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Citation	IEEE Transactions on Intelligent Transportation Systems, 2013, v. 14 n. 1, p. 480-485
Issued Date	2013
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Short Papers

Evacuation Planning Based on the Contraflow Technique With Consideration of Evacuation Priorities and Traffic Setup Time

J. W. Wang, H. F. Wang, W. J. Zhang, W. H. Ip, and K. Furuta

Abstract—Evacuation planning with the contraflow technique is a complex planning problem. The problem is further complicated when more realistic situations such as evacuation priorities and the setup time for the contraflow operation are considered. Such a complex problem has yet to be discussed in the present literature. In this paper, we present a multiple-objective optimization model for this problem and a two-layer algorithm to solve this model. Experiments on three transportation networks with different network scales are presented to show the excellent performance of the proposed model and algorithm.

Index Terms—Contraflow, evacuation, evacuation priority, multiple destinations, planning, single source.

I. INTRODUCTION

Evacuation planning has long been a topic in hazard preparedness and response management [1]–[3], [15]–[20]. The topic has gained a growing interest, owing to events such as the 9/11 terrorist attacks in 2001 and the hurricane in Florida in 2005. In evacuation-planning situations, roads are often partially destroyed, and transportation demands suddenly soar over transportation supplies. Evacuation planning upon such situations is the problem that this paper attempts to tackle. Contraflow is one of the most important methods to cope with this problem in both theory [3] and practice [4]–[9].

However, none of the existing methods in literature has considered the traffic setup time. The setup time is the time needed to reverse a traffic flow and/or to repair a new road. According to Wolshon *et al.* [3], in the U.S., the time needed to reverse one traffic flow can take up to 12 hr, which are quite significant in emergent evacuation. Another shortcoming in the current literature is that there is no consideration of different priorities on evacuees in evacuation planning.

Manuscript received April 25, 2011; revised September 23, 2011, January 2, 2012, and April 17, 2012; accepted May 29, 2012. Date of publication July 6, 2012; date of current version February 25, 2013. The work of H. F. Wang was supported by the National Science Foundation Corporation under Grant 71001018 of China. The work of W. J. Zhang was supported by the Natural Sciences and Engineering Research Council of Canada through a Strategic Project Grant on resilience engineering program. The Associate Editor for this paper was F.-Y. Wang.

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Digital Object Identifier 10.1109/TITS.2012.2204402

In this paper, we address these shortcomings and, particularly, propose a model that incorporates setup time and evacuation priorities. The different priorities considered in this paper are the following: 1) There are victims with different categories in one place, and 2) there is more than one safe place for victims to be transported. The model is solved by the proposed algorithm.

It should be noted that the evacuation problem under the aforementioned scenarios considerably differs from the case without consideration of setup time. In particular, without consideration of setup time, the solution to the problem is not unique; that is to say, there could be more than one flow pattern to achieve the same optimality, whereas with consideration of setup time, a unique optimal solution to the problem is achieved. This point will be further revealed in a later discussion.

In the following, first, we present a conceptual model to our problem and then an optimization model, followed by an algorithm to solve the optimization model. Finally, there is a conclusion with discussion of limitations of and future extension to this paper.

II. CONCEPTUAL MODEL OF THE PROBLEM

A. Transportation System

In our problem, there is one place in a dangerous area (single source) where there are a few categories of victims that are to be evacuated to a number of safe places. This problem may also be called the single-source and multiple-destination problem. There is a traffic network between the source and the multiple destinations. The traffic network system is composed of a set of places and a set of roads. Each road has lanes that have either directions, and these lanes are grouped in terms of their directions, so eventually there are two groups on the road. We further consider a road that has all its lanes in one direction as a special case of the general case that a road has two groups of lanes and they have the opposite directions. Each lane has a capacity and a travel time. The capacity of a lane is defined as the maximum number of evacuees who can be transported per unit period, and the capacity is given in this paper. Each edge also has a capacity and a travel time. The capacity of an edge is the sum of all lanes in this edge. The travel time of an edge is equal to the travel time of each lane in this edge.

