# A systematic evaluation of freight carrier response to receiver reordering behaviour

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## Abstract

The fields of behavioural transport modelling has been gaining momentum and many researchers have focused on incorporating some elements of stakeholder behaviour and decision making into their freight planning tools. However, investigation of the literature reveals that few papers are devoted to understanding and integrating logistics behaviour of freight *receivers* into urban transport simulations, and the impact of receiver reordering constraints on other freight agents in the urban transportation network has not been thoroughly investigated.

This paper is therefore concerned with evaluating the impacts that constraints set by freight receivers during reordering have on carriers' behaviour and cost in an urban freight transport simulation. To achieve this, three key receiver reordering constraints scenarios are simulated: delivery time window durations; delivery frequencies and its associated quantities; and delivery unloading or service time at receiver facilities. These scenarios are then implemented in an agent-based transport simulation and the carrier's behaviour and delivery cost are evaluated.

Results indicate that narrowing time windows could result in delivery and penalty cost increases of up to 93%. Extending unloading times can see costs and penalties increase by up to 111%. Delivery frequency (and therefore order quantity) also has a major impact of the carrier's cost, with cost increases of up to 142% when requesting more frequent deliveries of smaller quantities. These results confirm that carrier decisions are influenced significantly by changes in receiver reordering behaviour and unnecessary constraints imposed by receivers during reordering could have significant negative implications on the delivery cost of the carrier. This emphasises the importance of finding a balance between restrictions set by supply chain customers during reordering and the cost associated with those restrictions and highlights the importance of finding ways to urge freight agents, especially receivers, to change their current behaviour to lower the total delivery cost of the supply chain.

*Keywords:* Logistics behaviour, Reordering decisions, Urban freight transportation

## 1. Introduction

In 2015 it was estimated that around 53% of the world's population resided in urban areas. Considering that this figure was around 43% in 1990, the rapid rate of urbanisation around the world is evident (Moreno et al., 2016). Increased populations in urban areas results in increased demand for passenger and freight transportation in these areas, which in turn increases the pressure on the urban transportation system.

Freight transportation is an imperative aspect of urban transportation systems around the world, and although representing a small proportion of the road users, commercial vehicles make a disproportionately large contribution to congestion, infrastructure deterioration, and emissions. It is therefore important to ensure proper planning processes are in place to minimise the impact of freight movements in urban areas.

Until recently, little attention was devoted to the planning of the transportation of goods within city boundaries, henceforth referred to as *urban freight*, despite its importance in the functioning of cities (Giuliano and Dablanc, 2013).

In the context of urban freight, Boerkamps et al. (2000) identify the stakeholders associated with the creation, movement, and administering of the freight (and the organisations associated with it), collectively referred to as *freight agents*. Private sector freight agents include shippers, carriers and receivers, whereas public sector freight agents, such as authorities or municipalities, are referred to as administrators. Although these freight agents share the common objective of *transporting freight in an urban area*, they have conflicting individual interests that must be considered during freight transportation planning (Anand et al., 2012).

Shippers are the suppliers or producers of goods ordered by *receivers*, such as shopkeepers, retailers, restaurants, etc. These goods are typically transported by freight *carriers*, such as freight forwarders, from the shipper's location to the receiver's store. It is important to understand the interaction between different urban freight agents during demand fulfilment, as it provides insights about factors driving the movement of goods in urban areas (Anand et al., 2012). In addition, understanding the effects of logistics decisions on freight transportation flows can allow decision makers to better estimate the effects of changes in logistics systems and related policies on future transportation flows (Tavasszy et al., 2012). It is therefore necessary to understand the logistics behaviour of the different urban freight agents to better understand urban freight movements, and thereby enabling improved urban freight planning, management, and policy decision making.

Recognising this, many researchers have focussed their attention towards understanding and incorporating logistics behaviour into urban freight planning (Liedtke, 2005; De Jong and Ben-Akiva, 2007; Wang and Holguin-Veras, 2008; Holguín-Veras et al., 2011; McCabe et al., 2013; Liedtke et al., 2015; Schroeder and Liedtke, 2014). Most of these contributions focus on the logistics decisions familiar to transport modelling such as modal choice, route choice, fleet composition, shipment size, etc. These decisions are typically made by the shipper or carrier agents. However, understanding and incorporating receiver logistics behaviour, especially reordering behaviour, into urban freight planning did not receive much attention.

It is imperative to understand receiver reordering behaviour and incorporate such behaviour into urban freight transportation planning, since the receiver is a powerful freight agent whose reordering decisions generate a demand for freight movement in urban areas. This is confirmed by Holguín-Veras (2010) who notes that receivers mostly dictates how and when shippers and carriers must deliver their orders. Carriers must therefore plan their freight movements according to the reordering decisions made by the receiver since these decisions could potentially have a significant impact on the delivery cost.

Marcucci et al. (2017) also suggest that to be more efficient, urban freight policies should target receivers, as the generators of demand, instead of carriers. Understanding and considering receiver reordering behaviour during urban freight modelling can then enable urban freight planners and decision makers to consider the impact of such behaviour on the transportation network and its agents during urban freight planning and policy decision making more accurately.

This paper is therefore concerned with systematically evaluating the impact of constraints set by the receiver on carrier freight movements in an agent-based simulation model, to ascertain if model is sensitive to behavioural changes, and capable of representing the agents' behaviour accurately. More specifically, the paper investigates the receiver's time window restrictions, delivery times, and order frequency. These restrictions are measured in terms of their effect on a carrier's fleet composition and total delivery costs.

The remainder of the paper is structured as follows: Section 2 presents a discussion of the urban freight environment as well agent-based transport and logistics behavioural modelling advances in the literature. The multi-agent implementation and experimental setup for the simulation used to investigate carrier response to receiver constraints is presented in Section 3. Results and findings from the various experiments are presented in Section 4. The paper ends in Section 5 with concluding remarks along with directions for further development.

## 2. Literature review

The demand for freight movement in a transportation network is driven by the logistics decisions of freight agents (shippers, receivers, carriers and administrators) in that network. Understanding how these decisions influence freight demand and travel behaviour can enable various stakeholders involved in the planning, maintenance and utilisation of urban transportation networks to make better informed decisions.

Consider a scenario where a receiver places a product order at a particular shipper. The ordered product must then be transported from the shipper to the receiver during order fulfillment. Understanding how the receiver decides when and how much to order and what conditions to set for order delivery can enable planners to more accurately estimate freight movements between the shipper and receiver. Similarly, understanding the decision drivers of shippers during the selection of carriers, for example, can enable decision makers to estimate freight movements between shippers and receivers by different carriers, and along different modal corridors.

This could provide a more realistic picture of expected future urban freight movements which could provide a more realistic basis to evaluate the impact of changes to the urban freight systems and their associated policies, as well as the impact of logistics decisions made by freight agents interacting with those systems.

### *2.1. Agent-based transport modelling*

Agent-based transport modelling is a technique that provides the capability to model large populations of heterogeneous agents. Agents, be it private individuals or freight stakeholders, have individual and autonomous behaviour, and interact with one another in a transportation system. One consequence is that congestion need not be modelled explicitly but rather emerges due to many decision-makers and travellers co-existing and relying on limited transport infrastructure (Balmer et al., 2006).

The suitability of agent-based modelling approaches in complex urban freight environments have been widely illustrated over the last two decades. Anand et al. (2014) conclude that urban transport policies analysed using agent-based simulation techniques are more robust because they are evaluated under the dynamically changing circumstances of urban freight transportation. Other advantages of agent-based modelling approaches other conventional transport modelling approaches include the availability of richer, disaggregate output.

Contributions like Hunt and Stefan (2007), Joubert et al. (2010) and Nagel et al. (2014) included freight vehicles, often along with private cars in the large scale implementations. However, the activity chains of the freight vehicles were derived from historically observed activity and include little autonomous behaviour on the part of the freight vehicles. As a result the inclusion of these vehicles were little more than realistic additional load on the network (Schroeder et al., 2012). The modelling of adaptive logistics behaviour in transport simulation received increased attention in the last few years.

### *2.2. Logistics behavioural modelling in transport simulation*

During a review of past urban freight logistics modelling contributions, Anand et al. (2015) found that despite the influence of private sector stakeholder decisions on freight movements, most of the earlier urban logistics modelling efforts were done from the administrator's perspective. Only recently did researchers start considering the logistics decisions of private urban freight transportation stakeholders, i.e. shippers, carriers and receivers, and its effect of the urban freight transportation system. Many of these researchers used agent-based simulation models to investigate and evaluate a wide variety of urban freight problems (Boerkamps et al., 2000; Raney et al., 2003; Balmer et al., 2006; Roorda et al., 2010; Rieser, 2010; Marcucci et al., 2015, 2017).

