Mixed Global and Local Assignment Algorithms for Quasi Dynamic Local Truckload Trucking Operations with Strict Time-Windows

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Abstract

This paper examines the trade-offs associated with local and global, but myopic, assignment heuristics for local truckload trucking operations such as those associated with drayage operations near intermodal facilities. These operations involve a combination of loads that are known at the beginning of the day and those that arrive dynamically throughout the day. Some of the dynamically arriving loads are revenue generating moves while others are trailer, chassis or container repositioning moves. Since a significant fraction of the day’s loads are known a priori, dispatchers would like to be able to construct schedules for the day and then to make minor changes to these schedules as the day progresses. In this paper we examine the efficiency of an operation in which new loads are added to or appended to schedules constructed at the start of the day verses one in which the whole system is re-optimized several times during the day. The re-optimization does not seek to preserve current schedules while the local optimization techniques do. The examination of solutions is performed using a geographic information system (GIS) based simulation model developed for this purpose.

Key Words: Commercial Vehicle Operations, Dynamic Fleet Management, Intermodal Freight
INTRODUCTION

The context of this research is local truckload trucking operations in which a driver moves a single load at a time from its origin to its destination. Each load has a specified time-window within which it has to be picked up at the origin location and delivered at the destination location. Local truckload operations contain a fairly high degree of stochasticity. Carriers typically know only a portion of loads to be served at the start of the day. Further, unexpected delays at intermodal terminals or customer locations can require the reassignment of previously assigned loads. In addition the need to reposition containers, trailers or chassis can arise at any time, effectively adding new moves to the system. Decisions to accept (or reject) newly requested loads and assign a vehicle to serve an accepted load take place very quickly. In local operations, the acceptance decision determines whether a load is moved by a company’s drivers or contracted to another company. In the context of primary interest in this work, rail and maritime intermodal operations, there are many dray operators available that specialize in taking last minute requests for relatively short moves. Decisions made in the present affect the future state of the system. Since the decisions have to be made in real-time, the speed of decision making is extremely critical.

This research has two equally important goals. The first is to develop assignment strategies suitable for real-time implementation. The second is to examine the costs associated with two customer service-driven operational strategies. One of these strategies is to try to maintain schedules developed early in the day and to limit changes to fairly simple ones. The trade-offs between implementing global optimization techniques that minimize the overall cost to provide service but may make significant changes to previous schedules and those which make only “local” changes to schedules (insertions, additions and removal of at most one load at a time) are examined. Dispatchers favor solutions with few major mid-day changes so that repositioning moves and extra driver tasks not included in the assignment problem may be scheduled and so that drivers may predict at the beginning of the day to within 30 minutes or an hour when
their work day will end. The other strategy is one in which sub-fleets of drivers are fairly small and fairly stable, meaning drivers work in the same area every day and pickup and deliver to the same set of customers. The advantage here is that drivers become very familiar with the street network and traffic pattern in the relatively small geographic region to which they are assigned. This familiarity saves them time and, perhaps more importantly, can reduce the likelihood of accidents. In addition they develop good relationships with major customers in their primary zones. These relationships may facilitate a reduction in both the length and variability of dock times. The first of these operational considerations is examined in this paper. The second is the subject of ongoing research motivated in part by research that has shown that significant network economies of scale (and density) exist in truckload drayage services (Walker, 1992). Whether large companies take advantage of these economies despite sub-fleet and sub-area partitioning is of significant interest. A geographic information system (GIS) based simulation model that is integrated with a CPLEX based optimization model has been developed for this purpose.