B. Evacuation Demands

The victims on the source place are classified into different categories, as mentioned before. The classification of victims leads to the classification of destination places in such a way that the victims of the same category will be evacuated to the same corresponding destinations. For instance, the people who are injured need to be sent to the hospital, and the people without injury need to be sent to normal safe places. The priority of victims to be evaluated will depend on their urgency. For instance, the seriously injured victims need to be evacuated first.

C. Flow Pattern Planning

Evacuation planning in our case is thus flow pattern planning in essence. To meet the demand of evacuating different categories of victims, we need first to plan the flow pattern for the victims in the first category, then for the victims in the second category, and so on.

Usually, the best flow patterns for the victims of different categories are different. We assume that the flow pattern for the k th category of victims in the k th period is not changed during the time that the victims of the k th category are being evacuated. To adequately make use of the transportation network, during the k th period of the evacuation process, aside from evacuating the k th category victims, the victims whose priorities are less than the k th category are also evacuated whenever possible.

D. Objectives of Evacuation Planning

In our problem, flow patterns change with respect to different categories of victims during the whole evacuation process. This implies that setup time changes one flow pattern to another. Note that setup time can take 4 to 12 hr in most of the U.S. [3]. Therefore, our problem has two specific objectives: 1) to minimize the time to move evacuees to a safe area given a flow pattern in each period and 2) to minimize the setup time for flow patterns. It is noted that the two objectives have a conflict, as the first objective essentially requires changing the flow pattern, which thus increases setup time, whereas the second objective is in favor of no change of the flow pattern. Therefore, our problem is a multiple-objective optimization problem.

III. MATHEMATICAL MODEL OF THE PROBLEM

In this section, we give the mathematical model of the problem. The definitions of all variables are listed first for the convenience of readers. Then, we will discuss the key elements in our model.

A. Definition of Variables

$G = (N, A)$	Directed network with N as the set of nodes and A as the set of arcs (static network).
m	$= N $, number of elements in set N .
n	$= A $, number of elements in set A .
c_{ij}	Capacity of arc (i, j) .
λ_{ij}	Travel time of arc $(i, j) \forall (i, j) \in A$.
a_i	Node capacity, i.e., how many evacuees can stay in node i .
S	Source node.
Q	Category number of evacuees.
q_k	Initial number of evacuees of the k th category in node $s, k = 1, \dots, Q$.
$pred(i)$	$= \{j (j, i) \in A\}$, predecessors of node i .
$succ(i)$	$= \{j (i, j) \in A\}$, successors of node i .
D_k	Set of destinations that receive the evacuees of the k th category, with $k = 1, 2, \dots, Q$.
D	Set of destinations $D_k \subset D, k = 1, 2, \dots, Q$.
$G_T = (N_T, A_T)$	Time expansion of $G(N, A)$ over time horizon T , where T is the predetermined upper bound of the total travel time.
N_T	$= \{i(t) i \in N; t = 0, 1, \dots, T\}$.
A_T	Set of arcs over time horizon T .
D	Super destination node.
$f_{ijk}(t)$	Flow (number of evacuees) of the k th category that leaves node i at time t and reach node j at time $t + \lambda_{ij} \forall i, j \in N, k = 1, \dots, Q$.
$y_i(t+1)$	$= \sum_{k=1}^Q f_{i(t), i(t+1), k} \forall i \in N, t = 0, \dots, T$, number of evacuees who prefer to stay in node i at time t for at least one unit time.
x_{ij}^k	State of flow from i to j on arc (i, j) during the k th period, $k = 1, \dots, Q$.

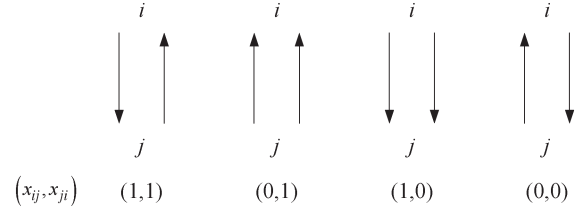


Fig. 1. Definition of the domain of the variable to represent the flow patterns on a single road.

