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The Impact of Dynamism on Motor Carrier Performance

Asvin Goel[1,2]

[1] MIT-Zaragoza Logistics Program
Zaragoza Logistics Center, Avda. Gómez Laguna 25, 50009 Zargaoza, Spain
asvin@mit.edu
[2] Applied Telematics/e-Business Group
Department of Computer Science, University of Leipzig, Germany
asvin.goel@uni-leipzig.de

Abstract: *Many motor carriers must generate tours for their vehicles without full knowledge about actual transportation demand. Often, new transportation demand is requested after vehicles have begun their tours and the motor carrier must dynamically modify tours in order to consider new transportation requests. Such dynamic changes can have a significant impact on tour length, emissions, costs, and profitability. This paper seeks to quantify the impact of dynamics on motor carrier performance. For this, the decision making process of motor carriers is simulated based on scenarios with different levels of dynamism to compare the resulting profitability. Simulation experiments indicate that motor carrier performance can be significantly increased if advance demand notification times are increased from below ten hours to above twelve hours. It appears that driver's working hour regulations as imposed by European Union legislation have a particular impact on this jump in profitability.*

Keywords: *Transportation, Dynamic Vehicle Routing, Advance Demand Notification, Information Sharing, In-Transit Visibility, EC Regulation 561/2006*

1 Introduction

While planning vehicle tours on a day-to-day basis used to be common practice in the motor carrier industry, the recent years have shown an increasing interest in dynamic vehicle routing. One reason for this development is the increasing commitment to just-in-time practices and the reduction of inventory levels. With reduced inventory buffers any mismatch between supply and demand can result into significant disturbances of supply chain performance. With sometimes only a few hours of safety stock at hand, companies committed to just-in-time practices are more likely to require emergency orders in order to prevent inventory shortages. Motor carriers must be able to modify already planned tours in order to fulfil such transportation requests arriving with short advance notice.

The level of dynamism a motor carrier has to deal with is often regarded as exogenous variable. However, in some cases the level of dynamism can be actively controlled. One source of dynamism is lacking visibility over transportation processes in intermodal transportation chains. Onward transportation can often only be organised after arrival of a container at an intermodal transshipment terminal. This, however, creates a high level of dynamism for motor carriers as transportation shall typically start as soon as possible. Advances in communication and information technology allow obtaining real-time information about containers in transit. For example, IBM and Maersk Logistics have jointly developed a system for tracking shipping containers around the world (Collins (2005)). The real-time tracking devices use a combination of wireless technologies to submit container-related data such as the physical location. If such container tracking devices are used, the arrival time of containers at terminals can be estimated with high accuracy. This allows for organising onward transportation before the container is unloaded. Consequently, the level of dynamism the motor carrier has to deal with is reduced.

Another source of dynamism is the time delay between realisation of transportation demand and the time the dispatcher receives the transportation request. Carriers and shippers can collaborate in order to change business processes and integrate information systems to increase the speed with which information about transportation requests travels to the dispatcher. The earlier the dispatcher knows about new transportation requests the more time is available to re-optimise vehicle tours. Decreasing the level of dynamism does not come for free. Improving visibility over containers in transit incurs costs for investing in the required technology. Modifying business processes and integrating information systems also incurs costs which are difficult to justify if the return on investment is not known.

Motor carriers operating on a day-to-day basis may want to increase flexibility of their services by improving their capability of fulfilling same day transportation requests. Building up this capability, however, may incur costs for equipping vehicles with telematics devices allowing to locate vehicles and to communicate with drivers. The increased flexibility achieved by considering same-day requests translates in a higher level of dynamism, but may result in gained market share. Whether costs for deploying fleet telematics systems are justified depends on whether the additional market share that can be gained outweighs a potentially lower operational efficiency resulting from the increased level of dynamism.

In order to justify investments into technology, redefinition of business process, and integration of information systems, one needs to understand how the level of dynamism impacts the performance of motor carrier operations. The goal of this paper is to assess the impact of dynamism in long-distance haulage where regulations concerning drivers' working hours must be considered. The remainder of this paper is organised as follows. First we survey related work. Then, the problem considered in this paper is described. Thereafter, the decision making process and the simulation conducted are described and discussed. Eventually, some concluding remarks are given.

