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Research paper

Fostering collaboration and coordination in urban delivery: a multi-agent microsimulation model

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ABSTRACT

Given the dynamic nature of Urban Freight Transport (UFT) processes, the involved transport and logistics operators face with internal and external issues that should tackle to improve last-mile levels of service and decrease total costs while performing delivery operations. Customers (i.e., freight receivers) perceive the level of service through the acceptance of their requests, while total operational costs are mainly determined by the total travel costs (i.e., distance and/or time) required to accomplish the customers' request. In addition, the vehicle-kilometres travelled are related to the externalities produced. Given that the actors involved in the process operate in a stochastic environment (with changes that can occur both in terms of demand – receivers' requests, and in supply – travel times), collaboration and coordination among the operators could play a key role in meeting the customers' requests as well as in reducing both internal and external delivery costs. Therefore, the paper proposes an UFT modelling framework that integrates collaboration and coordination processes among the different involved actors, and allows the benefits to be assessed. The model has a multi-agent architecture based on microsimulation. In particular, the multi-agent architecture allows us to point out the different actors' responses to various internal (e.g., delivery requests) and external (e.g., delivery times) changes occurring in the daily delivery operations. It consists of three layers. The first one simulates the interactions among actors operating collaboratively. The second layer microsimulates the collaborative processes of information management. Finally, a third layer integrates the two previous layers, facilitating a decision-making process in such a dynamic context. The whole modelling framework is tested in a real case study in which it is possible to validate pros and cons of working in a collaborative and coordinative environment. The results show significant benefits from actors/operators involved in the process and subsequently can address the policy/measure implementation towards a more sustainable and liveable city.

1. Introduction

Urban Freight Transport (UFT) refers to logistics processes that move freight from producers/wholesalers to the final markets (e.g., shops), including end consumers. These logistics processes allow retailers to be restocked with the required products and to deliver the items bought on e-markets (Cirianni et al., 2013; Comi, 2020; Rossolov et al., 2021; Russo & Comi, 2010; Wang et al., 2022). However, such operations are strongly impacted by the evolution occurring in last years: retailers are limiting their storage capacity (for reducing inventory costs) while they demand small and frequent deliveries. On the other hand, home deliveries are increasing, and end consumers are asking for quick and/or instant deliveries. It causes an increase in delivery costs (e.g., operational costs, increase of vehicle-km with subsequent increase of traffic impacts) and pushes operators to find new business patterns for accomplishing this dynamic world. Furthermore, local administrators involved in city logistics planning have to find solutions for preserving urban/metropolitan areas and to ensure their acceptance of the proposed actions to implement (Russo & Comi, 2023; UN, 2019) merging the conflicting interests of the different actors involved: producers,

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wholesalers, and distributors (freight suppliers), transport and logistics operators, retailers and end consumers (freight customers; Franceschetti et al., 2017; Marcucci et al., 2017; Musolino et al., 2019; Russo & Comi, 2020).

In this complex environment, UFT also faces a continuous dynamism that includes frequent changes in delivery requirements (e.g., delivery time and size) and in travel costs due to congestion (Comi et al., 2020; Firdausiyah et al., 2019; Gómez-Marín et al., 2023; Kang et al., 2020; Verlinden et al., 2020). Multiple dynamic variables can be used to describe these changes that impact delivery operations; for example, according to Gómez-Marín (2020), they can be classified into: *demand* (i. e., commodity requests) and *supply*-related (i.e., travel costs, mainly travel times) changes.

Since such changes are stochastic and impact the sequence of deliveries to perform (delivery plan), extra (internal and external) costs for transport and logistics operators can derive (Russo & Comi, 2021). Therefore, this dynamism needs to be pointed out because if it is not well taken into consideration, it could lead to a reduction in receivers' satisfaction (and acceptability) with a subsequent decrease in revenues for freight operators, and an increase in external costs due to the increase in vehicle-kilometers travelled. In fact, for transport and logistics operators, accepting more deliveries can yield more revenues, but this makes it harder to reliably deliver within the service constraints (e.g., time windows) as well as to contain the vehicle-kms produced with a subsequent impact on the operations costs (internal) and externalities produced. Efficient and reliable logistics are key factors for the economic success of new demanding deliveries (both to retailers and end consumers), but delivery costs and receivers' satisfaction are two of the biggest concerns of urban delivering (Kim et al., 2015; Psaraftis et al., 2016). As shown by some studies (Cleophas et al., 2019; Gomez-Marin et al., 2020; Gonzalez-Feliu et al., 2018), multi-actor collaboration and coordination can mitigate the negative impacts of demand and supply stochasticity while maintaining a high service level with a reasonable level of operational costs. Nowadays, telematics offers new opportunities to implement such solutions (Comi & Russo, 2022; Schroten et al., 2020). In fact, it is now possible to obtain large amounts of historical and online (real-time) data (Alho et al., 2018; Comi & Polimeni, 2021) that describe freight operations continuously in time and space. Finding out what to do with these data and how to share them in a way that the entire distribution network can benefit remains a challenging research area (Barenji et al., 2019; Comi et al., 2021; Kijewska et al., 2017; Zhou et al., 2021). However, although different urban freight actors often collect and store data on their operations, these data are not shared (Perboli et al., 2018) due to privacy issues as well as because the data contain a high value, which leads to avoid sharing. Then, it causes each actor to obtain local rather than global and shared optimal results. This lack of collaboration among the different actors can significantly reduce the performance of the entire urban distribution system, particularly when the initial plan must be changed to adapt to new and incoming requests from customers, as well as to the current status of the road network (Alves et al., 2019; Bjørgen et al., 2021; Russo & Comi, 2021). To address these issues, Gomez-Marin et al. (2020) proposed a decentralised collaboration framework to manage the changes that occur in demand and supply. Through a real case study developed in Colombia, they assessed the benefits obtained by the involved actors. However, they pointed out that further benefits could derive from integrating on-line coordination among actors for supporting their decision-making. Therefore, in light of exploring this opportunity, this paper aims to focus on such an aspect and to provide answers to the following research queries:

- How can the collaborative and coordinated integration of UFT actors' logistics processes be assessed ex ante?
- Which should be the requirements of such an ex-ante tool?
- What could be the benefits of such an operative delivery strategy, both in terms of internal and external costs?

To answer these questions, two objectives have been defined. The first is to review the literature on the definition and evaluation of collaboration and coordination strategies in urban freight delivery. Thus, a classification based on some specific criteria is proposed, with a focus on how they have been integrated into real contexts. Subsequently, based on the need to have tools for simulating and assessing ex ante the effects of collaborative and coordinated actions in freight delivery, the main objective of the paper is to propose a modelling framework that can be used for simulating and assessing ex ante the collaborative and coordinated delivery scenarios, estimating impacts, and optimizing system performance. Therefore, to test the goodness and features of such a modelling framework, a real-test case has been developed and the main results are discussed.

This paper is organised into five further sections. Section 2 analyses the literature related to different concepts and approaches, associated with collaboration and coordination strategies in UFT. Section 3 presents the model that has been developed for assessing collaboration and coordination among actors involved in UFT, and the multi-layer framework is presented. Section 4 presents the multi-agent micro-simulation architecture proposed for simulating the dynamism of UFT process. Then, Section 5 assesses the benefits of this delivery strategy through a real test case relative to the HoReCa (hotel, restaurant, and catering) in Medellín (Colombia), pointing out the internal costs in terms of offered service level and operational costs. Finally, Section 6 draws conclusions and outlines future research directions.

2. Literature review

Collaboration among urban stakeholders can take different forms and occurs at the transactional, informational, and decisional levels (Gonzalez-Feliu et al., 2018). This feature has been widely interpreted as a means to improve performance in urban freight processes at the strategic, tactic, and operational levels. For example, some authors, such as Cleophas et al. (2019), provided a comprehensive review of collaborative theories and identified a *vertical and horizontal collaboration mechanism* for transportation. Other studies such as those developed by Holguín-Veras et al. (2020) presented how the UFT can improve its performance through collaborative strategies.

