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An agent-based implementation of freight receiver and carrier collaboration with cost sharing

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ABSTRACT

Freight transport stakeholders can benefit from collaborative planning. Unfortunately, appropriate decision and planning support tools are lacking. Consequently, freight stakeholders remain unaware of collaboration opportunities and the potential benefit of those coalitions. This paper focuses on implementing collaboration between urban freight receivers and carriers. Collaboration takes the form of cost-sharing among coalition members when receivers are willing to extend their time windows. Rigorous experiments confirm the behavioural sensitivity of the model. A realistically-sized case study in the City of Cape Town, South Africa, demonstrates the usability of the agent-based simulation model. The case study considers the impact of collaboration on after-hour deliveries. Results indicate that delivery cost reduces significantly (nearly 30%) when carriers and receivers are willing to collaborate and adopt after-hour deliveries - the carrier's fleet composition changes to favour fewer but larger vehicles.

1. Introduction

Urban freight transport is a vital aspect of any economy. Freight vehicles only represent a small proportion of urban road users, but they can have notable negative impacts on congestion, the environment, infrastructure deterioration, and the safety of other users. Urban stakeholders ought to ensure that appropriate and effective planning processes and decision support systems are in place.

Boerkamps et al. (2000) identify four urban freight stakeholders, or agents, associated with the production, movement, and administration of goods. Private sector freight agents include *shippers*, *carriers* and *receivers*, while public sector freight agents, such as municipalities, road agencies, etc., are collectively referred to as *administrators*.

The Logistics Service Provider (LSP) is sometimes included as a separate, fifth freight agent during urban freight modelling and serves as the integrator among shippers, carriers and receivers. The LSP is potentially responsible for the placement of inventory throughout the network.

Joubert (2014) notes that most private sector agents are pursuing myopic profitability and reliability objectives. That is, seeking immediate solutions without contemplating the longer term effect or having the foresight on how their immediate responses will impact other stakeholders or the community at large. Public sector agents, on the other hand, need to plan in a way that serves *all* agents well. Administrators also need to resolve more general issues, which affect people and freight, like reducing pollution and traffic congestion.

The requirement for many less-than-truckload shipments and empty delivery vehicle trips often results in inefficient vehicle capacity utilisation during urban freight transportation (Janjevic et al., 2018). Collaboration can potentially alleviate these inefficiencies. One example is the consolidation of loads of various carriers, leading to fewer trips and improved vehicle capacity utilisation (Savelsbergh and Van Woensel, 2016).

There is renewed interest (Montoya-Torres et al., 2016; de Souza et al., 2014; Lindholm and Browne, 2013; Gonzalez-Feliu and Salanova, 2012) in understanding and modelling collaboration during freight transport, fuelled by the competitive landscape and increasing pressure on businesses to operate more efficiently (Ergun et al., 2007). An important consideration during collaborative freight transportation planning is how the various cooperating entities can share costs or benefits, such as cost savings, increased profits, etc., emanating from their coalitions. To this end, many researchers have focussed their attention on developing gain-sharing methods, or in some instance cost allocation methods, for collaborative transportation (Guajardo and Rönnqvist, 2016).

A deeper understanding of the potential benefits and pitfalls of

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collaboration in urban freight systems is essential if we want to encourage collaboration. The focus of the efforts should be on both the benefits and pitfalls of collaboration, with the end goal being an equitable gain (or pain) (Savelsbergh and Van Woensel, 2016).

Agent-based simulation (ABS) is a modelling technique that facilitates the interaction of autonomous agents with one another. The ability to model independent agents with different objectives lends itself to model the behaviour and goals of self-serving freight actors during collaborative urban freight transport. This paper implements carrier-receiver collaboration with a cost-sharing mechanism in an agent-based setting. Results confirm that the actors are behaviourally sensitive to changes in the collaboration mechanism. An after-hour deliveries case study in the City of Cape Town, South Africa, is used to demonstrate the collaboration on a more realistically sized problem.

Even though the administrator is an important agent who often facilitate the implementation of city logistics initiatives by means of policies or legislation , this paper adopts an industry focus. Adopting an industry focus can provide an economically viable way to implement city logistics improvement initiatives, because focusing on allocating cost savings to industry stakeholders (instead of penalising unacceptable behaviour using the proverbial *stick*) may lead to enough incentives to facilitate participation from industry (the proverbial *carrot*).

This paper starts, in the next section, with a review of the literature on collaboration and game theory. Section 3 presents the agent-based methods, with Section 4 containing the conceptual results. Section 5 describes the case study and specifically focusses on the results of an after-hour collaboration opportunity. Finally, Section 6 presents concluding remarks with a proposed research agenda.

2. Literature review

Current research on urban freight simulation, especially those with a behavioural component, considers freight agents as independent actors that myopically optimise its objectives. Self-serving actors rarely consider the potential benefits of collaboration. Savelsbergh and Van Woensel (2016) highlight the need for freight transport models to include collaborative logistics to enable efficient cost and benefit-sharing among stakeholders.

2.1. Collaborative logistics modelling in urban freight transport simulation

Collaboration occurs when businesses work together for mutual benefit (Coyle et al., 2016). In the context of urban freight, collaborative logistics refers to a situation where logistics stakeholders coordinate their resources and activities to collectivity improve their economies of scale; the overall system productivity and effectiveness; and their environmental sustainability without compromising their competitive advantage (de Souza et al., 2014).

Generally, collaboration is done vertically, horizontally, or both. Vertical collaboration typically refers to buyers and sellers along the supply chain working together to improve the efficiency and competitiveness of that supply chain (Coyle et al., 2016). In urban freight transportation, vertical collaboration typically involves shippers and carriers, shippers and receivers or carriers and receivers in a particular supply chain working together to improve the efficiency of urban freight transportation operations in that supply chain. An example of vertical collaboration during urban freight transportation is a receiver-led consolidation program where carriers collaborate with receivers to reduce commercial vehicle movements in urban areas (Holguín-Veras and Sánchez-Díaz, 2016). Conversely, horizontal collaboration typically refers to the collaboration between stakeholders that have parallel positions in the supply chain (Coyle et al., 2016). That is, companies that operate at the same level in the supply chain. An example of horizontal collaboration during urban freight transportation is co-loading between shippers or carriers (Janjevic et al., 2018).

Gonzalez-Feliu and Salanova (2012) note that even though collaborative urban freight transportation is a promising approach, stakeholders are reluctant to enter into such agreements due to a lack of understanding of the potential benefits and risks. This highlights the need for models that can help decision-makers gain more complete knowledge of the potential implications and benefits of collaborative urban freight transportation. The authors of Gonzalez-Feliu and Salanova (2012) subsequently develop a decision support framework that can help public and private urban freight agents to better understand the potential risks and benefits of collaboration during strategic decision making. The framework is then illustrated through five small scenarios and the authors conclude that even though collaboration during urban freight transportation shows some promise, more research is needed to better understand the potential and risks of collaborative urban freight transportation.

