Data-Based Sorting Algorithm for Variable Message Sign Location

Case Study of Beijing

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Variable message signs (VMSs) provide important traffic information to help drivers travel better on a transportation network. The effectiveness of VMSs largely depends on the numbers and locations of VMSs in a transportation network. Although a few optimization models have been proposed to find candidate roads for locating VMSs, few have been devoted to developing algorithms that can be used in a real transportation network. A large amount of traffic data, such as traffic flow data, is widely available, collected by various means. Based on those traffic data, a sorting algorithm for a VMS location problem is presented in this paper. The algorithm gave a VMS location order rather than a location set. The proposed method divided roads into categories according to multilevel attributes and preferentially selected roads of a higher class with larger flows and more information and the minimal effect of existing VMS in a certain order to locate VMS. The proposed algorithm was analyzed and verified through a practical case on the Beijing, China, urban road network.

With the global development of intelligent transportation systems, variable message signs (VMSs) have been widely applied in urban traffic management. By providing real-time traffic information about incidents, congestion, and estimated travel time, VMSs help travelers make better route choice decisions and alleviate traffic congestion as a result. In practice, VMS locations have a direct impact on VMS effectiveness and network performance.

Most studies on VMSs have focused on the impacts of display content (*1, 2*), the control logic for messages (*3, 4*), and the driver behaviors induced by VMSs (*5–9*). However, there is little literature on the VMS location problem: some studies proposed comprehensive models and algorithms for optimal locations of VMSs; most focused on the incident scenario. For example, Abbas and McCoy proposed an optimization model for finding a set of VMS locations when accidents occurred on freeways (*10*). The objective of the proposed model was to maximize the benefits of VMSs, and a generic algorithm was used to solve the model. Chiu et al. proposed a bilevel programming model for determining optimal VMS locations under traffic incident situations that were not known a priori (*11*). The feasible solutions were obtained with a tabu search algorithm. Chiu and Huynh extended their previous work and proposed a two-state stochastic program for designing VMS locations under stochastic incidents and advanced travelers information systems scenarios (*12*). A tabu search algorithm was also used to solve the model. Li and Fan (*13*) and Fu et al. (*14*) extended the work of Abba and McCoy by introducing a multiperiod benefit estimation model and incorporating a logit route choice model to determine a time-dependent diversion rate under incident conditions. Zhong et al. adopted a state, operator, and result cognitive architecture to simulate drivers' guidance behaviors while considering the effect of setting VMSs in various locations (*15*). The optimal VMS location can be found from numerous simulation results. In those studies, the objectives were usually to reduce driver delay in the incident scenario by setting the appropriate VMS locations. Various metaheuristics algorithms combined with traffic simulation were used to find the possible solution. However, the computational burden associated with many simulation runs was an obvious problem for a large network (*16*).

Recently, some researchers have given attention to improving networkwide performance by properly locating VMSs under recurrent congestion. For example, Ban et al. proposed a bilevel model to describe the VMS location problem, in which the lower problem was formulated as a stochastic user static equilibrium model (*17*). A simulated annealing algorithm was used to solve the model. Li et al. considered the impact of VMS information on drivers' route choices under recurrent congestion and proposed a mixed integer nonlinear program to describe the problem of designing VMS locations (*18*). An active set algorithm was then used to solve the optimal model.

In the existing studies, the VMS location problem was usually formulated as a 0-1 optimization problem. If the road user's reaction to VMSs is considered, the VMS location problem is further expressed as a bilevel programming model, in which the upper-level problem is formulated as a 0-1 optimization model and the lower-level problem is represented as a flow assignment model. However, the bilevel programming problem has been recognized as one of the most difficult problems for achieving global optimality because of its nonconvex nature. Nonnumerical optimization algorithms were used to solve the 0-1 bilevel programming (*19–21*), but the computational efficiency cannot be guaranteed. On one hand, such algorithms cannot be proved to have convergence properties. On the other hand, a large number of variables and parameters should be preset in the solution process, but it is difficult to obtain the values of those parameters that are usually related to driver behaviors. Therefore, these existing optimization algorithms for the VMS location problem may be feasible only for a small example network instead of a large-scale transportation network.

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Studies regarding driver response to VMS information have shown that the benefit of information released by VMSs will decrease gradually with the increase in distance between the congestion location and the VMS location (*7, 22*). This phenomenon is called information attenuation. For example, congestion on roads near an accident site may be reduced because of self-regulation of traffic or clearance of the accident when drivers who receive the information released by VMSs installed on an upstream road reach the congested road. Therefore, the factor of information attenuation should be considered in locating VMSs. However, none of the previous studies specifically considered this factor in locating VMSs. Only a set of roads, rather than location order, can be provided by the existing model-based algorithms.