Related Work

The long haul truckload trucking problem has attracted considerable attention in the past few years. The dynamic vehicle allocation problem has been attacked from many angles incorporating present and future (forecast) demands, deterministic and stochastic variables by optimization-based and heuristic algorithms. Powell (1996) presents various formulations and solution methods for this problem which is typically includes long distance moves and a longer planning horizon. Most of that work has involved a network with an explicit number of nodes (geographic regions or zones) and a set of discrete time stages. This research differs in that we restrict ourselves to local truckload moves such as those in and around intermodal facilities and to a set of work that must be completed during a single 24-hour period. Demands arise within a compact geographic region near one or more intermodal facilities (rail or maritime facilities or both). These problems are simpler in some respects than the traditional dynamic vehicle allocation problems in that
we do not consider repositioning moves made in anticipation of future demands. Vehicles are busy, waiting at an intermodal facility or waiting at the depot for an assignment. In certain respects however, these problems are more complicated than the traditional vehicle allocation problems. Loads have strict time window constraints, and dock times (loading, unloading and waiting times) may be unpredictable as can service times at intermodal facilities. These stochastic elements, combined with travel times subject to recurring and non-recurring congestion have a significant affect on the ability of dispatchers to assign a driver a full day's work, even if one hundred percent of the days' demands are known at the start of the day.

This problem lends itself to formulation as a vehicle routing problem with time windows but differs from typical VRPTW problems in that the vehicles are assigned only a small number of moves during the planning horizon (a single work day).

These problems fall into a class of those in which it is difficult to accurately describe the fluctuation of demands and service times and in which it is not cost effective to make the effort to characterize and explicitly include stochastic elements in the solution. In real time applications, trade-offs between computational complexity and solution quality exist. The complexity of accurately modeling uncertainty and the complexity of algorithms which explicitly consider stochastic elements justifies the use of a deterministic vehicle routing model as an important part of the strategies used to make online (real-time) assignments. Regan, Mahmassani and Jaillet (1996, 1998) presents a set of heuristics for real-time assignment and routing for dynamic carrier fleet operations. That work assumes that no demands are know a priori and that loads must be assigned (in order to ensure time-window feasibility) immediately after they are requested. Furthermore, the assignment rules rely on purely local optimization techniques, which miss out on system-wide assignment opportunities. The approach described in this research assumes that a significant fraction of demands are known at the beginning of the assignment period and seeks to take full advantage of this information while at the same time retaining flexibility to react to changes if need be. Yang, Jaillet and Mahmassani
(1999) extended earlier analysis considerably, and developed a global optimization-based formulation of the real-time truckload pickup and delivery problem which they call myopic because it involves only information known at the time of solution in a highly dynamic environment. Their work suggests that even a myopic system-wide optimization technique performs better than purely local assignment techniques. The problem they solve corresponds to our problem. However they examine systems which are even more dynamic. Because this method is intended for eventual implementation in operations, we assume, as is typically the case in real operations, that a large fraction of demands are know at the start of day. In addition, the research described in Yang et al. (1999) has as its focus smaller problems as it was intended to develop new insight into dynamic problems rather than lead to an operational system.

The real time local truckload pickup and delivery problem has attracted relatively little attention from the research community. Until recently, few carriers had intermodal operations of the size inviting the development of automated routing and scheduling systems and the large local pickup and delivery problems faced by private fleets typically involved primarily fixed routes. The motivation for this research is the intermodal operations of one of the largest truckload carriers in the US. The company uses optimization software to assist with the development of schedules for their long haul (over-the-road) drivers but not for their local operations. Current assignment methods rely on dispatchers (load managers) to solve, without the assistance of a scheduling system, what is essentially a bipartite assignment problem at the beginning of the day followed by nearest-load assignments for the rest of the day. The variability in handling and travel times in congested urban networks coupled with some uncertainties about equipment availability have made this assignment method the norm in most local operations.

In addition, local operations are driven by many somewhat intangible factors including customer service and safety constraints that favor sub-fleets of relatively few drivers working in the same areas and with the same customer set from day to day. These
operations have been historically fairly well managed by dispatchers. However, a sharp increase in recent years in the use of rail intermodal transportation has led local operations to become much more complex and increasingly large, inviting the development of computer aided dispatching systems. In addition to including more than a hundred drivers and hundreds of loads everyday, these problems increasingly include more than one rail terminal and a fairly wide geographic region.

