Mobile Traffic Sensor Routing in Dynamic Transportation Systems

Ning Zhu, Yang Liu, Shoufeng Ma, and Zhengbing He

***Abstract*—In transportation networks, traditional fixed sensors are used to monitor the operation of transportation systems. However, fixed sensors cannot move once they are installed. In this paper, the motion ability of traffic sensors is introduced to improve the performance of transportation network surveillance. A mobile traffic sensor routing problem is proposed, modeled as a novel vehicle routing problem. A measure of traffic information acquisition benefits is developed and used to gauge the surveillance performance. To solve this mobile-sensor routing problem, a hybrid two-stage heuristic algorithm is designed, which is based on particle swarm optimization and ant colony optimization. Numerical experiments are conducted. The results show that the mobile traffic sensor has a better network surveillance performance than the fixed sensor in most experimental cases.**

***Index Terms*—Ant colony optimization (ACO), hybrid two-stage heuristic algorithm, mobile traffic sensor routing, particle swarm optimization (PSO), vehicle routing problem (VRP).**

I. Introduction

Traffic information significantly affects transportation management and control. To obtain real-time traffic information, transportation surveillance network is necessary. Currently, traffic sensors serve as an important way to gain traffic information. Due to limited budgets, traffic sensors cannot be deployed everywhere in transportation networks. Traffic information collected from optimal sensor locations is used to provide real-time traffic data for various traffic information applications, such as flow observation and estimation [including origin–destination (OD) trips, route flow, and link flow], travel-time estimation, bottleneck identification, and so on.

The sensor location problem aiming to observe and estimate traffic flow has attracted considerable attention for several decades. To estimate OD, four important location rules and corresponding mathematical models that implement these rules are proposed [1]. A two-stage model [2] is presented to determine optimal sensor placement location to estimate OD demand. A mathematical model is formulated to intercept all or as many OD trips as possible [3]. To infer all link flows from partial observed links, an optimal location model on nodes [4] is determined to infer link flow in a transportation network. The linear algebra method is used to find an optimal sensor location to infer network-wide flow [5]. Regarding the path flow estimation, an optimal sensor deployment method is proposed so that path flow can be distinguished and estimated in [6] and [7]. A sensor location problem for flow observation and estimation is well reviewed in [8].

The travel-time estimation problem is another important direction for sensor location issues. The quality benefit of travel-time estimation is maximized by optimally locating automatic vehicle identification readers [9]. A simulation tool is employed in [10] and [11] to figure out the relationship between travel characteristics and sensor location. The impact of sensor spacing on travel-time estimation is investigated [12], [13]. A sequential modeling framework for optimal sensor location is also proposed [14]. Objective applications include ramp metering control and travel-time estimation.

Most of these studies are conducted in a static and deterministic transportation environment. Other studies in the field of traffic sensor location problem consider dynamic and stochastic environmental factors that influence sensor location patterns. The optimal sensor location problem is studied for the purpose of estimation in a dynamic transportation environment in [15] and [16]. Sensor failure [17] is considered in a sensor location model to achieve a more reliable location pattern. Demand estimation uncertainty is minimized in [18]. A nonlinear two-stage stochastic model is proposed in [19] to maximize the OD coverage and information gain against random events.

Most studies in the transportation field investigate how to maximize the usage of fixed sensors. Fixed traffic sensors cannot be relocated once installed. In the last several decades, mobile sensors have attracted considerable attention in other fields such as communication and automation. Several seed nodes [20] have been used to relocate all sensors in a network without additional hardware. A distributed energy-efficient deployment algorithm [21] is proposed for mobile sensors and intelligent devices in a general network. Distributed algorithms for mobile-sensor networks are presented against events that occur frequently [22]. In the field of information gathering, a delay/fault-tolerant mobile-sensor network is proposed [23]. Most studies of mobile sensors focus on network or algorithm design for different purposes. Only the work in [24] has used sensor-equipped vehicles to gather data from vibration and GPS sensors. Such detection aims to identify potholes and other severe road surface anomalies. Other mobile sensors in the field

Manuscript received May 15, 2013; revised August 30, 2013, November 22, 2013, and February 9, 2014; accepted March 19, 2014. This work was supported in part by the National Natural Science Foundation of China under Grants 71301115, 71271150, and 71101102 and in part by the Specialized Research Fund for the Doctoral Program of Higher Education of China under Grant 20130032120009. The Associate Editor for this paper was Q. Kong.

N. Zhu, Y. Liu, S. Ma are with the Institute of Systems Engineering, Tianjin University, Tianjin 300072, China (e-mail:liuyang89@tju.edu.cn).

Z. He is with the Ministry of Education Key Laboratory for Urban Transportation Complex Systems Theory and Technology, School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2014.2314732

of transportation include airborne imagery sensors [25], [26] and GPS-based traffic probes [27].

Mobile traffic sensors are assumed to have the surveillance ability of recording traffic flow and identifying license plates so that travel-time information can be obtained. We assume that mobile sensors are special vehicles with equipped surveillance device. The special vehicles are managed by transportation authorities. Probe vehicles equipped with sensor devices can be considered traffic mobile sensors. We model the motion of a mobile traffic sensor in a transportation network as a particular vehicle routing problem (VRP) that has a long research history. The first study can be traced back to [28] and [29], which focused on a large-scale traveling-salesman problem. In general, the traditional VRP can be classified into four categories [30].

- *Capacity- and Distance-Constrained VRP (CVRP).* The CVRP determines the routes for a fleet of vehicles without exceeding the capacity and distance constraints of each vehicle. An exact algorithm is proposed in [31] to solve the CVRP. Exact results for the CVRP are impossible even for medium networks. Several heuristic methods have been developed to solve the CVRP. These heuristics can be classified into ant colony optimization (ACO) [32], [33], simulated annealing [34], neighborhood search [35], [36], and particle swarm optimization (PSO) [37].
- *VRP with Time Windows (VRPTW).* The VRPTW is a problem in which routes should be designed in a way that each point is visited only once by exactly one vehicle within a given time interval. Similar to other traditional VRP and its variants, the VRPTW cannot be solved with an exact solution. Therefore, several state-of-the-art meta-heuristics have been proposed, such as ACO [38], tabu search [39], and simulated annealing [40].
- *VRP with Backhauls (VRPB).* The VRPB differs from the classic VRP mainly because, on each route, the backhaul customers are visited after all linehaul customers. An exact algorithm is given for VRPB for small and medium networks [41]. Recent studies about VRPB include [42] and [43].
- *VRP with Pickup and Delivery (VRPPD)* [44]. For the VRPPD, a request is defined by a pickup point and a related delivery point. A demand is defined as goods or service transportation between the pickup point and delivery point. Recent advances in VRPPD are reported in [37], [45], and [46].

Stochastic and dynamic VRPs have also been developed [47], [48]. A good taxonomic review for VRP is given in [49]. In [30] and [50], VRPs are comprehensively reviewed. Our model does not fit into any of these categories.

In this paper, the mobile traffic sensor has two different states on the transportation network. One is traveling on the network, and the other is staying on the links and collecting information simultaneously. We also assume that traffic information acquisition benefits are related to the stay time of links. In VRP context, the objective function depends on the service time of customers, which is the stay time of links. Mobile sensor captures as much traffic information as possible. The mobile-sensor routing problem proposed is named as the information-capture-oriented mobile-sensor routing problem (IMRP). The IMRP differs from the traditional VRP due to the following.

- Most customers in traditional VRPs need only a one-time service. In our IMRP model, the stay time on a link crucially affects the objective function. One link can be visited by one mobile sensor at different time more than once. However, from the basic idea of traffic information collection, it is wasteful that more than one mobile sensors visit an identical link at the same time. Duplicate observations do not increase the information collection performance. Longer observation time increases information acquisition benefits.
- A comparison with traditional VRPs indicates that most of them focus on minimizing travel time or travel distance. In this paper, cost pertaining to vehicle routing is unimportant. What matters is captured traffic information.
- One constraint for most VRPs is the number of vehicles. In our model, another constraint is included, i.e., the travel-time constraint. The travel time from one link to another link at specific departure time t should be consistent with the traffic condition of the dynamic transportation network.
- The total travel time and stay time of the mobile sensor should not exceed a predefined value.

The advantages of mobile traffic sensors are as follows. First, a transportation network is a dynamic environment. Network states differ among different time intervals. Fixed sensor networks may offer good surveillance performance in one state but bad at another. Mobile traffic sensors avoid this weakness of fixed sensor networks. Second, fixed sensors are subject to failure [51]. Traffic sensor network maintenance is a time-consuming job. Mobile traffic sensors are flexible and can be used as complements to provide surveillance service temporarily. Although mobile traffic sensors have several advantages, few studies have focused on them, not to mention their routing problem. This paper aims to fill this gap.

This paper uses mobile traffic sensors to collect real-time information. Dynamic transportation networks are considered in our modeling. A group of optimal mobile-sensor routes is to be designed by maximizing the benefits of traffic information acquisition. The remainder of this paper is organized as follows. In Section II, we measure traffic information acquisition benefits and develop a mobile-sensor routing model. In Section III, a hybrid two-stage heuristic algorithm is proposed by combining PSO and ACO. In Section IV, numerical examples are provided to demonstrate the effectiveness of the proposed model and algorithm. Section V concludes and summarizes the main outcomes in this paper.

II. Mobile Traffic Sensor Routing Problem

Routing mobile sensors aim to provide effective network surveillance. In contrast to fixed traffic sensors, mobile traffic sensors can move in the network. To collect traffic information as much as possible, the main problem of using mobile-sensor networks is to design a route for each mobile sensor. Statistically, more samples collected on a link leads to a more accurate estimation of the traffic state. Given that mobile sensor has a constant sampling rate, the mobile sensor's stay time on links significantly affects traffic information acquisition. Therefore, decision variables in the mobile traffic sensor routing problem are of two kinds: a route variable that decides which route to go for each mobile sensor and the stay time of mobile sensor on each link of the route. Note that, this paper, visiting a link or arriving at a link means that the mobile traffic sensor is going to move to the middle point of a link. This assumption does not influence the traffic information collection efficiency. On the other hand, it simplifies the calculation of the travel distance between adjacent links. More than one mobile sensor staying on the same link at the same time does not make traffic information surveillance performance better. Duplicate stay of more than one mobile sensors in an identical link at the same time is a kind of resource waste. The total time a mobile sensor can spend is defined as the summation of travel time and stay time. The total time is not allowed to exceed a predefined value.

In this paper, the objective traffic applications include link flow inference, path travel-time estimation, and OD estimation. These three applications require observations on the link, path, and network levels. A dynamic transportation network is adopted. We assume the time-sliced OD trips. For each time interval of a day and each link, OD demand is assumed stable from a long-term perspective. Further, we assume that the flow volume assigned on each link follows a probability distribution. This assumption is reasonable because the OD trips of each time interval are not strictly constant but has slight perturbation.

Let us denote a transportation network as $G(N, A)$, where N represents the set of intersections in a network and A represents the set of links that connect intersections. Mobile sensors travel from one link to another to obtain real-time traffic information on links. The total information acquisition benefits are determined by the total stay time on all observed links among all time intervals. First, the sample collection period is assumed fixed and dependent on the configuration of devices. A relationship between sample size and traffic state observation accuracy is built in Section II-A. Traffic state observation accuracy is used as a measure of information acquisition benefits. Second, the benefits of information acquisition are assumed determined on the link, path, and network levels, respectively. The measure of information acquisition benefits is developed accordingly.

A. Sample Size and Estimation Accuracy

In practice, link traffic states, such as link traffic flow and travel speed, for each time interval on a daily basis experience perturbation. We assume that authentic link traffic flow and link travel speed information follow a deterministic but unknown probability density distribution. More observations increase estimation accuracy for these unknown distributions. Thus, longer stay time increases estimation accuracy. Here, we figure out the impact of sample size on estimation accuracy. From the perspective of statistics, the basic idea behind sample size determination is that a large sample size increases the degrees of freedom and thus reduces the confidence interval. Assume that we have prior information about the mean and deviation of traffic flow or travel speed distribution. We denote prior mean

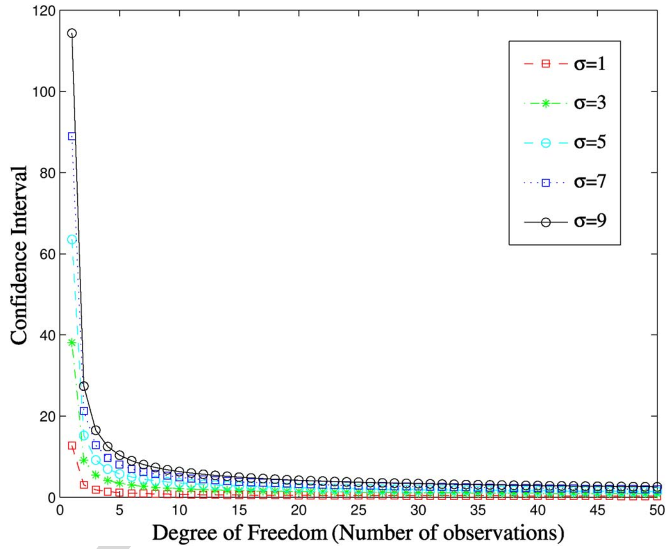


Fig. 1. t distribution sample size determination.

and deviation as μ and σ, respectively. The ground-truth value of the mean and deviation is unknown. Sampling is used to update prior mean and deviation. The longer the time spent on data collection, the higher the estimation accuracy we obtain. Data collected are assumed error free. Mean and deviation estimation is used to illustrate the relationship between sample size and observation accuracy.

Mean Estimation: Consider a sample $(X_1, X_2, X_3, \ldots, X_n)$ with size n from an unknown distribution. If we manipulate the definition for the t statistic, we obtain

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(n-1). \tag{1}$$

The right-hand side of (1) is $t(n-1)$, which is not dependent on any unknown parameters. The confidence level is denoted α. The half-length of the confidence interval is computed as

$$d = \frac{S}{\sqrt{n}} t_{\alpha/2}(n-1). \tag{2}$$

Because prior information is given, sample standard variance S can be substituted by prior standard variance σ as

$$d = \frac{\sigma}{\sqrt{n}} t_{\alpha/2}(n-1). \tag{3}$$

Deviation Estimation: Following the similar logic for mean estimation to estimate deviation, we calculate

$$P\left\{\chi^2_{1-\alpha/2}(n-1) \le (n-1)s^2/\sigma^2 \le \chi^2_{\alpha/2}(n-1)\right\} = 1-\alpha. \tag{4}$$

After some simple steps of manipulation, the length of the confidence interval can be stated as

$$d = \frac{(n-1)s^2}{\chi^2_{\alpha/2}(n-1)} - \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}(n-1)}. \tag{5}$$

In Figs. 1 and 2, it is shown that the confidence interval increases with deviation under the condition of identical degrees of freedom. More observations increase estimation accuracy.

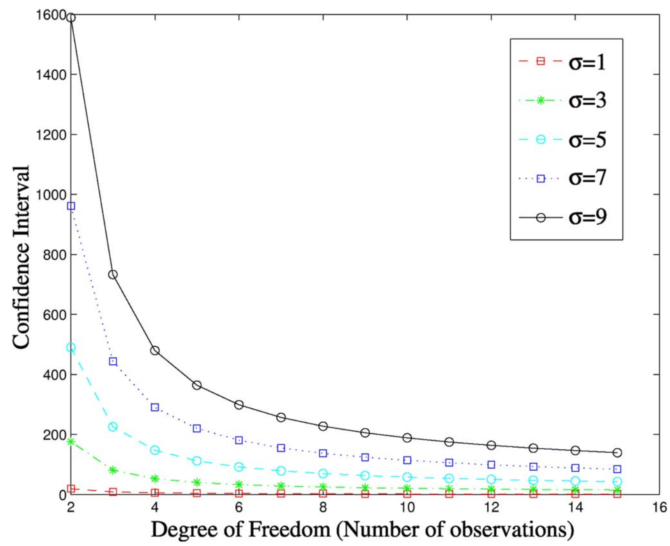


Fig. 2. Chi-square sample size determination.

To integrate this observation into our model, the benefit from the observations of a link is assumed as a nonlinear monotonic increasing function of the mobile sensor's stay time. We first use a hyperbola to fit the curve shown in Fig. 2 because the deviation is seen more informative. The R-square of this fit is greater than 99%, which shows a very good fitting performance. However, this hyperbola monotonically decreases and thus does not satisfy our requirements. After some simple manipulation of curve reversal and horizontal shift, we obtain a traffic information acquisition benefit curve as

$$f(s) = \begin{cases} \frac{p_1 s + p_2}{s + q_1}, & s > 0 \\ 0, & s = 0 \end{cases} \tag{6}$$

where s represents the stay time of mobile sensors on a link. p_1, p_2, and q_1 are the parameters from curve fitting. Deviation information σ is embedded in these three parameters. The marginal benefit of observation decreases as the first derivative of (6) decreases. Different σ results in different parameter combinations of (6).

B. *Link Importance in Transportation Network*

To obtain a good insight into the link contribution, the link importance of the transportation network should be identified. The contribution of a single link to the transportation network can be categorized into three aspects: 1) link level; 2) path level; and 3) network level. These three aspects are elaborated in the following.

1) Link Importance on Link Level: Single-link observation is helpful because it can be used together with historical data to contribute to link flow estimation. One possible application that uses link flow information is network-wide link flow inference [5]. We adopts a link-based V/C ratio to identify the contribution of links [52], where V is the link volume and C is the link capacity. The traffic information acquisition benefits on the link level is formulated as

$$b_l = \alpha_l \sum_{a \in A} \frac{V_a}{C_a} x_a \tag{7}$$

where b_l is the benefits based on the link level, α_l is the nonnegative coefficient of the link-level contribution, and V_a and C_a are the link volume and capacity, respectively, on link a. $x_a = 1$ shows that an observation is made on link a; otherwise, $x_a = 0$.

2) Link Importance on Path Level: We assume that traffic mobile sensors have the ability to record the vehicle's position as the vehicle passes. If two mobile sensors at the same time interval stay on two different links on one path, travel-time information can be obtained for this route between the first (head) sensor and the last (rear) sensor. We use a way similar to that in [17] to measure route coverage benefits from mobile sensors. The benefit on path level can be measured by

$$b_p = \alpha_p \sum_{p \in \mathrm{PS}} (P_{p,r} - P_{p,h}) \tag{8}$$

where b_p represents the benefits obtained from the views of travel-time estimation; α_p denotes the nonnegative coefficient of the path-level contribution; PS is the path set; $P_{p,r}$ and $P_{p,h}$ are the rear and head positions of the mobile sensor on specific path p, respectively; and $P_{p,r} - P_{p,h}$ shows the distance that mobile sensors on this specific path p can cover.

More factors and formulations can be applied to assess traffic information acquisition benefits from the perspective of travel time. One possible extensive factor for travel time is mobile-sensor failure. Long distance between two mobile sensors increases inaccuracy in travel-time estimation. In this case, more complicated benefit expression should be formulated by considering the aforementioned factors.