The main research topics regarding multi-actors collaboration include partnerships, resource sharing and pooling, and Mobility/Logistics-as-a-Service (MaaS/LaaS) systems. Several authors have focused on Urban Consolidation Centres (UCCs), partnerships in transport under a general perspective, multi-actor cooperation and its barriers, collaborative decision-making, traffic prediction, and urban congestion.

To model these types of collaborations different approaches have been used. Lai et al. (2017) proposed an iterative auction model that allows carriers to collaborate by iteratively exchanging shipping requests. In this model, the authors reduced the distance travelled by empty trucks. According to their results, the auction is individually rational, incentive-compatible, economically balanced, convergent, and monotonic. Guo et al. (2021) developed a two-stage combination stage as a collaborative mechanism for omnichannel on-demand distribution using a transhipment-based routing algorithm to minimise shippers' payments and maximise carriers' profits. Zibaei et al. (2016) proposed a methodology based on cooperative game theory to design vehicle routes from multiple depots. The proposed vehicle routing problem (VRP) model considers multiple owners (*players*) who manage one or multiple depots and facilitates collaborative management to save transport costs. In addition, it assesses different players' coalitions and the savings allocation methods. Wang et al. (2019) applied a game theory method based on the Shapley improved value to facilitate the collaborative alliance between actors and achieve an optimal distribution of benefits. In addition, they explored how the stochasticity of the freight supply and demand can be efficiently combined through collaborative mechanisms in urban environments. To optimise the resulting logistics network and improve urban sustainability and liveability conditions, the authors solved a collaborative pickup and delivery problem with time windows. They developed a multi-objective model to minimise the number of vehicles and total operational costs, and used a procedure based on a hybrid heuristic (Dijkstra and genetic algorithm). Furthermore, Ko et al. (2020) designed a collaborative model for last-mile delivery that maximises profits by considering the market density of each bidder included in the analysis. They proposed a multi-objective mathematical model and applied the Shapley value approach to find the most suitable profit allocation.

Other strategies for supporting collaborations concern the identification of a central authority that groups all requests and then assigns them to the carriers to minimise the total transport cost. However, since carriers may sometimes retain certain orders, the allocation of the request by the central authority could become more complex (Gansterer et al., 2018; Gomez-Marin et al., 2020; Padmanabhan et al., 2022). Gansterer et al. (2018) studied the decision problem based on a central authority in urban distribution processes under a collaborative framework. The proposed model was formulated as a VRP (vehicle routing problem) of pickup and delivery with several depots, and customer demand was redistributed among participants to minimise the total cost. The authors used exact solution methods. Padmanabhan et al. (2022) developed a collaboration model among carriers performing pickup and delivery processes and proposed a heuristic algorithm based on the large neighbourhood search (LNS).

On the other hand, some authors had worked on *decentralised coordination strategies*. Contini and Farinelli (2021) designed a decentralised coordination algorithm that assigns delivery tasks to a multi-robot system avoiding conflicts between them. The model was empirically evaluated using three different scenarios. The solution results reduce the computational effort, and the duration and distance of the trips obtained. Castrellón-Torres et al. (2015) presented a coordination strategy that aligns the different actors and processes for efficient consolidation and handling of cargo. The authors searched to minimise costs and facilitate proper management of the logistic infrastructure. The model was developed and simulated in an agricultural supply chain. Zhang et al. (2017) analysed a problem of departure time scheduling and coordination of vehicles transporting cargo in a travel time uncertainty scenario. The analysis focused on minimising cost with penalties for delays, lack of scheduling, and fuel cost. The strategy followed by the authors was based on evaluating the formation of groups of vehicles that carry out a joint delivery process, facilitating a more timely response to uncertainty.

Few studies *integrate collaboration and coordination strategies* for UFT. Among them, Clott and Hartman (2016) considered the efforts of stakeholders to collaborate in the Chicago metropolitan supply chain by planning freight corridors and their regional integration. Serna-Urán et al. (2018) used a multi-agent system to coordinate products' movement and agents' willingness to collaborate in a three-level distribution problem. Wang et al. (2021) introduced a collaborative mechanism for resource sharing among urban logistics actors. The coordination process for this resource is based on a heuristic algorithm to solve the VRP. Gomez-Lagos et al. (2021) and Li et al. (2021) proposed a collaborative routing problem between trucks and drones, and coordinated both fleets by locating the trucks in parking lots from the road network and from where the drones fly to deliver the order.

Although crowdshipping is one of the practices that uses stakeholder collaboration and resource coordination (Ermagun & Stathopoulos, 2020; Gatta et al., 2018; Le et al., 2019; Marcucci et al., 2017; Pourrahmani & Jaller, 2021), it faces with a great challenge when matching all the available resources for pickup and delivery in real-life scenarios. Coordination and collaboration could be improved by directly controlling the whole system resources as suggested in Section 3.

The above literature review shows that efforts were carried out in the urban freight transport and logistics for setting up models and methods to assess and support the implementation of collaboration and coordination among actors, on the other hand it guides towards further studies. Therefore, this paper focusses on the opportunity offered by the integration of collaboration and coordination strategies to improve urban freight transport. On the one hand, collaboration contributes to achieve a global goal where all the actors participate in the benefits. However, coordination allows the use of resources to be optimised.

3. Integration of decentralised collaboration and coordination for urban freight transport

3.1. The operations reference pattern

UFT concerns the pick-up and delivery of freight using a fleet of trucks and vans of different dimensions by different operators that have several features and constraints (Toth & Vigo, 2002). As a basic rule, vehicles are based on multiple depots (warehouse), and vehicle tours are performed by each operator on a single work shift and may include several pick-up and delivery locations. The optimisation process of assigning customers (pick-up and delivery locations) to trucks/vehicles and determining the visiting order of customers and routes refers to vehicle routing and scheduling problems, that are performed individually by each operator. Depending on the constraints and the volume of freight transported by each operator, there is the opportunity to merge the resources involved and to move from a single-user to system optimum, supporting collaboration and coordination.

Therefore, in order to explore the opportunity to integrate the pick-up and delivery operations in a collaborative and coordinative framework, it is possible to consider some aggregations deriving from the homogeneous goals and decisions taken in delivering.

Subsequently, three main classes of actors/agents can be identified:

- *customers*, i.e., they are the final receivers of freight, and can decide the quantity as well as the time when receiving the deliveries; such a class of actors includes two different categories of actors, which are different in terms of goals, process of delivery consolidation, and delivery tour to follow for delivering, as well as in required business delivery strategy; they are
  - o the retailers (business-to-business; B2B), which, in turn, sell goods to the end consumers,
  - o the end consumers (business-to-consumer; B2C) in the case of e-purchases;
- transport and logistics operators (transport enterprise), i.e., the operators responsible for managing the delivery operations (their choices are related to the vehicle load, the routing, and scheduling). In particular, according to the multi-echelon structure of the proposed system, this class of actors includes both the manager of the urban consolidation centre (*hub*) and the truck drivers that physically operate the freight transport (*vehicles*); therefore, the hub manager governs the delivery resources and information; truck drivers decide on delivery tour to perform (e.g., customer order to serve);
- freight *suppliers*, i.e., the providers of freight that aim to supply freight to customers. In general, this class includes all the facilities from where the goods movements can be produced, i.e., freight producers' firms, warehouses as well as any stakeholders that want to deliver freight to retailers or end consumers (customers).

Then, the delivery operations that need to be pointed out and simulated within the proposed modelling framework are as follows:

- order fulfilment, i.e., the process from inquiry to delivery to the customer;
- freight pickup, i.e., the physical operation to obtain freight from senders (suppliers) for delivery to customer(s);

- order consolidation, i.e., the process of merging the different orders (set of requests coming from the customers) aiming to optimise the loads and the tours to deliver to customers;
- customer and supplier allocations, i.e., for optimizing the delivery tours, each customer (differentiating retailer and end consumer given that the delivery requirements are significantly different) and supplier need to be pointed out, aiming to include in the same delivery tour only the consistent ones;
- transport plan, i.e., the definition of the delivery tours able to optimise internal and external costs;
- freight deliveries, i.e., the act of consigning the freight (products) to customers.