To address the presented issues, this paper introduces a new method for the VMS location problem, which is based on four important attributes inferred from traffic data: road classes, average flow, amount of traffic information, and cumulative impact of already-installed VMSs. These attributes are selected and regarded as critical factors for locating VMSs. A locating strategy is then proposed to ensure that the VMS location and the traffic information provided by VMSs are effective. Based on the idea of backtracking, a sorting algorithm is proposed to obtain the allocation order of VMSs. In particular, the proposed method can control the weights of attributes by adjusting the related parameters. The proposed algorithm is analyzed and verified with a practical case from the Beijing, China, urban road network.

CRITICAL FACTORS FOR VMS LOCATIONS

To obtain more benefits from VMSs, some basic principles are needed for selection of appropriate roads on which to locate VMSs. Gan et al. introduced some general principles for locating VMSs as well as typical location plans for urban road networks (*23*). For example, VMSs should be located upstream of the major flow-diversion intersections or recurrent congestion points; VMSs should be installed on road sections with higher traffic flows to deliver traffic information to more drivers. Meanwhile, information attenuation should be considered so information is coherent when many VMSs are installed in a transportation network. The following are principles for identifying critical road attributes:

- The factor should represent the importance of roads in the whole network.
- The factor should reflect the congestion or the level of service of roads.
- The factor should indicate the diminishing effect of VMS information.
- The factor should be easy to obtain and compute.

According to these basic principles and previous research (*1, 7, 24*), four factors were adopted as the critical ones affecting the benefits of VMSs in a transportation network. These are described next.

Class of Roads

The roads in an urban transportation network can be divided into four classes: expressways (also called urban freeways), arterial roads, secondary roads, and branch roads. A higher class indicates that the roads have more important functions in a transportation network, and traffic flows on them are usually larger. The class of roads is the first factor for VMS locations in this paper. Let g_i denote the class of road, i. For simplicity, expressways, arterial roads, secondary roads, and branch roads are expressed as Classes 1, 2, 3, and 4, respectively.

Average Flow on Roads

Traffic flow is the total number of vehicles passing through a road section during a time unit (minutes or hours). Traffic flow directly reflects the number of drivers who could receive the information released by VMSs within a given period. Therefore, traffic flow is the second factor affecting VMS locations.

Let x_i^n denote the traffic flow on road i during the observation period n. The average flow on road i, represented by f_i, is calculated with the following formula:

$$f_i = \frac{1}{N}\sum_{n=1}^{N} x_i^n \qquad \forall i \tag{1}$$

where N denotes the total observation periods.

Amount of Traffic Information

The main function of VMSs is to disseminate information about congestion on downstream roads. The frequency of congestion or incidents on roads differs, which implies that the amount of traffic information also differs.

The proportion of congestion on road i, defined as the percentage of congestion on road i of the total congestion, is calculated with the following formula:

$$t_i = \frac{\sum_{n=1}^{N} y_i^n}{\sum_{i=1}^{A}\sum_{n=1}^{N} y_i^n} \qquad \forall i \tag{2}$$

where

t_i = proportion of congestion on road i,
y_i^n = amount of congestion on road i within the observation period n, and
A = number of roads in the network.

In this paper, the amount of traffic information on roads is the sum of the proportion of congestion on its downstream roads. This index is the third factor for VMS locations. According to t_i, the amount of traffic information on road i, represented by v_i, is

$$v_i = \sum_{j \in O_i} t_j \qquad \forall i \tag{3}$$

where O_i is the set of immediate downstream roads of road i.

Cumulative Impact of Installed VMSs

The benefit of information released by VMSs decreases gradually with increasing distance from the VMS location to congestion locations. Therefore, the factor of information attenuation should be considered in locating VMSs. In this paper, the factor of information attenuation is the fourth factor for VMS locations and is calculated as follows:

$$s_i^j = \rho^{d_i^j} \qquad \forall i, j \tag{4}$$

where

s_i^j = information attenuation on road i generated by VMSs on road j,
ρ = parameter that takes the value of $0 < \rho < 1$, and
d_i^j = minimum distance from the ending node of road j to the starting node of road i, which can be obtained with the shortest path searching algorithm, such as Dijkstra's algorithm.