3) Link Importance on Network Level: Regarding the link observation's contribution to the transportation network level, two factors have significant effects. One is transportation network topology, and the other is travel demand assigned to the transportation network. For each time interval, travel demand is deemed relatively stable in this paper. One result derived from this assumption is that the OD-link coincident matrix is constant for each time interval. According to Yang's four rules for sensor location [1], sensors should be placed on links with a higher number of OD pairs passed. One potential traffic application from network-level benefits is OD estimation. An example for the OD-link coincident matrix is shown as

$$\begin{pmatrix} 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix}. \tag{9}$$

This small transportation network has five OD pairs and five links. The number of OD pairs passing through link1, link2, link3, link4, and link5 are 2, 2, 3, 1, and 4, respectively. The total number of OD pairs passing through a link reflects the combinatorial effects for both transportation network topology factors and traffic demand factors. The number of OD pairs that pass a specific link can be taken as a measure of link importance on the network level. The benefits on the network level are formulated as

$$b_n = \alpha_n \sum_{a \in A} B_a x_a \tag{10}$$

where b_n is the benefits obtained from the network level, A is the set of links, B_a represents the number of OD pairs passing through link a, α_n is the nonnegative coefficient of network-level contribution, and $x_a = 1$ represents an observation exists on link a.

C. Mathematical Formulation

Mathematical formulation is stated as

$$\begin{aligned} \text{Min } f(s) = &\sum_{t \in T} \left(\alpha_l \sum_{a \in A} \frac{V_{a,t}}{C_a} f(s_{a,t}) + \alpha_n \sum_{a \in A} B_{a,t} f(s_{a,t}) \right) \\ &+ \sum_{t \in T} \left(\alpha_p \sum_{p \in \text{PS}_t} (P_{p,r} - P_{p,h}) f(s_{p,t}) \right) \end{aligned} \tag{11}$$

subject to

$$\begin{aligned} &u_{ai,aj}^{ts,kv} \left(G_{ai}^{ts,kv} + \tau_{ai,aj} \left(G_{ai}^{ts,kv} \right) \right) \\ &\quad = L_{aj}^{ts+1,kv} \ \forall ai;\ \forall aj;\ \forall ts;\ \forall kv \end{aligned} \tag{12}$$

$$s_{ai,kv}^{ts} = G_{ai,kv}^{ts} - L_{ai,kv}^{ts} \ \forall ai;\ \forall kv;\ \forall ts. \tag{13}$$

$$\sum_{aj \neq ai} u_{aj,ai}^{ts,kv} = \sum_{ak \neq ai} u_{ai,ak}^{ts+1,kv} \quad \forall ai;\ \forall ts;\ \forall kv. \tag{14}$$

$$\sum_{ai} u_{a0,ai}^{1,kv} = 1 \ \forall kv. \tag{15}$$

$$\sum_{ts} \sum_{ai} u_{ai,a0}^{ts,kv} = 1 \ \forall kv. \tag{16}$$

$$u_{ai,aj}^{ts,kv} \in \{0, 1\} \ \forall ai;\ \forall aj;\ \forall kv;\ \forall ts. \tag{17}$$

$$G_{ai}^{ts,kv} \qquad L_{ai}^{ts,kv} \geq 0 \tag{18}$$

where ai, aj, and ak are the link indexes, $a0$ is the depot index, kv is the mobile-sensor index, and ts is a sequential index of the visited links. For example, there is a route as depot $\rightarrow$ link1 $\rightarrow$ link2 $\rightarrow$ link1 $\rightarrow$ link3 $\rightarrow$ depot. The corresponding sequential index for this route is 1, 2, 3, 4, 5, and 6, respectively. In our model, multiple visits of a identical link at different times are allowed. The sequential index for the first visit of link1 is 2, and the index for the second visit of link1 is 4. Different visit indexes are allowed to be associated with identical link. For the purpose of modeling, ts is chosen as a big number but do not significantly increase the model size. $G_{ai}^{ts,kv}$ and $L_{ai}^{ts,kv}$ are decision variable indicating the departure time and the arrival time of vehicle kv on link ai for its ts visit. $G_{ai}^{ts,kv} = 0$ and $L_{ai}^{ts,kv} = 0$ if vehicle kv does not leave or arrive at link ai at its ts visit; otherwise, $G_{ai}^{ts,kv} > 0$, and $L_{ai}^{ts,kv} > 0$. $u_{ai,aj}^{ts,kv}$ is a binary variable. $u_{ai,aj}^{ts,kv} = 1$ means vehicle kv moves from link ai to link aj for its ts visit; otherwise, $u_{ai,aj}^{ts,kv} = 0$. $\tau_{ai,aj}(t)$ is a piecewise constant function that indicates the travel time from link ai to link aj starting from departure time t.

The constraints are defined as follows. Mobile sensors' stay time on links must allow for travel time between links (12). For constraint (13), vectors G and L contain information on departure time and arrival time for all mobile sensors' all visits on each link; stay time information s can be easily obtained from G and L. s is also used as an objective function to compute the total traffic information acquisition benefits. If a mobile sensor arrives at a link, it must also depart from that link (14); the mobile sensor must start and end at the depot by (15) and (16). Constraint (16) also indicates that the mobile sensor can only return to the depot once. It is not allowed to return to the depot more than once. The type and domain of the decision variables are indicated in (17) and (18).

Objective function (11) is reformulated aiming to incorporate the stay-time-based traffic information acquisition benefits. It considers the aforementioned statistical properties of observations and three popular traffic applications. These three traffic applications are integrated with different weighs, which are specified by the transportation agencies. Since s contains information about stay time of each mobile sensor of each link at each time interval, the index system can be reused to include the link index a and the time interval index t. $s_{a,t}$ represents the stay time of traffic mobile sensors on link a at time interval t. $s_{p,t}$ is the stay time of path p at time interval t and is calculated by the shared stay time of two mobile sensors. For example, if one mobile sensor spends the first 40 min of a time interval in a path and another mobile sensor spends the last 40 min of an identical time interval on the same path (the time interval is assumed 1 h), the shared stay time is 20 min, which is the common time of these two mobile sensors on this path. $P_{p,r} - P_{p,h}$ is the longest covered distance of the two observations of path p. Regarding the final objective function (11), $f(s_{a,t})$ and $f(s_{p,t})$ represent the impact of the mobile sensor's stay time of each link and each time interval on the transportation network-wide information acquisition benefits, as shown in (6).

This formulation only provides a framework of information acquisition benefits based on mobile-sensor routing patterns. This mathematical formulation is used to describe proposed mobile-sensor routing problem and is not directly used for problem solving.

III. Hybrid Two-Stage Heuristic Algorithm

The VRP is an NP-hard problem. A hybrid two-stage heuristic algorithm is proposed to solve the IMRP. The proposed model requires the computation of both vehicle route and stay time. The ant colony algorithm performs well at finding optimal or near-optimal routes for the VRP. However, the ant colony algorithm is unsuitable for solving continuous problems that refer to stay-time decision-making in our model. PSO is a population-based stochastic approach suitable for solving continuous optimization problems. A hybrid algorithm that combines the ant colony algorithm and the PSO is designed to solve our proposed problem. The vehicle route is determined by the ant colony algorithm. The PSO is applied to figure out the optimal stay time on a given route. A fitness function is returned to the ant colony algorithm to update pheromone and next-round iteration.

A. Particle Swarm Algorithm

The mobile sensor's total time should not exceed a predefined value. The initial solution for a given route is set as the maximum travel time among all time intervals, i.e.,

$$h_{i,m} = \begin{cases} \theta_1 \dfrac{W - \sum\limits_{k \le M-1} \max t_k}{M}, & m \le M-1 \\ W - \sum\limits_{m \le M-1} h_{i,m} - \sum\limits_{m \le M-1} e_m, & m = M \end{cases} \tag{19}$$

where h represents the stay-time vector of particles that contains the stay time on each link of a given route; $h_{i,m}$ is the stay time of the mth link of the ith route, which is a value; M is the particle dimensionality, which is the number of links on a specific route; W is the predefined total time, which is the summation of the travel time and the stay time; θ_1 is a randomly generated value ranging from 0 to 1; $\max t_k$ is the largest travel time from the kth link to the $(k+1)$th link among all time intervals; and e_m is the real travel time from the mth link to the $(m+1)$th link after the first m links' stay time is determined.

The particle moves toward the optimum in terms of velocity and position. At each iteration, particle velocity and position are updated in terms of

$$\begin{aligned} v_{i,d} &= Zv_{i,d-1} + C_1 \times \theta_2 \times (\text{pbest}_{i,d-1} - h_{i,d-1}) \\ &\quad + C_2 \times \theta \times (\text{lbest}_{i,d-1} - h_{i,d-1}) \\ v_{i,d} &= \begin{cases} v_{i,d}, & v_{i,d} \le v_{\max} \\ v_{\max,d}, & v_{i,d} > v_{\max} \end{cases} \\ h_{i,d} &= h_{i,d-1} + v_{i,d} \end{aligned} \tag{20}$$

where d represents the dth generation for the ACO algorithm; $h_{i,d}$ represents the stay time of the ith particle of the dth generation; $h_{i,d}$ is a vector, and each element of $h_{i,d}$ is $h_{i,m}$; $v_{i,d}$ is the ith particle's velocity at the dth generation; $\text{pbest}_{i,d-1}$ is the personal optimal solution found by the ith particle among its own historical solutions, and $\text{lbest}_{i,d-1}$ is the local optimal solution; Z is a positive inertia parameter; C_1 and C_2 are positive constants; and θ_2 is a random generated value ranging from 0 to 1. $v_{i,d}$ is updated in the first expression of (20). $v_{i,d}$ is further restricted by $v_{\max}$, which is a predefined particle at maximal speed. $v_{i,d}$ is used to update st.

B. Ant Colony Algorithm

1) Route Construction Rule: A vector is used to represent a vehicle route. One example of a route solution is [1 2 7 8 1 0 1 9 2 3 1 0], where 1 denotes the vehicle depot and 0 is used as a separator to separate different mobile sensors. The other numbers in this vector are link IDs in the transportation network. We require that all vehicles should depart from the vehicle depot and return to the depot again before the total time is reached. In the example, two vehicles are separated by 0, and the routes for these two vehicles are 1-2-7-8-1 and 1-9-2-3-1, respectively.

Based on the idea from [53], mobile-sensor routes are conducted as follows. The ants sequentially choose links to visit. The state transition rule is used to give the probability with which the ants decide to visit the next link, i.e.,

$$S = \begin{cases} \arg\max\limits_{m \in J(a)} \tau_{m,d}^{\alpha} \times \eta_m^{\beta}, & q \le q_0 \\ s, & q > q_0 \end{cases} \tag{21}$$

where S is the next link determined by the right-hand side of (21); $J(a)$ is the candidate link set of link a; $S = 0$ represents that the mobile sensor returns to the depot; d represents the dth generation of the ACO algorithm; τ is the pheromone; η is the heuristic information; α and β are the parameters that control the influence of the pheromone and heuristic information, respectively; and q is a random variable. q_0 is a predetermined parameter $(0 \le q_0 \le 1)$. P_s is the probability that a mobile sensor chooses to stop moving. The probability of choosing s as the next visit link is determined by P. P is formulated as

$$P = \begin{cases} (1 - P_s) \dfrac{\tau_{s,d}^{\alpha} \times \eta_s^{\beta}}{\sum\limits_{m \in J(a)} \tau_{m,d}^{\alpha} \times \eta_m^{\beta}}, & s \in J(a) \\ P_s, & s = 0 \end{cases}. \tag{22}$$

In our model, a mobile sensor can visit the same link more than once. Therefore, a mechanism that stops the mobile sensor should be designed. A concept of physical power is created, as shown in (22) and defined in (23). The physical power of ants decreases when they make more visits. Given the gradual increase in the fatigue degree, ants are more likely to stop moving. The more links ants visit, the more time they consume. Therefore, the mechanism is designed in terms of travel-time consumption as

$$P_s = \frac{\sum c}{\text{maxpower}} \tag{23}$$

where c is the average travel time among links of all time intervals, and maxpower is a predefined parameter. Maxpower determines the maximum travel time that a mobile sensor can spend on its trip. Based on this logic, maxpower can decide the length of a solution in some degree.

2) Pheromone Update Rule: The pheromone update rule is a critical component of ACO and offers the possibility of obtaining a better solution. In this paper, we adopted the ant-weight strategy proposed in [32] and [54]. This method incorporates both global and local information for pheromone update as

$$\Delta\tau_m^p = \begin{cases} \frac{Q}{R \times V} \times \frac{V_p - V_m}{V_p}, & \text{if link } m \text{ is on route p} \\ 0, & \text{otherwise} \end{cases} \tag{24}$$

where $\Delta\tau_m^p$ is the increased pheromone on link m of route p, Q is a constant, R is the number of routes, V is the total traffic information acquisition benefits, and V_p and V_m are the benefits from route p and link m, respectively. Equation (24) yields the increased pheromone of link m on route p. Pheromone information on link m is updated by using (25) as

$$\tau_{m,\,d+1} = \rho\tau_{m,\,d} + \sum_{p}\sum_{m\in p}\Delta\tau_m^p, \quad \rho \in (0,\,1) \tag{25}$$

where ρ is the information evaporation speed, and $\sum_p \sum_{m\in p} \Delta\tau_m^p$ represents the total pheromone update from all p of link m.

In this way, the ants of the next generation use this updated information to create new solutions close to optimality. Once the pheromones are updated, they are used in (21) and (22) to construct new routes.

C. Hybrid Two-Stage Heuristic Algorithm

Algorithm 1 Hybrid two-stage heuristic algorithm based on PSO and ACO

```
Set parameters for PSO and ACO, respectively
while ACO termination condition not met do
   Construct route
   Pass the constructed route to PSO
   Initialize stay time solution particles for PSO
   while PSO termination condition not met do
      Evaluate all particles
      Update pbest and lbest
      Update velocity and position for each particle
   end while
   Return optimal stay time solution and fitness function
   value to ACO
   Update pheromones
end while
```

As shown in Algorithm 1, the ant colony algorithm aims to build routes for mobile sensors. PSO tries to determine the link's optimal stay time of each mobile sensor for a known route. The route is a critical connection between ACO and PSO. ACO is on the upper level and provides the routes which is used by PSO.

IV. Case Study

The mobile traffic sensor routing problem is tested on the regional transportation network shown in Fig. 3. The numbers on the links are the link IDs. This network has 9 nodes and 28 links. The S-Paramics software package is used as a simulation tool to generate basic traffic flow data. Time horizon is partitioned into 24 time intervals. The duration of each time interval is 1 h. The proposed hybrid two-stage heuristic algorithm is employed to solve this problem. In our implementation, each component in the objective function is standardized. Therefore, the maximum value for each component is 1, and the total maximum value of the objective function is 3.

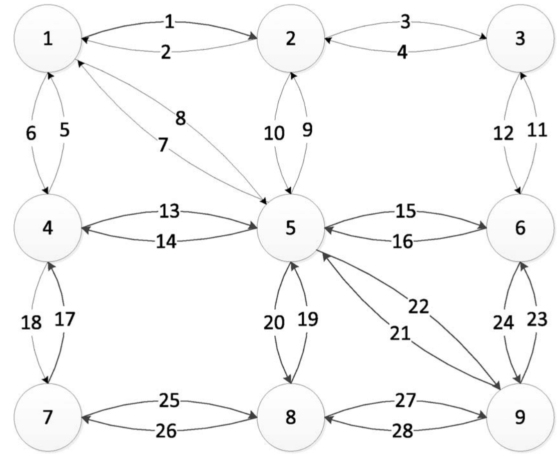


Fig. 3. Experimental transportation network.

TABLE I
PARAMETERS OF ACO

Parameter name	Value
Number of iterations	100
Number of ants	20
α	1
β	1
$maxpower$	6

TABLE II
PARAMETERS OF PSO

Parameter name	Value
Number of iterations	100
Number of particles	15
Size of neighborhood	3
$C1$	1.562
$C2$	2.135
$V0$	8.13
Z	ranging from 0.9 to 0.5

A. Parameters of Hybrid Two-Stage Heuristic Algorithm

The proposed hybrid two-stage heuristic algorithm sequentially employs ACO and PSO. The parameters used in our implementation are as follows:

$maxpower$ is designed in ACO to resolve the "revisit" issue in our mobile-sensor routing problem. In most of our experiments, $maxpower$ is set to 6 as shown in Table I. The parameters of α, β, C_1, C_2, V_0, and the size of neighborhood in Table II are optimized by the genetic algorithm. The number of iterations, number of ants, and number of particles are 100, 20, and 15, respectively, because the algorithm can converge under the setting in preliminary experiments.

B. Mobile Sensor Versus Fixed Sensor Under Different Traffic Conditions

Here, experiments of different numbers of mobile sensors are conducted. The number of mobile sensors ranges from 5 to 23. Different traffic conditions are adopted for our experiments, which have free flow conditions, slight congestion, and severe congestion. Travel time between links for slight congestion and severe congestion is 1.5 and 2 times those of the free

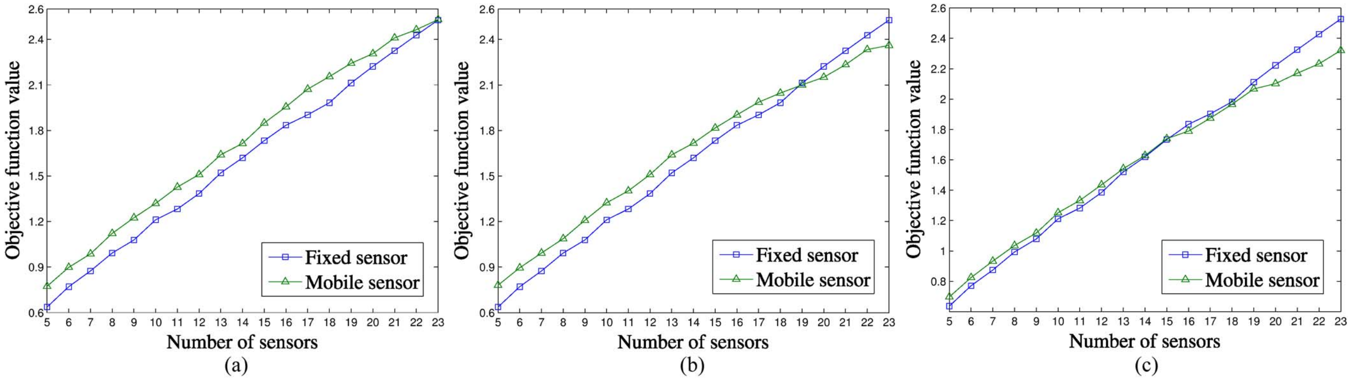


Fig. 4. Mobile sensor versus fixed sensor under different conditions. (a) Mobile sensor versus fixed sensor under free flow condition. (b) Mobile sensor versus fixed sensor under slight congestion. (c) Mobile sensor versus fixed sensor under severe congestion.

flow conditions. The optimal locations of fixed sensors are computed for comparison with those of mobile sensors. The fixed traffic sensor location model in dynamic transportation network condition aims to maximize the covered flow under the constraint of the given number of fixed sensors. The manner of calculating the traffic information acquisition benefits is the same with the mobile-sensor model. The difference between the mobile sensors and fixed sensors is that benefits from mobile sensors spans various links and benefits of fixed sensors comes from identical links. These optimized locations are obtained by using genetic algorithm. Equation (6) is also used to calculate the traffic information acquisition benefits. With fixed sensors, stay time s is set to be the maximal value. In this paper, this value is 60 min for each time interval. Since fixed sensors cannot move, the total traffic information acquisition benefit is computed as the summation of the benefits of all time intervals.

