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A New Efficient Algorithm for Hazardous Material Transportation Problem via Lane Reservation

ZHEN ZHOU[1], WEIDONG LEI[2], PENG WU[3], BO LI[4], AND YUNFEI FANG[3,5]

[1]School of Management, Northwestern Polytechnical University, Xi'an 710072, China
[2]School of Management, Post-Doctoral Research Station of Mining Engineering, Xi'an University of Science and Technology, Xi'an 710054, China
[3]School of Economics and Management, Fuzhou University, Fuzhou 350108, China
[4]Glodon Technology Inc., Xi'an 710032, China
[5]Laboratoire IBISC, Université Évry Val d'Essonne, 91025 Évry, France

Corresponding author: Yunfei Fang (yf.fang@fzu.edu.cn)

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ABSTRACT Hazardous material transportation is well-known for its high potential risk. Minimizing the transportation risk is an important issue for hazardous material transportation. This paper focuses on a novel algorithm for the hazardous material transportation problem via lane reservation, whose goal is to obtain a best compromise between the impact on normal traffic due to lane reservation and the transportation risk. Firstly, a bi-objective integer programming model for the considered problem is formulated and transformed into a series of single objective models by ε-constraint method. For the transformed single objective models, a cut-and-solve and cutting plane combined method is proposed to reduce the computational time. The performance of the proposed algorithm is evaluated by an instance using a real network topology and randomly generated instances. Computational results demonstrate that the cut-and-solve and cutting plane combined method runs faster than direct use of software package CPLEX.

INDEX TERMS Lane reservation, cut-and-solve method, cutting plane, transportation risk.

I. INTRODUCTION

It is well known that there are a large number of hazardous material shipments on highways every day. Many factors, such as weather, traffic condition, the type of trucks, the nature of cargo, could lead to hazardous material transportation accidents. Hazardous materials in transit can be regarded as dynamic hazards because of their own harmfulness. In spite of the low probability of hazardous material accidents, the public remains to pay close attention to hazardous material shipments, due to the high consequences of the potential accidents. Once a hazardous material transportation accident occurs, it can bring about disastrous consequences on the economy, public life and health, and even environment in a wide area over the long term. In fact, various measures are consequently taken in order to effectively prevent the occurrence of serious hazardous material transportation accidents. For example, governments enact some laws on hazardous material transportation and provide guidelines and specific requirements on it; as well as they try to design appropriate routes or/and time intervals for hazardous material shipments with the minimum transportation risk.

Meanwhile, in academia, researchers have begun to focus on hazardous material transportation problems. As we know, risk is the primary ingredient that distinguishes hazardous material transportation problems from others. Therefore, in hazardous material transportation management, it is essential to mitigate the transportation risk. Reducing the transportation risk can be achieved by selecting a proper path for each shipment between its given origin-destination (OD) pair in the transportation network for a given type of hazardous material, transport mode, and vehicle type, which is called as hazardous material routing problem. Hazardous material routing problem is usually a multi-objective optimization problem due to its nature of multiple stakeholders, e.g., Kalelkar and Brinks [1], Ma [2], Huang et al. [3]. Iakovou [4] investigated such a classical hazardous material routing problem that intended to minimize the transportation risk and the transportation cost. In his problem, shipments were considered independently from a carrier's perspective and a routing

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decision needed to be made for each shipment. Ma et al. [5] developed a multi-objective model with adjustable robustness for the hazardous material transportation problem with a single distribution center. Based on the characteristics of the proposed model, a multi-objective genetic algorithm was designed to solve it.

However, clearly different from the carriers, the authorities pay close attention to reduce the transportation risk by confining hazardous material trucks to a subset of available road segments. That is, shipment routes are designated for them. Erkut and Alp [6] designed such a hazardous material transportation network, in which there were two actors: the local government and the carriers. The former, primarily interested in risk minimization, would designate a subnetwork, while the latter, primarily interested in cost minimization, would choose the routes in the subnetwork. Once the government identified the subnetwork, the carriers would take least-cost routes between origin and destination on this subnetwork. In fact, it is also a bi-level problem from different stakeholders' perspectives, which is called hazardous material network design problem. They considered it as a Steiner tree selection problem. Based on the topology of this tree, the bi-level problem was converted into a single level one by prohibiting the carriers to select routes. However, this way might result in circuitous and high-cost routes. For avoiding the disadvantage, they added edges to the Steiner tree. They also proposed a greedy heuristic, in which shortest paths were added to the tree so as to keep the transportation risk increase to a minimum. Esfandeh et al. [7] formulated a time-dependent hazardous material network design problem using an alternative-based model, in which each alternative represented a combined path and departure-time choice. Heuristic algorithms based on column generation and label setting were presented for the extended model.

In recent three decades, hazardous material location and routing problem (LRP) has been also widely focused on by many researchers, for example, Current and Ratick [8], Alumur and Kara [9], Xie et al. [10], Boyer et al. [11], Zhao and Verter [12], Yilmaz et al. [13], Rabbani et al. [14]. The earliest hazardous material LRP work was done by Shobrys [15] on locating the storage facilities and selecting routes for the spent fuel shipments so as to simultaneously minimize the total transportation cost and total transportation risk. It is likely that List and Mirchandani [16] firstly considered minimizing risk equity as one of the objectives of their hazardous material location and routing model. Aydemir-Karadag [17] introduced a profit-oriented model for hazardous waste LRP model, which incorporated the energy recovery from waste and the application of the polluter pays principle. Hu et al. [18] presented a multi-objective LRP model for hazardous material logistics with traffic restriction constraint. A single genetic algorithm and an adaptive weight genetic algorithm were also proposed to solve the proposed model respectively.

One feasible way of decreasing the transportation risk is to reserve special lanes for hazardous material shipments. As we know, in the transportation network, risk varies with traffic flow and road structure etc. The strategy of lane reservation is to provide dedicated lanes for certain purpose of transportation, such as automated freight transportation and public bus transportation. It is proved that dedicated lanes can ensure a relative safe and rapid traffic environment, and the transportation with special purposes can be guaranteed. A realistic example of the lane reservation strategy was applied in Asian Games in 2010 in Guangzhou, China, to guarantee the corresponding sportive transportation. The concept of lane reservation has demonstrated its potential applications in future. More extensive studies about its application can be found in [19]–[24].

