IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 9, 2020, accepted March 20, 2020, date of publication March 30, 2020, date of current version April 17, 2020.
Digital Object Identifier 10.1109/ACCESS.2020.2984341

Locating Control Stations for Mobile Monitoring of Overloaded Trucks on Rural Highways

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This work was supported by the Science and Technology Project of Guizhou Provincial Department of Transportation under Grant 2018-121-027.

ABSTRACT In china, overloaded trucks are widespread on rural highways, and the current control measures are inefficient. We propose a new overloaded truck control method that finds overloaded trucks with enforcement vehicles. The enforcement vehicles detect the intercepted trucks with mobile weighing equipment and use the overloaded truck control station as a base. Based on the given number of stations and the number of enforcement vehicles, in order to detect more overloaded trucks, we need optimize the spatial distribution of the stations and the routes of the enforcement vehicles. For this reason, this paper first uses the analytic hierarchy process (AHP) to evaluate some initial alternative locations and selects a group of potential locations for the stations. Second, with the aim of maximizing the number of trucks being detected by the enforcement vehicles, we establish a model to optimize the spatial distribution of the stations and the routes of enforcement vehicles. Finally, a calculation is done with the data of the current rural highways in Guiyang city, China.

INDEX TERMS Highway transportation, location and routing problem, ant colony algorithm, overloaded truck control station, rural highway.

I. INTRODUCTION

Overloaded trucks, which have worsened road pavement quality and shortened highways' service lives, can be widely seen on Chinese highways. Therefore, the authorities have been continually enforcing controls on the overloaded trucks since 2004 [1]. A common way to intercept overloaded trucks is by setting up control stations (namely, overloaded truck control stations, hereafter OTCS) along roadways with serious overloaded traffic to check the trucks and punish them [2]. But this common method suffers from a number of limitations. It is difficult to safely perform checks on heavily trafficked highways and motorways. With the increase of traffic volume, the OTCS could not handle the heavy traffic resulting in a lower enforcement level and causing delay to truckers and motorists in general [3], [4]. In order to improve the operations at OTCS, weigh-in-motion (WIM) technology was first proposed in 1950s [5]. The WIM mainly consists of load cells and data processing system. The load cells are installed on the pavement to weigh moving trucks, and send the data to the system. The system filters out likely non-offenders based on a preset threshold value, and inform the offenders to go to the OTCS for punishment. However, with the help of a complex rural highway network, the overloaded trucks may detour the OTCSs and load cells due to the low cost of detouring. Therefore, on rural highways, it is hard to effectively catch the overloaded trucks with OTCSs and load cells. The effect and efficiency of OTCSs and load cells on overloading control are poor. In this context, to improve overloaded traffic control, an innovation in monitoring overloaded trucks on rural highways is a key issue to urgently study.

The associate editor coordinating the review of this manuscript and approving it for publication was Baozhen Yao.

II. LITERATURE REVIEW

It is difficult to find a large amount of literature on overloaded traffic control. Bagui (2013) has given the definition of overloaded traffic and proposed a method to compensate road damages due to overloaded traffic by punishing truck operators [6]. Quintero et al. (2013) proposed a bilevel modeling approach to represent the interactions between vehicle loading practices of freight transport carriers and the decisions of a road planning authority responsible both for road maintenance and for the enforcement of overloading control. The model can predict the reactions of the carrier under a series of planner decisions and then help the planner choose an appropriate combination of the number of inspection points and the punishment levels to have the minimal total expenditure (on repairs and overloading inspection costs) [7]. However, issues regarding locating control stations and routing enforcement vehicles have not been addressed. Li (2005) analyzed the interactions between a carrier's profit and transport price, operating cost, and overloading penalties, as well as the conditions for carriers to maximize their profits. Finally, he gave the solutions and the policy implications for China to deal with the overloaded issue [8]. Chen (2004) put forward the idea of tolling the trucks by their actual loaded weights and having axle loading quotas, and then studied the long-term effectiveness of controlling overloaded traffic through economic methods [9]. Almost all the existing studies are macroscopic ones. The specific optimization of the overloaded traffic control scheme (including station locations and enforcement vehicle routing) has not yet been involved.

In the above context, we propose a mode of mobile enforcement for overloaded traffic, namely, with OTCSs as bases to dispatch enforcement vehicles to dynamically monitor traffic and find overloaded trucks. An enforcement vehicle leaves from an OTCS in the morning to cruise roadways, and at the end of the working day, returns to the same OTCS. To maximize the utilization of OTCSs and enforcement vehicles, this paper optimizes the distribution and location of OTCSs, and further designs the cruising route for enforcement vehicles when the numbers of OTCSs and enforcement vehicles are given.