Lindawati et al. (2014) also call for more research as they perform an analysis of factors that motivate and hinder collaboration initiatives. They found that the two main factors promoting or hindering collaboration are the perceived benefits and the risk of losing their competitive intelligence.

Thompson and Hassall (2012) present an approach to estimate the benefits of collaborative agreements when shippers share the use of vehicles and storage areas during delivery. An urban distribution network is redesigned to reduce commercial vehicle movements. They then compare the number of vehicles, distance travelled and costs of the two options. The conclusion is that collaborative urban distribution systems can significantly reduce costs through a reduction in vehicle usage and travel distance.

Montoya-Torres et al. (2016) propose a mathematical modelling approach to compare collaborative and non-collaborative urban freight scenarios to determine the potential benefits of working together. Their work uses multiple, independent Vehicle Routing Problems (VRPs) for different carriers when there is no collaboration. However, they use a Multi-Depot Vehicle Routing Problem (MDVRP) for the collaboration scenario when considering the carriers collectively. The result from a case study in Colombia shows a significant reduction in total distance travelled.

The reviewed contributions are mostly conceptual. Although some illustrate and apply their approaches to actual scenarios, they do not focus on understanding *how* urban freight agents should collaborate. Instead, they focus on *why* benefits and cost can potentially emanate from collaborative urban freight transport.

Concepts from game theory can fill this gap. Simulating the negotiations between players leads to a potential state of equilibrium (Savelsbergh and Van Woensel, 2016). The results of these games indicate how urban freight agents should collaborate for a better overall solution. Results can also suggest how costs and benefits should be shared among the players justly.

Game theory provides a way to model interactions among decision-makers where their actions jointly determine the outcome (Fisk, 1984). More specifically, ideas from cooperative game theory hold much potential for urban freight (Guajardo and Rönnqvist, 2016). Cooperative games refer to situations where participating members' interests are neither completely conflicting nor completely complementary. In these types of games, or coalitions, members discuss their situation and agree on a sensible joint execution plan that is enforceable. For more information about cooperative game theory and various gain sharing methods, please refer to Appendix A.

2.2. The multi-agent transport simulation (MATSim) platform

The autonomous nature of agents in an agent-based setting provides a suitable mechanism to embed collaboration and coalition-forming in a more dynamic decision-support framework.

MATSim is a co-evolutionary, extendable, activity-based, multi-agent transport simulation toolkit implemented in the Java programming language. The simulation allows agents to execute their daily activity schedules and locations (travel demand) on a transport network (transport supply). Agents compete with one another, in time and space, trying to optimise their activity schedules through a variety of choice dimensions that may include rerouting, changing the timing of activities, or considering alternative modes (Horni et al., 2016). The co-evolutionary characteristic comes from the iterative way in which agents are allowed to pick an activity schedule from memory, execute it in the *mobility simulation*, then *score* the experience, and finally *replan* by making adjustments to the current activity schedule.

MATSim, at first, mainly considered commuter movement. Recent developments focus on including commercial vehicles and, more specifically, logistics behaviour (Joubert et al., 2010; Schroeder et al., 2012; Bean and Joubert, 2019). The disaggregated nature of the model allows for individual agents to make autonomous decisions. Each carrier, for example, independently solves a variant of the Vehicle Routing Problem, minimising its total, generalised cost. When a change in the environment occurs, like the toll introduced in Nagel et al. (2014), the carrier can respond by changing its routing behaviour or fleet sizing.

It is this interactive ability among freight agents that this paper wants to employ to demonstrate collaboration. The specific elements of interest are MATSim's carriers (Schroeder et al., 2012) and receivers (Bean and Joubert, 2019).

Why consider simulation and not analytical game-theoretic models? Because the former allows more erratic, non-deterministic behaviour that are better representations of reality. Another reason is that the game-theoretic dynamics among multiple players can get quite messy, leading to both intended and unintended consequences in large setups. Such larger cases are, again, more realistic if one aims to move beyond theoretic results and convince practitioners to consider collaboration.

3. Model and method

To model collaboration between receiver and carrier agents, we introduce a Coalition class into MATSim. This class contains collections of Carrier and Receiver agents that are part of a particular coalition instance, either the grand coalition or a specific sub-coalition.

Each receiver gets an attribute, `grandCoalitionMember`, to keep track of whether the receiver is willing to collaborate with other receivers and the carrier. The attributes are set at the start of the simulation and remain fixed. Receivers unwilling to be part of the grand coalition will be unable to join a coalition any time during the simulation run.

A second attribute, `collaborationStatus`, keeps track of whether a receiver is currently collaborating. Only those receivers with a `grandCoalitionMember` attribute value of `true` can have a `collaborationStatus` value of `true`, and only if they are currently in a sub-coalition. Grand coalition members choosing not to collaborate, and those receivers not part of the grand coalition, have a collaborationStatus value set to `false`.

The first replanning strategy allows any receiver to change its time window. A second replanning strategy allows grand coalition members, and only them, to either join or leave a current sub-coalition.

The scoring mechanism charges non-collaborating receivers a fixed rate per tonne for deliveries by the carrier. The fixed fee, in this paper, is an experimental attribute and is assumed to be set by the carrier. Conversely, receiver sub-coalition members are charged a variable cost for deliveries, depending on the gainsharing rule implemented. Although the MATSim framework is flexible and allows any gainsharing implementation – please refer to Appendix A for more information about the different gainsharing methods – this paper will only demonstrate the proportional allocation as the first step in this journey. The reason is twofold. Firstly, yes, literature acknowledges that proportional allocation may lead to inequitable distribution of gains if the volumes are of different receivers vary a lot. Still, it remains an intuitive way for practitioners to relate to and implement and, therefore, provides a basis for future comparison. Also, to counter the inequity of gain distribution we assume homogenous volumes in this paper's experiments. The main focus is to demonstrate that agent-based implementations are behaviourally sensitive and can capture the complex dynamics of collaborative decision-making.

Secondly, the proportional allocation approach is computationally more straightforward than, for example, marginal allocation and, by extension, the Shapley value. Modelling freight collaboration in this agent-based setting is already novel, so the goal in this paper is to start with a low computational burden and focus more on behavioural sensitivity.

3.1. Proportional cost allocation

This paper applies a cost allocation approach similar to the proportional allocation in Bean and Joubert (2019). However, the scoring in this paper is modified to account for coalition forming as a choice dimension. During every iteration, grand coalition members may or may not be part of a coalition. Only members of the coalition formed during that iteration benefit from the gainsharing. A receiver's share of the gain is proportional to its delivery volume relative to the total coalition volume. The carrier charges non-collaborating receivers, and those not part of the grand coalition, a fixed rate.