On the other hand, hazardous material transportation via dedicated lanes will make the overall traffic flow on these lanes more homogeneous and smoother, which may lead to a potential decrease in the probability of accidents [25]. However, it may worsen traffic conditions for other vehicles. Delicate analysis is as follows. If one of lanes on a road segment is chosen for a reserved lane, the other(s) are accordingly regarded as the general lane(s). Thus, the number of general lanes will decrease, which may cause the general lanes more congested and worsen traffic situation on the network. The most direct impact of reserved lanes on public traffic is the increase in the travel time on the general lanes. Therefore, it is important to effectively select lanes to be reserved in the existing transportation network so as to minimize the total traffic impact on the network. From the above analysis, the hazardous material transportation problem via lane reservation can be considered as a multi-objective problem with at least two objectives: minimizing the total transportation risk and the total traffic impact.

Zhou et al. [26] investigated a hazardous material transportation problem via lane reservation (HMTLR), which lied in how to choose lanes to be reserved in the transportation network and select the routes for each hazardous material shipment from the reserved lanes. Its objectives were to minimize the total impact due to lane reservation and minimize the total transportation risk. A multi-objective integer programming (IP) model was formulated and an ε-constraint method was employed for the proposed problem. With the ε-constraint method, the proposed problem was transformed into a series of single objective IP problems, which were solved by a commercial optimization software package CPLEX. It is well known that the performance of the ε-constraint method depends on the solution time of the transformed single objective IP problems. However, although CPLEX was able to optimally solve these problems, their consumption time was a big burden for medium and large size instances. So it is necessary to resort to other efficient algorithms for these single objective problems based on their properties, with which it may be possible to solve larger size problems within a shorter consumption time. Therefore, this paper deals with the single objective IP problem transformed from multi-objective HMTLR, and develops an efficient method based on some analytical properties for solving the problem.

Cut-and-solve method was firstly proposed by Climer and Zhang for combinatorial optimization problems and it was proved that this method was very effective for Asymmetric Traveling Salesman Problem [27]. As described in the literature, the cut-and-solve method has two favorable properties. Firstly, unlike the traditional tree searches, the cut-and-solve search has a search path without branching. That means that there are no "wrong" subtrees in which the search may get lost. In addition, the cut-and-solve search consumes very little memory space so that its memory requirement can be neglected. Due to these properties, the cut-and-solve method has high potential for problems that are difficult to solve using depth-first or best-first search tree methods. In this paper, to reduce the computational time of the transformed single objective problems, we propose a new cut-and-solve and cutting plane combined method for the problems.

In brief, the main contributions of this paper include the following. Firstly, we develop two elaborate properties of the considered problem to cut down its solution space without loss of its optimality and thus decrease the computational time. Secondly, we propose a new cut-and-solve and cutting plane combined method for the considered problem, in which a cutting plane method is embedded in the cut-and-solve method to obtain better lower bounds and consequently accelerate the convergence of the cut-and-solve method. The performance of the proposed algorithm is verified by comparing its computational time with that of CPLEX employed in literature, using the exactly identical instances that are solved on the same computation environment. Finally, we present an effective way of "cutting" technique for the cut-and-solve method, according to the characteristic of the considered problem.

The remainder of this paper is organized as follows. In Section II, we describe the considered problem and formulate it. Section III proposes several properties of the considered problem. On the basis of the properties, a new efficient exact algorithm for the considered problem is presented. Our computational experience and numerical results are given in Section IV. In Section V, we conclude this work.

II. MATHEMATICAL MODEL

A. PROBLEM DESCRIPTION

Let $G = (V, A)$ denote a bi-directed hazardous material transportation network, which is constituted by numbers of nodes and arcs. V and A denote respectively the set of nodes and the set of the arcs that connect the nodes. Accordingly, arc (i, j) represents a road segment from node i to node j. W is the set of hazardous material shipments that start from origins $O \subset V$ to their corresponding destinations $D \subset V$.

In the considered problem, there are two important challenges to be overcome. That is, one side is to choose lanes to be reserved in transportation network, and the other side is to select the path consisted of reserved lanes for each shipment. Both sides can guarantee that each shipment must be finished within its deadline and the transportation risk caused by all the shipments that pass the same road segment cannot exceed its threshold of the accident probability. In the transportation network, if one of the lanes on a road segment is selected as a reserved lane, the other(s) are called the general lane(s). Shipping hazardous materials through the reserved lanes can reduce the probability of accidents. Nevertheless, as mentioned above, lane reservation will probably impact the normal traffic because only special shipment can pass the reserved lanes. The aim of the considered problem is to minimize the total transportation risk and simultaneously minimize the total impact on the normal traffic.

B. ASSUMPTION, NOTATION AND FORMULATION

Before proposing an improved algorithm, we first recall the existing mathematical model proposed in [26], shown as follows.

Assumptions are presented as follows:

1. Both the probability of a hazardous material accident happening on a road segment and the population exposure along the road segment are constant.
2. Potential hazardous material accidents independently happen.
3. There are at least two lanes on a road segment such that one lane can be reserved; otherwise, the impact on the normal traffic will be too heavy.
4. If there is one or more hazardous material shipment passing through a road segment, it is required to reserve a lane on this road segment. That is to say, hazardous material shipments pass only through reserved lanes.

Notations are used here:

T_{ij}: travel time on the reserved lane of arc (i, j)

τ_{ij}: travel time on the general lane of arc (i, j), which is more than T_{ij}

C_{ij}: impact on the normal traffic on arc (i, j) due to lane reservation

M_{ij}: total number of lanes on arc (i, j)

S_w: deadline of accomplishing shipment w

Q_{ij}: threshold of the accident probability on arc (i, j)

P_{ij}^w: accident probability when shipping hazardous material w on a reserved lane of arc (i, j)

π_{ij}^w: accident probability when shipping hazardous material w on the general lane(s) of arc (i, j), which is more than P_{ij}^w

E_{ij}: population exposure along arc (i, j)

Decision variables include:

$$x_{ij}^w = \begin{cases} 1 & \text{if there is a reserved lane on arc } (i,j) \in A \\ & \text{and shipment } w \text{ passes the arc} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if there is a reserved lane on arc } (i,j) \in A \\ 0 & \text{otherwise} \end{cases}$$

The hazardous material transportation problem via lane reservation can be formulated as the following bi-objective integer linear programming model.

As above mentioned, there are two objectives of the considered problem. One of the objectives is to minimize the total impact of all reserved lanes on the normal traffic, where C_{ij} is defined by $\frac{\tau_{ij}}{M_{ij}-1}$ according to [22]. If the lane is not reserved, then $C_{ij} = 0$.

The other objective is to minimize the total transportation risk. The risk of transporting hazardous materials on arc (i, j) can be expressed by the following equation:

$$R_{ij} = P_{ij}E_{ij}$$

where P_{ij} refers to the hazardous material accident probability on arc (i, j) and E_{ij} is denoted by the population exposure within the danger zone along arc (i, j) [28].

