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Long-term Inventory-aware Equipment Planning in Service Networks

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Abstract

Parcel delivery companies manage changing load volumes in their networks across the year, especially during peak times – the holiday season, Black Friday, Prime Day, etc. Ensuring that sufficient capacity is available requires planning a linehaul equipment fleet that can accommodate load demand during these peak times. This research focuses on the trailer fleet for a large parcel transporter and considers a planning horizon of 3 to 6 months. Managing peak trailer demand using short-term leasing is often the most pragmatic approach. We develop an optimization-based planning methodology for making trailer leasing decisions and equipment repositioning decisions jointly over a planning horizon to manage predicted fluctuations in demand volumes. Leasing decisions include how many trailers to lease, for how long, and at which facilities to add and return leased trailers. Trailer leasing costs can be reduced potentially by repositioning both owned and leased equipment geographically over time. We track owned and leased trailers in time within a time-space network integer programming model. Minimum and maximum leasing periods for individual trailers are modeled. For tractability, a coarse time discretization is necessary, so we also develop a data-driven approximation technique within-period trailer usage to reduce model conservatism. A computational study demonstrates the utility of the model using data representative of extra-long trailer usage at our research partner, a large U.S. parcel carrier, including an investigation of the impact of different minimum leasing period durations on cost and empty miles performance metrics.

Keywords
Equipment leasing, empty repositioning, time-space network, integer programming, data-driven modeling

1 Introduction

According to the US Department of Commerce 2020, e-commerce sales have soared in the past decade with the sales in US alone being recorded at 11.4% for the fourth quarter of 2019, which was only 4% in 2009. US online sales are projected to touch the $795 billion mark by the end of 2020; and by 2024 it is estimated to surpass the $1 trillion mark [1]. Every year, parcel delivery companies have to deal with changing load volumes in their network, especially during peak times – holiday season, Black Friday, Prime day, etc. Over the years, surge in online shopping, due to the penetration of the internet and shift of customer trends towards online marketplaces, has put a lot of pressure on logistics operations [2]. Ensuring that the equipment fleet (i.e., trailers and containers) is sufficient to satisfy the load demand during these peak times constitutes a major challenge for the parcel carriers. These companies cannot rely entirely on their owned trailers because owning a sufficiently large fleet leads to low trailer utilization [4,5]. Often, it is cheaper and also necessary to lease trailers from third party leasing companies for a short period of time and reposition trailers in the network to address the expected fluctuations in load volume during the peak period [2].

We develop an optimization-based planning methodology for making trailer leasing decisions and trailer repositioning decisions jointly over a planning horizon to manage predicted fluctuations in demand volumes. The primary contributions of the paper are the following:

- A modeling framework that explores the value of leasing decisions, given that a certain number of units of trailers will be available for leasing (i.e., contracts have already been signed): when and where should we introduce (some of) the trailers available for leasing into the system and when should they be returned
- A modeling framework that determines appropriate trailer inventory levels at terminals over time to ensure cost-effective handling of forecast loads and an empty repositioning to achieve these inventory levels
- A data-driven approximation scheme to relax the conservative approach of modeling travel time

Preparing for increases in demand volume is a tactical planning problem where the planning horizon is typically several months (e.g., 3 to 6 months). As leasing and procurement decisions have to be made a few months prior to the peak period it is reasonable to assume that scheduled or forecasted load information is deterministic [3]. We focus on the service network of a large US parcel carrier which consists of Hub facilities and Non-Hub facilities. The Hub facilities are permanently owned by the company and operate large volumes of load, while the Non-Hub facilities operate low volume of loads and some of them are leased, to handle demand during the peak period. Each of these facilities has an initial inventory of owned trailers. To tackle high demand volume during the peak period these companies resort to short term leasing of trailers at Hub facilities, by signing contracts with trailer leasing companies at the beginning of the planning horizon, to use a certain number of trailers during the peak period. Each Non-Hub facility is associated with a nearest Hub facility from where it can receive empty trailers (leased or owned), in the event of any shortage (see Figure 1(a)); these facilities cannot lease trailers directly from trailer leasing companies. At the end of the planning horizon the leased trailers are returned to the respective leasing companies from the Hub facilities. The parcel delivery companies make tactical leasing decisions: when and where to inject the leased trailers and for how long, and empty trailer repositioning decisions to avoid any shortage during the peak period. In case there is any shortage of trailers, these companies are forced to lease from local rental companies, which is very costly during the peak period.