The coalition cost calculation is a function of the delivery cost of carriers and the total amount paid by non-collaborating receivers. The coalition cost for coalition $\boldsymbol{S}, C(\boldsymbol{S})$, is calculated at the end of each iteration using (1), in which we denote with C_c^T the delivery cost for carrier $c \in \boldsymbol{C}$, with F_c the fixed fee per tonne charged for deliveries by carrier c, and with V_{rc}^N the total order volume (in tonnes) of each non-collaborating receiver $r \in \boldsymbol{R}$ with carrier c.

$$C\left(\boldsymbol{S}\right) = \sum_{c \in \boldsymbol{C}} C_c^T - \sum_{c \in \boldsymbol{C}} F_c \left(\sum_{r \in \boldsymbol{R}} V_{rc}^N \right) \tag{1}$$

The scoring mechanism then allocates the coalition cost to collaborating members proportional to the members' order volume.

3.2. Experimental setup

To test the gainsharing functionality in MATSim, the experimental setup used has a single carrier servicing six receivers. The first three are part of the grand coalition and, therefore, form the experimental group. Their `grandCoalitionMember` attribute is set to `true`. Initially, at the start of each simulation, the `collaborationStatus` attribute for all three these receivers is set to `true`. The other three receivers form part of the control group: excluded from the grand coalition, and unable to collaborate.

In every experiment, all receivers, grand coalition members and otherwise, have a choice to change their time windows, which always starts at 06:00. The latest delivery time (end of the time window) may either be extended, making the time window wider, or contracted, making the time window narrower, provided that the time window is at least 2 h long. Grand coalition members may also choose to join or leave a coalition.

After each iteration in a simulation run, the scoring function performs the proportional gainsharing and allocation to receivers using (1). The experienced score is associated with the receiver's plan, and added to memory. If a receiver already accumulated 5 plans, the worst one is removed.

Since the carrier does not order any products itself, its contribution is zero. After every 20 iterations, the carrier replans by resolving a version of the Fleet Size and Mix Vehicle Routing Problem with Time Windows using the receiver demand and time windows from the preceding iteration. The resulting fleet, and its associated cost to the carrier, affects the receivers' experienced score for the subsequent 20 iterations until the carrier replans again. During the 20 iterations, receivers may choose to adapt their time windows, and learn from the experience. If the carrier misses a receiver's time-window, the carrier incurs a penalty, which increases the carrier's cost for that iteration.

Each experiment has two parameters. Firstly, the initial time window width, which takes on one of two values: either an extended 12-h time window from 06:00 to 18:00, or a much more constrained 2-h time window from 06:00 to 08:00. The choice to fix the time window opening time at 06:00 in the experiments is merely to strengthen the behavioural signal. The second experimental parameter is the fixed fee charged by the carrier, F_c, and with the single carrier in this case these values are from 800 to 2000 units in increments of 100 units.

4. Results and discussion

In this section, we report on the results for the small-scale experiments. Each experiment, with its unique time window and fixed fee configuration, is executed 50 times to account for the inherent variation resulting from scenario and the behavioural randomness during the replanning of both the carrier and the receivers. We refer to the set of instances as the *ensemble of runs*, and we report the results over them all. The small-scale experiments play out on a square, grid-like road network as illustrated in Fig. 1. Links are directional, imitating one-way streets that alternate from on block (row or column) to the next. In each of the 50 instances the carrier's depot and receiver locations are randomly placed on one of the $10 \times 10 = 100$ nodes. This allows us to not make scenario-specific inference regarding the collaboration behaviour, but rather check that the agent-based is consistently behaviourally sensitive. Each simulation instance was executed for 200 iterations, allowing for approximately ten 20-iteration cycles where the carrier replans the fleet and delivery routes, and the receivers respond with their time window and collaboration choices.

While detailed dynamics of the collaboration turns out to be compelling in specific instances, the overall behaviour remained sound. Receivers' willingness to collaborate is quite sensitive to the fixed fee. Recall that all the receivers, grand coalition members and otherwise, must absorb all of the carrier's cost. With a small fixed fee, the non-collaborators—those paying the fixed fee—account for only a tiny portion of a carrier's total cost. A substantial fraction of the carrier's cost then remains to be shared by the collaborators, making it quite unattractive to stay in the coalition. As the fixed fee increases, non-collaborators cover a more substantial portion of the carrier's cost, leaving a smaller burden for the collaborators to share. The more the collaborators, the lower each's share of the burden and the more luring the option to be part of the coalition. This dynamic is indeed observable in the results. Fig. 2 shows how the fraction of collaborators grows as the fixed fee increases. The fraction reported is the mean proportion of grand coalition members who choose to collaborate as taken over the ensemble of runs. The figure distinguishes between those experiments where the initial time windows were 2 h and 12 h, respectively. Consider first the 12-h line. A phase transition occurs between 1100 and 1400 units. Below 1200 units it is not attractive at all to join a coalition because the remainder of the carrier's cost that the collaborators must share, is too large. Above 1400 units there is no compelling reason *not* to collaborate as the remainder of the carrier's cost that the collaborators must share, becomes insignificant compared to the fixed fee.

The phase transition, when the initial time windows are 2 h, occurs at higher fixed fees: between 1300 and 1900 units. Why the difference? With tighter time windows, there is a higher probability that the carrier will incur penalties because of missed time windows. Penalties add to the carrier's cost, and as the receivers must absorb these in the end, a higher fixed fee is required before it becomes attractive to join a coalition.

The receivers' choice surrounding coalition-forming is quite dynamic in the phase transition and, consequently, varies quite a bit for different instances in the ensemble of runs for an experiment. For example, consider the case presented in Fig. 3, where the carrier imposes a fixed fee of 1400 units, and all receivers have an initial time window of 12 h. The figure reports on the experienced versus an expected score of the three grand coalition members referred to as A, B and C, respectively. At the end of run 28 (Fig. 3a), all three receivers are collaborating (illustrated by having filled symbols). Their expected scores reflect the best-performing plan that the receivers had in their memory of plans. It would be plausible to assume here that those best plans reflect a choice *not* to collaborate and instead incur the fixed cost because the points are lying on the fixed cost line. The plans they executed, however, scored quite a bit worse. At the end of run 28, after the 200th iteration, the carrier had a cost of 11 423 of which $(3 \times 1\,400) = 4\,200$ was accounted for by the non-collaborators: those not part of the grand coalition. The balance, split evenly between the three coalition members since they have equal volume, is then approximately $(11\,423 - 4\,200)/3 \approx 2\,408$. Since an expense has negative utility, it results in a negative score. Each receiver adds to this cost portion their time window costs. The result is their respective experienced scores.