Accordingly, the considered problem can be formulated as follows:

Problem P_0:

$$\text{Minimize } f_1 = \sum_{(i,j)\in A} C_{ij}y_{ij} \tag{1}$$

$$\text{Minimize } f_2 = \sum_{W}\sum_{(i,j)\in A} E_{ij}P_{ij}^{w}x_{ij}^{w} \tag{2}$$

$$\text{subject to } \sum_{j:(o_w,j)\in A} x_{o_wj}^{w} = 1, \quad \forall\, w \in W,\ o_w \in O, \tag{3}$$

$$\sum_{i:(i,d_w)\in A} x_{id_w}^{w} = 1, \quad \forall\, w \in W,\ d_w \in D, \tag{4}$$

$$\sum_{j:(i,j)\in A} x_{ij}^{w} = \sum_{j:(i,j)\in A} x_{ji}^{w}, \quad \forall\, w \in W,$$

$$\forall\, i \neq o_w,\ d_w, \tag{5}$$

$$x_{ij}^{w} \leq y_{ij}, \quad \forall\, (i,j) \in A,\ \forall\, w \in W \tag{6}$$

$$\sum_{(i,j)\in A} T_{ij}x_{ij}^{w} \leq S_w, \quad \forall\, w \in W \tag{7}$$

$$\sum_{w\in W} P_{ij}^{w}x_{ij}^{w} \leq Q_{ij}, \quad \forall\, (i,j) \in A \tag{8}$$

$$x_{ij}^{w} \in \{0,1\}, \quad \forall\, (i,j) \in A,\ \forall\, w \in W \tag{9}$$

$$y_{ij} \in \{0,1\}, \quad \forall\, (i,j) \in A \tag{10}$$

Constraints (3) and (4) mean that there is one and only one path starting from its origin and arriving to its destination for each hazardous material shipment, respectively. Constraint (5) ensures the flow conservation, which should be satisfied at all the nodes except for origin and destination. Constraint (6) expresses that if and only if a lane is reserved on arc (i, j), a shipment can pass through the reserved lane on arc (i, j). Constraint (7) guarantees that the total travel time of shipment w cannot exceed its pre-given deadline S_w. Constraint (8) requires that the transportation risk caused by all the shipments that pass arc (i, j) cannot exceed its risk threshold for the sake of risk equity in the spatial distribution. Constraints (9) and (10) specify that 0-1 restrictions on the variables.

III. SOLUTION APPROACH

A. E-CONSTRAINT METHOD FOR THE CONSIDERED PROBLEM

There are several common techniques to solve a multi-objective problem, such as the weighted sum method, the ε-constraint method and meta-heuristics [29]. In the weighted sum method, the multi-objective optimization problem can be transformed into a single objective problem by adding all the objective functions together with different weighting coefficients for each of them. This technique is quite easy to implement. But it has two significant weaknesses. First, it is difficult to determine appropriate weights of the objectives. Second, this method can only find the solutions on the convex hull of the Pareto optimal set. That is to say, it does not work for the non-convex search spaces. As for meta-heuristics, especially evolutionary algorithms, they may be able to find multiple solutions simultaneously in a single run of algorithms. However, their performance is highly dependent on an appropriate selection of initial population. Furthermore, evaluating the evolutionary algorithms fairly and reasonably is also a difficult task. In this paper, the ε-constraint method is used to solve the bi-objective problem. The ε-constraint method can alleviate the difficulties faced by the weighted sum method and Pareto-based evolutionary algorithm. With the ε-constraint method, the bi-objective IP problem P_0 can be transformed into a series of the following single objective IP problems $\mathrm{P}(\varepsilon)$, which has been proved to be NP-hard [26].

$$\text{Problem } \mathrm{P}(\varepsilon): \quad \text{Minimize } \sum_{(i,j)\in A} C_{ij}y_{ij}$$
$$\text{subject to } \sum_{W}\sum_{(i,j)\in A} E_{ij}P_{ij}^{w}x_{ij}^{w} \leq \varepsilon,$$
$$\text{and Constraints (3)-(10).} \tag{11}$$

where ε is an upper limit of the value of f_2.

It is difficult to obtain an appropriate value of ε. However, its range can be obtained and described in [26]. Denote $[f_2^I, f_2^N]$ as the range of value of f_2. Thus, it is divided into K intervals with equal length, and ε can be obtained by the following formula:

$$\varepsilon_k = f_2^N - \frac{f_2^N - f_2^2}{K} * k, \quad k = 0, 1, \ldots, K.$$

Repeatly solve problem $\mathrm{P}(\varepsilon)$, with $\varepsilon = \varepsilon_0, \varepsilon_1, \ldots, \varepsilon_K$, and finally obtain $K + 1$ solutions. These solutions obtained by the ε-constraint method have been proved to be Pareto optimal [29].

B. CUT-AND-SOLVE AND CUTTING PLANE COMBINED METHOD FOR THE SINGLE OBJECTIVE PROBLEMS TRANSFORMED FROM THE CONSIDERED PROBLEM

This section introduces the cut-and-solve and cutting plane combined method to solve the transformed single objective problems P(ε). In this method, two delicate pre-processings are developed to reduce the solution domain based on some properties of the considered problem. Then an effective way of "cutting" technique, which plays very important role in the convergence of the cut-and-solve method, is presented. To obtain better lower bounds, a cutting plane method is embedded in it to tighten the problem.

1) PRE-PROCESSING

Before solving the considered problem, some properties of this problem are analyzed so as to reduce the search space. One natural way is to reduce the search space by fixing the values of some variables in advance, which may help to reduce the solution time.

In Problem P(ε), for $\forall j \in N$, let $t(o_w, j)$ and $t(j, d_w)$ denote the shortest travel durations from o_w to j and from j to d_w in an exclusively reserved path, respectively, where o_w and d_w are the origin node and destination node of shipment w, respectively. Note that $t(o_w, j)$ and $t(j, d_w)$ can be obtained by Floyd's shortest path algorithm.

For $\forall\, w \in W$, define set A_w as follows:

$$A_w = \{j | t(o_w, j) + t(j, d_w) > S_w, \forall\, j \in N\}.$$

We have Property 1:

Property 1: In any feasible solution, shipment w will not pass through any node in A_w.

$$\sum_{i:(i,j)\in A} x_{ij}^w + \sum_{i:(j,i)\in A} x_{ji}^w = 0, \quad \forall\, w \in W,\ \forall\, j \in A_w \tag{12}$$

Proof: Apparently, if shipment w passes through the nodes in A_w, travel time deadline constraint (7) will be violated according to the definition of A_w.

Similarly, let $T_{\max}^{mnw}$ be the maximal shortest travel duration between any two nodes m and n for shipment w in an exclusively reserved path.