Equipment fleet sizing and fleet composition problems have been studied extensively in literature (see [4]-[8]) and a review of the existing literature on repositioning of empty equipment can be found in [9]. Fleet sizing and empty repositioning have been addressed for freight trucking operations in [10,11] and in railroad industry in [12]. The proposed model in [12] is built over a time-space network with uniform time discretization with the granularity of a day. Closely related to our research, [13] study the trade-off between cost of a larger fleet size and the cost of empty repositioning in a consolidation network and [3] develop an integrated rental fleet-sizing model with heterogeneous assets for truck-rental industry where they consider operational decisions: customer demand allocation and empty repositioning and tactical decisions: purchase and sale of assets over a time-space network. Building on the works of [3,13], we develop trailer leasing models for a parcel delivery company to make leasing and empty repositioning decisions to satisfy customer demand during the peak period.

2 Trailer Leasing Model (TLM)

In this section we formally define the *long-term inventory-aware equipment planning problem* that aims to find when, where and how many units of trailers are leased and returned at each Hub facility, appropriate trailer inventory levels at each facility and empty trailer repositioning plan to achieve these inventory levels at the facilities. We first describe the problem parameters, notations and assumptions and then present a mixed-integer linear programming (MILP) formulation of the *Trailer Leasing Model (TLM).*

2.1 Parameters

We model all potential leasing companies and their facilities as one *leasing node* with a maximum total leasing capacity (denoted by N) equal to the aggregated units of extra-long trailers available across all leasing companies (see Figure 1(a)). Leased trailers enter and leave the parcel delivery company's service network at the Hub facilities. For every Hub facility, the total number of leased trailers entering the service network is equal to the total number of leased trailers returned during the planning horizon, $[s, s+T]$, where s is the start of the planning horizon and T is the length of the planning horizon (see Figure 1(b)). Let δ^- and δ^+ be the minimum and maximum leasing periods in days. Let F_H be the set of Hub facilities, F_N be the set of Non-Hub facilities in the service network and $F = F_H \cup F_N$. Let L_{ft}^{arr} (resp. L_{ft}^{dep}) be total number of extra-long trailer loads arriving (resp. departing) from facility f at time t and let $L_{ff't}$ be the total number extra-long trailer loads departing facility f at time t and arriving at facility f' at time $t + \tau_{ff'}$, where $\tau_{ff'}$ is the travel time between the two facilities. Each facility f has an initial inventory of extra-long trailers, denoted by $I_{f,0}$. We assume that leased trailers can be introduced at any Hub facility and define cost c as the cost of using leased trailer per day per unit and $c_{ff'}$ as the cost of repositioning empty trailers (owned or leased) between facilities f and f'. The optimization model is defined over a time-space network with a node (i,t) for every facility i at time t and a node (L,t) for the leasing node at time $t \in \{s, s+1, \ldots, s+T\}$. Every time point t denotes a day in the planning horizon. We assume that travel times are deterministic.

2.2 Decision Variables

We define $x_{ft} \in Z_{\geq 0}$ as the number of trailers leased at a Hub facility f at time t , $y_{ftt'} \in Z_{\geq 0}$ as the number of trailers leased at Hub facility f at time t and returned at time t' (where $t + \delta^- \leq t' \leq t + \delta^+$), $w_{f,f',t} \in Z_{\geq 0}$ and $\widehat{w}_{f,f',t} \in Z_{\geq 0}$ as the number of owned and leased trailers (empty or loaded), respectively, moved from facility f to facility f' at time t, $I_{f,t} \in R_{\geq 0}$ as the number of owned trailers and $\hat{I}_{f,t} \in R_{\geq 0}$ as the number of leased trailers available at facility f at the end of time t.

2.3 Mixed-Integer Linear Programming formulation

$$\text{Minimize} \quad c \left(\sum_{f\in F_H} \sum_{t\leq T-\delta^-} \sum_{t'=t+\delta^-}^{t+\delta^+} (t'-t) y_{ftt'}\right) + \sum_t \left(\sum_{f\in F} \sum_{f'\in F} c_{ff'} (w_{ff't} + \widehat{w}_{ff't} - L_{ff't}) \right) \qquad (1)$$

$$\text{Subject to} \quad \sum_{f\in F_H} \sum_t x_{ft} \leq N, \qquad (2)$$

$$x_{ft} = \sum_{t'=t+\delta^-}^{t+\delta^+} y_{ftt'}, \qquad \forall\ f \in F_H, \forall\, t \leq T - \delta^- \qquad (3)$$

