless charging. Sensors with SOC below a given threshold are recharged by MCVs based on sensor charging priority.

The objective is the minimization of total MCV travel distance, that is,

$$\min_{h} Z_2(x, f, h, v) = \sum_{k \in K} \sum_{i,j \in N_0, i \neq j} d_{ij} h_{ij}^k , \tag{9}$$

where d_{ij} is the shortest path length between sensors i and j, calculated based on MCV travel time on the physical path between i and j. The objective is consistent with minimizing total MCV energy consumption assuming MCV energy consumption is proportional to distance traveled.

A sensor requiring service must be recharged at least once, that is,

$$\sum_{k \in K} \sum_{j \in N_0, i \neq j} h_{ij}^k \geq 0, \forall i \in N . \tag{10}$$

The MCV flow balance constraint at a sensor requiring recharging service is given as Eq (11), which means that the MCV flow arriving at the sensor is equal to the MCV flow leaving the sensor:

$$\sum_{k \in K} \sum_{i \in N_0, i \neq j} h_{ij}^k = \sum_{k \in K} \sum_{i \in N_0, i \neq j} h_{ji}^k, \forall j \in N . \tag{11}$$

An MCV must return to its origin after completing services, that is,

$$\sum_{i \in N} h_{0i}^k = \sum_{j \in N} h_{j0}^k, \forall k \in K . \tag{12}$$

The constraint on the total number of MCVs (n_{MCV}) is given as follows:

$$\sum_{k \in K} \sum_{j \in N} h_{0j}^k \leq n_{\text{MCV}} . \tag{13}$$

Before recharging, the current SOC of sensor i ($\hat{E}_i$) is determined by $E_i^0 - E_i$, where E_i is its consumed electricity of sensor i determined by the upper-level model. Sensor i requests for recharging if the current SOC is lower than σ times the initial SOC, that is, $E_i^0 - E_i < \sigma E_i^0$. If multiple sensors need recharging, they are served according to a priority sequence:

$$r_i - M\left(1 - h_{ji}^k\right) \leq r_j, \ \forall i, j \in N, i \neq j, k \in K , \tag{14}$$

where r_i is the recharging priority value of sensor i. M denotes a sufficiently large positive number. Equation (14) means that if the priority value of sensor *i* is not greater than that of sensor *j*, the corresponding MCV will visit sensor *j* prior to sensor *i*. The priority value is directly proportional to the traffic volume on the link where the sensor installed (greater traffic volume indicates more data to be handled and greater energy consumption by the sensor). It is inversely proportional to its current SOC (higher current SOC for the sensor implies it can work longer). We define r_i as follows:

$$r_i = \frac{v_a \varsigma_{ai}}{E_i^0 - E_i}, \ \forall i \in N . \tag{15}$$

Most existing wireless charging scheduling studies for WSNs determine charging priorities only by relying on internal attributes of sensors, such as remaining battery capacity [27,28]. For example, Shakhatreh et al. [27] formulated sensor recharging priority according to the energy consumption cost of the drone collecting data from the sensor. Distinct from these prior studies, the proposed priority additionally introduces road traffic flow, an exogenous dynamic environmental factor that has never been incorporated into the priority formulation in previous studies.

Through formulae (14) and (15), we determine the recharging priority sequence to extend WSN lifetime despite power imbalance among sensors. The service order will not be rearranged during MCV charging in one time call of the MCVRP.

The recharging amount q_i for sensor i is the minimum of its electricity demand (set as its consumed electricity) E_i and the remaining SOC Q_i^k of MCV k arriving at sensor i:

$$q_i = \min\{E_i, Q_i^k\}, \forall i \in N, k \in K . \tag{16}$$

The total energy consumption of an MCV (total MCV travel energy plus total energy recharged to sensors) is restricted by its initial energy (Q^e) that is equal to battery capacity:

$$\sum_{j \in N} \sum_{i \in N_0, i \neq j} q_i h_{ij}^k + \sum_{j \in N} \sum_{i \in N_0, i \neq j} ed_{ij} h_{ij}^k \leq Q^e, \forall k \in K , \tag{17}$$

where e is the MCV energy consumption rate.

To ensure a sensor's recharging demand can be satisfied in one visit of MCV, the MCV's SOC upon arrival must not be less than the sensor's total energy demand:

$$Q_j^k \geq E_j h_{ij}^k, \forall i, j \in N, i \neq j, k \in K \tag{18}$$

When an MCV travels from sensor i to j, its SOCs satisfy

$$Q_j^k \leq Q_i^k - ed_{ij} h_{ij}^k - q_i h_{ij}^k + M(1 - h_{ij}^k), \forall i, j \in N_0, i \neq j, k \in K . \tag{19}$$

An MCV can return to the garage (charging station) from any sensor:

$$ed_{i0} h_{i0}^k \leq Q_i^k, \forall i \in N, k \in K . \tag{20}$$

An MCV starts from the garage (charging station) with a full battery:

$$Q_j^k \leq Q^e - ed_{ij} h_{ij}^k, \forall i \in N_0^c, j \in N, i \neq j, k \in K , \tag{21}$$

where N_0^c is the set of garage and charging stations.