To date, most of the contributions that present working transport simulation models with integrated private sector agents' logistics decisions, focus on shipper or carrier decisions and, in some instances, the interactions between shippers and carriers. This is understandable since the shipper is often perceived as the most upstream player in the urban freight transportation arena who dictates how and when goods should be moved by the carrier (Liedtke et al., 2015). The carrier, on the other hand, is the one responsible for physical freight movements and its decisions are therefore often considered when modelling logistics behaviour during freight transportation.

Taniguchi et al. (2007) present a multi-agent simulation model that models and evaluates the interactions between shippers and carriers during urban freight transportation. Their model use a Vehicle Routing Problem with Time Windows (VRPTW) algorithm that dynamically adjusts carrier routes based on current travel times. They conclude that multi-agent simulation modelling can contribute to understanding the interactions between urban freight transportation stakeholders and the effects of changes to the environment on stakeholder profits and costs. In a similar approach, van Duin et al. (2012) evaluate the usage of urban distribution centres. They too conclude that multi-agent models show promise to help stakeholders understand the interactions between carriers, receivers, and administrators during urban transportation.

Schroeder et al. (2012) identify various freight agent types, their available information and their available decisions. Based on this work, Schroeder and Liedtke (2014) use an agent-based transport simulation model that includes various logistics behavioural elements like fleet sizing, customer allocation and routing of carriers to analyse different policies in urban areas. The model allows carriers to make operational and tactical decisions while attempting to minimise its total cost. This is achieved by using variants of the Vehicle Routing Problem (VRP) and a time-dependent least cost path algorithm to determine delivery fleet size and composition, vehicle departure times, the sequence of deliveries, and the least cost delivery routes through the urban road network. The model is applied to a case study of food retailers in Berlin to evaluate urban freight transport policies. The utility function of the carrier agents is a *generalised* cost that take both direct costs, like fixed capital and variable operational costs, and travel and delay time into account.

Based on the work of Schroeder and Liedtke (2014), Van Heerden and Joubert (2014) model supply chain stakeholders as agents with some logistics decisions and interactions in an agent-based transport simulation. They apply the model to a small case study to investigate the sensitivity of their model to changes in logistics operations. However, with reference to receiver logistics behaviour, the study only considers changes in order frequency of receivers.

Liedtke et al. (2015) also focus on shippers and carriers during and present a multi-agent model in which shippers are allowed to determine shipment sizes and select carriers, whereas carriers can combine single shipments into tours. The authors acknowledge that in many instances receivers dictate how and when shipments must be delivered instead of the shippers or carriers, creating an opportunity for the expansion of existing models to also include receiver logistics behaviour.

Anand et al. (2014) also note the importance of the receiver in urban freight decisions that has a major influence on the flow of commercial vehicles in the urban freight transportation network. They present an agent-based simulation model with integrated logistics behaviour of shippers, receivers and carriers during urban freight transportation. Their model includes two phases. During the first setup-phase the receiver selects its preferred shipper based on its distance from available shippers, and sets its maximum and minimum stock levels based on the estimated demand at that shop relative to its location in the urban area. During the second phase, simulation, each receiver calculates its monthly demand based on the demand of the previous months and determines its reordering point and order quantity. Required replenishment quantities are then ordered from shippers, who use external carriers (selected during the setup-phase) to deliver orders to receivers. Their simulation model is applied to a small numerical example to demonstrate the suitability of this approach to model urban freight logistics behaviour. Unfortunately they make strong, simplifying assumptions about the receivers' reordering behaviour. For example, they assume that all receivers use the economic order quantity order policy during reordering and that all receivers select suppliers based on the supplier's proximity to the receiver's facility.

Even though some noteworthy progress was made with regards to logistics behavioural modelling in agent-based urban freight simulation, the majority of contributions in the area focus on shipper and carrier logistics decisions and their interactions. Very few contributions consider receiver logistics behaviour. Those that do are limited in terms of its scalability to real life situations.

Most logistics behavioural models study independent agents who aim to maximise their own profits or minimise their own costs, with limited consideration of the potential benefits that can be realised through collaboration. Savelsbergh and Van Woensel (2016) highlight the increasing need for freight transportation models to include aspects of collaborative logistics that can enable urban freight agents to better understand the benefits and pitfalls related to collaborative urban freight transportation. To achieve that, the starting point would be a systematic evaluation of the impact that different urban freight stakeholders have on one another. That will allow us, as a base, to quantify the experienced costs and benefits that are available to share.

## 3. Model

To better understand the impact of receiver reordering behaviour on carrier delivery decisions and the resulting effect of these decisions on delivery cost, a quantitative research approach is adopted where various reordering scenarios are systematically simulated and evaluated. We acknowledge that evaluating the impact receivers will have on a carrier is essentially problem specific. Consequently, we generate 100 unique instances for each problem configuration and report the results as a distribution (that combines the results of all 100 instances) instead of point values.

Three key receiver reordering decisions are considered in this paper to develop the reordering scenarios. These scenarios are then implemented in a multi-agent simulation allowing the carrier to autonomously respond to those decisions. Each instance of each scenario is evaluated in terms of the resulting fleet composition, fleet utilisation and associated utility (generalised cost) from the carrier's perspective.

### *3.1. Delivery time window*

The receiver is essentially the carrier's end customer and therefore has significant power to influence delivery times. Without the receiver's willingness to accept deliveries during certain hours of the day, the carrier cannot deliver at the receiver during those hours (Holguín-Veras, 2010). The first scenario focuses on the delivery time windows prescribed by the receivers, where a delivery time window refers to the time in which the carrier must start unloading its delivery.

In this scenario different time window durations are investigated. More specifically, we investigate time window durations between 2 and 12 hours in 2 hour-increments. For any given scenario the time window duration, also referred to as the *width*, is the same for all receivers. The opening time for each receiver however, varies and is scattered randomly throughout the day between 06:00 and 18:00.

### *3.2. Delivery unloading time*

Although the size of a delivery influences the delivery time, delays as a result of receiver delivery requirements will impact the carrier's delivery unloading time (or service time) (McCabe et al., 2013). For example, if the receiver is equipped with unloading ramps, the carrier can just drop the tailgate and unload the products directly onto the unloading ramp rather quickly. However, if a tail-lift has to be lowered and the goods unloaded and transported via forklifts over a longer distance, the unloading time will increase (Müller and Klaus, 2009). In addition, unloading time can also increase if loose boxes must be unloaded instead of pallets.

Therefore, the second scenario investigates the impact of different unloading times on the number of vehicles used by the carrier, the associated vehicle capacity utilisation of these vehicles, and the resulting carrier delivery cost.

For these scenarios the delivery time window duration is fixed at 4 hours for each receiver, and are scattered randomly throughout the day. The specific unloading times investigated in this scenario are 30 minutes to 4 hours in 30 minute-increments. In each of these scenarios the same unloading time is set for all receivers.

### *3.3. Delivery frequency*

Depending on its own inventory levels, inventory carrying capacity and customers' demand, a receiver may require a specific quantity of products to be delivered within a planning horizon like a week or month. The overall demand stays the same, but a receiver may opt for smaller, more frequent deliveries, or a single, larger delivery provided it can handle and store the stock. The reordering policy employed by the receiver influences how and when products should be delivered at the receiver to satisfy its total weekly or monthly demand. As a result, the reordering (or delivery) frequencies prescribed by the receiver based on its reordering policy, influences the quantity of products being transported by a carrier on a particular day. The third scenario hence investigates the impact of varying delivery frequencies prescribed by receivers on carrier behaviour and delivery cost.

This is achieved by setting the prescribed number of deliveries per week, $N_r$, for receiver $r \in \boldsymbol{R}$, to $N_r \in \{1, 2, 3, 4, 5\}$. During each of these scenario's all the receivers in the simulation prescribe the same number of deliveries per week. The weekly demand, $D_r$, of receiver $r \in \boldsymbol{R}$ is then used with the number of deliveries per week, $N_r$, to determine the per-delivery quantity, $Q_r$, of each receiver in the simulation as indicated in equation (1).

$$Q_r = \frac{D_r}{N_r} \qquad \forall \quad r \in \boldsymbol{R} \tag{1}$$

The probability of a delivery, $P_r$, at receiver $r \in \boldsymbol{R}$ on a particular day is then calculated using equation (2), assuming there are five delivery days in a week.

$$P_r = \frac{N_r}{5} \qquad \forall \quad r \in \boldsymbol{R} \tag{2}$$

For each instance, the delivery probability, $P_r$, is compared to a randomly generated number between 0 and 1, $R_r$, and when $R_r < P_r$ a delivery of quantity $Q_r$ is required at receiver $r \in \boldsymbol{R}$ on that particular day. If not, the specific receiver $r$ is *not* serviced in that instance. In this scenario time window width is fixed to 4 hours, scattered randomly throughout the day for each receiver in the simulation.

Table 1 summarises the different simulation scenarios considered in this paper.

