MBTC 2004 Final Report:

Efficient Dispatching in a Terminal City Network

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Abstract:

In this project report, we describe new optimization and simulation tools to address several problems in transportation, specifically driver dispatching and tour formation in full truckload trucking. In this segment of transportation industry, one of the problems is low driver retention mainly due to the long routes that keep drivers away from home for long time. We address this issue first by extracting a network of high volume cities (called terminal city network) from the existing transportation network. Then, we regularize the tours for the drivers in the terminal network as much as possible using simulation and optimization. Specifically, we develop integer programming models and discrete-event system simulation tools to design and evaluate optimal or near-optimal delivery plans for truckload shipments between terminal cities in a truckload-trucking environment. We examine the problem primarily from a freight carrier's perspective, with a goal of providing driver tour pattern and domicile information to maximize carrier revenue while meeting shipment demands and driver needs. We provide multiple models which span from long-term aggregate planning problems to short-term driver-specific operational models and show how they can be used in different settings. We also provide realistically sized case studies to demonstrate the efficacy of the approaches using data supplied by J.B. Hunt Transport, Inc.

Keywords: Simulation, Optimization, Truckload Trucking, Distribution

1.0 Introduction

One of the most difficult tasks associated with agile and distributed manufacturing is that of logistics management for material movement activities between various sites. In fact, popular manufacturing strategies such as just-in-time manufacturing and agile manufacturing have driven logistics solutions to being more important and less tolerant of deviation from dispatch and delivery plans. This is especially true in situations where the geographical distances between design sites, raw material and component supply sites, manufacturing sites, distribution centers, and customer locations are of a national or even global scale. Efficient material movement between these sites is key to success and well designed supply chains are likely to play an even larger role in the future success of business entities.

In this report, the authors focus on the development of simulation and optimization methods to examine inter-site distribution alternatives in a dedicated truckload trucking environment, assuming a North American business platform. Solution methods, regardless of the techniques used, must consider two viewpoints. From a customer or shipper perspective, the primary areas of concern are price, delivery (on-time) performance, and service quality (lack of damage). These service needs are intensifying as manufacturing evolves into increasingly global systems and as it evolves into systems that are decreasingly dependent on buffer stock supplies. From a carrier perspective, the key issues are equipment utilization and driver tour length reduction. The highly competitive nature of North American truckload trucking, with its low capital requirements to become an industry participant, requires high equipment utilization, especially following US deregulation legislation in 1980. The improvements to carrier profitability brought about by driver tour length reduction are perhaps the most difficult to explain to persons outside the industry, but it is this key area of concern that motivates the development of the tools described in this paper.

It is difficult to recruit and retain drivers in North America. Schwartz (1992) discusses driver retention and recruiting as a key business strategy for truckload carriers. Carriers that are successful in recruiting and keeping drivers will likely emerge as industry leaders. The excessive tour lengths inherent to traditional truckload dispatching methodologies are a primary reason for losing drivers. Mele (1989a, b) provides statistics that support this premise. He states that annual turnover rates among truckload carriers can range from 85% to 110%, while less-than-truckload (LTL) carriers with more regular routes often experience turnover rates on the order of 4.5% for city drivers and 10% for linehaul drivers. If carriers can find ways to regularize and reduce driving routes, they have a better chance to retain drivers than their competitors. In this context, the term ‘regularize’ means to find patterns in seemingly random freight that would enable drivers to repeatedly drive the same short tour day after day or week after week, returning to their domicile (home city) at the end of each tour dispatch. Regularized tours enable the drivers to return home more frequently and with greater certainty, thus contributing to driver satisfaction and retention. Concurrently, regularized tour drivers are able to increase safety on the road because of familiarity with the roads they travel.

There are many ways to regularize driving routes. Several of these alternatives, including the development of hub & spoke networks, the development of regularly scheduled lanes similar to those used in intermodal transit with rail, and the development of regional zones are discussed in Taylor et al. (1999). The remainder of this report examines a new means of driver route regularization that is not represented in the current literature. The techniques used herein represent a compromise between random dispatching and strict regularization. This report examines the use of driver partitions into two sets of drivers; those that operate only within a limited network of high freight density delivery nodes (network drivers), and those that carry remaining freight in a random fashion (random drivers). Network drivers may drive highly regular routes or seemingly random routes, but only within the selected high freight density network. Network drivers, even if traveling randomly within the selected network, would experience reduced tour length based on the limited number of allowable network destinations. Random over-the-road (OTR) drivers would carry remaining non-network freight using traditional dispatching methods and may include sub-contract drivers. This strategy is wholly compatible with the use of dedicated fleets for large shippers, but is also a reasonable strategy for larger carriers who desire to partition their driver capacity into regular and random jobs.

The following sections describe two tools for examining the efficacy of limited network designs as a tour length reduction strategy. The first is simulation based and the other is optimization based. The literature is rich with examples of both types of tools in distribution problems, but no literature has been found directly addressing the problems presented herein. Many authors have addressed the use of optimization in trucking. Crainic and LaPorte (1997) provide an excellent overview of planning models in freight transportation at the strategic, tactical, and operational level. At the strategic level, they discuss location models, network design models, and regional multi-modal planning models. At the tactical level, they discuss service network design and vehicle routing problems. At the operational level, they discuss dynamic modeling to support carrier operations and capacitated routing with uncertainties. Powell (1991) also reviews a fairly wide range of optimization tools developed for trucking with an emphasis on real-time optimization in truckload trucking. Hall and Racer (1995) present methodologies that are somewhat similar to those presented herein in that they examine the use of private fleets. In some cases, their approach considers both transportation and inventory costs. Other authors also develop optimization models that minimize transportation and inventory costs using economic order quantity models and other tools, but no literature has been found dealing with multiple concurrent links of logistics networks. Frantzeskakis and Powell (1990) and Kleywegt and Papastavrou (1998) develop heuristic algorithms based on the formulation of dispatching problems as stochastic programming problems. Other papers of interest include Ronen (1992) who examines dispatching of mixed fleets from a single terminal, Equi et al. (1997) who examine, via Lagrangean decomposition, dispatching from several origins to several destinations within a single work day, and a multitude of papers in LTL trucking including an interesting paper by Crainic and Roy (1992) which addresses regular route building. Another paper of interest is presented by Powell and Carvalho (1997) in which the authors discuss a dynamic multicommodity network flow problem that can be used to solve large problems that are difficult to solve using integer programming. Simulation is also useful in solving large problems. Although the literature is less abundant in presenting simulation solutions in the trucking industry, some strong examples exist, including the previous work of the author of this paper. Much of this is reviewed in detail in Taylor et al. (1999).

Another related area from the literature is that of airline crew scheduling. The crew scheduling problem basically builds minimal cost pairings of flight crews and flights to satisfy constraints associated with labor rules and regulations. To some degree, most published solutions deal with schedule perturbations including weather, traffic, crew and equipment delays. As pointed out by Hoffman and Padberg (1993), the problem is very significant and has consequently been studied almost continually for the past 40 years. They also state that crew costs are exceeded only by fuel costs in the airline industry. As stated in Vance et al. (1997), the problem has traditionally been modeled as a set partitioning problem. Even so, many solution alternatives exist in the published literature involving both traditional and non-traditional approaches. For interesting examples of the state-of-the-art featuring more or less traditional solution methods, the reader is referred to Graves et al. (1993) and Stojkovic et al. (1998). Graves et al. (1993) present an applications based solution working with United Airlines. Stojkovic et al. (1998) focus on the operational aspects of the crew scheduling problem. Non-traditional approaches to solving the problem include a preferential bidding system by Gamache et al (1998), simulated annealing by Lucic and Teodorovic (1999), and even a decision support system developed by Mathaisel (1996). Effective crew scheduling systems can lead to huge savings, as documented by several authors. Graves et al. (1993) state that their system has led to annual savings of more than $16 million dollars at United Airlines. Similarly, Rushmeier and Kontogiorgis (1997) discuss annual savings of more than $15 million at USAir.