2 Related Work

In order to deal with dynamism motor carriers must have timely access to all relevant information about the transportation system, i.e. information about current transportation processes as well as information about transportation requests. Fleet telematics systems allow tracking vehicles and obtaining information about the state of drivers and vehicles. Data obtained by such fleet telematics systems can be automatically transferred to logistics systems as shown in Goel (2007), Gruhn et al. (2003), and Erkens and Kopfer (2001). Information concerning transportation requests can be obtained by integrating information systems throughout the supply chain. The integration of supply chain information systems is studied for example by Gunasekaran and Ngai (2004) and Themistocleous et al. (2004).

Psaraftis (1988) and Psaraftis (1995) provide comprehensive discussion of dynamic vehicle routing. Typical vehicle routing problems in long-distance haulage are so-called Pickup and Delivery Problems (PDP). Comprehensive surveys on the PDP are provided Mitrović-Minić (1998) and Desaulniers et al. (2002). Dynamic Pickup and Delivery Problems are studied for example by Savelsbergh and Sol (1998), Powell et al. (2000), Mitrović-Minić (2001), Fleischmann et al. (2004), Yang et al. (2004), Pankratz (2005), and Goel and Gruhn (2008). Most of the literature on dynamic vehicle routing seeks to present solution approaches for specific scenarios having a certain degree of dynamism.

This work seeks to quantify the value of advance notification times for transportation requests, i.e., the time between when transportation requests become known and when the requests can first be served. Jaillet and Wagner (2006) quantify the value of advance notification times for the online travelling salesman problem in form of improved competitive ratios. The certainly most related work to this paper is presented by Tjokroamidjojo et al. (2006) who present a dynamic load assignment problem to quantify the benefits of advance demand notifications. Although their approach is very similar to the approach presented in this paper, there are various differences. Tjokroamidjojo et al. focus on small-scale transportation problems with 50 transportation requests to be served in 20 days, while this paper focuses on large-scale transportation problems with 500 transportation requests to be served in 5 days. Consequently, the approach presented in this paper cannot rely on optimisation techniques. Instead, meta-heuristics are used to find solutions to the planning problem. Although also considering long-distance haulage, regulations concerning drivers' working hours are not regarded by Tjokroamidjojo et al.. This paper determines the value of advance notification times for long-distance haulage in which European Union regulations concerning drivers' working hours must be considered. Tjokroamidjojo et al. study various scenarios in which the time difference between notification of transportation demand and final decision on load/driver assignments is either zero, two, or four days. While there is a large efficiency gap between zero days and two days between notification of transportation demand and final decision on load/driver assignments, moving from two to four days difference does not improve efficiency very much. This paper provides a detailed study on the value of advance notification times ranging from two to 48 hours. Furthermore, this paper assumes that not all transportation requests arrive dynamically. Instead, various scenarios are studied in which ten to ninety per cent of all transportation requests are known well in advance and the remaining requests arrive dynamically.

3 Problem considered

The Pickup and Delivery Problem with Profits

In this paper we consider a generalisation of the Pickup and Delivery Problem with Time Windows (PDPTW). The PDPTW is the problem of finding a set of tours, for a fleet of vehicles, in order to serve a set of transportation requests at minimal costs. In the case of full truckloads each transportation request is specified by the origin and destination of the load, and time intervals during which origin and destination must be visited. Each vehicle has a given start location, and an end location, and can serve at most one transportation request at a time. In other words, the Pickup and Delivery Problem with Time Windows deals with the construction of routes in order to visit all pickup and delivery locations and satisfy precedence, pairing, and time window constraints. Precedence constraints deal with the restriction that each pickup location has to be visited prior to visiting the corresponding delivery location. Pairing constraints restrict the set of admissible routes such that one vehicle has to do both the pickup and the delivery of the load of one transportation request. Time window constraints restrict the time during which pickup and delivery locations may be visited.