(x_{ij}^k, x_{ji}^k) Flow pattern between nodes i and j during the k th period, $k = 1, \dots, Q$.
 $F(k)$ $= \{(x_{ij}^k, x_{ji}^k) | \forall (i, j) \in A\}$, flow pattern of the network during the k th period, $k = 1, \dots, Q$.

The decision variable of this model is $F(k)$.

B. Model

1) *Flow Pattern*: The road is composed of two groups of lanes. x_{ij}^k represents a lane from node i to node j in the k th period. $x_{ij}^k = 1$ represents the flow from i to j , and $x_{ij}^k = 0$ represents the flow from j to i . As such, the state of the road connecting place i and place j during the k th period can be expressed by (x_{ij}^k, x_{ji}^k) ; in particular, there are four states, as shown in Fig. 1. It is noted that the roads connected with the source node and the destination nodes are both represented by $(1, 0)$. Let the node in the graph model represent place and intersection and the arc in the graph model represent road. A transportation network can then be represented by a directed graph $G = (N, A)$, where N is a set of m nodes and A is a set of n arcs. A flow pattern or configuration is defined as a snapshot of network G . Note that each node has a capacity and each arc also has both capacity and constant travel time.

2) Objective functions:

a) *First objective function*: The total evacuation time of the k th category victims (TET_k) is defined as a period of time from the moment when the first evacuee of the k th category leaves from a source node to the moment when the last evacuee of the k th category arrives at a destination node. TET_k can be expressed by

$$TET_k = \left\{ T \mid f_{ijk}(t) = 0 \forall t > T \right\} \quad (1)$$

where $f_{ijk}(t)$ is the flow (number of evacuees) of the k th category that leaves node i at time t and reaches node j at time $t + \lambda_{ij} \forall i, j \in N, k = 1, \dots, Q$, and λ_{ij} is the travel time of arc $(i, j) \forall (i, j) \in A$.

Assume that, in the beginning, there are several categories of victims on a certain node. With consideration of the priorities of different categories of victims, the first objective of our model is to find flow patterns to minimize evacuation time of the k th category of victims ($k = 1, 2, \dots, Q$), i.e., TET_k , based on minimizing TET_{k-1} , which can be formulated as (2). In particular, TET_k in the special case $k = 0$ is defined as

$$F_1(k) = \{TET_k | \min TET_{k-1}\}, \quad k = 1, \dots, Q. \quad (2)$$

The second objective function: The second objective is to minimize the setup time of contraflow. It is noted that the setup time is proportional to the number of lanes that need to be reversed. Therefore, minimization of the setup time equals minimization of the total number of lanes to be reversed. The second objective function can thus be expressed by

$$F_2(k) = \sum_{\forall (i,j) \in A} x_{ij}^{k-1} \oplus x_{ij}^k, \quad k = 1, \dots, Q \quad (3)$$

where \oplus denotes XOR operation, i.e., $x_{ij}^{k-1} \oplus x_{ij}^k$ means lane x_{ij} needs to be reversed for the k th category.

C. Objective Functions and Constraints

$$\min F_1(k) = \{TET_k | \min TET_{k-1}\}, \quad k = 1, \dots, Q \quad (4)$$

$$\min F_2(k) = \sum_{\forall(i,j) \in A} x_{ij}^{k-1} \oplus x_{ij}^k, \quad k = 1, \dots, Q \quad (5)$$

$$\text{s.t. } TET_k = \{T | f_{ijk}(t) = 0 \quad \forall t > T\}$$

$$k = 1, \dots, Q, \quad TET_0 = 0 \quad (6)$$

$$x_{ij}^k = 0, 1 \quad \forall(i, j) \in A, \quad k = 1, \dots, Q \quad (7)$$

$$\bar{x}_{ij}^k = \begin{cases} 0, & x_{ij}^k = 1 \\ 1, & x_{ij}^k = 0 \end{cases} \quad \forall(i, j) \in A, \quad k = 1, \dots, Q \quad (8)$$