To perform such operations in a two-echelon structure, the actors considered are as follows:

i. an urban consolidation centre (or *hub*) manager, which facilitates the management of freight flows and information among the other involved UFT actors/agents;
ii. a set of *suppliers*, each offering a specific product/item to their customers; they produce the deliveries to the customers, i.e. commodity flow starts from them, therefore they are the places where the truck drivers pick up the freight;
iii. a set of *customers*, each one has individual requests and timings, which can be interested by changes along the working day; they are the final destinations of freight (i.e., freight receivers);
iv. a set of *transport operators* that manage the delivery operations (i.e., routing and scheduling) performed by the *vehicles*;
v. a set of homogeneous *vehicles* that operate for serving customers (e.g., freight pick-ups and deliveries); it is assumed that there are no restrictions on their driving within the study area.

As shown in Fig. 1, *customers* (both retailers and end consumers) make their requests to suppliers. The *supplier* delivery plan is then passed to the *hub,* which combines (consolidates and coordinates) these requests with the available fleet (*transport operators' fleets*) to define the optimal delivery plans to assign to each *vehicle*. Then, to take into account the dynamism of UFT (i.e., both in terms of changes in *customer' requests* and in delivery times due to *road network stochasticity*), such a flow can also be updated during the working time also if the *vehicles* have begun their delivery tours. In fact, the collaboration and coordination strategy provides that one actor (agent) involved in UFT can be helped by the others when a delivery service is requested. For example, if a further request for delivery comes from *customers*, the involved actors can ask other transport operators to perform the service on his/her behalf. In particular, this synergy becomes more relevant when changes occur during an ongoing work day. For example, a *customer* (e.g., retailer, *B2B*) can ask to increase the quantity of freight to be delivered from the supplier when the vehicle already left the warehouse. Therefore, to avoid refusing the delivery change, the supplier can ask for assistance from another supplier whose vehicle has not yet left the warehouse (or to review the security stock on the vehicles). The customer's request can then be fulfilled, and the supplier can avoid to reject the customer's request or to be forced to return to the warehouse, with the benefits for the customers, the suppliers, and the collectivity (i.e., optimisation of the veh-kms travelled).

3.2. The simulation framework

According to these operational patterns, the proposed modelling framework consists of two modelling tools: *microsimulation* and *multi-agent systems* (multi-agent microsimulation). This model allows decision makers to react quickly to dynamic conditions as described below. Its main goal is to achieve high service levels and competitive service costs based on the distances travelled (which can be considered a proxy of operational costs and of the externalities produced by transport operations).

The collaborative decentralised management of information (i.e., the exchanges of large amounts of data from customers, the urban context, and the many communication channels for information sharing among all the actors) is modelled via *microsimulation*. In synthesis, it allows us to model the stochasticity of the UFT context. Moreover, a *multi-agent system* (MAS) is used to describe coordination and integration between the considered UFT actors. The actors are represented as artificial *agents* to facilitate their analysis and management. Agents are simulated to use communication protocols to respond to dynamic changes taking place in urban environments (e.g., delay in deliveries due to traffic jams) and requests from other entities (e.g., customers). Despite individual goals, this MAS looks for common objectives for all agents (system's optimum *vs.* actor's optimum) aiming to minimise operational costs and maximise the number of served customers by reprogramming distribution plans (sequence and schedules for pick-up and delivery operations).

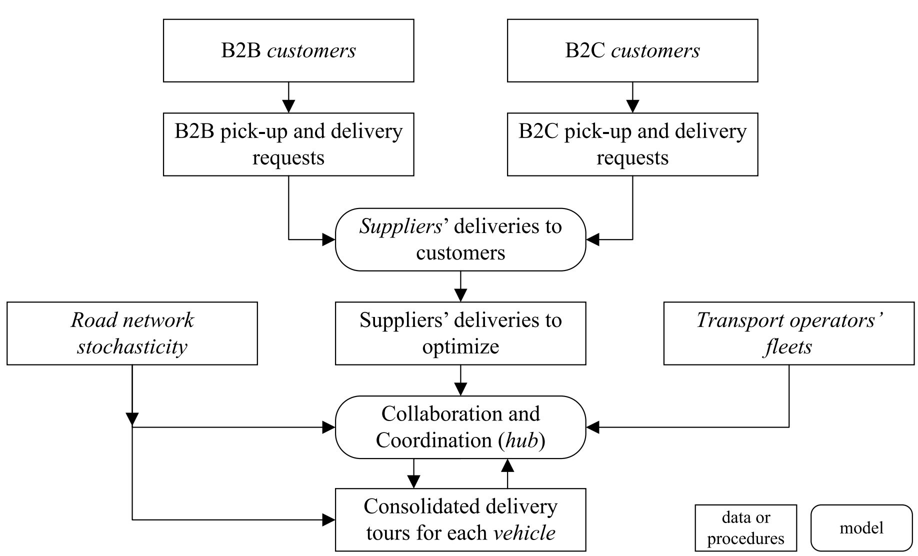


Fig. 1. Synopotic flowchart of the delivery reference pattern.

The integration between these two modelling tools (i.e., MAS and microsimulation) allows us to:

1) take into account the actors' behaviours in relation to past and real-time contexts (through historical and real-time data);
2) make decisions based on past and real-time knowledge.

This integration is modelled through a multi-layer modelling framework as discussed in the following sections.

4. Multi-layer framework for the collaboration and coordination

The multi-layer framework (Fig. 2) supports collaboration and coordination among the actors involved in UFT. Such a framework consists of three layers and serves as follows:

- the *multi-agent logistics network* layer, which represents UFT actors as artificial agents (i.e., suppliers, hub, transport operators, customers and vehicles);
- the *demand and urban context microsimulation* layer, which represents the stochasticity of the UFT context with changes from customers, travel and delivery times and the communication of these changes among the actors;
- the *dynamic multi-agent microsimulation*, which simulates the decision-making process of the different actors.

For the integration of the process defined in the multi-layer framework, a multi-agent microsimulation architecture was developed, where the different involved actors participate. In fact, the multi-agent microsimulation component represents the UFT actors (i.e., customers, hub, suppliers, transport operators, and vehicles) plus a virtual agent that serves as an intermediary for coordinating and integrating the activities performed by the other agents (*control agent*). In the next Section 4.1, the designed multi-agent microsimulation architecture is detailed.

4.1. Multi-agent microsimulation architecture

As previously discussed and according to the three-layer framework, the architecture of the multi-agent microsimulation (MSA) has been developed under dynamic conditions and includes three components (Fig. 3): *microsimulation*, *planning*, and *routing*.

The *microsimulation* component simulates the multiple dynamic events that occur in the operational UFT context. This component supports the collaborative management of the decentralised information among the actors (agents) of the distribution process. In the *planning* component, customers' allocation is managed, and the existing resources are coordinated among all the actors (agents). In the *routing* component, routes are defined and, if necessary, rescheduled to respond to changes in demand and supply. The vehicle activity is thus coordinated.

Although a specific goal is pursued in each component, there are one or more agents who coordinate their goals to fulfil a common objective. In fact, the routes can be recalculated when a new information arrives by analysing the different options that can be accomplished considering the changes in the delivery variables. Besides, the coordination is also achieved through standardised communication processes between actors (agents) using a standard language for actors' communication known as FIPA (FIPA, 2015). The architecture of the operations is described below.

A *customer* agent sends its different types of request to the *control* agent, who is responsible for filtering, consolidating, transmitting, and addressing these requests according to the capabilities of the system. The *control* agent sends (and receives) the messages to (from) the *customer agent* and *hub* agent (*planner*). The *hub* agent, based on the new information, allocates and consolidates the requests received from the control agent by coordinating the suppliers' resources and vehicle routes for the pickup and delivery operations. Once the *supplier* agent agrees with the request, the next step is to point out the routing.