In run 30 (Fig. 3b), receiver B chose not to join the coalition, picked its best plan from memory during the final iteration, and experienced a score very similar to the one expected, which is the fixed fee, and hence its point located close to the diagonal. The balance of run 30's carrier

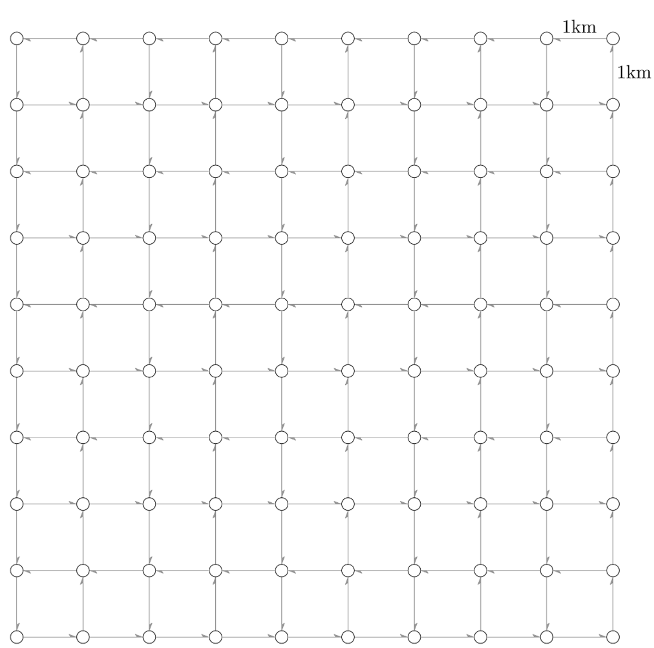


Fig. 1. Experimental grid network of 10×10 nodes with directional links.

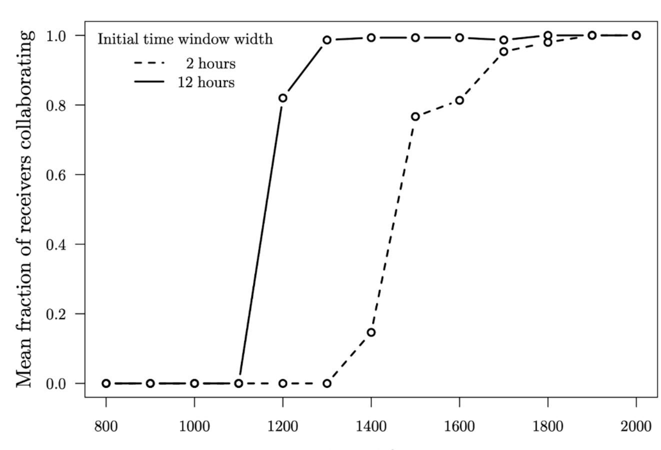
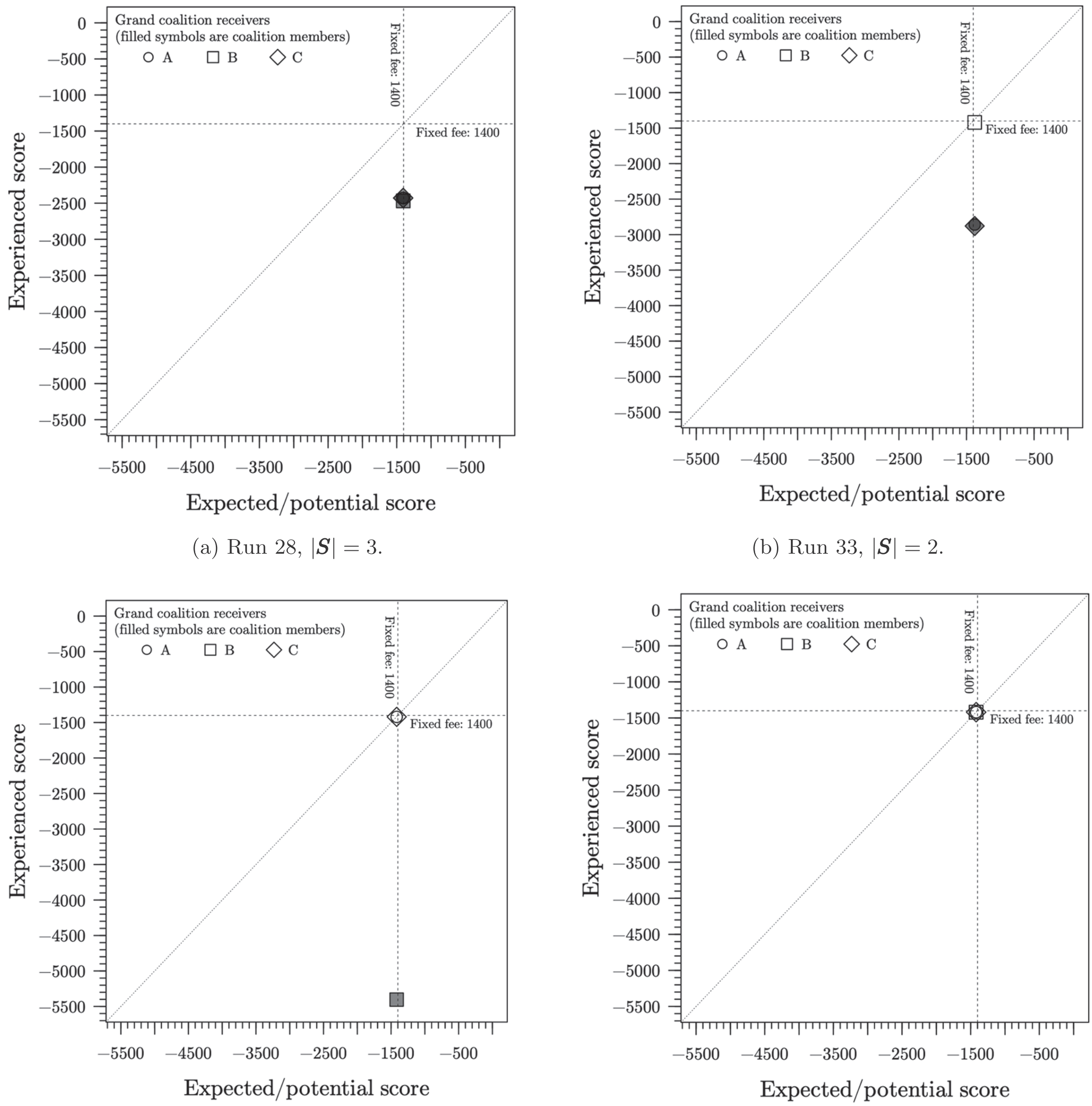


Fig. 2. Collaboration as a function of the carrier's fixed fee.



