Optimal Two-Lane Placement for Hybrid VANET-Sensor Networks

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***Abstract*—Vehicular ad hoc networks (VANETs) help improve traffic safety and lessen traffic congestion. Roadside units (RSUs) play a key role in serving as the event and data broker in the form of vehicle-to-infrastructure communication to supply wireless and mobile vehicle-to-vehicle communication. Recently, hybrid VANET-sensor networks have attracted much attention as events are detected by sensor nodes and are spread to a wider area via VANETs, in which number of RSUs is restricted due to high cost. This work investigates the problem of minimizing the total cost of deploying RSUs and sensor nodes along the two sides and the median island of a two-lane road to cover the whole road, represented as a grid, and to form a connected VANET-sensor network. This problem is NP-complete by reduction to the NP-complete placement problem for a single-lane road. Therefore, this work formulates the problem as an integer linear program, and then proposes a center particle swarm optimization approach, in which a center particle is adopted for increasing the convergence speed. Additionally, a theoretical analysis for the approach is provided. Experimental results show that the approach can perform well for moderate-size problems.**

***Index Terms*—Vehicular network, wireless sensor network, RSU placement, particle swarm optimization**

I. Introduction

WIRELESS sensor networks (WSNs) [1], [2], [3] comprised of considerable sensor nodes provide high efficiency in sensing environmental events, transmitting the data to each other via multi-hop communication, and finally reporting it to a base station, and have various applications, e.g., healthcare and manufacturing [4]. As the most important component of intelligent transportation system [5], vehicular ad hoc network (VANET) has attracted a lot of attention recently [6], [7], e.g., transmitting safety and emergency messages to drivers, assisting traffic managers in managing traffic [8].

Hybrid VANET-sensor network is a new network paradigm for VANET by employing wireless sensor nodes [9]. It consists

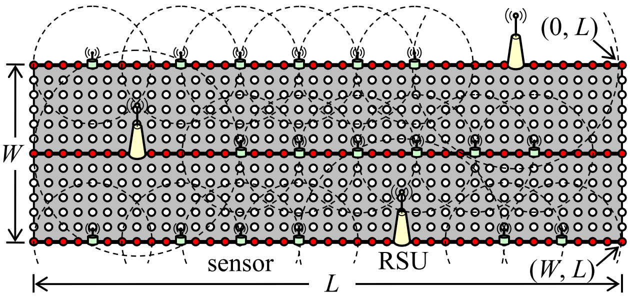

Fig. 1. System framework of a two-lane hybrid VANET-sensor network

of moving vehicles, fixed roadside units (RSUs), and fixed wireless sensor nodes, in which RSUs and sensors are deployed along the road and act as access points (APs) [10]; sensors may persistently detect road conditions and report them. The motivation behind this network is to improve transportation safety on highway roads, e.g., events of frozen road in some rural area are sensed by sensors, and spread to other vehicles in a wider area via VANET. Nonuniform vehicle population increase difficulty of communication in this network.

The work in [8] considered to deploy a minimal number of APs (i.e., RSUs and sensors) along the two sides of the road to cover the whole road such that each vehicle can communicate with a roadside AP within one hop, i.e., users in vehicles can always access the Internet services. By representing the road as a grid, the problem in [8] became to deploy APs to cover all the grid points in the road. However, this problem is NP-complete via reduction to a 2-dimentional critical grid coverage problem, which is NP-complete [11]. Hence, the work in [8] proposed an integer linear program (ILP) for the problem and employed the CPLEX optimizer to solve the ILP for small-size problems.

This work further extends the work in [8] with the following two concerns. First, different from the previous work that considered to deploy APs along the two sides of a single-lane road, this work considers a more practical situation (Fig. 1) that covers a two-lane road and allows APs to be deployed along the two sides and the median island of the road. Although some previous works (e.g., [12]) have considered multiple lanes, their VANETs did not include sensor nodes on the road side. The setting of the two-lane road increases one more dimension, and hence complicates establishment of the ILP model.

Second, the two-lane placement problem is NP-complete by reduction to the NP-complete single-lane placement problem in [8]. Particle swarm optimization (PSO) [13], [14] is a popular metaheuristic algorithm that imitates a swarm of particles

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(candidate solutions) to search a position in the solution search space based on each particle's and global experiences, e.g., see the PSO applied to traffic flow forecasting using on-road sensor systems [15]. Hence, this work solves the two-lane placement problem by the center PSO (CenterPSO for short) [16], which additionally considers a center particle located as the center of positions of other particles, because the center position tends to be close to the optimal position.

II. Related Work

Most related works focused on the placement problems for VANETs, hardly for hybrid VANET-sensor networks. Hence, this section mainly reviews notable works for placement problems for VANETs, categorized according to different objectives, different approaches, different scenarios, and joint problems, including hybrid VANE-sensor networks.

First, consider different objectives in placements. Li et al. [10] coped with the problems of deploying gateways in 1D, 2D, and dense vehicular networks with objective of minimizing average number of hops from APs to gateways, and in turn, the communication delay. Lochert et al. [17] first employed a domain specific aggregation scheme to minimize the required overall bandwidth, and then proposed a genetic algorithm to determine good positions for static RSUs. Given a limited number of RSUs due to huge cost, Aslam and Zou [18] found the RSUs placement with the minimal average time consumed by a vehicle to report an event of interest to a neighboring RSU. Cavalcante et al. [19] studied the RSUs deployment in VANETs with the maximal number of vehicles circulating to be covered. They reduced it to the problem of maximum coverage with time threshold, and solved it by a genetic algorithm. Liya et al. [20] proposed a randomized algorithm to find the minimal number of wire-connected RSUs for VANETs to keep good network connectivity. Chi et al. [21] proposed greedy, dynamic, and hybrid algorithms for the intersection-priority based RSU placement problem which finds an optimal number and positions of RSUs for full distribution providing with maximal connectivity between RSUs and minimal RSU setup costs.