To coordinate traffic information and make it more coherent, VMSs should be installed on a road with smaller cumulative impact of installed VMSs. The cumulative impact of all VMSs installed in the whole network on road i is computed with the following formula:

$$q_i = \sum_{j=1}^{A} s_i^j \cdot \delta_j \qquad \forall i \tag{5}$$

where q_i is the cumulative impact of all VMSs on road i and δ_j is a 0-1 variable, where $\delta_j = 1$ when a VMS has been installed on road j and otherwise $\delta_j = 0$.

Of the four attributes for each road, g_i, f_i, and v_i are statistical data and fixed, meaning that these three properties do not change when one more VMS is added on a given road. In contrast, the attribute q_i is dynamic, that is, it will change with the installation of a new VMS. For example, $q_i = 0$ for all roads when no VMS has been installed in a network. After the first VMS is placed on a road in the network, the values of q_i are different for the other roads and greater than 0. Generally, the farther the road is from the VMS location, the smaller the value of q_i.

STRATEGY OF VMS LOCATION IN TRANSPORTATION NETWORK

In this paper, vector $\mathbf{E} = (g_i, f_i, v_i, q_i)$ describes a specific state for road i without a VMS. Such a road of a higher class with larger f_i and v_i and smaller q_i should be preferentially selected for installation of a VMS. This paper proposes the following strategy for locating VMSs according to the critical factors stated above, that is, (*a*) the set of roads belonging to a higher class should be selected first from all roads, (*b*) the subset of roads with larger f_i in a set of higher-class roads is then selected, (*c*) the subset of roads with larger v_i is the set of alternate roads derived from the subset of roads with larger f_i, and (*d*) the road with minimum q_i from the set of roads with larger v_i is selected for installation of a VMS.

Roads without a VMS can be divided into categories based on the three attributes g_i, f_i, and v_i. The attribute of class, that is, g_i, is categorical data. Let G_m denote the set of roads with class $m \in (1, 2, 3, 4)$, and let N_m be the number of elements in G_m. Both f_i and v_i are numerical data. The following statistical method is used to divide these two indicators.

Sort the roads in G_m according to f_i in descending order. Let α_m denote the quantile of G_m that determines the range of the selection from G_m. The position of minimum flow in such a sequence is the integer of $\alpha_m(N_m + 1)$. Let $f_m^{(\mathrm{MIN})}$ denote the corresponding minimum flow and $f_m^{(\mathrm{MAX})}$ be the maximum flow in G_m. Then, the interval $(f_m^{(\mathrm{MIN})}, f_m^{(\mathrm{MAX})})$ is the flow range for a candidate location. Put the roads that belong to this interval into set F_m. Let M_m denote the number of elements in F_m. Similarly, F_m can be divided into serial intervals according to f_i by using the same method, that is, $F_m^{(1)}$, $F_m^{(2)}$, and so on. Such serial intervals satisfy the following conditions:

$$F_m^{(1)} \cup F_m^{(2)} \cup \cdots = F_m \tag{6}$$

$$F_m^{(1)} \cap F_m^{(2)} \cap \cdots = \phi \tag{7}$$

The subset V_m, which is obtained from F_m, can be obtained with the same process. The position of minimum v_i in V_m is the integer of $\beta_m(M_m + 1)$, where β_m is the quantile of F_m that determines the range of selection from F_m. Let $v_m^{(\mathrm{MIN})}$ denote the corresponding minimum v_i and $v_m^{(\mathrm{MAX})}$ be the maximum v_i in F_m. Then, the interval $(v_m^{(\mathrm{MIN})}, v_m^{(\mathrm{MAX})})$ is the range of v_i for candidate locations in set F_m. Similarly, V_m can be divided into serial intervals according to v_i, that is, $V_m^{(1)}$, $V_m^{(2)}$, and so on. Similarly, such serial intervals satisfy the following conditions:

$$V_m^{(1)} \cup V_m^{(2)} \cup \cdots = V_m \tag{8}$$

$$V_m^{(1)} \cap V_m^{(2)} \cap \cdots = \phi \tag{9}$$

Finally, the road with smallest q_i is selected from V_m as the next VMS location. For all roads without a VMS, q_i must be recalculated after a VMS location is assigned.

Essentially, the VMS location problem is a search problem. All roads in a transportation network are checked one by one. For road i without a VMS, it must be checked whether the state vector (g_i, f_i, v_i) meets the requirement of G_m, F_m, and V_m. If yes, the road with smallest q_i is selected from V_m for the VMS location. The simplest method with which to solve the problem is enumerating. However, this approach is difficult for a large-scale transportation network because of its high computational burden. Thus, the following section presents a simple sorting algorithm based on the idea of backtracking that makes the searching process suitable for a large-scale transportation network.