(a) Run 28, $|S| = 3$.

(b) Run 33, $|S| = 2$.

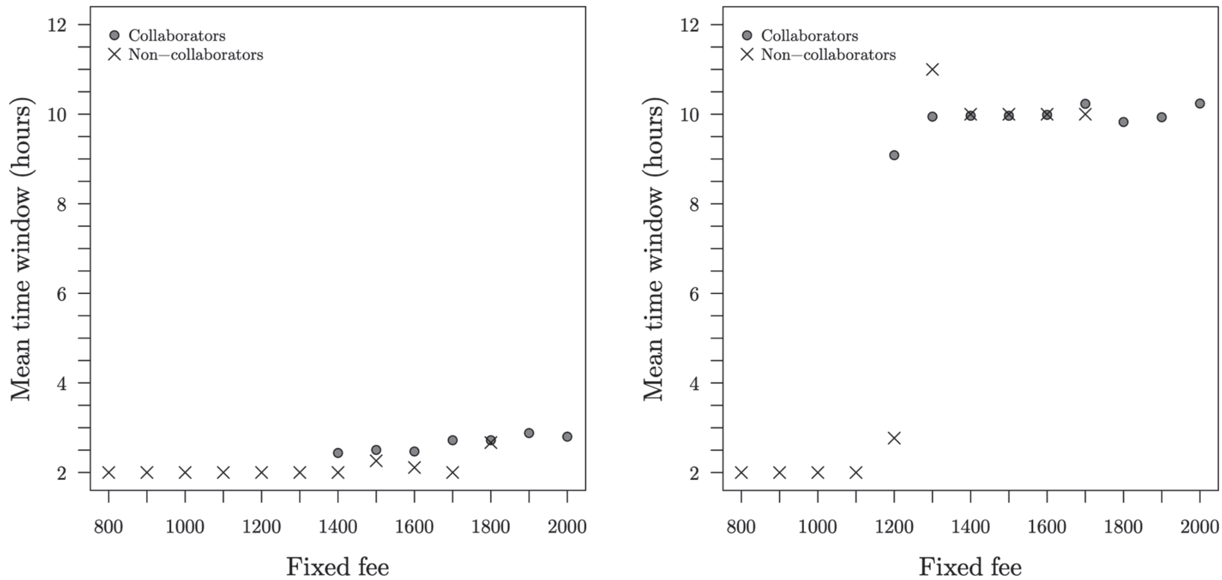
(c) Run 30, $|S| = 1$.

(d) Run 42, $|S| = 0$.

Fig. 3. During the phase transition when the fixed fee is 1400 units, and the initial time windows are 2 h, the experienced scores are much worse for the grand coalition receivers when one or more of them decide to not collaborate. The size of the remaining coalition is denoted with $|S|$.

cost, 11 278, is for A and C's account and is calculated as $(11\,278 - 4(1\,400))/2 \approx 2\,839$. Hence, the two collaborators having lower scores in Fig. 3b compared to Fig. 3a. This reasoning carries over to Fig. 3c, which represents run 33, where receiver B is left to carry the balance alone, resulting in B's experienced score of $-5\,383$. In the case where no-one collaborates (Fig. 3d), which occurred in run 42, the carrier has to absorb a loss of 4 625.

It is, therefore, critical to be more robust and infer the behavioural sensitivity over multiple instances. The next insightful finding in the results is that, even within 200 iterations, the model captures the behaviour that collaborating receivers indeed adapt their time windows in a way that benefits the carrier because they too then benefit, given that costs are shared. Fig. 4 shows the time window migration at different fix fee levels. Fig. 4a represents the experiments where all the receivers' initial time windows are 2 h. In the no-collaboration zone, that is where the fixed fee is in the 800–1300 range (Fig. 2), none of the grand coalition members collaborates, and hence there are no points for collaborators on the graphic at those fixed fee values. As non-collaborator, there is no use in widening the time window since it will merely incur a time window cost, but yield no benefit. Collaborators, on the other hand, have an incentive to widen their time windows at higher fixed fee values as wider time windows give the carrier more flexibility, which results in fewer missed time window penalties and, subsequently, lower carrier costs.



(a) Initial time window of 2 hours. (b) Initial time window of 12 hours.

Fig. 4. Time window migration of the grand coalition members at different fixed fees imposed by the carrier.

All receivers in Fig. 4b started with a 12-h time window. In the no-collaboration zone, that is where the fixed fee is in the 800–1100 range (Fig. 2), none of the grand coalition members collaborates, and they all contract their time windows to 2 h. When collaboration occurs, it seems that the time window width stabilises around 10 h, which is probably a function of the size of the experimental grid setup. That is, the carrier can comfortably service all receivers with a suitable and economically efficient fleet within the 10 h.

One can therefore conclude that the complex collaboration dynamics is effectively captured in the autonomous machinery of the agent-based model. The model is indeed behaviourally sensitive to parameters like the carrier's fixed fee, and other receivers' time window choices. But is the implementation scalable to more realistic policy scenarios? To answer this question, the next section extends the scenario to a more realistic case (in both size and operational parameters).

5. After-hour delivery collaboration case study

This section presents a case study in the City of Cape Town in the Western Cape province of South Africa, to investigate an after-hour delivery coalition between receivers and carriers.

5.1. Experimental setup

As with the experiments of Bean and Joubert (2020), the simulation uses the road network of the City of Cape Town, and the 87 store locations of a well-known retailer as the receivers. The retailer owns 40% of the receivers corporately. Private entities own the remaining 60% as franchise stores. Since the retailer has more direct control over its corporately owned stores, we assume these are part of the grand coalition. The larger, corporately-owned stores order 50% more than the privately owned stores that are not part of the grand coalition, with weekly order sizes of 7.2 tonnes and 4.8 tonnes for corporately owned and franchise stores, respectively.

In our case study, the retailer is the shipper and is responsible for its deliveries; serving as the carrier too. The central distribution centre in Cape Town acts as both the shipper facility and the carrier depot, which is typical for large fast-moving consumer goods firms. The carrier must satisfy the demand of all 87 receivers using a fleet of delivery vehicles from the three available vehicle categories indicated in Table 1.

Table 1
Carrier vehicle types and cost (*Source*: (Bean and Joubert, 2020)), with ZAR 1 ≈ EUR 0.061 (USD 0.068).