$$\sum_{t=0}^T \sum_{i \in \text{succ}(s)} f_{sik}(t) = q_k, \quad k = 1, \dots, Q \quad (9)$$

$$\sum_{t=0}^T \sum_{i \in D_k} f_{idk}(t) = q_k, \quad k = 1, 2, \dots, Q \quad (10)$$

$$y_i(t+1) - y_i(t) = \sum_{l \in \text{pred}(i)} \sum_{k=1}^Q f_{lik}(t - \lambda_{li}) - \sum_{j \in \text{succ}(i)} \sum_{k=1}^Q f_{ijk}(t) \quad \forall i \in N, \quad t = 0, \dots, T \quad (11)$$

$$y_i(0) = 0 \quad \forall i \in N, \quad i \neq s \quad (12)$$

$$y_i(t) = 0 \quad \forall i \in D, \quad t = 0, \dots, T \quad (13)$$

$$0 \leq y_i(t) \leq a_i, \quad t = 1, \dots, T \quad \forall i \in N - D \quad (14)$$

$$0 \leq \sum_{k=1}^Q f_{ijk}(t) \leq x_{ij}^k c_{ij} + \bar{x}_{ij}^k c_{ji},$$

$$t = 0, \dots, TET_k - \lambda_{ij} \quad \forall(i, j) \in A, \quad k = 1, \dots, Q \quad (15)$$

$$x_{si}^k = 1, x_{is}^k = 0 \quad \forall(s, i) \in A, \quad k = 1, \dots, Q \quad (16)$$

$$x_{ij}^k = 1, x_{ji}^k = 0 \quad \forall(i, j) \in D_k, \quad k = 1, \dots, Q \quad (17)$$

$$x_{ij}^0 = 1 \quad \forall(i, j) \in A. \quad (18)$$

IV. ALGORITHM

Our previous study about flow pattern planning [8], [9] demonstrated that there is more than one flow pattern that achieves the minimum total evacuation time. Therefore, among all the flow patterns that optimize the first objective function, there must be one that optimizes the second objective function. Such a solution is the Pareto optimal solution according to the definition of the Pareto optimal solution. This observation leads to the algorithm proposed in this paper to this two-objective model, which, in particular, has two layers. The lower layer is to find the evacuation time, given a flow pattern. The upper layer is to find Pareto solution based on the result of the first layer.

A. Lower Layer Algorithm

The lower layer algorithm, which is called priority-based minimum cost multicommodity flow (P-MCMF) algorithm, is to seek the minimum flow time for multicommodities, given a flow pattern. The main ideas of the P-MCMF algorithm are given as follows: 1) During the k th period of the evacuation process, evacuate all the k th category victims as soon as possible, which has the same function as any existing minimum cost flow algorithm, and 2) at the same time, the k' th ($k' = k + 1, \dots, Q$) category victims are evacuated to be as many as possible. The second idea here implies that the transportation network may have an ability to evacuate the k' th ($k' = k + 1, \dots, Q$) category victims when evacuating the k th category victim.

B. Upper Layer Algorithm

The upper layer algorithm is the so-called three-pattern particle swarm optimization (TPSO). TPSO is a novel discrete version of PSO for multiobjective optimization. It is designed by adding different particle flying patterns and a novel fitness evaluation method into the original PSO [10], [11]. The main ideas of TPSO are given here.

- 1) Three flying patterns: Every particle has three different flying patterns, i.e., standard pattern, dimension-decreasing pattern, and dimension-increasing pattern, respectively.
- 2) The memory of the multiobjective information: When flying, the particles consider the two different objectives at the same time, instead of only one objective in the standard PSO, and each particle decides its flying patterns in each iteration according to the two fitness values.
- 3) The synchronous procedure for fitness evaluation: In each iteration, immediately evaluate a particle after it has been updated, instead of after the whole swarm has been updated.
- 4) The self-adaptive control mechanism for time horizon T : Time horizon T , i.e., the predetermined upper bound of the total travel time, is updated by the latest TET got by far, which has an important effect on the running time of the algorithm.