Therefore, the *vehicle-control* agent evaluates incoming requests,

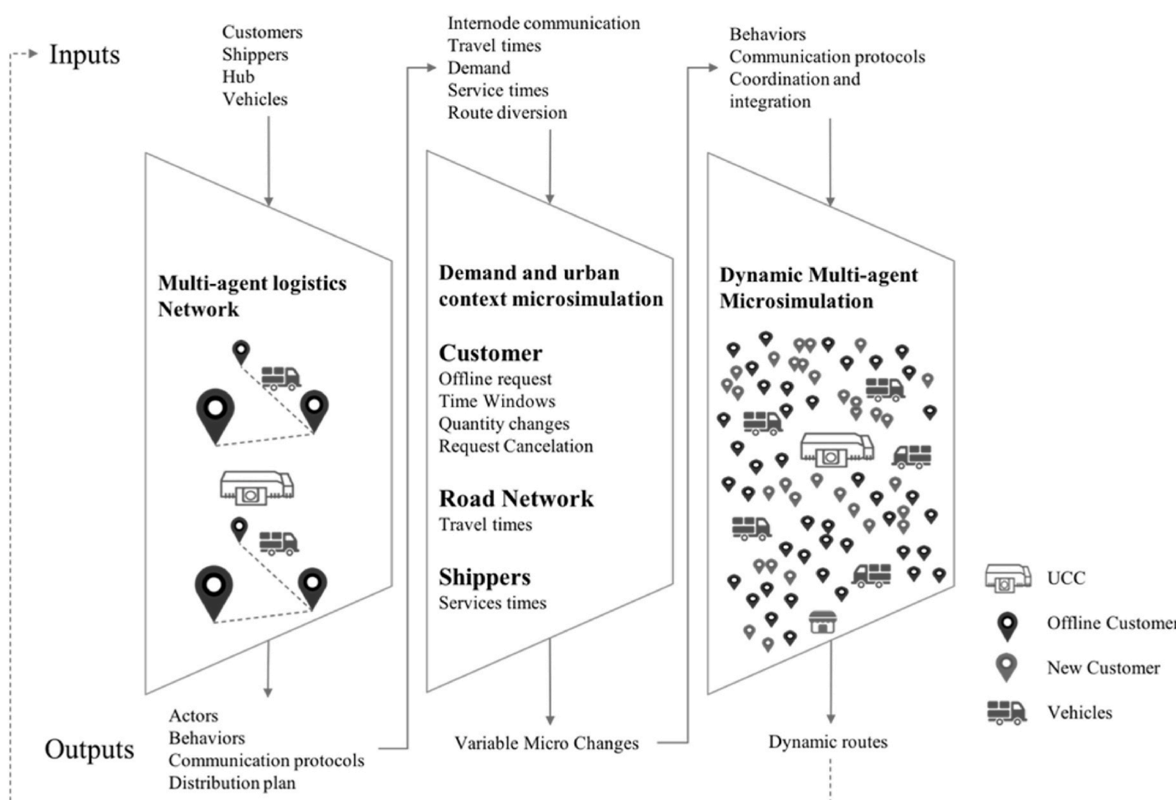


Fig. 2. Multi-layer framework for the collaboration and coordination model.

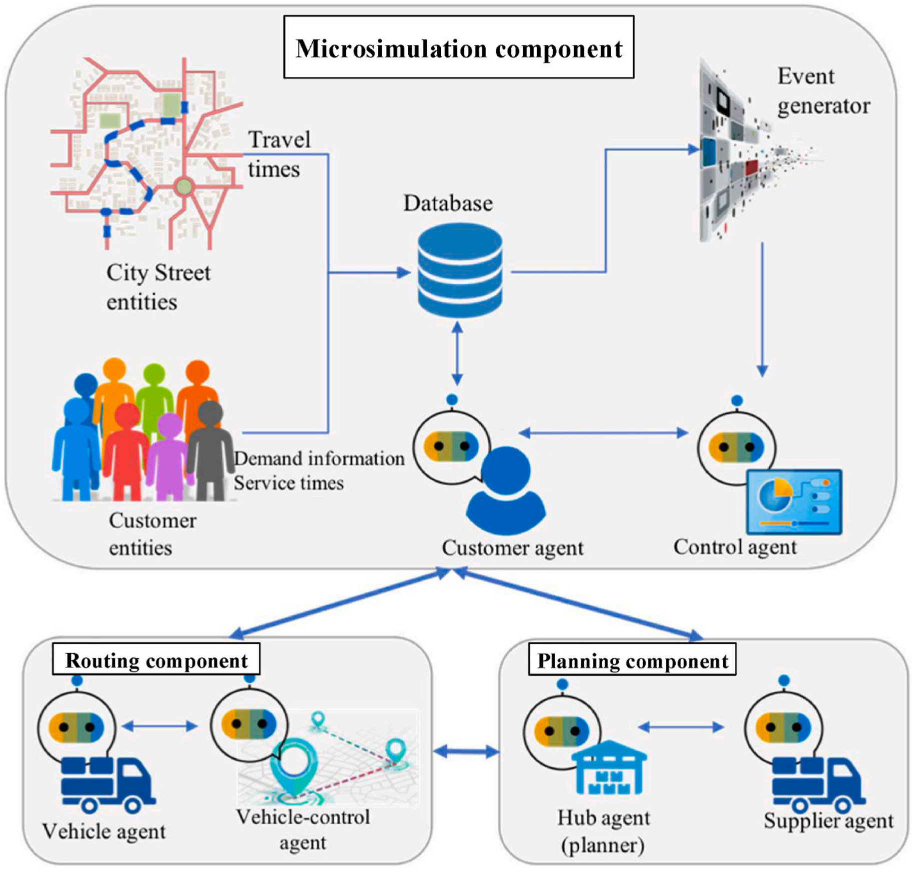


Fig. 3. UFT-MicroSim-MSA architecture.

sends its offers back to the *hub* agent (*planner*), and determines the feasibility of reaching each new assigned *customer*. This *vehicle-control* agent generates the routes considering the capacity of the *vehicles* and the *customers'* location as determined by the *hub* agent (*planner*). The *vehicle-control* agent is aware of the capacity of its fleet considering an additional stock in each vehicle aimed to accomplish changes on demand from the customer's request, and adjusts/designs the new routes. It also updates data on visited and unvisited customers, on vehicle locations in real time, and determines the exact moment when routes will be reprogrammed depending on the dynamic events occurring during the working day.

The *vehicle* agent performs the pick-up and delivery routes considering the tour route configuration (*plan*), the demand of customers, and the offer of suppliers. It also evaluates the response to events communicated by other agents and controls the type and quantity of available product stock to respond to these dynamic changes. Following Gomez-Marin et al. (2022) and Rieck et al. (2014), for producing efficient and specialized routes, three types of routes can be considered, i.e., pick-up, pick-up and delivery, and delivery. Let r_1, r_2 and r_3 be the pick-up, pick-up and delivery, and delivery routes, respectively. Besides, safety stock can be used for accomplishing new unexpected order changes with a relatively small cost (Mckinnon, 2016). Table 1 shows the three defined route configurations based on customers' demand and suppliers' supply.

Table 2 summaries each agent's scope related to the decisions that can be taken and the choice to be made taking the interaction with the other agents into consideration. The agents' behaviours use input data according to the changes in the dynamic variables defined in the microsimulation component and perform specific actions that impact the other agents. An important assumption for this model is that agents have rational economic behaviours (Cavalcante, 2013), which means

Table 1
Distribution routes.

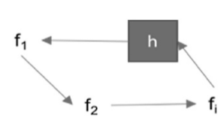
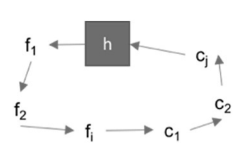
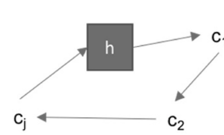
Route configuration	Description
Route r_1 (the vehicle departs empty from the hub, *h*) 	Pickup routes (r_1): These routes are designed only for product pickup at the suppliers' facilities (*f*). According to demand, they can be performed as a single direct trip (pickup at a single supplier) or a tour (pickup at multiple suppliers).
Route r_2 (the vehicle departs loaded from the hub) 	Pickup and delivery routes (r_2): These routes include freight pickup at the suppliers' facilities (*f*) and its delivery to customers (*c*) without consolidating operations at the hub (*h*).
Route r_3 (the vehicle departs fully loaded from the hub) 	Delivery routes (r_3): These routes are designed only for delivery. They can be performed as a single trip or a tour (serving more than one customer per route).