Many existing papers have studied the location and routing combination issue. Nagy (2007) defined the location-routing problem (LRP) as an operation problem to minimize the total cost (including the construction cost and the transport cost) by determining the locations of facilities and the vehicle travel routes when the location alternatives and client locations are given [10]. Sun (2017) studied the location of distribution center and the multivehicle routing problem in the situation of simultaneous deliveries and pick-ups [11]. Aiming at minimizing the total cost and social impacts, Caballero et al. (2007) studied a multi-objective location-routing issue with capacity constraints for multi-type vehicles [12]. Zeng et al. (2009) established a bilevel programming model for the location of distribution centers. They optimized the vehicle routing at the upper level and optimized the total cost of the distribution system at the lower level [13]. To minimize the environmental risk and the total cost, Zhao (2014) proposed a two-objective location model that optimizes the facility location for used oil storage and treatment, facility capacity and travel routes of the used oil [14]. Subject to the facility and vehicle capacities, and with the aim of minimizing the total cost and maximizing the clients' satisfaction, Luo and Sun (2014) established a two-objective location-routing model based on a fuzzy time window. The model is used to optimize the location of warehouses and the routing of delivery vehicles [15]. More contributions to location and routing problem can be found in literature [16]–[19]. From the literature review, we find that most of the existing studies are concentrated on locating distribution centers or warehouses and routing the delivery vehicles. There are few studies on optimizing facility locations and vehicle routings according to the overloaded vehicle density on the cruise paths. In the exiting literature, the location alternatives in facility location and vehicle routing is given, while in our study, the location alternatives are unknown. All possible initial alternative must be selected from the studied rural highway network first, and then be screened by analytic hierarchy process (AHP) and cluster analysis to get the final alternative locations. Finally integer programming is used to optimize the facility locations and vehicle routes. Therefore, this paper involves the whole process from the selection of location alternatives to the optimization of facility locations and vehicle routes, which can provide a more completed theoretical analysis method for the location-routing problem.

III. LOCATION ALTERNATIVES FOR OTCSs

First, we discretize the roadways with heavily overloaded traffic into points (these points are represented by the midpoints of the roadways with heavily overloaded traffic) to form an initial alternative set $U_0 = (1, 2, 3, \ldots, n)$. Based on the maximum cruising range of an enforcement vehicle, we determine the roadways with heavy overloaded traffic that can be covered by OTCS, namely, the other initial alternative points able to be visited by the enforcement vehicles within daily cruising range. Next, we use an integrated method to evaluate the initial location alternatives and screen the unfeasible alternatives from the initial alternatives.

TABLE 1. Evaluation indices for the alternative locations.

Main criterion	Sub criteria
Environmental factor	Geological condition
	Weather condition
	Terrain conditions
Infrastructure factor	Transport convenience
	Communication convenience
	Electricity convenience
Economic factors	Demolition cost
	Construction cost
Force majeure factor	Military base
	Planned land
Overloaded degree	Overloaded degree of the alternative location point
	Overloaded degree on the covered roadways

Analytic hierarchy process (AHP), which first put forth in 1980 by Thomas L. Saaty, is a practical method for comprehensive evaluation. It can combine qualitative and

TABLE 2. The meaning of grade.

Grade	Meaning
1	A1 and A2 equally important
3	A1 slightly more important than A2
5	A1 significantly more important than A2
7	A1 much more important than A2
9	A1 more important than A2
2, 4, 6, 8	Indicates the importance between adjacent odd scales
Reciprocals	The comparison value of A1 and A2 is the reciprocal of the comparison value of A2 and A1

quantitative factors together for choosing a scheme in the case of complex, unpredictable, multi-criteria decision problems [20]. Because the evaluating factors for screening the initial alternatives are systematic and complex, we adopt the AHP to evaluate the initial alternatives. The indicator system is shown in Table 1.

Overload traffic is widespread on rural highway, we assume that the more trucks on a roadway, the more the overloaded trucks and the more serious the overloaded degree on the highway will be. Therefore, in Table 1, the overloaded degree is expressed by the number of trucks, and its value is directly proportional to the number of trucks.

As mentioned in Baffoe (2019) and Bilal(2019) [21], [22], to obtain the weights of the factors at each level, we divide their relative importance into 1-9 grades (Table 2, where A1 and A2 represent any two factors). The importance scores may be obtained by a questionnaire survey. The judgment matrix of each level can be obtained by processing the surveyed scores, and then, eigenvectors corresponding to the largest eigenvalue in the judgment matrices can be calculated. If a judgment matrix is consistent, the eigenvectors may be used as the weight vectors.