After recharging, the SOC of sensor i is updated as follows:

$$\hat{E}_i = E_i^0 - E_i + q_i^k, \forall i \in N, k \in K . \tag{22}$$

The link choice constraints for MCV are given as follows:

$$h_{ij}^k \in \{0,1\}, \forall i, j \in N_0, i \neq j, k \in K \, . \tag{23}$$

5.3. Automated vehicle traffic flow assignment model

Assume that all vehicles in the road network are automated vehicles. One lower-level model describes UE for automated vehicles, which is given as (24)~(27):

$$\min_{v} \; Z_3(x, f, h, v) = \sum_{a \in A} \int_0^{v_a} t_a(w)dw, \tag{24}$$

subject to

$$\sum\nolimits_{m \in R_{rs}} \bar{f}_m^{rs} = q_{rs}, \forall r, s \in V \, , \tag{25}$$

$$v_a = \sum\nolimits_r \sum\nolimits_s \sum\nolimits_m \bar{f}_m^{rs} \delta_{a,m}^{rs}, \forall a \in A \, , \tag{26}$$

$$\bar{f}_m^{rs} \geq 0, v_a \geq 0, \forall a \in A, r, s \in V \, , \tag{27}$$

where q_{rs} is the traffic demand between origin–destination (OD) pair $(r,s) \in V \times V$; $V' \subset V$ is the set of nodes of the road network; R_{rs} is the set of paths between (r,s); $\delta_{a,m}^{rs}$ is a link–path correlation variable indicating that $\delta_{a,m}^{rs} = 1$ if link a lies on path m and 0 otherwise; and $\bar{f}_m^{rs}$ is the automated vehicle flow on path m between (r,s).

This model depicts selfish route choice behavior that each automated vehicle chooses the shortest path measured by travel time. The link travel time t_a is calculated by the Bureau of Public Roads function

$$t_a(v_a) = t_a^0 \left(0.15 + \left(v_a / C_a^s \right)^4 \right), \forall a \in A \, ,$$

where t_a^0 is the free flow travel time on link a, and C_a^s is the new link capacity defined by considering that automated vehicles receive traffic information from sensors.

Automated vehicles receive traffic information (especially that they cannot “see” with the help of the onboard sensors) from roadside WSNs. Because automated vehicles make decisions by referring to the received information, the spatial distance between automated vehicles becomes closer if the information is more complete and accurate. More active sensors on a link provide more complete and accurate information for decision-making of automated vehicles on the link. Thus, the spatial distance between automated vehicles can be closer, which leads to greater link capacity. Therefore, we formulate the new road capacity as follows:

$$C_a^s = C_a \exp\left(\alpha \frac{Card\{i \in \Gamma_a \mid x_i \hat{E}_i > 0\}}{l_a} \right), \tag{28}$$

where C_a is the traditional designed capacity before sensors are installed on the link, and α is an adjustment coefficient denoting the sensitivity of road capacity to active roadside sensors, which governs the marginal growth rate of link capacity with the density of deployed sensors. A higher α corresponds to a stronger capacity promotion effect brought by each additional sensor, and a lower α represents weaker marginal efficiency of sensing equipment. l_a denotes the physical length of link a; $Card()$ returns the number of elements of a set; Γ_a is the set of locations where sensors installed; and $x_i\hat{E}_i > 0$ means that a sensor is installed at location i and is active.

6. Solution algorithms

Bi-level programming is NP-hard and computationally expensive to solve exactly, so we solve the proposed bi-level model within a particle swarm optimization (PSO) framework. We design a heuristic solution method integrating PSO, depth-first search (DFS), and the Frank–Wolfe algorithm. The PSO-based Algorithm 1 solves the upper-level rechargeable WSN deployment problem. The DFS-based Algorithm 2 solves the MCVRP. The Frank–Wolfe algorithm (Algorithm 3) solves the traffic flow assignment model.

Key points are as follows.

1) Population initialization

A particle consists of two parts: sensor deployment decision variables and intersensor data flows. Particle i can be represented by $(x_i, y_i) = (x_{i1}, x_{i2}, \cdots, x_{iD_1}, y_{i1}, y_{i2}, \cdots, y_{iD_2})$, $i = 1, 2, \cdots, \vartheta$, where ϑ is population size, and D_1 and D_2 are dimensions of integer variable and real variable with $D_1 = |V|$ and $D_2 = |V| \times |V|$. For simplicity, denote $(x_i, y_i) = X_i = (X_{i1}, X_{i2}, \cdots, X_{iD})$, $D = D_1 + D_2$. Initial population is generated by initializing integer variables and real variables for each particle i:

$$x_i = round(x^L + random(0,1) \times (x^U - x^L)),$$

$$y_i = y^L + random(0,1) \times (y^U - y^L),$$

where x^U and x^L are the upper and lower bounds of x. The $random(0,1)$ function generates random numbers following a uniform distribution on $[0,1]$. The $round()$ function produces an integer value.

Algorithm 1. Particle swarm optimization algorithm.

1: Generate the initial particles $X_i, i = 1, 2, \cdots, \vartheta$ randomly.
2: **do**
3: Call Algorithm 2 to update sensor SOC values.
4: Call Algorithm 3 to obtain link traffic flows $v_a, a \in A$.
5: Obtain individual optimal solutions $P_i, i = 1, 2, \cdots, \vartheta$ for each particle, and update the current global optimal solution according to these individual optimal solutions.
6: Compare the current global optimal solution with the historical optimal solution, and retain the best one as the updated historical optimal solution P_g.
7: Update particle velocity and position.
8: **while** the maximum number of iteration $Ite_{\max}$ is not reached
9: **Return** the optimal sensor deployment scheme and the energy consumption of each sensor.

2) Velocity and position update

Update the particle velocity and position for $i = 1, 2, \cdots, \vartheta$, $d = 1, 2, \cdots, D$ as follows:

$$X_{id} = X_{id} + V_{id},$$

$$V_{id} = \omega V_{id} + C_1 \times random(0,1) \times (P_{id} - X_{id}) + C_2 \times random(0,1) \times (P_{gd} - X_{id}),$$

where C_1 and C_2 are accelerating constants in $[0,4]$, and $\omega \in [0.5, 1.0]$ is a momentum factor. P_{id} is the dth dimension of the individual extremum of particle i.