Second, consider different approaches for placements. Kchiche and Kamoun proposed a group-centrality based RSUs deployment strategy based on group centrality [22] for optimizing end-to-end delay, and a strategy based on centrality and equidistance [23] for optimizing end-to-end delay and ensuring a regular and stable service access. Patil and Gokhale [24] proposed a Voronoi network-based RSUs deployment algorithm, based on the delay amount incurred by the data packets transmitted over RSUs. They [25] further extended it with both packet delay and loss as a criteria.

Third, consider placements in different scenarios. Abdrabou and Zhuang [26] adopted the theory of effective bandwidth to address a disrupted V2I communication scenario with no end-to-end path between a vehicle and its nearest RSU. Wu et al. [12] considered to place RSUs in a highway with multiple lanes and exits or intersections. Liu et al. [27] proposed a depth-first-traversal RSUs deployment strategy for the content downloading scenario in VANETs, in which the road network is represented as a weighted undirected graph. Liu et al. [28] proposed an RSUs placement strategy based on road traffic characteristics, maximizing average connectivity probability of searching an optimal position combination of the given RSUs.

Last, consider the joint problems with placement. Liang et al. [29] established a linear programming model for the joint problem of RSU deployment and configuration selection (including power level, types of antenna, and wired/wireless back haul network connectivity) in a vehicular network, minimizing the total cost to deploy and maintain the RSUs network, under constraint of minimum coverage of RSUs. Another extension to the placement problem is to introduce sensor nodes in VANETs. Rebai et al. [8] was the first to consider the problem of deploying RSUs and sensors to cover the whole road in hybrid VANET-sensor networks. They created an ILP model for the optimization problem of placing RSUs and sensors along the two sides of the road, such that the whole road is covered; the total network cost is minimized; connectivity between sensors and RSUs is maintained.

III. The Proposed Method

A. Problem Description

Consider a hybrid VANET-sensor network [8] composed of RSUs, sensors, and vehicles, in which each sensor is equipped with a ZigBee interface for communication with other sensors and vehicles; each RSU or vehicle is equipped with a WiFi interface for communication with other vehicles and RSUs; and a ZigBee interface for communication with sensors.

Different from [8], this work considers a two-lane road represented as a $W \times L$ grid (Fig. 1), i.e., the road has $(W + 1) \times (L + 1)$ grid points, in which the points along the two sides and the median island of the road are red; the points on the road surface are white. The point at i-th row and j-th column of the grid is said to be at position (i, j), e.g., the points at upper-left and lower-right corners are at (0, 0) and (W, L), respectively. In Fig. 1, RSUs (yellow devices) and sensors (green devices) can be deployed only at red points, i.e., along the two sides and the median island (i.e., 0-th, W/2-th, and W-th rows) of the road.

Generally, an RSU has a larger radio coverage G_{cov} than the radio coverage R_{cov} of a sensor, and number of the used RSUs ($\geq n^g_{\min}$) is less than that of the used sensors ($\leq n^s_{\max}$). The function of each sensor is to sense road conditions and relay messages; and the function of each RSU is to discover and communicate with vehicles. After deploying RSUs and sensors along the road, if an RSU covers a sensor, it can communicate with this sensor via its ZigBee interface; if two sensors cover each other, they can communicate via their respective ZigBee interfaces. Hence, RSUs and sensors constitute a connected network (Fig. 1). The concerned problem is to find an optimal placement of RSUs and sensors on the two sides and the median island of a two-lane road to form a connected hybrid VANET-sensor network that can cover the whole road surface such that cost of the used RSUs and sensors is minimized.

Theorem 1. The concerned two-lane problem is NP-complete.

Proof. It is obvious that the problem is in NP; hence, it suffices to show the NP-hardness. Establish the reduction from the one-lane NP-complete problem [8] to our two-lane problem as follows. Let $\beta = 2(G_{cov}^2 - W^2)^{1/2}$ and $\delta = \lceil L/2\beta \rceil + 1$. Given a one-lane problem instance I_1 that uses at least $n_{\min}^g$ RSUs and at most $n_{\max}^s$ sensors to cover the $W \times L$ road grid, consider a two-lane problem instance I_2 that uses at least $n_{\min}^g$ RSUs and at most $n_{\max}^s + \delta$ sensors to cover the $2W \times L$ road grid, in which RSUs and sensors can only be deployed at the 0-th, W-th, or $2W$-th row of the road grid. We show that x sensors and y RSUs cover the $W \times L$ road grid for I_1 if and only if $x + \delta$ sensors and y RSUs cover the $2W \times L$ road grid for I_2.

Suppose that x sensors and y RSUs cover the $W \times L$ road grid for I_1. If no RSU is deployed at the W-th row of the road grid, at least one RSU at the 0-th row must exist to connect between the two road sides for I_1. Flipping the road vertically, there must be at least one RSU at the W-th row. Then, extend the $W \times L$ road grid for I_1 to a $2W \times L$ road grid for I_2, in which deployments of the 0-th and the W-th rows are the same. Then, put δ sensors evenly cover the $2W$-th row with horizontal positions 0, β, 2β, …, $(\delta - 1)\beta$. Hence, at least one RSU at the W-th row is connected with sensors at 0-th and $2W$-th rows. Then, $x + \delta$ sensors and y RSUs cover the $2W \times L$ road grid for I_2.

Conversely, consider the solution A_1 in which $x + \delta$ sensors and y RSUs cover the $2W \times L$ road for I_2. However, solution A_1 must be no better than the solution A_2 for I_2 where δ sensors are evenly deployed at the $2W$-th row of the road grid; while x sensors and y RSUs are deployed at the 0-th or the W-th rows. Remove the δ sensors at the $2W$-th row and the lane between the W-th and $2W$-th rows in solution A_2. Then, the resultant deployment with x sensors and y RSUs is optimal for I_1. □

By extending the model for the single-lane placement for hybrid VANET-sensor networks in [8], we creates an ILP model for the two-lane placement. Notations are as follows:

C_s Cost of installing a sensor.

C_g Cost of installing an RSU.

R_{cov} Coverage radius of a sensor.

G_{cov} Coverage radius of an RSU.