Finally, the comprehensive weights of the initial location alternatives at the lowest level can be calculated based on weight vectors at each level to obtain the final scores of the alternatives. The method is shown as Eq. (1).

$$W_a = \sum_{x=1}^{12} w_x^{(1)} w_x^{(2)} w_{xa}^{(3)}, \quad a = 1, 2, 3, \ldots, n \tag{1}$$

where W_a denotes the comprehensive weight of an alternative a, $w_x^{(1)}$ is the weight of the main criterion that includes the subcriteria x, $w_x^{(2)}$ is the weight of the subcriteria x, and $w_{xa}^{(3)}$ is the weight of the initial location alternative a by comparing all the location alternatives under subcriteria x.

To reduce the set size of the initial alternatives and reduce the workload for screening alternatives, it is necessary to cluster initial alternatives that cover similar roadways and use the best one in each cluster to replace the other alternatives in the same cluster. By first making each initial alternative one cluster, it means that at the beginning one cluster only has one alternative. This way, we obtain n initial clusters as: $v_a^0 \in V^0$, $a = 1, 2, 3, \ldots, n$. Then, we calculate the similarity of their covered roadways. The initial alternative in the current cluster is used as a reference point, and the initial alternatives in other clusters are compared. The similarity is expressed by the overlapping ratio of the covered initial alternative points, and the calculation method is given as Eq. (2):

$$S_{ab} = L_{ab}/L_a, \quad a \neq b;\; b = 1, 2, 3, \ldots, n \tag{2}$$

Here, a denotes the reference point of an alternative and b denotes the comparing point of an alternative. S_{ab} is the similarity between them, L_{ab} is the number of overlapping initial alternative points between them, and L_a is the total number of initial alternative points that are covered by reference point a.

If alternative point b is similar to reference point a in some degree, we put it in the cluster holding initial alternative point a. In this way, we can obtain a cluster containing multiple initial alternatives, and then retain the one with the highest weight and delete all other alternatives. At last, a cluster, renamed v_a^1, is left that contains only one initial alternative. Let the reference point $a = 1, 2, 3, \ldots, n$, and the same operations are performed for the reference point to obtain new groups of clusters, renamed as $v_a^1 \in V^1$, $a = 1, 2, 3, \ldots, n$, which are grouped into a set of U_1. By deleting the overlapping candidate points in U_1, we can obtain the practical candidate set $j_i \in J$, $i = 1, 2, 3, \ldots, d$, which is the input of the model in section 4.

Next, in order to optimize the location of the OTCSs and the routes of the enforcement vehicles, we establish an optimization model in Chapter 4, which with the objective to find as many overloaded trucks as possible, subject to the constraints that each demand point can be visited at most once and the cruising range is within the vehicle's maximum range. In Chapter 5, we design the improved ant colony algorithm to solve the model. Finally, to verify the effectiveness of the model and algorithm, we use the actual data of Guiyang City for case analysis in Chapter 6.

IV. MATHEMATICAL MODEL

A. PROBLEM DEFINITION

We discretize the roadways with heavy overloaded traffic into points (these points are also represented by the midpoints of the roadways with heavily overloaded traffic) to form a demand point set. To control the overloaded traffic, each OTCS should be equipped with at least one enforcement vehicle that carries mobile weighing equipment and starts from the OTCS to visit the demand points to detect the passing trucks. The cruising duration has to be shorter than the vehicle's maximum travel range. After cruising, the enforcement vehicle should return to the same OTCS. This working process is shown in Figure 1.

The decision-making issue is to screen out m OTCS from J (J is the output in section 3) and design the routes of the

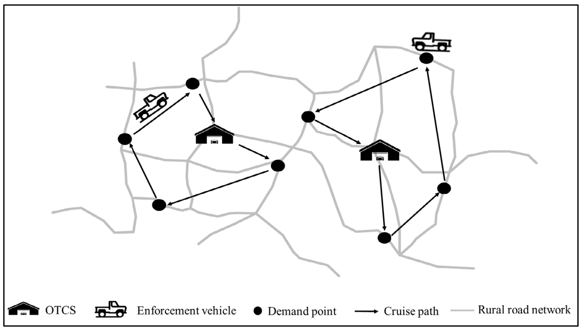

FIGURE 1. The schematic diagram of controlling overloading with mobile facilities.

enforcement vehicles when the number of the vehicles is given, with the objective to find as many overloaded trucks as possible, subject to the constraints that each demand point can be visited at most once and the cruising range is within the vehicle's maximum range.

B. MODEL FORMATION

Assume that the overloading probability at all demand points is the same and that the overloaded trucks are evenly distributed in time. Therefore, the more traffic that passes a demand point, the more overloaded trucks may be found at that point. Thus, in the case of a known numbers of OTCSs and enforcement vehicles, we can establish a programing model for locating OTCSs and routing enforcement vehicles with the objective to make the vehicle meet as much traffic as possible.