3) Construct and update the recharging matrix

Determine the shortest distance from sensor $i \in \hat{N}$ to the garage using a shortest path algorithm. All sensors in $\hat{N}$ are sorted by their priorities. Then, construct a matrix (**P-M**) whose rows contain sensor ID, electricity demand, and shortest distance.

4) Recharge sensors

Calculate the energy consumption of the MCV from its current position to the next charging station, and from the next charging station back to the garage. To ensure the MCV can return to the garage, compare its SOC with the energy demands of each sensor sequentially according to the row order of matrix **P-M**. Recharge each sensor in order of full, partial, or no recharging modes.

Algorithm 2. Mobile charging vehicle routing problem algorithm.

1: Set the initial SOC and recharging threshold of each sensor. Initialize the sensor deployment scheme using the results of Algorithm 1.
2: Determine a set of sensors to be recharged ($\hat{N}$) based on the recharging threshold and sensor SOCs.
3: **do**
4: Construct and update the charging matrix **P-M**.
5: Treat the garage as two virtual points (origin and destination). Adopt DFS to find the optimal route for MCVs to recharge sensors in $\hat{N}$.
6: Recharge the target sensors.
7: Update the electricity demand of each sensor.
8: **while** not all MCVs have returned to the garage
9: **Return** the optimal solution.

Algorithm 3. Frank–Wolfe algorithm.

1: Initialization. Initialize the sensor deployment scheme via Algorithm 1. Set the convergence threshold (ε). Set the free flow travel time as $t_a^0(v_a) = t_a(0), \forall a \in A$. Assign traffic demands to the shortest path using the "all-or-nothing" method to obtain the initial link flow pattern.
2: **do**
3: Update link travel times $t_a^n = t_a(v_a^n), a \in A$.
4: Obtain a auxiliary flow pattern $\{\bar{y}_a, a \in A\}$ by assigning traffic demands to the shortest path via the "all-or-nothing" method. Determine descent direction.
5: Obtain the optimal step size ∂^n by solving the following one-dimensional minimization problem

$$\min_{0 \le \partial \le 1} \sum_{a \in A} \int_0^{v_a^n + \partial\left(\bar{y}_a^n - v_a^n\right)} t_a(w) dw .$$

6: Update link traffic flow as follows:

$$v_a^{n+1} = v_a^n + \partial^n (\bar{y}_a^n - v_a^n), \forall a \in A .$$

$$n \leftarrow n+1 .$$

7: **while** ($\sqrt{\sum_a \left(v_a^{n+1} - v_a^n\right)^2} \Big/ \sum_a v_a^n \ge \varepsilon$)

8: **Return** the assigned link flow pattern.

5) Theoretical convergence analysis

The PSO (Algorithm 1) saves the global optimal solution (gbest) at each iteration to guarantee stable bi-level convergence. First, the lower-level MCVRP (Algorithm 2) and traffic assignment (Algorithm 3) yield unique objective values under fixed upper deployment, and the system objective has a physical lower bound. With gbest retained, the global objective sequence is monotonically nonincreasing and bounded below, which converges to a finite steady value by the monotone bounded convergence theorem and prevents divergence. Second, the fixed gbest serves as a stable reference for particle updates, limiting drastic jumps of upper decisions and suppressing iterative objective oscillation. Third, the alternating iteration decouples two layers: the lower level feeds objective values back to the upper PSO, and the accumulated gbest stores historical high-quality solutions to maintain orderly, effective cross-level information feedback.

7. Example analysis

The Nguyen–Dupuis network (Figure 2) is used to test the proposed models and algorithms. There are 13 nodes (1, 4, 12, 14, 17, 18, 20, 27, 30, 31, 33, 37, and 38) and 38 two-way and symmetric links. Link parameters are shown in Table 1. Thick and thin solid lines represent urban main and secondary arterial roads with the free flow speed of 60 km/h and 40 km/h, respectively. There are 4 OD pairs with OD demand shown in Table 2. There are 38 candidate sensor positions indicated by circles with numbers. Each road segment is evenly divided by the candidate positions that exclude the candidates at intersections. Node 17 serves as the garage and the charging station.

Assume that each real-time data received by a sensor includes vehicle arrival time, vehicle speed, vehicle type, and license plate number. Time data occupies 8 bytes, and other information each occupies 4 bytes. Thus, information of each vehicle occupies $B=4{+}4{+}8{+}4=20$ bytes. The amount of data received by each sensor is $\rho_i = Bv_a\varsigma_{ai}{=}20v_i\varsigma_{ai}$. Note that video data is not considered for simplicity.

Parameters: $|N|=30,\ n_{\mathrm{MCV}}=2,\ E_j^0=258910\ \mathrm{J}$ (J=joule), $R=500\ \mathrm{m}, E^c=3.6\ \mathrm{mJ}$ (mJ = millijoule), $E^T=(5+0.01\bar{d}_{ij}^2)\ \mathrm{mJ}$, $E^R=5\ \mathrm{mJ}$, $Q^e{=}5\times10^7\ \mathrm{J}$, $e=643\ \mathrm{J/m}$, $\sigma=90\%$, $\alpha=100$, $Ite_{\max}=500$, $\vartheta=30$, and $\varepsilon=0.001$.