$n_{\min}^g$ The minimal number of RSUs to be used.

$n_{\max}^s$ The maximal number of sensors to be used.

W Width of the road.

L Length of the road.

M_z A large number used for penalty in (7).

S_{ij}^s Set of sensor positions that may cover position (i, j) in the road grid, i.e., $S_{ij}^s = \{(k,t) \mid (i-k)^2 + (j-t)^2 \le R_{cov}^2, k \in \{0, W/2, W\}, t \in \{0,1,...,L\}\}$.

S_{ij}^g Set of RSU positions that may cover position (i, j) in the road grid, i.e., $S_{ij}^g = \{(k,t) \mid (i-k)^2 + (j-t)^2 \le G_{cov}^2, k \in \{0, W/2, W\}, t \in \{0,1,...,L\}\}$.

C_{kt}^s Subset of sensor positions on the right of t-th column that may communicate with a sensor at position (k, t), i.e.,

$$\begin{aligned}
C_{0t}^s = & \{(0,j) \mid j - t \le R_{cov}, j \in \{t+1,...,L\}\} \\
& \cup \{(W/2, j) \mid W^2/4 + (j-t)^2 \le R_{cov}^2, j \in \{t,...,L\}\} \\
& \cup \{(W, j) \mid W^2 + (j-t)^2 \le R_{cov}^2, j \in \{t,...,L\}\}; \\
C_{(W/2)t}^s = & \{(0,j) \mid W^2/4 - (j-t)^2 \le R_{cov}^2, j \in \{t,...,L\}\}\} \\
& \cup \{(W/2, j) \mid j - t \le R_{cov}, j \in \{t+1,...,L\}\} \\
& \cup \{(W, j) \mid W^2/4 - (j-t)^2 \le R_{cov}^2, j \in \{t,...,L\}\}; \\
C_{Wt}^s = & \{(0,j) \mid W^2 + (j-t)^2 \le R_{cov}^2, j \in \{t,...,L\}\} \\
& \cup \{(W/2, j) \mid W^2/4 + (j-t)^2 \le R_{cov}^2, j \in \{t,...,L\}\} \\
& \cup \{(W, j) \mid j - t \le R_{cov}, j \in \{t+1,...,L\}\}.
\end{aligned}$$

D_{kt}^s Subset of sensor positions on the left of t-th column that may communicate with a sensor at position (k, t), i.e.,

$$\begin{aligned}
D_{0t}^s = & \{(0,j) \mid t - j \le R_{cov}, j \in \{0,1,...,t-1\}\} \\
& \cup \{(W/2, j) \mid W^2/4 + (t-j)^2 \le R_{cov}^2, j \in \{0,...,t\}\} \\
& \cup \{(W, j) \mid W^2 + (t-j)^2 \le R_{cov}^2, j \in \{0,1,...,t\}\}; \\
D_{(W/2)t}^s = & \{(0,j) \mid W^2/4 + (t-j)^2 \le R_{cov}^2, j \in \{0,1,...,t\}\} \\
& \cup \{(W/2, j) \mid t - j \le R_{cov}, j \in \{0,1,...,t-1\}\} \\
& \cup \{(W, j) \mid W^2/4 + (t-j)^2 \le R_{cov}, j \in \{0,1,...,t\}\}; \\
D_{Wt}^s = & \{(0,j) \mid W^2 + (t-j)^2 \le R_{cov}^2, j \in \{0,1,...,t\}\} \\
& \cup \{(W/2, j) \mid W^2/4 + (t-j)^2 \le R_{cov}^2, j \in \{0,1,...,t\}\} \\
& \cup \{(W, j) \mid t - j \le R_{cov}, j \in \{0,1,...,t-1\}\}.
\end{aligned}$$

C_{kt}^g Subset of RSU positions on right of t-th column that may communicate with a sensor at position (k, t), which can be expressed by analogy with C_{kt}^s.

D_{kt}^g Subset of RSU positions on left of t-th column that may communicate with a sensor at position (k, t), which can be expressed by analogy with D_{kt}^s.

Decision variables in the mathematical model are as follows:

$$x_{ij} = \begin{cases} 1, & \text{if a sensor is placed at position } (i, j); \\ 0, & \text{otherwise.} \end{cases}$$

$$y_{ij} = \begin{cases} 1, & \text{if a RSU is placed at position } (i, j); \\ 0, & \text{otherwise.} \end{cases}$$

$$\omega_{ij} = \begin{cases} 1, & \text{if a RSU at position } (i, j) \text{ is connected to a sensor or a RSU on the other two roadsides;} \\ 0, & \text{otherwise.} \end{cases}$$

$$z = \begin{cases} 1, & \text{if only one RSU is used to cover all the road;} \\ 0, & \text{otherwise.} \end{cases}$$

The proposed mathematical model is detailed as follows:

$$\text{Minimize } \sum_{i \in \{0, W/2, W\}} \sum_{j=0}^{L} (C_s x_{ij} + C_g y_{ij}) \quad (1)$$

s.t.

$$\sum_{(k,t) \in S_{ij}^s} x_{kt} + \sum_{(k,t) \in S_{ij}^g} y_{kt} \ge 1$$

$$\forall i \in \{0,1,...,W\}, \forall j \in \{0,1,...,L\} \quad (2)$$

$$x_{kt} \le \sum\nolimits_{(i,j)\in C_{kt}^{s}} x_{ij} + \sum\nolimits_{(i,j)\in C_{kt}^{g}} y_{ij} + z$$
$$\forall k \in \{0, W/2, W\}, \forall t \in \{0,1,...,L\} \quad (3)$$

$$x_{kt} \le \sum\nolimits_{(i,j)\in D_{kt}^{s}} x_{ij} + \sum\nolimits_{(i,j)\in D_{kt}^{g}} y_{ij} + z$$
$$\forall k \in \{0, W/2, W\}, \forall t \in \{0,1,...,L\} \quad (4)$$