Fig. 4(a) shows that, under free flow condition, the mobile sensor outperforms the fixed sensor. For example, when the number of sensors is five, the objective function value of mobile sensors and fixed sensors is 0.7732 and 0.6363, respectively; the gap is about 17.7%. The whole trend of the difference between the mobile sensor and the fixed sensor gradually decreases. When the number of sensors is 23, the traffic information acquisition benefits are almost the same. The result implies that mobile sensors have advantage in flexibility compared with fixed sensors. Mobile sensors are good at moving; thus, they can move to other more informative links.

Experiments under slight and severe congested conditions [see Fig. 4(b) and (c)] show that the mobile sensor outperforms the fixed sensor when the number of sensors is small. The intersection points of the two curves are 15 and 19, respectively. The advantage of the mobile sensor over the fixed sensor decreases as the traffic becomes congested. The performance gap between the mobile sensor and the fixed sensor decreases from slight congestion to severe congestion. For example, when the number of sensors is 17, the traffic information acquisition benefits are 2, 1.98, and 1.87 for free flow, slight congestion, and severe congestion, respectively. By contrast, the information benefits are 1.9 for the fixed sensor.

The three experiments indicate that, first, when the number of sensors is small, the mobile sensor outperforms fixed sensor regardless of traffic conditions. Given the limited number of mobile sensors, each mobile sensor has a larger space to move around in, and the performance of the mobile sensor is better. The mobile sensor is relatively crowded when the number of sensors is large. Second, when the number of sensors increases, the advantage of mobile sensors gradually decreases. Particularly, in congested traffic conditions, travel time between link becomes longer. The advantage of mobile sensors weakens. The fixed sensor outperforms the mobile sensor. Finally, as a general trend, the advantage of the mobile sensor to the fixed sensor gradually reduces and eventually disappears as the traffic condition becomes extremely congested. This observation is intuitive because the mobile sensor cannot move when the whole network is completely congested.

C. Mobile Sensor Plus Fixed Sensor Versus Fixed Sensor Under Different Traffic Conditions

Here, the fixed sensor network is assumed to be existent, and its location has been optimized. We consider adding one more mobile sensor to the fixed sensor network. Two experiments are conducted under free flow conditions and severe congestion. Fig. 5(a) and (b) show the results. Complete usage of fixed sensors is employed as a comparison. The numbers on the x-axis represent the number of sensors. Adding one more mobile sensor always has a better performance than complete fixed sensors experiment under both free flow and congested traffic conditions. The average gap of the objective function value between one more mobile sensor condition and all fixed sensors are 0.11 and 0.05 for free flow and congested traffic conditions, respectively. Free flow conditions give more performance advantage than congested traffic conditions. The potential application of this observation is to employ a combination of the mobile sensor and the fixed sensor to enhance performance. Another application is to employ a mobile sensor for temporal use during the maintenance period.

Table III summarizes the experiments. In most cases, the mobile sensor outperforms the fixed sensor. Only when traffic is congested and the number of sensors is large does the mobile sensor perform worse than the fixed sensor.

D. Robust Experiment

To discuss the application of the proposed mobile-sensor routing problem, two different kinds of experiments are

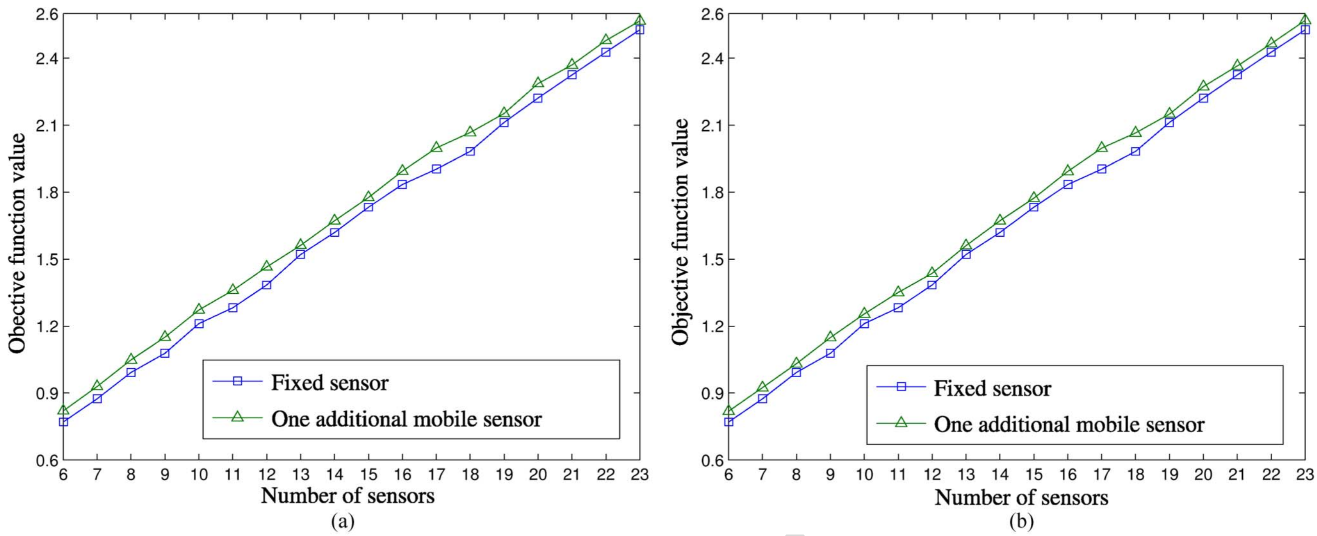


Fig. 5. One additional mobile sensor plus fixed sensor versus fixed sensor under different conditions. (a) One additional mobile sensor plus fixed sensor versus fixed sensor under free flow condition. (b) Mobile sensor versus fixed sensor under slight congestion.

TABLE III
SUMMARY OF MOBILE SENSOR VERSUS FIXED SENSOR

	Small number sensor	Large number sensor
Mobile sensor vs. Fixed sensor under free flow condition	Mobile > Fixed	Mobile > Fixed
Mobile sensor vs. Fixed sensor under slight congested condition	Mobile > Fixed	Mobile < Fixed
Mobile sensor vs. Fixed sensor under sever congested condition	Mobile > Fixed	Mobile < Fixed
Mobile plus fixed sensor vs. Fixed sensor under free flow condition	Mobile > Fixed	Mobile > Fixed
Mobile plus fixed sensor vs. Fixed sensor under severe congested condition	Mobile > Fixed	Mobile > Fixed

TABLE IV
ROBUSTNESS OF MOBILE SENSOR

Experiment code	Performance loss	Experiment code	Performance loss
A01	0.9%	B03	0.88%
A02	1.5%	B05	1.7%
A04	3.2%	B07	2.7%
A06	4.3%	B10	4.8%
A08	5.9%	B12	6.6%
A10	7.3%	B14	8.8%

designed to show the robustness of our model. One is to fluctuate the link travel time with certain percentage. The other is to incorporate the nonrecurrent incident factor.

1) Stochastic Fluctuation of Travel Time: Six different experiments are conducted under this category. Stochastic fluctuation of travel time are set to 10%, 20%, 40%, 60%, 80%, and 100%, respectively, based on the severe congestion condition. Stochastic fluctuation is designed to increase the travel time. Experiments of each percentage level are conducted for 100 times. Traffic information acquisition benefits are recalculated for the original route results based on the stochastic fluctuated travel time. Comparative result between the stochastic fluctuated travel time and the severe congestion condition is in Table IV.

2) Nonrecurrent Incident Caused Congestion: In reality, traffic incident is not uncommon. A stochastic nonrecurrent incident is also considered. Six different experiments are conducted, and 3, 5, 7, 10, 12, and 14 links are randomly chosen as fully congested links out of all 28 links. It is not very common that more than 50% of the links are fully congested in reality. Fully congested links are assumed unavailable for vehicles, and the travel time is set to be extremely large. Traffic information acquisition benefits are also recalculated for the original route results based on the case of stochastic fully congested links. As to each link that is fully congested, a shortest path is generated between its adjacent two links that are not blocked. Therefore, a new route is produced that bypasses these fully congested links. Experiments for each number of fully congested situation are conducted for 100 times. Comparison between the new route of nonrecurrent incident caused congestion and the severe congestion condition is also in Table IV.

Table IV shows the results of the robust experiments. A01, A02, A04, A06, A08, and A10 represent that the stochastic travel-time fluctuation is 10%, 20%, 40%, 60%, 80% and 100%, respectively. B03, B05, B07, B10, B12, and B14 represent that 3, 5, 7, 10, 12, and 14 links are fully congested, respectively. The results of the performance loss compared with the severe congestion condition is shown in Table IV. It is shown that performance of utilizing a mobile sensor does not lose very much, although there is sharp increase in stochastic travel time or high probabilistic traffic incident.

E. Mobile Sensor Route Analysis Based on Topological Position

The numerical results are also analyzed on the route level. All links on this transportation network is divided into five areas in terms of its topological position (see Table V). AQ2

The summation of stay time in each area of a mobile sensor is calculated. The percentage of stay time in each area is obtained accordingly. The mean of the highest percentage of stay time among mobile sensors is 68.9%, which indicates that mobile

TABLE V
LINK AREA PARTITION

Area name	Link IDs
Northwest area	1 2 5 6 7 8 9 10 13 14
Southwest area	13 14 17 18 19 20 25 26
Northeast area	2 3 9 10 11 12 15 16
Southeast area	15 16 19 20 23 24 27 28
Central area	7 8 9 10 13 14 15 16 19 20 21 22

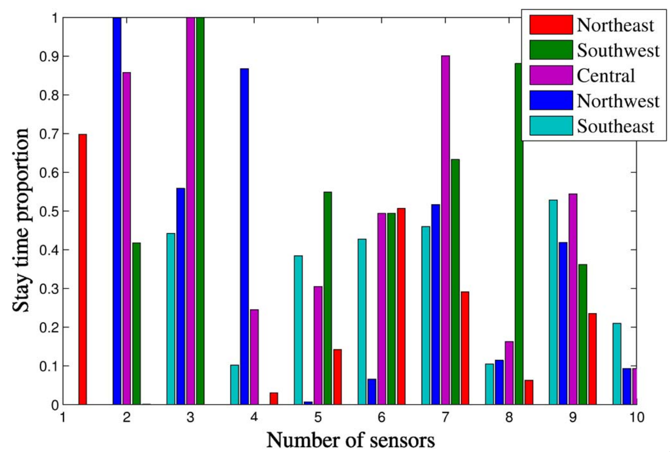


Fig. 6. Proportion of stay time for five areas when number of mobile sensors is ten.

TABLE VI
CLASSIFICATION OF LINKS BASED ON HEURISTIC INFORMATION VALUE

Classification	Link IDs
Low heuristic information	2 4 7 8 10 11 21 22 25 26
Middle heuristic information	5 6 9 13 17 18 23 24 27 28
High heuristic information	1 3 12 14 15 16 19 20

sensors spend most stay time on an identical area. Fig. 6 shows the difference of the stay time proportion in each area that is taken as an example. The number of sensors is ten for Fig. 6. Let us take the second mobile sensor as a further example. The proportion of this mobile sensor in different areas is 0.87, 0, 0.03, 0.10, and 0.25. The sum of these proportions exceeds 1 because some links are located in more than one area because of their topological position. The situation of the other number of mobile sensors has a similar stay-time proportion pattern with Fig. 6, which shows that mobile sensors spend most time in a limited number of areas.

F. Mobile Sensor Route Analysis Based on Heuristic Information

In ACO, heuristic information represents prior information. We now classify all links into different categories based on different heuristic information levels. Links are classified into three different levels based on heuristic information value (see Table VI).

Given the link classification based on heuristic information, the proportion of stay time in different heuristic information categories can be calculated. The results are shown in Fig. 7. The proportion of each category fits a curve, indicating that the proportion of stay time in high-heuristic information areas decreases monotonically. The proportion of stay time in low-

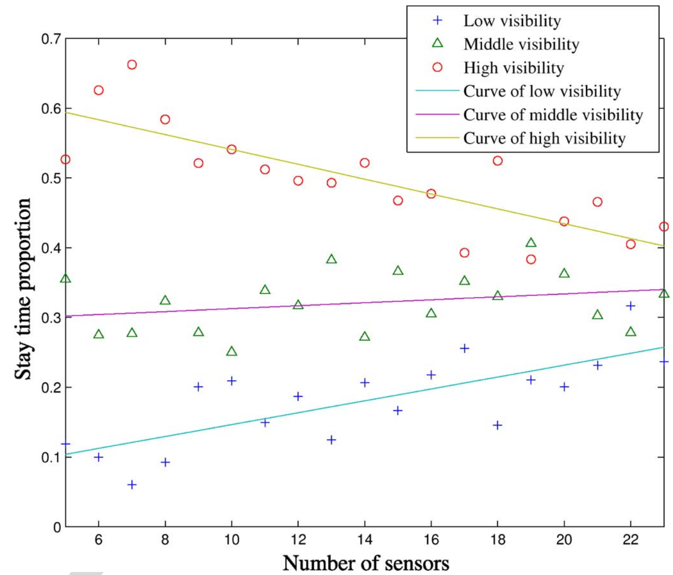


Fig. 7. Proportion of stay time for different heuristic information classification.

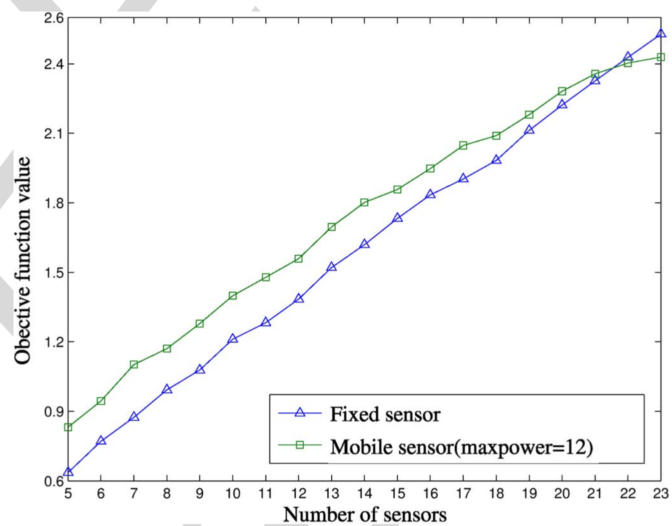


Fig. 8. maxpower = 12 versus fixed sensor.

heuristic information areas increases monotonically. Thus, mobile sensors are inclined to move in high-heuristic information areas when the number of mobile sensors is small. When the number of sensors is large, stay time on high-heuristic information areas decreases, and that on low-heuristic information areas increases.

G. Sensitivity Analysis of Maxpower

In our proposed hybrid two-stage heuristic algorithm, a key component in ACO that distinguishes our algorithm from traditional ACO for the VRP is the design of the parameter maxpower. Maxpower represents the maximum travel time of a mobile sensor on the network. Two case studies are conducted for maxpower = 12 and maxpower = 6, respectively. Fig. 8 shows a very similar pattern with Fig. 4(a). A comparison of the results of maxpower = 12 and maxpower = 6 (see Fig. 9) indicates that the case of maxpower = 12 shows a better

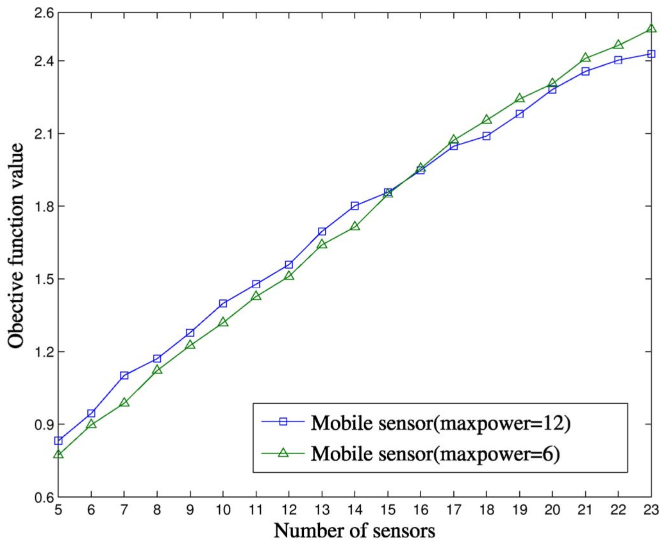


Fig. 9. maxpower = 12 versus maxpower = 6.

TABLE VII
CLASSIFICATION OF LINKS BASED ON HEURISTIC INFORMATION VALUE

Instances	Mean			Deviation			Best Value		
	HB	GA	SA	HB	GA	SA	HB	GA	SA
SN-5	0.72	0.63	0.61	0.06	0.07	0.09	0.77	0.73	0.69
SN-10	1.21	1.08	1.02	0.18	0.14	0.15	1.34	1.28	1.20
ND-5	0.74	0.60	0.58	0.04	0.04	0.06	0.77	0.73	0.63
ND-10	1.21	1.02	1.0	0.07	0.11	0.17	1.30	1.18	1.20
ND-15	1.53	1.37	1.34	0.14	0.15	0.18	1.65	1.58	1.53
ND-20	1.8	1.58	1.56	0.16	0.23	0.21	1.92	1.87	1.78
ND-25	1.99	1.81	1.76	0.12	0.18	0.28	2.13	2.04	2.06

performance when the number of sensors is from 5 to 15. This observation can be explained by the fact that, when the number of sensors is small, a mobile sensor is supposed to have a relatively long distance route to gain a high traffic information acquisition benefits. However, the advantage of a large maxpower value weakens, and a mobile sensor is expected to move in a limited area in that more moves increase travel-time wastage.

H. Hybrid Two-Stage Algorithm Performance

To show the performance of our proposed hybrid algorithm, the results of simulated annealing and the genetic algorithm are employed for comparison. Experiments with different number of mobile sensors are conducted in both the simulated network and Nguyen–Dupius network[55]. All these experiments are done for 20 times, and statistics are extracted accordingly. Three statistics are mean, deviation, and best value of the 20 experiments.

Table VII shows these results. For the " Instances " column of Table VII, "SN-x" represents the experiments on simulated network with x number of mobile sensors. "ND-x" represents the experiments on the Nguyen–Dupius network with x number of mobile sensors. HB, GA and SA represents hybrid two-stage heuristic algorithm, genetic algorithm, and simulated annealing, respectively. The results show that the proposed algorithm outperforms the GA and SA in all three criteria.