For analysis, we define two performance indexes. (1) Total energy consumption of optimal deployment scheme (TECODS) is defined as the sum of energy consumption of all arranged sensors for sensing, compressing, receiving and transmitting data. (2) Total energy consumption of mobile charging vehicles (TECMCV) is defined as the sum of energy consumed by MCVs during traveling and energy consumed for recharging sensors.

Table 1. The link characteristics of the Nguyen–Dupuis network.

Link	Length ($10^3\mathrm{m}$)	Capacity ($\mathrm{veh}\cdot\mathrm{h}^{-1}$)	Free flow travel time (h)	Link	Length ($10^3\mathrm{m}$)	Capacity ($\mathrm{veh}\cdot\mathrm{h}^{-1}$)	Free flow travel time (h)
1→4	1	600	0.025	20→18	0.7	450	0.012
1→14	0.8	550	0.02	20→33	1	400	0.017
4→1	1	600	0.025	27→12	1.3	500	0.02
4→17	0.8	550	0.02	27→14	1	400	0.017
4→20	1.8	900	0.045	27→30	1	700	0.017
12→14	0.8	400	0.013	27→37	1.2	800	0.03
12→27	1.3	500	0.02	30→17	1	400	0.017
14→1	0.8	550	0.02	30→27	1	700	0.017
14→12	0.8	400	0.013	30→31	0.9	600	0.015
14→17	1	400	0.017	31→18	1	400	0.017
14→27	1	400	0.017	31→30	0.9	600	0.015
17→4	0.8	550	0.02	31→33	0.7	500	0.012
17→14	1	400	0.017	31→38	0.6	600	0.015
17→18	0.9	400	0.015	33→20	1	400	0.017
17→30	1	400	0.017	33→31	0.7	500	0.012
18→17	0.9	400	0.015	37→27	1.2	800	0.03
18→20	0.7	450	0.012	37→38	0.9	700	0.023
18→31	1	400	0.017	38→31	0.6	600	0.015
20→4	1.8	900	0.045	38→37	0.9	700	0.023

Table 2. OD demands.

OD pair	Demand	OD pair	Demand
(1,33) and (33,1)	340	(12,33) and (33,12)	200
(1,38) and (38,1)	340	(12,38) and (38,12)	320

7.1. Optimal sensor deployment schemes

The optimal deployment scheme of sensors we obtained is shown by light-blue filled circles in Figure 2. Two MCVs participate. Their optimal routes (red and green arrows) recharge specific sensors. MCV1 recharges sensors numbered 30, 31, 36, 1, 29, 21, 17, 18, 25, and 10. Its total energy consumption is 23,154,000 J. MCV2 recharges sensors 33, 38, 28, 12, 22, 20, 15, 26, and 11 and consumes 49,117,000 J in total. Detours occur due to varying sensor energy consumption (proportional to segment traffic flow) leading to irregular recharging priority distribution (Table 3). Although detours increase MCV energy, prioritizing low-SOC sensors on high-traffic links ensures better operation and connectivity of the WSN, as well as effective monitoring of road traffic, justifying the detour.

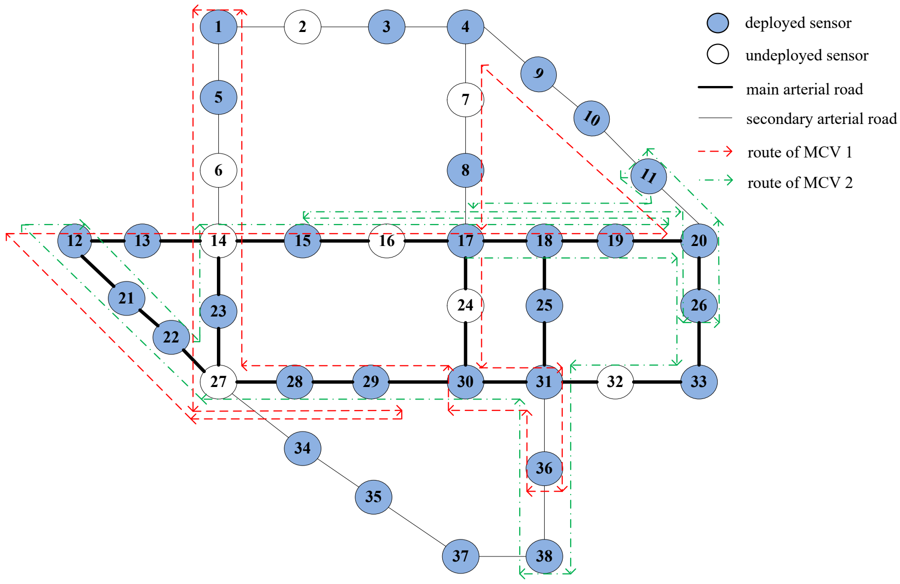

Figure 2. The Nguyen–Dupuis network, the optimal sensor deployment scheme, and the optimal routes for MCVs considering recharging priority.

Table 4 compares MCV energy consumption with and without recharging priorities. Without priority (Figure 3), the optimal routes are shorter, and MCV energy consumption is lower, as some detours are avoided. However, considering priority reduces TECODS (the sensor network energy consumption). Thus, higher MCV energy consumption extends the sensor network lifetime.

Table 3. The energy consumption of deployed sensors.

Sensor no.	1	3	4	5	8	9	10	11	12	13
Energy consumption (J)	29607	7858	20209	23073	3048	24634	34713	34891	76412	20544
Sensor no.	15	17	18	19	20	21	22	23	25	26
Energy consumption (J)	22238	14041	109947	15511	64884	74493	43586	14446	55999	56849
Sensor no.	28	29	30	31	33	34	35	36	37	38
Energy consumption (J)	41778	137441	32166	128545	58992	7953	31896	48907	3724	28735

Table 4. The energy consumption of MCVs with and without priority consideration .