$$y_{kt} \le \sum\nolimits_{(i,j)\in C_{kt}^{s}} x_{ij} + \sum\nolimits_{(i,j)\in C_{kt}^{g}} y_{ij} + z$$
$$\forall k \in \{0, W/2, W\}, \forall t \in \{0,1,...,L\} \quad (5)$$

$$y_{kt} \le \sum\nolimits_{(i,j)\in D_{kt}^{s}} x_{ij} + \sum\nolimits_{(i,j)\in D_{kt}^{g}} y_{ij} + z$$
$$\forall k \in \{0, W/2, W\}, \forall t \in \{0,1,...,L\} \quad (6)$$

$$\sum\nolimits_{i\in\{0,W/2,W\}} \sum\nolimits_{j=1}^{L} (x_{ij} + y_{ij}) \le 1 + M_z(1-z) \quad (7)$$

$$y_{(W/2)t} - \omega_{(W/2)t} \ge 0, \forall t \in \{0,1,...,L\} \quad (8)$$

$$\sum\nolimits_{t=1}^{L} \omega_{(W/2)t} \ge 2 \quad (9)$$

$$\omega_{(W/2)t} \le \sum\nolimits_{(i,j)\in C_{kt}^{g} \cup D_{kt}^{g}; i\ne W/2; i\ne 0} x_{ij}, \forall t \in \{0,1,...,L\} \quad (10)$$

$$\omega_{(W/2)t} \le \sum\nolimits_{(i,j)\in C_{kt}^{g} \cup D_{kt}^{g}; i\ne W/2; i\ne W} x_{ij}, \forall t \in \{0,1,...,L\} \quad (11)$$

$$\sum\nolimits_{i\in\{0,W/2,W\}} \sum\nolimits_{j=1}^{L} y_{ij} \ge n_{\min}^{g} \quad (12)$$

$$y_{ij} \le n_{\max}^{s} - \sum\nolimits_{k=1}^{j} x_{ik}, \forall i \in \{0, W/2, W\}, \forall j \in \{0,...,L\} \quad (13)$$

$$x_{ij}, y_{ij}, w_{ij}, z \in \{0,1\}, \forall i \in \{0, W/2, W\}, \forall j \in \{0,1,...,L\} \quad (14)$$

Objective (1) minimizes the total cost of RSUs and sensors placed along the two sides and the median island of the road to cover the whole road surface and form a connected network of RSUs and sensors. Constraint (2) enforces that each point at position (i, j) in the road grid must be covered by a certain sensor (i.e., x_{kt} = 1 for some k and t) or RSU (i.e., y_{kt} = 1 for some k and t). Constraints (3) and (4) enforce that each sensor at position (k, t) must connect to another sensor or RSU on the right and the left of position (k, t), respectively, along the two sides or the median island of the road, i.e., each sensor is connected to an RSU directly, or indirectly via multi-hop communication of other sensors. Note that binary variable z controls if only one RSU is used to cover all the road. Because z = 0 in the optimal solution (i.e., not only one RSU in the optimal solution), z has no effect in the two constraints when the optimal solution is achieved. Similar to the above two constraints, Constraints (5) and (6) enforce that each RSU at position (k, t) must be connected with another sensor or RSU on the right and the left of position (k, t), respectively, along the two road sides or the median island. Since each RSU has a large radio coverage than each sensor, the case where an RSU covers a sensor but this sensor does not cover this RSU exist (Fig. 1). Constraint (7) is used to cancel the functions of Constraints (3)–(6) when only one RSU and no sensors are used in the optimal solution. Constraints (8)–(11) enforce connections among the median island and the two road sides by at least an RSU. Constraint (12) enforces that number of the used RSUs is not less than $n_{\min}^{g}$. Constraint (13) enforces that number of the used sensors is not greater than $n_{\max}^{s}$. Constraint (14) enforces variables x_{ij}, y_{ij}, w_{ij} and z to be binary.

The model differs from [8]. Each constraint in the model additionally considers the median island of the road, not just the two road sides. Hence, definitions of S_{ij}^{s}, S_{ij}^{g}, C_{kt}^{s}, C_{kt}^{g}, D_{kt}^{s}, and D_{kt}^{g} in the model are more complex. Furthermore, we consider that connectivity among the median island and the two road sides must be made by at least an RSU (i.e., Constraints (8)–(11)) in the two cases: connectivity between the median island and the upper road side (resp., the lower road side).

B. Our CenterPSO Algorithm

In population-based metahuristic algorithms, each candidate solution of the problem can be encoded as a position on the solution search space. PSO [13], [14] is a popular metaheuristic algorithm that considers to move a number of particles (candidate solutions) on the solution search space to efficiently find a sufficient optimal solution. Each iteration k of the main loop of PSO moves each particle i at the original position X_k^i to a new position X_{k+1}^i on the solution space at a new velocity V_{k+1}^i that is determined by the original velocity V_k^i, the best position P_k^i found by particle i so far, and the best position P_k^* found by all particles so far as follows:

$$V_{k+1}^{i} = w \cdot V_k^i + c_1 \cdot r_1 \cdot (P_k^i - X_k^i) + c_2 \cdot r_2 \cdot (P_k^* - X_k^i) \quad (15)$$

$$X_{k+1}^{i} = X_k^i + V_{k+1}^i \quad (16)$$

where w is the inertia factor of velocity, which is decreased linearly from 0.9 to 0.4 during the search process in the linearly decreasing weight PSO [30]; c_1 is the scaling factor of particle i moving towards P_k^i; c_2 is the scaling factor of particle i moving towards P_k^*; r_1 and r_2 are random real numbers from [0, 1].

This work applies the CenterPSO [16], an improved version of PSO that introduces a so-called *center particle* (whose position is the center of the positions of all the other particles, as calculated as follows) to increase the algorithm convergence.

$$X_{k+1}^{\eta} = \left(\sum\nolimits_{i=1}^{\eta-1} X_{k+1}^{i}\right) / (\eta - 1) \quad (17)$$

where η is the total number of particles. Positions of the other ($\eta - 1$) particles are calculated by (15) and (16); and position of the center particle is calculated by (17). This is motivated from that in the PSO, each particle relies on direct and indirect interaction and cooperation with other particles to determine the next search direction and step-size, so the swarm will move around and gradually converge toward candidates of the global or local optimal solutions. Since the center of positions of all particles is probably near to the optimal solution, it provides useful information for improving algorithm convergence.