While the airline crew scheduling problem has many similarities to the truckload trucking problem presented herein, there are several key differences. Most notable are differences in freight characteristics. Airlines travel between well defined air hubs. Truckload trucking carriers can be asked to travel from anywhere to anywhere. Airlines can establish specific departure and arrival schedules that are known months in advance. In truckload trucking, load information is often not known until 8 hours or less prior to pick-up. At best, the truckload trucking industry can use aggregate past information for rough stochastic scheduling. Consequently, it is impossible to know with certainty where trucks and drivers will be at a future point. Another difference is that it is possible to make use of small empty asset repositioning moves in trucking that would be cost prohibitive in airline scheduling. Finally, truckload trucking, unlike the airline industry or LTL trucking, cannot partially fill an asset via customer or order aggregation. Therefore, making use of yield management strategies to maximize revenue while adhering to a regular schedule is very difficult in the industry.

The remainder of this report focuses on the development of simulation and optimization approaches for the dispatching problem within a limited network design. Several techniques for regularizing the driving job for network drivers are presented and test results verify the efficacy of the various approaches. J.B. Hunt Transport, Inc. (JBHT) has served as a project sponsor for the tool development activities presented herein and has provided valuable data and information to support the work, especially in the development of the simulation-based tools. As North America’s largest publicly held trucking company (J.B. Hunt 1999), their participation serves to validate the topics as viable and necessary tools for the truckload trucking industry.

2.0 Case Study Setting

All solution approaches in this report will be presented in a case study setting to demonstrate the efficacy and practical use of the tools in solving pertinent problems of continental scale. The case study setting involves North American freight movements for JBHT during a one-quarter year time period in 1998. Although the freight density data supplied by JBHT is historical, the data provide the best indicator available in predicting future aggregate freight density in a particular lane, where a lane is defined as a city-to-city pairing.

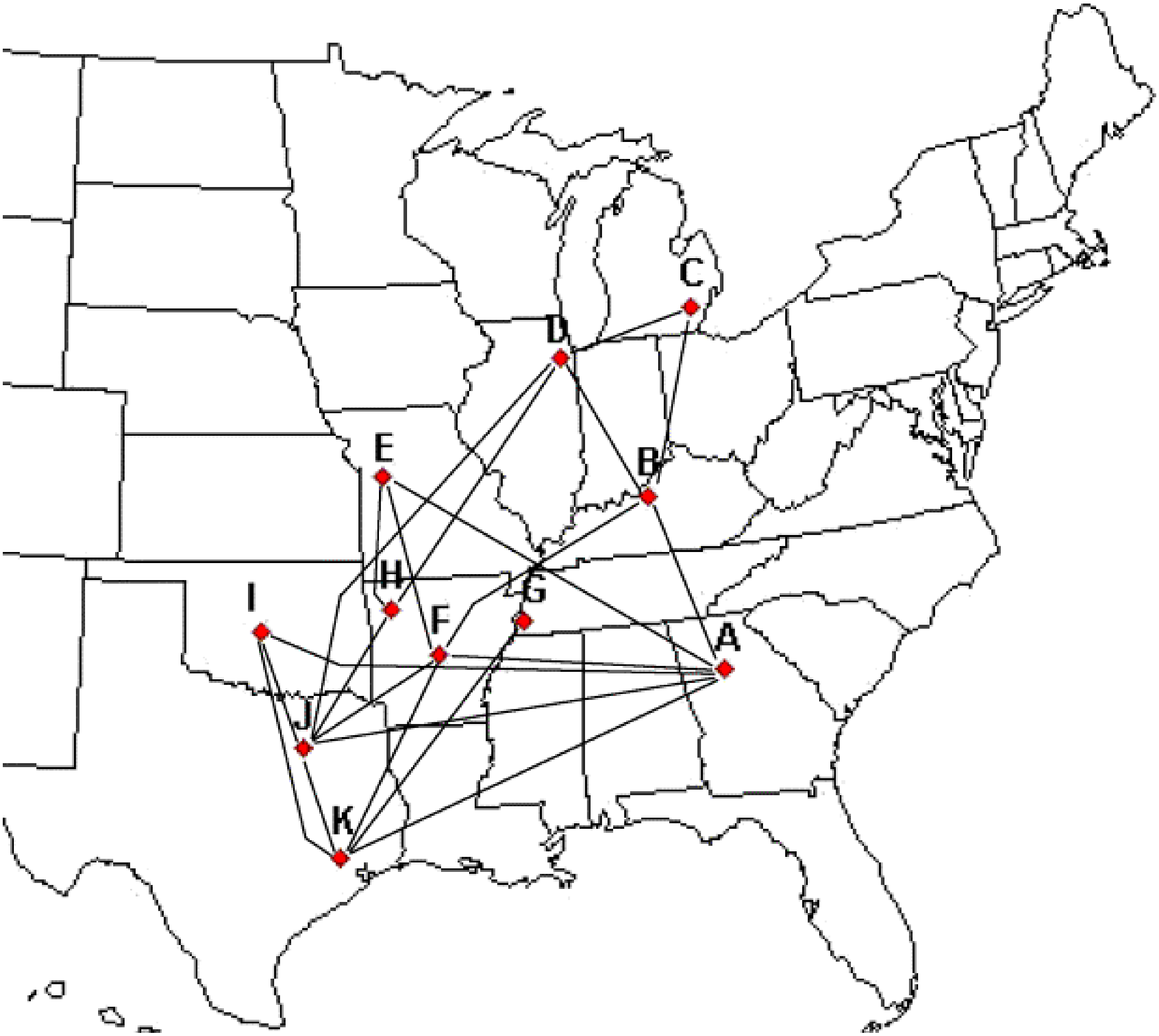
The driver partitioning system takes advantage of a partial delivery network composed of 11 high freight density terminal cities within the JBHT terminal city network. Network drivers are partitioned to include terminal city drivers with domiciles in these 11 network cities and with permissible freight origins and destinations only in these network cities. The remaining drivers handle random OTR freight outside the terminal city network. The focus of this report is on the network drivers only.

The terminal city network and freight lanes used in the study are indicated in figure 1. Table 1 provides aggregate freight information in the form of expected freight volume and lane mileage for each lane.