Recharging priority	Route length of MCV1 (m)	TECMCV1 (J)	Route length of MCV2 (m)	TECMCV2 (J)	TECODS (J)
No	8200	5892556	7200	5075422	2015637
Yes	17720	23154000	21634	25963050	1267120

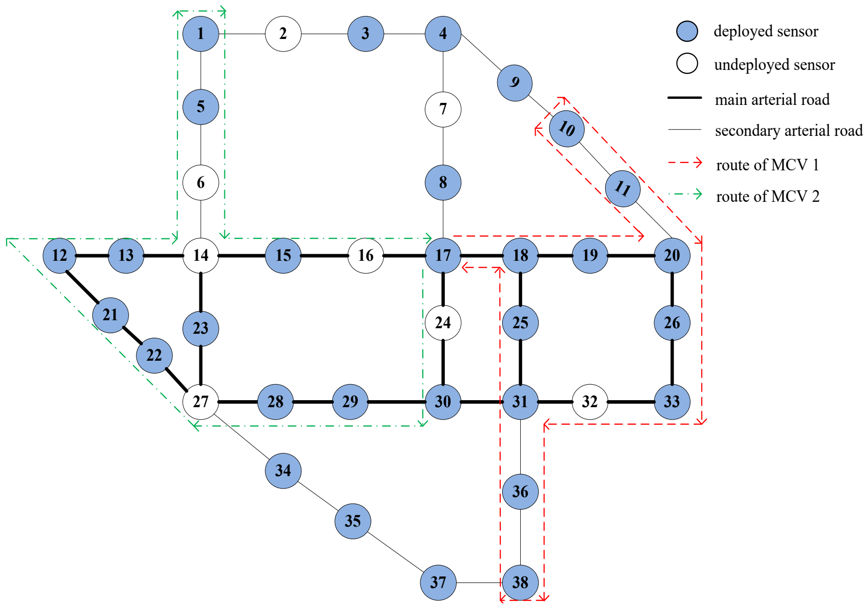

Figure 3. The optimal sensor deployment scheme and the optimal routes for MCVs obtained without considering recharging priority.

7.2. Sensitivity analyses of performance

1) Sensitivity analysis for recharging thresholds

Set the communication radius as 500 m. Other parameters remain unchanged in this and subsequent subsections. This subsection conducts sensitivity analysis for different recharging thresholds: 50%, 60%, 70%, 80%, and 90%.

In all threshold cases, two MCVs are required to recharge the sensor network. The upper-level objective function values of the optimal schemes corresponding to these thresholds are 161,262 J, 161,255 J, 148,852 J, 133,868 J, and 133868 J. The results of TECODS and TECMCV (Figure 4) indicate that TECODS decreases with a higher threshold, whereas TECMCV (especially for MCV2) increases. A higher threshold reduces WSN energy consumption and extends its lifetime.

2) Sensitivity analysis for OD demand

The OD demand is scaled by factors from 0.6 to 1.4. The upper-level objective function values corresponding to the optimal sensor deployment scheme under each demand are 80,569 J, 113,868 J, 103,243 J, 120,213 J, 133,868 J, 133,428 J, 133,191 J, 137,326 J, and 139,463 J, respectively. As shown in Figure 5, TECMCV (represented by bars) and TECODS roughly increase with demand (Figure 5), as higher traffic flow increases sensor energy consumption and MCV workload.

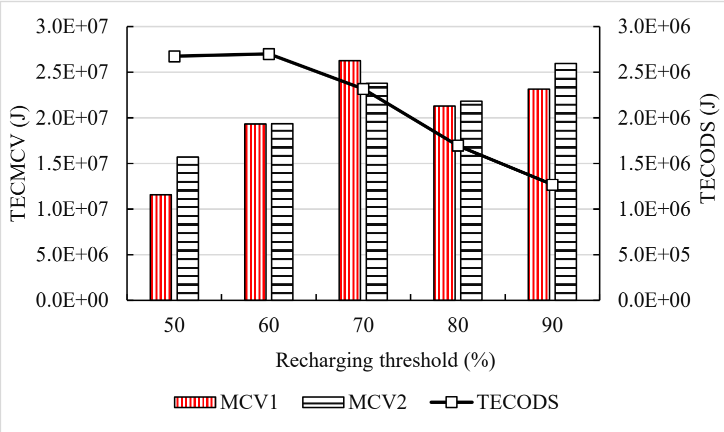

Figure 4. TECODS and TECMCV obtained for all recharging thresholds.

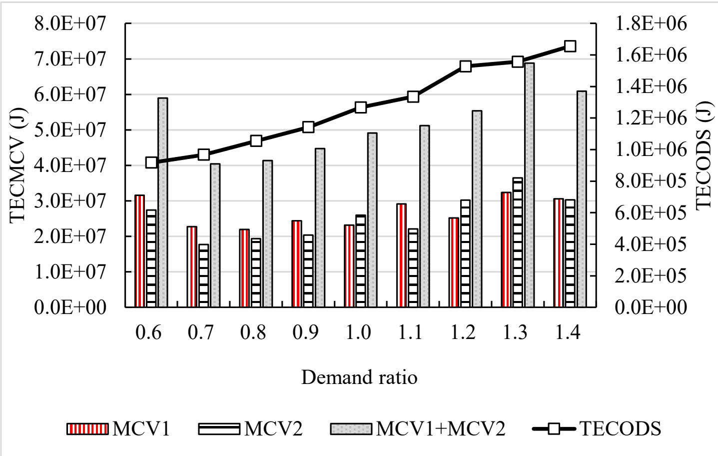

Figure 5. TECODS and TECMCV obtained under different OD demands.