DATA-BASED ALGORITHM FOR LOCATING VMS

Backtracking is a general algorithm that searches every possible combination to solve an optimization problem. The backtracking algorithm enumerates a set of partial candidates that, in principle, could be completed in various ways to give all possible solutions to the given problem (*25*). In this paper, backtracking is used for the VMS location problem in a transportation network.

First, a database for a transportation network should be created according to basic traffic data, including road classes, traffic flows, and congestion conditions. The values of g_i, f_i, v_i for each road are assigned according to the database and following Equations 1, 2, and 3.

The state space of road $E = \{(g_i, f_i, v_i, q_i) | i = 1, 2, \ldots, A\}$ is represented with an ordered tree T with four layers. The tree is constructed as follows: (*a*) the root is a set of all roads without VMSs; (*b*) there are four sons of the root node belonging to the first layer node, and each node represents a set of different classes of road G_m, $m \in (1, 2, 3, 4)$; (*c*) each node in Layer 2 represents sets $F_m^{(1)}$, $F_m^{(2)}$, and so on; (*d*) each node in Layer 3 represents sets $V_m^{(1)}$, $V_m^{(2)}$, and so on; and (*e*) the nodes in Layer 4 are the leaves, which are min{q_i,

$i \in G_m \cap F_m \cap V_m\}$. The problem of searching $\min\{q_i, i \in G_m \cap F_m \cap V_m\}$ in E is then converted to the problem of searching all $\min\{q_i, i \in G_m \cap F_m \cap V_m\}$ in the tree T.

With the backtracking algorithm, all roads in a transportation network can be divided into categories according to the given four attributes, which are described as four layers in the tree T. After an attribute belonging to one layer is used to check roads for identifying the set of VMS locations, the attribute belonging to the next layer is used to continue scanning, or the attribute in the upper layer will be reused to repeat scanning. The process is repeated until the order of VMS locations is determined.

For each road without a VMS, q_i should be updated once a new road is added into the set of VMS locations, because this attribute reflects the impact of the road with a VMS on the road without a VMS. In addition, it is assumed that the total number of VMSs is predetermined, and only one VMS will be added in the network during each iteration. If the number of VMSs placed in the network reaches a given value, the algorithm is terminated.

The proposed data-based sorting algorithm for locating VMSs is summarized as follows, and a flowchart of the proposed method is shown in Figure 1.

Step 0. Initialization. Set X and Ω, where X is the preset number of VMSs and Ω is the set of uninstalled roads. Given the values of parameters α_m and β_m for $m \in (1, 2, 3, 4)$, set the number of serial intervals in F_m and V_m, denoted by M and N, respectively. Let $S_i = 0\ \forall i \in \Omega$, where S_i represents the location order for road i. Set the serial number of road class $m = 1$ and iteration $k = 1$.

Step 1. Get subset G_m from Ω according to $g_i\ \forall i \in \Omega$.

Step 2. Sort the roads in G_m according to f_i, and set $a = 1$, where a is a counter.

Step 3. Obtain subset $F_m^{(a)}$ from G_m with the statistical method given above.

Step 4. Sort the roads in $F_m^{(a)}$ according to v_i, and set $b = 1$, where b is another counter.

Step 5. Obtain subset $V_m^{(b)}$ with the same statistical method.

Step 6. If $a = b = 1$ and $S_i = 0$ for road i with maximum v_i in $V_m^{(b)}$, set $S_i = k$ for the road with maximum v_i in $V_m^{(b)}$, and delete the selected road from $V_m^{(b)}$, $F_m^{(a)}$, G_m, and Ω; otherwise, go to the next step.

Step 7. Compute q_i for all roads in Ω according to Equations 4 and 5.

Step 8. Set $S_i = k + 1$ for the road with minimum q_i in $V_m^{(b)}$ and delete the selected road from $V_m^{(b)}$, $F_m^{(a)}$, G_m, and Ω; judge whether $k = X$. If yes, then stop the iteration; otherwise, set $k = k + 1$ and go to the next step.

Step 9. Judge whether $V_m^{(b)}$ is null. If not, go to Step 7; otherwise, go to the next step.

Step 10. Judge whether $b = N$. If not, set $b = b + 1$, and go to Step 5; otherwise, go to the next step.

Step 11. Judge whether $a = M$. If not, set $a = a + 1$, and go to Step 3; otherwise, go to the next step.

Step 12. Judge whether $m = 4$. If yes, then set $m = 1$; otherwise, set $m = m + 1$; then go to Step 1.