Table 1: Summary of the delivery parameters for the various scenarios.

| | **Delivery parameter(s)** | | |
|---|---|---|---|
| **Scenario group** | **Time window (h)** | **Unloading time (h)** | **Frequency (deliveries per week)** |
| *Base* | *4* | *0.5* | *1* |
| Time window | $2, 4, 6, 8, 10, 12$ | 0.5 | 1 |
| Unloading times | 4 | $\frac{1}{2}, 1, 1\frac{1}{2}, 2, 2\frac{1}{2}, 3, 3\frac{1}{2}, 4$ | 1 |
| Frequency | 4 | 0.5 | $1, 2, 3, 4, 5$ |

### *3.4. Simulation setup*

For each scenario we generate 100 instances to account for the variability. For each instance there is a single supplier with a fixed depot location. The supplier performs its transportation function in-house and therefore serves as both the shipper and carrier in the simulation. Each simulation instance has 50 customers, or receivers, located on nodes and scattered randomly throughout a simple $10 \times 10$ grid network with 1 kilometre one-directional links between nodes. This network is similar to the network used by Schroeder et al. (2012).

Figure 1 depicts the network, the fixed shipper and carrier depot at location $D$ and an example of 50 randomly located receiver facilities (labelled 1–50). All the vertical

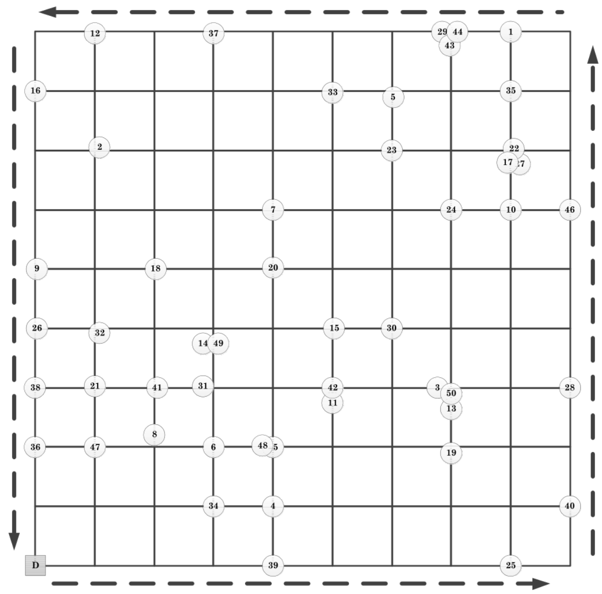



Figure 1: Simulation network example

links on the far-left runs from top to bottom, while those second from left all run from bottom to top. Vertical links third from left all run from top to bottom again, and this alternates in each column until the links far right all run from bottom to top. Similarly, the horizontal links alternate by row. For example, the top-most horizontal links all run from right to left, while those second from the top all run from left to right. Horizontal links third from the top run from right to left again, and this continues until the bottom-most links all run from left to right.

The carrier must satisfy all daily demand using two types of freight vehicles, namely heavy vehicles (6x4 rigid) and light delivery vehicles, or a combination of both. In line with Fleetwatch's market related truck operating benchmarks, the heavy vehicle capacity is set to 14 tonnes, and these vehicles incur a fixed cost of R 2 604/day (South African Rand, with USD 1 $\approx$ ZAR 12.95) and a variable cost of R 7.34/km, whereas light vehicles in the simulation have capacities of 3 tonnes, and incur a fixed cost of R 1 168/day and a variable cost of R 4.22/km (Braun, 2016). In addition, the value of time for heavy vehicles and light vehicles is set to R 614/h and R 320/h (with EUR 1 $\approx$ ZAR 13.95), respectively (De Jong et al., 2014).

In instances where the vehicle responsible for a particular delivery fails to start unloading its delivery during the time window specified by the receiver, a penalty cost of R 6.50/min from the time window end time until the vehicle arrives at the receiver facility and starts unloading its delivery.

In the model setup each receiver has a weekly demand of 5 tonnes and requires a daily delivery, therefore the daily demand of each receiver is taken as 1 tonne. In addition, the delivery time window duration is set to four hours and the time window start time scattered randomly throughout the day for each receiver agent. Finally, the unloading time at each receiver's facility is set to 30 minutes.

### *3.5. Multi-agent implementation*

In this paper we choose the Multi-Agent Transport Simulation (MATSim) toolkit to implement each simulation run. It allows us to model and monitor each vehicle independently, and provides infrastructure like routing on the road network that we did not have to implement ourselves.

According to Horni et al. (2016) MATSim starts with the generation of an initial demand, a full day plan of activities for each person, or agent, in the study area's population. In the context of this paper an agent will be a carrier vehicle. Although we refer to the *vehicle* itself, we always imply the driver-vehicle combination. Given a scenario instance a carrier knows the location and demand for each receiver. It also knows the time window imposed by each receiver, and the expected delivery duration. A simulation instance represents a day for which the carrier then needs to plan their logistics by assigning the receivers to vehicles, and determining the sequence of deliveries for each vehicle. Since the carrier has access to different vehicle types, this problem essentially is an instance of the Fleet Size and Mix Vehicle Routing Problem (FSMVRPTW) where each receiver must be serviced on the specific day.

The output is a sequence of receivers for each vehicle, referred to as the vehicle's *plan* in MATSim. Each plan indicates the time the vehicle should leave the depot, and the estimated arrival and departure time for each receiver allocated to that vehicle. Each vehicle, with its plan, is then injected into the mobility simulation. During this step all vehicles execute their plans simultaneously and as closely as possible. That is, each leaves the depot at the designated time, and chooses a shortest path on the road network to the first receiver in its plan. The actual arrival time is then known, and if it falls within the time window then the delivery starts immediately. If the vehicle is too early, it will wait until the start of the time window. If it is too late, the penalty time is noted and the arrival will start.

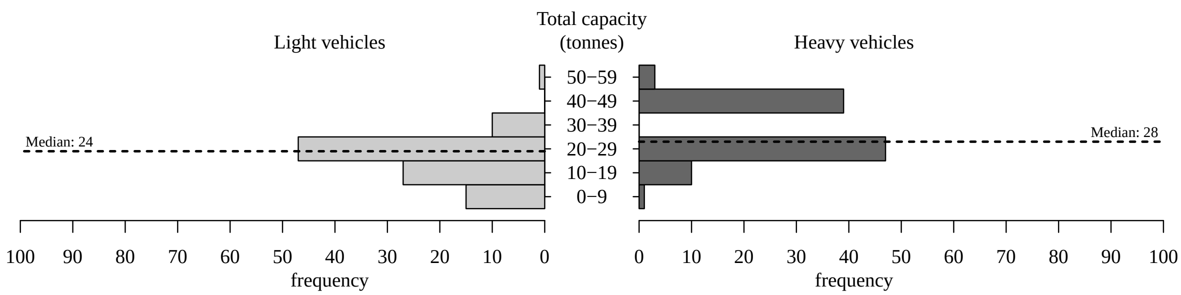
Similarly, the vehicle will navigate from one receiver to the next in the same sequence as stipulated in its plan. In this paper we only simulate the freight vehicles on the network, but MATSim allows other agents and vehicles to be injected into the simulation as well. This can cause congestion, resulting in the actual travel times differing quite substantially from the expected travel times for the freight vehicle between receivers. Adding and studying the impact of congestion is left for future research.

At the end of the simulation run we observe the actual performance of vehicles, which includes the distances travelled for each vehicle, the total travel time, the actual utilisation of each vehicle, and time penalties, if any. Each vehicle's actual performance is quantified as the sum of all activity utilities plus the sum of all travel (dis)utilities (Horni et al., 2016) into a single *generalised cost*. This allows us to combine a vehicle's daily fixed cost, it's distance-based operating cost, travel time (using the value of time) and time penalties.

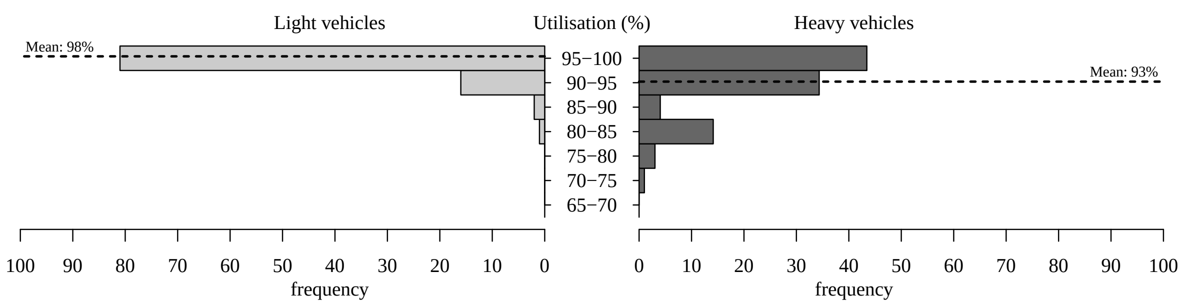
## 4. Results and discussion

The base model assumes that each receiver has a fixed demand of 1 ton per day. Stated otherwise, a demand of 5 tonnes per week with five equal-sized deliveries per week, one per day. Time windows have a constant width of 4 hours, and deliveries take 30 minutes each.