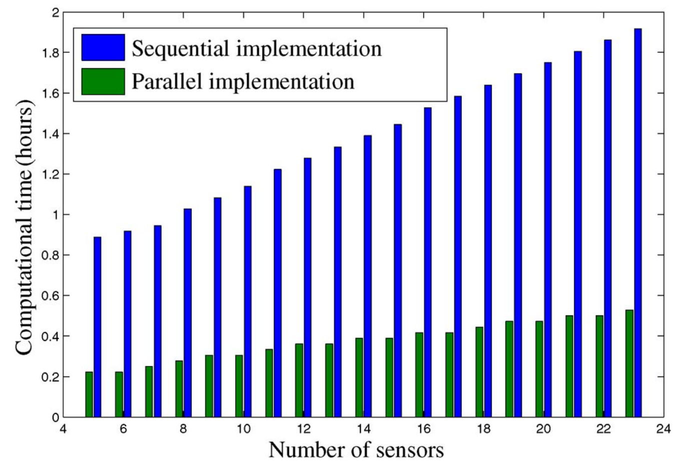


Fig. 10. Computational time comparison between sequential and parallel implementation.

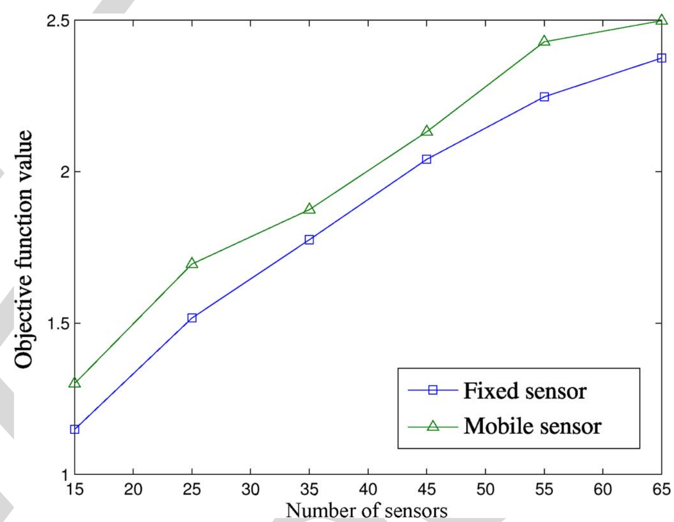


Fig. 11. Mobile sensor versus fixed sensor for the Sioux–Fall network.

Regarding the computational time, it takes 0.89 h when the number of mobile sensors is five. A parallel implementation in a four-core machine decreases the computational time significantly to 0.22 h. A comparison between the sequential and the parallel implementation is shown in Fig. 10.

Fig. 10 shows that computational time dramatically decreases after the parallel implementation. As to sequential implementation, computational time increases almost linearly with the increase in the number of mobile sensors. However, computational time keeps relatively stable for the parallel implementation. The average time saving percentage is 73%, which is significant.

1) Applicability in Practical Problems: Here, the Sioux–Fall network is employed to show the practicability of our algorithm. The Sioux–Fall network is widely used in transportation. It has 76 links and 24 nodes. This experiment is conducted under free flow condition.

In this experiment, different numbers of mobile sensors are tested: 15, 25, 35, 45, 55, and 65. When the number of sensors is 35, the traffic information acquisition benefits is 1.87, which is more than half of total benefits. The mobile sensor outperforms the fixed sensor under free flow traffic conditions (see Fig. 11). AQ4

This numerical experiment shows that our proposed algorithm can be applied to practical transportation networks.

V. Conclusion

Traditionally, fixed traffic sensors are employed to collect traffic information. Given the lack of flexibility of fixed sensors, the mobile traffic sensors are introduced to enhance the traffic surveillance effect. This paper aims to design optimal routes for mobile traffic sensors to maximize traffic information acquisition benefits.

By considering the dynamics of transportation networks, we have proposed an information-capture-oriented mobile-sensor routing problem. Unlike traditional VRPs, our problem has two kinds of decision variables: the route variable and the stay-time variable. An objective function is designed to measure the traffic information acquisition benefits. A hybrid two-stage heuristic algorithm that combines PSO and ACO is designed to solve this mobile-sensor routing problem effectively. The mobile sensor outperforms the fixed sensor network in most cases. The route of a mobile sensor is normally restricted in a portion of the network. The sensitivity analysis of the parameter maxpower is also analyzed.

The proposed problem differs from traditional VRPs in that it assumes that mobile sensors can benefit more if they stay on the customer side longer (the link is treated as the customer). Mobile sensor is helpful for both urban and freeway transportation network surveillance. In reality, the mobile sensors can be used alone or serves as a supplement to the fixed sensor network. The proposed information-capture-oriented VRP is applicable in many other applications. Future direction may consider the stochastic factor of the transportation network and design an optimal mobile-sensor route that maximizes expected traffic information acquisition benefits.

References

[1] H. Yang and J. Zhou, "Optimal traffic counting locations for origin destination matrix estimation," *Transp. Res. B, Methodol.*, vol. 32, no. 2, pp. 109–126, Feb. 1998.

[2] L. Bianco, L. Confessore, and P. Reverberi, "A network based model for traffic sensor location with implications on o/d matrix estimates," *Transp. Sci.*, vol. 35, no. 1, pp. 50–60, Feb. 2001.

[3] H. Yang, C. Yang, and L. Gan, "Models and algorithms for the screen line-based traffic counting location problems," *Comput. Oper. Res.*, vol. 33, no. 3, pp. 836–858, Mar. 2006.

[4] L. Bianco, G. Confessore, and M. Gentili, "Combinatorial aspects of the sensor location problem," *Ann. Oper. Res.*, vol. 144, no. 1, pp. 201–234, Apr. 2006.

[5] S.-R. Hu, S. Peeta, and C.-H. Chu, "Identification of vehicle sensor locations for link-based network traffic applications," *Transp. Res. B, Methodol.*, vol. 43, no. 8/9, pp. 873–894, Sep. 2009.

[6] E. Castillo, J. M. Menendez, and P. Jimenez, "Trip matrix and path flow reconstruction and estimation based on plate scanning and link observations," *Transp. Res. B, Methodol.*, vol. 42, no. 5, pp. 455–481, Jun. 2008.

[7] R. Mínguez, S. Sánchez-Cambronero, E. Castillo, and P. Jimenez, "Optimal traffic plate scanning location for od trip matrix and route estimation in road networks," *Transp. Res. B, Methodol.*, vol. 44, no. 2, pp. 282–298, Feb. 2010.

[8] M. Gentili and P. Mirchandani, "Locating sensors on traffic networks: Models, challenges and research opportunities," *Transp. Res. C, Emerging Technol.*, vol. 24, pp. 227–255, Oct. 2012.

[9] H. D. Sherali, J. Desai, and H. Rakha, "A discrete optimization approach for locating automatic vehicle identification readers for the provision of roadway travel times," *Transp. Res. B, Methodol.*, vol. 40, no. 10, pp. 857–871, Dec. 2006.

[10] G. B. Thomas, "The relationship between detector location and travel characteristics on arterial streets," in *Proc. Transp. Frontiers Next Millennium, 69th Annu. Meet. Inst. Transp. Eng.*, 1999, pp. 1–16.

[11] S. Oh and K. Choi, "Optimal detector location for estimating link travel speed in urban arterial roads," *KSCE J. Civil Eng.*, vol. 8, no. 3, pp. 327–333, May 2004.

[12] I. Fujito, R. Margiotta, W. Huang, and W. A. Perez, "Effect of sensor spacing on performance measure calculations," *Transp. Res. Board*, no. 1945, pp. 1–11, 2006.

[13] J. Kim, J. Lee, and J. Won, "Determining optimal sensor locations in freeway using genetic algorithm-based optimization," *Eng. Appl. Artif. Intell.*, vol. 24, no. 2, pp. 318–324, Mar. 2011.

[14] X. J. Ban, L. Chua, R. Herring, and J. D. Margulici, "Sequential modeling framework for optimal sensor placement for multiple intelligent transportation system applications," *J. Transp. Eng.*, vol. 137, no. 2, pp. 112–120, Feb. 2011.

[15] C. Yang, P. Chootinan, and A. Chen, "Traffic counting location planning using genetic algorithm," *J. Eastern Asia Soc. Transp. Studies*, vol. 5, pp. 898–913, 2003.

[16] X. Fei, H. Mahmassani, and S. Eisenman, "Sensor coverage and location for real-time traffic prediction in large-scale networks," *Transp. Res. Board*, no. 2039, pp. 1–15, 2007.

[17] X. Li and Y. Ouyang, "Reliable sensor deployment for network traffic surveillance," *Transp. Res. B, Methodol.*, vol. 45, no. 1, pp. 218–231, Jan. 2010.

[18] X. Fei and H. Mahmassani, "Structural analysis of near-optimal sensor locations for a stochastic large-scale network," *Transp. Res. C, Emerging Technol.*, vol. 19, no. 3, pp. 440–453, Jun. 2011.

[19] X. Fei, H. S. Mahmassani, and P. Murray-Tuite, "Vehicular network sensor placement optimization under uncertainty," *Transp. Res. C, Emerging Technol.*, vol. 29, pp. 14–31, Apr. 2013.

[20] L. Hu and D. Evans, "Localization for mobile sensor networks," in *Proc. 10th Annu. Int. Conf. Mobile Comput. Netw.*, 2004, pp. 45–57.

[21] N. Heo and P. K. Varshney, "Energy-efficient deployment of intelligent mobile sensor networks," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 35, no. 1, pp. 78–92, Jan. 2005.

[22] Z. Butler and D. Rus, "Event-based motion control for mobile-sensor networks," *IEEE Pervasive Comput.*, vol. 2, no. 4, pp. 34–42, Oct.–Dec. 2003.

[23] Y. Wang and H. Wu, "Delay/Fault-Tolerant Mobile Sensor Network (dft-msn): A new paradigm for pervasive information gathering," *IEEE Trans. Mobile Comput.*, vol. 6, no. 9, pp. 1021–1034, Sep. 2007.

[24] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: using a mobile sensor network for road surface monitoring," in *Proc. ACM MobiSys*, 2008, pp. 29–39.

[25] A. Angel, M. Hickman, P. Mirchandani, and D. Chandnani, "Methods of analyzing traffic imagery collected from aerial platforms," *IEEE Trans. Intell. Transp. Syst.*, vol. 4, no. 2, pp. 99–107, Jun. 2003.

[26] M. Hickman and P. Mirchandani, "Airborne data and traffic management," in *Proc. Symp. 75th Anniv. Greenshields, Transp. Res. Boards Traffic Flow Theory Committee Meet.*, 2008, pp. 1–27.

[27] F. W. Cathey and D. J. Dailey, "Transit vehicles as traffic probe sensors," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1804, no. 1, pp. 23–30, 2002.

[28] R. F. Dantzig, George, and S. Johnson, "Solution of a large-scale traveling-salesman problem," *J. Oper. Res. Soc. Amer.*, vol. 2, no. 4, pp. 393–410, Nov. 1954.

[29] G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," *Oper. Res.*, vol. 12, no. 4, pp. 568–581, Jul./Aug. 1964.

[30] P. Toth and D. Vigo, *The Vehicle Routing Problem*. Philadelphia, PA, USA: SIAM, 2002.

[31] R. Baldacci, P. T., and D. Vigo, "Exact algorithms for routing problems under vehicle capacity constraints," *Ann. Oper. Res.*, vol. 175, no. 1, pp. 213–245, Mar. 2010.

[32] B. Yu, Z.-Z. Y, and B. Yao, "An improved ant colony optimization for vehicle routing problem," *Eur. J. Oper. Res.*, vol. 196, no. 1, pp. 171–176, Jul. 2009.

[33] M. Reimann, K. D, and R. F. Hartl, "D-ants: Savings based ants divide and conquer the vehicle routing problem," *Comput. Oper. Res.*, vol. 31, no. 4, pp. 563–591, Apr. 2004.

[34] S.-W. Lin, Z.-J. Lee, K.-C. Ying, and C.-Y. Lee, "Applying hybrid metaheuristics for capacitated vehicle routing problem," *Exp. Syst. Appl.*, vol. 36, no. 2, pp. 1505–1512, Mar. 2009.

[35] Ö. Ergun, J. B. Orlin, and A. Steele-Feldman, "Creating very large scale neighborhoods out of smaller ones by compounding moves," *J. Heuristics*, vol. 12, no. 1/2, pp. 115–140, Mar. 2006.

[36] H.-k. H. Huang, P. Chen, and X.-Y. Dong, "Iterated variable neighborhood descent algorithm for the capacitated vehicle routing problem.," *Exp. Syst. Appl.*, vol. 37, no. 2, pp. 1620–1627, Mar. 2010.

[37] V. Kachitvichyanukul, "Particle swarm optimization and two solution representations for solving the capacitated vehicle routing problem," *Comput. Ind. Eng.*, vol. 56, no. 1, pp. 380–387, Feb. 2009.

[38] A. V. Donati, R. Montemanni, N. Casagrande, A. E. Rizzoli, and L. M. Gambardella, "Time dependent vehicle routing problem with a multi ant colony system," *Eur. J. Oper. Res.*, vol. 185, no. 3, pp. 1174–1191, Mar. 2008.

[39] É. Taillard, P. Badeau, M. Gendreau, F. Guertin, and J.-Y. Potvin, "A tabu search heuristic for the vehicle routing problem with soft time windows," *Transp. Sci.*, vol. 31, no. 2, pp. 170–186, May 1997.

[40] W.-C. Chiang and R. A. Russell, "Simulated annealing metaheuristics for the vehicle routing problem with time windows," *Ann. Oper. Res.*, vol. 63, no. 1, pp. 3–27, 1996.

[41] P. Toth and D. Vigo, "An exact algorithm for the vehicle routing problem with backhauls," *Transp. Sci.*, vol. 31, no. 4, pp. 372–385, Nov. 1997.

[42] N. Wassan, S. Said, and M. Hajarat, "The fleet size and mix vehicle routing problem with backhauls: Formulation and set partitioning-based heuristics," *Transp. Res., Logist. Transp. Rev.*, vol. 56, pp. 22–35, Sep. 2013.

[43] J.-Y. P. Duhamel, X. Christophe, and J.-M. Rousseau, "A tabu search heuristic for the vehicle routing problem with backhauls and time windows," *Transp. Sci.*, vol. 31, no. 1, pp. 49–59, Feb. 1997.

[44] P. Toth and D. Vigo, *The Vehicle Routing Problem*. Philadelphia, PA, USA: SIAM, 1987.

[45] A. Subramanian, L. M. A. Drummond, C. Bentes, L. S. Ochi, and R. Farias, "A parallel heuristic for the vehicle routing problem with simultaneous pickup and delivery," *Comput. Oper. Res.*, vol. 37, no. 11, pp. 1899–1911, Nov. 2010.

[46] Y. Gajpal and P. Abad, "An Ant Colony System (acs) for vehicle routing problem with simultaneous delivery and pickup," *Comput. Oper. Res.*, vol. 36, no. 12, pp. 3215–3223, Dec. 2009.

[47] M. Gendreau and G. Laporte, "A tabu search heuristic for the vehicle routing problem with stochastic demands and customers," *Oper. Res.*, vol. 44, no. 3, pp. 469–477, May/Jun. 1996.

[48] B. Fleischmann, S. Gnutzmann, and E. Sandvoss, "Dynamic vehicle routing based on online traffic information," *Transp. Sci.*, vol. 38, no. 4, pp. 420–433, Nov. 2004.

[49] A. V. Vural, E. Burak, and A. Reisman, "The vehicle routing problem: A taxonomic review," *Comput. Ind. Eng.*, vol. 57, no. 4, pp. 1472–1483, Nov. 2009.

[50] S. R. Golden, L. Bruce, and E. E. A. Wasil, *The Vehicle Routing Problem [Electronic Resource]: Latest Advances and New Challenges*. New York, NY, USA: Springer-Verlag, 2008.

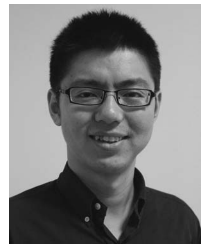
[51] R. Rajagopal and P. P. Varaiya, "Health of California's loop detector sytem," California PATH Program, Inst. Transp. Studies, Univ. California Berkeley, Berkeley, CA, USA, 2007.

[52] D. Scott, D. Novak, L. Aultman-Hall, and F. Guo, "Network robustness index: A new method for identifying critical links and evaluating the performance of transportation networks," *J. Transp. Geogr.*, vol. 14, no. 3, pp. 215–227, 2006.

[53] M. Dorigo and L. M. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 53–66, Apr. 1997.

[54] B. Yu, Y. Zhongzhen, and C. Cheng, "A parallel ant colony algorithm for bus network optimization," *Comput. Aided Civil Infrastruct. Eng.*, vol. 22, no. 1, pp. 44–55, Jan. 2007.

[55] S. V. Ukkusuri, T. V. Mathew, and S. T. Waller, "Robust transportation network design under demand uncertainty," *Comput. Aided Civil Infrastruct. Eng.*, vol. 22, no. 1, pp. 6–18, Jan. 2007.



Ning Zhu received the Ph.D. degree in management science and engineering from Tianjin University, Tianjin, China.

He is an Assistant Professor with the Institute of Systems Engineering, Tianjin University. His research interests include transportation management and planning, and intelligent transportation system and location problems in transportation.

Yang Liu received the B.S. degree in information management and management science from Tianjin University, Tianjin, China, in 2012. He is currently working toward the M.S. degree with the Institute of Systems Engineering, Tianjin University.

His research interests include transportation management, traffic sensor location, and origin–destination estimation.

Shoufeng Ma received the B.S., M.S., and Ph.D. degrees from Tianjin University, Tianjin, China, in 1988, 1991 and 1999, respectively.

He is a Professor with the Institute of Systems Engineering, Tianjin University. His research interests include transportation management, traffic behavior and its impact on transportation networks, and traffic flow theory and its applications.

Zhengbing He received the Ph.D. degree from Tianjin University, Tianjin, China, in 2011.

From 2011 to 2013, he was a Postdoctoral Researcher with the School of Traffic and Transportation, Beijing Jiaotong University, Beijing, China, where he researched urban route guidance strategies. He is currently an Assistant Professor with the School of Traffic and Transportation, Beijing Jiaotong University. His research interests include traffic flow theory, intelligent transportation systems, and traffic simulation.

AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

AQ1 = Fig. 3 was cited here. Please check if the following changes are appropriate. If not, kindly provide the necessary corrections.

AQ2 = Table 5 was uncited in the body. The citation was inserted here. Please check if appropriate, and correct if necessary.

AQ3 = Table 6 was uncited in the body. The citation was inserted here. Please check if appropriate, and correct if necessary.

AQ4 = Fig. 11 was cited here. Please check if the following changes are appropriate. If not, kindly provide the necessary corrections.