In the Pickup and Delivery Problem with Profits (PDPP) it is not necessary to serve all transportation requests. Each transportation request is associated a revenue which only can be collected if the transportation request is served. The goal of the PDPP is to maximise profits, i.e. the difference between all collected revenues and the costs for operating the tours. The PDPP is a combined load acceptance and routing problem which generalises the PDPTW and the Travelling Salesman Problem with Profits studied by Feillet et al. (2005). Furthermore, the PDPP is a special case of the General Vehicle Routing Problem (GVRP) introduced by Goel and Gruhn (2008).

We will now give a mathematical formulation of the PDPP. Let $\mathcal{O}$ denote the set of transportation requests (orders) and $\mathcal{V}$ denote the set of vehicles. For all $o \in \mathcal{O}$ let $n_{(o,1)}$ and $n_{(o,2)}$ denote the pickup and delivery locations. For all $v \in \mathcal{V}$ let $n_{(v,1)}$ and $n_{(v,2)}$ denote the start and end locations of the vehicle's tour. Let

$$\mathcal{N} := \bigcup_{o\in\mathcal{O}} \{n_{(o,1)}, n_{(o,2)}\} \cup \bigcup_{v\in\mathcal{V}} \{n_{(v,1)}, n_{(v,2)}\}$$

and

$$\mathcal{A} := \mathcal{N} \times \mathcal{N} \setminus \{(n,n) \mid n \in \mathcal{N}\}.$$

For each node $n \in \mathcal{N}$ lower and upper bounds specifying the time windows are denoted by $t_n^{\min}$ and $t_n^{\max}$. For each vehicle $v \in \mathcal{V}$ the travel time for an arc $(n,m) \in \mathcal{A}$ including some possible service time at node n is denoted by d_{nm}^v. For each vehicle $v \in \mathcal{V}$ the cost for travelling from node $n \in \mathcal{N}$ to node $m \in \mathcal{N}$ is denoted by c_{nm}^v. For each order $o \in \mathcal{O}$ the revenue gained when the order is served is denoted by p_o. Every vehicle has a capacity of r. At every node a shipment may be loaded or unloaded which requires or releases a certain amount of the vehicle's capacity. For every $n \in \mathcal{N}$ let r_n denote the amount loaded or unloaded at the node. If a shipment is loaded r_n is non-negative, if it is unloaded r_n is non-positive.

The PDPP can be modelled using the binary variables x_{nm}^v and y_n^v. x_{nm}^v indicates whether $m \in \mathcal{N}$ is visited immediately after node $n \in \mathcal{N}$ by vehicle $v \in \mathcal{V}$ ($x_{nm}^v = 1$), or not ($x_{nm}^v = 0$). y_n^v indicates whether node $n \in \mathcal{N}$ is visited by vehicle $v \in \mathcal{V}$ ($y_n^v = 1$), or not ($y_n^v = 0$). For each node $n \in \mathcal{N}$ the PDPP contains the variables t_n and ρ_n. If node $n \in \mathcal{N}$ is visited by a vehicle t_n specifies the arrival time and ρ_n specifies the current load of the vehicle. If no vehicle visits node $n \in \mathcal{N}$ both t_n and ρ_n are without any meaning.

The PDPP is

maximise

$$\sum_{v\in\mathcal{V}} \Big(\sum_{o\in\mathcal{O}} y_{n_{(o,1)}}^v p_o - \sum_{(n,m)\in\mathcal{A}} x_{nm}^v c_{nm}^v \Big) \tag{1}$$

subject to

$$\sum_{(n,m)\in\mathcal{A}} x_{nm}^v = \sum_{(m,n)\in\mathcal{A}} x_{mn}^v \text{ for all } v \in \mathcal{V}, n \in \mathcal{N} \tag{2}$$

$$y_n^v = \sum_{(n,m)\in\mathcal{A}} x_{nm}^v \text{ for all } v \in \mathcal{V}, n \in \mathcal{N} \tag{3a}$$

$$\sum_{v\in\mathcal{V}} y_n^v \leq 1 \text{ for all } n \in \mathcal{N} \tag{3b}$$

$$\begin{aligned} &\text{for all } v \in \mathcal{V}, (n,m) \in \mathcal{A} \text{ with } n \neq n_{(v,2)}: \\ &\text{if } x_{nm}^v = 1 \text{ then } t_n + d_{nm}^v \leq t_m \end{aligned} \tag{4a}$$