	Medium	Large	Extra-large
Description	Cargo van	6 × 4 Rigid	Semi
Capacity	8 tonnes	14 tonnes	26 tonnes
Fixed cost	ZAR 1 887/day	ZAR 2 893/day	ZAR 3 500/day
Variable cost	ZAR 6.21/km	ZAR 8.32/km	ZAR 8.99/km
Value of time	ZAR 390/h	ZAR 746/h	ZAR 746/h
Missed time window penalty	ZAR 1.00/min	ZAR 1.00/min	ZAR 1.00/min

The first of the two scenarios is the daytime-only delivery scenario, where all receivers prescribe a four hour delivery time window randomly scattered between 06:00 and 18:00. The second scenario is an after-hour delivery scenario, where collaborating receivers can prescribe a four hour delivery time window randomly scattered between 18:00 and 06:00. Non-collaborating receivers can pick a four hour delivery time window randomly scattered between 06:00 and 18:00. All receivers incur a cost of ZAR 100/h for the duration of their delivery time windows.

In line with the experiments of Bean and Joubert (2020), each receiver can change its order preferences after every 50 iterations. The choices available to a receiver are: selecting its best prior plan from experience, or picking a plan and moving its time window start time, or end time, earlier or later by one hour (subject to a minimum time window duration of two and a maximum time window duration of 12 h). Grand coalition members are further allowed to join or leave the current (sub) coalition during replanning. Initially, the `collaborationStatus` attribute is set to `true` for 75% of the receivers in the grand coalition. For the rest of the receivers, those are non-collaborators and those privately owned stores not part of the grand coalition, the attribute is set to `false`.

The proportional cost allocation method was used to allocate the coalition cost to collaborating receivers based on their order volumes. The remaining receivers that are not part of an iteration's coalition are charged a fixed rate of ZAR300/tonne for deliveries at the end of that iteration.

The experiments of Bean and Joubert (2020) excluded passenger and other commercial vehicle traffic that do not form part of the simulated retailer's distribution network. The reason for omitting other traffic was mainly due to the increase in computational complexity associated with a full-scale scenario, and the ability to get a reasonable estimate of expected carrier and receiver logistics behaviour without the additional background load of passenger and other commercial vehicle movements on the network. However, the value of after-hour deliveries lies in the ability of commercial vehicles to avoid congestion: it's increased travel time, increased emissions, and decreased travel time reliability. Consequently, we include the effects of other network traffic into our simulation for a more accurate estimate of the effects of after-hour deliveries.

Each simulation instance runs for 1 000 iterations, and for the ensemble of runs we simulate both the daytime-only and the after-hour delivery scenarios 20 times each to account for the effect of uncertainty.

5.2. Results and discussion

Similar to simulation results without other traffic (Bean and Joubert, 2020), results here indicate that a significant delivery cost reduction was achieved when receivers were willing to accept their deliveries between 18:00 and 06:00, instead of during the day. The reduction achieved in this paper's more realistic simulation that includes general traffic was slightly higher than in the case without the general traffic, with results indicating that the carrier's mean daily delivery cost reduced by 15.8% from ZAR 143 055 in the day-time delivery case to ZAR 120 4164 in the after-hour delivery case. In line with these results, the 5^{th} and 95^{th} percentiles of the carrier's daily delivery cost also reduced, from ZAR 136 018 and ZAR 146 917, respectively, in the daytime delivery scenario, to ZAR 114 434 and ZAR 126 236, respectively. This is equivalent to a 15.9% reduction in the 5^{th} percentile and a 14.1% reduction in the 95^{th} percentile.

The reduction was facilitated by the ability of the carrier to use more extra-large delivery vehicles and better utilise the capacity of these vehicles during deliveries, which decreased the carrier's delivery cost per tonne. Results visualised in Fig. 5 indicate that the average carrier delivery fleet changed to larger vehicles in the after-hour case. The mean tonnage (Fig. 5a) shipped using medium vehicles reduced from 191 tonnes (42.5% of total carrier capacity) in the daytime scenario to 75 tonnes (17.0% of capacity) in the after-hours scenario. For heavy vehicles (Fig. 5b) the mean tonnage reduced from 56 tonnes (12.7% of capacity) to 16 tonnes (3.6%). Extra-large vehicles' mean tonnage (Fig. 5c), on the other hand, nearly doubled from 198 tonnes (44.8% of capacity) to 354 tonnes (79.4% of capacity). In addition to the cost reductions realised as a result of the increased use of larger vehicles for deliveries with lower costs per tonne, a slightly larger delivery cost saving was realised when including general traffic into the simulation. This is quite plausible and provides a more realistic estimate of the potential effects of traffic congestion on carrier delivery cost.

Results indicate that the benefits of better utilising larger delivery vehicles and the ability to avoid congestion during daytime hours, could lead to sizeable savings. Having fewer commercial vehicles on congested roads in urban areas during the day reduces congestion and the negative environmental impact (due to unnecessary idling) of commercial vehicles. That said, the impact on infrastructure is not known or modelled at this point. That is, what damage do the (more) heavier vehicles cause on the pavement?

Analysis of receiver collaboration preferences during the daytime delivery and after-hour delivery scenarios indicated that, similar to the simulation without other traffic, the vast majority receivers preferred to collaborate during both scenarios. Over the ensemble of runs, an average of 95.6% of receivers collaborate in the daytime scenario, and 95.9% of receivers collaborate during the after-hour scenario. This implies that it was more cost effective for the receivers to join the coalition and share the carrier delivery cost than to pay the fixed delivery fee. This is confirmed in Fig. 6. The average total daily delivery cost paid by

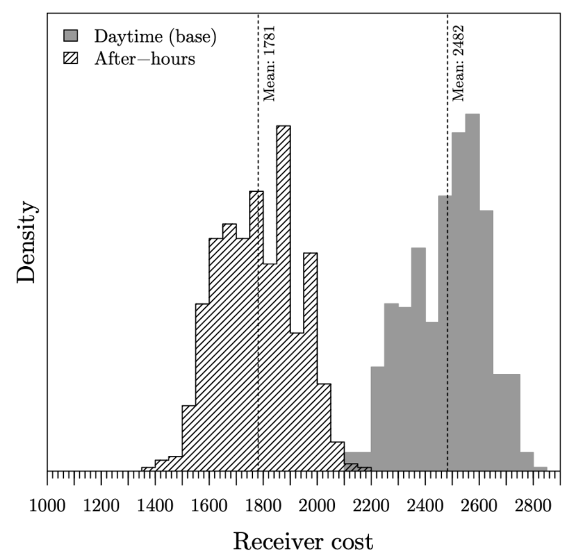


Fig. 6. Receiver cost distribution for collaborators of the simulation runs with other traffic.