Table 2
Agents' behaviours.

Agent	Variables	Behaviours	Model features
Customer agent	Product quantity and type, time windows, and service time	It seeks to be served under the initial conditions agreed with the supplier	Depending on the event generator, it can be a new or offline customer.
Control agent	Demand events (product quantity and type, and service time)	It accepts or rejects customer requests	Microsimulation feedback as decision support
	Impact of each change on route performance (i.e., total kms, service level)	It informs customers of the acceptance or rejection of orders	
Hub agent (planner)	Product quantities	It collects the requests of the control agent	Based on the demand, it consolidates the orders.
	Time windows	It asks for suppliers' commodity	
		It allocates pickup and delivery places to the vehicles	
		It asks for transport services	
Supplier agent	Service time	It accepts or rejects hubs' orders	Dynamic service times
Vehicle-control agent	Capacity	It assesses the capacity of the vehicles and products availability.	It generates r_2 routes for their final performance
	Number of routes	Proposes the routes and their cost	
Vehicle agent	Travel time	It performs pickup and delivery routes	It designs r_1 and r_3 routes
	Service time	It filters the event variables	It coordinates the acceptance of changes among vehicles
	Unvisited customer	It verifies the impact of accepting or rejecting new events	
	Change in time windows.		
	Impact level on distribution process	It informs the other actors sharing data online	

that they seek to maximise profit (or minimise total costs).

4.1.1. Microsimulation component

In this first component (Fig. 2), the process of decentralised collaboration for information communication is initiated. This process defines the generation, transmission, and analysis of the different dynamic variables in real time, as well as the behaviours of each agent (actor) to establish dynamic scenarios. Through its integration with the MAS, the best responses to such changes in the operational environment can be forecasted.

This component considers the roles, behaviours, and interactions between the UFT actors and, for simulating the real world, integrates the following elements:

i) data storage and management (*database*);
ii) an *event generator*, which develops logistics scenarios with different levels of dynamism;
iii) a *control agent*, whose purpose is to filter the necessary information before sending it to the other components.

Therefore, the microsimulation layer allows to simulate the real stochastic and dynamic world. It identifies the actors (agents) of the logistics distribution network, the urban road network, and simulates the stochasticity of actors' requests and road network functioning/evolution. In addition, in such a layer, the actors' behaviour to respond to the incoming changes is pointed out, and the impacts of such changes on the initial delivery plans (*vehicle routes*) are evaluated in terms of costs and service level.

In detail, the database includes such an information on:

- *customers*, i.e., their location and demand (in terms of product quantity and type), and time windows (in terms of loading and unloading times) preferred for receiving the commodity;
- *suppliers*, i.e., their product offers, and loading service times;
- *vehicles*, i.e., the loading capacity;
- *travel times*, which depend on the times of the day when the vehicles move between the nodes of the distribution network (i.e. warehouses, depots, customers) in order to consider the different levels of congestion occurring during the day.

As introduced earlier, there are two types of customer agents (actors):

(i) *offline customer* agents, i.e., known customers who have made their requests in advance,
(ii) *new customer* agents, i.e., customers who send new requests in real time.

Offline customer agents (actors) can change their initial requests and ask for changes, whose feasibility subsequently needs to be evaluated.

A further agent involved in this component is the *control* agent, who is responsible for:

- consolidating the initial information on customer requests;
- communicating specific events to the other agents (actors) according to the information provided by the customer;
- informing *customers* whether the order is accepted or rejected based on the associated cost and the service level achieved by accepting such changes.

4.1.2. Planning component

In this component (Fig. 2), the freight is allocated for both pick-up and delivery operations. The logistics distribution networks, the available capacity, and the allocation for suppliers, hubs, and vehicles must be considered to plan efficient routes that meet customer requirements.

In the allocation process, customer requests are *clustered* in terms of the type of product provided by the different suppliers. It aims to reduce work levels at the hub and to identify the different types of routes beginning by routes r_2 and following r_1 and r_3. Subsequently, vehicles are allocated to these identified service routes.

This allocation allows us to cover a wide range of possibilities and to react quickly and efficiently to market requirements and changes in the initial conditions so that the pick-up and delivery service can be provided.

For the pick-up and delivery route (r_2) first, the supplier are randomly allocated until the maximum vehicle capacity has been reached. Then, product types are identified from customer orders, and the customers that can be served entirely are selected. This task will be repeated until the possible matching between suppliers and customers is completed. The algorithm proposed for matching suppliers and customers is reported in the Appendix.

Once all the customers for route r_2 are allocated, this information is transferred to the *routing component* in order to design the best routes for serving each customer in the allocation set.

When a change occurs in this initial plan, customers are informed whether the new order (*change*) is accepted or rejected based on the current availability of the vehicles. The two agents (actors) involved in such a modelling component are:

- *hub* agent *(planner)*, as stated, it plans and coordinates product requests from customers and sends this information to suppliers in order to pick up, consolidate, and deliver the requested products to customers according to time windows and vehicle capacity through a *request protocol.* This agent communicates with the *vehicle-control* agent and determines the initial number of the required vehicles to ensure successful deliveries for offline customers. It also establishes the routes to be travelled by each vehicle based on the designed route type;
- *supplier* agent, i.e., it receives the orders of items/products to send/ship from the *hub* agent. The pickups are also organized. Customers also communicate the service (*load*) time for receiving the vehicles. During the service, this initial time proposal could change, for example, due to the stochasticity of the road network.

4.1.3. Routing component

This component coordinates and performs the three different pick-up and/or delivery routes (r_1, r_2, r_3) introduced earlier. The routes are generated by the well-known Solomon's insertion heuristic (Solomon, 1987), while the 2-Opt algorithm is used for their optimisation.

The generated routes are optimised by the activities performed by the *vehicle-control* and *vehicle* agents:

- *vehicle-control* agent, it generates the routes according to the load capacity of the vehicles and the customers to be visited as allocated by the *hub* agent. Based on the requests, it sends its offers to the *hub* agent. These offers are then sent to the *vehicle* agents using a *contract net protocol* (CNP) in order to coordinate the resources and to determine the feasibility of reaching each allocated customer under the predefined terms. This agent controls the capacity of its fleet and the allocated routes. It updates, in real time, information on the customers who have already visited and those who have not yet visited, vehicle location, and the type and quantity of products in vehicles (en-route vehicle load). It also controls the times for which routes are rescheduled depending on the dynamic events occurring during the working day, and it is responsible for improving the routes by coordinating the *vehicle* agents;
- *vehicle agent*, it performs the pick-up and/or delivery routes. It evaluates the possibility of accepting or rejecting a new request received by the *vehicle-control* agent and can swap the list of costumers to serve accordingly (this could be done by using a hybrid insertion algorithm as the proposed metaheuristic). The decisions performed by such an agent aim to respond to events by considering their effect on the vehicles' initial route (plan) and determine whether to accept or reject them. It also assesses their safety stock to react to new orders or quantity changes. The pseudocode of the proposed metaheuristic is reported in the Appendix.

For each event due to changes in the order quantity, the service time, the time windows, and the travel times, this agent evaluates their impact level on the predefined route considering the service level and time-window violations. When an event is rejected, it becomes a "new customer" event and it is re-evaluated through the CNP. In this protocol, all participating vehicles assess the possibility of accepting the request sent by the new customer.

4.2. Implementation process

Two Java platforms were used to integrate decentralised collaboration for information management and coordination among actors. In particular, JAS-mine was used for collaboration, while JADE was employed for coordination. These two platforms allow us to code the different heuristics in order to react to the demand and supply changes.