$$t_n^{\min} \leq t_n \leq t_n^{\max} \text{ for all } n \in \mathcal{N} \tag{4b}$$

$$t_{n_{(o,1)}} \leq t_{n_{(o,2)}} \text{ for all } o \in \mathcal{O} \tag{5}$$

$$y^v_{n_{(v,1)}} = y^v_{n_{(v,2)}} = 1 \text{ for all } v \in \mathcal{V} \tag{6a}$$

$$y^v_{n_{(o,1)}} = y^v_{n_{(o,2)}} \text{ for all } o \in \mathcal{O}, v \in \mathcal{V} \tag{6b}$$

$$\rho_{n_{(v,1)}} = r_{n_{(v,1)}} \text{ for all } v \in \mathcal{V} \tag{7a}$$

$$\begin{array}{l} \text{for all } v \in \mathcal{V}, (n,m) \in \mathcal{A} \text{ with } n \neq n_{(v,2)} : \\ \text{if } x^v_{nm} = 1 \text{ then } \rho_m = \rho_n + r_m \end{array} \tag{7b}$$

$$0 \leq \rho_n \leq r \tag{7c}$$

$$\begin{array}{l} x^v_{nm} \in \{0,1\} \text{ for all } v \in \mathcal{V}, (n,m) \in \mathcal{A}, \\ y^v_n \in \{0,1\} \text{ for all } v \in \mathcal{V}, n \in \mathcal{N} \end{array} \tag{8}$$

The objective function is represented by (1). Equation (2) represents the flow conservation constraints which impose that each vehicle which reaches a node $n \in \mathcal{N}$ also departs from the node. Constraints (3a) and (3b) impose that each node is visited at most once. Inequality (4a) imposes that each node which is not the starting point of a tour is reached no earlier than the preceding node plus the time required to travel from the preceding node to the node. Inequality (4b) impose that each arrival time is within the time windows of the node. Constraint (5) represents the precedence constraint imposed on the sequence in which customer nodes are visited. Equation (6a) imposes that each tour passes the specified start and end point of the vehicle. Equation (6b) represents the pairing constraint which imposes that pickup and delivery location of an order are visited by the same vehicle. Constraints (7a) to (7c) are the capacity constraints. Finally, constraints (8) impose that the values of x^v_{nm} and y^v_n are binary.

Drivers' Working Hours

Drivers' working hours in the European Union are regulated by EC regulation 561/2006 which entered into force in April 2007. According to the regulation driving periods, breaks, and rest periods for a single manned vehicle must be scheduled as follows:

- After a driving period (i.e. the accumulated driving time between subsequent breaks and rest periods) of four and a half hours a driver shall take an uninterrupted break of not less than 45 minutes, unless she/he takes a rest period.
- The daily driving time (i.e. the accumulated driving time between the end of one daily or weekly rest period and the beginning of the following daily or weekly rest period) shall not exceed 9 hours. A regular daily rest period is any period of rest of at least 11 hours.

Further regulations apply, e.g. for drivers engaged in multi-manning, the maximum weekly working time, the accumulated driving time during any two consecutive weeks, and the duration of weekly rest periods. However, they are not considered in this paper for simplicity. Figure 1 illustrates an example of the schedule of a drivers' working day. As we can see, drivers' working hour regulations have a high impact on total travel times, i.e. the time required to travel from one location to another including driving periods, breaks, and rest periods. In this paper we assume that vehicle tours must comply with above regulations. For a more comprehensive discussion of EC regulation 561/2006 and approaches for considering drivers' working hours in vehicle routing the reader is referred to Goel (2009). In order to consider drivers' working hours within the PDPP we need to treat the parameter d^v_{nm} as a variable depending on the previous activities performed by the driver. That is, d^v_{nm} must include the pure driving time plus the time required for compulsory break and rest periods.