CASE STUDY OF BEIJING URBAN ROAD NETWORK

The Beijing urban road network is one of the largest networks in the world with more than 4 million vehicles traveling in the network every day (*26*). Here 228 VMSs have been installed, most located on expressways and urban arterial roads (*27*). According to Beijing Transportation Development and Planning, more than 1,000 VMSs will be installed in the near future. Choosing the right roads for VMS installation is an enormous challenge because of the scale of the Beijing road network.

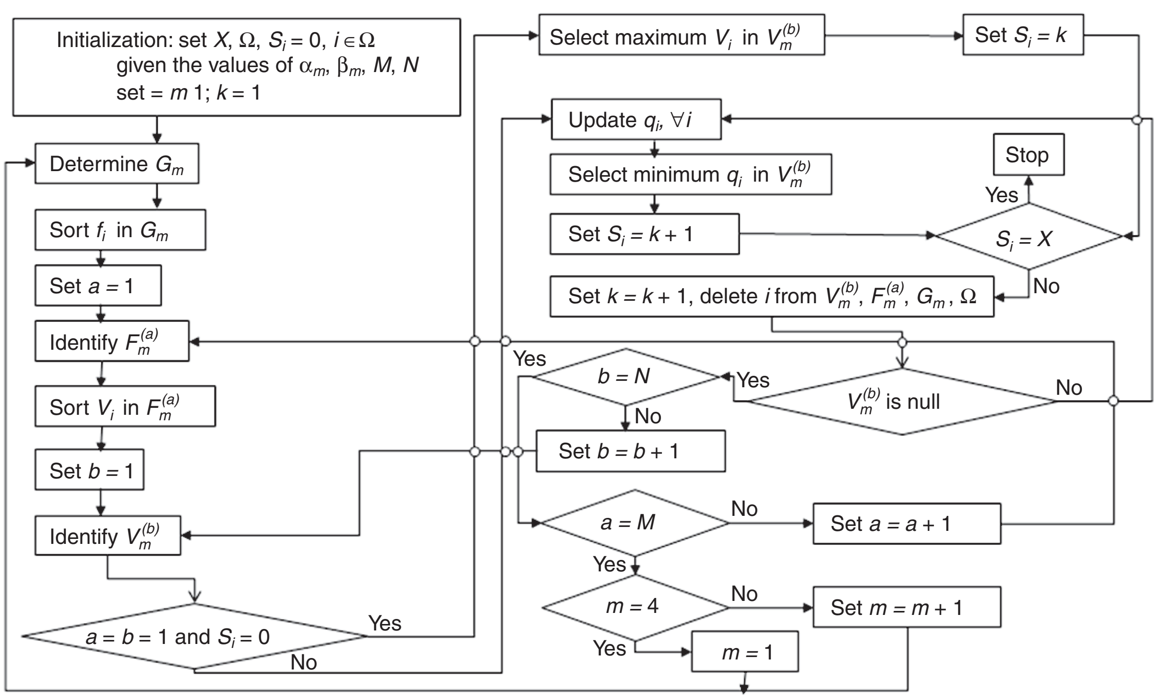
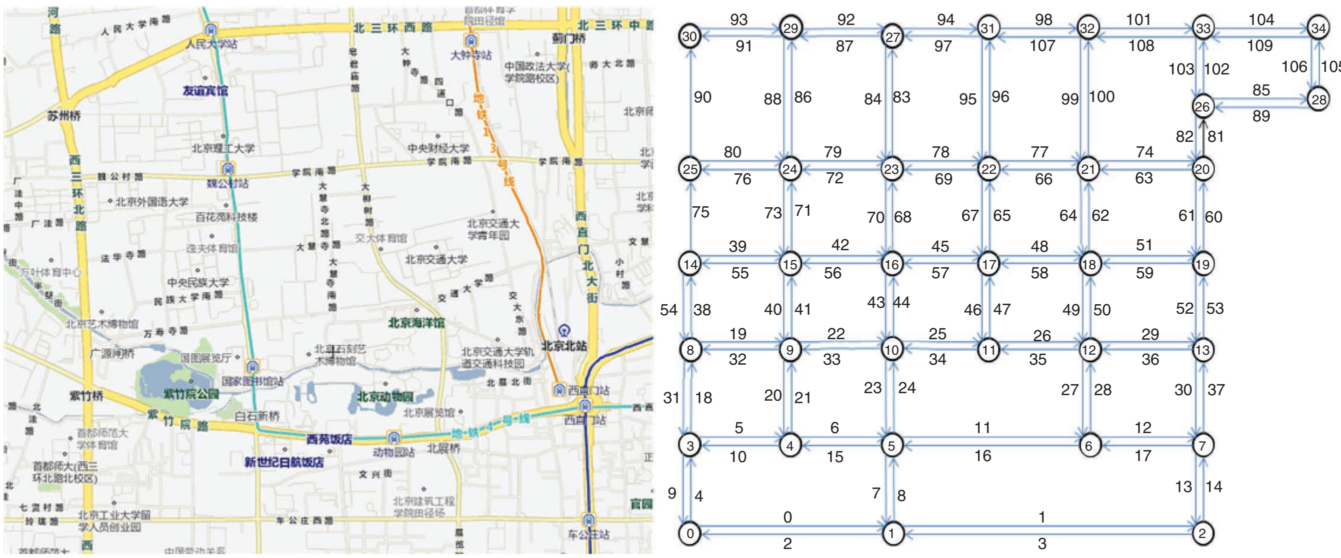