For $\forall\, w \in W$, define set B_w as follows:

$$B_w = \{(i,j) | t(m_w, i) + t(j, n_w) > T_{\max}^{mnw} - T(i,j), \forall\, (i,j) \in A\}.$$

We have Property 2:

Property 2: In any feasible solution, shipment w will not pass through any arc in B_w.

$$\sum_{i:(i,j)\in B} x_{ij}^w + \sum_{i:(j,i)\in B} x_{ji}^w = 0, \quad \forall\, w \in W,\ \forall\, (i,j) \in B_w \tag{13}$$

Proof: Assume that there exists an ellipse, denoted as $E(m_w, n_w, T_{\max}^{mnw})$, whose foci are m_w and n_w and major axis is $T_{\max}^{mnw}$. One node of a given arc (i,j) lies outside this ellipse, as shown in Fig. 1.

We can derive (14) from the ellipse property:

$$t(m_w, j) + t(j, n_w) > T_{\max}^{mnw} \tag{14}$$

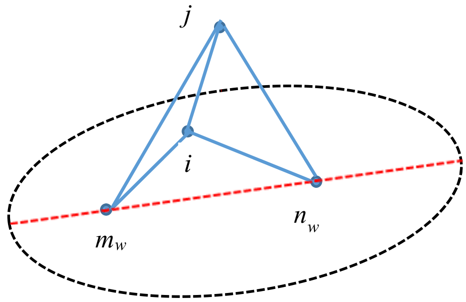

FIGURE 1. An illustration for Property 2.

Due to the bi-directed transportation network, a shipment can pass arc (i,j) in two directions. If shipment w firstly passes through node i, then the total travel duration of shipment w is

$$t_w = t(m_w, i) + T(i,j) + t(j, n_w) \tag{15}$$

The following inequality can be obtained from the triangle inequality property, that is,

$$t(m_w, i) + T(i,j) > t(n_w, j) \tag{16}$$

Then we deduce (17) from (15) and (16)

$$t_w > t(m_w, j) + t(j, n_w) > T_{\max}^{mnw} \tag{17}$$

The inequalities above mean the total travel duration of shipment w would be greater than $T_{\max}^{mnw}$, which implies that arc (i, j) cannot be part of the route of shipment w. In other words, if one node of arc (i, j) lies outside the ellipse, shipment w passes through the arcs in B_w. Thus, we have Property 2. Proof of the case that node j is firstly passed through is the same and it is omitted here. In this paper, we set $T_{\max}^{mnw}$ to be double of the shortest travel duration between m_w and n_w according to a mass of computation.

With the pre-processings, the solution space of Problem P(ε) is reduced without loss of its optimality, because the values of some decision variables are fixed to zero and no feasible solution of P(ε) is excluded. After the pre-processings, a new tightened model P′(ε) is obtained by adding (12) and (13) to P(ε). In next subsection, a cut-and-solve and cutting plane combined method for P′(ε) will be presented.

2) PRINCIPLE OF THE CUT-AND-SOLVE METHOD

Climer and Zhang [27] introduced the cut-and-solve method and expounded detailly its principle. As mentioned above, the cut-and-solve method is a special tree search method without branching steps. For a minimization IP problem, each level has a sparse problem (*SP*) and a remaining problem (*RP*) in the cut-and-solve search tree. The optimal solution of *SP* can be gotten in a short time, as its solution space is relatively small. If an optimal solution of *SP* exists, its optimal value is an upper bound *UB* of the original IP problem. The current best upper bound UB_{min} should be updated if *UB* is smaller than it. The linear relaxation problem of *RP* can be solved easily and provides a lower bound *LB* of *RP*. Apparently,

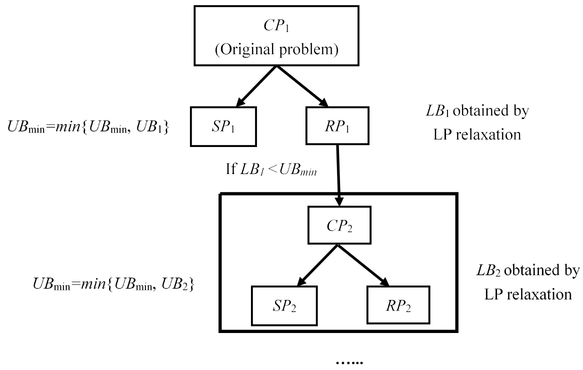

FIGURE 2. An illustration of the cut-and-solve method.

if $LB \geq UB_{min}$, no solution in *RP* will be better than the solution corresponding to UB_{min}. That is to say, the optimal solution of the original problem emerges. Otherwise, a new iteration begins, in which the current *RP* is divided into a new *SP* and *RP* by a constraint associated with piercing cut. Repeat the steps described above until an optimal solution of the original problem is obtained. Fig.2 illustrates the principle of the cut-and-solve method.

SP and *RP* are very important part of the cut-and-solve method, especially piercing cut (PC) plays a key role in the convergence of this method. For example, if *SP*'s solution space, partitioned by piercing cut, is not small enough, it will be difficult to solve *SP* within a reasonable time; on the other hand, if *RP*'s solution space is too small, there may exist no better feasible solutions, and $UB_{\min}$ cannot be updated fast. Consequently, the size of the solution space of *SP* should be appropriate, and the performance of the cut-and-solve method greatly depends on the piercing cuts. In the next subsection, we develop an effective way of defining *PC*, *SP* and *RP*.

3) DEFINITION OF PIERCING CUT, SPARSE PROBLEM AND REMAINING PROBLEM

In the r-th iteration, RP_r is divided by PC_r into SP_{r+1} and RP_{r+1}. So we can firstly define piercing cuts. The technique of generating piercing cuts for P(ε) is presented as follows. In P(ε), there are some decision variables whose *reduced cost* values are greater than a given value *alpha*. Note that the reduced cost of a decision variable is defined as a lower bound on the increase of the objective value if the value of the variable is increased by one unit. And the value of reduced cost can be obtained by solving the linear relaxation problem of a considered IP. Assume that these decision variables compose a *variable set*. Then the piercing cut is defined as a constraint such that the sum of the decision variables in this special variable set is greater than or equal to one. Once the variable set is determined, piercing cuts can be generated.

Denote the variable set as $U_r(r \geq 1)$. Different from Asymmetric Traveling Salesman Problem studied in Climer and Zhang's work, U_r should be also appropriately defined according to the considered problem.

Note that there are two kinds of decision variables corresponding to two different levels in our problem: the lane reservation variable y_{ij} in the strategic level and the shipment path variable x_{ij}^w in tactical level. Suppose that the path of each shipment is composed of all reserved lanes, the concepts of two decision variables imply that only the arc where there is a reserved lane can be selected for the shipment path. For example, given an arc (i, j), if $y_{ij} = 0$, then x_{ij}^w absolutely equal to 0 for all shipments. Because if there is no reserved lane on arc (i, j), any shipment cannot pass through it. As implied in (6), reserving one lane or not may result in different potential shipment paths. Therefore, y_{ij} is considered as the more relevant variable to U_r, rather than x_{ij}^w.