END OF ALL QUERIES

Mobile Traffic Sensor Routing in Dynamic Transportation Systems

Ning Zhu, Yang Liu, Shoufeng Ma, and Zhengbing He

***Abstract*—In transportation networks, traditional fixed sensors are used to monitor the operation of transportation systems. However, fixed sensors cannot move once they are installed. In this paper, the motion ability of traffic sensors is introduced to improve the performance of transportation network surveillance. A mobile traffic sensor routing problem is proposed, modeled as a novel vehicle routing problem. A measure of traffic information acquisition benefits is developed and used to gauge the surveillance performance. To solve this mobile-sensor routing problem, a hybrid two-stage heuristic algorithm is designed, which is based on particle swarm optimization and ant colony optimization. Numerical experiments are conducted. The results show that the mobile traffic sensor has a better network surveillance performance than the fixed sensor in most experimental cases.**

***Index Terms*—Ant colony optimization (ACO), hybrid two-stage heuristic algorithm, mobile traffic sensor routing, particle swarm optimization (PSO), vehicle routing problem (VRP).**

I. Introduction

TRAFFIC information significantly affects transportation management and control. To obtain real-time traffic information, transportation surveillance network is necessary. Currently, traffic sensors serve as an important way to gain traffic information. Due to limited budgets, traffic sensors cannot be deployed everywhere in transportation networks. Traffic information collected from optimal sensor locations is used to provide real-time traffic data for various traffic information applications, such as flow observation and estimation [including origin–destination (OD) trips, route flow, and link flow], travel-time estimation, bottleneck identification, and so on.

The sensor location problem aiming to observe and estimate traffic flow has attracted considerable attention for several decades. To estimate OD, four important location rules and corresponding mathematical models that implement these rules are proposed [1]. A two-stage model [2] is presented to determine optimal sensor placement location to estimate OD demand. A mathematical model is formulated to intercept all or as many OD trips as possible [3]. To infer all link flows from partial observed links, an optimal location model on nodes [4] is determined to infer link flow in a transportation network. The linear algebra method is used to find an optimal sensor location to infer network-wide flow [5]. Regarding the path flow estimation, an optimal sensor deployment method is proposed so that path flow can be distinguished and estimated in [6] and [7]. A sensor location problem for flow observation and estimation is well reviewed in [8].

The travel-time estimation problem is another important direction for sensor location issues. The quality benefit of travel-time estimation is maximized by optimally locating automatic vehicle identification readers [9]. A simulation tool is employed in [10] and [11] to figure out the relationship between travel characteristics and sensor location. The impact of sensor spacing on travel-time estimation is investigated [12], [13]. A sequential modeling framework for optimal sensor location is also proposed [14]. Objective applications include ramp metering control and travel-time estimation.

Most of these studies are conducted in a static and deterministic transportation environment. Other studies in the field of traffic sensor location problem consider dynamic and stochastic environmental factors that influence sensor location patterns. The optimal sensor location problem is studied for the purpose of estimation in a dynamic transportation environment in [15] and [16]. Sensor failure [17] is considered in a sensor location model to achieve a more reliable location pattern. Demand estimation uncertainty is minimized in [18]. A nonlinear two-stage stochastic model is proposed in [19] to maximize the OD coverage and information gain against random events.

Most studies in the transportation field investigate how to maximize the usage of fixed sensors. Fixed traffic sensors cannot be relocated once installed. In the last several decades, mobile sensors have attracted considerable attention in other fields such as communication and automation. Several seed nodes [20] have been used to relocate all sensors in a network without additional hardware. A distributed energy-efficient deployment algorithm [21] is proposed for mobile sensors and intelligent devices in a general network. Distributed algorithms for mobile-sensor networks are presented against events that occur frequently [22]. In the field of information gathering, a delay/fault-tolerant mobile-sensor network is proposed [23]. Most studies of mobile sensors focus on network or algorithm design for different purposes. Only the work in [24] has used sensor-equipped vehicles to gather data from vibration and GPS sensors. Such detection aims to identify potholes and other severe road surface anomalies. Other mobile sensors in the field

Manuscript received May 15, 2013; revised August 30, 2013, November 22, 2013, and February 9, 2014; accepted March 19, 2014. This work was supported in part by the National Natural Science Foundation of China under Grants 71301115, 71271150, and 71101102 and in part by the Specialized Research Fund for the Doctoral Program of Higher Education of China under Grant 20130032120009. The Associate Editor for this paper was Q. Kong.

N. Zhu, Y. Liu, S. Ma are with the Institute of Systems Engineering, Tianjin University, Tianjin 300072, China (e-mail:liuyang89@tju.edu.cn).

Z. He is with the Ministry of Education Key Laboratory for Urban Transportation Complex Systems Theory and Technology, School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2014.2314732

of transportation include airborne imagery sensors [25], [26] and GPS-based traffic probes [27].

Mobile traffic sensors are assumed to have the surveillance ability of recording traffic flow and identifying license plates so that travel-time information can be obtained. We assume that mobile sensors are special vehicles with equipped surveillance device. The special vehicles are managed by transportation authorities. Probe vehicles equipped with sensor devices can be considered traffic mobile sensors. We model the motion of a mobile traffic sensor in a transportation network as a particular vehicle routing problem (VRP) that has a long research history. The first study can be traced back to [28] and [29], which focused on a large-scale traveling-salesman problem. In general, the traditional VRP can be classified into four categories [30].

- *Capacity- and Distance-Constrained VRP (CVRP).* The CVRP determines the routes for a fleet of vehicles without exceeding the capacity and distance constraints of each vehicle. An exact algorithm is proposed in [31] to solve the CVRP. Exact results for the CVRP are impossible even for medium networks. Several heuristic methods have been developed to solve the CVRP. These heuristics can be classified into ant colony optimization (ACO) [32], [33], simulated annealing [34], neighborhood search [35], [36], and particle swarm optimization (PSO) [37].
- *VRP with Time Windows (VRPTW).* The VRPTW is a problem in which routes should be designed in a way that each point is visited only once by exactly one vehicle within a given time interval. Similar to other traditional VRP and its variants, the VRPTW cannot be solved with an exact solution. Therefore, several state-of-the-art metaheuristics have been proposed, such as ACO [38], tabu search [39], and simulated annealing [40].
- *VRP with Backhauls (VRPB).* The VRPB differs from the classic VRP mainly because, on each route, the backhaul customers are visited after all linehaul customers. An exact algorithm is given for VRPB for small and medium networks [41]. Recent studies about VRPB include [42] and [43].
- *VRP with Pickup and Delivery (VRPPD)* [44]. For the VRPPD, a request is defined by a pickup point and a related delivery point. A demand is defined as goods or service transportation between the pickup point and delivery point. Recent advances in VRPPD are reported in [37], [45], and [46].

Stochastic and dynamic VRPs have also been developed [47], [48]. A good taxonomic review for VRP is given in [49]. In [30] and [50], VRPs are comprehensively reviewed. Our model does not fit into any of these categories.

In this paper, the mobile traffic sensor has two different states on the transportation network. One is traveling on the network, and the other is staying on the links and collecting information simultaneously. We also assume that traffic information acquisition benefits are related to the stay time of links. In VRP context, the objective function depends on the service time of customers, which is the stay time of links. Mobile sensor captures as much traffic information as possible. The mobile-sensor routing problem proposed is named as the information-capture-oriented mobile-sensor routing problem (IMRP). The IMRP differs from the traditional VRP due to the following.

- Most customers in traditional VRPs need only a one-time service. In our IMRP model, the stay time on a link crucially affects the objective function. One link can be visited by one mobile sensor at different time more than once. However, from the basic idea of traffic information collection, it is wasteful that more than one mobile sensors visit an identical link at the same time. Duplicate observations do not increase the information collection performance. Longer observation time increases information acquisition benefits.
- A comparison with traditional VRPs indicates that most of them focus on minimizing travel time or travel distance. In this paper, cost pertaining to vehicle routing is unimportant. What matters is captured traffic information.
- One constraint for most VRPs is the number of vehicles. In our model, another constraint is included, i.e., the travel-time constraint. The travel time from one link to another link at specific departure time t should be consistent with the traffic condition of the dynamic transportation network.
- The total travel time and stay time of the mobile sensor should not exceed a predefined value.

The advantages of mobile traffic sensors are as follows. First, a transportation network is a dynamic environment. Network states differ among different time intervals. Fixed sensor networks may offer good surveillance performance in one state but bad at another. Mobile traffic sensors avoid this weakness of fixed sensor networks. Second, fixed sensors are subject to failure [51]. Traffic sensor network maintenance is a time-consuming job. Mobile traffic sensors are flexible and can be used as complements to provide surveillance service temporarily. Although mobile traffic sensors have several advantages, few studies have focused on them, not to mention their routing problem. This paper aims to fill this gap.

This paper uses mobile traffic sensors to collect real-time information. Dynamic transportation networks are considered in our modeling. A group of optimal mobile-sensor routes is to be designed by maximizing the benefits of traffic information acquisition. The remainder of this paper is organized as follows. In Section II, we measure traffic information acquisition benefits and develop a mobile-sensor routing model. In Section III, a hybrid two-stage heuristic algorithm is proposed by combining PSO and ACO. In Section IV, numerical examples are provided to demonstrate the effectiveness of the proposed model and algorithm. Section V concludes and summarizes the main outcomes in this paper.

II. Mobile Traffic Sensor Routing Problem

Routing mobile sensors aim to provide effective network surveillance. In contrast to fixed traffic sensors, mobile traffic sensors can move in the network. To collect traffic information as much as possible, the main problem of using mobile-sensor networks is to design a route for each mobile sensor. Statistically, more samples collected on a link leads to a more accurate estimation of the traffic state. Given that mobile sensor has a constant sampling rate, the mobile sensor's stay time on links significantly affects traffic information acquisition. Therefore, decision variables in the mobile traffic sensor routing problem are of two kinds: a route variable that decides which route to go for each mobile sensor and the stay time of mobile sensor on each link of the route. Note that, this paper, visiting a link or arriving at a link means that the mobile traffic sensor is going to move to the middle point of a link. This assumption does not influence the traffic information collection efficiency. On the other hand, it simplifies the calculation of the travel distance between adjacent links. More than one mobile sensor staying on the same link at the same time does not make traffic information surveillance performance better. Duplicate stay of more than one mobile sensors in an identical link at the same time is a kind of resource waste. The total time a mobile sensor can spend is defined as the summation of travel time and stay time. The total time is not allowed to exceed a predefined value.

In this paper, the objective traffic applications include link flow inference, path travel-time estimation, and OD estimation. These three applications require observations on the link, path, and network levels. A dynamic transportation network is adopted. We assume the time-sliced OD trips. For each time interval of a day and each link, OD demand is assumed stable from a long-term perspective. Further, we assume that the flow volume assigned on each link follows a probability distribution. This assumption is reasonable because the OD trips of each time interval are not strictly constant but has slight perturbation.

Let us denote a transportation network as $G(N, A)$, where N represents the set of intersections in a network and A represents the set of links that connect intersections. Mobile sensors travel from one link to another to obtain real-time traffic information on links. The total information acquisition benefits are determined by the total stay time on all observed links among all time intervals. First, the sample collection period is assumed fixed and dependent on the configuration of devices. A relationship between sample size and traffic state observation accuracy is built in Section II-A. Traffic state observation accuracy is used as a measure of information acquisition benefits. Second, the benefits of information acquisition are assumed determined on the link, path, and network levels, respectively. The measure of information acquisition benefits is developed accordingly.

A. *Sample Size and Estimation Accuracy*

In practice, link traffic states, such as link traffic flow and travel speed, for each time interval on a daily basis experience perturbation. We assume that authentic link traffic flow and link travel speed information follow a deterministic but unknown probability density distribution. More observations increase estimation accuracy for these unknown distributions. Thus, longer stay time increases estimation accuracy. Here, we figure out the impact of sample size on estimation accuracy. From the perspective of statistics, the basic idea behind sample size determination is that a large sample size increases the degrees of freedom and thus reduces the confidence interval. Assume that we have prior information about the mean and deviation of traffic flow or travel speed distribution. We denote prior mean

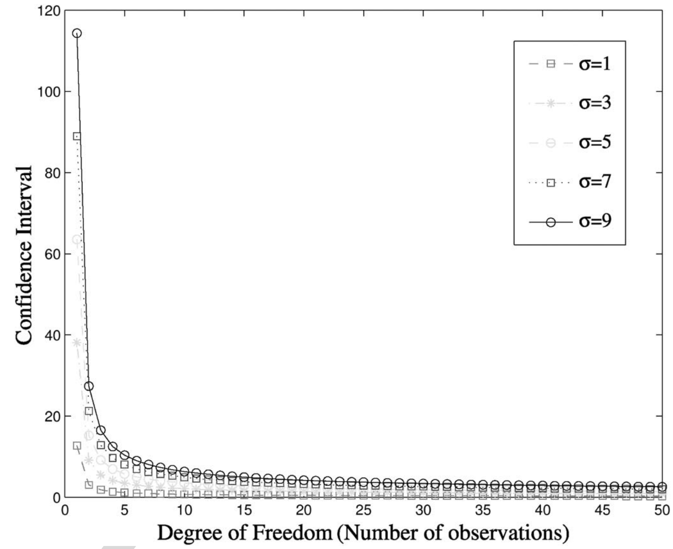


Fig. 1. t distribution sample size determination.

and deviation as μ and σ, respectively. The ground-truth value of the mean and deviation is unknown. Sampling is used to update prior mean and deviation. The longer the time spent on data collection, the higher the estimation accuracy we obtain. Data collected are assumed error free. Mean and deviation estimation is used to illustrate the relationship between sample size and observation accuracy.

Mean Estimation: Consider a sample $(X_1, X_2, X_3, \ldots, X_n)$ with size n from an unknown distribution. If we manipulate the definition for the t statistic, we obtain

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(n-1). \tag{1}$$

The right-hand side of (1) is $t(n-1)$, which is not dependent on any unknown parameters. The confidence level is denoted α. The half-length of the confidence interval is computed as

$$d = \frac{S}{\sqrt{n}} t_{\alpha/2}(n-1). \tag{2}$$

Because prior information is given, sample standard variance S can be substituted by prior standard variance σ as

$$d = \frac{\sigma}{\sqrt{n}} t_{\alpha/2}(n-1). \tag{3}$$

Deviation Estimation: Following the similar logic for mean estimation to estimate deviation, we calculate

$$P\left\{\chi^2_{1-\alpha/2}(n-1) \le (n-1)s^2/\sigma^2 \le \chi^2_{\alpha/2}(n-1)\right\} = 1-\alpha. \tag{4}$$

After some simple steps of manipulation, the length of the confidence interval can be stated as

$$d = \frac{(n-1)s^2}{\chi^2_{\alpha/2}(n-1)} - \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}(n-1)}. \tag{5}$$

In Figs. 1 and 2, it is shown that the confidence interval increases with deviation under the condition of identical degrees of freedom. More observations increase estimation accuracy.

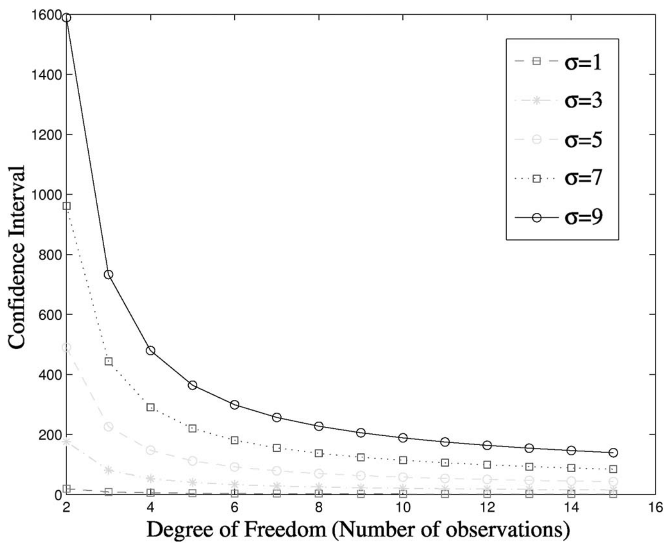


Fig. 2. Chi-square sample size determination.

To integrate this observation into our model, the benefit from the observations of a link is assumed as a nonlinear monotonic increasing function of the mobile sensor's stay time. We first use a hyperbola to fit the curve shown in Fig. 2 because the deviation is seen more informative. The R-square of this fit is greater than 99%, which shows a very good fitting performance. However, this hyperbola monotonically decreases and thus does not satisfy our requirements. After some simple manipulation of curve reversal and horizontal shift, we obtain a traffic information acquisition benefit curve as

$$f(s) = \begin{cases} \frac{p_1 s + p_2}{s + q_1}, & s > 0 \\ 0, & s = 0 \end{cases} \tag{6}$$

where s represents the stay time of mobile sensors on a link. p_1, p_2, and q_1 are the parameters from curve fitting. Deviation information σ is embedded in these three parameters. The marginal benefit of observation decreases as the first derivative of (6) decreases. Different σ results in different parameter combinations of (6).

B. Link Importance in Transportation Network

To obtain a good insight into the link contribution, the link importance of the transportation network should be identified. The contribution of a single link to the transportation network can be categorized into three aspects: 1) link level; 2) path level; and 3) network level. These three aspects are elaborated in the following.

1) Link Importance on Link Level: Single-link observation is helpful because it can be used together with historical data to contribute to link flow estimation. One possible application that uses link flow information is network-wide link flow inference [5]. We adopts a link-based V/C ratio to identify the contribution of links [52], where V is the link volume and C is the link capacity. The traffic information acquisition benefits on the link level is formulated as

$$b_l = \alpha_l \sum_{a \in A} \frac{V_a}{C_a} x_a \tag{7}$$

where b_l is the benefits based on the link level, α_l is the nonnegative coefficient of the link-level contribution, and V_a and C_a are the link volume and capacity, respectively, on link a. $x_a = 1$ shows that an observation is made on link a; otherwise, $x_a = 0$.

2) Link Importance on Path Level: We assume that traffic mobile sensors have the ability to record the vehicle's position as the vehicle passes. If two mobile sensors at the same time interval stay on two different links on one path, travel-time information can be obtained for this route between the first (head) sensor and the last (rear) sensor. We use a way similar to that in [17] to measure route coverage benefits from mobile sensors. The benefit on path level can be measured by

$$b_p = \alpha_p \sum_{p \in \mathrm{PS}} (P_{p,r} - P_{p,h}) \tag{8}$$

where b_p represents the benefits obtained from the views of travel-time estimation; α_p denotes the nonnegative coefficient of the path-level contribution; PS is the path set; $P_{p,r}$ and $P_{p,h}$ are the rear and head positions of the mobile sensor on specific path p, respectively; and $P_{p,r} - P_{p,h}$ shows the distance that mobile sensors on this specific path p can cover.

More factors and formulations can be applied to assess traffic information acquisition benefits from the perspective of travel time. One possible extensive factor for travel time is mobile-sensor failure. Long distance between two mobile sensors increases inaccuracy in travel-time estimation. In this case, more complicated benefit expression should be formulated by considering the aforementioned factors.