Table 1. Lane Data for Case Study

From City	To City	Volume	Miles	From City	To City	Volume	Miles
(A) Atlanta, GA	(B) Louisville, KY	72	436	(F) Little Rock, AR	(E) Kan. City, MO	62	470
(A) Atlanta, GA	(E) Kan. City, MO	59	862	(F) Little Rock, AR	(J) Dallas, TX	1082	341
(A) Atlanta, GA	(F) Little Rock, AR	307	538	(F) Little Rock, AR	(K) Houston, TX	417	481
(A) Atlanta, GA	(I) Okla. City, OK	47	869	(G) Memphis, TN	(K) Houston, TX	34	575
(A) Atlanta, GA	(J) Dallas, TX	249	804	(H) Lowell, AR	(D) Chicago, IL	148	610
(A) Atlanta, GA	(K) Houston, TX	89	814	(H) Lowell, AR	(E) Kan. City, MO	151	289
(B) Louisville, KY	(A) Atlanta, GA	109	436	(H) Lowell, AR	(J) Dallas, TX	142	328
(B) Louisville, KY	(C) Detroit, MI	218	355	(I) Okla. City, OK	(A) Atlanta, GA	61	869
(B) Louisville, KY	(D) Chicago, IL	212	324	(I) Okla. City, OK	(J) Dallas, TX	40	233
(B) Louisville, KY	(F) Little Rock, AR	23	513	(I) Okla. City, OK	(K) Houston, TX	62	476
(C) Detroit, MI	(B) Louisville, KY	220	355	(J) Dallas, TX	(A) Atlanta, GA	341	804
(C) Detroit, MI	(D) Chicago, IL	260	265	(J) Dallas, TX	(D) Chicago, IL	74	899
(D) Chicago, IL	(B) Louisville, KY	248	324	(J) Dallas, TX	(F) Little Rock, AR	1127	341
(D) Chicago, IL	(C) Detroit, MI	262	265	(J) Dallas, TX	(H) Lowell, AR	278	328
(D) Chicago, IL	(H) Lowell, AR	90	610	(J) Dallas, TX	(I) Okla. City, OK	93	233
(D) Chicago, IL	(J) Dallas, TX	94	899	(J) Dallas, TX	(K) Houston, TX	396	258
(E) Kan. City, MO	(A) Atlanta, GA	59	862	(K) Houston, TX	(A) Atlanta, GA	132	814
(E) Kan. City, MO	(F) Little Rock, AR	140	470	(K) Houston, TX	(F) Little Rock, AR	107	481
(E) Kan. City, MO	(H) Lowell, AR	73	289	(K) Houston, TX	(G) Memphis, TN	34	575
(F) Little Rock, AR	(A) Atlanta, GA	121	538	(K) Houston, TX	(I) Okla. City, OK	23	476
(F) Little Rock, AR	(B) Louisville, KY	22	513	(K) Houston, TX	(J) Dallas, TX	702	258

Figure 1. Case Study Network



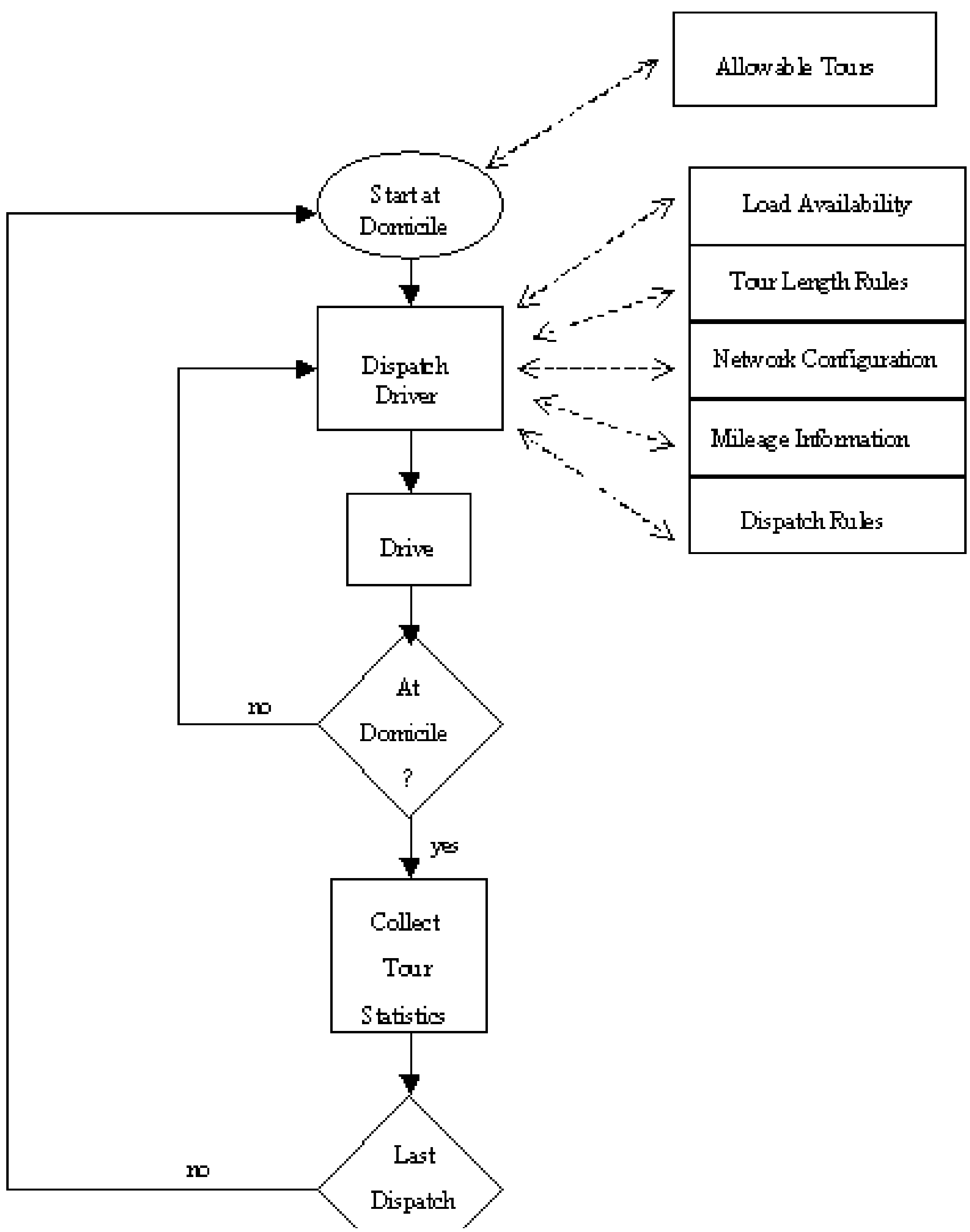
3.0 Simulation tools

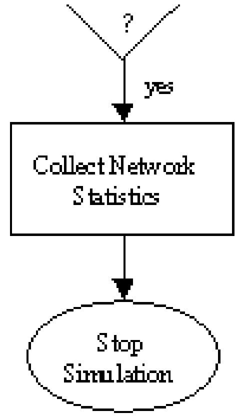
Simulation methods are non-optimizing by nature, but often provide excellent results for problems of practical size. Although the optimization methods presented below are appropriate for use in relatively large problems, they are somewhat restricted by the assumptions that make the problem tractable. For example, some of the data requirements for optimization include inputs that could arguably be reasonable model outputs. Specifically, the optimization formulation (for some applications) requires that we know the number of drivers and their domiciles. The simulation methods presented in this section are not restricted in this way. They are designed to assist in the determination of the number of required drivers and their domiciles for various dispatching methodologies. Using the simulation model, the user is able to quickly iterate to a good (but not optimal) solution to the driver fleet size and domicile determination problems.

3.1 Simulation model development

The simulation model is written in the SIMNET II simulation language (Taha 1988) and has been developed in a highly modular fashion that should be easily transportable into other languages. Consider the flowchart in figure 2. Model input includes the load availability table, tour length rules, network configuration and mileage tables, and dispatching rules. Also, the model requires initial inputs regarding the maximum number of allowable tour starts permitted during the planning horizon (one-quarter year in this report) from each domicile. Tour start inputs are the primary user input to the model. The simulation uses the allowable tour start inputs to source entities into the model at each proposed domicile. The entities represent drivers

Figure 2. Simulation Flowchart





(with their trucks) starting new tours. These entities are immediately sent to a modular section of code to dispatch the driver entities to network destinations.

