Transportation Research Part E 109 (2018) 331–355

Contents lists available at ScienceDirect

Transportation Research Part E

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

The importance of considering non-linear layover and delay costs for local truckers

Hossein Zolfagharinia[a,*], Michael Haughton[b]

[a] Ted Rogers School of Management, Ryerson University, 575 Bay Street, Toronto, ON, Canada
[b] Lazaridis School of Business & Economics, Wilfrid Laurier University, 75 University Avenue, Waterloo, ON, Canada

ARTICLE INFO

Keywords:
Mixed integer non-linear programming
Integer programming
Collaborative transportation
Truckload transportation
Time window discretization
Traffic imbalance

ABSTRACT

Adopting a time-discretization method, we propose an iterative algorithm that solves a series of integer programming models to effectively handle non-linear costs in the trucking industry. The numerical analysis illustrates the importance of acknowledging nonlinear costs in improving the operational performance of local carriers specifically under the following conditions: (a) limited advance load information, (b) high load density, and (c) high traffic imbalance. This improvement can reach an average of 8.5% when subcontracting cost is high. Furthermore, we statistically analyze the impact of various factors (e.g., traffic imbalance) on the performance of a carrier with nonlinear costs.

1. Introduction

Collaborative transportation (CT), which involves multi-firm working relationships that are based on a commitment to information sharing among the firms, is widely considered as an effective strategy to improve freight transportation operations in the truckload sector. Such relationships can be among shippers (Özener and Ergun, 2008; Audy et al., 2011; Yilmaz and Savasaneril, 2012; Kuyzu, 2017), among carriers (Ergun et al., 2007; Berger and Bierwirth, 2010; Caballini et al., 2016; Fernández et al., 2016), or between carriers and their clients (e.g., Tjokroamidjojo et al., 2006; Scott, 2015; Zolfagharinia and Haughton, 2016). This study extends previous work on shipper-carrier relationships by incorporating two real-world phenomena that, heretofore, have not been adequately addressed in the research literature.

First, as will be fully demonstrated in the literature review, the costs incurred by the carrier when truck drivers experience layover (defined as the driver's idle time for serving the next load due to restrictions on shipper's time windows) and when deliveries are late have been treated in the extant literature as linear functions of time. However, that is not always the reality so the literature has overlooked the matter of non-linearity. Thus, in light of the real-world case study that motivated this research, we consider the case of the carrier's payment to drivers following a step-wise structure. Specifically, drivers are only paid if the layover exceeds one full day ($360 per 24 h). Indeed, the step-wise payment method is very common in practice: For example, refer to Arnold Bros. Transport Ltd (www.arnoldbros.com); AYR Motor (www.ayrmotor.com); SLH Transport Inc. (www.slh.ca); Smith Drivers (www.smithdrivers.com); Southern AG Carriers (www.sou-ag.com).

Non-linearity also occurs for delivery delays because shippers are time sensitive about deliveries, especially when they operate based on a Just-in-Time Philosophy. In this case, missing the delivery time is compensated in the form of a refund or credit to the shippers (it is more common among express delivery service providers such as UPS or FedEx). Unlike most studies in the literature however, our observations show that the margin of clients' dissatisfaction does not necessarily grow linearly as the duration of the

---

[*] Corresponding author.
E-mail address: h.zolfagharinia@ryerson.ca (H. Zolfagharinia).

https://doi.org/10.1016/j.tre.2017.10.007
Received 19 November 2016; Received in revised form 23 September 2017; Accepted 10 October 2017

delay increases. This paper introduces a novel adaptation of the Wang and Regan (2002) time window discretization and incorporates it into our unique method for solving dynamic pickup and delivery problems with full truckload (DPDFTL). Our approach shows that non-linearity can be handled in an effective and computationally efficient way so there is no need to continue with the literature's restrictive and unrealistic assumption of linearity. We also show that non-linearity impacts the carrier's optimal profit. The literature's second overlooked reality that this paper addresses is unbalanced freight flows in transportation networks; i.e., between any two network nodes, more freight flows in one direction than in the reverse direction. This enables the present study to answer the question of the extent to which flow imbalance affects the gains from shipper-carrier information sharing CT.