Before demonstrating the PSO algorithm, representation of a candidate solution for the concerned problem and the cost function for evaluating performance of each solution are explained as follows. Each solution for the problem is to determine positions of sensors and RSUs alone the two road sides and the median island of the road, but numbers of the used sensors and RSUs are unknown. Suppose that n and m denote numbers of sensors and RSUs, respectively. This work sets $n = n^s_{\max}$ (maximal number of the used sensors), and determines m from the range $[n^g_{\min}, n^s_{\max}]$ according to several experimental trials. If no priori experimental trials are conducted, the simplest way is to set $m = n^s_{\max}$ but consume more CPU time.

Let n sensors denoted by $s_1, s_2, \ldots, s_n$ and m RSUs denoted by $g_1, g_2, \ldots, g_m$. A solution of the concerned problem is encoded as a $3(n+m)$-length vector: $\langle \sigma_1, \sigma_2, \ldots, \sigma_{1m+n} \,|\, s_{11}, s_{12}, s_{21}, s_{22}, \ldots, s_{n1}, s_{n2} \,|\, g_{11}, g_{12}, g_{21}, g_{22}, \ldots, g_{m1}, g_{m2} \rangle$, with three parts. First, $\langle \sigma_1, \sigma_2, \ldots, \sigma_{1m+n} \rangle$ determines a permutation of mixed n sensors and m RSUs, in which each $\sigma_i \in \{s_1, s_2, \ldots, s_n, g_1, g_2, \ldots, g_m\}$. Road coverage of sensors and RSUs is calculated in the order from left to right of the permutation, which is used to calculate cost function. Second, $\langle s_{11}, s_{12}, s_{21}, s_{22}, \ldots, s_{n1}, s_{n2} \rangle$ determines the positions of n sensors on the two road sides and the median island, in which (s_{i1}, s_{i2}) is the position of sensor s_i for each $i \in \{1, 2, \ldots, n\}$, i.e., $s_{i1} \in \{0, W/2, W\}$ and $s_{i2} \in \{0, 1, \ldots, L\}$. Third, $\langle g_{11}, g_{12}, g_{21}, g_{22}, \ldots, g_{m1}, g_{m2} \rangle$ determines the positions of m RSUs on the two road sides and the median island of the road, in which (g_{i1}, g_{i2}) is the grid position of RSU g_i, $\forall i \in \{1, \ldots, n\}$, i.e., $g_{i1} \in \{0, W/2, W\}$ and $g_{i2} \in \{0, 1, \ldots, L\}$.

The $3(n+m)$-length vector is discrete, but the PSO can only handle real-value vectors, unless some delicate design. Hence, a mechanism of transforming real values in the solution representation into discrete values is designed as follows. Consider a position $X^i_k = (X^i_{k1}, X^i_{k2}, \ldots, X^i_{k(n+m)}, X^i_{k(n+m+1)}, \ldots, X^i_{k(3n+m)}, X^i_{k(3n+m+1)}, \ldots, X^i_{k(3n+3m)})$ of particle i at k-th iteration of the main loop, in which each value in this vector is real. To obtain the first part of the corresponding solution, $X^i_{k1}, X^i_{k2}, \ldots, X^i_{k(n+m)}$ are first sorted in a nondecreasing order. Then, consider each X^i_{kj} for $j \in \{1, \ldots, n+m\}$. Suppose that X^i_{kj} is ranked t in this order. If $t \le n$, then it represents sensor s_t; otherwise, it represents RSU g_{t-n}.

For the second part of the corresponding solution, each odd-ranked value in $\langle X^i_{k(n+m+1)}, \ldots, X^i_{k(3n+m)} \rangle$ (i.e., $X^i_{k(n+m+2j-1)}$ for $j \in \{1, 2, \ldots\}$) should be corresponded to a value in $\{0, W/2, W\}$. We restrict a range for $X^i_{k(n+m+2j-1)}$ such that $0 \le X^i_{k(n+m+2j-1)} \le 10$. If it falls in [0, 10/3), then it represents 0; else if it falls in [10/3, 20/3), then it represents $W/2$; else (i.e., it falls in [20/3, 10)), it represents W. Similarly, each even-ranked value in $\langle X^i_{k(n+m+1)}, \ldots, X^i_{k(3n+m)} \rangle$ (i.e., $X^i_{k(n+m+2j)}$ for $j \in \{1, 2, \ldots\}$) should be corresponded to a value in $\{0, 1, \ldots, L\}$. Our algorithm restricts a range for $X^i_{k(n+m+2j)}$ such that $0 \le X^i_{k(n+m+2j)} \le 10$, and uses the similar way to discretize the value in the CenterPSO. The third part of the corresponding solution can be obtained in a similar way.

Given X^i_k, a cost function $c(X^i_k)$ is used to evaluate performance of this position. The algorithm of calculating $c(X^i_k)$ is given in Algorithm 1, which is explained as follows. Lines 1 and 2 initialize two counter variables $count_s$ and $count_g$ to be zero, used to count numbers of the used sensors and RSUs, respectively. Then, the main loop of Lines 3–12 considers each σ_i in the order of permutation $\langle \sigma_1, \sigma_2, \ldots, \sigma_{1m+n} \rangle$ of sensors and RSUs in S^i_k. In Lines 4–6, if σ_i represents a sensor s_j, then the algorithm places sensor s_j at position (s_{j1}, s_{j2}), and covers all the grid points within the circle centered at (s_{j1}, s_{j2}) with radius R_{cov}; if an uncovered grid point is covered, then this sensor is recorded and $count_s$ is increased by one. In Lines 7–9, if σ_i does not represent a sensor s_j, i.e., it represents an RSU g_j, then g_j is placed at position (g_{j1}, g_{j2}), and covers all the grid points within the circle centered at (g_{j1}, g_{j2}) with radius G_{cov}; if an uncovered grid point is covered here, then this sensor is recorded, and $count_g$ is increased by one. The end of the loop (Line 11) checks if all grid points have been covered; if true, then it breaks the for loop. Line 13 computes number of uncovered grid points, $count_u$. Line 14 computes number of disconnected sensors and RSUs, $count_c$. Line 15 calculates the cost $c(X^i_k)$ as follows:

$$C_s \cdot count_s + C_g \cdot count_g + M_u \cdot count_u + M_c \cdot count_c \qquad (18)$$

where M_u is a large number used for the penalty for uncovered grid points; M_c is a large number used for the penalty for disconnected sensors and RSUs. Note that the first two terms in (18) constitute the objective in (1). If $count_u \ne 0$, then X^i_k implies an infeasible solution in which some grid points are not covered. If $count_c \ne 0$, then X^i_k implies an infeasible solution in which some sensor or RSU is disconnected. The proposed CenterPSO algorithm is given in Algorithm 2.

Algorithm 1 CALCULATE COST (POSITION X^i_k)

1: $count_s = 0$
2: $count_g = 0$
3: **for each** $i = 1, 2, \ldots, n+m$ **do**
4:     **if** σ_i represents a sensor s_j **then**
5:         Place sensor s_j at position (s_{j1}, s_{j2}), and cover all the grid points within the circle centered at (s_{j1}, s_{j2}) with radius R_{cov}
6:         **if** an uncovered grid point is covered here **then** record this sensor, and $count_s = count_s + 1$
7:     **else**   // σ_i represents an RSU g_j
8:         Place sensor g_j at position (g_{j1}, g_{j2}), and cover all the grid points within the circle centered at (g_{j1}, g_{j2}) with radius G_{cov}
9:         **if** an uncovered grid point is covered here **then** record this RSU, and $count_g = count_g + 1$
10:     **end if**
11:     **if** all the grid points have been covered, **then** break the for loop
12: **end for**
13: Compute $count_u$ (i.e., number of uncovered grid points)
14: Compute $count_c$ (i.e., number of disconnected sensors and RSUs)
15: Compute and output $c(X^i_k)$ by (18)

IV. ALGORITHM ANALYSIS FOR CENTERPSO

Convergence analysis of CenterPSO is derived by analogy from [32]. The CenterPSO considers $\eta - 1$ ordinary particles and one center particles. Analysis of the $\eta - 1$ ordinary particles in the CenterPSO is the same as the original, so only the convergence analysis for the center particle is discussed.

Algorithm 2 THE PROPOSED CENTERPSO

Initialize the first (η – 1) particles' positions X_0^1, X_0^2, …, $X_0^{\eta-1}$ and velocities $V_0^1, V_0^2, ..., V_0^{\eta-1}$ randomly
Calculate the center particle's position X_0^η by (17)
Evaluate the cost $f(X_0^i)$ of each particle for $i \in$ {1, 2, …, η} by Algorithm 1
For each $i \in$ {1, 2, …, η}, let $P_0^i = X_0^i$
Let P_k^* be the best position among all P_0^i's
while $k \le$ maximal number of iterations **do**
    Update the first (η – 1) particles' velocities X_k^1, X_k^2, …, $X_k^{\eta-1}$ by (15)
    Update the first (η – 1) particles' positions V_k^1, V_k^2, …, $V_k^{\eta-1}$ by (16)
    Calculate the center particle's position X_k^η by (17)
    Evaluate the cost $f(X_k^i)$ of each particle for $i \in$ {1, 2, …, η} by Algorithm 1
    Update the previous best position P_k^i found by particle i, and the best position P_k^* found by all particles so far
end while

The generalized equations of updating positions and velocities for each particle i among the η – 1 ordinary particles at iteration k + 1 are rewritten, respectively, as follows:

$$X_{k+1}^i = X_k^i + V_{k+1}^i \cdot \Delta t \quad (19)$$

$$\begin{aligned} V_{k+1}^i &= w \cdot V_k^i + c_{1g} \cdot r_{1g} \cdot (P_k^i - X_k^i) / \Delta t \\ &+ c_{1b} \cdot r_{1b} \cdot (X_k^i - B_k^i) / \Delta t + c_2 \cdot r_2 \cdot (P_k^* - X_k^i) / \Delta t \end{aligned} \quad (20)$$

where Δt is a time step. For $i = \eta$ (center particle), the velocity and position updating equations with considering time division are revised, respectively, as follows:

$$X_{k+1}^\eta = \frac{1}{\eta - 1} \sum_{i=1}^{\eta-1} X_{k+1}^i \quad (21)$$

$$V_{k+1}^\eta = \frac{X_{k+1}^\eta - X_k^\eta}{\Delta t} = \frac{1}{\eta-1} \sum_{i=1}^{\eta-1} \frac{X_{k+1}^i - X_k^i}{\Delta t} = \frac{1}{\eta-1} \sum_{i=1}^{\eta-1} V_{k+1}^i \quad (22)$$

Substitute (19) into (21) as follows:

$$\begin{aligned} X_{k+1}^\eta &= \frac{1}{\eta-1} \sum_{i=1}^{\eta-1} (X_k^i + w V_k^i \Delta t) + \frac{1}{\eta-1} \sum_{i=1}^{\eta-1} (c_1 \cdot r_1 + c_2 \cdot r_2) \\ &\cdot \left(\frac{c_1 \cdot r_1 \cdot P_k^i + c_2 \cdot r_2 \cdot P_k^*}{c_1 \cdot r_1 + c_2 \cdot r_2} - X_k^i \right) \end{aligned} \quad (23)$$