The proposed process consists of four phases:

1) design of the initial distribution plan,
2) dynamic event generation (microsimulation),
3) multi-agent microsimulation,
4) sensitivity analysis.

The first three phases are related to the multi-layer framework for the UFT collaboration and coordination model as previously detailed, while the fourth phase considers data analysis. Each phase is summarised below through an illustrative example with *100* customers:

- phase 1 (*design of the initial distribution plan)*, all the actors and their different behaviours, through their relative agents, are defined. The initial distribution plan is built using the allocation algorithm and the Solomon's insertion heuristic;
- phase 2 (*microsimulation)*, the dynamic events occurring during a working day are defined based on the distribution probabilities obtained from historical data. The JAS-mine behavioural engine is employed to generate the micro changes. Each entity responsible for demand and supply changes is associated with the distribution probabilities obtained from customers (demand) and the historical data on road links (supply; Comi & Polimeni, 2021; Musolino et al., 2021).
- phase 3 (*multi-agent microsimulation)*, decentralised collaboration for information management and coordination among agents are integrated to react to the different micro-changes. Such a process is simulated by integrating the two Java platforms (i.e., JAS-mine and JADE). In addition, such integration is achieved through communication protocols that guide the reaction of each vehicle to different events from customers and road links using a CNP. The CNP allows agents to be asked for their availability to serve the change and to select the offer at the minimum (internal) cost;
- phase 4 (*sensitivity analysis)*, the sensitivity for different dynamic scenarios is analysed. To validate the model, a sensitivity analysis is performed to evaluate the achievement of the service level based on the percentage of acceptance of changes for the six different variables (new orders, cancelled orders, changes in product quantity, changes in time windows, changes in service time, and changes in travel times). Although *total distance* is the other output variable of the model, it is not considered in the analysis developed below, and given its relevance in assessing the externalities produced as well as the operational costs, it will be detailed in the further development of this study. Below, it has been omitted to avoid compensative effects and to concentrate the analysis by pointing out the two main internal indicators (variables) identified by urban freight transport and logistics operators.

5. Case study: the HoReCa sector in Medellín (Colombia)

To test the goodness of the proposed dynamic collaboration and coordination of the urban freight transport and logistics operators, the proposed framework was applied to Medellín (Colombia). The benefits and possible advantages of the integration between decentralised collaboration for information management and coordination among UFT actors are also thus assessed. This case study analyses the distribution process under different levels of dynamism in operational contexts. Through discrete event simulation, it is possible to simulate urban goods delivery and network stochasticity, and to take into account several effects on operators' choices of implementing coordination and collaborative schemes, including the support offered by an advanced delivery hub planner. Besides, the framework forms a bridge between theory and practice, as shown by its high applicability as summarised below.

5.1. Operational context

The distribution network of the case study consists of 200 *customers* (hotels, *B2B*) located in different parts of the city, seven *suppliers* (wholesalers in this case) offering different products, and an urban consolidation centre (UCC or *hub*). The actors (agents) involved in the case study are summarised in Table 3. Suppliers have to respond to customer requests, while the *hub* pools all the orders and coordinates all actors' resources to react to the different changes occurring during a daily distribution operation (*plan*).

At the beginning of a simulated working day, information on the orders from 100 random offline customers is assumed to be known. During the simulated day, other customer requests arrive randomly and customers may also request cancellations, as well as changes in the ordered quantities, the time windows and the service times. There may also be changes in travel times between all customers, shippers, and the UCC. No constraints on fleet size are considered.

The georeferenced locations of customers, shippers, and the hub, as well as the quantity demanded, time windows, and offers, are available online at the data repository at *https://figshare.com/articles/dataset/Instance_data/12509927*. Fig. 4 shows these different locations in Medellín, which were obtained by entering the geographic coordinates of each customer, supplier, and the hub into the OpenStreetMap's OpenLayer API.

A typical 10-h working day (from 07:00 to 17:00) was simulated. The day was divided into five-time slides: (a) 07:00 to 08:30, (b) 08:30 to 11:00, (c) 11:00 to 14:00, (d) 14:00 to 15:30, and (e) 15:30 to 17:00. The time step for the simulation has been set to 1 min.

Based on data reported by Gonzalez-Calderon et al. (2018) and Metropolitana (2018), the travel times between different actors followed an empirical time-dependent probability distribution. Table 4 summarises the input data values of the simulation.

Urban freight transport for a single day of operations was simulated using the three different route types shown in Table 1.

5.2. Simulation results

30 runs were performed on a computer with 4 Gb of RAM and an Intel Core2 duo i5 2.4 GHz processor, with an average computation time of 34.26 s for the first layer, 11.79 s for the second layer, and 296.28 s to simulate a working day of 600 min +50 min to reach the hub.

According to the whole framework, the orders from offline customers were assigned to each route type, starting with routes r_2, followed by routes r_1, and finally by routes r_3. Operatively, the suppliers are numbered from 1 to 7 and customers from 1 to 100. Table 5 summarises the initial distribution plan for the predefined instance with the 100 offline customers and seven shippers.

Change begins to occur from the first minute (07:00 a.m.) and finishes at the end of the day. In particular, in order to represent what really and operatively happens, if a new order appears, but it is evaluated as unservable during the current working day, it is moved to the next working day. The time-window change can be accepted if it is by the next 100 min and before 16:30 p.m. Table 6 displays the frequency of the changes simulated in the 30 runs, while Table 7 summarises the number of changes generated for the different types of change. Fig. 5 reports the box-and-whisker plot for the two identified response variables (i.e., service level and total distance). Each allows us to determine the median and distribution of the results obtained in each of the quartiles.

Table 3
The actors (agents) involved in the case study.

Entity	Quantity
Customers (hotels)	200
Shippers	7
Hub	1
Road links	43,264
Vehicles	9

5.3. Sensitive analysis

Based on the previous results, the following four scenarios were considered:

- Scenario 1 (*S1 - LL*), it considers a low number of changes in demand (*L*) and travel time variables (*L*) that do not exceed 40% of the total changes generated in the distribution process;
- Scenario 2 (*SH - HL*), it considers a high number of changes in demand variables (which may be greater than 40% of the total number of changes for these variables) and a low number of changes in time variables (less than 40% of the total changes);
- Scenario 3 (*S3 - LH*), it considers a low number of changes in demand variables (up to 40% of the total number of changes for these variables) and a high number of changes in travel time variables (greater than 40% of the total changes for these variables).
- Scenario 4 (*S4 - HH*), it considers a high number of changes in demand and travel time variables, i.e., both variables exceed 40% of the total number of changes generated in the distribution process.

Table 8 summarises the results for the mean service level according to the number of micro changes that occur in the four above scenarios and shows their variations.

According to these box-and-whisker plots, there are some similarities between scenarios *1 (LL)* and *3 (LH)*and scenarios *2* (*HL*) and *4 (HH)* that guide the sensitivity analyses.

For scenarios *1* (*LL*) and *3 (LH)*, the model generates responses to customers' requests with high service levels, with a median and a mean above 90%. In these two scenarios, when changes in demand quantity are low, the *service level* variable repeatedly reaches values of 100%. This is mainly due to the decentralised collaboration for information management, which enables a good communication of variations and activates coordination among the agents (actors) in order to react to such changes. The integration between these concepts allows to respond to changes by adjusting the capacities and resources of the distribution network and allocating services with more flexible reaction times.

For scenarios *1 (LL)* and *3 (LH)*, some results with a service level below 80% were also observed. They can be explained by the fact that changes in demand have a greater impact on collaboration and coordination. Furthermore, when reaction time or agents' resources and capacities are not sufficient to achieve a positive response, there is a decrease in service level.

In scenario *2 (HL)*, the simulation achieves 75% of the times, service levels above 83% and a median value of 89%. A high number of changes requested by customers affects the service level because since these requests arrive during operational time, there is less time available to react to them. As a result, some are rejected and postponed to the next day.