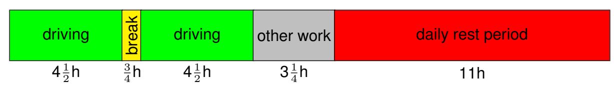

Figure 1: Driving periods, breaks, and rest periods

Dynamics

In this paper it is assumed that the only external source of dynamism is the arrival of new transportation requests. More precisely, we assume that in the beginning of the planning period a certain percentage of all transportation requests is known and new transportation requests arrive dynamically. Furthermore, it is assumed that vehicles move with constant speed and that drivers take their breaks and rest periods as planned by the decision maker, i.e. at any point in time the decision maker has full knowledge about position and state of all vehicles. Within our dynamic planning scenario we must regularly update the start location for each vehicle according to the current progress of transportation processes. Furthermore, we need to keep track of each served transportation request.

4 Decision making process

This section describes the decision making process used to assess the impact of dynamism on motor carrier performance. Whenever new transportation requests become known the decision maker seeks to insert the new requests into tours using the insertion heuristic described in Goel and Gruhn (2008). Each iteration of this method can be divided into the following three phases:

1. **Determine incremental costs of insertion:** For each unscheduled transportation request and each vehicle, determine the incremental costs of inserting the transportation request into the tour of the vehicle.
2. **Propose insertion:** For each unscheduled transportation request, propose insertion to the tour with lowest incremental costs.
3. **Accept proposal:** Among all proposals received for a tour, determine the most profitable transportation request, i.e., the transportation with the biggest (positive) difference between revenue and incremental costs.

This method continues to insert transportation requests to tours until no further insertion is profitable. Thereafter, a Large Neighbourhood Search is performed to dynamically optimise the schedule considering all transportation requests known. The Large Neighbourhood Search algorithm can be described as follows:

0. **Initialisation:** Choose an initial solution; choose a stopping condition
1. **Repeat** the following until the stopping condition is met:
   (a) **Remove:** Choose a number k and randomly remove k transportation requests from their tours
   (b) **Re-insert:** Generate a new solution by applying the insertion method
   (c) **Move or not:** If the new solution is feasible and better than the current solution, replace the current solution by the new solution

We assume that drivers are continuously instructed about new task via mobile communication devices. That is, drivers are either busy fulfilling their current tasks or idle waiting for a new task. It is assumed that drivers immediately start travelling towards the next destination when they are informed about a new task. Furthermore, it is assumed that once a driver has started travelling towards the next destination he/she cannot be diverted until the destination is reached. Under these assumptions it is easy to see that drivers should not be informed too early, as this would reduce the possibilities for dynamically reoptimising tours considering new transportation requests. On the other hand, drivers should neither be informed too late, as this would result in unproductive waiting times. Therefore, we assume that drivers are informed according to a *Minimum-Wait Least-Commitment* strategy. That is, if a travel time of Δ is required to reach the next destination and the time window at the destination opens at time t, the driver will be informed at time $t-\Delta$ or the earliest time thereafter. With this strategy we do not commit to travel to the next destination unnecessarily early. Furthermore, this strategy minimises the unproductive waiting time of the vehicle.

5 Simulation

We simulate the routing of a fleet of homogeneous vehicles in order to fulfil a set of full-truckload pickup and delivery requests. Different test cases are generated which distinguish themselves by the percentage of transportation requests which are known well in advance and by the advance notification times for dynamically arriving transportation requests. By simulating decision making processes of motor carriers we can show how the profitability depends on the level of dynamism.