1) VARIABLES AND PARAMETERS

Sets: J- Location alternatives of OTCSs;

C- Demand points;

K- Enforcement vehicles.

Parameters: m- Number of OTCSs;

v- Speed of enforcement vehicles;

t- Working time of an enforcement vehicle at a demand point;

$t_{\max}$- Maximum cruise time of an enforcement vehicle;

q_c- The truck traffic volume at demand point c;

q_{j_i}- The truck traffic volume at OTCS j_i.

Intermediate variables:

D_k- Number of visited demand points by enforcement vehicle k;

L_k- The travel distance of enforcement vehicle k.

Decision variables:

$z_{j_i} = 1$ if an OTCS is located at point j_i, 0 otherwise;

$x_{cc'k} = 1$ if enforcement vehicle k travels from demand point c to demand point c', 0 otherwise;

$x_{j_ick} = 1$ if enforcement vehicle k travels from OTCS j_i to demand point c, 0 otherwise.

2) MODEL EQUATIONS

$$\text{Max } Q = \sum_{j_i \in J} z_{j_i} q_{j_i} + \sum_{j_i \in J} \sum_{c \in C} \sum_{k \in K} x_{j_ick} q_c$$

$$+ \sum_{c \in C} \sum_{c' \in C} \sum_{k \in K} x_{cc'k} q_{c'} \tag{3}$$

$$S.T: \; z_{j_i} \in (0, 1) \tag{4}$$

$$x_{cc'k} \in (0, 1) \tag{5}$$

$$x_{j_ick} \in (0, 1) \tag{6}$$

$$\sum_{j_i \in J} z_{j_i} = m \tag{7}$$

$$z_{j_i} = \sum_{c \in C} x_{j_ick} = \sum_{c' \in C} x_{c'j_ik}, \quad j_i \in J, \; k \in K \tag{8}$$

$$\sum_{c \in C} x_{cc'k} - \sum_{c'' \in C} x_{c'c''k} = 0, \quad c' \in C, \; k \in K \tag{9}$$

$$\sum_{k \in K} \sum_{c \in C} x_{cc'k} + \sum_{k \in K} \sum_{j_i \in J} x_{j_ic'k} \leq 1, \quad c' \in C \tag{10}$$

$$L_k/v + D_k t \leq t_{\max} \tag{11}$$

$$x_{j_ij_{i'}k} = 0, \quad j_i, \; j_{i'} \in J, \; k \in K \tag{12}$$

where Q denotes the sum of the traffic volume passing the OTCSs and routes of all enforcement vehicles. Equation (7) is the number of OTCSs. Equation (8) indicates that when an OTCS is set, at least one enforcement vehicle should start from and return to it. Equation (9) ensures that an enforcement vehicle must cruise in a closed route. Equation (10) ensures that a demand point is visited only by one enforcement vehicle. Equation (11) ensures that the cruise time of an enforcement vehicle should be less than its maximum cruising time. Equation (12) guarantees that an enforcement vehicle will not move from one OTCS to another.

V. ANT COLONY OPTIMIZATION FOR LRP

Because the above model contains a location allocation problem (LAP) and a vehicle routing problem (VRP), it is a nonlinear programming and NP-hard problem. The location-routing problem is usually solved using heuristic algorithms [23], [24].

Ant colony algorithm (ACA) is a probabilistic heuristic algorithm to find an optimal route. Ants select routes according to pheromones and convert the selection result into a pheromone increment to update the pheromones between nodes. It can effectively narrow the range of feasible solutions and quickly find the optimal route. Therefore, ant colony algorithm is often used to solve large-scale route optimization problems.

The idea of the solution is to first use the ant colony algorithm to optimize the routes of enforcement vehicles for all potential location groups to get the route set with the maximum traffic volumes, and then to take the route scheme with the most traffic volumes from the set and the corresponding location group as the optimal location-routing scheme.

During the solution, due to the complexity of solving the routing problem for multiple bases and multiple vehicles, we transform it into a single base and multiple vehicles routing problem. Following MA et al. (2011), the transform method uses a virtual OTCS to replace a group of real OTCS and then thinks that the virtual one is both the starting and ending points of enforcement vehicles. Additionally, enforcement vehicles must cover all the demand points. In this case, the distance from demand point i to the nearest real OTCS is used as the distance between the demand point i and the virtual OTCS [25]. Afterwards, we use the improved ACA to solve the location-routing model as follows:

Step 1: Parameter Determination

Determine the value of m (the number of OTCSs), N (the number of enforcement vehicles), t (the working time of enforcement vehicles at each demand point), $t_{\max}$ (the maximum cruise time of an enforcement vehicle), and N_{IT} (the maximum number of iterative calculations).