When there are more requests to accomplish, the communication between decentralised collaboration processes for information management and coordination among agents is performed more frequently to find the best combination between total distances and service level. A balance between these two goals lowers the service level in order to avoid cost increases. Only 10% of the runs yield service levels below 80%, indicating that the model's results are consistent at higher service levels in this scenario.

Finally, in scenario *4 (HH)*, which has the greatest variation in changes, the model exhibits service levels above 83% in most runs and a median of 87.5%, with a higher dispersion of the results. This is because by increasing the number of demand and time changes, the possibility to react to them decreases. Although the processes developed in the model seek to respond to all the changes that may occur, constraints in agents' resources and capacities also limit the model's reactions. For example, when changes arrive close to the end of the working day, the service levels will be deeply affected.

The results of the simulations made for the proposed scenarios show the importance of using such a tool as well as the opportunity offered by

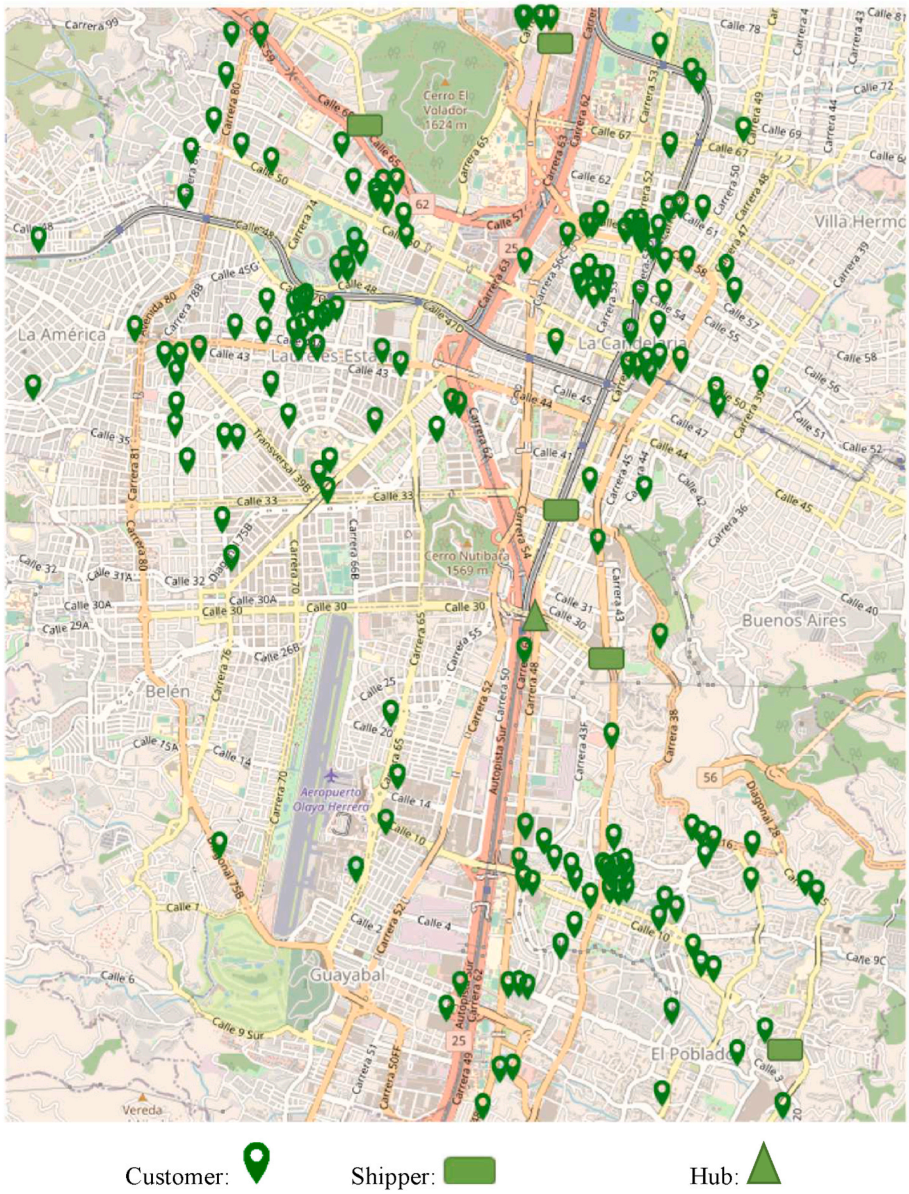


Fig. 4. Urban distribution network of the case study.

the dynamic collaboration and coordination strategy. The use of a system that provides suggestions on if and how to accept further requests from customers can help to satisfy the customers' expectations. In fact, according to the model outputs in all the simulated scenarios, service levels are above 80%. Furthermore, the simulation results show the goodness of the proposed reorganisation of delivery activities, which allows the stochasticity in demand and supply to be governed to ensure a satisfactory service level (Table 8). The developed assessment pushes to consider that the integration between decentralised collaboration for information management and coordination among actors could provide a successful action to implement in terms of internal costs, as well as in terms of external ones due to the optimisation of the use of the fleet load capacity, with subsequent reduction of vehicle-kilometers travelled.

However, further analyses are ongoing for including the assessment of external costs and in order to test how service level and operational costs change when the externalities are taken into account in defining delivery collaborative and coordinative routes.

6. Conclusions

The high variability in both internal and external process conditions (represented by demand and supply stochasticity) impacts the performance of the distribution network in terms of service levels and travelled distances, which subsequently increase internal and external costs. Therefore, in such an environment, methods and models need for supporting the planning and implementation of successful city logistics actions. In addition, telematics offers a new opportunity: to obtain real-time traffic and to indicate real-time changes in customers' requests that can immediately be processed. This has led to the development of methods, such as multi-agent systems, to support decision-making in complex scenarios. In this sense, multi-agent microsimulation, as demonstrated in this study, is an means to develop intelligent systems that facilitate the automation of decisions in the UFT in a framework of collaboration and coordination. The main function of a multi-agent microsimulation is to link autonomous agents in a single and integrated system that facilitates collaboration and interaction (coordination) between all of them, achieving a more efficient system for decision-making.

Table 4
Input data values.

Initial parameters					
Class	Value				
Initial customers	100				
Vehicle capacity	200 units				
Service time (load/unload)	10 min				
Travel speed	20–25 km/h (time-dependent)				
Minimum time required to accept changes in time windows	60 min between simulation time and final time window				
Limit time for a new order request	100 min				
Demand changes					
Variable	Probability distribution				
New order probability	N (150, 70) minutes				
Order cancellation probability	~ U (0.02667)				
Probability of quantity change in an order	~ U (0.03333)				
Time changes					
Variable	Probability distribution				
Probability of time window change	~ U (0.03000)				
Probability of service time change	~ U (0.09475)				
Time slide of the day	a	b	c	d	e
Probability of travel time change (~U)	0.05	0.017	0.085	0.0017	0.05

The implementation of this type of model should start, first, from a real interest in integration between UFT actors, which entails sharing information in real time and seeking solutions focused on improving the system globally instead of individual solutions with single prioritised goals and interests. A second element for the implementation of this type of system is the integration that should be carried out by the support of the technological tools that facilitate decision-making based on automated processes through the use of algorithms for real-time information management and optimisation of logistics problems.

According to the queries that guided the development of this study, a collaborative and coordinative framework has been presented, and the benefits of its implementation have been assessed through a real case study, pointing out the B2B delivery strategy In particular, the internal costs have been assessed in relation to the different possible stochasticity of the system, postponing the assessment of external ones to further development of this study. Preliminary results confirm the goodness of the proposed methodological framework and, at the same time, demonstrate that in those areas where high stochasticity exists both in terms of internal (i.e., customer demand in the just-in-time context) and external (e.g., high level of congestion) costs, the ameliorative margins of the dynamic collaboration and coordination can be significant. Such a modelling framework allows us to assess the distribution strategy by explicitly considering the behaviours of the different actors, which are built using historical data and collaboration to update information and, thus, improve decision-making.