which can be regarded as a general gradient line-search form $X_{k+1}^\eta = \widehat{X}_k^\eta + \alpha \cdot \overline{P}_k$ where $\widehat{X}_k^\eta = (\sum_{i=1}^{\eta-1} X_k^i + w(\sum_{i=1}^{\eta-1} V_k^i)\Delta t) / (\eta - 1)$, $\alpha = c_1 \cdot r_1 + c_2 \cdot r_2$, and $\overline{P}_k = \sum_{i=1}^{\eta-1} ((c_1 \cdot r_1 \cdot P_k^i + c_2 \cdot r_2 \cdot P_k^*) / (c_1 \cdot r_1 + c_2 \cdot r_2) - X_k^i) / (\eta - 1)$. In this form, α is regarded as the stochastic step size; and $\overline{P}_k$ is regarded as the stochastic search direction. Since α is restricted to c_1 and c_2, and $r_1, r_2 \in$ [0, 1], α falls in [0, $c_1 + c_2$] and its expected value is $(c_1 + c_2)/2$, i.e., α is interdependent with c_1 and c_2. (23) is rearranged as follows:

$$\begin{aligned} X_{k+1}^\eta &= \frac{1 - c_1 \cdot r_1 - c_2 \cdot r_2}{\eta - 1} \sum_{i=1}^{\eta-1} X_k^i + w \cdot \frac{1}{\eta-1} (\sum_{i=1}^{\eta-1} V_k^i) \Delta t \\ &+ \frac{1}{\eta-1} \sum_{i=1}^{\eta-1} (c_1 \cdot r_1 \cdot P_k^i + c_2 \cdot r_2 \cdot P_k^*) \\ &= (1 - c_1 \cdot r_1 - c_2 \cdot r_2) X_{k+1}^\eta + w \cdot \Delta t \cdot V_k^\eta \\ &+ c_1 \cdot r_1 \cdot \sum_{i=1}^{\eta-1} P_k^i / (\eta - 1) + c_2 \cdot r_2 \cdot P_k^* \end{aligned}$$

Substitute (20) into (22) as follows:

$$\begin{aligned} V_{k+1}^\eta &= -\frac{c_1 \cdot r_1 + c_2 \cdot r_2}{\Delta t} \cdot X_k^\eta + w \cdot V_k^\eta \\ &+ \frac{c_1 \cdot r_1}{\Delta t} \cdot \sum_{i=1}^{\eta-1} P_k^i / (\eta - 1) + \frac{c_2 \cdot r_2}{\Delta t} \cdot P_k^* \end{aligned}$$

The above two equations constitute the following matrix:

$$\begin{aligned} \begin{bmatrix} X_{k+1}^\eta \\ V_{k+1}^\eta \end{bmatrix} &= \begin{bmatrix} 1 - c_1 \cdot r_1 - c_2 \cdot r_2 & w \cdot \Delta t \\ -(c_1 \cdot r_1 + c_2 \cdot r_2) / \Delta t & w \end{bmatrix} \cdot \begin{bmatrix} X_k^\eta \\ V_k^\eta \end{bmatrix} \\ &+ \begin{bmatrix} c_{1g} \cdot r_{1g} & c_2 \cdot r_2 \\ c_{1g} \cdot r_{1g} / \Delta t & c_2 \cdot r_2 / \Delta t \end{bmatrix} \cdot \begin{bmatrix} \sum_{i=1}^{N-1} P_k^i / (\eta - 1) \\ P_k^* \end{bmatrix} \end{aligned} \quad (24)$$

which can be viewed as a discrete-dynamic system for CenterPSO, where the system of $[X^\eta, V^\eta]^T$ considers an external input $[\sum_{i=1}^{\eta-1} P_k^i / (\eta - 1), P^*]^T$.

In the case when this dynamic system is not affected by external stimulation, $[\sum_{i=1}^{\eta-1} P_k^i / (\eta - 1), P^*]^T$ is constant, so the system converges. Let k approach infinity. Then, $[X_{k+1}^\eta, V_{k+1}^\eta]^T = [X_k^\eta, V_k^\eta]^T$, and the matrix becomes

$$\begin{aligned} \begin{bmatrix} 0 \\ 0 \end{bmatrix} &= \begin{bmatrix} -c_1 \cdot r_1 - c_2 \cdot r_2 & w \cdot \Delta t \\ -c_1 \cdot r_1 + c_2 \cdot r_2 / \Delta t & w - 1 \end{bmatrix} \cdot \begin{bmatrix} X_k^\eta \\ V_k^\eta \end{bmatrix} \\ &+ \begin{bmatrix} c_1 \cdot r_1 & c_2 \cdot r_2 \\ c_1 \cdot r_1 / \Delta t & c_2 \cdot r_2 / \Delta t \end{bmatrix} \cdot \begin{bmatrix} \sum_{i=1}^{\eta-1} P_k^i / (\eta - 1) \\ P_k^* \end{bmatrix} \end{aligned}$$

which holds only when $V_k^\eta = 0$ and $X_k^\eta = \sum_{i=1}^{\eta-1} P_k^i / (\eta - 1) = P_k^*$. In the case when the dynamic system is affected by external stimulation, the solution has a tendency to move towards the optimal condition. During the optimization process, the system can find a better optimal position P_k^i of each particle and the global optimal position P_k^* of all particles.

The stable and dynamic behavior of this system can be realized by the characteristic equation of (24), which can derive the same condition with [32].

V. IMPLEMENTATION AND EXPERIMENTAL RESULTS

A. Experimental Environment

The parameter setting is given as follows: swarm size is 20 or 40; maximal number of iterations is set to 1000–4000; range of each particle's position is in [0, 100]; V_{max} = 100; $w \in$ [0.4, 0.9];

c_1 = 2.0; c_2 = 2.0; C_s = 0.07; C_g = 0.07; M_u = 15000; M_c = 1500000. The first 7 parameters are related to the CenterPSO and are determined by lots of experimental trials; the other 4 parameters are related to the problem, in which costs C_s and C_g are from [8]; while penalty costs M_u and M_c are 10^4 and 10^6 times of C_g to make much difference. Note that unit of all the costs used in this experiments are 10^{-3} times of those in [8].