$$I_{f,t-1} + \sum_{f'} w_{f',f,t-\tau_{f'f}} = I_{f,t} + \sum_{f'} w_{f,f',t}\,, \qquad \forall\ f \in F, \forall\, t \qquad (4)$$

$$\hat{I}_{f,t-1} + \sum_{f'} \widehat{w}_{f',f,t-\tau_{f'f}} = \hat{I}_{f,t} + \sum_{f'} \widehat{w}_{f,f',t}\,, \qquad \forall\ f \in F_N, \forall\, t \qquad (5)$$

$$\hat{I}_{f,t-1} + x_{ft} + \sum_{f'} \widehat{w}_{f',f,t-\tau_{f'f}} = \hat{I}_{f,t} + \sum_{t'=t-\delta^+}^{t-\delta^-} y_{ft't} + \sum_{f'} \widehat{w}_{f,f',t}\,, \qquad \forall\ f \in F_H, \forall\, t \qquad (6)$$

$$w_{f,f',t} + \widehat{w}_{f,f',t} \geq L_{ff't}\,, \qquad \forall\ f, f' \in F, \forall\, t \qquad (7)$$

The first term in the objective function (1) represents the total leasing cost and the second term represents the total cost of repositioning empty trailers in the service network. The term $(w_{f,f',t} + \widehat{w}_{f,f',t} - L_{ff't})$ represents the total number of empty trailers moved from facility f at time t to facility f' at time $t + \tau_{ff'}$. Constraint (2) ensures that the maximum leasing capacity is respected. To understand constraints (3) imagine that we create a copy of leasing node for each Hub facility f for every time point t, then constraints (3) are flow balance constraints at the leasing node corresponding to facility f at time t (see Figure 1(b)). These constraints ensure that minimum and maximum leasing periods are respected. Constraints (4) are flow balance constraints for owned trailers while constraints (5) and (6) are flow balance constraints for leased trailers at Non-Hub and Hub facilities, respectively. Constraints (7) ensure that the load demand from facility f at time t to facility f' at time $t + \tau_{ff'}$ is satisfied.

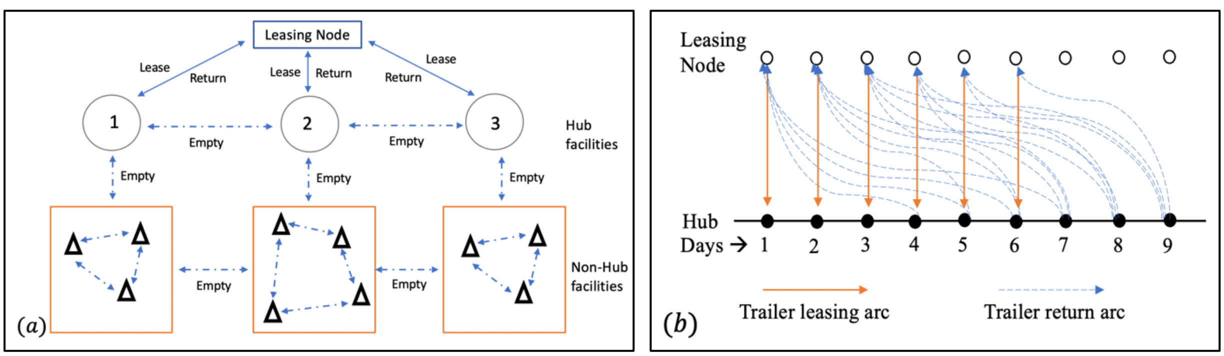

Figure 1: Example in (a) shows the service network model for real-life operations and example in (b) demonstrates a time-space network for leasing and returning trailers at a Hub facility, with $\delta^- = 3$, $\delta^+ = 6$ and $T = 9$ days

3 Data-driven approximation scheme to model travel time

The *TLM* with a time discretization of one day has around 7 million variables for a planning horizon of 6 months. Therefore, solving the *TLM* with a finer time discretization, to track the flow of trailers more accurately, might not be a good strategy because of the explosion in the number of integer variables in the model. A different approach would be to use the daily time discretization level and exploit information from available data which can help develop approximation techniques that work well in practice.