3) Link Importance on Network Level: Regarding the link observation's contribution to the transportation network level, two factors have significant effects. One is transportation network topology, and the other is travel demand assigned to the transportation network. For each time interval, travel demand is deemed relatively stable in this paper. One result derived from this assumption is that the OD-link coincident matrix is constant for each time interval. According to Yang's four rules for sensor location [1], sensors should be placed on links with a higher number of OD pairs passed. One potential traffic application from network-level benefits is OD estimation. An example for the OD-link coincident matrix is shown as

$$\begin{pmatrix} 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix}. \tag{9}$$

This small transportation network has five OD pairs and five links. The number of OD pairs passing through link1, link2, link3, link4, and link5 are 2, 2, 3, 1, and 4, respectively. The total number of OD pairs passing through a link reflects the combinatorial effects for both transportation network topology factors and traffic demand factors. The number of OD pairs that pass a specific link can be taken as a measure of link importance on the network level. The benefits on the network level are formulated as

$$b_n = \alpha_n \sum_{a \in A} B_a x_a \tag{10}$$

where b_n is the benefits obtained from the network level, A is the set of links, B_a represents the number of OD pairs passing through link a, α_n is the nonnegative coefficient of network-level contribution, and $x_a = 1$ represents an observation exists on link a.

C. Mathematical Formulation

Mathematical formulation is stated as

$$\begin{aligned} \text{Min } f(s) = &\sum_{t \in T} \left(\alpha_l \sum_{a \in A} \frac{V_{a,t}}{C_a} f(s_{a,t}) + \alpha_n \sum_{a \in A} B_{a,t} f(s_{a,t}) \right) \\ &+ \sum_{t \in T} \left(\alpha_p \sum_{p \in \mathrm{PS}_t} (P_{p,r} - P_{p,h}) f(s_{p,t}) \right) \end{aligned} \tag{11}$$

subject to

$$\begin{aligned} &u_{ai,\,aj}^{ts,\,kv} \left(G_{ai}^{ts,\,kv} + \tau_{ai,\,aj} \left(G_{ai}^{ts,\,kv} \right) \right) \\ &\quad = L_{aj}^{ts+1,\,kv} \; \forall ai;\ \forall aj;\ \forall ts;\ \forall kv \end{aligned} \tag{12}$$

$$s_{ai,\,kv}^{ts} = G_{ai,\,kv}^{ts} - L_{ai,\,kv}^{ts} \; \forall ai;\ \forall kv;\ \forall ts. \tag{13}$$

$$\sum_{aj \neq ai} u_{aj,\,ai}^{ts,\,kv} = \sum_{ak \neq ai} u_{ai,\,ak}^{ts+1,\,kv} \quad \forall ai;\ \forall ts;\ \forall kv. \tag{14}$$

$$\sum_{ai} u_{a0,\,ai}^{1,\,kv} = 1 \; \forall kv. \tag{15}$$

$$\sum_{ts} \sum_{ai} u_{ai,\,a0}^{ts,\,kv} = 1 \; \forall kv. \tag{16}$$

$$u_{ai,\,aj}^{ts,\,kv} \in \{0,\,1\} \; \forall ai;\ \forall aj;\ \forall kv;\ \forall ts. \tag{17}$$

$$G_{ai}^{ts,\,kv} \qquad L_{ai}^{ts,\,kv} \geq 0 \tag{18}$$

where ai, aj, and ak are the link indexes, $a0$ is the depot index, kv is the mobile-sensor index, and ts is a sequential index of the visited links. For example, there is a route as depot $\rightarrow$ link1 $\rightarrow$ link2 $\rightarrow$ link1 $\rightarrow$ link3 $\rightarrow$ depot. The corresponding sequential index for this route is 1, 2, 3, 4, 5, and 6, respectively. In our model, multiple visits of a identical link at different times are allowed. The sequential index for the first visit of link1 is 2, and the index for the second visit of link1 is 4. Different visit indexes are allowed to be associated with identical link. For the purpose of modeling, ts is chosen as a big number but do not significantly increase the model size. $G_{ai}^{ts,\,kv}$ and $L_{ai}^{ts,\,kv}$ are decision variable indicating the departure time and the arrival time of vehicle kv on link ai for its ts visit. $G_{ai}^{ts,\,kv} = 0$ and $L_{ai}^{ts,\,kv} = 0$ if vehicle kv does not leave or arrive at link ai at its ts visit; otherwise, $G_{ai}^{ts,\,kv} > 0$, and $L_{ai}^{ts,\,kv} > 0$. $u_{ai,\,aj}^{ts,\,kv}$ is a binary variable. $u_{ai,\,aj}^{ts,\,kv} = 1$ means vehicle kv moves from link ai to link aj for its ts visit; otherwise, $u_{ai,\,aj}^{ts,\,kv} = 0$. $\tau_{ai,\,aj}(t)$ is a piecewise constant function that indicates the travel time from link ai to link aj starting from departure time t.

The constraints are defined as follows. Mobile sensors' stay time on links must allow for travel time between links (12). For constraint (13), vectors G and L contain information on departure time and arrival time for all mobile sensors' all visits on each link; stay time information s can be easily obtained from G and L. s is also used as an objective function to compute the total traffic information acquisition benefits. If a mobile sensor arrives at a link, it must also depart from that link (14); the mobile sensor must start and end at the depot by (15) and (16). Constraint (16) also indicates that the mobile sensor can only return to the depot once. It is not allowed to return to the depot more than once. The type and domain of the decision variables are indicated in (17) and (18).

Objective function (11) is reformulated aiming to incorporate the stay-time-based traffic information acquisition benefits. It considers the aforementioned statistical properties of observations and three popular traffic applications. These three traffic applications are integrated with different weighs, which are specified by the transportation agencies. Since s contains information about stay time of each mobile sensor of each link at each time interval, the index system can be reused to include the link index a and the time interval index t. $s_{a,\,t}$ represents the stay time of traffic mobile sensors on link a at time interval t. $s_{p,\,t}$ is the stay time of path p at time interval t and is calculated by the shared stay time of two mobile sensors. For example, if one mobile sensor spends the first 40 min of a time interval in a path and another mobile sensor spends the last 40 min of an identical time interval on the same path (the time interval is assumed 1 h), the shared stay time is 20 min, which is the common time of these two mobile sensors on this path. $P_{p,\,r} - P_{p,\,h}$ is the longest covered distance of the two observations of path p. Regarding the final objective function (11), $f(s_{a,\,t})$ and $f(s_{p,\,t})$ represent the impact of the mobile sensor's stay time of each link and each time interval on the transportation network-wide information acquisition benefits, as shown in (6).

This formulation only provides a framework of information acquisition benefits based on mobile-sensor routing patterns. This mathematical formulation is used to describe proposed mobile-sensor routing problem and is not directly used for problem solving.

III. Hybrid Two-Stage Heuristic Algorithm

The VRP is an NP-hard problem. A hybrid two-stage heuristic algorithm is proposed to solve the IMRP. The proposed model requires the computation of both vehicle route and stay time. The ant colony algorithm performs well at finding optimal or near-optimal routes for the VRP. However, the ant colony algorithm is unsuitable for solving continuous problems that refer to stay-time decision-making in our model. PSO is a population-based stochastic approach suitable for solving continuous optimization problems. A hybrid algorithm that combines the ant colony algorithm and the PSO is designed to solve our proposed problem. The vehicle route is determined by the ant colony algorithm. The PSO is applied to figure out the optimal stay time on a given route. A fitness function is returned to the ant colony algorithm to update pheromone and next-round iteration.

A. Particle Swarm Algorithm

The mobile sensor's total time should not exceed a predefined value. The initial solution for a given route is set as the maximum travel time among all time intervals, i.e.,

$$h_{i,m} = \begin{cases} \theta_1 \dfrac{W - \sum\limits_{k \le M-1} \max t_k}{M}, & m \le M-1 \\ W - \sum\limits_{m \le M-1} h_{i,m} - \sum\limits_{m \le M-1} e_m, & m = M \end{cases} \tag{19}$$

where h represents the stay-time vector of particles that contains the stay time on each link of a given route; $h_{i,m}$ is the stay time of the mth link of the ith route, which is a value; M is the particle dimensionality, which is the number of links on a specific route; W is the predefined total time, which is the summation of the travel time and the stay time; θ_1 is a randomly generated value ranging from 0 to 1; $\max t_k$ is the largest travel time from the kth link to the $(k+1)$th link among all time intervals; and e_m is the real travel time from the mth link to the $(m+1)$th link after the first m links' stay time is determined.

The particle moves toward the optimum in terms of velocity and position. At each iteration, particle velocity and position are updated in terms of

$$\begin{aligned} v_{i,d} &= Zv_{i,d-1} + C_1 \times \theta_2 \times (\text{pbest}_{i,d-1} - h_{i,d-1}) \\ &\quad + C_2 \times \theta \times (\text{lbest}_{i,d-1} - h_{i,d-1}) \\ v_{i,d} &= \begin{cases} v_{i,d}, & v_{i,d} \le v_{\max} \\ v_{\max,d}, & v_{i,d} > v_{\max} \end{cases} \\ h_{i,d} &= h_{i,d-1} + v_{i,d} \end{aligned} \tag{20}$$

where d represents the dth generation for the ACO algorithm; $h_{i,d}$ represents the stay time of the ith particle of the dth generation; $h_{i,d}$ is a vector, and each element of $h_{i,d}$ is $h_{i,m}$; $v_{i,d}$ is the ith particle's velocity at the dth generation; $\text{pbest}_{i,d-1}$ is the personal optimal solution found by the ith particle among its own historical solutions, and $\text{lbest}_{i,d-1}$ is the local optimal solution; Z is a positive inertia parameter; C_1 and C_2 are positive constants; and θ_2 is a random generated value ranging from 0 to 1. $v_{i,d}$ is updated in the first expression of (20). $v_{i,d}$ is further restricted by $v_{\max}$, which is a predefined particle at maximal speed. $v_{i,d}$ is used to update st.

B. Ant Colony Algorithm

1) Route Construction Rule: A vector is used to represent a vehicle route. One example of a route solution is [1 2 7 8 1 0 1 9 2 3 1 0], where 1 denotes the vehicle depot and 0 is used as a separator to separate different mobile sensors. The other numbers in this vector are link IDs in the transportation network. We require that all vehicles should depart from the vehicle depot and return to the depot again before the total time is reached. In the example, two vehicles are separated by 0, and the routes for these two vehicles are 1-2-7-8-1 and 1-9-2-3-1, respectively.

Based on the idea from [53], mobile-sensor routes are conducted as follows. The ants sequentially choose links to visit. The state transition rule is used to give the probability with which the ants decide to visit the next link, i.e.,

$$S = \begin{cases} \arg \max\limits_{m \in J(a)} \tau^{\alpha}_{m,d} \times \eta^{\beta}_{m}, & q \le q_0 \\ s, & q > q_0 \end{cases} \tag{21}$$

where S is the next link determined by the right-hand side of (21); $J(a)$ is the candidate link set of link a; $S = 0$ represents that the mobile sensor returns to the depot; d represents the dth generation of the ACO algorithm; τ is the pheromone; η is the heuristic information; α and β are the parameters that control the influence of the pheromone and heuristic information, respectively; and q is a random variable. q_0 is a predetermined parameter $(0 \le q_0 \le 1)$. P_s is the probability that a mobile sensor chooses to stop moving. The probability of choosing s as the next visit link is determined by P. P is formulated as

$$P = \begin{cases} (1 - P_s) \dfrac{\tau^{\alpha}_{s,d} \times \eta^{\beta}_{s}}{\sum\limits_{m \in J(a)} \tau^{\alpha}_{m,d} \times \eta^{\beta}_{m}}, & s \in J(a) \\ P_s, & s = 0 \end{cases}. \tag{22}$$

In our model, a mobile sensor can visit the same link more than once. Therefore, a mechanism that stops the mobile sensor should be designed. A concept of physical power is created, as shown in (22) and defined in (23). The physical power of ants decreases when they make more visits. Given the gradual increase in the fatigue degree, ants are more likely to stop moving. The more links ants visit, the more time they consume. Therefore, the mechanism is designed in terms of travel-time consumption as

$$P_s = \frac{\sum c}{\text{maxpower}} \tag{23}$$

where c is the average travel time among links of all time intervals, and maxpower is a predefined parameter. Maxpower determines the maximum travel time that a mobile sensor can spend on its trip. Based on this logic, maxpower can decide the length of a solution in some degree.

2) Pheromone Update Rule: The pheromone update rule is a critical component of ACO and offers the possibility of obtaining a better solution. In this paper, we adopted the ant-weight strategy proposed in [32] and [54]. This method incorporates both global and local information for pheromone update as

$$\Delta\tau^{p}_{m} = \begin{cases} \frac{Q}{R \times V} \times \frac{V_p - V_m}{V_p}, & \text{if link } m \text{ is on route p} \\ 0, & \text{otherwise} \end{cases} \tag{24}$$

where $\Delta\tau^{p}_{m}$ is the increased pheromone on link m of route p, Q is a constant, R is the number of routes, V is the total traffic information acquisition benefits, and V_p and V_m are the benefits from route p and link m, respectively. Equation (24) yields the increased pheromone of link m on route p. Pheromone information on link m is updated by using (25) as

$$\tau_{m,d+1} = \rho\tau_{m,d} + \sum_{p}\sum_{m\in p}\Delta\tau_m^p, \quad \rho \in (0, 1) \tag{25}$$

where ρ is the information evaporation speed, and $\sum_p \sum_{m\in p} \Delta\tau_m^p$ represents the total pheromone update from all p of link m.

In this way, the ants of the next generation use this updated information to create new solutions close to optimality. Once the pheromones are updated, they are used in (21) and (22) to construct new routes.

C. Hybrid Two-Stage Heuristic Algorithm

Algorithm 1 Hybrid two-stage heuristic algorithm based on PSO and ACO

```
Set parameters for PSO and ACO, respectively
while ACO termination condition not met do
   Construct route
   Pass the constructed route to PSO
   Initialize stay time solution particles for PSO
   while PSO termination condition not met do
      Evaluate all particles
      Update pbest and lbest
      Update velocity and position for each particle
   end while
   Return optimal stay time solution and fitness function
   value to ACO
   Update pheromones
end while
```

As shown in Algorithm 1, the ant colony algorithm aims to build routes for mobile sensors. PSO tries to determine the link's optimal stay time of each mobile sensor for a known route. The route is a critical connection between ACO and PSO. ACO is on the upper level and provides the routes which is used by PSO.

IV. Case Study

The mobile traffic sensor routing problem is tested on the regional transportation network shown in Fig. 3. The numbers on the links are the link IDs. This network has 9 nodes and 28 links. The S-Paramics software package is used as a simulation tool to generate basic traffic flow data. Time horizon is partitioned into 24 time intervals. The duration of each time interval is 1 h. The proposed hybrid two-stage heuristic algorithm is employed to solve this problem. In our implementation, each component in the objective function is standardized. Therefore, the maximum value for each component is 1, and the total maximum value of the objective function is 3.

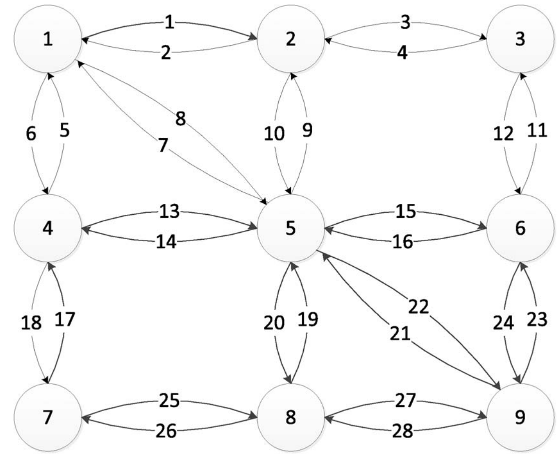


Fig. 3. Experimental transportation network.

TABLE I
Parameters of ACO

Parameter name	Value
Number of iterations	100
Number of ants	20
α	1
β	1
$maxpower$	6

TABLE II
Parameters of PSO

Parameter name	Value
Number of iterations	100
Number of particles	15
Size of neighborhood	3
$C1$	1.562
$C2$	2.135
$V0$	8.13
Z	ranging from 0.9 to 0.5

A. Parameters of Hybrid Two-Stage Heuristic Algorithm

The proposed hybrid two-stage heuristic algorithm sequentially employs ACO and PSO. The parameters used in our implementation are as follows:

$maxpower$ is designed in ACO to resolve the "revisit" issue in our mobile-sensor routing problem. In most of our experiments, $maxpower$ is set to 6 as shown in Table I. The parameters of α, β, C_1, C_2, V_0, and the size of neighborhood in Table II are optimized by the genetic algorithm. The number of iterations, number of ants, and number of particles are 100, 20, and 15, respectively, because the algorithm can converge under the setting in preliminary experiments.

B. Mobile Sensor Versus Fixed Sensor Under Different Traffic Conditions

Here, experiments of different numbers of mobile sensors are conducted. The number of mobile sensors ranges from 5 to 23. Different traffic conditions are adopted for our experiments, which have free flow conditions, slight congestion, and severe congestion. Travel time between links for slight congestion and severe congestion is 1.5 and 2 times those of the free

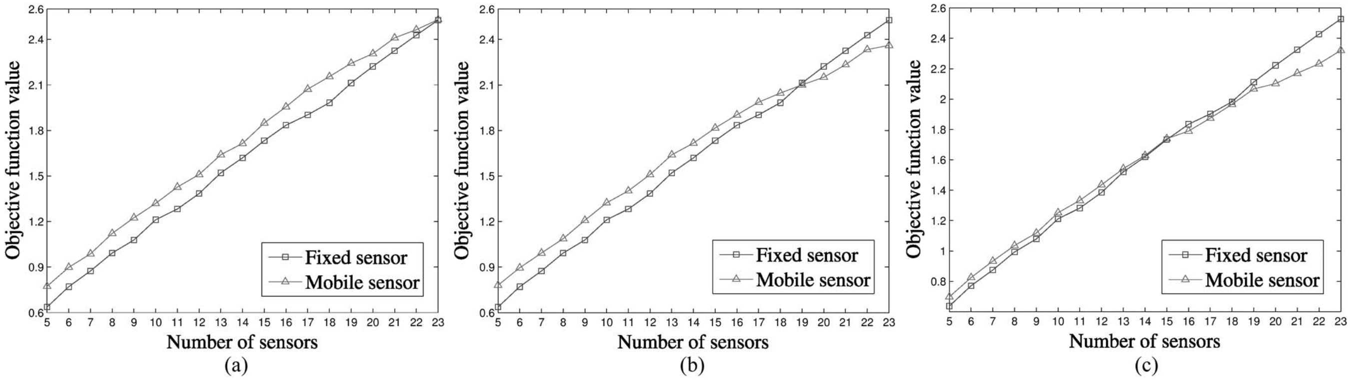


Fig. 4. Mobile sensor versus fixed sensor under different conditions. (a) Mobile sensor versus fixed sensor under free flow condition. (b) Mobile sensor versus fixed sensor under slight congestion. (c) Mobile sensor versus fixed sensor under severe congestion.

flow conditions. The optimal locations of fixed sensors are computed for comparison with those of mobile sensors. The fixed traffic sensor location model in dynamic transportation network condition aims to maximize the covered flow under the constraint of the given number of fixed sensors. The manner of calculating the traffic information acquisition benefits is the same with the mobile-sensor model. The difference between the mobile sensors and fixed sensors is that benefits from mobile sensors spans various links and benefits of fixed sensors comes from identical links. These optimized locations are obtained by using genetic algorithm. Equation (6) is also used to calculate the traffic information acquisition benefits. With fixed sensors, stay time s is set to be the maximal value. In this paper, this value is 60 min for each time interval. Since fixed sensors cannot move, the total traffic information acquisition benefit is computed as the summation of the benefits of all time intervals.