FIGURE 1 Flowchart of proposed algorithm.



(a) (b)

FIGURE 2 Example of road network in Beijing.

To manage the Beijing road network more effectively and efficiently, the transportation authority has installed thousands of remote traffic microwave sensors (RTMS) on most of the expressways. Each RTMS installed at a roadside can count passing vehicles and calculate time mean speeds and time occupancies. Traffic volume and speed are collected every 5 min over 24 h. In addition, more than 40,000 taxis, equipped with GPS devices, run in the Beijing road network; these can be treated as floating cars. These floating cars upload their instantaneous latitude, longitude, and speed to the data processing center for 1-min intervals (*28*). Based on the speed on each road weighted by traffic flow, the transportation performance index, published by the Beijing Municipal Commission of Transport every 15 min, is the measure of road congestion. By matching the transportation performance index with a digital map, the frequency of congestion on each covered road can be obtained.

After a careful review and evaluation of the quality of the data, RTMS data and floating car data (FCD) collected during 1 week in 2012 were selected for calculating key parameters of locating VMSs. The data quality control process, including deleting wrong data and repairing missing data, was completed for these data. The time granularity of FCD and RTMS data is in minutes, whereas the data used in this paper are in hours. Therefore, the data available for the proposed algorithm can be obtained from the FCD and RTMS data by accumulating them in hours.

A part of the road network in Beijing is used to illustrate the proposed algorithm. The selected area and the road network structure in this example are shown in Figure 2, where the expressways, the arterial roads, and the secondary roads are selected as the candidate set of VMS locations. There is a total of 109 roads in this area—37 expressways, 12 arterial roads, and 60 secondary roads.

The characteristics of the roads, including road ID, starting nodes, ending nodes, road classes, average flow, and congestions, are given in Table 1.

The first step of the proposed algorithm is initialization. Set $X = 25$ and $\Omega = \{\text{all the roads in the network}\}$; set the parameters $\alpha_m = \beta_m = 30\%$, $M = N = 3$; and set $S_i = 0\ \forall i \in \Omega$ and $m = 1$, $k = 1$.

Next, traverse all roads in Ω and put all expressways into G_1. The number of elements in G_1 is 38. Sort f_i in G_1 in descending order, and set $a = 1$; select the top 10% of f_i from G_1 and put them into $F_1^{(1)}$. The number of elements in $F_1^{(1)}$ is 4. The set $F_1^{(1)} = \{7, 23, 43, 70\}$. Sort v_i in $F_1^{(1)}$ in descending order, and the order is {23, 70, 7, 43}. The corresponding v_i are respectively 40.5662%, 33.5935%, 33.3826%, and 32.3262%. Table 2 gives the computational results.

TABLE 1 Data for Roads in Example

Road ID	Starting Node	Ending Node	g_i	f_i (vph)	Congestion
23	10	5	1	5,100	30
109	34	33	1	5,100	69
84	27	23	1	5,100	38
108	33	32	1	5,100	43
70	23	16	1	5,100	37
7	5	1	1	5,100	24
43	16	10	1	5,100	30
107	32	31	1	5,100	48
97	31	27	1	5,100	39

NOTE: vph = vehicles per hour.