V. EXPERIMENT

A. Example Problem Definition

Three cases are given in this section (seven places and 11 roads in the first case, 11 places and 15 roads in the second case, and 19 places and 30 roads in the third case) to test the effectiveness of our model and the performance of the proposed algorithm. Assume that there are two categories of evacuees and two corresponding categories of destinations, the number of victims in the first category is 15, and the number of victims in the second category is 93. As a result, in each case, there are two periods during the whole evacuation, and there are different flow patterns for the different periods. In the following, we only give the details of the network of case 1.

Fig. 2 shows the first case, which has seven places and 11 roads. The capacity of the place is represented by a bracket “{ },” e.g., the capacity of Place 1 is 120; furthermore, in Fig. 2, the “-” in the bracket adjacent to Place 6 and Place 7 means that Place 6 and 7 are two shelters, and their capacities are regarded as infinitely large. The capacity and travel time of the lane are indicted on the arc by a parenthesis “().” For example, Lane 1- > 2 has travel time 2 and capacity 1, and Lane 2- > 1 has travel time 2 and capacity 2 (see Fig. 2).

Furthermore, Place 1 is a source node, and Place 6 and 7 are sink nodes. Place 1 has two categories of evacuees. The victims in the first category must be evacuated to Place 6, and the victims in the second category must be evacuated to Place 7. Furthermore, according to the constraint equations (17) and (18), we have already known that

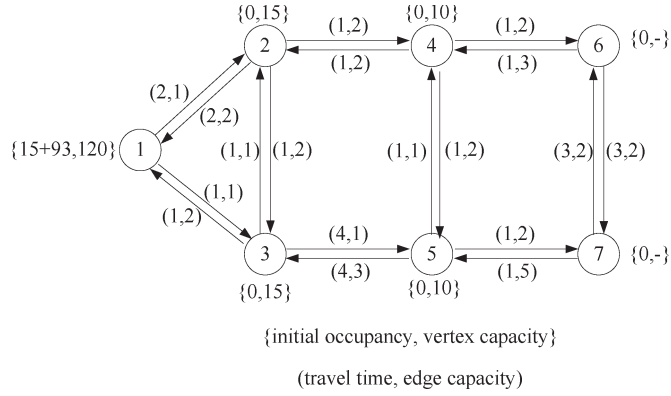


Fig. 2. Example transportation system of case 1. (The source node is 1; the destination node for the first category is 6, and that for the second category is 7.)

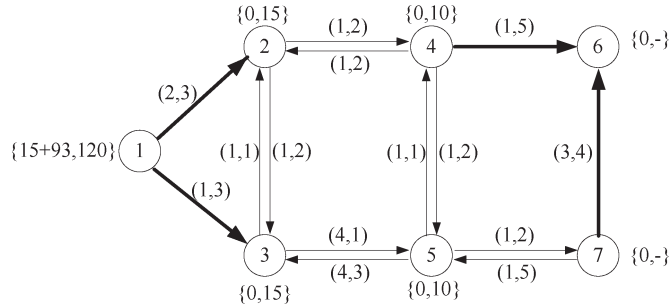


Fig. 3. Predefined transportation network of case 1 for the first category victims.

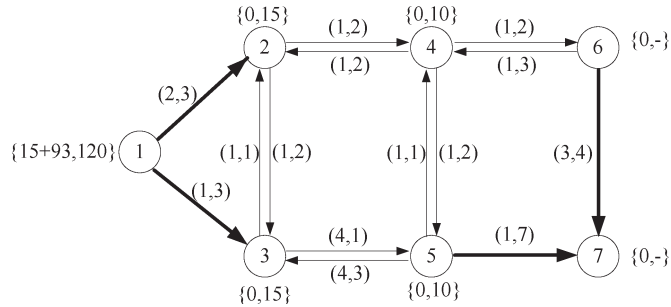


Fig. 4. Predefined transportation network of case 1 for the second category victims.

the flow patterns for arc (1,2), (1,3), (4,6), and (6,7) during the first evacuation period should be the one, as shown in Fig. 3, and the flow patterns for arc (1,2), (1,3), (5,7), and (6,7) during the second evacuation period should be the one, as shown in Fig. 4. This implies that these arcs are no longer a decision variable.