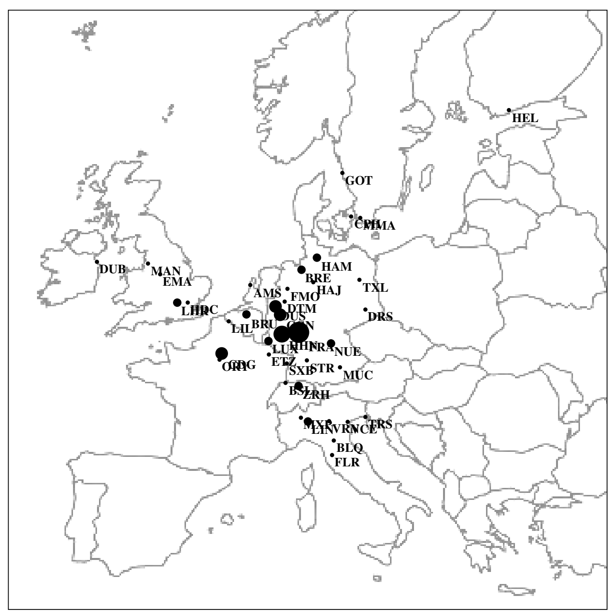

Figure 2: Distribution of pickup and delivery locations

In all simulation experiments tours for 100 vehicles are generated considering 500 transportation request. Each vehicle travels at a speed of 75 km/h and regulations concerning drivers' working hours as described above must be complied with. Travel distances are based on the direct distances, however are multiplied by 1.3 in order to consider deviation occurring in road transport. Travel costs are proportional to the travel distance. The revenue of all transportation requests is set to double the costs arising for travelling between pickup and delivery location. That is, shippers are not only willing to pay for the transport itself, but also for the return trip of the vehicle to the pickup location. Pickup and delivery locations of transportation requests are distributed as illustrated in Figure 2 in which the frequency of a location being either pickup or delivery location of a transportation request is indicated by the size of the circle. Most of the transportation requests incur a pickup or delivery in the region between Paris, Düsseldorf, and Frankfurt. Some transportation requests, however, have very remote pickup or delivery locations, for example Florence, Dublin, Gothenburg, and Helsinki. Time windows at pickup and delivery locations are set to either 2 or 12 hours. The difference between the begin of the time windows at pickup and delivery location is equal to the minimal time required to travel from the pickup location to the delivery location, i.e. the sum of handling times, pure driving times, and the minimal time required for breaks and rest periods. The begin of time windows at pickup locations are equally distributed within the 5 days of our planning horizon.

In the beginning of our simulation, tours are generated from scratch using the insertion method described above. Afterwards, the Large Neighbourhood algorithm is used to optimise the solution. The resulting solution after one hour of computation time is used as in initial solution for the simulation experiments. In each time period new transportation requests become known dynamically. In our simulations the Large Neighbourhood Search algorithm was only allowed 60 seconds of computing time per timestep (representing one hour in our simulation scenario). All decisions made may be revised at any time unless the driver is already informed about the respective task. With the beginning of a new timestep the start location of every vehicle is updated in order to consider the execution of drivers' tasks.

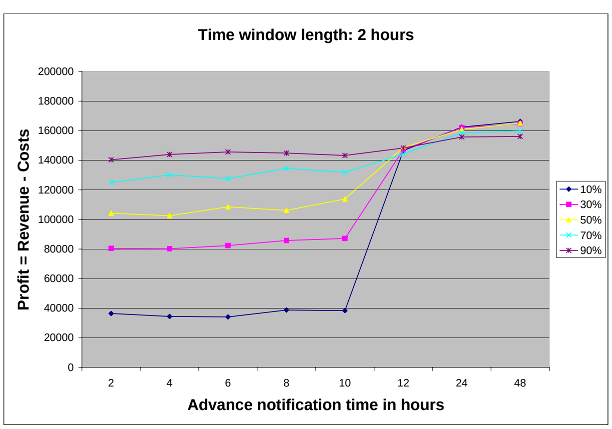

Figure 3: Results of computational experiments with small time windows

Figures 3 illustrates the results of our computational experiments for test cases in which the length of each time window is 2 hours. As can be seen, with advance notification times of two hours, profitability of the carrier grows significantly with an increase in the percentage of transportation requests known in advance. Interestingly, the profitability does not increase significantly when increasing advance notification times to ten hours or below. In fact, profitability may even decrease slightly. This, of course, is an outcome of the inherent randomness of the Large Neighbourhood Search and the dynamic nature of the planning problem. As each decision made at one point in time influences the options available at a future point in time, long-term profitability can decrease even if decisions are optimal in the short-term. When advance notification times are increased from below 10 hours to above 12 hours, profitability can be significantly improved. Furthermore, advance notification times of more than a day may be reduced to 12 hours with only moderate reduction of profitability. An interesting observation is that the sharp increase in profitability occurs when advance notification times approximately match the duration of a daily rest period of 11 hours. An explanation that may come to mind is, that when advance notification times are above 11 hours, a driver can take a daily rest period immediately before beginning to serve a transportation request. This is of particular importance if time windows are very narrow and there is no possibility to take an additional rest period between pickup and delivery of a load. Looking at the results of our simulation experiments for test cases with large time windows in Figure 4, we can see that very similar results are obtained even though it is possible to include an additional rest period between pickup and delivery of a load. As similar simulation experiments conducted for problems without drivers' working hours do not show this sharp increase, it appears that drivers' working hour regulations are a crucial factor in dynamic vehicle routing.