It is the dispatching code that makes the simulation truly modular. The model architecture permits easy ‘what-if’ analysis. All network configuration and mileage information supporting the dispatch function is table-driven, so that network configuration issues can be addressed without modifying source code. Similarly, load availability information is table-driven. Load availability information can be input for all available loads or for all ‘balanced’ available loads, where 'balance' is defined as a network in which the total loads into each node is equal to the total loads out of each node. Beginning with a balanced network increases the probability of being able to create regular driving routes for drivers that begin and end at the driver's domicile, without the need to return empty to the domicile at the end of a tour. A balanced network is found by using the following simple node balance formulation:

$$\text{Maximize: } \sum_{\ell}\sum_{m\neq\ell} L^{\ell}_{m}(Z^{\ell}_{m}) \qquad (1)$$

Subject to:

$$L^{\ell}_{m} \leq A^{\ell}_{m} \qquad \forall \ell, m \neq \ell \qquad (2)$$

$$\sum_{m\neq\ell} L^{\ell}_{m} - \sum_{m\neq\ell} L_{m}{}^{\ell} = 0 \qquad \forall \ell \qquad (3)$$

$$L^{\ell}_{m} = \text{Integer} \qquad \forall \ell, m \qquad (4)$$

Where:

L^{ℓ}_{m} = Number of loads to move from city ℓ to city m.

Z^{ℓ}_{m} = Miles (or revenue-costs) from city ℓ to city m.

A^{ℓ}_{m} = Maximum allowable moves from city ℓ to city m (from the 'volume' column in Table 1.

The objective function in equation 1 seeks to make use of the maximum number of loaded miles. The objective is constrained by load availability for all freight lanes ($\forall \ell, m \neq \ell$ in equation 2), and by the need to balance freight flow at each node (equation 3) at an aggregate level, i.e., the number of moves out of each node must equal the number of moves into each node. Note in equation (3) that $L^{\ell}{}_{m}$ represents loads from ℓ to m and that $L_m{}^{\ell}$ represents loads from m to ℓ. Equation (3) is repeated for all values of ℓ. Equation 4 ensures the integrality of $L^{\ell}{}_{m}$ values.

The examination of alternative tour length and dispatching rules require minor changes to the source code, but in well-defined modular locations with pre-defined information transfer protocols to ensure that alternative methods are easily tested. The dispatching systems used can range from very sophisticated to very simple or even random.

After the simulated completion of a dispatch, the simulation entity representing the driver and his or her truck is sent back to the dispatcher for the next driving assignment. Each dispatching assignment is made based on node specific discrete probability density functions driven by historical freight availability. Upon return to the individual driver domicile, tour statistics are collected. After completion of the final tour, network statistics are collected and the simulation is stopped. Using simulation iterations featuring varied tour start profiles, it is a simple matter to quickly converge to near-optimal solutions to the driver domicile problem.

Simulation outputs include driver tour lengths by domicile and the overall weighted driver tour length for all drivers and all domiciles. It also calculates a final value for the number of drivers required (by domicile) and provides an overall number of required drivers in the total network (for network drivers only). Because some dispatching systems being simulated (i.e. random dispatching) would not necessarily require node balance or full compliance with load requirement profiles, additional system level metrics are collected to determine node balance and lane coverage in comparison with load requirements. Node balance is achieved when the observed departures from a node (terminal city) are equal to the desired departures from the node. Desired departures are an input to the simulation while observed values are simulation output. A positive node balance indicates that observed departures exceed actual requirements. A negative node balance indicates that actual requirements exceed observed departures. Similarly, lane balance is achieved when the observed lane volume is equal to the desired lane volume, where a lane is defined as a node-to-node (terminal city to terminal city) driving route.

In summary, the simulation requires initial estimates of driver tour starts by domicile and outputs performance information in terms of driver requirements and tour lengths in both summary and detailed formats for a given dispatching method. It also provides node balance and lane coverage information for various dispatching rules. The simulationist can iterate with the tool by varying tour start profiles to find near-optimal solutions for driver fleet size and domicile determination problems.

3.2 Case studies and model validation

In this section, the authors demonstrate the efficacy of use of the simulation model using the case study information supplied by JBHT and described in section 2.0 above. Additional validation for both the simulation and optimization approaches is offered in section 5.0 via comparison with solutions from state-of-the-art proprietary tools at JBHT.

The case study involves a network composed of 11 cities within the JBHT terminal-city network. The city nodes are not fully connected to all other city nodes via direct arcs (see figure 1) and no pre-conceived notions exist regarding the number of drivers to domicile at each city in support of the inter-city moves. First, the use of the model for domicile determination will be demonstrated. Subsequently, the use of the model to examine alternative dispatching methodologies will be presented.

The use of the simulation model as a means of determining driver fleet size and driver domiciles is demonstrated using a totally random dispatching method. Upon arrival at a system node, drivers are routed to a next city location totally randomly with the exceptions that only connected nodes can be used and that the probability of moving along a specific arc is driven by the long-term freight density profiles provided in table 1.

Initially, the simulation is used to iterate to a driver tour start profile that balances system nodes and covers the required inter-city moves for a one-quarter year planning period. This tour start profile is presented in table 2 under the heading of ‘driver scenario 1’. Note that 1200 tour starts are permitted. The tour starts are limited to 5 domiciles in scenario 1. This scenario recommends 81.01 drivers on duty at any given time to support inter-city deliveries. The drivers have an average tour length of 6.08 days with a maximum tour length of 12.35 days for drivers domiciled at Chicago. In the simulation model, the tour length in days is obtained by dividing the tour length in miles by 500, under the assumption that drivers can travel 500 miles/day. Throughout this report, the number of recommended drivers refers to the average number of drivers required to be on duty at any given time. Additional drivers would be taking days off and are not explicitly considered. The on duty drivers can service all necessary freight movements with a slight positive balance in lane coverage (0.64 loads per lane over the planning period) and with slight overall node imbalance (7.09 loads per node).

Table 2. Sample Simulation Output for Domicile Planning

	City	**Driver Scenario 1**	**Driver Scenario 2**
Allowable	Atlanta	230	220
Tour	Louisville	0	10
Starts	Detroit	0	10
By	Chicago	150	140
City	Kansas City	0	10
	Little Rock	290	280
	Memphis	0	10
	Lowell	0	10
	Okla. City	0	10
	Dallas	400	380
	Houston	130	120
Total Tour Starts		1200	1200
Avg. Tour Length (Days)		6.08 days	8.35 days
Max Tour Length		12.35 days at Chicago	227.38 days at Memphis
Total Drivers Required		81.01	111.34
Weighted Node Balance		7.09	293.18
Weighted Lane Balance		0.64	26.65

Driver scenario 2 in table 2 indicates a slightly different driver domicile plan with permissible tour starts in all 11 terminal cities involved in the study. Note that the overall number of tour starts remains the same at 1200, and that the dispersion of tour starts has changed only slightly. This scenario demonstrates the efficacy of the simulation system in determining the effects of seemingly small changes to domicile planning. Again assuming random dispatching upon arrival at a city, the drivers now take an average of 8.35 days to return to their point of origin (their domicile). At worst case (Memphis), drivers take a totally unacceptable mean of 227.38 days to return to their domicile for the case network. This is of course a function of the random freight movements in a partially connected network and would not happen using non-random dispatching methods, but it does highlight the need to place drivers in domiciles appropriate to freight availability and network connectivity. The longer tour lengths lead to greater coverage. 1200 tour starts in driver scenario 2 is equivalent to 111.34 drivers (25.1% more than in driver scenario 1). The node freight coverage is also higher, with drivers carrying 26.65 more loads per arc than required by freight density. Similarly, node imbalance is increased to 293.18 loads per node.

In both cases, the simulation is replicated 10 times and generally results in tight confidence intervals. The results of driver scenario 1 are therefore statistically significantly different from driver scenario 2 for all metrics.