In the experiment, we consider three different methods to evacuate: 1) original transportation network; 2) predefined networks in which the flow patterns of those arcs connecting from the source node to the destination nodes are set as those in Fig. 3 and Fig. 4; and 3) transportation network with flow pattern planning. We have the following settings: 1) the swarm sizes in PSO, $m = 5, 10$ for cases 1 and 2 and period 1 in case 3; $m = 5, 10, 20, 30$ for period 2 in case 3; 2) the maximum iteration number in PSO, $NG = 10$ for case 1; $NG = 100$ for case 2; $NG = 500$ for case 3; 3) the inertia weight in PSO (ω) linearly decreases from 1 to 0.1. The whole algorithm is programmed by java, and the experiment is performed on a computer

TABLE I
EVACUATION RESULTS

	Case 1		Case 2		Case 3	
	Period 1	Period 2	Period 1	Period 2	Period 1	Period 2
O	f_1	f_2	f_1	f_2	f_1	f_2
ON	11	0	62	0	13	0
PN	9	4	44	3	12	4
FPP	7	5	27	4	9	7
TR	36.36%	56.45%	30.77%	43.14%	28.57%	53.33%

O = Objectives, ON = Original network, PN = Predefined network; FPP = Flow pattern planning, TR = Time reduced (%).

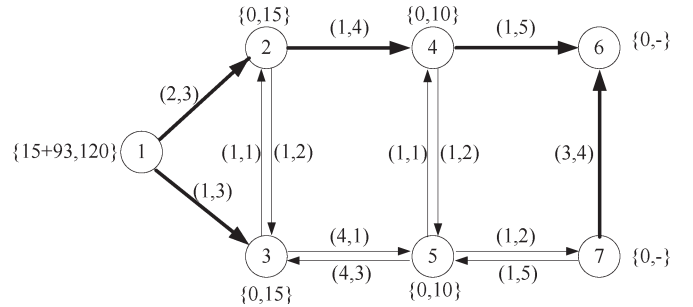


Fig. 5. Optimal flow patterns for the first category victim in case 1.

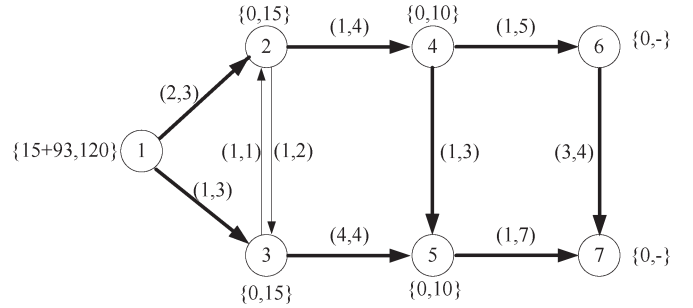


Fig. 6. Optimal flow patterns for the second category victim in case 1.

with a dual-1.66-GHz central processing unit and a 1.5-GB memory. The algorithm runs 50 times for each case.

B. Results and Discussion

The result of the evacuation performance of the three network settings is listed in Table I. The detail of the best flow patterns for each category in case 1 is shown, respectively, in Figs. 5 and 6. It can be seen from Table I that, in the three cases, the total evacuation times (TET s) of the first category with flow pattern planning significantly decrease in comparison with those with the original network, 36.36%, 30.77%, and 28.57%, respectively. The TET s of the second category with flow pattern planning also dramatically drop as opposed to those with the original network by 56.45%, 43.14%, and 53.33%, respectively.