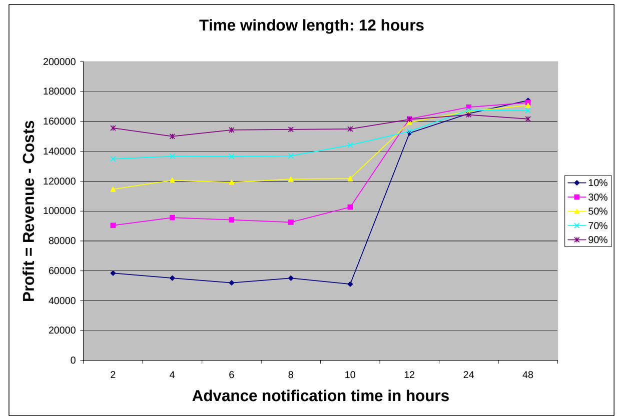

Figure 4: Results of computational experiments with large time windows

Another interesting phenomenon which can be observed in both Figure 3 and Figure 4 contradicts our intuition. One would expect that a higher percentage of transportation requests known well in advance would always result in higher profitability. However, our results show that best results are obtained when only 10% of transportation requests are known in advance and advance notification times are 48 hours. Of all experiments with advance notification times of 48 hours the worst results are obtained when 90% of transportation requests are known in advance. One explanation for this phenomenon is that with an increase in problem size the search space grows exponentially. In a small search space a larger percentage of the search space can be explored by the heuristic, resulting in a higher probability of finding high quality solutions.

In the PDPP an increase in profitability does not necessarily coincide with a reduction of empty mileage as not all transportation requests must be served. Therefore, increases in profit may be achieved by selecting highly profitable transportation requests even if the resulting plan has a high ratio between empty mileage and total mileage. A final result of our computational experiments is that we could observe that the ratio between empty and total mileage is strongly negatively correlated with the profit. We found a correlation factor of $-.86$ which indicates that despite the carrier's objective to maximise profits we can decrease the ratio between empty and total mileage and resulting carbon dioxide emissions when reducing the level of dynamism the carrier has to deal with.

6 Concluding remarks

This paper studies the impact of dynamism on motor carrier performance by simulating the carrier's decision making process in different scenarios with different advance notification times and different percentage of transportation requests known well in advance. It is shown that in our setup profitability can be significantly improved if advance notification times are increased from below 10 hours to above 12 hours. That is, if advance notification times are below the length of a daily rest period, profitability can be significantly improved by increasing them to above the length of a daily rest period. The increase in profitability can justify investments in technology, collaborations with shippers, and integration of information systems and investments in technology in order to increase advance notification times.

We can see that the reduction in profitability is fairly moderate if advance notification times are reduced from 24 hours or more to just above 12 hours. If increased flexibility would allow gaining market share by accepting same-day transportation requests, carriers operating on a day-to-day basis may consider investing into capabilities for dynamic fleet management as operational efficiency is not affected very much.

Our computational experiments also show that profits are strongly negatively correlated with the ratio between empty and total mileage. Thus, managing the level of dynamism helps a carrier to increase profits and reduce emissions simultaneously.

We could see that additional information is not always beneficial in large-scale dynamic vehicle routing. As the size of the search space grows exponentially compared to the number of transportation requests considered, one should carefully choose those transportation requests which are most relevant for optimisation. Reducing the planning horizon in order to reduce the size of the search space can be a more adequate approach than including all information available.

References

Collins, J. (2005). IBM, Maersk Developing Cargo Tracker. RFID Journal, 22.09.2005.