3) Sensitivity analysis for communication radius

Set the communication range as 200 m, 300 m, 400 m, 500 m, and 600 m. The upper-level objective values corresponding to the optimal sensor deployment schemes under the five radii are 26,505 J, 47,635 J, 48,620 J, 133,868 J, and 251,812 J, respectively. Figure 6 shows that TECODS and TECMCV increase with radius, rising steeply beyond 400 m. At a 200 m radius, one MCV suffices; for radii not less than 500 m, both MCVs are required to keep sensors active.

4) Sensitivity analysis for the initial SOC of sensors

Set initial sensor SOC values as 158 kJ, 208 kJ, 258 kJ, 308 kJ, and 358 kJ. The upper-level objective values of the optimal sensor deployment schemes are all approximately 133,868 J. As shown in Figure 7, TECMCV first decreases and then increases with SOC; TECODS fluctuates but increases markedly from 308 kJ to 358 kJ (Figure 7). The total system cost is lower when the initial SOC falls within 258–308 kJ. For the WSN lifetime, a smaller initial SOC (e.g., 158 kJ) is better.

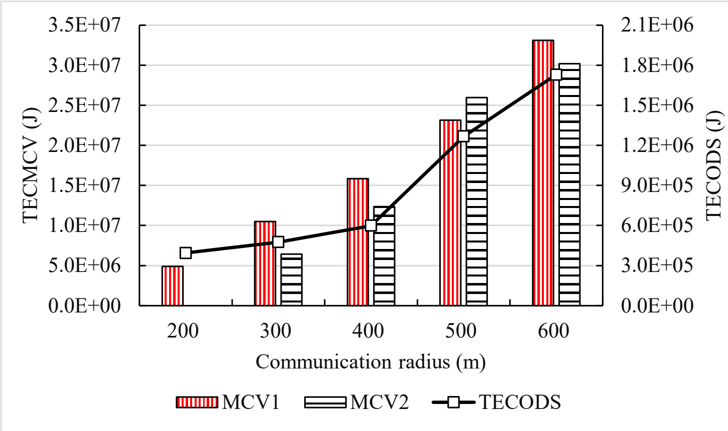

Figure 6. TECODS and TECMCV obtained under different communication radii.

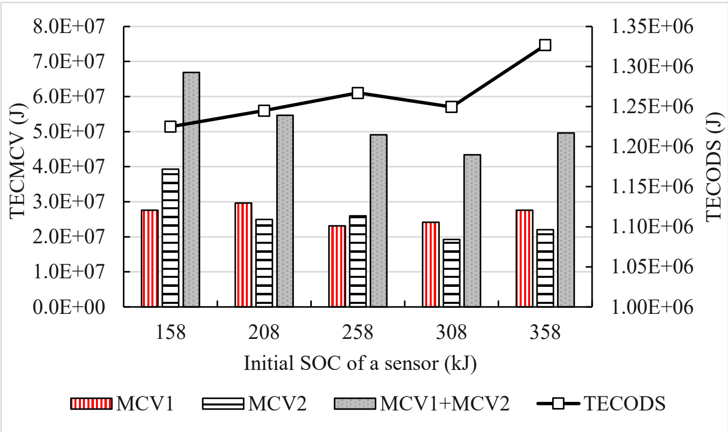

Figure 7. TECODS and TECMCV obtained for all initial SOCs.

5) Sensitivity analysis for the number of deployed sensors

Set the number of sensors to be deployed as 24, 27, 30, 33, and 36. The upper-level objective function values of the optimal sensor deployment schemes are 124,151 J, 124,678 J, 133,868 J, 134,232 J, and 169,458 J, respectively. Figure 8 shows that TECODS and TECMCV increase with sensor count. More sensors improve coverage but increase system energy consumption, requiring a trade-off.

Summarizing the above research results, we can obtain the following approximate conclusions. (1) The proposed model and heuristic solution method yield an optimal rechargeable WSN deployment scheme under road traffic influence that has not previously considered, together with a new charging priority-based MCV routing strategy. (2) More sensors, larger communication radius, or higher traffic demand increase energy consumption for both MCVs and optimally deployed WSN, validating the model. (3) A smaller initial SOC, a larger recharging threshold, or a priority-based sensor recharging scheme increases MCV energy consumption but reduces the energy consumption of the optimally deployed WSN. For these three parameters, lower energy consumption of the optimally deployed WSN always comes at the cost of higher energy consumption of MCVs. Nevertheless, these parameter settings are good choices in practice for prolonging WSN lifetime and ensuring their stable and reliable operation.

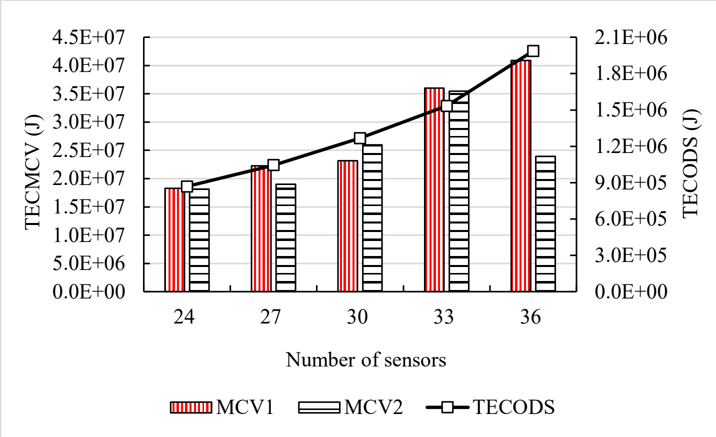

Figure 8. TECODS and TECMCV obtained for different number of sensors.