Let $Y(y_{ij})$ denote the reduced cost value of y_{ij} in the optimal solution of the linear relaxation problem of CP_r. Then $U_r(r \geq 1)$ is defined as follows:

$$U_r = \{y_{ij} | Y(y_{ij}) > h_r, \forall (i, j) \in A\} \tag{18}$$

where h_r is a given positive number.

In this paper, we present a way of determining h_r. Suppose that the expected number of variables in U_r is n. We sort the reduced cost value of all the variables in U_r in increasing order. The value of h_r is set as the reduced cost value of the n-th variable. Then, we can obtain piercing cut PC_r by U_r.

Remark 1: $PC_r(r \geq 1)$ is defined by the following formula:

$$PC_r: \quad \sum_{y_{ij} \in U_r} y_{ij} \geq 1, \quad \forall (i, j) \in A \tag{19}$$

Note that the solution space of CP_r is separated by PC_r into two subspaces, which correspond to the solution space of SP_r and RP_r, respectively. Therefore, SP_r and RP_r can be obtained by adding new constraints to CP_r. The new constraints are related to PC_r.

Remark 2: SP_r and RP_r are defined as follows:

$$SP_r: \quad \text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij}$$

$$\text{subject to } \sum_{y_{ij} \in U_l} y_{ij} \geq 1, \quad l = 1, \ldots, r-1, \tag{20}$$

$$\sum_{y_{ij} \in U_r} y_{ij} = 0. \tag{21}$$

and Constraints (3)-(13).

$$RP_r: \quad \text{Minimize } f_1 = \sum_{(i,j) \in A} C_{ij} y_{ij}$$

$$\text{subject to } \sum_{y_{ij} \in U_r} y_{ij} \geq 1, \tag{22}$$

and Constraints (3)-(13), (20).

Note that when $r = 1$, the problem P$'(\varepsilon)$ is considered as CP_1. Accordingly, (20) should be removed for RP_1 and SP_1.

4) CUTTING PLANE METHOD TO TIGHTEN REMAINING PROBLEM

In the cut-and-solve method, bounding is commonly considered to be crucial for solving IP problems. One of the bounding techniques can resort to valid inequalities. In this subsection, a cutting plane method is proposed as a way of finding valid inequalities to obtain a tighter lower bound for the linear relaxation problems of remaining problem. The cutting plane method helps to accelerate the convergence of the cut-and-solve method.

In the cutting plane method, the cutting planes are iteratively generated and their corresponding constraints are added successively to the current relaxed problem until its fractional solution becomes an integer one. Valid inequalities separated by the cutting plane method can reduce the solution space. A tight lower bound of remaining problem for the considered problem can be obtained by the cutting plane method. As stated previously, in the cut-and-solve method, when the lower bound obtained from remaining problem is greater than or equal to the current best upper bound, the cut-and-solve method stops and the current best upper bound is returned as the global best value of Problem $P'(\varepsilon)$. Note that the stopping criteria of the method, the tighter the lower bound is, the less iteration is required. On the other hand, a tighter lower bound can also offer some flavors for the generation of piercing cut. In a word, the convergence of the cut-and-solve method can be accelerated by the cutting plane method.

To obtain effective valid inequalities, the separation algorithm for the considered problem is proposed and presented as follows.

As we know, a knapsack constraint can be written in the following form:

$$\sum_{i\in\Pi} \omega_i \delta_i \leq b \tag{23}$$

where Π, ω_i, and b are a set of items, the weight of item i, and the capacity of the knapsack, respectively. δ_i is a binary variable, and if $\delta_i = 1$, item i is selected in the knapsack; otherwise, it is not.

Set $C \subset \Pi$ is called a *cover* for (23) if $\sum_{i\in C} \omega_i > b$. Then, the *cover inequality* for (23) is defined as follows:

$$\sum_{i\in C} \delta_i \leq |C| - 1. \tag{24}$$

A cover inequality is called *valid* if it is satisfied by the feasible solution and violated by a given fractional solution of the original problem.

To facility the description, let T_{ij}, S_w, x_{ij}^w in the considered problem correspond to ω_i, b and δ_i in the knapsack problem, respectively. Then, the travel time deadline constraint (7), $\sum_{(i,j)\in A} T_{ij} x_{ij}^w \leq S_w, \forall\, w \in W$ can be considered as a standard knapsack constraint form. Therefore, the cover inequality for (7) has the following form:

$$\sum_{(i,j)\in A_x} x_{ij}^w \leq |A_x| - 1, \quad \forall\, w \in W \tag{25}$$

where A_x refers to a subset of A.

Remark 3: Valid cover inequalities for (7) can be obtained by solving 0-1 knapsack problem, P_{kp1}, as follows:

$$\text{Problem } P_{KP1}: \quad \theta_1 = \min \sum_{w\in W} (1 - x_{ij}^{w*}) v_w \tag{26}$$

$$\text{subject to} \sum_{w\in W} T_{ij} v_w > S_w, \tag{27}$$

$$v_w \in \{0, 1\}, \quad w \in W. \tag{28}$$

where x_{ij}^{w*} is pre-given value of fractional solution. Then the cover A_x^* for the valid cover inequality of (25) can be defined as the set of selected items in the optimal solution of P_{kp1}.

Similarly, the cover inequality for risk threshold constraint, (8), has the following form:

$$\sum_{w\in W_x} x_{ij}^w \leq |W_x| - 1, \quad \forall\, (i,j) \in A \tag{29}$$

where W_x refers to a subset of W.

Remark 4: Valid cover inequalities for (8) can be obtained by solving 0-1 knapsack problems, P_{kp2}, as follows:

$$\text{Problem } P_{kp2}: \quad \theta_2 = \min \sum_{(i,j)\in A} (1 - x_{ij}^{w*}) u_{ij} \tag{30}$$

$$\text{subject to} \sum_{(i,j)\in A} P_{ij}^w u_{ij} > Q_{ij}, \tag{31}$$

$$u_{ij} \in \{0, 1\}, \quad (i,j) \in A. \tag{32}$$

Then the cover W_x^* for the valid cover inequality of (29) can be defined as the set of selected items in the optimal solution of P_{kp2}.

Problems P_{kp1} and P_{kp2} can be solved by the dynamic program, which was introduced by Kaparis and Letchford [30]. The pseudocode of the separation algorithm for finding valid cover inequalities for (7) is presented in Fig. 3. For (8), the pseudocode is similar to that of (7), and it is omitted here.