The Start of Day Problem

The start of day assignment problem is formulated in the following way:

Notation: Let \( N = \{1, \ldots, n\} \) be the set of loads and \( K \), indexed by \( k \), be the set of available vehicles to be assigned. Consider the graph \( G = (V, A) \) consisting of the set \( V \) of nodes and \( A \) of Arcs. For each arc \((i,j) \in A\), \( C_{ij} \) represents the cost of serving demand \( j \) directly after demand \( i \). In a more general form the cost would be the revenue gained by moving the load minus the cost of making the move. In our case only the cost is considered since most of the revenue-generating portion of the intermodal moves are not relevant to the local operations. Let \( t_{ij} \) represent the travel time from the destination of the load \( i \) to the origin of load \( j \) plus dock time, and loaded travel time associated with load \( i \). That is, it represents the time between the start of service to load \( i \) and the start of service to load \( j \). Let \( y_{ij} \) represent the idle time associated with assignment of a vehicle to load \( j \) after load \( i \). The parameter \( \beta \) represents the rate assigned to the cost of this idle time. Let \( \alpha \) be the weight assigned to the time of service. If there is a perception that better customer service involves not only serving loads within their time windows but also early in their time windows then this coefficient is assigned a non-zero positive value this parameter can also be assigned a different value for different customers (in that case it would be indexed as \( \alpha_i \)). The parameters \([a_i, b_i]\) represent the beginning and ending of the service time window for load \( i \). \( M \) is a large positive number.

Formulation: The problem of finding the minimum cost set of routes can be formulated
as follows. This is a variation of the formulation for the VRPTW given in the survey paper by Desrosiers, Dumas, Solomon and Soumis (1995).

$$\text{Max} \sum_{i \in N} \sum_{j \in N} (M - c_{ij})x_{ij} - \alpha \sum_{i \in N} T_i - \beta \sum_{i \in N} \sum_{j \neq i} y_{ij} \quad (1.0)$$

$$\sum_{j \in N} x_{O_i j} \leq 1 \quad \forall i \in K \quad (1.1)$$

$$\sum_{i \in N} \sum_{j \in N} x_{ij} \leq 1 \quad \forall j \in N \quad (1.2)$$

$$\sum_{i \in N} \sum_{j \in N} x_{ij} - \sum_{m \in N} x_{jm} \geq 0 \quad \forall j \in N \quad (1.3)$$

$$x_{ij}(T_i + t_{ij} - T_j) \leq 0 \quad (1.4)$$

$$a_i \leq T_i \leq b_i \quad \forall i \in N \quad (1.5)$$

$$y_{ij} = X_{ij}(T_j - T_i - t_{ij}) \quad (i,j) \in A \quad (1.6)$$

$$x_{ij} \text{ is binary; for all } i \in N + \{0\}, k \in K, j \in N, i \neq j \quad (1.7)$$

Solution approaches for the VRPTW problem have typically relied on Lagrangian relaxation or decomposition methods. These methods rely on the solution of shortest path sub-problems with time window or in more general terms, resource constraints. According to Desrosiers, Soumis and Sauve (1983), in order to obtain satisfactory bounds with Lagrangian relaxation when the gap between $Z_{np}$ and $Z_{ip}$ is large, integer sub-problems obtained without relaxing time window constraints must be solved, where $Z_{np}$ is the objective value of the linear relaxation of the integer problem. One of the requirements of these algorithms is the solution of the elementary shortest path problem with time window (ESPPTW) constraints. The ESPPTW is NP-hard in the strong sense, as has been shown by reduction from the problem denoted *sequencing within interval* (Dror, 1994). Shortest path problems with time window constraints are typically solved using dynamic programming. When using dynamic programming, non-elementary
shortest paths exist and deteriorate the quality of the lower bound obtained from the coordinating master problem (Desrosiers et al., 1995). In addition, dynamic programming usually involves a very large state space for any real-life transportation system (Levin, 1971). An alternative way to deal with the time window constraints is to discretize the time windows. This method is not a new one; in fact, early work applying this method can be seen in Appelgren (1969) and Levin (1971). Appelgren (1969) solved a ship scheduling problem using time window discretization method. More recent application of time window discretization can be seen in Swersey and Ballard (1984), where a school bus scheduling problem is solved using a time window discretization method to minimize fleet size, linear programming relaxation of the resulting integer programming problem is solved. We describe our implementation of the method in detail in Wang and Regan (1999). The method developed is particularly well suited to problems in which the typical number of loads assigned to a vehicle at one time is fairly low; it suffers when long chains are developed. We demonstrate in that work that we can solve problems of reasonable size quite well. Since we do not find the optimal solution we rely on the reducing the gap between an upper bound which is likely infeasible and a lower bound for which the corresponding solution provides a time-window feasible solution to the original problem. We show in that paper that we can solve typical problems to within a gap of 95% on a standard desktop computer (233 MHz Pentium with 128 mb ram) in less than five minutes using a straightforward implementation of the CPLEX integer linear programming solution code. We are confident that we will soon improve solution times and increase the size of problems that can be solved both off-line and on-line.