B. Experimental Analysis

This section first checks convergence and stability of the algorithm. Plots of fitness values versus number of iterations for CenterPSO and PSO are given in Fig. 2, in which both of the two approaches can converge to a fixed fitness value as iterations increase. Specifically, the fitness values at the early iterations for the CenterPSO decrease faster than those for the PSO, i.e., the CentrPSO is capable of taking fewer iterations to find better solutions. At the middle stage (i.e., at about 250 to 700 iterations), the PSO yields better fitness values than the CenterPSO; at the final iteration, the CenterPSO can converge to obtain a better fitness value than the PSO. Next, sensitivity of the Center PSO and PSO algorithms is checked by the plots of fitness values versus number of different runs (Fig. 3). From Fig. 3 the fitness values of both approaches fall into the range [6.0, 6.4], which confirms stability of the algorithm.

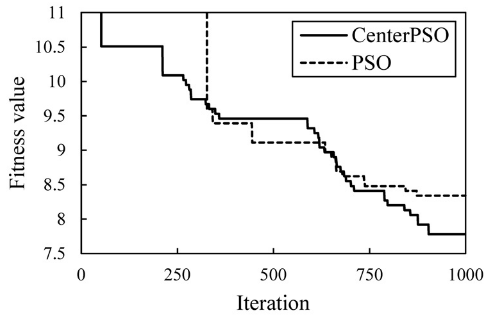

Fig. 2. Convergence analysis

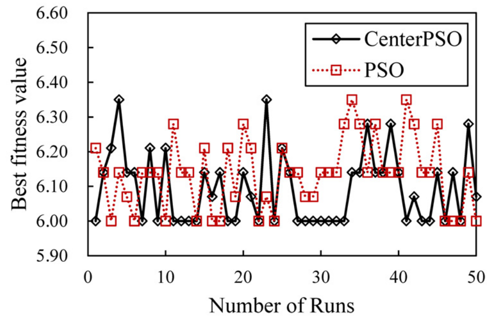

Fig. 3. Sensitivity analysis

The experimental statistics under different parameters are given in Table I. Parameters W and L determine different road sizes. Note that the work in [8] applied W = 8 and 10; L = 100, 200, and 300; R_{cov} = 5; G_{cov} = 30 and 80. Different from [8] for single-lane roads, the experiments applies W = 16 and 20 for two-lane roads. Additionally, longer road lengths are considered, i.e., L = 400 and 500. Note that this paper proposes a generalized framework for the concerned problem that can be applied to different-size practical applications.

In Table I, the best fitness, average fitness, worst fitness, the standard deviation among 20 runs of the CenterPSO are recorded; additionally, the CPU time (in seconds) for each case is recorded. From Table I, all the values are feasible (less than M_u = 15000). For the case of W = 20, since the setting of R_{cov} = 10 and G_{cov} = 80 (with larger coverage ranges) can cover more road surface, the cases with this setting can be solved efficiently (see the 6th to 10th rows in Table I). In contrast, the cases with the setting of R_{cov} = 5 and G_{cov} = 30 (with smaller coverage ranges) take relatively more time to find the solutions.

TABLE I
EXPERIMENTAL STATISTICS UNDER DIFFERENT PARAMETERS

W	L	R_{cov}	G_{cov}	Best	Average	Worst	StdDev	Time
16	100	5	30	3.14	3.55	4.71	0.567	1.62
16	200	5	30	6.77	8.07	8.73	0.565	3.029
16	300	5	30	13.09	14.92	16.44	1.105	4.5344
16	400	5	30	15.84	15.98	16.12	0.140	26.144
16	500	5	30	42.88	43.79	44.7	0.910	444.726
20	100	10	80	1.57	1.57	1.57	0.001	1.452
20	200	10	80	3.07	3.09	3.28	0.063	2.316
20	300	10	80	3.14	4.13	4.78	0.714	3.377
20	400	10	80	4.99	6.03	6.84	0.667	4.542
20	500	10	80	6.49	7.23	8.41	0.577	5.306

To analyze the problem size that the CenterPSO can handle, this work conducts experiments for problems with different road lengths when W = 20, R_{cov} = 10, and G_{cov} = 80. Figs. 4 and 5 show plots of best fitness and running time for each 100 units of road length, in which number of RSUs is kept fixed (i.e., 50); and number of sensors could be 200, 300, and 400 because it is the main factor to affect performance after lots of experimental trials. From Fig. 4, when a line goes upwards the top boundary, it means that the fitness is too large, i.e., the solution of the next plot is infeasible. It is concluded that as number of sensors increases, the problem with longer road length could be addressed (Fig. 4). From Fig. 5, the running time increases when road length or number of sensors increases.

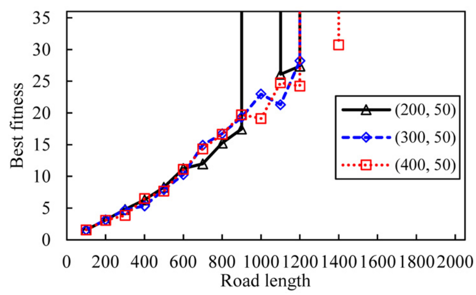

Fig. 4. Plot of best fitness versus road length

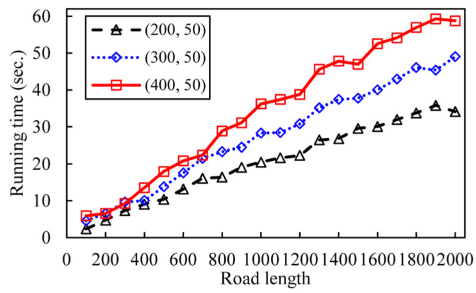

Fig. 5. Plot of running time versus road length

VI. Conclusion

This work has proposed and implemented a PSO approach for the two-lane placement problem for hybrid VANET-sensor networks. An ILP model for the two-lane problem is established first. Then, a CenterPSO approach for the problem is proposed, and a theoretical analysis for the CenterPSO is derived. Experimental results show that this approach can perform well for moderate-size problems. A future work is to consider other objective functions, constraints, heterogeneity, and hybrid approaches in practice. Another challenge is to propose cross-layer design for this hybrid network.

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