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Discrete Optimization

Effective truckload dispatch decision methods with incomplete advance load information

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ABSTRACT

We investigate the following question of relevance to truckload dispatchers striving for profitable decisions in the context of dynamic pick-up and delivery problems: "*since not all future pick-up/delivery requests are known with certainty (i.e., advance load information (ALI) is incomplete), how effective are alternative methods for guiding those decisions*?" We propose a simple intuitive policy and integrate it into a new two-index mixed integer programming formulation, which we implement using the rolling horizon approach. On average, in one of the practical transportation network settings studied, the proposed policy can, with just second-day ALI, yield an optimality ratio equal to almost 90 percent of profits in the static optimal solution (i.e., the solution with asymptotically complete ALI). We also observe from studying the policy that second-day load information is essential when a carrier operates in a large service area. We enhance the proposed policy by adopting the idea of a multiple scenario approach. With only one-day load information, the enhanced policy improves the ratio of optimality by an average of 6 percentage points. That improvement declines with more ALI. In comparison to other dispatching methods, our proposed policy and the enhanced version we developed were found to be very competitive in terms of solution quality and computational efficiency.

1. Introduction

Two issues loom large for carriers in the truckload industry as they undertake efforts to assure prosperity and survival in the ongoing economic recession: (i) asset repositioning and (ii) driver turnover. Asset repositioning, which has been studied by, e.g., Crainic (2000) and Wieberneit (2008), is due to natural characteristics of truckload transportation networks such as demand dynamism and network imbalance between supply and demand. Ergun, Kuyzu, and Savelsbergh (2007a) reports that empty movement of trucks costs U.S. carriers nearly 165 billion dollars annually. Based on the American Trucking Association (ATA) (2013), the ratio of empty to total mileage is usually higher for small carriers (22 percent) with a sparser network of lanes than larger ones with a more sophisticated lane network (17 percent).

The issue of driver turnover is strongly influenced by drivers' dissatisfaction with work schedules requiring overly long periods away from home. Studies confirming this fact include Rodriguez and Griffin (1990), Shaw, Delery, Jenkins, and Gupta (1998), Keller (2002), and Suzuki, Crum, and Pautsch (2009). The driver turnover problem is significant (according to the Council of Supply Chain Management Professionals (2006), it can reach 130 percent in a year) and costly: the replacement cost of a driver (e.g., including training and loss of experience) is estimated to be between $2200 and over $20,000 with an average of $8000 (e.g., Rodriguez, Kosir, Lantz, Griffen, & Glatt, 2000). Given the size of the U.S. trucking industry, driver turnover translates to approximately three billion dollars a year (Suzuki et al., 2009).

To address these issues, a commonly used strategy is collaborative transportation (CT); e.g., CT networks such as Nistevo (www.nistevo.com) and Transplace (www.transplace.com). In CT, logistics participants (i.e., shippers/consignees and carriers) collaborate to improve transportation performance; e.g., reduce total transportation costs and driver turnover and increase truck utilization (Ergun, Kuyzu, & Savelsbergh, 2007b). Collaboration could be among transportation clients (e.g., Ergun et al., 2007a), among carriers (e.g., Özener, Ergun, & Savelsbergh, 2011), or between client(s) and carrier(s) (e.g., Bookbinder and Lynn 1986; Tjokroamidjojo, Kutanoglu, & Taylor, 2006; Zolfagharinia and Haughton, 2012) or all the above scenarios.

The focus of this study is the collaboration between a carrier and its clients. One of the least costly methods when freight transportation service clients and carriers collaborate with each other is to communicate timely load information (from clients to carriers).

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Although sharing advance load information (ALI) can improve the carrier's performance by expanding its knowledge window (KW) into the future (Powell, 1996; Tjokroamidjojo et al., 2006), there is always uncertainty after the KW (Caplice & Sheffi, 2003). In the absence of exact information about future loads beyond the knowledge window, the dispatcher's range of decisions (load acceptance/rejection, load sequencing, etc.) is influenced by *the matter of where the truck will be positioned for serving future (unknown) loads*. Consider two extreme options open to the dispatcher in deciding which known loads the truck should be assigned to:

i. the conservative policy of preferring loads that take the truck close to its home; i.e., to avoid large empty truck repositioning costs to the home base (called deadheading costs in this study) when the truck must eventually return deadhead to the home base.
ii. the more optimistic policy of making truck–load assignments with greater risk of large deadheading costs in the hope that those assignments will put the truck in a better position to access highly profitable future (unknown) loads.