Step 2: Locations Grouping

Select all possible groups of locations from the alternative set to number them as $1, 2, 3, \ldots, A$.

Step 3: Set the group number $G = 1$.

Step 4: Initialize the ants and the pheromones between nodes.

Set the number of ants equal to the number of demand points, and let all ants start from the virtual OTCS of group G. The initial pheromone between the demand points is set to 1. The initial number of enforcement vehicles n and the number of iterative calculations n_{IT} are both set to be 0.

Step 5: Calculate the expected value of each feasible node selected by the ant.

The expected value when an ant chooses point j from point i is marked by η_{ij}, and $\eta_{ij} = q_j/l_{ij}$ (q_j is the traffic volume at point j, l_{ij} is the length of link (i, j)).

Step 6: Calculate the probability of feasible node being selected by ant.

By the pheromone and expected value, the probability of an ant choosing point j from point i is as follows:

$$p_{ij} = \frac{(\tau_{ij})^{\alpha} \times (\eta_{ij})^{\beta}}{\sum_{h\in H} (\tau_{ih})^{\alpha} \times (\eta_{ih})^{\beta}} \tag{13}$$

where τ_{ij} is the pheromone of link (i, j), η_{ij} is the expected value of an ant choosing point j from point i, α and β are heuristic factors, and H is the set of feasible nodes.

Step 7: Determine the OTCS that has the shortest distance from the first node selected by the ant.

When we use an ant's route to simulate the cruising process of an enforcement vehicle, the ants are thought to start from a virtual OTCS. To meet the constraint that the OTCS is both the starting point and the ending point, we need to determine a real OTCS in the calculation process so that the ants can return to the real OTCS after cruising to form a closed travel loop. The specific determination process is as follows:

When an ant selects the next node from the virtual OTCS, the probability of choosing each feasible node can first be calculated by Eq. (13). Following He et al. (2017), to avoid falling into a local optimum, a roulette choice method is used to increase the randomness of the next node [26]. The step is: accumulating the choice probabilities of feasible nodes to get $\sum p_{ij}$, if $\sum p_{ij} \geq \varepsilon$($\varepsilon \in (0, 1)$ a random number), take point j as the next node. Next, find the closest OTCS in G to point j. If the closest OTCS is O, we take O as the real OTCS.

Step 8: Determine the next node.

After the ant chooses the next node, we need to judge whether its cruise time will exceed the maximum cruise time if the next node is added to the ant's journey. Assuming j' is the next node selected by an ant, $t_{o\to j'}$ is the time from O to j' for the ant, and $t_{j'o}$ is the time from point j' directly to OTCS O. We should judge whether $t_{o\to j'} + t_{j'o}$ is less than the maximum cruise time $t_{\max}$. If $t_{o\to j'} + t_{j'o} \leq t_{\max}$, then we take j' point as the next node and add it to the list. The ant continues to select the next node from point j' according to Eq. (13), and the roulette selection method; otherwise, the ant gives up point j', ends the journey, and directly returns to OTCS O from the current node. The ant's cruise time returns to 0 and the number of enforcement vehicles $n = n + 1$. The ant will start from the virtual OTCS again. The calculation turns to Step 7. When the number of enforcement vehicles $n = N$, go to Step 9.

Step 9: Pheromone Updating.

After all ants finish their journeys, the pheromone on each edge should be updated. The method is as follows:

$$\tau_{ij}^{\text{new}} = \rho\tau_{ij}^{\text{old}} + \sum_{b\in B} b_{ij}\Delta\tau_{ij}^{b}; \quad \rho \in (0, 1) \tag{14}$$

where τ_{ij}^{old} denotes the pheromone of edge (i, j) before updating, τ_{ij}^{new} denotes the pheromone of edge (i, j) after updating, ρ is the pheromone evaporation parameter in the range of $[0, 1]$, and b_{ij} is a 0-1 variable. When edge (i, j) is on the route of ant b, then $b_{ij} = 1$. Otherwise $b_{ij} = 0$. $\Delta\tau_{ij}^{b}$ denotes the pheromone left on edge (i, j) by ant b, namely, the pheromone increment on edge (i, j), and its value equals the total traffic volume on the route of ant b. B is the set of ants.

After updating the pheromones of each edge, we have completed one calculating iteration, and we should update the iteration number $n_{IT} = n_{IT} + 1$. If $n_{IT} = N_{IT}$, go to Step 10; otherwise, return to Step 4 for the next calculation iteration.

Step 10: Calculation for the next OTCS group.

Update the group number $G = G + 1$. If $G \leq A$, return to Step 3 to optimize the enforcement vehicle's route for the next OTCS group. If $G > A$, end the calculation.