The model can also be used to evaluate the effects of various dispatching methods. Table 3 summarizes the results of using three different dispatching methodologies, ranging from totally random to very restrictive dispatching rules. The first dispatching method is the random dispatch described above. The second makes use of random dispatching also, but with forced returns based on certain conditions. The conditions for these simulation runs are that a maximum of four dispatches or 2,500 miles per tour is allowed. After three dispatches or 2,000 miles, the driver must return to his or her domicile even if the resulting dispatch leads to an empty move. This type of forced return system would be essential in practical use even though the forced returns leads to significant increases in the required number of on duty drivers. The third dispatching system is even more restrictive. It permits drivers to travel only one city (one dispatch) from their domicile with forced returns to the domicile on the very next dispatch.

Table 3. Simulation Output for Various Dispatching Methods

	City Number	**Random Dispatch**	**Forced Returns**	**One-City Dispatch**
Allowable	Atlanta	230	531	412
Tour	Louisville	0	0	281
Starts	Detroit	0	0	240
By	Chicago	150	347	347
City	Kansas City	0	0	136
	Little Rock	290	670	852
	Memphis	0	0	16
	Lowell	0	0	221
	Okla. City	0	0	82
	Dallas	400	924	1155
	Houston	130	300	499
Total Tour Starts		1200	2772	4241
Avg. Tour Length (Days)		6.08 days	2.89 days	1.69 days
Max Tour Length		12.35 days at Chicago	3.97 days at Atlanta	2.70 days at Atlanta

Total Drivers Required	81.01	88.96	79.83
Weighted Node Balance	7.09	17.36	0.18
Weighted Lane Balance	0.64	1.58	0.02

The domicile plans for the three dispatching methods are different as well. The domiciles for the forced returns dispatching method differ from random dispatching domiciles primarily in scale. The forced returns create the need for more tour starts at each domicile. A total of 2,772 tour starts are required in the forced returns model compared to only 1,200 for the random dispatching model. The one-city dispatching rules, on the other hand, lead to the need for driver domiciles at each city in the network instead of only at five cities. The one-city dispatching method requires a total of 4,241 tour starts.

It should be noted that the only stochastic element in the simulation is the use of multiple replications of repeated sampling from discrete probability density functions for dispatching purposes. Therefore, the simulation model could also be implemented using dispatching heuristics with almost any general purpose software.

4.0 Optimization methods

As discussed in the literature review, a number of optimization approaches exist for a broad array of problem formulations in truckload trucking and dispatching. In this section, the authors formulate an integer programming (IP) model to optimize material movements between the various supply chain locations in limited networks. The IP model presented in this section produces optimal results for the dispatching problem relative to the stated objective function, but the computational complexity is increased and the operational efficacy is decreased relative to the simple rule based dispatching systems used in the simulation models. This section introduces the IP formulation used, demonstrates its feasibility for solving realistically sized planning and operations problems using the JBHT case data, and briefly discusses problem complexity and constraint management issues. In addition to the notation presented earlier to describe equations 1-4, the following notation is used to describe the IP model:

$X_{jk\ell m}$ = The number of times during the planning horizon that some driver domiciled at city j makes their k^{th} move from city ℓ to city m in a loaded status.

$Y_{jk\ell m}$ = The number of times during the planning horizon that some driver domiciled at city j makes his or her k^{th} move from city ℓ to city m in an unloaded status.

T_{max} = Maximum allowable tour length (or distance).

4.1 Model formulation

The IP model supports driver tour development in a seemingly random dispatch environment within a limited delivery network. It is suitable for building tours for a dedicated trucking fleet within a supply chain for a large company or companies, or for a truckload carrier operating within some limited network (i.e. between cities with existing terminals or between large customers and intermodal ramps, etc.). The formulation follows below:

$$\text{Maximize: } \sum_{j}\sum_{k}\sum_{\ell}\sum_{m\neq\ell} X_{jk\ell m}(Z_{\ell m}) - \sum_{j}\sum_{k}\sum_{\ell}\sum_{m\neq\ell} Y_{jk\ell m}(Z_{\ell m}) \qquad (5)$$

Subject to:

$$\sum_{j}\sum_{k} X_{jk}^{\ell}{}_{m} \leq A^{\ell}{}_{m} \qquad \forall\, \ell, m \neq \ell \qquad (6)$$

$$\sum_{\ell \neq j}\sum_{m \neq \ell} X_{jk}^{\ell}{}_{m} + \sum_{\ell \neq j}\sum_{m \neq \ell} Y_{jk}^{\ell}{}_{m} = 0 \qquad \forall\, j, k=1 \qquad (7)$$

$$\sum_{\ell \neq m} X_{jk}^{\ell}{}_{m} + \sum_{\ell \neq m} Y_{jk}^{\ell}{}_{m} - \sum_{\ell \neq m} X_{j(k+1)m}^{\ell} - \sum_{\ell \neq m} Y_{j(k+1)m}^{\ell} = 0 \qquad \forall\, j, k<K, m \neq j \qquad (8)$$

$$\sum_{\ell \neq m}\sum_{m \neq j} X_{jk}^{\ell}{}_{m} + \sum_{\ell \neq m}\sum_{m \neq j} Y_{jk}^{\ell}{}_{m} = 0 \qquad \forall\, j, k=K \qquad (9)$$

$$\sum_{k}\sum_{\ell}\sum_{m \neq \ell} X_{jk}^{\ell}{}_{m}(Z^{\ell}{}_{m}) + \sum_{k}\sum_{\ell}\sum_{m \neq \ell} Y_{jk}^{\ell}{}_{m}(Z^{\ell}{}_{m}) \leq T_{max} \qquad \forall\, j \qquad (10)$$

$$X_{jk}^{\ell}{}_{m} = \text{Integer} \qquad \forall\, j, k, \ell, m \qquad (11)$$

$$Y_{jk}^{\ell}{}_{m} = \text{Integer} \qquad \forall\, j, k, \ell, m \qquad (12)$$

The objective function in equation (5) maximizes the loaded miles minus empty miles, which is directly proportional to profit (carriers are normally not paid for empty repositioning moves). Actually $Z^{\ell}{}_{m}$ values can take on profit (revenue minus cost) values for a slightly different objective function that would penalize empty moves more heavily. In this report, we assume that $Z^{\ell}{}_{m}$ holds mileage values for city-to-city pairs to facilitate direct comparison with other tools that attempt to maximize the miles used in 'regular' tours. This comparison appears subsequently in this report. The first constraint (equation 6) is an expression that restricts network flow to known or assumed lane capacity based on the total number of shipments available during the time period under consideration. In other words, the carrier cannot move freight that does not exist but can use empty repositioning moves once freight on a particular lane is exhausted. Equation 7 ensures that all drivers begin their tours at their domicile by requiring that the sum of all empty or loaded moves for the first dispatch is zero when the dispatch is not from the driver domicile. Equation 8 ensures that all transshipment nodes (excluding the domicile) in each driver tour maintain a balance of capacity. Each driver that enters a node that is not his or her domicile must leave that node on the next dispatch. Drivers reaching their domicile prior to the k^{th} dispatch are not required to leave on the next dispatch but can stay at home. The next constraint (equation 9) ensures that each driver must return to his or her domicile prior to the end of the planning period. Actually, the constraint requires that the sum of moves during the last dispatch is zero at every node except the driver domicile. Equation 10 is an optional constraint that ensures that some maximum number of miles restricts driver tour lengths. This helps to ensure that drivers return to their domicile according to carrier goals. An alternative means of achieving this goal is by controlling the number of allowed dispatches per tour through specification of the upper bound, K, on the driver subscript, k, representing the dispatch number. Finally, equations 11 and 12 specify that $X_{jk}^{\ell}{}_{m}$ and $Y_{jk}^{\ell}{}_{m}$ are positive integers.