From the above, it is clear that in a given context (load density, radius of service, etc.), and for a given truck at a given instance of time (e.g., current and future truck location vis-à-vis its home base), the following is true: a significant factor in a dispatching policy is the deadhead cost. The dispatcher's dilemma is that the true deadhead costs can be known only *a posteriori* because it is only later that the exact information such as the locations, pick-up time windows, and trip lengths of future loads becomes known. To tackle the dilemma, we attempt getting a priori *signal* of the efficacy of a dispatching policy by proposing the concept of a deadhead coefficient Θ ($0 \leq \Theta \leq 1$). In essence, the coefficient is only a *signal* of the extent to which the chosen dispatching policy might affect profits because at the time of decision making, the dispatcher, while knowing the revenue of serving loads and some of the cost components, has no information beyond the last known load to be served. Thus, the dispatcher's decision is directly influenced by the conservatism level of his/her policy, which can be portrayed by what we label as the Θ***-dependent profit*** estimate (π_Θ). We calculate this estimate as:

- π_Θ= total revenue − total known cost (including loaded movement and empty repositioning, dwelling, and lateness cost) − $\Theta\times$ (travel cost from the destination of the last load in the sequence to the home base/depot).

In the above formulation, the dwell cost is calculated based on the time that a vehicle spends idle at the customers' locations and the penalty (waiting cost) per unit time. And, the lateness is calculated if a load is served after its availability. The basic intuition of the deadhead coefficient is as follows. First, consider using large Θ values for potential end of sequence loads. Those Θ values are associated with more conservative policies in that they raise the attractiveness of such loads with destinations close to the home base. That is, based on the last term in the above expression π_Θ, those loads are *predicted* to have a smaller negative financial impact so they are more likely to be selected over alternatives that are distant from the home base. Conversely, small Θ values lower the negative *predicted* financial effect of accepting end-of-sequence loads with destinations that are distant from the home base. In other words, the dispatcher will lean towards selecting loads that, despite requiring the truck to be further from the home base, have high values for the excess of revenue over known cost.

A small numerical example is presented in the next section to further clarify the above observations and the process of using the deadhead coefficient to tackle the dispatcher's dilemma of unavailable exact information (i.e., uncertainty) about future loads. As the example illustrates, different Θ values can yield different load selection decisions, and thereby may result in different values of profit. Thus, an obvious question of managerial interest is which Θ value yields the best attainable profit in a given transportation context (e.g., load density, radius of service, trip length, and time windows). Addressing this question is one of this paper's major contributions.

In this study, we focus on three key points. We first develop a flexible dispatching mixed integer program (MIP) model that can incorporate important operational details of trucking companies (e.g., current location of trucks, number of hours that a truck is away from home, previous commitments) to make profitable decisions given different levels of advance load information. Second, a simple policy (based on the deadhead coefficient) is proposed to help dispatchers make load acceptance decisions in dynamic environments. The proposed deadhead coefficient policy is tuned based on different transportation network settings. Finally, the proposed policy is enhanced to improve the solution quality of the dynamic problem at the expense of a longer running time. To achieve the goals of this research, we briefly introduce the idea of the simple policy with one small example in Section 2. Section 3 is devoted to reviewing the related literature for positioning this study among the existing works and highlighting its novelty. In Section 4, the model assumptions, notations, and parameters are defined and the conceptual model is formulated as a mixed integer program. Section 5 explains how experiments are designed for conducting a comprehensive simulation study. In Section 6, the proposed policy is evaluated through simulation results. In Section 7, the proposed policy will be enhanced by applying sample scenario hedging heuristic proposed by Hvattum, Løkketangen, and Laporte (2006) for stochastic dynamic vehicle routing problems. We also examine our proposed policy and its enhanced version against two other dispatching methods. Conclusions and future research directions are provided at the end.

2. Proposed deadhead coefficient policy: an illustrative example

For ease of exposition, we use the case of a single-truck carrier to illustrate how the proposed policy works with different Θ values. An underlying logic of the policy is that trucks not scheduled to serve any loads return to the depot. This policy is intuitive if the dispatcher has access to advance load information (e.g., knowing that there is no request available for the rest of the day). The logic is also sound because the average repositioning is typically shorter from the depot (if it is located at the center) and dwelling cost is much lower at the depot. This is because there is no extra facility usage cost for, say, a driver to dwell at his/her home or at accommodations provided by the carrier (e.g., Challenger Motor Freight's well-equipped rest facility for drivers at its Cambridge depot, more detail about this trucking company can be found at its official website: http://www.challenger.com). We label this policy as ***Deadhead Coefficient Policy*** because its success depends on selecting a proper Θ value. We will also refer to this as the Pure-Θ Policy.

In our illustrative example, the truck is idle at the depot (the driver's home base) at the beginning of the planning horizon, the dispatcher's knowledge window is set to 2 days (48 hours), and system information is updated daily. The truck earns \$130/hour for serving a load while incurring \$60/hour when moving either empty or loaded. Without loss of the generality, dwell and lateness costs are not taken into account to make the example simple enough to follow.

Fig. 1 depicts how loads are distributed over time and revealed to the dispatcher. In Fig. 1a, the information of loads A, B, C, and D is available at the beginning of day 1 while load E will be realized when the system information is updated at the start of day 2 (Fig. 1b). Fig. 2a represents a 7-city transportation network