In the base case simulation, a tendency to rather use heavy vehicle capacity instead of light vehicle capacity is observed. However, in the majority of instances these heavy vehicles are not filled to capacity for deliveries (Refer to Figure 2).




(a) Total available vehicle capacity for used vehicles




(b) Capacity utilisation of used vehicles

Figure 2: Base case simulation results. The frequency distribution reports the number of occurrences over the 100 simulation runs executed for the base scenario.

This could be attributed to the lower cost per tonne-km associated with the use of heavy vehicles and the fact that 4-hour time windows and 30 minute unloading duration provide enough flexibility for the carrier to use fewer vehicles with larger capacity whilst still avoiding the penalty costs associated with late deliveries.

Considering the carrier's cost for the base case simulation, it can be observed that the carrier attempts to find a balance between the penalty cost of missed time windows and the additional transportation cost associated with under-utilising vehicle capacity, in order to reduce its own cost as far as possible. The resulting daily carrier delivery cost (where cost is depicted as a negative utility), for all the base case simulation runs, is illustrated in Figure 3.

Considering the carrier's cost for the base case simulation, it can be observed that the carrier attempts to minimise its own delivery cost as far as possible. Since the carrier's transportation cost in this paper comprises the fixed daily vehicle cost, variable vehicle cost (per kilometre) and the value of time (per hour) (Braun, 2016), the carrier therefore attempts to find a balance between the penalty cost of missed time windows and the additional transportation cost associated with under-utilising vehicle capacity, in order to reduce its own cost as far as possible. The resulting daily carrier delivery cost, for all the base case simulation runs, is illustrated in Figure 3.

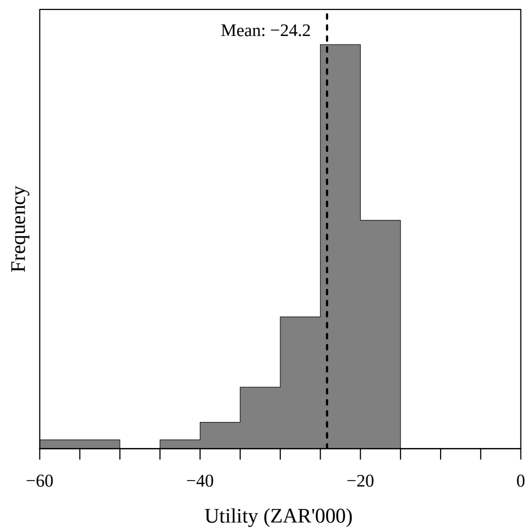



Figure 3: Carrier daily delivery (generalised) costs in base case simulation. The frequency distribution reports the number of occurrences over the 100 simulation runs executed for the base scenario.

From this it can be deduced that the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the carrier's daily delivery cost are R 27 470 and R 17 469, respectively.

These amounts represent the daily cost of delivering products to customers and must be absorbed somewhere in the supply chain. One way to absorb this cost is to increase the amount charged to the supply chain customer (the receiver) for delivery of products. It is therefore necessary to not only investigate the impact of receiver constraints on carrier behaviour, but also on the delivery cost (and potentially the amount charged to receivers) enabling receivers to better understand the potential impact of their decisions and restrictions on their own bottom line.

### *4.1. Delivery time windows*

During analysis of the impact of delivery time window constraints set by receivers on carrier behaviour, it was found that the carrier has a tendency to select more light vehicles when narrower time window are imposed, and fewer light vehicles when wider time windows are imposed (Figure 4).

When considering heavy vehicle usage, it can be seen that the carrier prefers to use more heavy vehicles for wider time window durations and fewer heavy vehicles for tighter time window durations. This is due to the ability of the carrier to serve more receivers with a single heavy vehicle when wide time windows are imposed. This allows

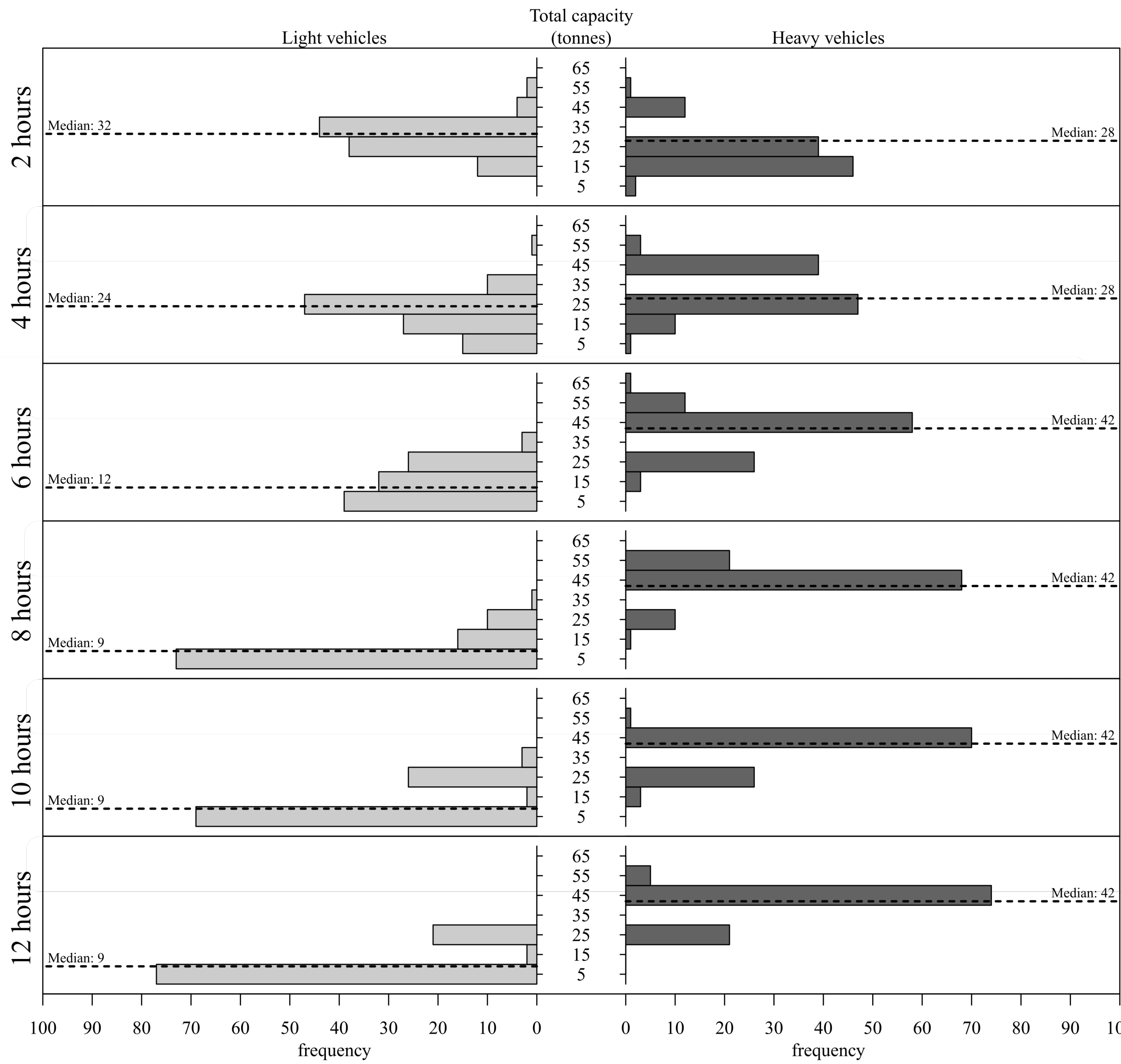



Figure 4: Total available vehicle capacity for different time window durations. The frequency distributions report the number of occurrences over the 100 simulation runs executed for the different time window duration scenarios.

the carrier to reduce its transportation cost per tonne without incurring additional missed time window penalties.

This is confirmed when investigating the effect of time window durations on vehicle capacity utilisation of the carrier, as shown in Figure 5. More customers can be served by a single heavy vehicle in instances with longer time window durations. This allows the carrier to load more products into each heavy vehicle it uses and results in improved heavy vehicle capacity utilisation and therefore a lower transportation cost per tonne.

The effect of time window duration on light vehicle capacity utilisation is not as pronounced and it appears as if light vehicle capacity is utilised well irrespective of time window width. This is understandable since a light vehicle cannot carry more than three tonnes, i.e. serve more than three customers at a time, and in most instances has the ability to serve three customers (with a 30 minute service time) without incurring missed time window penalties, irrespective of whether the time window duration is two hours or 12 hours.