4.2 Numerical example

To illustrate the optimization model and to demonstrate its efficacy of use, the same national scale case study used to illustrate the simulation methods will be used. It should be noted at this point that the IP model (and the simulation models) can be used in two distinctly different ways. It can be used for aggregate planning or for detailed operational dispatching. In this section, the results of an aggregate planning case example are presented. The differences between the two applications will be more clearly presented in section 4.3. For convenience in making comparisons between the simulation and optimization methods, we have assumed that we will use the same five driver domiciles that resulted in near-optimal performance in the random OTR simulation model (Atlanta, GA, Chicago, IL, Little Rock, AR, Dallas, TX, and Houston, TX).

The example problem has been formulated and solved using the LINDO solver (Schrage 1986) which required less than 2 seconds on a 750 MHz Pentium PC. The solution output is shown in table 4. To aid in understanding the table, consider the first row. Tour A-1 indicates that this is the first tour in domicile A (Atlanta, GA). The tour description A-F-K-J-A indicates a tour that starts at domicile city A (Atlanta, GA), makes a first dispatch to city F (Little Rock, AR), makes a second dispatch to city K (Houston, TX), makes a third dispatch to city J (Dallas, TX) and makes a fourth and final dispatch back to the domicile in Atlanta, GA. The optimal solution indicates that this tour should be driven 302 times during each one-quarter year time period. The tour is 2081 miles in length, should take about 4.16 days (assuming that a driver

Table 4. Tour Summary From Optimization Solution

Domicile	Tour Number	Tour Description	Tour Quantity	Tour Miles	Tour Days	Required Drivers
(A) Atlanta, GA	A-1	A-F-K-J-A	302	2081	4.16	13.97
	A-2	A-B-A	72	872	1.74	1.40
	A-3	A-K-J-I-A	61	2174	4.35	2.95
	A-4	A-E-F-A	59	1870	3.74	2.45
	A-5	A-J-F-E-A	57	2477	4.95	3.14
	A-6	A-I-K-J-A	39	2407	4.81	2.09
	A-7	A-J-F-A	29	1683	3.37	1.09
	A-8	A-K-J-F-A	28	1951	3.90	1.21
	A-9	A-J-F-B-A	14	2094	4.19	0.65
	A-10	A-F-E-F-A	5	2016	4.03	0.22
(D) Chicago, IL	D-1	D-C-D	224	530	1.06	2.64
	D-2	D-B-C-B-D	210	1358	2.72	6.34
	D-3	D-H-E-H-D	73	1798	3.60	2.92
	D-4	D-B-A-J-D	23	2463	4.93	1.26
	D-5	D-H-J-H-D	17	1876	3.75	0.71
	D-6	D-B-F-J-D	15	2077	4.15	0.69
	D-7	D-C-B-D	2	944	1.89	0.04
(F) Little Rock, AR	F-1	F-J-F	758	682	1.36	11.49
	F-2	F-J-H-J-F	125	1338	2.68	3.72
	F-3	F-J-K-J-F	108	1198	2.40	2.88
	F-4	F-J-H-E-F	76	1428	2.86	2.41
	F-5	F-K-A-J-F	8	2440	4.88	0.43
	F-6	F-B-C-B-F	8	1736	3.47	0.31

(J) Dallas, TX	J-1	J-K-A-J	116	1876	3.75	4.84
	J-2	J-K-F-K-J	107	1478	2.96	3.51
	J-3	J-H-D-J	58	1837	3.67	2.37
	J-4	J-D-C-D-J	36	2328	4.66	1.86
	J-5	J-K-G-K-J	34	1666	3.33	1.26
	J-6	J-I-J	32	466	0.93	0.33
	J-7	J-K-I-K-J	23	1468	2.94	0.75
	J-8	J-K-A-I-J	8	2174	4.35	0.39
	J-9	J-H-E-A-J	2	2283	4.57	0.10
(K) Houston, TX	**K-0**	No tours specified	0	0	0	0

covers approximately 500 miles per day), and collectively would occupy the full-time activities of 13.97 drivers to satisfy the freight demand on the network tour arcs.

All loads contributing to the objective of increasing loaded miles (or revenue) are included in the solution. Note that each driver starts his or her tour at the appropriate driver domicile, and that no load availability constraints are exceeded. Similarly, note that each driver returns to his or her domicile at the end of each tour. In this example, it is assumed that a maximum of K = 4 dispatches are permitted. This example makes use of 100% of the allowed maximum freight in all lanes and the naturally integer solution is equal to the linear programming (LP) maximum. No additional random OTR drivers are needed to handle excess network freight and there is no need for subcontract drivers.

4.3 Driver-based aggregate planning problem

In addition to the above aggregate planning problem, we developed a formulation for a driver-based aggregate problem. The problem is inherently the same with the pure aggregate problem; the only difference is that the solutions of this problem are able to identify the drivers that are needed from each domicile. This is done by defining an additional set I of drivers domiciled at any domicile, indexed by i=1, …, n_j where n_j is the number of drivers at domicile j. While in this driver-based aggregate model we still treat the decision variables $X_{ijk}{}^{\ell}{}_{m}$ and $Y_{ijk}{}^{\ell}{}_{m}$ to be general integers, we will later discuss a model for a more detailed driver-based operational problem where $X_{ijk}{}^{\ell}{}_{m}$ and $Y_{ijk}{}^{\ell}{}_{m}$ will be binary integers.

The mathematical model for this driver based aggregate planning is very similar with the aggregate based planning model outlined in section 4.1. In the driver based aggregate planning model, we add an index i as set of drivers and one additional constraint which enforces the tour to have the domicile be initiated at the first move and be ended at the last move.

$$\sum_{\ell \neq j}\sum_{m \neq \ell} X_{ijk\ell m} + \sum_{\ell \neq j}\sum_{m \neq \ell} Y_{ijk\ell m} = 0 \qquad \forall\ i,\ j,\ k\ >\ 1\ \&\ \ k\ <\ K$$

Alternatively we can do this constraint by assigning each variable in the equality to be zero, i.e., $X_{ijk}{}^{\ell}{}_{m} = 0$ and $Y_{ijk}{}^{\ell}{}_{m} = 0$; $\forall i, j, k = 2,3,4 \ldots K-1$, ℓ 1 j and m 1 ℓ.

4.3.1 A Numerical Example

We provide examples of the driver-based aggregate model by analyzing a small-scale problem (See Table 5 for the data of the example). We have only two domiciles, Atlanta and Detroit in this example. The number of moves is restricted to be three, the number of drivers at each domicile is five, and the number of origin and destination cities is three.

Table 5. Data for the small scale problem

From City	To City	Volume	Miles
Atlanta	Louisville	72	436
Atlanta	Detroit	297	265
Louisville	Atlanta	109	436
Louisville	Detroit	218	355
Detroit	Louisville	220	355
Detroit	Atlanta	260	265

Table 6. Solution of small scale problem

Tour	Driver	Domicile	Tour Description	Tour Quantity	Tour Miles
1	1	Detroit	Det-Atl-Det	1	530
2	1	Detroit	Det-Lou-Det	62	710
3	2	Detroit	Det-Lou-Det	3	710
4	3	Detroit	Det-Atl-Det	2	530
5	3	Detroit	Det-Atl-Lou-Det	34	1056
6	3	Detroit	Det-Lou-Det	1	710
7	3	Detroit	Det-Lou-Atl-Det	6	1056
8	4	Detroit	Det-Lou-Det	63	710
9	5	Detroit	Det-Lou-Det	2	710
10	5	Detroit	Det-Lou-Atl-Det	41	1056
11	1	Atlanta	Atl-Det-Atl	83	530
12	1	Atlanta	Atl-Lou-Atl	1	872
13	2	Atlanta	Atl-Det-ATl	31	530
14	2	Atlanta	Atl-Det-Lou(Y)-Atl	1	1056
15	3	Atlanta	Atl-Det-ATl	8	530
16	3	Atlanta	Atl-Lou_Atl	17	872
17	3	Atlanta	Atl-Lou-Det-Atl	18	1056
18	4	Atlanta	Atl-Det-Lou-Atl	42	1056
19	5	Atlanta	Atl-Det-Atl	82	530
20	5	Atlanta	Atl-Lou-Atl	1	872