8. Conclusions

This paper studies the deployment optimization of rechargeable WSNs, considering MCV recharging routes and automated vehicle traffic flow distribution in a smart city. The problem is formulated as a bi-level programming model with two parallel lower-level models. A heuristic solution method is designed. Numerical tests show that the proposed model and algorithm effectively generate optimal sensor network layout schemes, and capture complex interactions between sensor deployment and other important factors such as road network traffic flow, energy consumption, recharging priority, and vehicle routing. Sensitivity analysis is conducted on key parameters and valuable insights are obtained. However, this study still has several deficiencies, and the derived conclusions have inevitable limitations when directly applied to practical engineering scenarios. To further improve the engineering practicality of the proposed model, future research will relax the idealized assumptions and incorporate more realistic practical factors, such as MCV operation cost and wireless charging infrastructure investments, while refining and diversifying the experimental design. It is also worthwhile for further studies to consider the dynamics, reliability, and latency of the data collection, transmission, and processing processes in the proposed model. Because transportation systems contain a variety of uncertain factors, exploring the impact of traffic flow uncertainty on sensor placement is another valuable research direction. In addition, fluctuating charging power and nonlinear energy consumption will enlarge the uncertainty of task completion time. Therefore, incorporating these practical characteristics would likely improve the engineering practicability and developing new solution methods based on the variable neighborhood search algorithm [29] and deep reinforcement learning algorithm [30] is valuable to explore high quality solutions.

Author contributions

Minghua Zeng: conceptualization, methodology, supervision, writing – original draft, writing – review & editing, funding acquisition, project administration; Danye Wang: investigation, data curation, software, validation, visualization, writing – original draft; Rong Zhang: visualization; Wei Xu: investigation, resources. Ni Dong: writing – review & editing, funding acquisition, formal analysis, project administration.

Use of Generative-AI tools declaration

No generative artificial intelligence tools were used during the preparation of this manuscript. All modeling, simulation, writing and revision work was completed independently by the authors.

Acknowledgements

This work was supported by the National Natural Science Foundation of China under Grant 72571229 and the Guangzhou Municipal Bureau of Science and Technology under Grant 2024B03J1326.

Conflicts of interest

We declare that we have no conflicts of interest.

References

1. S. Sengupta, S. Das, M. D. Nasir, B. K. Panigrahi, Multi-objective node deployment in WSNs: In search of an optimal trade-off among coverage, lifetime, energy consumption, and connectivity, *Eng. Appl. Artif. Intel.,* **26** (2013), 405–416. https://doi.org/10.1016/j.engappai.2012.05.018
2. M. Rebai, M. Leberre, H. Snoussi, F. Hnaien, L. Khoukhi, Sensor deployment optimization methods to achieve both coverage and connectivity in wireless sensor networks, *Comput. Oper. Res.,* **59** (2015), 11–21. https://doi.org/10.1016/j.cor.2014.11.002
3. E. Karabulut, N. Aras, İ. K. Altınel, Optimal sensor deployment to increase the security of the maximal breach path in border surveillance, *Eur. J. Oper. Res.,* **259** (2017), 19–36. https://doi.org/ 10.1016/j.ejor.2016.09.016
4. E. Güney, N. Aras, İ. K. Altınel, C. Ersoy, Efficient solution techniques for the integrated coverage, sink location and routing problem in wireless sensor networks, *Comput. Oper. Res.,* **39** (2012), 1530–1539. https://doi.org/10.1016/j.cor.2011.09.002
5. A. Alfieri, A. Bianco, P. Brandimarte, C. F. Chiasserini, Maximizing system lifetime in wireless sensor networks, *Eur. J. Oper. Res.,* **181** (2007), 390–402. https://doi.org/ 10.1016/j.ejor.2006.05.037
6. F. Sangare, Y. Xiao, D. Niyato, Z. Han, Mobile charging in wireless-powered sensor networks: Optimal scheduling and experimental implementation, *IEEE T. Veh. Technol.,* **66** (2017), 7400–7410. https://doi.org/10.1109/TVT.2017.2668990
7. C. Lin, J. Zhou, C. Guo, H. Song, G. Wu, M. S. Obaidat, TSCA: a temporal-spatial real-time charging scheduling algorithm for on-demand architecture in wireless rechargeable sensor networks, *IEEE Trans. Mob. Comput.,* **17** (2018), 211–224. https://doi.org/10.1109/TMC.2017.2703094
8. A. Tomar, L. Muduli, P. K. Jana, An efficient scheduling scheme for on-demand mobile charging in wireless rechargeable sensor networks, *Pervasive. Mob. Comput.,* **59** (2019), 101074. https://doi.org/10.1016/j.pmcj.2019.101074