Besides, the modelling framework provides a multi-layer structure that integrates capabilities, resources, and objectives for multiple UFT actors. Additionally, it allows us to update information on the operational context permanently and take into consideration the different changes while balancing cost reductions and service level improvements. This multi-layer modelling structure and its process integration between collaboration and coordination strategies applied to UFT represent, as shown in the literature review, a significant contribution to this area of knowledge.

Another relevant contribution of this research is the integration between different modelling tools (microsimulation and multi-agent systems) to represent decentralised collaboration for information management and coordination, as well as integration among UFT actors. Behavioural rules and historical and real-time data are thus merged and used for supporting decision-making in order to react to changes in the ongoing distribution plan aiming at reducing system costs. As a result, the proposed modelling framework captures timely responses to changes in the operational context and generates a balance between distribution costs and the service levels achieved in serving customers. Besides, the optimisation of travelled distances determines a reduction of external

Table 6
Change generation.

Micro change	Frequency
New orders	18
Cancellations	7
Time windows	2
Product quantity	4
Service time	9
Travel time	20
Total	**60**

Table 7
Summary of the micro changes.

	Max number of demand micro changes	Min number of demand micro changes	Max number of time micro changes	Max number of time micro changes	Average number of micro changes
Total number of demand changes	**32**	**21**	**27**	**21**	**19**
New orders	21	10	15	18	12
Cancellations	7	2	2	7	1
Time windows	2	1	5	2	2
Order changes	2	1	5	4	4
Percentage of acceptance of changes	**93.75%**	**92.86%**	**96.30%**	**90.32%**	**89.47%**
Total number of time changes	**19**	**16**	**44**	**11**	**17**
Service time	10	7	14	7	11
Travel time	9	9	20	4	6
Total route distance (km)	**405.65**	**391.44**	**400.38**	**391.33**	**395.76**

Table 5
Summary of the initial distribution plan.

Number of routes	r_1		r_2		r_3		Total distance of routes (km)
	Capacity utilization	Distance (km)	Capacity utilization	Distance (km)	Capacity utilization	Distance (km)	
1	89.33%	11.36	39.00%	80.36	68.67%	78.75	170.47
2	88.67%	13.85			59.00%	67.61	81.46
3	38.00%	9.98			56.33%	58.30	68.28
4					25.00%	49.18	49.18
5					6.67%	10.41	10.41
Total routes							**9**
Total distance for the distribution plan (km)							**379.80**

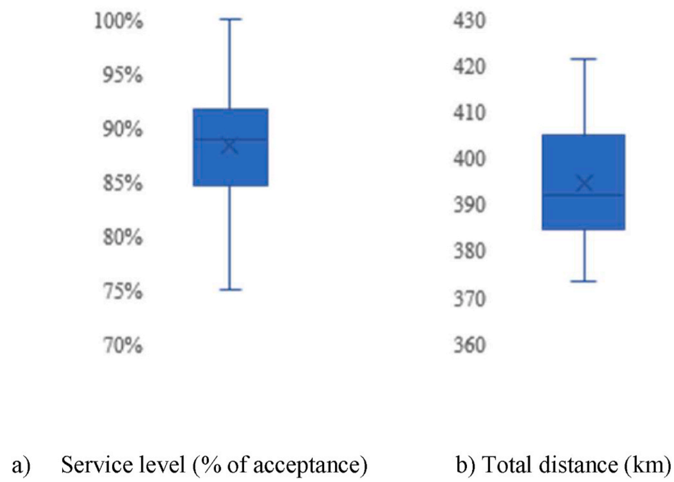


Fig. 5. Variability in the simulation results.

costs as many external impacts are a function of the vehicle-kms.

According to these satisfactory results, future research directions derive. First, the opportunity to compare the simulation results with empirical evidence, and to calibrate the modelling framework in another economic field to assure that simulation reflects more accurately the reality. Then, future research should be addressed to analyse this integration between decentralised collaboration for information management and coordination at tactical and strategic planning levels. This integration involves actors' intentions and resources, and their willingness to join this type of initiative as well as to assess the impact on the entire UFT network performance, with a special focus on the participation of public administration bodies. In this sense, it will be important to focus on the reliability of the microsimulation multi-agent system architecture, and the roles of each actor that allow sharing information. Besides, how to push actors to participate in such initiatives should be pointed out. Also, such a task could be simulated including a virtual agent (*control agent*) that model the will of each actors to be involved in such pick-up and delivery operations.

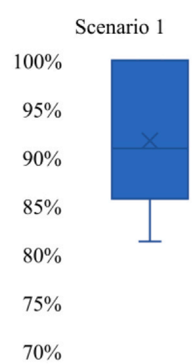
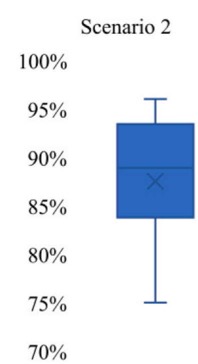
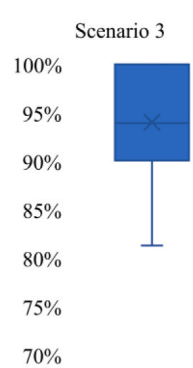
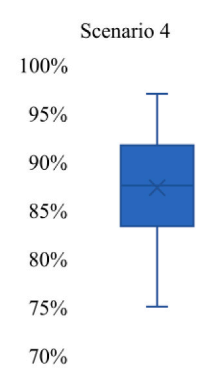
The tools in question could also be further improved including the opportunity to book the delivery areas before approaching the customers (it optimises delivery operation timing). Besides, recent ITS developments (e.g., automatic vehicle location) and implementation within a citywide ITS platform could provide personalised and predictive information (travel times or ,in general, generalised transport costs) on a path to follow between each stop, taking into account real-time road network states.

Such tools may constitute effective support for both transport and logistics operators and city administrators as well. While the time spent on freight operations and delivery costs can be reduced, from the city administrators' perspective, this research can provide the right number of vehicle driving in urban areas and hence also contribute to reduce interference with other components of city mobility, thereby improving the city sustainability and liveability.

CRediT authorship contribution statement

Cristian Giovanny Gómez-Marín: Conceptualization, Methodology, Writing – review & editing, Formal analysis, Data curation.

Table 8
Service level variation in the four different scenarios.

		Number of changes in demand variables	
		Low (0 - 14)	**High (> 14)**
Number of changes in supply variables (time)	**Low (0 - 14)**		
	High (> 14)		

Antonio Comi: Writing, Methodology, Formal analysis, Writing – review & editing, Supervision. **Conrado Augusto Serna-Urán:** Methodology, Writing – review & editing, Supervision. **Julián Andrés Zapata-Cortés:** Formal analysis, Supervision.

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

Allocation algorithm (algorithm 1)

```
Read known static data
Route r2 matrix=0
vehicle_number=1; vehicle_load=0
  for( i=1 to maximum number of suppliers i)
     if vehicle_Load <= vehicle Capacity
     Assign randomly a supplier  to vehicle_number
     vehicle_load = vehicle_load + supplier offer
        else
        add suppliers to r2 matrix
        i=i+1
     end if
     vehicle_number = vehicle_number +1; vehicle_load=0
  end for
for Possible routes r2 selected
    Compare products collected from suppliers with customer demands
    If Product type demand can be fully served by suppliers visited
       Assign Customer to Route r2
    else identify node as route r3 or r1
    end if
end for
```

Procedure for building routes (algorithm 2)

```
Read initial route settled by Agent control
Allocate new order data at the second-last position of the vector route.
Find last visited customer and turn it on a dummy depot (Dd)
Initialize new route vector with Dd as initial point.
Assign a number to each customer according to the initial route.
Initial position i=0
Insertion point u=i+1; j=u+1
Insert new customer at u
for (u=0 to route vector length) do
 Compute travel distance and time form i to u and u to j
 if begining_time + travel_time i to u + travel_time u to j < j initial time window then
   insert new customer at u and save position and distance
   else if begining_time + travel_time i to u + travel_time u to j > j initial time window
then
   "it is not possible to insert the customer in the route"
   else i=i+1;u=u+1;j=j+1
 end if
end for
Choose the route with the minimum distance
```

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