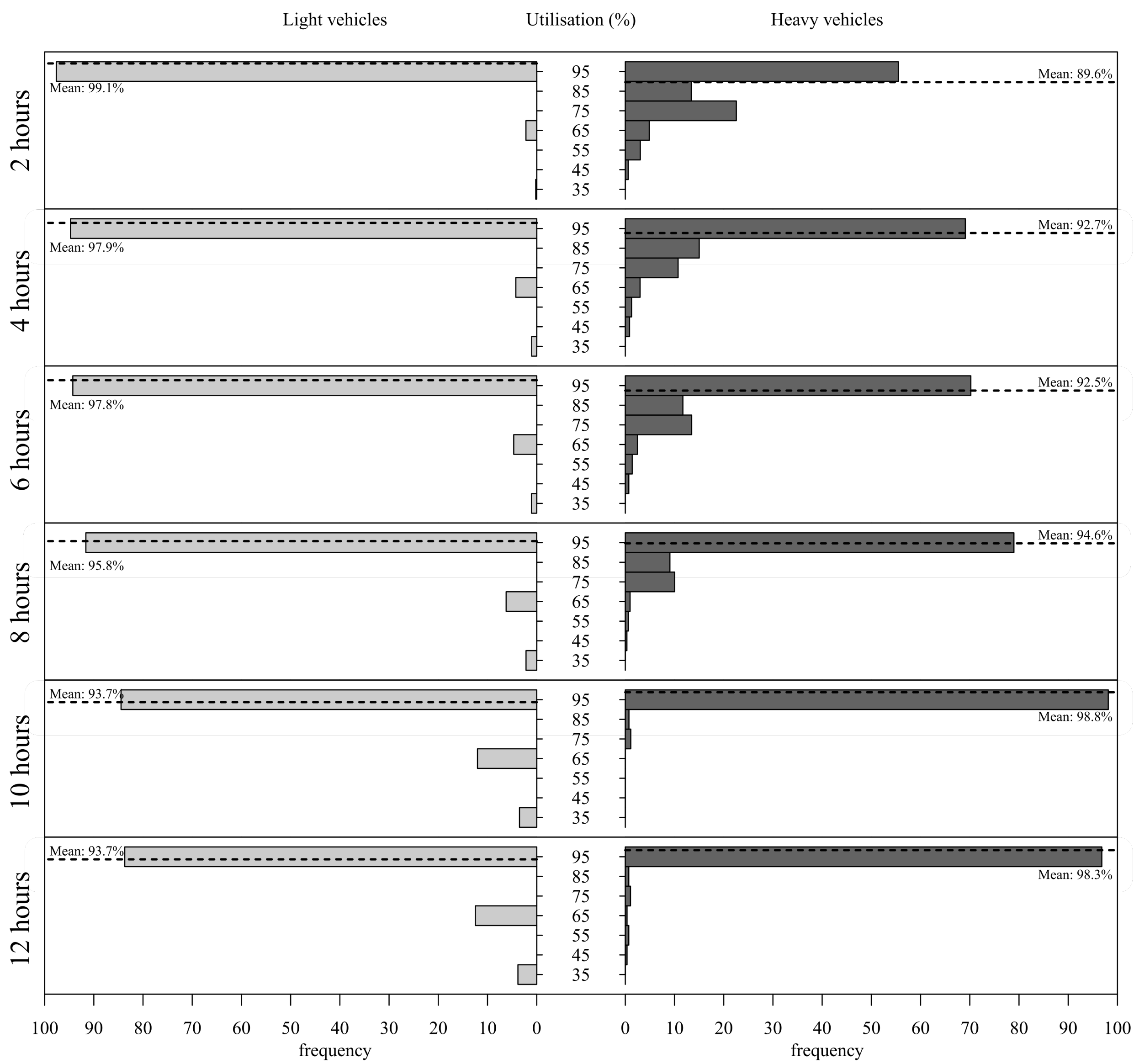



Figure 5: Capacity utilisation of carrier vehicles for different time window durations. The frequency distributions report the number of occurrences over the 100 simulation runs executed for the different time window duration scenarios.

During analysis of the effect of time window duration on the carrier's delivery cost, it was found that the cost decreases with increasing time window durations, as indicated in Figure 6. Interestingly, no notable benefits can be observed when the time window duration increases beyond 8 hours. This could to be due to the ability of the carrier to better utilise heavy vehicle capacity without incurring any missed time window penalties, thereby lowering the transportation cost per tonne.

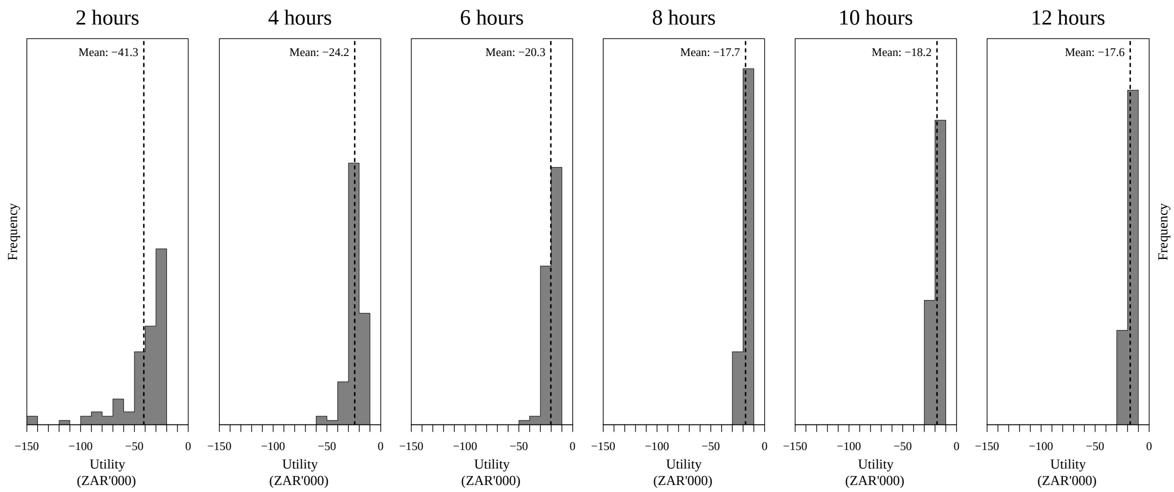



Figure 6: Carrier daily delivery costs for different time window durations. The frequency distributions report the number of occurrences over the 100 simulation runs executed for the different time window duration scenarios.

With two hour time window durations it can be seen that the $5^{\text{th}}$ and $95^{\text{th}}$ percentiles of the daily carrier delivery cost are R 53 147 and R 21 304 respectively, whereas these values decrease to R 20 219 and R 15 494 with 12 hour time windows. Compared to the base case simulation with four hour time windows, it can be concluded that the carrier transportation and time window penalty cost, could potentially be reduced by 11%–26% when increasing the time window durations to 12 hours. Conversely, this cost could potentially be increased by 22%–93% when reducing the time window durations to two hours.

Considering that this increase or decrease in carrier delivery cost could potentially be transferred to the amount paid by the receiver for order delivery, unnecessarily limiting delivery time window durations could potentially have a significant negative impact on the receiver's own bottom line.

### *4.2. Delivery unloading times*

Analysis of the second scenario results indicates a tendency of the carrier to use more light vehicles and fewer heavy vehicles with increasing unloading times (Figure 7). This is due to the increasing inability of the carrier to deliver to more than two customers without incurring missed time window penalties when unloading increases to two hours or more (recall that receivers impose a four hour delivery time window). Since one light vehicle has the capacity to serve up to three customers, the carrier prefers to use light vehicles for deliveries with longer unloading times in order to minimise its own transportation cost per tonne.