5) OVERALL ALGORITHM

The proposed algorithm combining the cut-and-solve method with the cutting plane method is given in Fig. 4.

IV. COMPUTATIONAL RESULTS

In this section, the performance of the cut-and-solve and cutting plane combined method is evaluated by comparing CPLEX employed in [26], using both an instance based on a real network topology and 60 sets of randomly generated instances. Each set includes five randomly generated instances. The proposed algorithm was implemented in C. All the computational experiments were carried out on an HP PC with an Intel Core processor 3.10-GHz and 12.00-GB RAM in Windows 10 environment.

A. GENERATION OF TEST INSTANCES

In this paper, test instances were constructed based on transportation networks. Then the parameters related to the transportation network were generated based on Dijkstra's shortest

Separation algorithm

Given a fraction solution x^*, for $h = 1, \ldots, |W|$ and $n = 0, \ldots, S_w$, define:

$$g(h,n) := \min\{\sum_{w=1}^{h}(1-x_{ij}^{w*})v_w \mid \sum_{w=1}^{h} T_{ij}v_w = n, v_w \in \{0,1\}, w = 1,\ldots,h\}$$

$$f(h) := \min\{\sum_{w=1}^{h}(1-x_{ij}^{w*})v_w \mid \sum_{w=1}^{h} T_{ij}v_w \geq S_w + 1, v_w \in \{0,1\}, w = 1,\ldots,h\}$$

Let $g(h, n) := \infty$ for $h = 1, \ldots, |W|$ and $n = 0, \ldots, S_w$.
  Let $g(0, 0) := 0$.
Let $f(h) := \infty$ for $h = 1, \ldots, |W|$.
for $h = 1$ to $|W|$ **do**
  for $n = 0$ to S_w **do**
    if $g(h-1, n) < g(h, n)$ **then**
      Let $g(h, n) := g(h-1, n)$
    end if
  end for
  for $n = 0$ to $S_w - T_{ij}$ **do**
    if $g(h-1, n) + (1-x_{ij}^{h*}) < g(h, n+T_{ij})$ **then**
      Let $g(h, n+T_{ij}) := g(h-1, n) + (1-x_{ij}^{h*})$
    end if
  end for
  for $n = S_w - T_{ij} + 1$ to S_w **do**
    if $g(h-1, n) + (1-x_{ij}^{h*}) < f(h)$ **then**
      Let $f(h) := g(h-1, n) + (1-x_{ij}^{h*})$
    end if
  end for
  if $f(h) < 1$ **then**
    Output the violated cover inequality.
  end if
end for

FIGURE 3. Pseudocode of the separation algorithm.

Cut-and-solve and cutting plane combined method

1. Set $r := 0$ and the best upper bound of Problem P(ε), $UB_{min} := +\infty$.
2. After the pre-processings for Problem P(ε), a new problem P′(ε) is generated and let current problem $CP_1 :=$ P′(ε).
3. Solve the linear relaxation problem of CP_1 and obtain a lower bound LB_0 and its corresponding solution. If the solution is integral, an optimal solution of Problem P′(ε) is found and the proposed algorithm stops.
4. Search for feasible cover inequalities using the separation algorithm described in Fig.3. If there exist any cover inequalities, add them to CP_1 and go to step 3.
5. **While** ($LB_r \leq UB_{min}$) **do**
6. Let $r := r + 1$.
7. Define piercing cut PC_r by (19) and obtain SP_r and RP_r.
8. Solve SP_r and obtain its optimal value UB_r if it exists. Let $UB_{min} := UB_r$ if $UB_r < UB_{min}$.
9. Solve the linear relaxed RP_r and obtain a lower bound LB_r and its corresponding solution. If the solution is integral, let $UB_{min} := LB_r$ if $LB_r < UB_{min}$, and go to step 12.
10. Search for feasible cover inequalities using the separation algorithm described in Fig. 3. If there exist any cover inequalities, add them to RP_r and go to step 9; otherwise set $CP_{r+1} := RP_r$.
11. **end while**
12. Return UB_{min} and its corresponding solution as the optimal value and the optimal solution of Problem P′(ε), respectively.

FIGURE 4. Procedure of the cut-and-solve and cutting plane combined method.

path algorithm and uniform distribution. The way of generating test instances can be completely described as follows.

Firstly, transportation network $G(V, A)$ is generated according to the random network topology generator introduced by Waxman [31]. The nodes are randomly and uniformly generated in the plane [0, 100] × [0, 100] and the arcs are produced by the probability function that depends on the distances between the nodes. The probability function between any two nodes is defined by $p_{(i,j)} = \beta \exp \frac{-d(i,j)}{\alpha L}$, where $d(i, j)$ and L are the Euclidean distance and the maximum distance between nodes i and j, respectively, and $0 < \alpha$, $\beta \leq 1$. Consequently, OD pairs, (o_w, d_w), are randomly selected from nodes.

Secondly, the parameters are set as follows. Let $\tau_{ij} = d(i, j)$ and $T_{ij} = \tau_{ij}$*U(0.5, 0.8). The deadline S_w is set to be $dis(o_w, d_w)$*U(1, $\sqrt{2}$), where $dis(o_w, d_w)$ is the shortest travel time from o_w to d_w in a reserved path [22]. Similarly, let $\pi_{ij}^w = d(i, j)$*U(8, 20), considering the effects of the number of lanes, truck configuration, population density, and road condition on the accident probability given by Qiao, et al [32]. $P_{ij}^w = \pi_{ij}^{w}$*U(0.2, 0.3), whose unit is 10^{-7}. Note that $Q_{ij} = \sum_{w=1}^{W} p_{ij}^{w}$*U(0.4, 0.6). E_{ij} is generated by U(1, 8), whose unit is 10^6. Lastly, M_{ij} is generated by U(2, 5) [32].

Note that $|V|$ and $|A|$ is the number of nodes and arcs in network G, respectively. The average degree of network G is defined as $AD = |A|/|V|$, which implies the number of arcs per node, i.e., the density of the network [33], [34]. Parameter K is set to 20 according to [26], in order to easily compare with the computational results in [26]. This means that 21 Pareto optimal solutions can be obtained for an instance.

B. EXPERIMENTS ON TEST INSTANCES

1) EXPERIMENTS ON A REAL NETWORK TOPOLOGY

In this subsection, firstly, the problem considered in this paper will be evaluated in order to check that lane reservation can reduce the transportation risk or not.

An auxiliary problem, hazardous material transportation problem without lane reservation, is introduced. It contributes to compare the transportation risk, the impact of the reserved lane on normal traffic and the average transportation time of the considered problem with that of the auxiliary problem.