Fig. 4(a) shows that, under free flow condition, the mobile sensor outperforms the fixed sensor. For example, when the number of sensors is five, the objective function value of mobile sensors and fixed sensors is 0.7732 and 0.6363, respectively; the gap is about 17.7%. The whole trend of the difference between the mobile sensor and the fixed sensor gradually decreases. When the number of sensors is 23, the traffic information acquisition benefits are almost the same. The result implies that mobile sensors have advantage in flexibility compared with fixed sensors. Mobile sensors are good at moving; thus, they can move to other more informative links.

Experiments under slight and severe congested conditions [see Fig. 4(b) and (c)] show that the mobile sensor outperforms the fixed sensor when the number of sensors is small. The intersection points of the two curves are 15 and 19, respectively. The advantage of the mobile sensor over the fixed sensor decreases as the traffic becomes congested. The performance gap between the mobile sensor and the fixed sensor decreases from slight congestion to severe congestion. For example, when the number of sensors is 17, the traffic information acquisition benefits are 2, 1.98, and 1.87 for free flow, slight congestion, and severe congestion, respectively. By contrast, the information benefits are 1.9 for the fixed sensor.

The three experiments indicate that, first, when the number of sensors is small, the mobile sensor outperforms fixed sensor regardless of traffic conditions. Given the limited number of mobile sensors, each mobile sensor has a larger space to move around in, and the performance of the mobile sensor is better. The mobile sensor is relatively crowded when the number of sensors is large. Second, when the number of sensors increases, the advantage of mobile sensors gradually decreases. Particularly, in congested traffic conditions, travel time between link becomes longer. The advantage of mobile sensors weakens. The fixed sensor outperforms the mobile sensor. Finally, as a general trend, the advantage of the mobile sensor to the fixed sensor gradually reduces and eventually disappears as the traffic condition becomes extremely congested. This observation is intuitive because the mobile sensor cannot move when the whole network is completely congested.

C. Mobile Sensor Plus Fixed Sensor Versus Fixed Sensor Under Different Traffic Conditions

Here, the fixed sensor network is assumed to be existent, and its location has been optimized. We consider adding one more mobile sensor to the fixed sensor network. Two experiments are conducted under free flow conditions and severe congestion. Fig. 5(a) and (b) show the results. Complete usage of fixed sensors is employed as a comparison. The numbers on the x-axis represent the number of sensors. Adding one more mobile sensor always has a better performance than complete fixed sensors experiment under both free flow and congested traffic conditions. The average gap of the objective function value between one more mobile sensor condition and all fixed sensors are 0.11 and 0.05 for free flow and congested traffic conditions, respectively. Free flow conditions give more performance advantage than congested traffic conditions. The potential application of this observation is to employ a combination of the mobile sensor and the fixed sensor to enhance performance. Another application is to employ a mobile sensor for temporal use during the maintenance period.

Table III summarizes the experiments. In most cases, the mobile sensor outperforms the fixed sensor. Only when traffic is congested and the number of sensors is large does the mobile sensor perform worse than the fixed sensor.

D. Robust Experiment

To discuss the application of the proposed mobile-sensor routing problem, two different kinds of experiments are

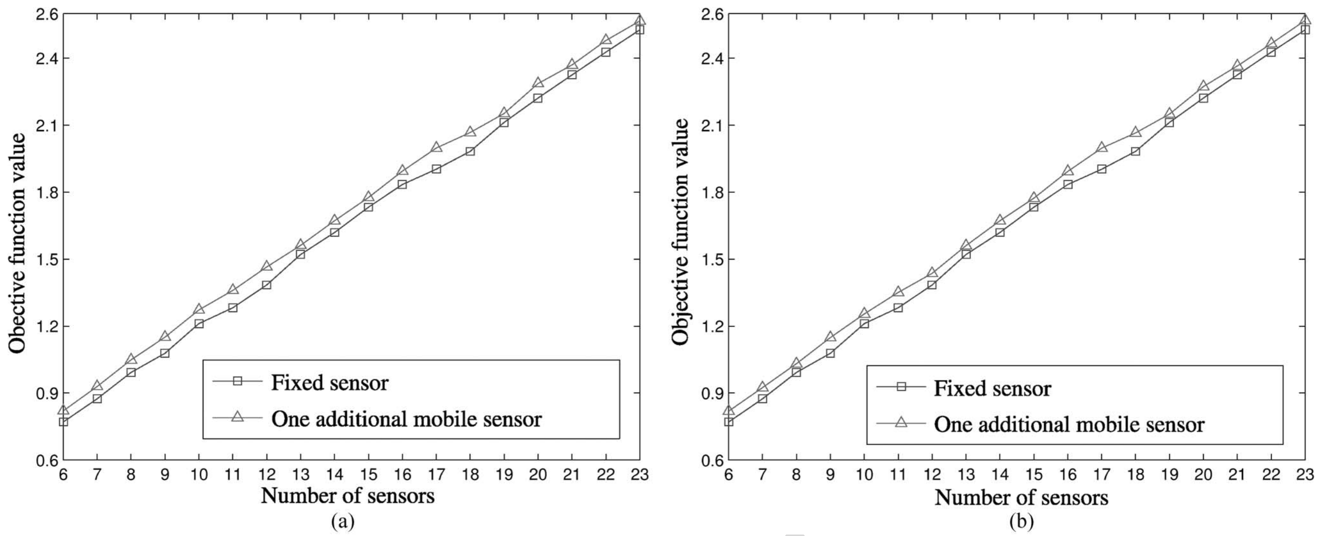


Fig. 5. One additional mobile sensor plus fixed sensor versus fixed sensor under different conditions. (a) One additional mobile sensor plus fixed sensor versus fixed sensor under free flow condition. (b) Mobile sensor versus fixed sensor under slight congestion.

TABLE III
SUMMARY OF MOBILE SENSOR VERSUS FIXED SENSOR

	Small number sensor	Large number sensor
Mobile sensor vs. Fixed sensor under free flow condition	Mobile $>$ Fixed	Mobile $>$ Fixed
Mobile sensor vs. Fixed sensor under slight congested condition	Mobile $>$ Fixed	Mobile $<$ Fixed
Mobile sensor vs. Fixed sensor under sever congested condition	Mobile $>$ Fixed	Mobile $<$ Fixed
Mobile plus fixed sensor vs. Fixed sensor under free flow condition	Mobile $>$ Fixed	Mobile $>$ Fixed
Mobile plus fixed sensor vs. Fixed sensor under severe congested condition	Mobile $>$ Fixed	Mobile $>$ Fixed

TABLE IV
ROBUSTNESS OF MOBILE SENSOR

Experiment code	Performance loss	Experiment code	Performance loss
A01	0.9%	B03	0.88%
A02	1.5%	B05	1.7%
A04	3.2%	B07	2.7%
A06	4.3%	B10	4.8%
A08	5.9%	B12	6.6%
A10	7.3%	B14	8.8%

designed to show the robustness of our model. One is to fluctuate the link travel time with certain percentage. The other is to incorporate the nonrecurrent incident factor.

1) Stochastic Fluctuation of Travel Time: Six different experiments are conducted under this category. Stochastic fluctuation of travel time are set to 10%, 20%, 40%, 60%, 80%, and 100%, respectively, based on the severe congestion condition. Stochastic fluctuation is designed to increase the travel time. Experiments of each percentage level are conducted for 100 times. Traffic information acquisition benefits are recalculated for the original route results based on the stochastic fluctuated travel time. Comparative result between the stochastic fluctuated travel time and the severe congestion condition is in Table IV.

2) Nonrecurrent Incident Caused Congestion: In reality, traffic incident is not uncommon. A stochastic nonrecurrent incident is also considered. Six different experiments are conducted, and 3, 5, 7, 10, 12, and 14 links are randomly chosen as fully congested links out of all 28 links. It is not very common that more than 50% of the links are fully congested in reality. Fully congested links are assumed unavailable for vehicles, and the travel time is set to be extremely large. Traffic information acquisition benefits are also recalculated for the original route results based on the case of stochastic fully congested links. As to each link that is fully congested, a shortest path is generated between its adjacent two links that are not blocked. Therefore, a new route is produced that bypasses these fully congested links. Experiments for each number of fully congested situation are conducted for 100 times. Comparison between the new route of nonrecurrent incident caused congestion and the severe congestion condition is also in Table IV.

Table IV shows the results of the robust experiments. A01, A02, A04, A06, A08, and A10 represent that the stochastic travel-time fluctuation is 10%, 20%, 40%, 60%, 80% and 100%, respectively. B03, B05, B07, B10, B12, and B14 represent that 3, 5, 7, 10, 12, and 14 links are fully congested, respectively. The results of the performance loss compared with the severe congestion condition is shown in Table IV. It is shown that performance of utilizing a mobile sensor does not lose very much, although there is sharp increase in stochastic travel time or high probabilistic traffic incident.

E. Mobile Sensor Route Analysis Based on Topological Position

The numerical results are also analyzed on the route level. All links on this transportation network is divided into five areas in terms of its topological position (see Table V). AQ2

The summation of stay time in each area of a mobile sensor is calculated. The percentage of stay time in each area is obtained accordingly. The mean of the highest percentage of stay time among mobile sensors is 68.9%, which indicates that mobile

TABLE V
LINK AREA PARTITION

Area name	Link IDs
Northwest area	1 2 5 6 7 8 9 10 13 14
Southwest area	13 14 17 18 19 20 25 26
Northeast area	2 3 9 10 11 12 15 16
Southeast area	15 16 19 20 23 24 27 28
Central area	7 8 9 10 13 14 15 16 19 20 21 22

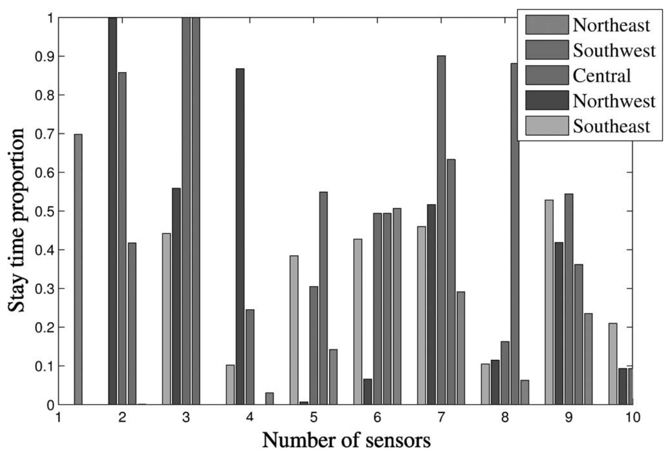


Fig. 6. Proportion of stay time for five areas when number of mobile sensors is ten.

TABLE VI
CLASSIFICATION OF LINKS BASED ON HEURISTIC INFORMATION VALUE

Classification	Link IDs
Low heuristic information	2 4 7 8 10 11 21 22 25 26
Middle heuristic information	5 6 9 13 17 18 23 24 27 28
High heuristic information	1 3 12 14 15 16 19 20

sensors spend most stay time on an identical area. Fig. 6 shows the difference of the stay time proportion in each area that is taken as an example. The number of sensors is ten for Fig. 6. Let us take the second mobile sensor as a further example. The proportion of this mobile sensor in different areas is 0.87, 0, 0.03, 0.10, and 0.25. The sum of these proportions exceeds 1 because some links are located in more than one area because of their topological position. The situation of the other number of mobile sensors has a similar stay-time proportion pattern with Fig. 6, which shows that mobile sensors spend most time in a limited number of areas.

F. Mobile Sensor Route Analysis Based on Heuristic Information

In ACO, heuristic information represents prior information. We now classify all links into different categories based on different heuristic information levels. Links are classified into three different levels based on heuristic information value (see Table VI). AQ3

Given the link classification based on heuristic information, the proportion of stay time in different heuristic information categories can be calculated. The results are shown in Fig. 7. The proportion of each category fits a curve, indicating that the proportion of stay time in high-heuristic information areas decreases monotonically. The proportion of stay time in low-heuristic information areas increases monotonically. Thus, mobile sensors are inclined to move in high-heuristic information areas when the number of mobile sensors is small. When the number of sensors is large, stay time on high-heuristic information areas decreases, and that on low-heuristic information areas increases.

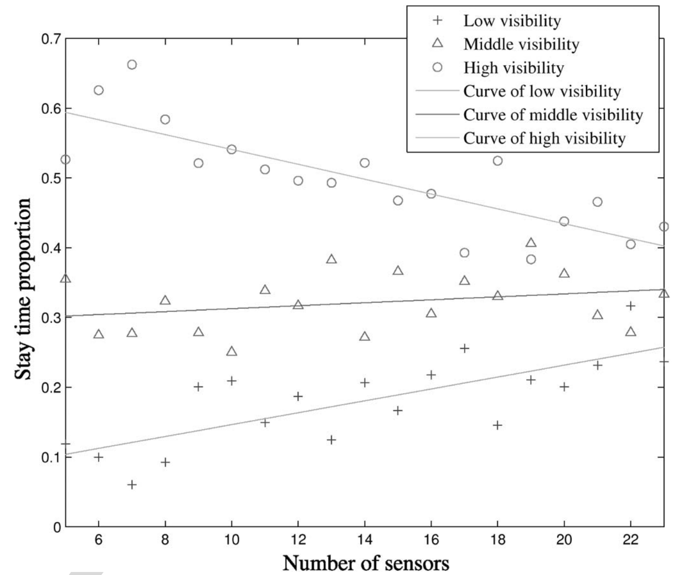


Fig. 7. Proportion of stay time for different heuristic information classification.

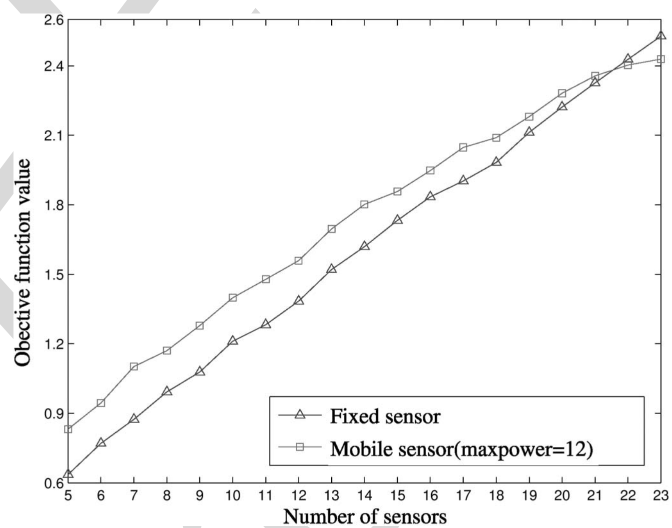


Fig. 8. maxpower = 12 versus fixed sensor.

G. Sensitivity Analysis of Maxpower

In our proposed hybrid two-stage heuristic algorithm, a key component in ACO that distinguishes our algorithm from traditional ACO for the VRP is the design of the parameter maxpower. Maxpower represents the maximum travel time of a mobile sensor on the network. Two case studies are conducted for maxpower = 12 and maxpower = 6, respectively. Fig. 8 shows a very similar pattern with Fig. 4(a). A comparison of the results of maxpower = 12 and maxpower = 6 (see Fig. 9) indicates that the case of maxpower = 12 shows a better

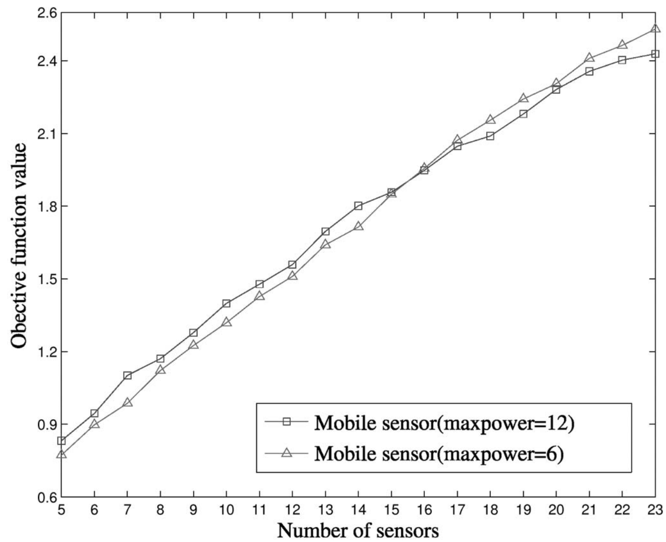


Fig. 9. maxpower = 12 versus maxpower = 6.

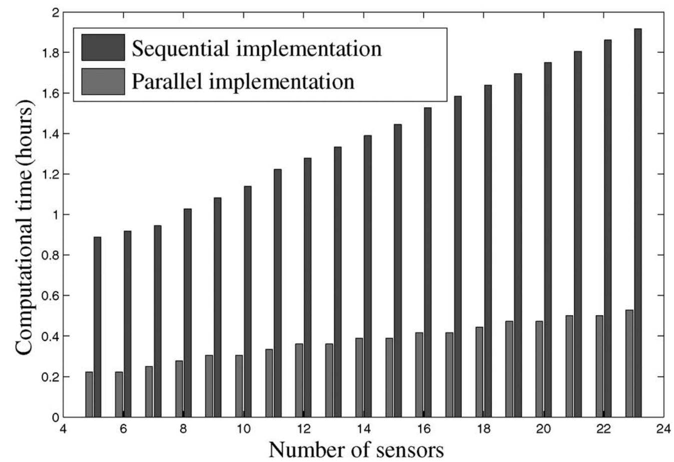


Fig. 10. Computational time comparison between sequential and parallel implementation.

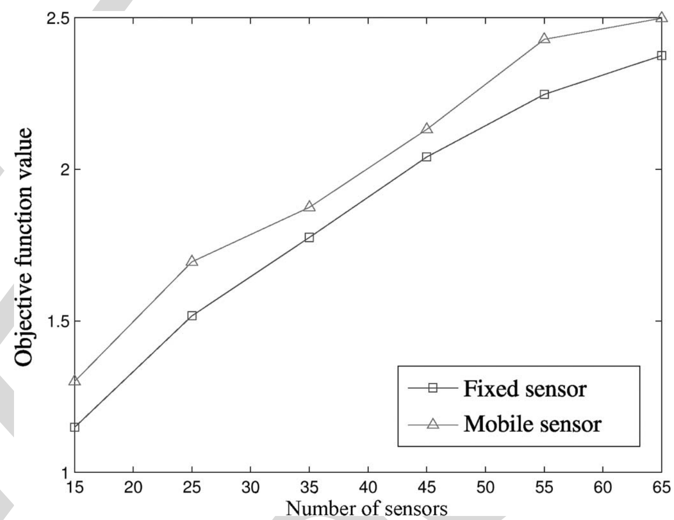


Fig. 11. Mobile sensor versus fixed sensor for the Sioux–Fall network.