In this paper we concern ourselves with the following: if dispatchers prefer purely local rather than global changes to assignments, what is the cost in terms of operational efficiency? Can we develop local assignment and reassignment techniques, which satisfy the desire of dispatchers and at the same time, provide good solutions relative to the optimal one? We compare a system in which we re-optimize (by solving the start of day problem) during the day to one in which we rely on local techniques for mid day
reassignments.

**Mid-Day Assignment and Reassignment**

For mid-day assignments we rely on solving a set of asymmetric traveling salesman problems with time windows. Whenever a new load arrives in the system or a load currently assigned either requires reassignment or is a candidate for reassignment because of the relative inefficiency of its assignment, we solve a traveling salesman problem with time windows problem for each vehicle. The traveling salesman problem (TSP) is one of the fundamental routing problems and has been a subject of extensive research. It requires the determination of a minimal cost cycle that passes through each demand node in a network exactly once. The costs considered could be the total distance traveled, the empty distance traveled, or the travel time. In this research context where each demand node is an origin-destination pair, we minimize the empty distances traveled. The costs therefore are asymmetric (Figure 1).

![Figure 1. Asymmetric costs](image)

The TSP with time windows (TSPTW) is a TSP with time window constraints introduced at each demand node. Without loss of generality, as in the start of day VRPTW, we consider time windows at only the pickup locations. Dual time windows may be easily transformed to one in which only pickup time windows are required.
The TSPTW can be formulated as a mathematical program to obtain an optimal solution. See for example, Desrosiers et al. (1995). However, in this research we assume that we can solve the TSPTW problems encounter by complete enumeration. The characteristics of the problem limit the number of tasks assigned to any vehicle at a time to around five, though three is a more typical number.

The local assignment rules (dynamic dispatching heuristics) allow for the en-route diversion of vehicles moving empty in the system (figure 2). That is, in addition to being a candidate for assignment to any vehicle in the system, new loads may be assigned to be the current load of any vehicles not moving loaded. The rule used to assign the load to a vehicle simply looks for the vehicle for which the sum of the empty distances is least. That is, we solve a TSPTW for each vehicle that includes the candidate load and select the vehicle for which the cost of the TSPTW is least.

![Diagram of vehicle diversion]

Figure 2. En-Route Diversion

**The Simulation Model**
A simulation model was developed to analyze the efficiency of various assignment techniques. It works in the following way. Assignments are provided to the simulation model, which then moves loads over a street network. Customer locations are drawn from a set of actual customer locations. As new loads arrive to the system they are immediately assigned to a vehicle. At preset reoptimization points the simulation is paused and a new globally optimal assignment is generated. This assignment is provided to the simulation model, which resumes moving vehicles and serving loads.

The GIS Component

Described in detail in Jagannathan, (1999) the simulation model developed as a custom application using the TransCAD Caliper Script programming language and GISDK. Many of the functions listed in GISDK are used to manipulate the data and maps. For example, to find the shortest path between any two points in the network, the function ShortestPath() can be used. TransCAD database files provide the data (network information) for the analysis. The visualization of the routes is accomplished using the GIS tool. There are many in-built functions that can be used to achieve this. For example: the function AddRoutes() can be used to add and display routes. Another function AddAnnotation() displays routes, but as a freehand item.