Our current approach for modeling travel time restricts trailers to be used at most once per day, even if the travel time for loads is less than a day (24 hours) (Figure 2(a)). Consider the example, in Figure 2(b), for a facility f where we have six inbound trailers and five outbound trailers during the interval [*8pm Day1, 8pm Day2*]. Assuming that there is no initial inventory or leasing available, if we use our current approach of modeling travel time, then there will be a shortage of five trailers at *8pm* on *Day1* and an excess of six trailers at *8pm* on *Day2*. However, in real-life operations as trailers can be used on multiple loads during the day, we develop a data-driven approximation technique to relax the conservatism without having to resort to a finer time discretization. The idea is to use information from input load dataset to find the number of trailers that can be used for (or matched with) outbound loads on the same day. For example, in Figure 2(b), three out of five departures (denoted by green vertical lines) can be matched with three prior arrivals while the remaining two departures (denoted by red vertical lines) cannot be served because there are no trailers available. We define a parameter $\alpha_{tt'}$ as the total number of inbound trailers which can be matched with outbound trailers in the interval $[t, t']$ at a facility f and add a "*backward*" inventory arc from day t' to day t. We define the flow variable on the "*backward*" arc as $z_{tt'} \geq 0$ and impose a flow upper bound of $\alpha_{tt'}$ on the arc, i.e., $z_{tt'} \leq \alpha_{tt'}$. In Figure 2(b) and 2(c), $\alpha_{tt'} = 3$, where $t = 8pm\ Day1$ and $t' = 8pm\ Day2$. Figure 2(c) shows the flow balance at the two nodes (f, t) and (f, t'). The concept of using the "*backward*" arc is pragmatic and relaxes the conservative approach of modeling travel time which restricts trailers to be used at most once per day.

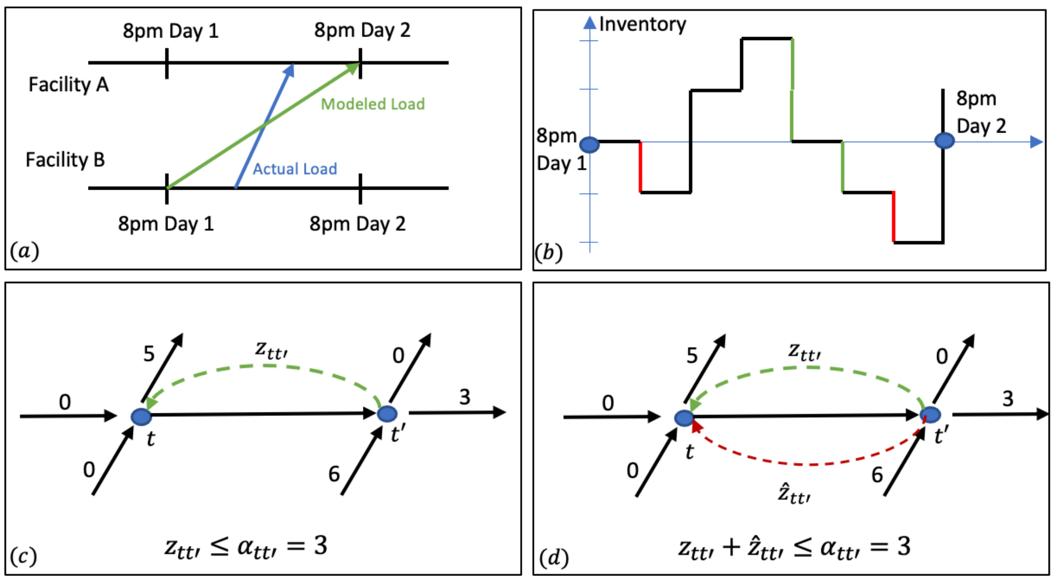

Figure 2: Example (a) showing the conservative approach for modeling travel time. Example in Figure (b) shows the variation in inventory due to inbound load (L_{ft}^{arr}) and outbound load (L_{ft}^{dep}) at a facility f on day 1 and day 2. Example in Figure (c) shows a flow diagram for the example in Figure (b). Example in Figure (d) shows the flow diagram for the example in Figure (b) when there are two fleet types: owned and leased.