TABLE VII
CLASSIFICATION OF LINKS BASED ON HEURISTIC INFORMATION VALUE

Instances	Mean			Deviation			Best Value		
	HB	GA	SA	HB	GA	SA	HB	GA	SA
SN-5	0.72	0.63	0.61	0.06	0.07	0.09	0.77	0.73	0.69
SN-10	1.21	1.08	1.02	0.18	0.14	0.15	1.34	1.28	1.20
ND-5	0.74	0.60	0.58	0.04	0.04	0.06	0.77	0.73	0.63
ND-10	1.21	1.02	1.0	0.07	0.11	0.17	1.30	1.18	1.20
ND-15	1.53	1.37	1.34	0.14	0.15	0.18	1.65	1.58	1.53
ND-20	1.8	1.58	1.56	0.16	0.23	0.21	1.92	1.87	1.78
ND-25	1.99	1.81	1.76	0.12	0.18	0.28	2.13	2.04	2.06

performance when the number of sensors is from 5 to 15. This observation can be explained by the fact that, when the number of sensors is small, a mobile sensor is supposed to have a relatively long distance route to gain a high traffic information acquisition benefits. However, the advantage of a large maxpower value weakens, and a mobile sensor is expected to move in a limited area in that more moves increase travel-time wastage.

H. Hybrid Two-Stage Algorithm Performance

To show the performance of our proposed hybrid algorithm, the results of simulated annealing and the genetic algorithm are employed for comparison. Experiments with different number of mobile sensors are conducted in both the simulated network and Nguyen–Dupius network[55]. All these experiments are done for 20 times, and statistics are extracted accordingly. Three statistics are mean, deviation, and best value of the 20 experiments.

Table VII shows these results. For the " Instances " column of Table VII, "SN-x" represents the experiments on simulated network with x number of mobile sensors. "ND-x" represents the experiments on the Nguyen–Dupius network with x number of mobile sensors. HB, GA and SA represents hybrid two-stage heuristic algorithm, genetic algorithm, and simulated annealing, respectively. The results show that the proposed algorithm outperforms the GA and SA in all three criteria.

Regarding the computational time, it takes 0.89 h when the number of mobile sensors is five. A parallel implementation in a four-core machine decreases the computational time significantly to 0.22 h. A comparison between the sequential and the parallel implementation is shown in Fig. 10.

Fig. 10 shows that computational time dramatically decreases after the parallel implementation. As to sequential implementation, computational time increases almost linearly with the increase in the number of mobile sensors. However, computational time keeps relatively stable for the parallel implementation. The average time saving percentage is 73%, which is significant.

1) Applicability in Practical Problems: Here, the Sioux–Fall network is employed to show the practicability of our algorithm. The Sioux–Fall network is widely used in transportation. It has 76 links and 24 nodes. This experiment is conducted under free flow condition.

In this experiment, different numbers of mobile sensors are tested: 15, 25, 35, 45, 55, and 65. When the number of sensors is 35, the traffic information acquisition benefits is 1.87, which is more than half of total benefits. The mobile sensor outperforms the fixed sensor under free flow traffic conditions (see Fig. 11). AQ4

This numerical experiment shows that our proposed algorithm can be applied to practical transportation networks.

V. Conclusion

Traditionally, fixed traffic sensors are employed to collect traffic information. Given the lack of flexibility of fixed sensors, the mobile traffic sensors are introduced to enhance the traffic surveillance effect. This paper aims to design optimal routes for mobile traffic sensors to maximize traffic information acquisition benefits.

By considering the dynamics of transportation networks, we have proposed an information-capture-oriented mobile-sensor routing problem. Unlike traditional VRPs, our problem has two kinds of decision variables: the route variable and the stay-time variable. An objective function is designed to measure the traffic information acquisition benefits. A hybrid two-stage heuristic algorithm that combines PSO and ACO is designed to solve this mobile-sensor routing problem effectively. The mobile sensor outperforms the fixed sensor network in most cases. The route of a mobile sensor is normally restricted in a portion of the network. The sensitivity analysis of the parameter maxpower is also analyzed.

The proposed problem differs from traditional VRPs in that it assumes that mobile sensors can benefit more if they stay on the customer side longer (the link is treated as the customer). Mobile sensor is helpful for both urban and freeway transportation network surveillance. In reality, the mobile sensors can be used alone or serves as a supplement to the fixed sensor network. The proposed information-capture-oriented VRP is applicable in many other applications. Future direction may consider the stochastic factor of the transportation network and design an optimal mobile-sensor route that maximizes expected traffic information acquisition benefits.

References

[1] H. Yang and J. Zhou, "Optimal traffic counting locations for origin destination matrix estimation," *Transp. Res. B, Methodol.*, vol. 32, no. 2, pp. 109–126, Feb. 1998.

[2] L. Bianco, L. Confessore, and P. Reverberi, "A network based model for traffic sensor location with implications on o/d matrix estimates," *Transp. Sci.*, vol. 35, no. 1, pp. 50–60, Feb. 2001.

[3] H. Yang, C. Yang, and L. Gan, "Models and algorithms for the screen line-based traffic counting location problems," *Comput. Oper. Res.*, vol. 33, no. 3, pp. 836–858, Mar. 2006.

[4] L. Bianco, G. Confessore, and M. Gentili, "Combinatorial aspects of the sensor location problem," *Ann. Oper. Res.*, vol. 144, no. 1, pp. 201–234, Apr. 2006.

[5] S.-R. Hu, S. Peeta, and C.-H. Chu, "Identification of vehicle sensor locations for link-based network traffic applications," *Transp. Res. B, Methodol.*, vol. 43, no. 8/9, pp. 873–894, Sep. 2009.

[6] E. Castillo, J. M. Menendez, and P. Jimenez, "Trip matrix and path flow reconstruction and estimation based on plate scanning and link observations," *Transp. Res. B, Methodol.*, vol. 42, no. 5, pp. 455–481, Jun. 2008.

[7] R. Mínguez, S. Sánchez-Cambronero, E. Castillo, and P. Jimenez, "Optimal traffic plate scanning location for od trip matrix and route estimation in road networks," *Transp. Res. B, Methodol.*, vol. 44, no. 2, pp. 282–298, Feb. 2010.

[8] M. Gentili and P. Mirchandani, "Locating sensors on traffic networks: Models, challenges and research opportunities," *Transp. Res. C, Emerging Technol.*, vol. 24, pp. 227–255, Oct. 2012.

[9] H. D. Sherali, J. Desai, and H. Rakha, "A discrete optimization approach for locating automatic vehicle identification readers for the provision of roadway travel times," *Transp. Res. B, Methodol.*, vol. 40, no. 10, pp. 857–871, Dec. 2006.

[10] G. B. Thomas, "The relationship between detector location and travel characteristics on arterial streets," in *Proc. Transp. Frontiers Next Millennium, 69th Annu. Meet. Inst. Transp. Eng.*, 1999, pp. 1–16.

[11] S. Oh and K. Choi, "Optimal detector location for estimating link travel speed in urban arterial roads," *KSCE J. Civil Eng.*, vol. 8, no. 3, pp. 327–333, May 2004.

[12] I. Fujito, R. Margiotta, W. Huang, and W. A. Perez, "Effect of sensor spacing on performance measure calculations," *Transp. Res. Board*, no. 1945, pp. 1–11, 2006.

[13] J. Kim, J. Lee, and J. Won, "Determining optimal sensor locations in freeway using genetic algorithm-based optimization," *Eng. Appl. Artif. Intell.*, vol. 24, no. 2, pp. 318–324, Mar. 2011.

[14] X. J. Ban, L. Chua, R. Herring, and J. D. Margulici, "Sequential modeling framework for optimal sensor placement for multiple intelligent transportation system applications," *J. Transp. Eng.*, vol. 137, no. 2, pp. 112–120, Feb. 2011.

[15] C. Yang, P. Chootinan, and A. Chen, "Traffic counting location planning using genetic algorithm," *J. Eastern Asia Soc. Transp. Studies*, vol. 5, pp. 898–913, 2003.

[16] X. Fei, H. Mahmassani, and S. Eisenman, "Sensor coverage and location for real-time traffic prediction in large-scale networks," *Transp. Res. Board*, no. 2039, pp. 1–15, 2007.

[17] X. Li and Y. Ouyang, "Reliable sensor deployment for network traffic surveillance," *Transp. Res. B, Methodol.*, vol. 45, no. 1, pp. 218–231, Jan. 2010.

[18] X. Fei and H. Mahmassani, "Structural analysis of near-optimal sensor locations for a stochastic large-scale network," *Transp. Res. C, Emerging Technol.*, vol. 19, no. 3, pp. 440–453, Jun. 2011.

[19] X. Fei, H. S. Mahmassani, and P. Murray-Tuite, "Vehicular network sensor placement optimization under uncertainty," *Transp. Res. C, Emerging Technol.*, vol. 29, pp. 14–31, Apr. 2013.

[20] L. Hu and D. Evans, "Localization for mobile sensor networks," in *Proc. 10th Annu. Int. Conf. Mobile Comput. Netw.*, 2004, pp. 45–57.

[21] N. Heo and P. K. Varshney, "Energy-efficient deployment of intelligent mobile sensor networks," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 35, no. 1, pp. 78–92, Jan. 2005.

[22] Z. Butler and D. Rus, "Event-based motion control for mobile-sensor networks," *IEEE Pervasive Comput.*, vol. 2, no. 4, pp. 34–42, Oct.–Dec. 2003.

[23] Y. Wang and H. Wu, "Delay/Fault-Tolerant Mobile Sensor Network (dft-msn): A new paradigm for pervasive information gathering," *IEEE Trans. Mobile Comput.*, vol. 6, no. 9, pp. 1021–1034, Sep. 2007.

[24] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: using a mobile sensor network for road surface monitoring," in *Proc. ACM MobiSys*, 2008, pp. 29–39.

[25] A. Angel, M. Hickman, P. Mirchandani, and D. Chandnani, "Methods of analyzing traffic imagery collected from aerial platforms," *IEEE Trans. Intell. Transp. Syst.*, vol. 4, no. 2, pp. 99–107, Jun. 2003.

[26] M. Hickman and P. Mirchandani, "Airborne data and traffic management," in *Proc. Symp. 75th Anniv. Greenshields, Transp. Res. Boards Traffic Flow Theory Committee Meet.*, 2008, pp. 1–27.

[27] F. W. Cathey and D. J. Dailey, "Transit vehicles as traffic probe sensors," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1804, no. 1, pp. 23–30, 2002.

[28] R. F. Dantzig, George, and S. Johnson, "Solution of a large-scale traveling-salesman problem," *J. Oper. Res. Soc. Amer.*, vol. 2, no. 4, pp. 393–410, Nov. 1954.

[29] G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," *Oper. Res.*, vol. 12, no. 4, pp. 568–581, Jul./Aug. 1964.

[30] P. Toth and D. Vigo, *The Vehicle Routing Problem*. Philadelphia, PA, USA: SIAM, 2002.

[31] R. Baldacci, P. T., and D. Vigo, "Exact algorithms for routing problems under vehicle capacity constraints," *Ann. Oper. Res.*, vol. 175, no. 1, pp. 213–245, Mar. 2010.

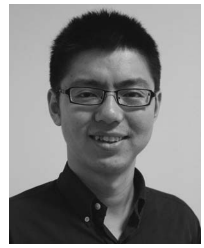
[32] B. Yu, Z.-Z. Y, and B. Yao, "An improved ant colony optimization for vehicle routing problem," *Eur. J. Oper. Res.*, vol. 196, no. 1, pp. 171–176, Jul. 2009.

[33] M. Reimann, K. D, and R. F. Hartl, "D-ants: Savings based ants divide and conquer the vehicle routing problem," *Comput. Oper. Res.*, vol. 31, no. 4, pp. 563–591, Apr. 2004.

[34] S.-W. Lin, Z.-J. Lee, K.-C. Ying, and C.-Y. Lee, "Applying hybrid metaheuristics for capacitated vehicle routing problem," *Exp. Syst. Appl.*, vol. 36, no. 2, pp. 1505–1512, Mar. 2009.

[35] Ö. Ergun, J. B. Orlin, and A. Steele-Feldman, "Creating very large scale neighborhoods out of smaller ones by compounding moves," *J. Heuristics*, vol. 12, no. 1/2, pp. 115–140, Mar. 2006.

[36] H.-k. H. Huang, P. Chen, and X.-Y. Dong, "Iterated variable neighborhood descent algorithm for the capacitated vehicle routing problem.," *Exp. Syst. Appl.*, vol. 37, no. 2, pp. 1620–1627, Mar. 2010.
[37] V. Kachitvichyanukul, "Particle swarm optimization and two solution representations for solving the capacitated vehicle routing problem," *Comput. Ind. Eng.*, vol. 56, no. 1, pp. 380–387, Feb. 2009.
[38] A. V. Donati, R. Montemanni, N. Casagrande, A. E. Rizzoli, and L. M. Gambardella, "Time dependent vehicle routing problem with a multi ant colony system," *Eur. J. Oper. Res.*, vol. 185, no. 3, pp. 1174–1191, Mar. 2008.
[39] É. Taillard, P. Badeau, M. Gendreau, F. Guertin, and J.-Y. Potvin, "A tabu search heuristic for the vehicle routing problem with soft time windows," *Transp. Sci.*, vol. 31, no. 2, pp. 170–186, May 1997.
[40] W.-C. Chiang and R. A. Russell, "Simulated annealing metaheuristics for the vehicle routing problem with time windows," *Ann. Oper. Res.*, vol. 63, no. 1, pp. 3–27, 1996.
[41] P. Toth and D. Vigo, "An exact algorithm for the vehicle routing problem with backhauls," *Transp. Sci.*, vol. 31, no. 4, pp. 372–385, Nov. 1997.
[42] N. Wassan, S. Said, and M. Hajarat, "The fleet size and mix vehicle routing problem with backhauls: Formulation and set partitioning-based heuristics," *Transp. Res., Logist. Transp. Rev.*, vol. 56, pp. 22–35, Sep. 2013.
[43] J.-Y. P. Duhamel, X. Christophe, and J.-M. Rousseau, "A tabu search heuristic for the vehicle routing problem with backhauls and time windows," *Transp. Sci.*, vol. 31, no. 1, pp. 49–59, Feb. 1997.
[44] P. Toth and D. Vigo, *The Vehicle Routing Problem*. Philadelphia, PA, USA: SIAM, 1987.
[45] A. Subramanian, L. M. A. Drummond, C. Bentes, L. S. Ochi, and R. Farias, "A parallel heuristic for the vehicle routing problem with simultaneous pickup and delivery," *Comput. Oper. Res.*, vol. 37, no. 11, pp. 1899–1911, Nov. 2010.
[46] Y. Gajpal and P. Abad, "An Ant Colony System (acs) for vehicle routing problem with simultaneous delivery and pickup," *Comput. Oper. Res.*, vol. 36, no. 12, pp. 3215–3223, Dec. 2009.
[47] M. Gendreau and G. Laporte, "A tabu search heuristic for the vehicle routing problem with stochastic demands and customers," *Oper. Res.*, vol. 44, no. 3, pp. 469–477, May/Jun. 1996.
[48] B. Fleischmann, S. Gnutzmann, and E. Sandvoss, "Dynamic vehicle routing based on online traffic information," *Transp. Sci.*, vol. 38, no. 4, pp. 420–433, Nov. 2004.
[49] A. V. Vural, E. Burak, and A. Reisman, "The vehicle routing problem: A taxonomic review," *Comput. Ind. Eng.*, vol. 57, no. 4, pp. 1472–1483, Nov. 2009.
[50] S. R. Golden, L. Bruce, and E. E. A. Wasil, *The Vehicle Routing Problem [Electronic Resource]: Latest Advances and New Challenges*. New York, NY, USA: Springer-Verlag, 2008.
[51] R. Rajagopal and P. P. Varaiya, "Health of California's loop detector sytem," California PATH Program, Inst. Transp. Studies, Univ. California Berkeley, Berkeley, CA, USA, 2007.
[52] D. Scott, D. Novak, L. Aultman-Hall, and F. Guo, "Network robustness index: A new method for identifying critical links and evaluating the performance of transportation networks," *J. Transp. Geogr.*, vol. 14, no. 3, pp. 215–227, 2006.
[53] M. Dorigo and L. M. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 53–66, Apr. 1997.
[54] B. Yu, Y. Zhongzhen, and C. Cheng, "A parallel ant colony algorithm for bus network optimization," *Comput. Aided Civil Infrastruct. Eng.*, vol. 22, no. 1, pp. 44–55, Jan. 2007.
[55] S. V. Ukkusuri, T. V. Mathew, and S. T. Waller, "Robust transportation network design under demand uncertainty," *Comput. Aided Civil Infrastruct. Eng.*, vol. 22, no. 1, pp. 6–18, Jan. 2007.



Ning Zhu received the Ph.D. degree in management science and engineering from Tianjin University, Tianjin, China.

He is an Assistant Professor with the Institute of Systems Engineering, Tianjin University. His research interests include transportation management and planning, and intelligent transportation system and location problems in transportation.

Yang Liu received the B.S. degree in information management and management science from Tianjin University, Tianjin, China, in 2012. He is currently working toward the M.S. degree with the Institute of Systems Engineering, Tianjin University.

His research interests include transportation management, traffic sensor location, and origin–destination estimation.

Shoufeng Ma received the B.S., M.S., and Ph.D. degrees from Tianjin University, Tianjin, China, in 1988, 1991 and 1999, respectively.

He is a Professor with the Institute of Systems Engineering, Tianjin University. His research interests include transportation management, traffic behavior and its impact on transportation networks, and traffic flow theory and its applications.

Zhengbing He received the Ph.D. degree from Tianjin University, Tianjin, China, in 2011.

From 2011 to 2013, he was a Postdoctoral Researcher with the School of Traffic and Transportation, Beijing Jiaotong University, Beijing, China, where he researched urban route guidance strategies. He is currently an Assistant Professor with the School of Traffic and Transportation, Beijing Jiaotong University. His research interests include traffic flow theory, intelligent transportation systems, and traffic simulation.

AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

AQ1 = Fig. 3 was cited here. Please check if the following changes are appropriate. If not, kindly provide the necessary corrections.
AQ2 = Table 5 was uncited in the body. The citation was inserted here. Please check if appropriate, and correct if necessary.
AQ3 = Table 6 was uncited in the body. The citation was inserted here. Please check if appropriate, and correct if necessary.
AQ4 = Fig. 11 was cited here. Please check if the following changes are appropriate. If not, kindly provide the necessary corrections.

END OF ALL QUERIES