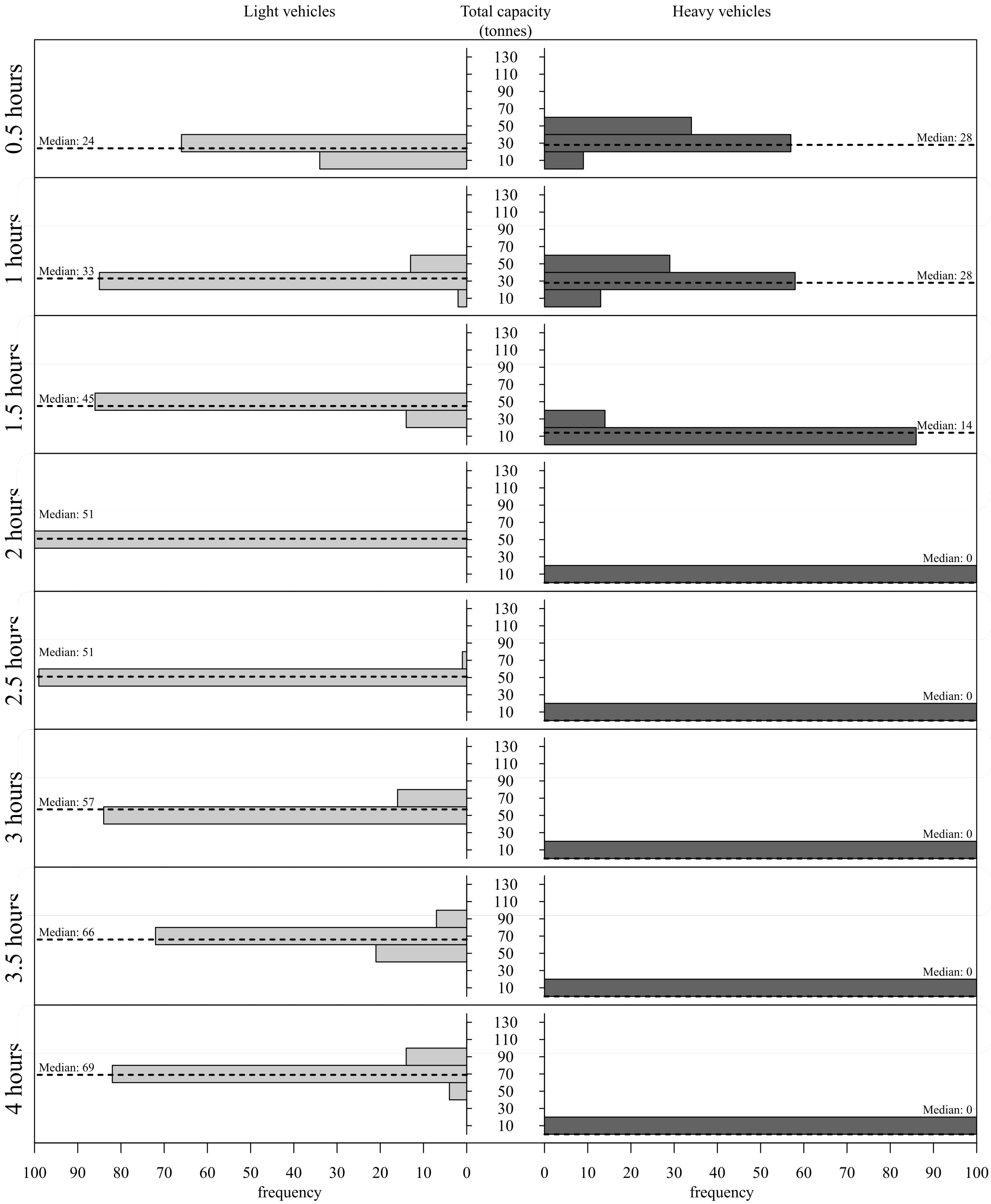



Figure 7: Total available vehicle capacity for different delivery unloading times.

This is confirmed by the vehicle capacity utilisation results depicted in Figure 8 where a decrease in heavy vehicle capacity utilisation is observed for increasing unloading times and no heavy vehicle capacity are used for unloading times longer than two hours. Conversely, light vehicle capacity utilisation remains relatively high for all unloading times, but a slight decrease in utilisation is observed for unloading times exceeding two hours. This decrease could be attributed to the notion that one vehicle is increasingly unable to serve more than one customers (with four hour delivery time window durations) when the time to unload the delivery at each customer increases to three hours or more.

The carrier transportation and missed time window penalty cost increases significantly with longer unloading times, as indicated in Figure 9. The $5^{\text{th}}$ and $95^{\text{th}}$ percentiles of this cost are R 29 038 and R 18 004, respectively, with a 30 minute unloading time, whereas it increases to between R 34 828 and R 29 038 when it takes four hours to unload a delivery at each customer.

Considering that a 30 minute unloading time was used in the base case simulation, it can be concluded that the carrier's transportation and time window penalty cost can potentially be increased by 93%–111% when delivery unloading time increases from 30 minutes to four hours. Since this cost could potentially be transferred to the receiver's reordering cost, it is imperative for the receiver to avoid imposing unnecessary restrictions and causing unnecessary delays during order delivery.

### *4.3. Delivery frequencies*

The results of the delivery frequency scenario highlight a tendency to rely more on heavy vehicle capacity and less on light vehicle capacity when delivering smaller quantities more frequently to customers (Figure 10). This is due to the carrier's ability to achieve a lower cost per tonne for deliveries by using larger vehicles for higher volume deliveries to more customers, since more frequent deliveries imply that more customers require delivery of smaller orders.

Interestingly, the carrier prefers to use light vehicle capacity for less frequent deliveries, except when one delivery per week is required per receiver. This is due to the 3 tonne available capacity of light vehicles which implies that light vehicles will not be able to serve any customer with one delivery of five tonnes per week due to inadequate loading capacity for those deliveries. The carrier therefore refrains from using any light vehicles for deliveries of more than three tonnes per customer. We note that we did not allow for *split deliveries*, that is, breaking up a receiver's order into multiple deliveries.

Considering the carrier's vehicle capacity utilisation in Figure 11, heavy vehicle capacity is utilised well when smaller, more frequent deliveries are required. However, the heavy vehicle capacity utilisation percentage reduces when less frequent but higher volume deliveries are required. This can be explained when considering the experimental parameters. When one delivery is required per week per customer, the delivery size becomes 5 tonnes, and light vehicles cannot be used due to inadequate capacity. However, since heavy vehicles can carry up to 14 tonnes, in this instance, no heavy vehicle will be used to carry more than two customer's orders, i.e. 10 tonnes, resulting in a lower capacity utilisation.

When looking at light vehicle capacity utilisation, it appears as if light vehicle capacity is not utilised well when two, three or four deliveries per week are required. However, light vehicle capacity is utilised well when daily delivery of smaller quantities are requested. This is because if five deliveries per week of one tonne each are required by each receiver, each light vehicle can be used to serve three customers and thereby achieve 100% capacity utilisation. However, when less frequent deliveries are required, the delivery quantities change to 1.25 tonnes, 1.67 tonnes, and 2.5 tonnes for four, three and two deliveries per week respectively. Implying that the maximum capacity utilisation for light vehicles in these three instances are 83%, 56% and 83% for four, three and two deliveries per week, respectively.

The daily delivery cost of the carrier for different delivery frequencies are depicted in Figure 12. The $5^{th}$ and $95^{th}$ percentiles of this cost are R 12 449 and R 26 187, respectively, when one delivery of five tonnes is required per receiver per week. The $5^{th}$ and $95^{th}$ percentiles of carrier delivery cost of the base case, where daily delivery of one tonne is required by each receiver, indicate a slight decrease in cost compared to one delivery of five tonnes per week, mainly due to the high light vehicle capacity utilisation the carrier achieves when delivering five deliveries of one tonne per week.

However, the carrier delivery cost increases significantly when two and three deliveries are required per week. Results indicate that the $5^{th}$ and $95^{th}$ percentiles of carrier delivery cost increase to R 66 508 and R 42 490, respectively, when receivers require three deliveries per week of 1.67 tonnes each and to R 47 293 and R 21 300, respectively, when when two deliveries of 2.5 tonnes are required by each customer per week. This could be attributed to the increased use of light vehicles with lower vehicle capacity utilisation, resulting in an increase in the transportation cost per unit.

The results of the delivery frequency scenario indicate that changes in order quantities and delivery frequencies could potentially have a major negative impact on the delivery cost of the carrier and should be planned carefully to avoid unnecessary cost escalations in the supply chain.

### *4.4. Results summary*

Results indicate that the carrier indeed responds. The carrier aimed to minimise its own delivery cost by maximising vehicle capacity utilisation and giving preference to the use of heavy vehicles, provided that it could still meet prescribed delivery time windows and therefore avoid missed time window penalties.

It was noted that changes in time window durations could potentially result in delivery and time window penalty cost increases of 22%–93% when tightening time window durations to 2 hours instead of 4 hours. However, this cost could potentially be reduced by 11%–26% when relaxing the time window durations from 4 hours to 12 hours. Results of the delivery unloading time scenario indicate that the carrier's delivery and time window penalty cost can increase by 93%–111% when delivery unloading time increases from 30 minutes to four hours. Changes in order quantities and delivery frequencies could potentially have a major negative impact on the delivery cost of the carrier with results indicating increases of up to 142% when requesting more frequent deliveries of smaller quantities.

These results confirm that carrier decisions and costs are influenced significantly by receiver reordering behaviour and imposed constraints. This emphasises the importance of finding a balance between constraints set by receivers during reordering and the cost associated with those constraints. It also demonstrates that the agent-based approach used in this paper is capable of capturing the essential phenomena of the receiver-carrier interactions. In addition, results highlight the importance of finding ways to convince or compel urban freight agents to change their current behaviour during reordering, possibly though the introduction of new policies, to lower the total delivery cost of the supply chain.