TABLE 2 Road Information in Set J_1

Road ID	Starting Node	Ending Node	g_i	f_i (vph)	v_i (%)
23	10	5	1	5,100	40.5662
70	23	16	1	5,100	33.5939
7	5	1	1	5,100	33.3826
43	16	10	1	5,100	32.3262

TABLE 3 VMS Location Order When $\alpha_m = \beta_m = 30\%$, $M = N = 3$

Order	Road ID	Starting Node	Ending Node	g_i	f_i (vph)	v_i (%)	q_i
1	23	10	5	1	5,100	40.5662	0
2	70	23	16	1	5,100	33.5939	0.0909
3	108	33	32	1	5,100	34.0165	0.0428
4	109	34	33	1	5,100	35.2842	0.1258
5	102	26	33	2	4,800	35.2842	0.3025
6	1	1	2	2	3,200	33.8052	0.3602
7	77	22	21	3	4,500	42.2565	0.4026
8	57	17	16	3	4,700	33.5939	0.5785
9	39	14	15	3	1,900	38.0308	0.2457

Let $b = 1$, select the top 10% of v_i from $F_1^{(1)}$, and put them into $V_1^{(1)}$. The set $V_1^{(1)}$ is {23}. Since there is no VMS in the example network, the information attenuations of all roads are 0. Select the road with maximum information intensity from $V_1^{(1)}$ for installation of a message sign. Clearly, the road is 23. Then delete 23 from Ω and update the information attenuations of the remaining roads. Next, set b = 2, select the top 10% to 20% of v_i from $F_1^{(1)}$, and put them into $V_1^{(2)}$. Since the number of elements in $F_1^{(1)}$ is 4, then $4 \times 0.2 = 0.8 < 1$ and $V_1^{(2)}$ is null. Then, set $b = 3$, and select the top 20% to 30% of v_i from $F_1^{(1)}$ and put them into $V_1^{(3)}$. Since the number of elements in $F_1^{(1)}$ is 4, then $4 \times 0.3 = 1.2 < 2$ and $V_1^{(3)} = \{70\}$. Select the road with minimum q_i from $V_1^{(3)}$ for installation of VMSs. Clearly, the road is 70. The corresponding q_i is 0.090901. Then delete 70 from Ω and update q_i for the remaining roads. Until then, finish scanning the roads in $F_1^{(1)}$. Let $a = 2$. Select the top 10% to 20% of f_i from G_1 and put them into $F_1^{(2)}$. Scan the roads in $F_1^{(2)}$ following the above-mentioned process. Repeat this process until the termination condition is met. Table 3 gives the order of the top nine locations.

Table 3 shows that the expressways in this area are preferentially selected for installation of VMSs, followed by arterial roads and secondary roads. In the set of candidate roads with the same class, the roads with larger traffic flows are selected for locating VMSs. Similarly, among the roads with larger flows, the roads with more information are preferentially selected for installation of VMSs.

In the proposed algorithm, the parameters α_m and β_m can control the proportion of VMS locations for the various classes. Next, the results obtained by the proposed algorithm were analyzed with different parameter values. Figures 3 and 4 show the results of VMS locations in the road network when $\alpha_d = \beta_d = 0.3$ and $\alpha_d = \beta_d = 0.6$, respectively, and the numbers on the links indicate the location order.

Comparison of the results in Figure 3 with those in Figure 4 shows that with the increase of the value of parameter α_m, the

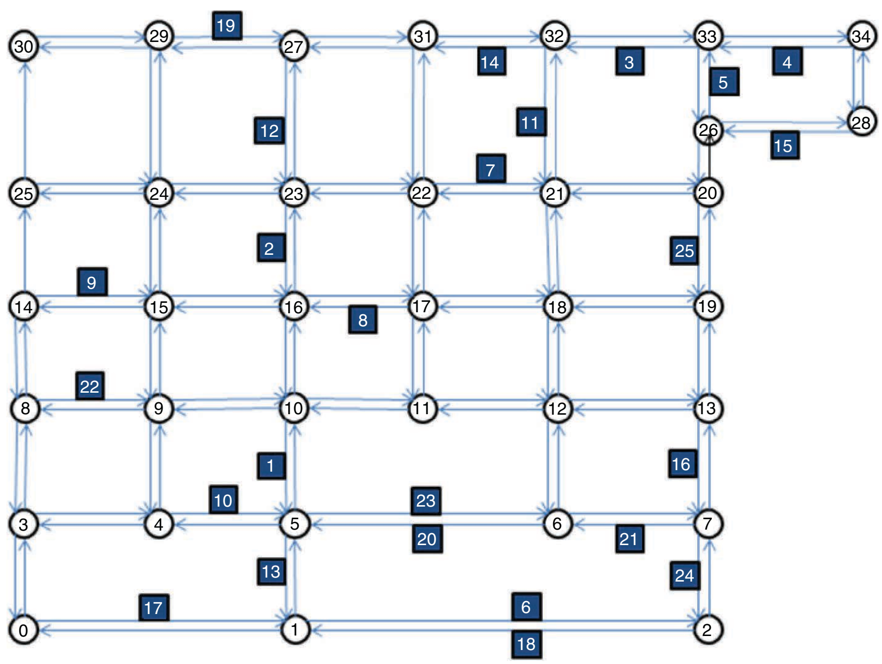


FIGURE 3 Results of VMS locations when $\alpha_m = \beta_m = 0.3$.

