Computers & Industrial Engineering 110 (2017) 59–66

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

An efficient two-phase exact algorithm for the automated truck freight transportation problem

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ARTICLE INFO

Article history:
Received 22 September 2016
Received in revised form 25 February 2017
Accepted 14 April 2017
Available online 20 May 2017

Keywords:
Transportation
Automated truck
Lane reservation
Integer programming
Exact algorithm

ABSTRACT

A recent study has developed an integer linear program and an exact algorithm for the automated truck transportation freight problem with lane reservation. However, due to its NP-hard nature, their proposed method becomes difficult to solve large-size problems within acceptable time. In this paper, we firstly present an improved integer linear program by adding valid inequalities and identify that its several special cases are classical combinatorial optimization problems. Based on analyzed properties, a new efficient two-phase exact algorithm is developed. Computational results on benchmark and new larger-size instances with up to 700 nodes and 55 tasks show that the new algorithm outperforms very favorably the state-of-the-art one.

1. Introduction

Efficient shipments of cargos has attracted much attention and considerable freight transportation planning problems have been investigated extensively over the past decades (Goksal, Karaoglan, & Altiparmak, 2013; Prins, 2004; Shaabani & Kamalabadi, 2016). However, increasing travel demand results in increasingly severe congestion, which causes many problems in transportation, such as low efficiency, unpredictable transport time, traffic accidents, and fuel waste. These problems increasingly prevent the freight transportation from being operated in an efficient, reliable and safe fashion (Fang, Chu, Mammar, & Che, 2013). Introducing automated driving for trucks would be a promising solution to cope with such challenge, as automated trucks could provide remarkable advantages such as high safety and efficiency, and lower fuel consumption.

Unlike manually driven trucks, automated ones must have the ability of detecting possible dangers and responding to them correctly and promptly. Dedicated truck lanes would be ideal in this sense. Since constructing new network dedicated to automated trucks may be infeasible due to the high costs and limited geographic space, converting existing general-purpose (GP) lanes in the existing network to dedicated ones is an effective alternative. But due to the exclusive use of reserved lanes by automated trucks, the available lanes in the network for GP vehicles are reduced, and negative impact, such as the increase in travel time of GP vehicles, will be generated on the adjacent lanes. It is necessary to well decide appropriate lanes to be reserved to achieve the safe and time-guaranteed automated truck transportation, while minimizing the negative traffic impact. Such an optimization problem is called the automated truck transportation problem with lane reservation (ATP) (Fang et al., 2013). We note that there have also been studies investigating lane reservation for other applications, such as large sport events, hazardous material transportation, bus transit (Che, Wu, Chu, & Zhou, 2015; Fang, Chu, Mammar, & Che, 2014; Fang, Chu, Mammar, & Shi, 2015; Fang, Chu, Mammar, & Zhou, 2012; Wu, Che, & Chu, 2013; Wu, Che, Chu, & Fang, 2016; Wu, Che, Chu, & Zhou, 2015; Wu, Chu, Chu, & Wu, 2009; Zhou, Chu, Che, & Zhou, 2013).

Fang et al. (2013) have formulated an integer linear program (ILP) and developed an exact cut-and-solve algorithm for the ATP. However, due to the NP-hardness of the ATP, their proposed methods become difficult to solve large-size problems within acceptable computational time. In this paper, we first provide an improved ILP by adding valid inequalities. Then, we identify that several special cases of the ATP are classical combinatorial optimization problems. Based on the analyzed properties, a new efficient two-phase

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http://dx.doi.org/10.1016/j.cie.2017.04.030
0360-8352/

exact algorithm is developed. Computational results on 120 benchmark and 210 new larger-size instances with up to 700 nodes and 55 tasks confirm the effectiveness of the proposed algorithm.

The remainder of the paper is organized as follows. Section 2, recalls the problem description and provides the improved ILP. In Section 3, we derive several optimal properties of the ATP. Based on them, a new efficient exact algorithm is presented in Section 4. Section 5 reports the computational results. Section 6 concludes this study.

2. Problem description and formulation

The ATP considered in this study has been addressed by Fang et al. (2013). For the sake of self-consistency, the problem description is first recalled as follows.

The ATP can be defined on a transportation network that can be represented by a directed graph $G(N, A)$ with a node set N and an arc set A. A node (resp. an arc) represents a road intersection (resp. a road segment). Given a set of automated truck transportation tasks to be accomplished and their corresponding origin-destination (OD) pair, the ATP consists in optimally selecting lanes from the existing network to be reserved and designing a reserved path for each task in order to ensure that it can be completed within its travel deadline safely. However, such lane reservation reduces the available lanes of GP vehicles such that the negative impact such as the increase of travel time on the adjacent lanes may be caused. The objective is to minimize the total negative impact caused by reserved lanes.

As stated in Fang et al. (2013), some assumptions are made to facilitate the formulation of the ATP. First, the negative impact caused by a reserved lane is assumed as the increase of travel times on the remaining GP lanes. More details on the impact parameters can be found in Section 5. Second, at most one reserved lane is allowed on each road segment. Third, there is only one path for each task from its origin to destination in order to ensure the transport safety and the path only consists of reserved lanes. Fourth, there are at least two lanes on each road segment allowing one reserved lane. We first summarize the parameters and decision variables in Table 1.