VI. CASE STUDY

We use Guiyang, the capital city of Guizhou, for the case study. From field surveys, we know that in Guiyang's rural highway network, there are 50 roadways with heavy overloaded trucks. The truck volumes on the survey roadways are shown in Table 3. Assuming that three OTCSs will be built in Guiyang and a total of six enforcement vehicles are equipped, the travel speed of each enforcement vehicle is 40 km/h, the working time at a point is 30 minutes, and the maximum cruising time of an enforcement vehicle is 4 hours.

For the calculation, we first digitize the rural highway network in Guiyang with the MapInfo platform, and discretize the 50 roadways with heavy overloaded trucks into points to form a demand point set. They are also the initial location alternatives for OTCS. The spatial distribution of the demand points is shown in Figure 2.

TABLE 3. The traffic volumes on the surveyed roadways.

ID	Traffic volume (pcu/d)	ID	Traffic volume (pcu/d)
1	603	26	985
2	589	27	1 322
3	1 355	28	879
4	707	29	554
5	1 055	30	1 265
6	590	31	621
7	667	32	877
8	687	33	880
9	1 098	34	601
10	598	35	901
11	566	36	569
12	758	37	592
13	1 089	38	1 011
14	913	39	910
15	909	40	859
16	998	41	764
17	1309	42	545
18	669	43	892
19	534	44	912
20	1 170	45	1 002
21	577	46	701
22	1 381	47	655
23	790	48	1 512
24	593	49	1 331
25	1 005	50	1 211

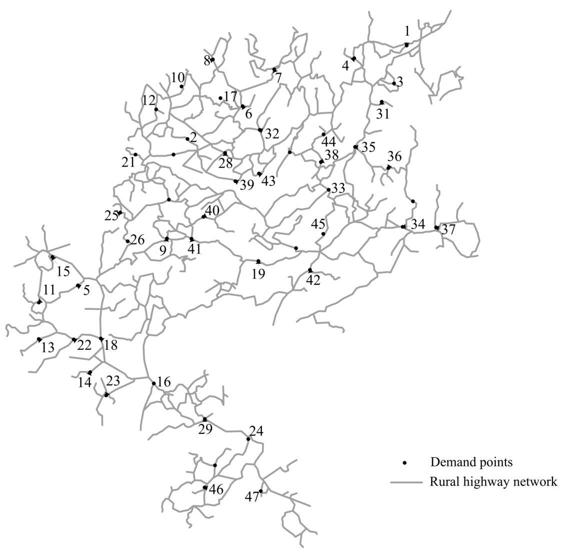

FIGURE 2. The spatial distribution of the demand points.

Then, according to each roadway's length and the maximum cruise time (4 hours) of enforcement vehicle, we calculate the covering roadways of each initial location alternative to obtain the covering set of the initial location alternatives. Considering the return time of enforcement vehicle and the enforcement vehicle need to visit at least one demand point, we can know that the travel time of each enforcement vehicle is at most $(4 - 0.5)/2$ hours, which is 1.75 hours. Calculating the roadways with heavy overloaded trucks that can be reached by the enforcement vehicle within 1.75 hours, and Table 4 shows the truck volume on the covered roadways of each initial location alternative.

TABLE 4. Truck volume on the covering roadways of each initial location alternative.

ID	Traffic volume (pcu/d)	ID	Traffic volume (pcu/d)
1	14 173	26	29 824
2	27 813	27	35 159
3	25 052	28	28 466
4	20 322	29	13 162
5	23 511	30	29 668
6	26 394	31	24 511
7	21 757	32	27 853
8	23 716	33	28 079
9	34 508	34	16 922
10	22 422	35	25 510
11	17 228	36	23 195
12	23 017	37	16 931
13	18 556	38	28 330
14	21 386	39	27 046
15	18 080	40	34 508
16	18 381	41	37 178
17	23 100	42	21 726
18	21 230	43	28 330
19	32 287	44	34 508
20	32 792	45	24 841
21	18 898	46	6 720
22	15 981	47	6 766
23	9 756	48	6 757
24	29 824	49	25 663
25	27 830	50	16 914

TABLE 5. The weight of each initial location alternative.

ID	weight	ID	weight
1	0.0121	26	0.0247
2	0.0236	27	0.0310
3	0.0244	28	0.0252
4	0.0173	29	0.0112
5	0.0198	30	0.0273
6	0.0228	31	0.0206
7	0.0186	32	0.0245
8	0.0203	33	0.0229
9	0.0291	34	0.0134
10	0.0191	35	0.0207
11	0.0133	36	0.0190
12	0.0191	37	0.0134
13	0.0160	38	0.0256
14	0.0171	39	0.0245
15	0.0140	40	0.0288
16	0.0154	41	0.0306
17	0.0191	42	0.0171
18	0.0171	43	0.0255
19	0.0271	44	0.0289
20	0.0280	45	0.0207
21	0.0152	46	0.0075
22	0.0165	47	0.0075
23	0.0084	48	0.0097
24	0.0241	49	0.0211
25	0.0259	50	0.0151

Analytic hierarchy process was used to comprehensively evaluate all the initial location alternatives, and the weight value of each initial location alternative is shown in Table 5.