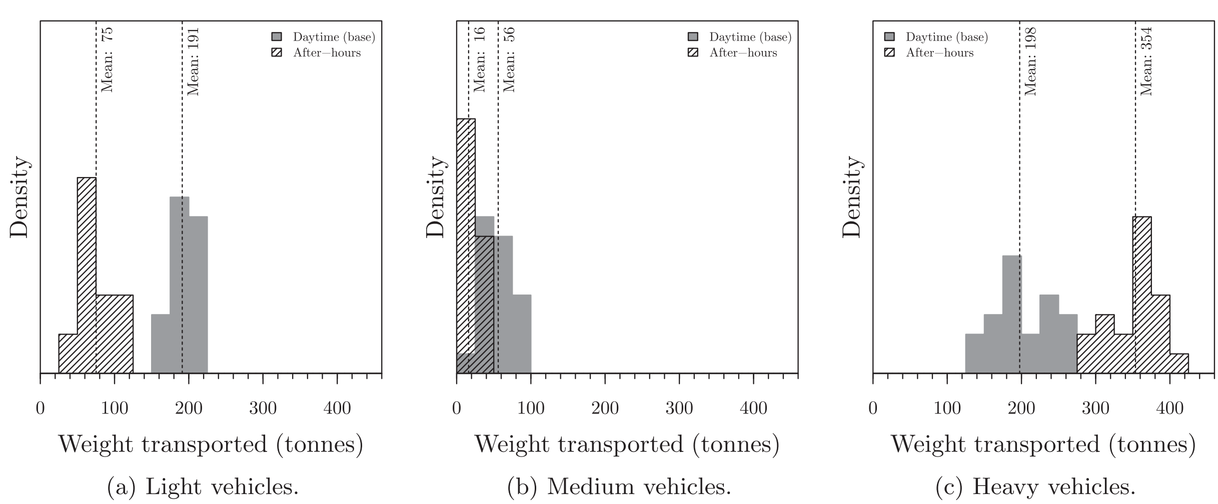


Fig. 5. Carrier fleet composition for the simulations runs with passenger and other commercial vehicle movements.

collaborators for their 7.2 tonne deliveries reduced from a mean cost of R 2 482 over the ensemble of runs for the daytime base case, to a mean cost of R 1 781 in the after-hour scenario. Receivers who choose to join the coalition during the daytime delivery scenario were charged an effective delivery cost of ZAR 345/tonne, whereas receivers who joined the coalition during the after-hour delivery case were charged a significantly lower delivery fee of ZAR 247/tonne. The average delivery fee charged to collaborating receivers during the after-hour delivery scenario, is more or less the same when comparing the simulations with and without general traffic.

Even though a more accurate scenario could be simulated by including passenger and other commercial vehicles in the simulation, the computational requirements of this expanded simulation increased significantly (from around two hours per run for the simulation without general traffic to around 24 h per run for the simulation with traffic), limiting its scope of use. That said, waiting 24 h is not impractical if the decisions one aim to support are of this magnitude. The simulation without general traffic can comfortably be used to inform fleet planning decisions.

6. Conclusion

This paper focused on integrating carrier-receiver collaboration and cost sharing into MATSim to enable improved understanding of the potential impacts and benefits of collaboration during reordering. To this end, collaborative behaviour and functionality to deal with proportional cost sharing between coalition members were introduced into MATSim. Even though only the proportional cost allocation method was used, the developed coalition cost allocation infrastructure in MATSim was designed with the ability to be extendable and accommodate other cost allocation models. MATSim with integrated logistics and collaborative behaviour was applied to a sample problem case to test its validity and functionality. Results indicated that, even though some interesting behaviours were noted in the experiments, the behaviourally rich model plausibly captures the dynamics of urban freight transportation and can potentially be used to inform decision making and investigate the potential effects of collaborative logistics during goods delivery in real world scenarios.

To determine if real world scenarios are achievable it was necessary to illustrate the applicability and potential of MATSim with integrated carrier and receiver behaviour in a larger scenario. Therefore, this paper included a case study in the City of Cape Town to investigate an after-hour delivery coalition between receivers and carriers. Results of this case study indicate that the mean carrier's delivery cost reduced by 15.8% when more receivers were willing to accept after-hour deliveries. This reduction was facilitated by the ability of the carrier to use more extra-large delivery vehicles and better utilise the capacity of its vehicles during deliveries. In addition, further cost reductions were achieved by the carrier during after-hour deliveries since its vehicles avoided day-time traffic congestion and its associated travel time *unreliability*.

Results indicated that there is benefit in using cost or gain sharing approaches in coalitions. It was found that when carrier cost savings were transferred to collaborating receivers in the case study, they were more willing to participate in the after-hour delivery coalition. Finally, the case study's results illustrate that MATSim with integrated receiver reordering behaviour and carrier-receiver collaboration can be used to analyse urban freight decisions and policies in realistic, large-scale scenarios.

This paper makes a notable contribution to the field of collaborative transport modelling, since the integration of carrier-receiver collaboration into MATSim has not been done before. In addition, MATSim with integrated logistics and collaborative behaviour has the potential to support freight transportation planning and decision making in real-world instances, thereby addressing the need for practical and usable freight planning tools.

This paper focused on using the existing MATSim infrastructure that does not accommodate multi-day runs. Introducing multi-day simulation runs into MATSim and running simulations over a five day work week could provide a way to more accurately capture the effects of delivery frequency on freight agents' logistics behaviour, whilst avoiding unintentional behaviours resulting from considering only one day. Therefore MATSim should be expanded in the future to include multi-day runs.

Results from proof of concept experiments emphasised the significant impact of the selected cost allocation method on receiver cost and collaboration preferences. Therefore, MATSim should also be expanded to include other cost allocation methods. Other cost allocation methods, such as the marginal and Shapley methods, could potentially increase computational complexity exponentially, resulting in even longer simulation runs. An avenue worth pursuing in the future to circumvent this problem is to use approximation approaches, such as the approach used by Liedtke and Scholz (2009), to allocate coalition cost between coalition members in MATSim.

CRediT authorship contribution statement

Wilna L. Bean: Methodology, Software, Validation, Investigation, Writing - original draft. **Johan W. Joubert:** Conceptualization, Formal analysis, Resources, Supervision, Writing - review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Cooperative game theory

According to Winston and Venkataramanan (2003), a cooperative game, (N, v), comprises two elements: a set of players or coalition members $N = \{1, 2, \ldots, n\}$, also called the *grand coalition*, and a characteristic function, $v(S)$, representing the value created when all the members in S act together and form a coalition, where $S \subseteq N$. This function may often represent the coalition's cost, $C(S)$.