The solution presented in Table 6 has additional information about who is responsible for a particular tour. The solution produces the objective function value, which is the loaded mileage of 365,895 and 20 tours (not necessarily different). For example, there are two drivers (driver 3 and driver 5) responsible for tour Detroit-Louisville-Atlanta-Detroit (tours 7 and 10). Driver 3 would drive the tour (tour 7) for 6 times, driver 5 would drive the tour (tour 10) for 41 times. In addition to this tour, driver 5 is also responsible for another tour Detroit-Louisville-Detroit (tour 9) for two times, driver 3 also has three other tours (tours 4, 5, and 6). We should note that a quick analysis of the solution might improve the assignment of tours to driver. For example, driver 3 domiciled at Detroit drives tour Detroit-Louisville-Detroit (tour 6) just once. An improvement to the solution would be to assign tour 6 to driver 1 since s/he already drives the same tour 62 times. In this way, we can relieve driver 3 from driving tour 6. We can think of this as a consolidation of the tours so that at least some regularization of “tour types” is realized. We can achieve this by introducing a lower bound on the number of tours a driver can be assigned, which is left for future research.

To see how factors such as the number of drivers and the number of moves affect the solution and its associated total mileage, we conducted additional experiments. Table 7 shows the results for different number of drivers (5,6,7,8, and 9 per domicile) and different number of moves allowed (2,3, and 4).

Table 7. Objective Function Value for Different Scenarios

Set I (# of drivers) per domicile	Set K (# of moves)	**Objective Function** (in loaded miles)
5	2	355364
6	2	355364
7	2	355364
5	3	369586
6	3	369586
7	3	369586
8	3	369586
9	3	369586
5	4	369586
6	4	369586

The results show that using the same number of moves (|K| =3 or |K| = 4) the objective function value would be the same regardless of the number of drivers available. However, if we reduce the number of moves allowed, then the objective function value decreases, which shows the need for determining the number of moves carefully.

In addition to the above model, we also modify the model slightly by changing the objective function. This objective function is to minimize the total number of drivers needed to cover the demanded loads; $\sum_{i\in I}\sum_{j\in J} O_{ij}$, where O_{ij} is a binary decision variable which is 1 if driver i from domicile j is actively utilized (used in the solution), zero otherwise. We need to add a set of constraints to the existing constraints above to satisfy the logical relationship between O_{ij} and $X_{ijk}{}^{\ell}{}_{m}$. This constraint set is as follows:

$$\sum_{k\in K}\sum_{\ell\in L}\sum_{m\in M} X_{ijk\ell m} \le O_{ij}M \qquad \forall i,j$$

The new constraints make sure that if O_{ij} is zero then $X_{ijk}{}^{\ell}{}_{m}$ is also zero and if O_{ij} is one then some $X_{ijk}{}^{\ell}{}_{m}$ can be greater than zero. In other words, if driver i from domicile j is not used (O_{ij} is zero) then the number of tours by driver i from any origin cities to any destination cities in any move has to be zero. We left the further exploration of this more detailed and complex formulation as a future research. In the next section, we discuss another driver-based model, which is called operational dispatching model where driver-load assignment decisions are made for shorter term planning horizon.

4.4 Constraint management, model use, and problem relaxations

The IP models presented above can be used for detailed operational dispatching as well as aggregate planning, and driver based aggregate planning as discussed previously. Aggregate planning provides the tour overview information provided in table 4. This is very useful information for hiring and asset planning. When used for aggregate planning or driver based aggregate planning, equations 11 and 12 indicate that $X_{jk}{}^{\ell}{}_{m}$ and $Y_{jk}{}^{\ell}{}_{m}$ are general integers. Normally, this would lead to solution difficulty. However, when used for aggregate planning, the model is naturally integer and solution times are trivial, even for relatively large problems.

Detailed operational planning creates a more challenging environment for the IP model. When used for detailed dispatching, the model provides information about which particular driver will need to pick up which particular load during each dispatch cycle. The variables

$X_{jk}{}^{\ell}{}_{m}$ and $Y_{jk}{}^{\ell}{}_{m}$ now need an additional subscript for each driver i:

$X_{ijk}{}^{\ell}{}_{m}$ = 1 if driver i from domicile j makes his or her k^{th} move from city ℓ to city m in a loaded status, 0 otherwise.

$Y_{ijk}{}^{\ell}{}_{m}$ = 1 if driver i from domicile j makes his or her k^{th} move from city ℓ to city m in am unloaded status, 0 otherwise.

Similarly, the formulation must recognize the additional subscript needs. $X_{ijk}{}^{\ell}{}_{m}$ and

$Y_{ijk}{}^{\ell}{}_{m}$ values in equations (5) and (6) must be summed over all i and equations (7-10) must be repeated for all i.

Equations 11 and 12 now specify that $X_{ijk}{}^{\ell}{}_{m}$ and $Y_{ijk}{}^{\ell}{}_{m}$ values are binary (0,1) integers, because a particular driver can pick up only one load at a time.

The optimization model, whether used for aggregate planning or for operational dispatching, provides a means of developing optimal tours for problems of national scale. Even so, as pointed out in Crainic and LaPorte (1997), vehicle routing problems can quickly become cumbersome in terms of the number of integer variables required. The current formulation is much more cumbersome computationally when used as an operational dispatching tool. Consider the computational complexity information for the operational problem formulation presented in table 8. The table reveals that when four dispatches per tour are permitted (a reasonable number of dispatches given the goal to reduce tour length), this problem remains quite reasonable in terms of the number of constraints but that the number of variables quickly grows as a function of problem size. The optional mileage constraint (equation 10) that caps T_{max} (maximum tour length in miles) adds very little computational burden in terms of added constraints.

In general, recognizing that each driver has only one domicile, we let I' = the unique driver/domicile combinations (I' = I). Similarly, we let ℓ' = the unique combinations of ℓ and m where $\ell \neq$ m (mℓ -m). In the worst case, the model results in {2(I')(k)(ℓ')} variables but only {I'[3+(k-1)(m-1)]+ ℓ'} constraints. Only

{I'[2+(k-1)(m-1)]+ ℓ'} constraints are required when the optional constraints (equation 10) indicating T_{max} are omitted.

Table 8. Worst Case Computational Complexity When K=4

Drivers	Nodes	Variables	Constraints With T_{max}	Constraints Without T_{max}
3	3	144	33	30
3	5	480	65	62
3	10	2160	180	177
3	20	9120	560	557
5	3	240	51	46
5	5	800	95	90
5	10	3600	240	235
5	20	15200	680	675
10	3	480	96	86
10	5	1600	170	160
10	10	7200	390	380
10	20	30400	980	970

Although data input and output needs are considerable with large dispatching problems, this difficulty is easily defeated by the development of simple data entry tools. Therefore, the difficulty associated with large problems lies not in formulation, but in solution. To solve larger dispatching problems in an acceptable amount of time, it is necessary to find ways to decrease the number of integer variables. Problem structure can be exploited in three ways to find more tractable solutions.

The first relaxation involves network structure. The worst case analysis of computational complexity presented in table 8 assumes a delivery network with each node directly connected to each other node via a direct arc. In networks with less direct connectivity, the problem is greatly simplified. Only the most necessary or most likely arcs should be included in the network.