9. S. Priyadarshani, A. Tomar, P. K. Jana, An efficient partial charging scheme using multiple mobile chargers in wireless rechargeable sensor networks, *Ad Hoc Netw.,* **113** (2021), 102407. https://doi.org/10.1016/j.adhoc.2020.102407
10. R. Kumar, J. C. Mukherjee, On-demand vehicle-assisted charging in wireless rechargeable sensor networks, *Ad. Hoc. Netw.,* **112** (2021), 102389. https://doi.org/10.1016/j.adhoc.2020.102389
11. A. Hossain, P. K. Biswas, S. Chakrabarti, Sensing models and its impact on network coverage in wireless sensor network, *Proc. ICIIS 2008,* 2008, 1–5. https://doi.org/10.1109/ICIINFS.2008.4798455
12. X. Wang, S. Han, Y. Wu, X. Wang, Coverage and energy consumption control in mobile heterogeneous wireless sensor networks, *IEEE T. Automat. Contr.,* **58** (2013), 975–988. https://doi.org/10.1109/TAC.2012.2225511
13. C. Xu, Y. Dong, Z. Ren, H. Jiang, X. Yu, Sensor deployment for pipeline leakage detection via optimal boundary control strategies, *J. Ind. Manag. Optim.,* **11** (2015), 199–216. https://doi.org/10.3934/jimo.2015.11.199
14. M. Sheikh-Hosseini, S. R. S. Hashemi, Connectivity and coverage constrained wireless sensor nodes deployment using steepest descent and genetic algorithms, *Expert. Syst. Appl.,* **190** (2022), 116164. https://doi.org/10.1016/j.eswa.2021.116164
15. H. Feng, C. Xu, B. Jin, M. Zhang, A deployment optimization for wireless sensor networks based on stacked auto encoder and probabilistic neural network, *Digit. Commun. Netw.,* 2024, https://doi.org/10.1016/j.dcan.2024.06.003
16. M. J. Nene, R. S. Deodhar, L. M. Patnaik, Algorithm for autonomous reorganization of mobile wireless camera sensor networks to improve coverage, *IEEE Sens. J.,* **15** (2015), 4428–4441. https://doi.org/10.1109/JSEN.2015.2389268
17. A. A. Ababneh, Error and energy aware sensor deployment for RSS localization—A linear quadratic regulator formulation, *IEEE Sens. J.,* **22** (2022), 15584–15595. https://doi.org/10.1109/JSEN.2022.3186470
18. N. T. Boardman, K. M. Sullivan, Approximate dynamic programming for condition-based node deployment in a wireless sensor network, *Reliab. Eng. Syst. Safe,* **243** (2024), 109803. https://doi.org/10.1016/j.ress.2023.109803
19. S. Xiang, J. Yang, A novel adaptive deployment method for the single-target tracking of mobile wireless sensor networks, *Reliab. Eng. Syst. Safe,* **234** (2023), 109135. https://doi.org/10.1016/j.ress.2023.109135
20. C. F. Cheng, C. C. Hsu, The deterministic sensor deployment problem for barrier coverage in WSNs with irregular shape areas, *IEEE Sens. J.,* **22** (2022), 2899–2911. https://doi.org/10.1109/JSEN.2021.3137626
21. T. Zou, W. Xu, W. Liang, J. Peng, Y. Cai, T. Wang, Improving charging capacity for wireless sensor networks by deploying one mobile vehicle with multiple removable chargers, *Ad Hoc Netw.,* **63** (2017), 79–90. https://doi.org/10.1016/j.adhoc.2017.05.006
22. K. Lin, M. Chen, S. Zeadally, J. J. P. C. Rodrigues, Balancing energy consumption with mobile agents in wireless sensor networks, *Future. Gener. Comp. Sy.,* **28** (2012), 446–456. https://doi.org/10.1016/j.future.2011.03.001

23. Z. Lyu, Z. Wei, J. Pan, H. Chen, C. Xia, J. Han, et al., Periodic charging planning for a mobile MCV in wireless rechargeable sensor networks based on hybrid PSO and GA algorithm, *Appl. Soft Comput. J.,* **75** (2018), 388–403. https://doi.org/10.1016/j.asoc.2018.11.022
24. Y. Jin, J. Xu, S. Wu, L. Xu, D. Yang, K. Xia, Bus network assisted drone scheduling for sustainable charging of wireless rechargeable sensor network, *J. Syst. Architect.,* **116** (2021), 102059. https://doi.org/10.1016/j.sysarc.2021.102059
25. C. Lin, Y. Sun, K. Wang, Z. Chen, B. Xu, G. Wu, Double warning thresholds for preemptive charging scheduling in Wireless Rechargeable Sensor Networks, *Comput. Netw.,* **148** (2019), 72–87. https://doi.org/10.1016/j.comnet.2018.10.023
26. X. Wang, J. Zhao, Distributionally robust optimization of the vehicle routing problem with uncertain customers, *J. Ind. Manag. Optim.,* **21** (2025), 1983–2006. https://doi.org/10.3934/jimo.2024159
27. H. Shakhatreh, W. Malkawi, A. Al-Fuqaha, A practical drone trajectory control approach for energy and data management in wireless sensor networks, *Control Eng. Pract.,* **165** (2025), 106605. https://doi.org/10.1016/j.conengprac.2025.106605
28. Y. Lei, J. Yu, D. Cao, Z. Feng, S. Chan, An energy urgency priority based mobile charging scheme in Wireless Rechargeable Sensor Network, *Ad Hoc Netw.,* **140** (2023), 103067. https://doi.org/10.1016/j.adhoc.2022.103067
29. W. Zhang, M. Kong, Y. Zhang, A. M. Fathollahi-Fard, Proximal policy optimization with population-based variable neighborhood search algorithm for coordinating photo-etching and acid-etching processes in sustainable storage chip manufacturing, *J. Ind. Inf. Integr.,* **42** (2024), 100727. https://doi.org/10.1016/j.jii.2024.100727
30. W. Zhang, M. Kong, Y. Zhang, A. M. Fathollahi-Fard, G. Tian, A revised deep reinforcement learning algorithm for parallel machine scheduling problem under multi-scenario due date constraints, *Swarm Evol. Comput.,* **92** (2025), 101808. https://doi.org/10.1016/j.swevo.2024.101808