Next, we examine the performance of the proposed algorithm. The success rates and the average run times for the two evacuation periods of the three cases are listed in Table II. The transportation network in case 1 is a small-size network. From Table II, we can see that PSO with two different sizes (5 and 10, respectively) can both achieve 100% success rate within ten iterations for the two evacuation periods. This result implies that a very small swarm size, e.g., $m = 5$, is enough to

TABLE II
PERFORMANCE OF THE ALGORITHM

m		Case 1		Case 2		Case 3	
		P 1	P 2	P 1	P 2	P 1	P 2
5	SR	1	1	1	1	1	76%
	RT	0.022	0.625	0.200	4.917	2.767	89.728
10	SR	1	1	1	1	1	84%
	RT	0.039	1.060	0.222	5.886	3.005	109.145
20	SR	-	-	-	-	-	96%
	RT	-	-	-	-	-	129.033
30	SR	-	-	-	-	-	1
	RT	-	-	-	-	-	117.375

P = Period, SR = Success rate, RT = Run time (s).

get a very good performance for this case. It should be noted that the average run time of the algorithm is related to the number of evacuees. The large number of evacuees results in the large size of the time expanded static network for the same dynamic network. For example, there are about ten time units in the first period of case 1, which means that the time expanded network in the first period has about 78 nodes; there are about 30 time units in the second period of case 2, which means that the time expanded network in the second period has about 218 nodes. The difference of the sizes of the two time expanded networks results in significant difference of the average run times of periods 1 and 2 in case 1, 0.022 and 0.625 s ($m = 5$), respectively. When getting 100% success rate, the average run time with ten particles is almost twice that with five particles, so swarm size 5 is a better choice for case 1.

The number of nodes of the transportation network in case 2 increases to 11. The results in Table II show that PSO can find the optimal solutions for the two evacuation periods, and the corresponding average run times are about 0.2 and 5 s, respectively. The little difference between the average run times with the two swarm sizes indicates that either of the swarm size is fit for the optimization of flow pattern planning in case 2.

Compared with cases 1 and 2, case 3 has a transportation network with a relatively large size. The results in Table II indicate that a small swarm size, e.g., 5 and 10, can get 100% success rate for period 1 in case 3. The average run times with swarm size 5 and 10 for period 1 are 2.767 and 3.005 s, respectively. For the optimization of the second period in case 3, swarm size 5 or 10 cannot get very high success rate. Therefore, we further conducted the experiment with another two relatively bigger swarm sizes, i.e., 20 and 30, for the second period. Results show that PSO with the swarm size 20 and 30 can obtain more than 95% success rate within 500 iterations and average run times are 129.003 and 117.375 s, respectively. It should be noted that, here, we take a relatively restricted standard to evaluate the performance of the algorithm. Usually, 50% is a good success rate for the big-size optimization problem. From this point of view, even with small swarm sizes, e.g., 5 and 10, PSO can achieve satisfying performance for case 3.

The computer running time of our proposed algorithm mainly come from the iterations of PSO, which has much better potential to find the global optimum than simple heuristic algorithms. It should be noted that, however, since PSO is a stochastic searching algorithm, it is hard to predict the time complexity of the proposed algorithm because of three coupled factors: 1) the size of the transportation network; 2) the number of evacuees; and 3) the success rate. The third factor further

shows that the longer the algorithm runs the better solutions can be obtained, and so, one can terminate the algorithm at the time that the solution meets the evacuation demand. As shown in Table II, when we use the same number of evacuees and the success rates are 100%, the average running time of the three cases with seven places and 11 roads, 11 places and 15 roads, and 19 places and 30 roads, are about 1, 6, and 120 s, respectively. This computation time is acceptable because it is much less than the setup time of the contraflow in practice, which is about 4–5 hr.

VI. CONCLUSION

This paper has discussed the problem of evacuation planning for victims with consideration of setup time; different categories of victims, who have different demands for evacuation; and different destinations. To the best of our knowledge, this problem has never been discussed in the literature. We have developed a model to capture these features and developed an algorithm to quite effectively and efficiently solve this model. Our algorithm can achieve the global optimum yet with an acceptable efficiency in terms of computation time. The result of our study may lead to the following conclusions: 1) The proposed two-layer optimization model can capture the characteristics of our problem, particularly with consideration of setup time in contraflow operation, and 2) the modified PSO-based algorithm for the optimization at the two layers is very effective and efficient; besides, they can be applied to many other two-layer optimization problems.