An important requirement of the local assignment rules (dynamic dispatching heuristics) is the determination of the state of the system at any instant in time and specifically when new loads arrive to be serviced. (This is to enable diversion of a vehicle from one task to another to serve a load with close time-window constraints). By state of the system, we mean, the location of the new load, each vehicle’s position and status and the sequence of loads assigned to each load. All but the vehicle’s location are easily determined.

The vehicle’s location is the point on its path (on which it is traveling) at the current time. Although the distance traveled from its origin can be calculated using the speed, current time and time it began its move, it is not possible to find the coordinates (latitude,
longitude) of the location using TransCAD or the functions defined. To obviate this problem, a simple scheme was devised wherein the location of the vehicles and loads is identified using the node numbers.

Therefore, at any instant in time, a node number will identify the vehicle’s location (each network is made of a set of nodes and corresponding links). This is made possible by the fact that the function that is used to calculate the shortest path between any two points (ShortestPath()) returns an array of links lying on the path. Using this information and the link lengths, a milepost between the origin and destination is created. This can be done for any given origin and destination. The milepost not only has the distance from origin information but also the node number and the link number. A schematic diagram of the milepost is shown in Figure 3.

![Schematic diagram of the milepost created](image)

**Figure 3.** Schematic diagram of the milepost created

The positions of the vehicles are updated at the occurrence of every event. The update is done as follows: the distance traveled by the vehicle in the elapsed time (time between events) from its previous location can be calculated (speed is given). Using the milepost distance and node information, the node on the route closest to the distance traveled is identified as the current location of the vehicle. If the distance traveled is greater (or lesser) than the milepost of the closest node, that distance is stored as the extra distance traveled (or to be traveled) by the vehicle. For example: In Figure 3, if the distance traveled in the elapsed time is 0.55 distance units, and its previous location was the
origin, then the current location will be Node 3212, and the extra distance to be traveled will be 0.15 distance units.

**Test Problems**

We present results based on thirty test problems that are similar to problems solved in the field. Demands are generated by selecting randomly from among known customers in the service area of the Los Angeles Basin region of Southern California (figure 4). All moves either originate or terminate at the rail intermodal facility. Time windows for loads known at the start of the day are randomly assigned based on the distribution shown in table 1, which roughly corresponds to the time windows associated with loads known at the start of day. Time windows for loads arriving during the day are randomly assigned as well and are equally likely to be two, four or eight hours. The objective function used in the optimization system is a simplified version in which $\alpha$ and $\beta$, the bonus for early service and the penalty for driver idle time are set to zero. The objective function simply seeks to minimize empty distance traveled while serving as many loads as possible.

**Table 1a. Probabilities associated with time windows for the start of day problem**

<table>
<thead>
<tr>
<th>Time window</th>
<th>7:00-7:30 AM (0.5 hours)</th>
<th>8:00-9:30 AM (1.5 hours)</th>
<th>8:00AM-12:00PM (4 hours)</th>
<th>12:00-5:00PM (5 hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>0.1</td>
<td>0.15</td>
<td>0.35</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**Table 1b. Probabilities associated with time windows for the mid day problem**

<table>
<thead>
<tr>
<th>Time window</th>
<th>2 hours from request</th>
<th>4 hours from request</th>
<th>8 hours from request</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>0.333</td>
<td>0.333</td>
<td>0.333</td>
</tr>
</tbody>
</table>

For the problems in the test set, we begin with the vehicles at the depot (which in this problem is very near the rail yard) and make all vehicles available for the duration of the day. Vehicles are not required to return to depot after each service. Travel distances
correspond to the shortest network travel distance. Travel time is assumed to be 35 miles per hour, reflecting congestion levels in the test region. The average loaded distance is quite short, less than twenty miles long. A handling time (typically dock time) of forty minutes is assumed for each load though in an actual operation the handling time could be customer specific. We present here results related to solving 30 problems involving 20 vehicles in which 75 loads are known at the beginning of the day and an addition 75 loads are requested according to a Poisson arrival process between the hours of 10:00 AM and 2:00 PM. Twenty was selected because is the typical maximum size of a local sub-fleet handled by a single dispatcher. Four solution methods are compared. In the base case the start of day solution is augmented only by local assignments. En-route diversion is allowed. In the second case the start of day solution is augmented by local assignments in which a re-assignment rule is applied whenever a new load is added to the system. This re-assignment rule seeks to identify sub-optimal assignments and improve these using exactly the same assignment technique as with new loads. Several simple reassignment rules have been examined (Jagannathan, 1999). The one used in this test is the following.