Notice that there are no reserved lanes for the auxiliary problem, its objective function is only to minimize the transportation risk. For availably formulating and solving this problem, the hazardous material accident probability and the travel time in each road segment are higher than those with lane reservation. Therefore, the risk threshold constraint and the travel time deadline constraint in the considered problem should be relaxed to ensure to obtain feasible solutions. Let R represent the ratio between the transportation risk in the considered problem in this paper and the counterpart in the problem without lane reservation, and T means the ratio between the average travel time of all the shipments in the considered problem in this paper and the counterpart in the problem without lane reservation. While the impact of the reserved lane on normal traffic can be measured by the growth rate of vehicles' travel time on the non-reserved lane, denoted as I. It can be deduced that $I = \frac{\sum_{w}\sum_{(i,j)\in A} C_{ij}x_{ij}^{w}}{\sum_{w}\sum_{(i,j)\in A} t_{ij}x_{ij}^{w}}$.

We test an instance based on a real network topology of Ravenna city, Italy, in which there are 105 nodes and 134 arcs [6]. The transportation network with the same number of nodes and arcs as those of the network of Ravenna is produced based on Waxman's network topology generator. Twelve OD pairs, indicating twelve shipments, are randomly generated. The data of the parameters, including τ_{ij}, T_{ij}, π_{ij}^{w}, P_{ij}^{w}, and S_w, are produced by the way of generating test instances mentioned above.

The cut-and-solve and cutting plane combined method finds 21 Pareto solutions in 21.764s for the instance of Ravenna city. Lane reservation strategy can respectively reduce the transportation risk and the transportation duration by 73.8% and 12.5% for all the hazardous material shipments, at the expense of the travel time on the non-reserved lane(s) that increases by 11.9%. The conclusion is drawn from ratios R, T and I, as mentioned above.

2) EXPERIMENTS ON RANDOMLY GENERATED INSTANCES

In this subsection, the performance of the cut-and-solve and cutting plane combined method will be evaluated by some random generated instances. On account that both CPLEX and the proposed algorithm can optimally solve these instances, we just only compare their computational times by exactly identical randomly generated instances that will be solved on the same computation environment mentioned above.

The computational results on the randomly generated instances with whose average degree is four are presented in Table 1. Each item in the computational result tables is the average value of the five instances in a set. Columns T_c and $T_{cs\text{-}cp}$ represent the average computational time (in CPU seconds) of five instances for each set solved by CPLEX and the proposed algorithm, respectively. We can easily observe that the total computational times of the proposed algorithm slightly increase with the number of nodes

TABLE 1. Computational results on the random generated instances that $AD = 4$.

set	$\|V\|$	$\|W\|$	T_c	$T_{cs\text{-}cp}$	$T_{cs\text{-}cp}/T_c$
1	30	10	5.298	13.578	2.562
2	40	10	8.182	14.145	1.729
3	50	10	8.426	17.387	2.063
4	60	10	13.693	17.254	1.260
5	70	10	22.809	21.557	0.945
6	40	15	13.364	18.986	1.421
7	50	15	28.257	22.855	0.809
8	60	15	63.141	46.254	0.733
9	70	15	84.926	69.636	0.819
10	80	15	118.100	83.630	0.708
11	50	20	89.398	80.052	0.896
12	60	20	132.230	95.105	0.719
13	70	20	193.037	128.252	0.664
14	80	20	305.323	204.527	0.670
15	90	20	630.965	369.851	0.586
16	100	20	679.669	571.357	0.841
17	110	20	1307.878	832.008	0.636
18	120	20	2438.041	1215.841	0.497
19	130	20	3107.024	1628.596	0.524
20	140	20	8771.252	3572.104	0.407
21	150	20	13256.765	5279.453	0.398
22	160	20	12159.779	4196.547	0.345
23	170	20	17876.545	4556.227	0.254
24	180	20	20469.845	5342.124	0.261
25	190	20	22664.948	5456.386	0.241
26	60	25	252.977	157.453	0.622
27	70	25	636.027	468.631	0.737
28	80	25	2654.154	435.425	0.164
29	90	25	3085.388	609.086	0.197
30	100	25	3400.786	1654.231	0.486
31	70	30	920.223	653.876	0.711
32	80	30	1280.794	864.989	0.675
33	90	30	2962.138	1567.086	0.529
34	100	30	9875.364	4568.097	0.463
35	110	30	22008.598	7907.876	0.359

and shipments. Given the number of shipments, the more the number of nodes, the more the computational time is expended. Take the computational times for sets 11-20 for an example; they moderately increase with the number of nodes. Similarly, as for instances with any given number of nodes, the more the number of shipments, the more time is expended. For example, the computational time for sets 26-30 is at least 1.647 times as much as that for sets 12-16, respectively.

Secondly, it can be also observed from Table 1 that the proposed algorithm is more efficient than CPLEX for large size instances, i.e., sets 7-35, and set 5. For example, for most instances in this table, the computational time required by the proposed algorithm is within a reasonable time. Fig. 5 gives the shapes of T_c and $T_{cs\text{-}cp}$ for instances with 20 shipments. As illustrated in the figure, the trend of T_c and $T_{cs\text{-}cp}$ curve is similar, while T_c increases more sharply than $T_{cs\text{-}cp}$ with the number of nodes. For example, for set 11 with 50 nodes, $T_{cs\text{-}cp}$ is 89.6 percent as much as T_c. However, for set 25 with 190 nodes, $T_{cs\text{-}cp}$ is only 24.1 percent as much as T_c.

TABLE 2. Computational results on the random generated instances with different average degrees.

set	|V|	|W|	AD	T_c	$T_{cs\text{-}cp}$	$T_{cs\text{-}cp}/T_c$
36	50	5	5	4.807	13.875	2.886
37			6	5.293	14.578	2.754
38			7	5.505	16.474	2.992
39			8	5.891	17.055	2.895
40			9	7.166	18.655	2.603
41	60	10	5	20.934	35.588	1.700
42			6	21.190	36.574	1.726
43			7	21.304	36.047	1.692
44			8	26.405	42.012	1.591
45			9	79.975	49.236	0.615
46	70	15	5	85.236	75.232	0.883
47			6	120.104	76.581	0.638
48			7	202.782	111.087	0.548
49			8	224.643	154.368	0.687
50			9	291.137	182.037	0.625
51	80	20	5	346.914	220.057	0.634
52			6	426.884	256.579	0.601
53			7	776.228	543.752	0.701
54			8	1844.799	836.004	0.453
55			9	2850.017	1350.753	0.474
56	90	25	5	2115.739	1025.455	0.485
57			6	8809.579	5622.454	0.638
58			7	7857.443	5124.055	0.652
59			8	9183.860	4564.253	0.497
60			9	35172.882	12963.572	0.368

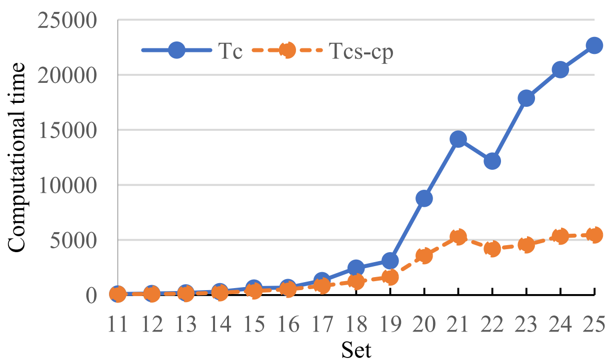

FIGURE 5. Trend of T_c and $T_{cs\text{-}cp}$ for Table 1.