There are some limitations in our work. In evacuation, there may be multiple sources, i.e., victims staying in several different places. A more realistic situation for evacuation is thus multiple sources to multiple destinations. In this paper, we only considered single source to multiple destinations. However, a network with multiple sources and multiple destinations can easily be converted to a network with a single source and a single destination according to [12]. Another limitation is that we have not considered the flow of emergency vehicles, which share the transportation infrastructure with the victims as well. Inclusion of the emergency vehicles is a more realistic scenario worthy of future study.

Finally, evaluation usually takes place in the event of natural disasters such as flooding (e.g., flooding happens every year at the province of Saskatchewan, Canada, and the provincial emergency department has to evacuate victims every year). In such events, it often happens that some roads are damaged perhaps partially. In this case, evacuation planning may need to consider the option of recovery of the damaged roads. This further leads to a concept recently proposed called "resilience," which is an ability of the system to recover its function when it is partially damaged [13], [14]. In connecting resilience with the road or transportation system in general, there is an issue of how to design the transportation system with high resilience property, and future research should be directed to study this issue.

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A New Approach to Video-Based Traffic Surveillance Using Fuzzy Hybrid Information Inference Mechanism

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Abstract—This study proposes a new approach to video-based traffic surveillance using a fuzzy hybrid information inference mechanism (FHIM). The three major contributions of the proposed approach are background updating, vehicle detection with block-based segmentation, and vehicle tracking with error compensation. During background updating, small-range updating is adopted to overcome environmental changes under congested conditions. During vehicle detection, the proposed approach detects the vehicle candidates from the foreground image, and it resolves problems such as headlight effects. The tracking technique is employed to track vehicles in consecutive frames. First, the method detects edge features in congested scenes. Next, FHIM is employed to determine the tracked vehicles. Finally, a method that compensates for error cases under congested conditions is applied to refine the tracking qualities. In our experiments, we tested scenarios both inside and outside the tunnel with three lanes. The results showed that the proposed system exhibits good performance under congested conditions.

Index Terms—Congested condition, traffic surveillance, vehicle detection, vehicle tracking.

I. INTRODUCTION

The use of vehicles for transport is rapidly increasing with improvement in our quality of life. However, such an increase in the use of vehicles compounds traffic problems. Therefore, intelligent transportation systems have become very popular research fields. To monitor traffic, vision-based traffic surveillance is one of the most popular methods, and comprehensive and up-to-date surveys are provided in [1] and [2].

Although many surveillance methods have been presented, two problems still need to be solved in congested situations, especially inside tunnels. First, the low angle of the camera means that vehicles are easily connected visually in images. Therefore, occluded vehicles need to be separated to achieve detection accuracy. Second, the background updating in congestion is important because of the cover of vehicles. In this brief, we propose three methods for resolving these problems. First, a modified background-updating procedure is proposed to smoothly update a background image during congestion. Second, occluded vehicles are segmented based on their interinformation. Third, tracking verification is performed by our proposed fuzzy hybrid information inference mechanism (FHIM), where compensation is invoked when the comparison result is dissimilar.

This brief is organized as follows: Section II describes related works. Section III describes the background extraction and updating procedure. Vehicle extraction and vehicle tracking are addressed in Sections IV and V. The experimental results are presented in Section VI, and finally, our conclusions are stated in Section VII.

Manuscript received January 19, 2012; revised April 16, 2012; accepted June 19, 2012. Date of publication August 9, 2012; date of current version February 25, 2013. This work was supported by the National Science Council, Taiwan, under Grant NSC 100-2221-E-009-041. The Associate Editor for this paper was J. Zhang.

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Digital Object Identifier 10.1109/TITS.2012.2208190