*Reassignment rule*

After the newly arriving load is assigned to a vehicle, ratio of the empty distance to loaded distance associated with each load is calculated. These costs are arranged in descending order and the top five percent of the loads are candidates for immediate reassignment. We consider reassignment for only those loads assigned to vehicles with more than two loads currently assigned. The loads to be reassigned are treated as new loads and are considered sequentially (beginning with the “worst”) for assignment to any of the vehicles.
The third case is one in which reassignment is not considered but at noon, after approximately half of the dynamically arriving loads are known the system is reoptimized. The fourth case is one in which the system is reoptimized at noon and then again at 2:00 after all of the new loads are known.

Figure 4. Map of study region

The test results are fairly conclusive. They indicate that significant opportunities for improvement lie in the re-optimization of the system. Test results are quite similar to those found by Yang et al. (1999), in simulation experiments in an idealized network in which loads are generated randomly in a unit square and vehicles move according to Euclidean distance. In some cases they are more dramatic, this is likely travel in a realistic street network favors the global optimization solutions more than Euclidean travel.

Figures 5-7 present the average total distance traveled, the average system time (total
length of day from start to finish) and the average idle time per vehicle under the four scenarios. The average values for the performance measures are presented as well as the upper and lower bounds on the confidence intervals for each performance measure. In all cases the system in which reoptimization is done twice (after which point no changes occur) performs best, followed by the system in which reoptimization is done after about half of the new loads have arrived, followed by the system in which in addition to local assignment heuristics the local reassignment technique is used.

Figure 5. Average total empty distance traveled under four scenarios
Figure 6. Average system time under four scenarios

Figure 7. Average idle time per vehicle under four scenarios

Some caution should be taken in the interpretation of these results. Though they make a strong case for the implementation of a system wide (or sub-fleet wide) optimization
system in which at any time schedules are subject to change, the effect of stochastic dock and travel times has not been examined in these tests. While these may make the system wide optimization system method perform better with respect to the base case involving only local changes, in order to maintain time window feasibility the system would need to be reoptimized more often during the day producing less stable assignments. On-going research is examining this question. In addition it may be possible to improve the base case. Its likely that afternoon loads assigned at the beginning of the day “anchor” schedules in ways that become inefficient as the day progresses. Excluding some of these loads in the beginning of the day may improve the overall efficiency of the assignment. Finally, from the point of view of service requests, the system examined has a higher degree of dynamism than most actual intermodal operations. Since loads that must be picked up at the rail yard are pre scheduled (albeit subject to delay) only around half of the loads can be requested dynamically (in fact, the Los Angeles region favors consumption over production so this value is less than half). In operations that are only twenty or thirty percent dynamic a start of day optimization system followed by local mid day changes may have advantages over the alternative.

CONCLUSIONS

Test results suggest that global optimization methods hold significant benefits over local assignment techniques for the development of cost-effective schedules. The purely local assignment and reassignment techniques under-perform global reoptimization with respect to all measures examined.

The GIS based simulation model developed provides a robust environment for studying the performance of assignment strategies. Travel times, now based on stable congestion levels could be modified to reflect typical traffic network conditions. Handling times could be easily drawn from a distribution rather than assumed static. These distributions can be developed easily from historical data.
Continuing research has the following goals: 1) to develop assignment techniques which combine the benefits of local assignment techniques and global optimization; 2) to examine the operational impacts of implementing the global reoptimization techniques; 3) to examine the level of information technology necessary to successfully implement a computer aided dispatching system for local rail intermodal operations; 4) to examine the trade-offs associated with larger or smaller sub-fleets and sub-regions.

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REFERENCES


Wang, X and A.C. Regan (1999), Local Truckload Vehicle Routing and Scheduling with Strict Time Window Constraints, submitted for presentation at the 79th annual meeting of the Transportation Research Board and for publication in the *Transportation Research Record*.