## 5. Conclusion

This paper focused on evaluating the impact of constraints, set by the receiver during reordering, on the carrier's fleet composition and associated cost. To achieve this, three common scenarios were evaluated systematically. These are time window durations, delivery frequency, and unloading time at receiver facilities. The scenarios were evaluated using a disaggregate agent-based simulation model in which the carrier sensibly responded to the constraints.

To the best of the authors' knowledge, a rigorous analysis of the sensitivity of carrier behaviour and delivery cost to constraints set by receivers during reordering in an agent-based urban transport simulation has not been done before. This paper therefore makes a notable contribution to the field of behavioural transport modelling.

Results confirm that tighter time windows, more frequent but smaller deliveries, and extended delivery times all contribute negatively to the carrier's cost. In practice these higher costs are passed on to the receiver and, ultimately, the consumer.

The authors acknowledge that the systematic approach followed in this paper has limitations. First and foremost, the scale of the experiments were limited to a fairly small urban-like network. However, the chosen agent-based implementation, MATSim, has been demonstrated to be scalable to very large scenarios. A natural next step would therefore be to test the findings on a more realistic, urban scale.

Secondly, only one choice dimension was changed at a time. This was done because interpreting the absolute values of changes is only useful for realistic scenarios as they are inherently problem-specific. Nothing prohibited multi-dimensional changes, but that would have made interpretation of the causal relationships more messy. Instead the authors opted for multiple, randomly generated problem instances to account for variation and uncertainty.

In this paper it was demonstrated that the dynamic behaviour of receiver and carrier agents can be elegantly captured in an agent-based setting. The disaggregate costs can be calculated and attributed to individual carrier and receiver stakeholders. A useful direction for future research is therefore to model the agent interactions in, for example, a game-theoretic manner so that potential benefits can be shared among the players. That is, a receiver may relax its time windows if the corresponding benefit to the carrier is shared.

Finally, the rise of e-commerce could have a significant impact on urban freight decisions and movements. Even though this was not considered in this paper it is an important area that should be investigated in the future.

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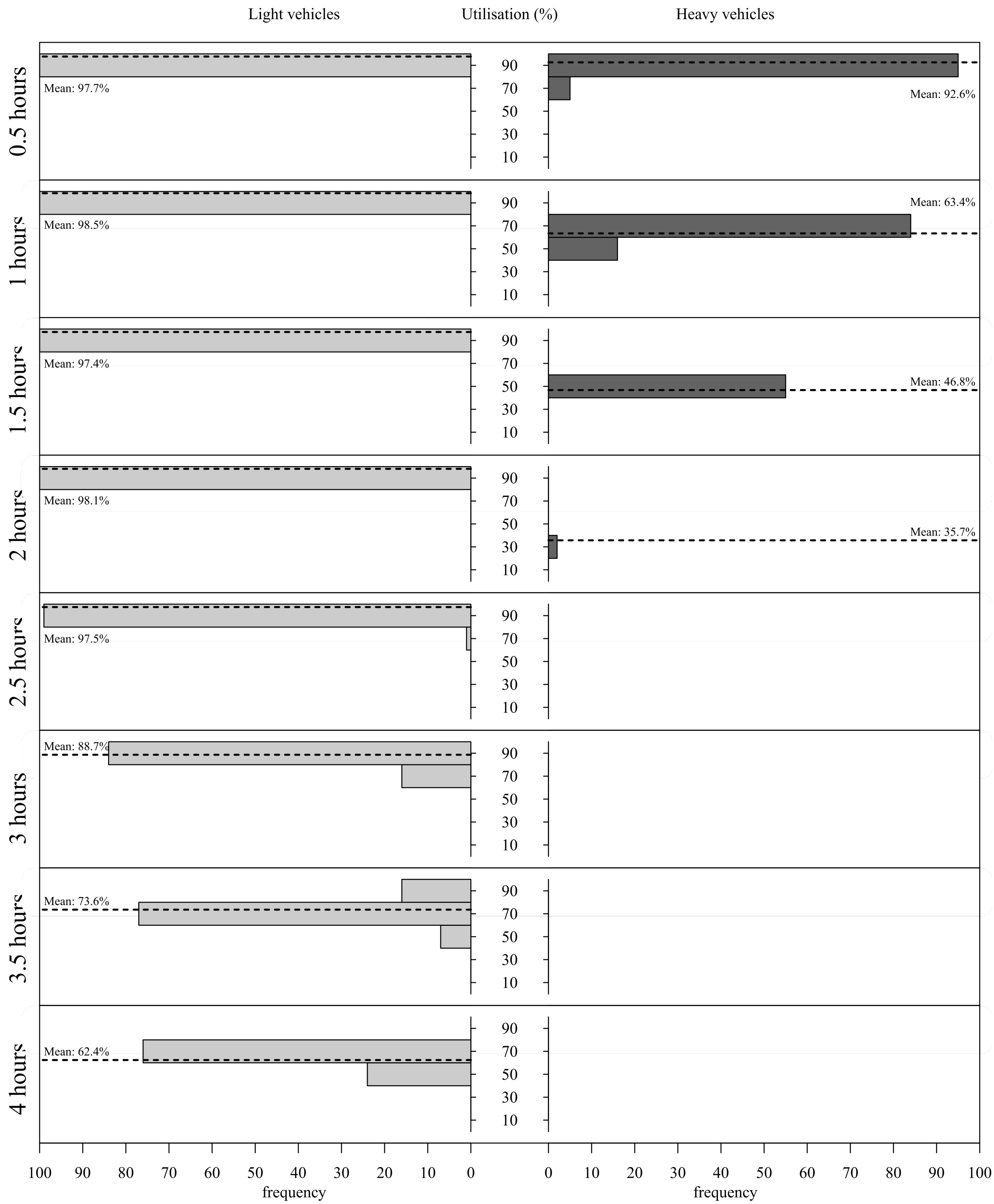


Figure 8: Capacity utilisation of carrier vehicles for different delivery unloading times. The frequency distributions report the number of occurrences over the 100 simulation runs executed for each of the offloading time configurations.

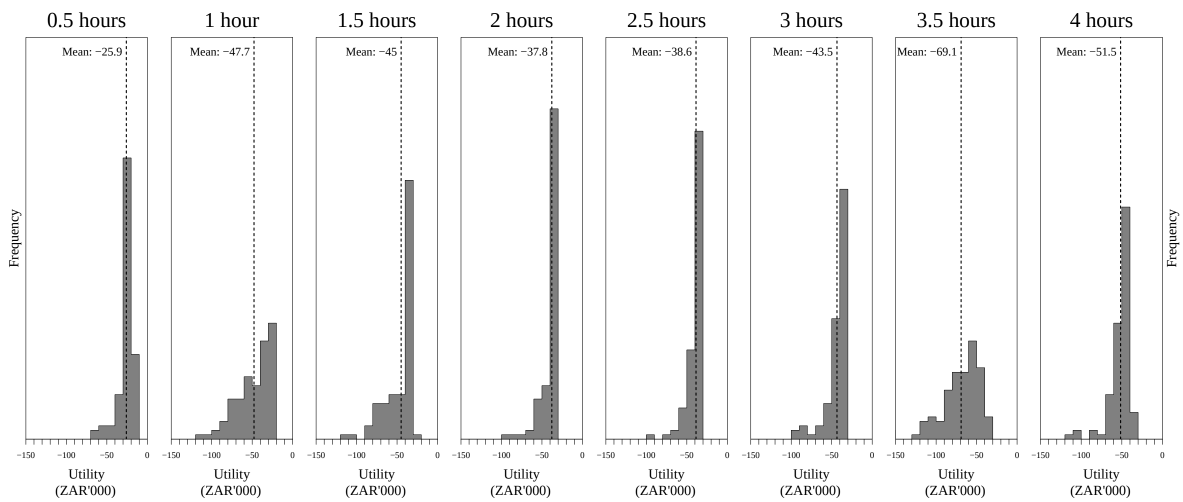


Figure 9: Carrier daily delivery costs for different unloading times. The frequency distributions report the number of occurrences over the 100 simulation runs executed for each of the offloading time configurations.