Using the method in Chapter 2, we group the initial location alternatives based on the rule that 85% of the covered demand points are the same in two covering sets. Finally, we keep the location alternatives that have the highest comprehensive weights to get a set of real alternatives,

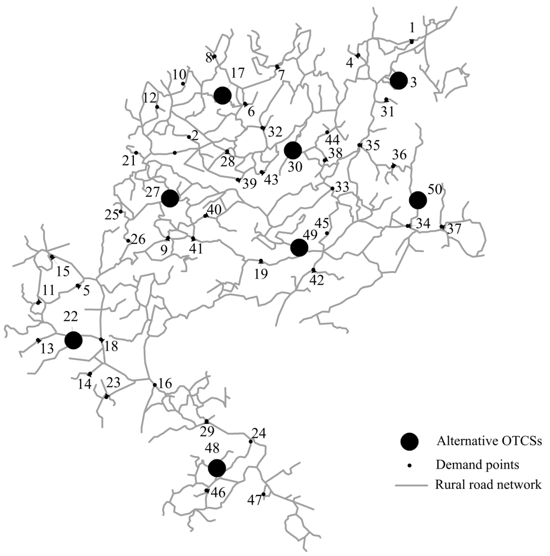

FIGURE 3. The spatial distribution of the location alternatives.

namely, $J = (3, 17, 22, 27, 30, 48, 49, 50)$, which are shown in Figure 3.

In the case of choosing three locations from eight alternatives, there are 56 total combinations. For the 56 combinations, we change the multiple depots and the multiple vehicles routing problem into a single depot and multiple vehicles routing problem by integrating the three OTCSs into a virtual OTCS. We can then solve the problem using the above updated ACA.

For the calculation, we suppose that there are 50 ants, we set the heuristic factor equal to 1, the expected factor equal to 2, and the pheromone volatilization coefficient equal to 0.50. The total traffic volume on a travel path is set as the pheromone increment on the path. The number of calculation iterations is set as 100.

We compile the computing program using VBA in Excel 2016. Under one of the combinations, the relationship between the pheromone increment and the number of calculating iterations is shown in Figure 4.

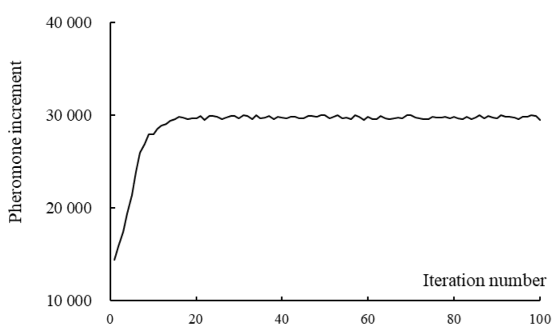

FIGURE 4. The relationship between the pheromone increment and the iteration number.

Figure 4 shows that the pheromone increment increases before the 20th generation of the calculation, but the increasing speed decreases gradually. After the 21st generation, the pheromone increment is stable. This result means that the routes of all the ants have been determined, and the cruising routes in the context of this location combination are obtained. For the 56 combinations, the traffic volumes on the optimal cruising routes are shown in Figure 5.

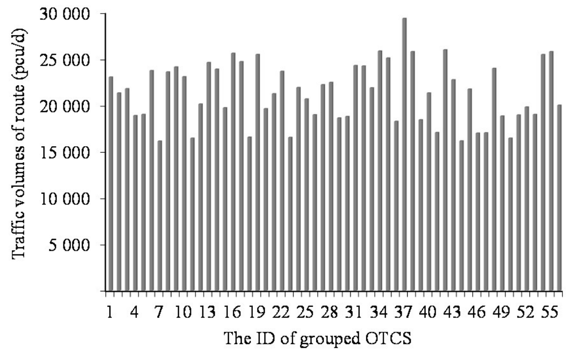

FIGURE 5. Traffic volumes of routes with a different group number of OTCS.

It can be seen that the traffic volume on the cruising routes of Group 37 is the largest. At this time, $z_{22} = 1, z_{27} = 1$ and $z_{30} = 1$. This means that three OTCSs should be located at alternatives 22, 27 and 30, respectively, and the corresponding cruising routes are shown in Figure 6.