The rest of this paper is organized as follows. The next section reviews the relevant research studies to position this work in literature and clearly point out its novelty. In Section 3, we first define the underlying assumptions, parameters, and notations. Then, common mathematical models are reviewed, the preprocessing procedure is explained, and the MINLP model is formulated. The MINLP model is designed to capture existing time windows. However, due to the locality issues associated with nonlinear models, an iterative solution method is proposed based on a special case of the problem that is linear when no lateness is allowed. Section 4 is devoted to a solution method based on time window discretization. We start by breaking time windows into only two time points while introducing under- and over-constrained versions for the special case of the problem. Afterwards, we provide the properties of under- and over-constrained problems with more than two time points. Section 5 focuses on the design of the experiments (i.e., choice of parameters and factors of interest) and on the evaluation of the solution method's performance. In section 6, we first assess the importance of considering nonlinearity and then run additional test instances to conduct the statistical analysis. A detailed discussion is presented to draw useful managerial insights for our industry partner and similar truckload carriers. Lastly, we conclude this paper by addressing some limitations to open doors for further research in this area.

2. Literature review

According to the literature, the dynamic pickup and delivery problems can be categorized into two major groups: (1) dynamic and deterministic problems, and (2) dynamic and stochastic problems. The first group includes cases where part or all of the input is unknown and gradually revealed to a carrier when the routes are designed or executed (e.g., Yang et al., 1998; Tjokroamidjojo et al., 2006; Zolfagharinia and Haughton, 2014; Wang and Kopfer, 2015). The second group is similar to the first group but with one major difference: the exploitable stochastic knowledge on future load information is available (Powell, 1987, 1996; Powell et al., 1988; Yang et al., 2004; Simão et al., 2009). Interested readers are referred to comprehensive reviews by Berbeglia et al. (2010), Pillac et al. (2013), and Psaraftis et al. (2016). This study belongs to the former group as no stochastic load information is available to the decision maker.

There has been a growing body of research in the area of dynamic pickup and delivery problems. We distinguish between less than truckload (e.g., Mitrović-Minić et al., 2004; Ferrucci and Bock, 2014) and truckload literature. Moreover, our focus on the latter section is not to fully survey the DPDFTL literature. Instead, to help clarify our contributions, the scope of our review is portrayal of how past research handled layover and lateness cost, particularly in studying the effect of advance load information (ALI). Readers seeking a more comprehensive review that goes beyond this targeted scope are referred to Berbeglia et al. (2010).

Using the Frank-Wolfe algorithm previously applied by Cooper and Leblanc (1977), Powell (1986) addressed a stochastic vehicle allocation problem in which the layover cost was implicitly considered: if a vehicle was held at a city for one day, the cost was calculated as empty movements. In a later work that also studied the effect of ALI on empty repositioning, Powell (1996) developed a stochastic DPDFTL model in which he demonstrates the model's superiority over myopic models used in practice. The model could impute linear or non-linear layover costs when they were not assigned to any loads. This could be accomplished *before* solving the model since the decision was to assign a maximum of one load to a truck at each decision time (i.e., no tour capability: the capability of assigning *a sequence of loads* to a truck). That costing logic is reasonable for medium or large trucking carriers operating in a relatively large service area with a long trip length (two to four days). However, this cannot be done for our research context in which there is tour capability based on advance load information because, in that context, layover cost cannot be determined upfront.

In their study that found cost reductions from ALI, Yang et al. (1998) assumed a linear delay penalty in their proposed online algorithms for minimizing the total cost of empty repositioning, delay penalty cost, and the cost of rejecting loads. In their extended work to incorporate opportunity cost into the DPDFTL, Yang et al. (2004) retained that assumption. Recently, Srour et al. (in press) built on Yang et al. (1998, 2004) by modeling the static version of the problem as MIP using a rolling horizon approach for its dynamic implementation. The objective was to minimize the total cost of empty repositioning and load rejections; however, the driver's wage was not considered because it was assumed to be fixed regardless of the driving and layover hours. Gronalt et al. (2003) also formulated the DPDFTL as a cost minimization problem (minimize total empty repositioning costs) that did not consider layover cost or delay cost.

Godfrey and Powell (2002a, 2002b) present a novel method for solving dynamic fleet management problems. The problem was modeled using dynamic programming and solved using piecewise linear functional approximations. Layover time was considered in defining state variables; however, the objective function only considered the cost of repositioning and the reward from serving loads.

One of the closest studies to this work is by Tjokroamidjojo et al. (2006) who modeled the DPDFTL as a MIP and dynamically implemented it by using a rolling horizon approach. Their investigation of the potential benefits of ALI incorporated both layover and delay penalty costs. The series of works by Zolfagharinia and Haughton (2014, 2016, 2017) built on that work by incorporating a range of relevant considerations. In particular, Zolfagharinia and Haughton (2014) added crucial features such as ensuring that drivers return to their home base at specified intervals and Zolfagharinia and Haughton (2016) efficient dispatch method in the presence of uncertainty after dispatcher's knowledge window. Similar to Srour et al. (in press), they chose the common multiple