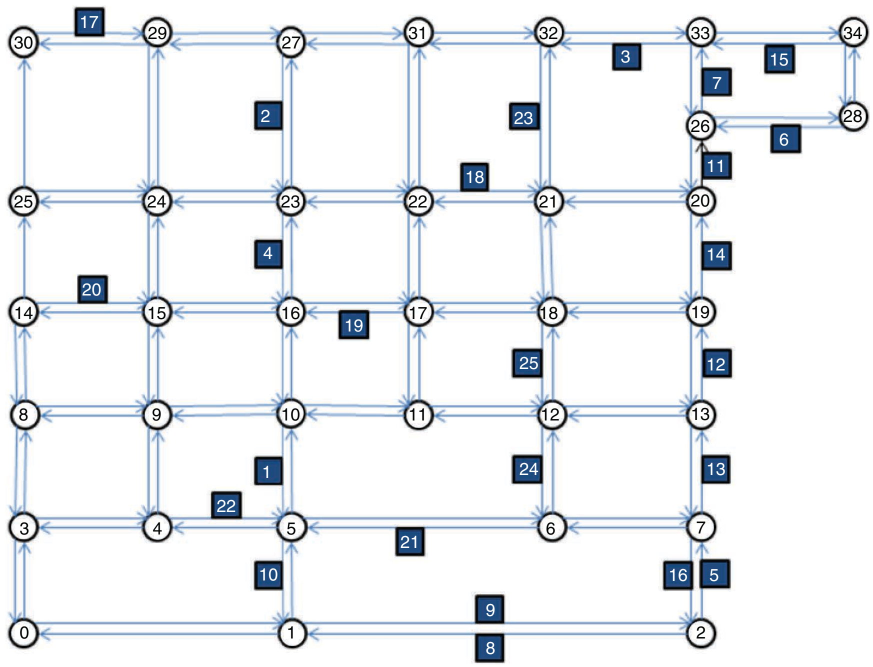


FIGURE 4 Results of VMS locations when $\alpha_m = \beta_m = 0.6$.

number of the selected roads for VMS installation from the set of high-class roads will be increased. Accordingly, the location order is changed. Such roads with relatively low flows but belonging to the high class will be preferentially selected for VMS installations. Meanwhile, since the percentage range of traffic flows will be extended with the increase in the value of parameter β_m, the number of selected roads from the set of traffic flows will be increased, which implies that the roads with larger v_i will be preferentially selected as VMS locations. Obviously, the range of road class and flow can be respectively controlled by adjusting the parameters α_m and β_m. This is equivalent to adjusting the weights of different attributes indirectly.

CONCLUSIONS

The strategic decision for effectively deploying VMS is of key interest for both long-term planning and short-term operation. However, transportation agencies still highly rely on experience and subjective judgment for VMS locations. To address this issue rigorously, this paper proposed a method for finding a location order in which to deploy VMSs. Features of the proposed approach are as follows: (*a*) a set of roads with a certain order can be obtained with the proposed algorithm; (*b*) not only are common attributes such as road classes, traffic flow, and amount of information considered, but also the attribute of information attenuation; (*c*) the weights of various attributes can be adjusted indirectly by changing the values of the related parameters.

Evaluating the resulting VMS locations in terms of systematically alleviating traffic congestions is necessary, but it is also difficult because of the complexity of the network systems and various exogenous factors, such as seasonal impacts and autonomous travel developments. Although many publications exist on evaluation methods for VMSs (*29–33*), applying these methods for Beijing's case may not be easy. To collect data for the evaluation, a variety of techniques should be applied, including mail-back surveys, collection of traffic data before and after the introduction of the signs, logging of VMS messages, observation of traffic on the underlying network, and interviews with involved parties, such as drivers and police. Such future work is expected using a microscopic traffic flow simulation model.

In addition, this study focused on the VMS location problem from the macroscopic perspective of roads and networks. The availability of related traffic data was also taken into account in the selection of such factors. Many complex factors influence the effect of VMS location. The others, such as driver behavior, also have a significant impact on effects of VMS location, which was not considered in this research because of a lack of data. Considering more microscopic factors, such as driver behaviors or responses, is also of interest and will be part of future investigations.

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