2.1. Problem formulation

Before giving an improved model, we first recall the existing ILP for the ATP proposed by Fang et al. (2013), shown as follows.

$$IP: \quad \min \sum_{(i,j)\in A} C_{ij} Z_{ij} \tag{1}$$

$$s.t. \sum_{(o_k,i)\in A} X_{ko_k i} = 1, \quad \text{for all } k \in K \tag{2}$$

Table 1
Notation and its explanation for the formulation.

Notation	Explanation
$G = \{V, A\}$	Transportation network, where N and A denote the set of nodes and arcs, respectively
i, j	Node index, $i, j \in N$
k	Task index, $k \in K$
O	Set of transportation tasks with $\lvert K\rvert$ tasks
D	Set of destination nodes, $D \subseteq N$
o_k	Origin node of task $k \in K, o_k \in O$
d_k	destination node of task $k \in K, d_k \in D$
T_k	Travel deadline of task $k \in K$
T_{ij}	Travel time on a reserved lane on arc $(i, j) \in A$
C_{ij}	Negative impact caused by a reserved lane on arc $(i, j) \in A$
Z_{ij}	Equal to 1 if arc (i, j) is reserved, and 0 otherwise, $(i, j) \in A$
X_{kij}	Equal to 1 the path of task k pass arc (i, j) which is reserved, and 0 otherwise, $(i, j) \in A, k \in K$

$$\sum_{(i,d_k)\in A} X_{kid_k} = 1, \quad \text{for all } k \in K \tag{3}$$

$$\sum_{j:(i,j)\in A} X_{kij} = \sum_{j:(j,i)\in A} X_{kji}, \quad \text{for all } j \in N \setminus \{o_k, d_k\}, \text{ and all } k \in K \tag{4}$$

$$\sum_{(i,j)\in A} X_{kij} T_{ij} \leqslant T_k, \quad \text{for all } k \in K \tag{5}$$

$$X_{kij} \leqslant Z_{ij}, \quad \text{for all } (i,j) \in A, \text{ and all } k \in K \tag{6}$$

$$Z_{ij} \in \{0, 1\}, \quad \text{for all } (i,j) \in A \tag{7}$$

$$X_{kij} \in \{0, 1\}, \quad \text{for all } (i,j) \in A \text{ and all } k \in K \tag{8}$$

Objective (1) is to minimize the total negative impact of all reserved lanes. Constraints (2)–(4) guarantee that there exists a feasible path for each OD pair. To be more specific, constraint (2) (resp. (3)) implies that there exists only one arc outgoing from (resp. coming into) origin node o_k (resp. destination node d_k). Constraint (4) ensures the flow conservation for intermediate nodes between origin and destination for each task $k \in K$. Constraint (5) indicates that the total travel duration for task k from its origin to destination should not exceed its travel deadline. Constraint (6) ensures that task k can pass a reserved lane on arc $(i, j) \in A$ only if this arc is reserved. Constraints (7) and (8) enforce the bounds of all decision variables.

The benefit to be achieved for the ATP is the time-efficient automated truck transport service, i.e., each task should be completed within the given transportation deadline. Based on this goal, constraint (5) is formulated to specify the requirement of time-efficient transportation. For the ATP, the transport delay is not accepted, but trucks are allowed to arrive early since they achieve higher transport efficiency. We note that model *IP* can be adapted to the case that does not allow trucks arrive too early but allows an acceptable delay by changing constraint (5) to a time window constraint.

2.2. An improved integer linear program for the ATP

We improve the above formulation based on the following observations.

Observation 1. For any task $k \in K$, there will be no arcs entering into (resp. outgoing from) its origin o_k (resp. destination d_k) on its path.

With Observation 1, we add the following valid inequalities into *IP* without excluding optimal solutions.

$$X_{kio_k} = 0, \quad \text{for all } (i, o_k) \in A \text{ and all } k \in K \tag{9}$$

$$X_{kd_k i} = 0, \quad \text{for all } (d_k, i) \in A \text{ and all } k \in K \tag{10}$$

Obviously, constraints (9) and (10) reduce the search space of the original problem since part of variables are prefixed.

Observation 2. For any task $k \in K$, each node in the network will be passed at most once.

Note that if a node in the network is passed more than once by a task (i.e., cycles exist on the transport path), this obviously generates larger negative impact compared with the case without cycles. With Observation 2, we also add the following constraints into *IP*.

$$\sum_{j:(i,j)\in A} X_{kij} \leqslant 1, \quad \text{for all } j \in N \setminus \{o_k, d_k\} \text{ and all } k \in K \tag{11}$$

$$\sum_{j:(j,i)\in A} X_{kji} \leqslant 1, \quad \text{for all } j \in N \setminus \{o_k, d_k\} \text{ and all } k \in K \tag{12}$$

Constraints (11) and (12) are also valid inequalities, which tighten the search space of the original problem. Note that there have also been similar inequalities in Che et al. (2015). With the newly obtained constraints, we derive the following improved IP model.