An important aspect of cooperative game theory is deciding how coalition members share the overall value created. These compensation rules of a coalition are called *gainsharing* methods (Janjevic et al., 2018). Guajardo and Rönnqvist (2016) review many different gainsharing methods used in transportation literature. Some are simple proportional allocation rules, while others implement more advanced principles of game theory. Irrespective of the gainsharing method used in cooperative game theory, most methods select a subset from a set of *imputations* as the solution to the game. An imputation refers to a particular gain sharing instance between participating players. It must satisfy certain conditions or axioms, three of which are *efficiency*, *individual rationality* and *stability*.

The *efficiency* condition dictates that all the gains from the coalition are shared exactly between all coalition members or players. The *individual rationality* condition dictates that the benefit allocated to each player participating in a coalition must never be less than the value each player could have received on its own, without cooperating with the other players. The *stability* condition prescribes that the sum of the benefit allocated to the agents in any sub-coalition, $S \subset N$, is at least as much as the benefit they could have received if they decided to form that sub-coalition. Unstable solutions imply that some sub-coalitions may appear more attractive than the *grand coalition* and will, therefore, result in players being more likely to form sub-coalitions. The *core* of a cooperative game is often used to evaluate the stability condition and refers to the set of all efficient and stable solutions (Winston and Venkataramanan, 2003). A solution will lie in the core of the game if it satisfies both the efficiency and stability conditions simulataneously.

Even though stability is an important consideration to establish a sustainable coalition, Özener and Ergun (2008) note that it could be acceptable to consider cost and benefit allocation methods with relaxed stability constraints. They assert that, in reality, sub-coalitions are typically not formed due to the cost associated with managing coalitions, possible membership fees, insufficient information sharing, or the burden of contractual agreements. As a result, it is acceptable for a gainsharing method to relax the stability condition slightly.

In every cooperative game, the final solution is selected from a set of possible solutions, called *imputations*, depending on the gainsharing method applied. Not all gainsharing approaches result in an equitable distribution of the benefits, or costs. Since equitable distribution is desirable, it is worth reviewing some of the prominent gainsharing approaches in the literature.

Proportional allocation methods The use of proportional rules for cost allocation during collaborative urban freight transport focuses on distributing the coalition costs by proportionally linking it to a single measure, such as transport volumes or weights (Janjevic et al., 2018). The proportion is often not necessarily related to the player's contribution to the coalition cost. The drawback of this approach is that it tends to favour one particular member or group of members. As a result, gainsharing can be inequitable.

Nguyen et al. (2014) confirm the inequity when they investigate a situation where shippers of perishable products consolidate deliveries to reduce cost. In their study, the proportion of items in a shipment belonging to a particular shipper determines the shipper cost. While all shippers benefitted from lower collaboration cost, the distribution of benefits was not equitable. If a shipment is relatively small, one can easily consolidate it into another partial truckload, benefitting that shipment owner unduly.

Marginal contribution allocation methods Various studies in the literature focus on allocating the cost of a coalition, $c(\boldsymbol{N})$, according to the marginal cost added by each coalition member $i \in \boldsymbol{N}, m_i$, calculated using (A.1).

$$m_i = c(\boldsymbol{N}) - c(\boldsymbol{N} \setminus \{i\}) \tag{A.1}$$

Essentially, the marginal reward captures the difference between the cost of the grand coalition, the coalition of all members in $\boldsymbol{N}$, and the coalition cost without member *i*. However, allocating cost using the marginal contribution allocation method generally does not result in a solution that satisfies the *efficiency* condition (Guajardo and Rönnqvist, 2016).

There are many other marginal contribution allocation methods used in the literature, such as the Alternative Cost Avoided (ACA) method (Frisk et al., 2010; Filsberg et al., 2015; Hezarkhani et al., 2016), the Equal Charge Method (ECM) or Equal Profit Method (EPM) (Frisk et al., 2010; Filsberg et al., 2015; Janjevic et al., 2018), and the Cost Gap Method (CGM) (Frisk et al., 2010). Even though these methods frequently result in efficient solutions, such solutions often do not satisfy the *stability* condition, and therefore do not lie in the *core* of the game. However, as indicated earlier in this section, it is acceptable to relax the *stability* condition in the context of collaborative transportation.

Shapley value allocation method One of the most commonly used gainsharing methods in collaborative transport literature is using the *Shapley value* (Shapley, 1953). The approach focuses on allocating value (or cost) as the average of the marginal value each coalition member *i* adds to the overall value of a coalition when joining that coalition.

Solutions obtained using the Shapley value allocation method will always satisfy the *efficiency* condition (Guajardo and Rönnqvist, 2016). Also, the Shapley value method invariably satisfies the *symmetry*, *dummy*, and *additivity* conditions (Winston and Venkataramanan, 2003). One disadvantage of the Shapley value is that it often results in solutions that do no satisfy the *stability* condition and, therefore, do not belong to the *core* of the game (Özener and Ergun, 2008; Guajardo and Rönnqvist, 2016). However, as indicated earlier, this condition may be relaxed.

Nucleolus allocation method The nucleolus method originates from Schmeidler (1969). Contrary to other allocation methods, the nucleolus method focuses on maximising the satisfaction of members with a coalition during cost or benefit allocation instead of looking at the most equitable coalition. To achieve this, one defines an excess vector of all sub-coalitions. This excess vector, $\overline{\varepsilon}$, measures how satisfied members in a coalition are with that coalition. Larger values of $\overline{\varepsilon}$ signify more satisfied members (Guajardo and Jörnsten, 2015). The nucleolus is the result of solving a sequence of linear programs. The objective is to find the reward allocation vector, $\overline{x}$, that maximises the minimum excess over all sub-coalitions. One then uses the nucleolus to determine cost or reward allocation, which is generally both stable and fair (Guajardo and Rönnqvist, 2016). This approach, however, is computationally more demanding than other methods.

Janjevic et al. (2018) analyse the performance of different gainsharing methods, to determine its suitability, in a case study in Brussels, Belgium. They use a proportional allocation method, a marginal contribution allocation method, EPM, and the Shapley value to allocate benefits in various instances and analyse each method's performance using the *efficiency*, *individual rationality*, *stability*, *symmetry*, and *dummy* conditions. They find that all three methods result in solutions that satisfy the *efficiency*, *symmetry*, and *dummy* conditions. However, in the majority of instances, proportional allocation methods lead to allocations that do not satisfy the *individual rationality* and *stability* conditions. The authors conclude that of all the methods evaluated, the Shapley value results in the highest share of stable solutions and provides the best compromise between *individual rationality* and *stability*.

In another comparison, Lozano et al. (2013) consider a delivery consolidation scenario between various shippers to reduce transport costs. They estimate the potential cost savings of such a coalition with linear programming and then use the Shapley value and nucleolus methods, amongst others, to allocate the expected benefit among coalition members. The authors conclude that all of their tested methods result in stable and fair solutions.

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