Moreover, the above procedure can be easily extended to the general case where we have two types of trailers: owned and leased. We introduce two new variables: $z_{ftt'} \geq 0$ and $\hat{z}_{ftt'} \geq 0$ to track the "*backward*" flow of owned (green-dotted arc in Figure 2(d)) and leased (red-dotted arc in Figure 2(d)) trailers from time t' to time t at facility f in the network. To use this approach, we replace constraints $(4) - (6)$ with $(4') - (6')$ as shown below and add constraint (9) to the *TLM*:

$$I_{f,t-1} + \sum_{f'} w_{f',f,t-\tau_{f'f}} + z_{f,t,t+1} = I_{f,t} + \sum_{f'} w_{f,f',t} + z_{f,t-1,t}, \quad \forall\ f \in F, \forall\ t \quad (4')$$

$$\hat{I}_{f,t-1} + \sum_{f'} \hat{w}_{f',f,t-\tau_{f'f}} + \hat{z}_{f,t,t+1} = \hat{I}_{f,t} + \sum_{f'} \hat{w}_{f,f',t} + \hat{z}_{f,t-1,t}, \quad \forall\ f \in F_N, \forall\ t \quad (5')$$

$$\hat{I}_{f,t-1} + x_{ft} + \sum_{f'} \hat{w}_{f',f,t-\tau_{f'f}} + \hat{z}_{f,t,t+1} = \hat{I}_{f,t} + \sum_{t'=t-\delta^+}^{t-\delta^-} y_{ft't} + \sum_{f'} \hat{w}_{f,f',t} + \hat{z}_{f,t-1,t}, \quad \forall\ f \in F_H, \forall\ t \quad (6')$$

$$z_{f,t,t+1} + \hat{z}_{f,t,t+1} \leq \alpha_{f,t,t+1}, \quad \forall\ f \in F, \forall\ t \quad (9)$$

4 Results

We test our model using real-life instances representative of extra-long trailers from a large parcel carrier for a humongous network of 150 Hub facilities, 574 Non-Hub facilities in US and around one million departures from these facilities over a 6-month planning horizon. We analyze the impact of varying minimum leasing period and owned fleet size while using the data-driven approximation scheme. We consider the base case instance where $N = 20{,}000$ units, $T = 180$ days, owned fleet size is 34,340. Increasing δ^- from 30 days to 60 days reduces the total units of leased trailers and increases the average leasing period. Figure 3 shows the number of trailers leased and returned during the planning horizon. The results show that most of the trailers are leased early on and returned at the end of the planning horizon and the model avoids frequent leasing and returning of trailers which makes the leasing decisions more appealing to managers. Having a large value of δ^- reduces the total empty miles due to excess trailers in the network but also increases the total leasing cost due to increase in average leasing period. Increasing the owned fleet size reduces the total number of leased trailers but at the expense of increased empty miles.

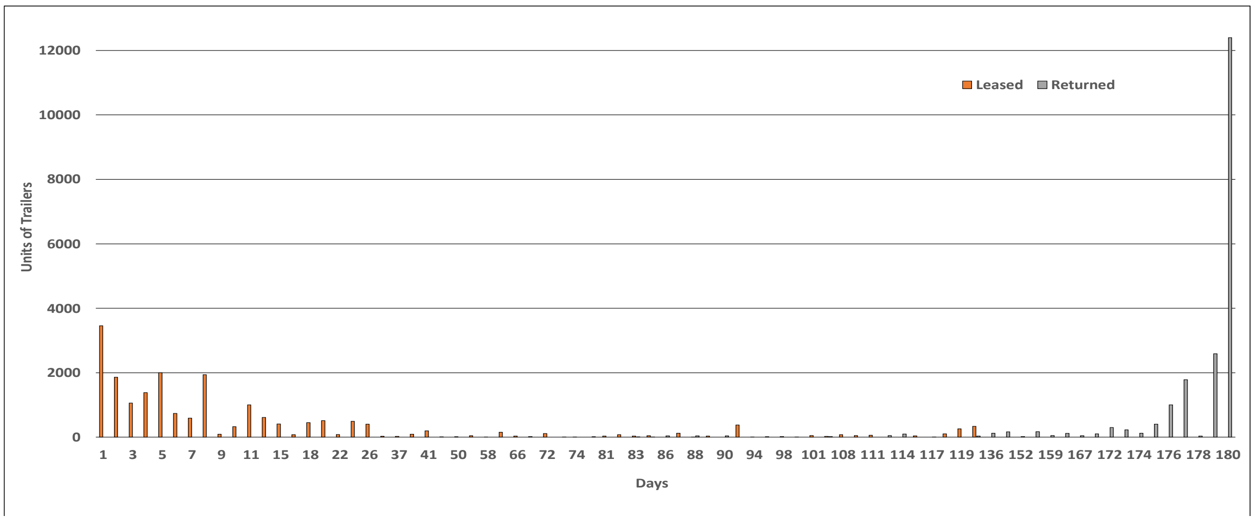

Figure 3: Figure shows the units of trailers leased and returned from Hub facilities in US states when $\delta^- = 60$ days.