Desaulniers, G., J. Desrosiers, A. Erdmann, M. Solomon, and F. Soumis (2002). VRP with pickup and delivery. In P. Toth and D. Vigo (Eds.), *The Vehicle Routing Problem*, pp. 225–242. SIAM Monographs on Discrete Mathematics and Applications, Philadelphia.

Erkens, E. and H. Kopfer (2001). WAP-LOG: Ein System zur mobilen Fahrzeugeinsatzsteuerung und Auftragsfortschrittkontrolle. In: Logistik Management - Supply Chain Management und e-Business, Teubner Stuttgart.

European Union (2006). Regulation (EC) No 561/2006 of the European Parliament and of the Council of 15 March 2006 on the harmonisation of certain social legislation relating to road transport and amending Council Regulations (EEC) No 3821/85 and (EC) No 2135/98 and repealing Council Regulation (EEC) No 3820/85. Official Journal of the European Union L 102, 11.04.2006.

Feillet, D., P. Dejax, and M. Gendreau (2005). Traveling Salesman Problems with Profits. *Transportation Science 39*(2), 188–205.

Fleischmann, B., S. Gnutzmann, and E. Sandvoß (2004). Dynamic vehicle routing based on on-line traffic information. *Transportation Science 38*(4), 420–433.

Goel, A. (2007). *Fleet Telematics - Real-Time Management and Planning of Commercial Vehicle Oper-*

ations. Operations Research/Computer Science Interfaces, Vol. 40, Springer.

Goel, A. (2009). Vehicle scheduling and routing with drivers' working hours. *Transportation Science 43*(1), 17–26.

Goel, A. and V. Gruhn (2008). A general vehicle routing problem. *European Journal of Operational Research 191*(3), 650–660.

Gruhn, V., R. Ijioui, M. Hülder, and L. Schöpe (2003). Mobile communication systems for truckage companies. In G. Giaglis (Ed.), *The Second International Conference on Mobile Business*, pp. 337–344. Austrian Computer Society.

Gunasekaran, A. and E. W. T. Ngai (2004). Information systems in supply chain integration and management. *European Journal of Operational Research 159*, 269–295.

Jaillet, P. and M. R. Wagner (2006). Online routing problems: Value of advanced information as improved competitive ratios. *Transportation Science 40*(2), 200–210.

Mitrović-Minić, S. (1998). Pickup and delivery problem with time windows: A survey. Technical report TR 1998-12, School of Computing Science, Simon Fraser University, Burnaby, BC, Canada.

Mitrović-Minić, S. (2001). The dynamic pickup and delivery problem with time windows. Ph.D. thesis, School of Computing Science, Simon Fraser University, Burnaby, BC, Canada.

Pankratz, G. (2005). Dynamic vehicle routing by means of genetic algorithm. *International Journal of Physical Distribution & Logistics Management 35*(5), 362–383.

Powell, W., M. Towns, and A. Marar (2000). On the value of optimal myopic solutions for dynamic routing and scheduling problems in the presence of user noncompliance. *Transportation Science 34*(1), 67–85.

Psaraftis, H. (1988). Dynamic vehicle routing problems. In B. Golden and A. Assad (Eds.), *Vehicle routing: Methods and studies*, pp. 233–248. North-Holland Amsterdam.

Psaraftis, H. (1995). Dynamic vehicle routing: Status and prospects. *Annals of Operations Research 61*, 143–164.

Savelsbergh, M. and M. Sol (1998). DRIVE: dynamic routing of independent vehicles. *Operations Research 46*, 474–490.

Themistocleous, M., Z. Irani, and P. E. D. Love (2004). Evaluating the integration of supply chain information systems: A case study. *European Journal of Operational Research 159*, 393–405.

Tjokroamidjojo, D., E. Kutanoglu, and G. D. Taylor (2006). Quantifying the value of advance load information in truckload trucking. *Transportation Research Part E 42*, 340–357.

Yang, J., P. Jaillet, and H. Mahmassani (2004). Real-time multi-vehicle truckload pickup-and-delivery problems. *Transportation Science 38*(2), 135–148.