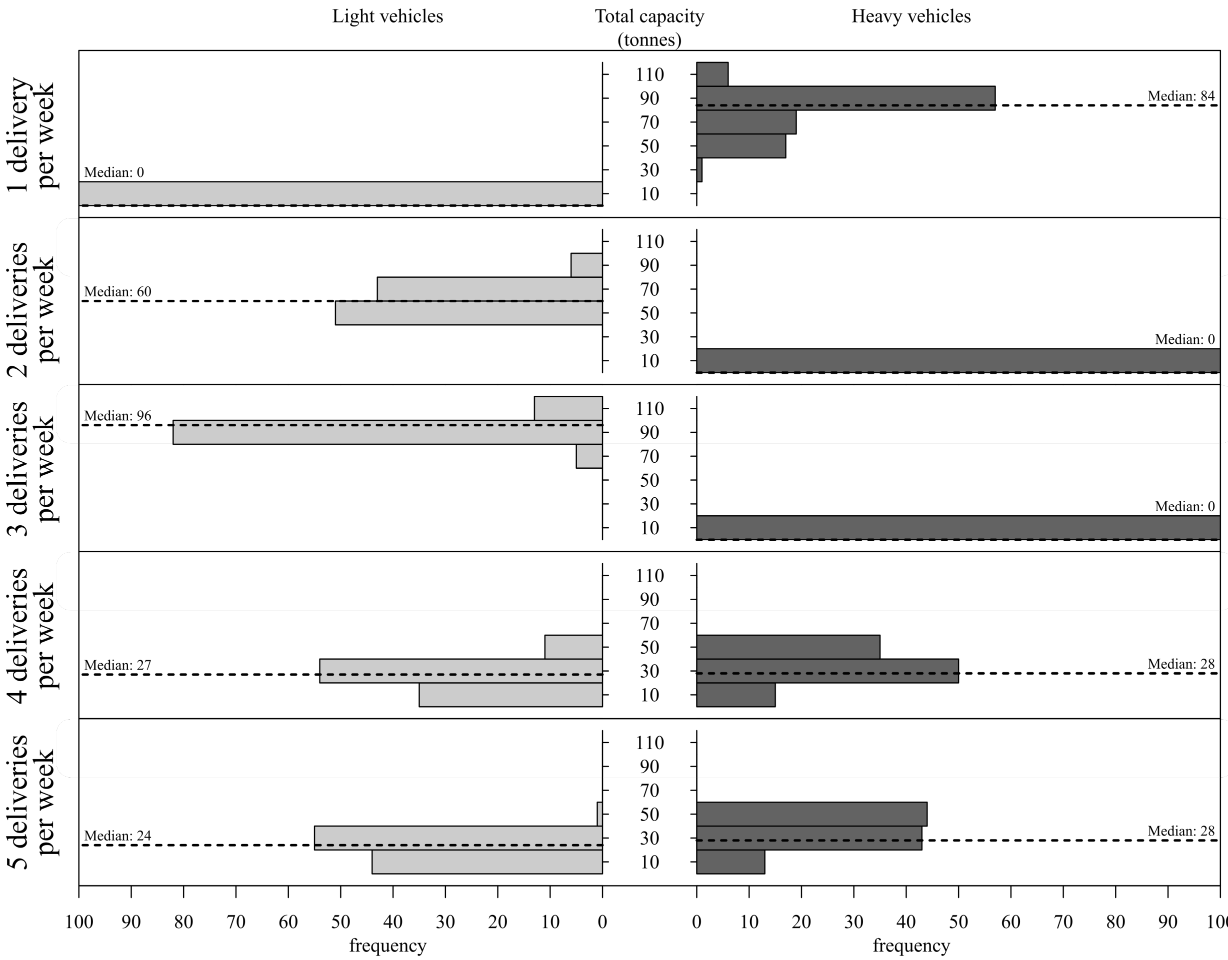


Figure 10: Total available vehicle capacity for different delivery frequencies. The frequency distributions report the number of occurrences over the 100 simulation runs executed for each of the delivery frequency configurations.

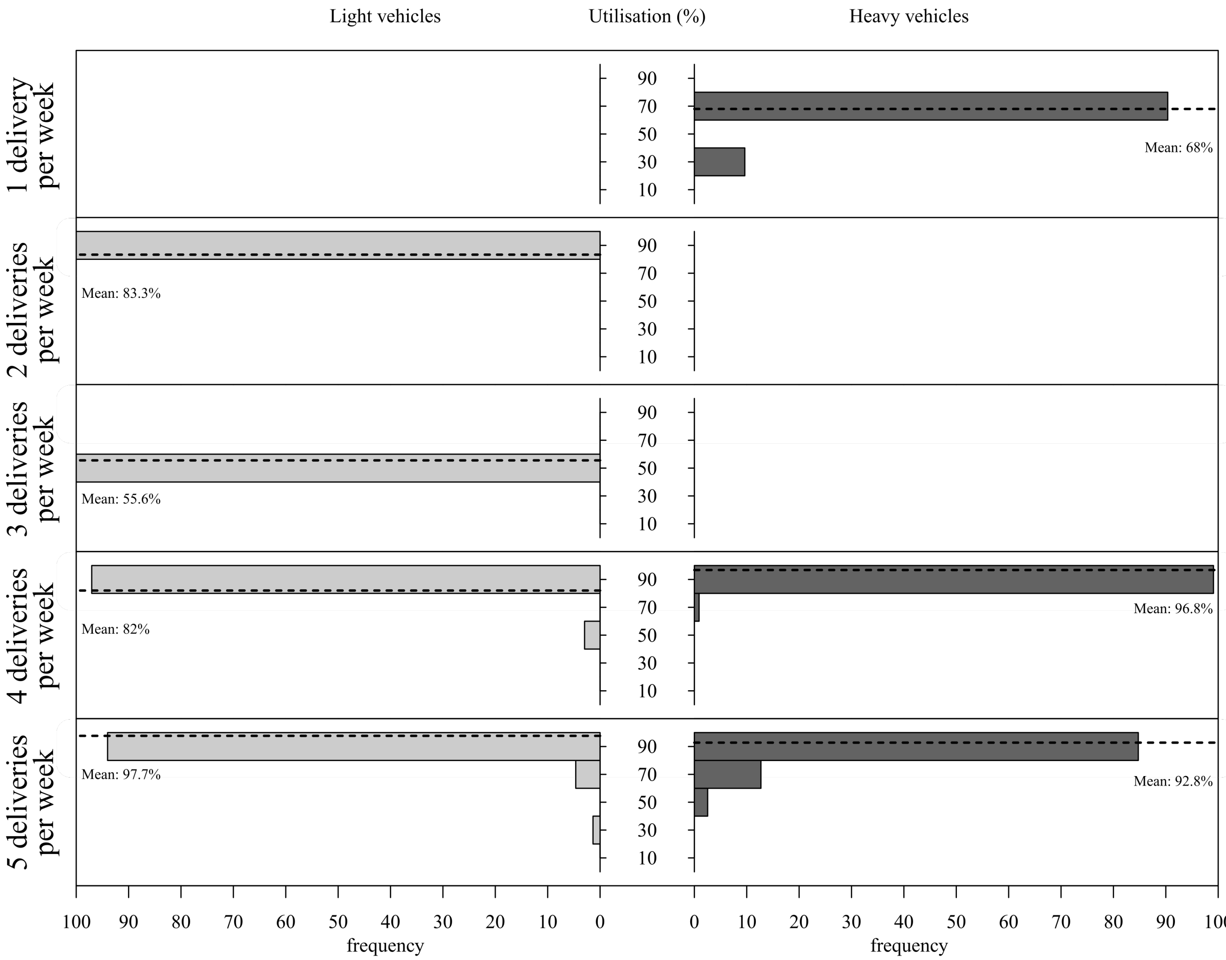


Figure 11: Capacity utilisation of carrier vehicles for different delivery frequencies. The frequency distributions report the number of occurrences over the 100 simulation runs executed for each of the delivery frequency configurations.

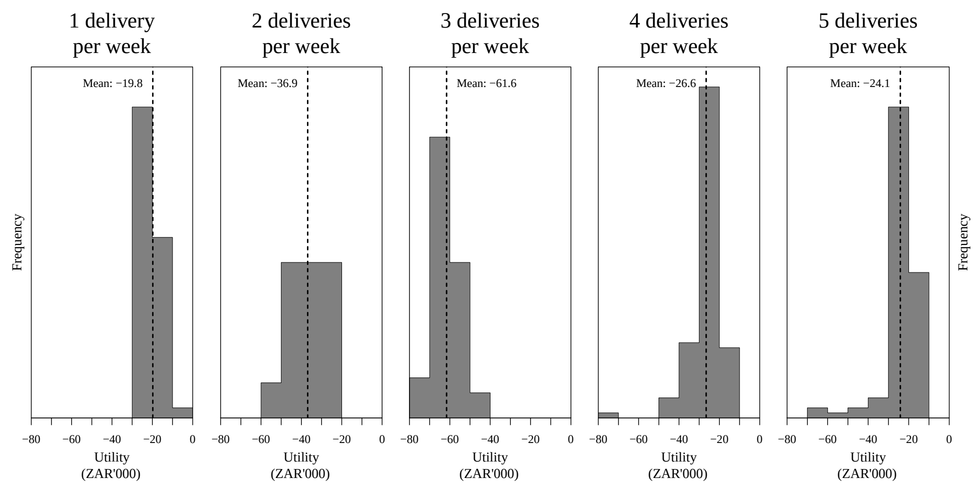


Figure 12: Carrier daily delivery costs for different delivery frequencies. The frequency distributions report the number of occurrences over the 100 simulation runs executed for each of the delivery frequency configurations.