The second relaxation exploits the fact that in large networks, multiple drivers would likely be domiciled in the same location and many would likely drive the same tours. Recall, for example, the output presented in table 4 for the case problem. Tour A-1 involves approximately 14 drivers making 302 tours during each 90-day period. The problem can therefore be greatly simplified by combining model entities representing individual drivers into model entities representing groups of drivers. The model formulation can be adjusted to account for this by multiplying $X_{ijk\ell m}$ and $Y_{ijk\ell m}$ values in the objective function (equation 5) and in some constraints (equation 6) by the driver multiples. In this case, the solution is slightly less flexible, but much more tractable. By exploiting the network structure and by relaxing the driver tour requirements via consolidation, the formulation was used with binary integers to solve a detailed dispatching plan for the JBHT case problem. The simulation output from the random dispatching model (with forced returns) was used to provide initial input regarding the quantity of drivers per domicile. It is assumed that the 89 drivers are partitioned into 5 sets. The 23 Atlanta drivers drive the same tours, as do the 10 Chicago drivers, 20 Little Rock drivers, 26 Dallas drivers, and 10 Houston drivers. Even this dispatching problem is difficult to solve. In this solution, 500,000 pivots were permitted following the LP solution. The problem did not iterate to optimality, but an integer solution that made use of 77% of the available loads was found. Given the strict driver partition, this solution is likely very near optimal.

The third opportunity for problem relaxation is to simply complete the dispatching problem on a domicile-by-domicile basis using individual drivers or smaller partitions. Driver needs by domicile can be determined via aggregate planning through simulation or optimization methods and the IP can be regularly used at the domicile to complete specific dispatching plans in support of daily operations.

5.0 Comparison with state-of-the-art solution tools

To validate the simulation and optimization tools presented in this report; a further comparison is made with proprietary state-of-the-art route regularization tools owned by JBHT. Similar to the tools presented in this report, the JBHT regularization system, called HOT (hub optimization technique) seeks to find regular routes from seemingly random freight. The JBHT system seeks to find “closed-loop” tours designated CL2 or CL3, to indicate 2-legged or 3-legged closed-loop tours, respectively. To facilitate comparison, the heuristic-based JBHT system has been used to evaluate the same case data used to illustrate the simulation and optimization methods. Two runs of the JBHT system have been completed. The first looks for CL2 tours and then finds CL3 tours from the remaining freight. The second run looks for CL3 tours first, and then finds CL2 tours from the remaining freight. A comparison of all three simulation dispatching methods, the IP solution, and the two JBHT HOT solutions appears in table 9.

Table 9. Solution Comparison Table

	Tour Length (days)	**Percent of Freight Used**	**Number of Regular Tours**	**Number of Drivers Required**	**Adjusted Number of Drivers**

Simulation With Random Dispatch	6.08	100.90	0	81.01	80.29
Simulation With Forced Returns	2.89	102.3	0	88.96	86.96
Simulation With One-City Dispatch	1.69	100.02	0	79.83	79.81
Integer Programming Solution	2.65	100.00	32	80.39	80.39
JBHT-HOT (CL2 then CL3)	2.25	95.14	15 CL2 **12 CL3** 27	76.49	80.39
JBHT-HOT (CL3 then CL2)	1.73	86.72	21 CL3 **4 CL2** 25	69.72	80.39

The first column in table 9 indicates the average tour length for all network drivers. The second column indicates the percent of available freight used. Note that this can be greater than 100% for the simulation methods, indicating that the somewhat random dispatching methods used would actually require more freight in some lanes than is actually available. The number of regular tours generated is found in the third column. The last two columns indicate the number of required drivers and the “adjusted” number of required drivers. The required drivers column simply states the number of drivers calculated by the various methods. The adjusted number of drivers estimates the number of drivers that would be required if exactly 100% of the freight were used in the solutions. For example, the simulation with forced returns suggests 88.96 drivers but actually moves 2.3% more freight than required. The 'adjusted' drivers required to carry exactly 100% of the freight is 86.96 drivers (88.96/1.023). Similarly, the JBHT (HOT) tool (with CL2 then CL3) requires 76.49 drivers to move 95.14% of the freight. It would take 80.39 (76.49/.9514) drivers to move all of the freight. In this case, the 80.39 adjusted drivers is equal to the number of adjusted drivers suggested by the IP model because the IP model recommends a solution that utilizes 100% of the freight. The common assumption of 500 miles/driver/day assures the equivalency of all solutions making use of 100% of the freight.

Let us complete the comparison by using the IP solution as a baseline. The IP system uses all freight, produces 32 regular tours at four domicile cities with a 2.65-day mean tour length, and requires 80.39 drivers. This is an outstanding solution. 2.65 days is a much better tour length than the truckload trucking industry standard tour length of 14 or more days. The JBHT solution finds better tour lengths, but does so by restricting tours to 2 or 3 dispatches instead of 4 in the IP model. The JBHT HOT tool also does not result in a solution that includes as much freight in regular tours as the IP solution (86.77 and 95.14% of the freight compared to 100%). The adjusted number of drivers is identical to the IP solution. The simulation solutions do not find regular tours, but still produce excellent tour durations, even in a random dispatching environment. The fully random solution indicates that 80.29 drivers could handle 100% of the volume and the one-city random dispatching system indicates that 79.81 drivers are needed to handle all of the volume. The fact that these methods do not suggest exactly 80.39 drivers is not disturbing because the simulations were replicated 10 times and some random error exists. The confidence interval for the adjusted number of drivers includes 80.39. The only difference in adjusted drivers comes with the forced dispatch model. The additional drivers are needed to support empty returns from distant cities that do not have direct network arc connections with the domicile.

6.0 Concluding remarks

The goals for the tools presented in this report are to provide state-of-the-art capability in designing and operating delivery networks for truckload trucking moves in support of modern manufacturing systems. Specifically, the optimization and simulation tools discussed herein provide new means of achieving driver tour regularization that represent a reasonable compromise between traditional random OTR dispatching and strict regularization. The literature has addressed many related issues but has not directly addressed this problem. Related work considers many ways to deal with single dispatches and addresses many ways to deal with single domicile or distributor locations for both truckload and LTL situations. No literature was found in support of multiple drivers, multiple domiciles, and multiple dispatches that made use of random pattern types in partial freight networks.

The optimization methods provide a means of determining optimal freight movements for problems of national scale. The IP model presented herein is especially useful for aggregate planning due to the manageable computational complexity of IP models at that level, but with relaxation is also very useful as an operational dispatching tool. Additional computational complexity of operational IP models at the operational level is somewhat handled by introducing an intermediate level solution, defining a driver-based planning model. The simulation methods also provide an excellent planning tool for use in determining driver needs, including both driver quantity and domicile decisions, for small or large problems. The simulation solutions are not as strong as those found by the IP model, but the computational complexity of the simulation systems is much less prohibitive and extremely large problems can be formulated and solved quickly. Also, the simulation platform provides a much simpler tool for use in operational dispatching. Current research focuses on developing more sophisticated dispatching methods for use in the simulation system so that results can more closely approximate those developed by the IP solution.

Both simulation and optimization methods support the development of unique driver dispatching methodologies that restrict driver movements to limited networks without restricting the dispatch function within that network and both compare very favorably to state-of-the-art proprietary tools. Both the optimization and simulation alternatives are supported by industrial case studies of continental scale, thus assuring that the ideas presented within the report are practically motivated and industrially relevant. JBHT is now making use of these tools to design dedicated fleet operations in support of their corporate goal to regularize driving jobs. Because JBHT is the largest publicly held truckload trucking company in the United States, the tools and the strategies they support have the potential to fundamentally change the dispatching function in truckload trucking for the better, thus advancing the state-of-the-art in dispatching methods in multi-facility supply chains and contributing significantly to supply chain management technologies in agile or distributed manufacturing settings.

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