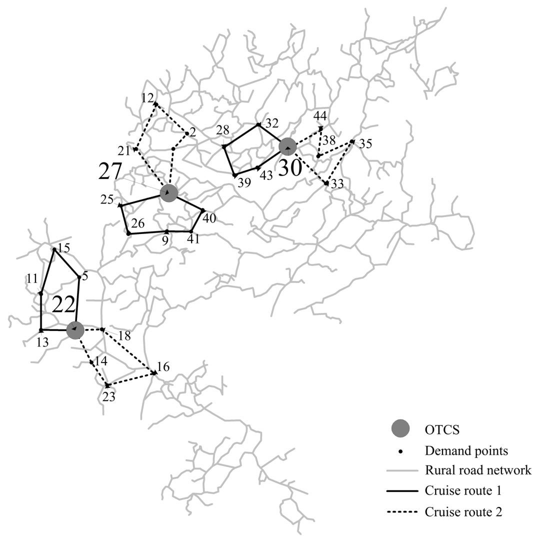

FIGURE 6. Scheme of locations in the VRP.

The OTCSs of 22, 27 and 30 are located in Xiazhai of Qingzhen City, Daba of Xiuwen County, and Yongshaba of Kaiyang County, respectively. Near the three OTCSs, there are plentiful mineral resources. Thus, there are many mine trucks on the roadways, and most trucks are overloaded. The cruising Route 1 of OTCS 22 passes through three towns (Liyou, Lichangxiang and Wangzhuang) and many coal mining areas. At the same time, the cruising Route 1 of OTCS 22 mainly covers roadways S310, S106, S211, X068, which are the main connectors between the cities and towns. They are high-grade rural highways with heavy truck flows

(3912 trucks per day). Cruising route 2 passes through two towns (Zhanjie and Qingzhen), three scenic spots (such as Hongfeng Lake), and several coal mines and cement factories, and it also covers roadways S106, S210, X198, X067 and Y019, which are high-grade rural highways with many trucks (4850 trucks per day). The cruising route of OTCS 30 crosses Xifeng County and Kaiyang County.

Figure 6 shows that by using the optimal location-routing scheme, the enforcement vehicles can cover 28 roadways, which accounts for 56% (28/50) of the roadways with heavy overloaded traffic. The total daily traffic volume on the 50 rural highways is 45 493 trucks, and the total daily traffic volume along the cruising routes is 29 387 trucks, which accounts for 64.6% of the total. This means that the enforcement vehicles cover 56% of the roadways but can monitor 64.6% of the trucks. The ratio of the truck coverage rate to the roadway coverage rate may be used to represent the OTCSs' working efficiency. The calculation method is given as Eq. (15). The bigger the value is, the more the trucks will be monitored, and the higher the working efficiency of the OTCS is and vice versa.

$$W = S_1/S_2 \tag{15}$$

Here, W denotes the working efficiency of the OTCSs, S_1 denotes the truck coverage rate, and S_2 denotes the road coverage rate.

If we use the working efficiency in the case that the truck coverage rate equals the road coverage rate ($S_1 = S_2$) is the normal working efficiency. From Eq. (15), we know that the normal working efficiency should be 1. Using the optimal location-routing scheme, the working efficiency is 1.15 (64.6%/56%), which is higher than the normal working efficiency. We can consider that the work efficiency of OTCSs in the case study is better.

VII. CONCLUSION

With the new working mode for overloading traffic control, we determine a set of candidate sites for locating the OTCSs by cluster analysis and analytic hierarchy processes, and we collaboratively optimize the locations of OTCSs and the cruising routes of the enforcement vehicles. The optimization model is helpful to raise the effectiveness of overloading traffic control when the number of OTCSs and the number of enforcement vehicles are given. The case study based on the data of Guiyang rural highway shows that in the case of the optimal scheme, there are rich mineral resources and a large number of mine trucks around the location of the OTCSs, the cruising routes of the enforcement vehicles mainly cover the high-grade roadways with large traffic volumes, and the efficiency of the overloading traffic control is high. This result illustrates that the method in this paper can effectively help decision makers to implement location decisions for the OTCSs and help to design cruising routes for enforcement vehicles.

In order to simplify the study, we used the number of overloaded trucks to represent the overloaded degree on roadways. However, in fact, the overloaded degree dose relate to not only the number of overloaded trucks but also the overloaded cargos on the trucks. For some roadways with small number of overloaded trucks, if the all overloaded trucks are overloaded lots of cargos the overloaded degrees is not necessarily smaller than the roadways with a large number of overloaded trucks but each truck is overloaded a few cargos. In this study this phenomenon is not taken into account. For future studies, the definition of overloaded degree should be given by considering more details. Moreover, we did not consider the fluctuation of traffic flow at the demand point in this study. For a more realistic and objective description of the traffic flow at the demand point, in the future we may consider put some method to forecast the traffic fluctuation on roadways.

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