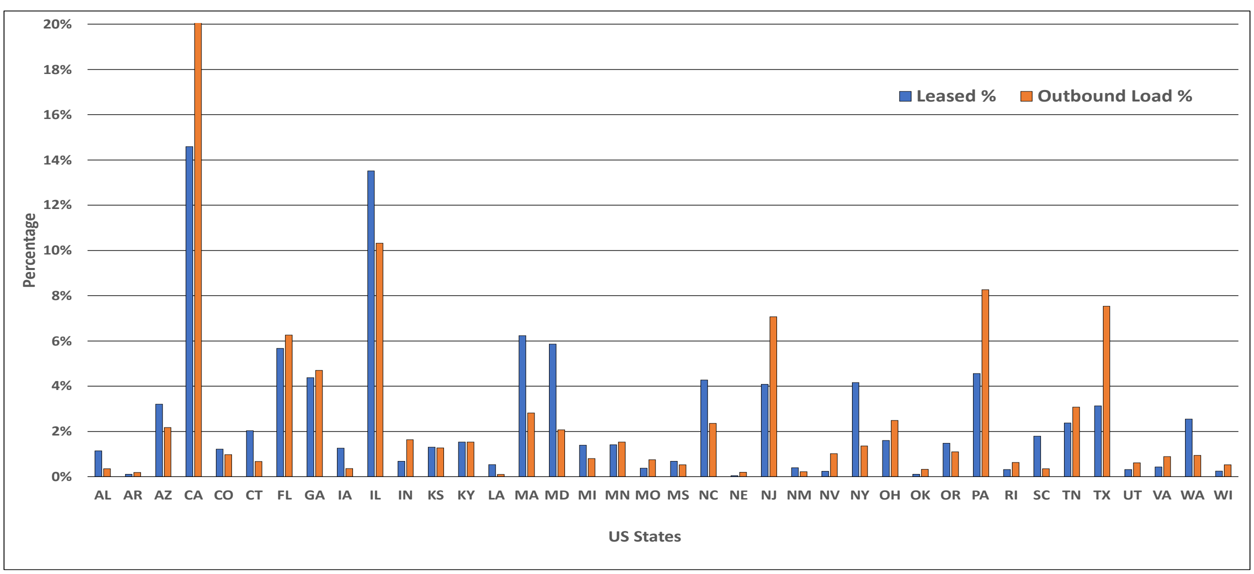

Figure 4: Figure shows the percentage of scheduled load departures and leased units at Hub facilities in 38 US states.

To manage trailers effectively, it is important to proactively place trailers where they will likely be needed based on the demand forecast [2]. Figure 4 shows the percentage of total units of leased trailers at Hub facilities in 38 US states. It is interesting to observe that it follows a similar trend as the percentage of total loads departing from the facilities in these states. Therefore, it might be a good strategy to pre-position initial inventory of owned trailers at the Hub facilities in proportion to the estimated load departures.

Developing a model that allows trailers to be re-used on a day reduces the need to lease additional trailers or reposition empty trailers at the facilities and helps to estimate the total leasing and empty repositioning cost in the network more accurately. Using the data-driven approximation scheme in the *TLM*, as described in Section 3, for the base case instance with $\delta^- = 60$ days reduces the optimal objective value: total leasing and empty repositioning cost by 1.8%, which is significant considering the scale of the network and the planning horizon.

5 Conclusions and Future Research

We develop an optimization-based planning methodology that can assist managers to make the right leasing and empty repositioning decisions in anticipation of changes in demand volume during the peak period. Results from a computational study, using data representative of extra-long trailers show that having the right minimum lease period is important to get realistic leasing decisions. Small minimum leasing periods lead to frequent leasing and returning of trailers which is undesirable. The results also indicate that it might be tactically beneficial to pre-position owned trailers at the Hub facilities in proportion to load departures from the facilities. We have developed a data-driven approximation scheme that helps to track the flow of trailers, and hence estimate the total cost, more accurately in the time-space network without resorting to a finer time discretization. As time-expanded networks quickly become prohibitively large, we are currently developing dynamic variable generation strategies using pre-processing and column generation techniques for instances with a planning horizon of 6 months. In our current model we use a simple cost structure: cost per day per unit leased, which is independent of the location and time. An interesting extension could use a cost structure with all-unit quantity discount and variable leasing cost which depends on time of leasing, as it is costly to lease trailers closer to or during the peak period.

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