Table 2 summarizes the total computational results on the random generated instances with different nodes and average degrees. As Table 2 demonstrates, the computational time for set 50 is 2.420 times more than that for set 46. The table also leads us to the conclusion that given the number of nodes and shipments, the total computational time for instances increases with the average degree of networks. It has to be noticed that the larger the size of the instances is, the rapider the increase is. For example, the computational time for set 40 whose average degree is 9 is 1.345 times as much as that of set 36 whose average degree is 5, while the computational time for set 60 whose average degree is 9 is 12.642 times more than that of set 56 whose average degree is 5.

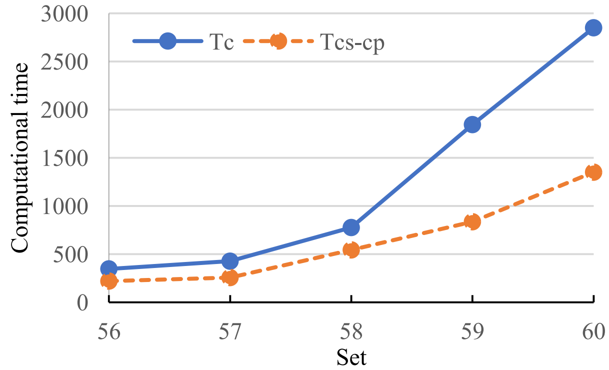

FIGURE 6. Trend of T_c and $T_{cs\text{-}cp}$ for Sets 51-55 in Table 2.

V. CONCLUSION

In this paper, we proposed a novel algorithm to solve the bi-objective hazardous material transportation problem based on lane reservation. The ε-constraint method was adopted to transform the bi-objective problem into a single objective one. Then we proposed a cut-and-solve and cutting plane combined method to solve the transformed single objective problem. We explored two specific properties for the considered problem to reduce its solution space, and developed a cutting plane method to tighten remaining problem, which could help to accelerate the convergence of the cut-and-solve method. Computational results showed that the proposed algorithm could solve the bi-objective hazardous material transportation problem based on lane reservation within a reasonable time and it runs faster than direct use of the software package CPLEX.

Although the hazardous material transportation problem via lane reservation can be solved by the cut-and-solve and cutting plane combined method within reasonable time, it also takes considerable some computational time to find Pareto optimal solutions due to its NP-hardness, especially when the size of problems increases to 200 nodes and 30 shipments. A promising future work is to find efficient heuristics for the large size problems [35], [36]. In other hands, the considered problem can be extended into the dynamic one or the one with time-dependent constraint. This also represents a future study. Finally, other future work includes improving the impact due to lane reservation based on the traffic flow or transport sustainability [37].

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ZHEN ZHOU received the B.S. degree in information management and systems and the M.S. degree in management science and engineering from Northwestern Polytechnical University, Xi'an, China, in 2007 and 2010, respectively, and the Ph.D. degree in information science from the University of Evry-Val d'Essonne, Evry, France, in 2014, and in management science and engineering from Northwestern Polytechnical University, in 2015, respectively.

She is currently working at Northwestern Polytechnical University. Her research interests include transportation optimization, transportation and logistics, and industrial systems optimization. She has authored or coauthored over 10 journals and conference proceedings, including the IEEE Transactions on Intelligent Transportation Systems, the *Applied Mathematical Modeling*, and the *International Journal of Production Research*.

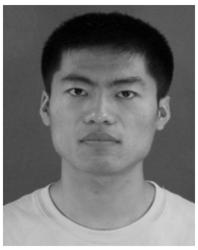
Dr. Zhou has won a number of prizes. She also serves as a Reviewer for some top journals.

WEIDONG LEI received the B.S. degree in information management and information system from Tianjin Polytechnic University, China, in 2008, and the M.S. and Ph.D. degrees in management science and engineering from Northwestern Polytechnical University, China, in 2011 and 2016, respectively.

He currently works at the Xi'an University of Science and Technology, China. His main research interest includes robotic scheduling problems in advanced manufacturing systems.

PENG WU received the B.S. and M.S. degrees in management science and engineering from Northwestern Polytechnical University, Xi'an, China, in 2010 and 2013, respectively, the Ph.D. degree in mathematics and computer science from Université Paris-Saclay, France, in 2016, and the Ph.D. degree in management science and engineering from Northwestern Polytechnical University, China, in 2017.

He joined Fuzhou University, in 2016, where he is currently an Associate Professor. His research interests include intelligent transportation systems, transportation and logistics, and production scheduling. He has authored or coauthored over 30 journals and conference proceedings in the above areas, including the IEEE Transactions on Intelligent Transportation Systems, the IEEE Transactions on Systems, Man and Cybernetics: Systems, and the *Computers & Industrial Engineering*. He is an IPC member of 2018 and 2019 IEEE ICNSC, and a Co-Organizer of 2019 IESM. He serves as a Reviewer for a number of leading journals.



BO LI received the B.S. degree in information and computational science and the M.S. degree in computational mathematics from Xi'an Jiaotong University, Xi'an, China, in 2006 and 2009, respectively.

He currently works as a Software Engineer with Glodon Technology Inc., China.

YUNFEI FANG received the B.S. degree in biology science from Southwest Normal University, Chongqing, China, in 2005, the M.S. degree in basic mathematics from Southwest University, Chongqing, in 2008, and the Ph.D. degree in optimization and security of system from the University of Technology of Troyes, Troyes, France, in 2013.

He is currently working as an Associate Professor with Fuzhou University, Fuzhou, China. He has authored/coauthored over 20 articles. He has won several prizes in Fujian province, China. His research interests include optimization and management of transportation and logistics systems, operation research, and optimization algorithm.

Dr. Y. Fang serves as a Reviewer for more than ten journals, including the IEEE Transactions on Intelligent Transportation Systems, the IEEE Transactions on Automation Science and Engineering, the IEEE Transactions on Systems, Man and Cybernetics: Systems and Information Sciences.