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Integrating Multi-agent System and Microsimulation for Dynamic Modeling of Urban Freight Transport

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Abstract
This work aims to apply an integration between a multi-agent system and microsimulation to take advantage of the large amount of data generated in urban freight transport to improve the overall performance of the urban supply chain without forgetting the principles of autonomy that govern each of its actors, responding to the different dynamic scenarios that may arise in the operational context. The integration framework produces a satisfactory communication process in those modeling methods measured by two indexes: throughput and latency. The results of this integration show a robust response to dynamic scenarios and allow reacting to the different quantity of changes without dismissing the search for optimum solutions.

Keywords
multi-agent systems, microsimulation, hybrid simulation, information management, urban freight transportation

1 Introduction

The design of dynamic systems that allow the capture of internal and external conditions and respond to different changes searching for a decrease in the negative impacts on their performance is becoming more frequent (Amorim et al., 2019; Martins et al., 2021; Serrano-García et al., 2021). The information on the changes occurring in the system comes from different elements and actors that generate or receive such information. These actors are in permanent interaction producing changes in individual characteristics and the whole system (Mendonça et al., 2020).

The management of different information sources delivering online data to a system becomes a fundamental tool for analysis of reactions to possible events that affect the individual behavior of the system elements (Barenji et al., 2019). The supply chain is a dynamic system that continuously receives information from its multiple actors, which must be managed to improve the overall performance of the entire system (Gómez-Marín et al., 2020).

Nowadays, the amount of data generated by supply chain stakeholders is high. Companies can be confused by this large volume of data (Maddikunta et al., 2022; Song et al., 2021; Tseng et al., 2022). In this case, modern tools such as Big Data and analytics support the performance of detailed information analysis (Taniguchi et al., 2016; Gangwar et al., 2023). But beyond knowing the history and what has happened in supply chain management, it is necessary to design tools that allow converting this data into useful information to improve the overall performance of the entire chain considering the different actors, their behaviors, and economic, environmental, social objectives.

Data-driven models such as microsimulation and agent-based modeling make it possible to define, based on historical data and rules, the future behaviors of each actor in response to different internal and external stimuli. But it is not enough to identify these possible behaviors. It is also necessary that supply chain models allow process optimization through different tools, considering both historical behaviors and collaborative processes. Using these two elements in modeling brings a closer representation and achieves an overall objective without forgetting the individual stakeholder's goals.

Multi-agent systems (MAS) are used when the capabilities of a single agent are not sufficient to represent the

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complexity of the problem, thus allowing to capture interactions among independent actors (Anand et al., 2014). These interactions are mainly based on the communication skills of each agent, which are two of the main characteristics of multi-agent systems; that is, each agent needs to communicate with the system resources and with the other agents to cooperate, collaborate and negotiate with each other (Bellifemine et al., 2007). These communication acts are carried out through communication, coordination, and negotiation protocols between agents (Kalia and Singh, 2015; Viroli et al., 2015). In a supply chain context, MAS consider each of the individual objectives of the supply chain actors but, at the same time, share resources and capabilities that seek a primary common objective (de Souza Henriques, 2019; Hu et al., 2022; Serna-Urán et al., 2018).

The integration of both modeling tools could allow the use of multiple source data, the stakeholder's characterization of these data, and the coordination and collaboration processes among all stakeholders in the urban freight system. The development of this integration is not very well studied in the literature.

This paper's objective is to present a novel proposal, on the one hand, on the integration between the management of real-time information from multiple channels (collaborative decentralization information management) that permanently updates the news in a system through microsimulation, and on the other hand, on the coordination process among system actors to react efficiently and timely to most possible number of changes to respond, by using of a MAS. The authors present an integration of the multiagent microsimulation proposal. It models the stochasticity present in the different situations that occur to each system actor and how, through the processes of negotiation and communication between these actors, results are reached with global optimums instead of local optimums. MAS consider each of the individual objectives of the supply chain but at the same time share resources and capabilities that seek the common good.

This paper is organized as follows: in Section 2, the relevant literature review is presented. Section 3 presents the proposed framework for integration between MAS and microsimulation. In Section 4 a case study in urban freight transport is presented, this application case shows the integration process of these two modeling tools and assesses the feasibility of this integration. Conclusions and future research are presented in Section 5.

2 Literature review

Microsimulation is a modeling tool used to assess impacts on different systems. This tool is based on the simulation of micro study units (individuals, households, companies, farms, vehicles) by representing individual behaviors based on population data for analysis before direct interventions by simulating possible changes (Li and O'Donoghue, 2013). As a modeling tool, it has been used since the 1950s to evaluate public policies (Absalón and Urzúa, 2012) from different areas of knowledge, such as economic and social sciences, and it has migrated to a wider range of knowledge fields. As a modeling method, microsimulation helps to better-understand systems' complexity from the population structure, the variety of policies and their impacts, the behavioral responses to such policies, the dynamic components, and the Spatio-temporal context (O'Donoghue, 2014).

Microsimulation models achieve a high detail level by representing the system with a high resolution (Lang et al., 2017; Reggelin et al., 2022) and individual activities for each unit of analysis. It implies higher computational efforts that have been tackled for the increasing improvements in hardware, allowing for simulation, in reasonable processing time, systems with millions of analysis units, each with individual behaviors (Gomez-Marin et al., 2018; Petrik et al., 2020; Waddell et al., 2018).

Another modeling methodology that has been used to appropriately represent the dynamic interactions between the different actors in a system to support decision-making is agent-based modeling (Le Pira et al., 2017; Zheng et al., 2013). This type of modeling is associated with the behaviors of multiple agents in a socio-economic system (Ballas et al., 2019). It focuses on the interactions between agents and the environment in which they move. These agents are governed by assumptions of rational economic models such as "perfect information", rational expectations, absence of centralism, etc. (Richiardi and Richardson, 2016).

In this modeling methodology, some researchers represent real population dynamics. Sajjad et al. (2016) and Singh et al. (2015) developed an agent-based simulation model with a Beliefs, Desires, and Intentions (BDI) architecture. The Beliefs were driven by the census microdata of the population that allows the development of plans that fulfill the Desires and Intentions, thereby aligning the simulation results with the actual data. However, this simulation does not use interaction and coordinated communication among agents. Berndt et al. (2017) generated a hybrid simulation between agent-based simulation and microsimulation to forecast the demand for healthcare services based on census data and communication between cognitive agents influencing their nearby social network. However, the communication process between the two modeling tools is not clarified to complete the feedback between the two modeling methods.

A variation of agent-based modeling is the multi-agent systems (MAS), in which emphasis is placed on the interactions and communications between the different agents, their type of reasoning, as well as the architectures with which these virtual systems are designed to respond to the characteristics to be modeled (Boman and Holm, 2004; Wooldridge, 2002; Zheng et al., 2013).

With MAS, it is possible to generate an architecture that allows actors' coordination to respond to internal and external changes that affect a system (Serna-Urán et al., 2018). It takes advantage of the benefits of distributed computing to improve the use of resources and the speed of computational response to this type of NP-Hard or hard-to-solve problems.

Generally, when using MAS, an agent is dedicated to reproducing the behavior of one or several specific processes and employs exact solution methods such as linear programming, which are often used in small or medium-sized problems. For larger or more complex problems, heuristics, and metaheuristics such as genetic algorithms, tabu search, simulated annealing, etc., and their combinations should be used (Miliauskas, 2022; Seyedhosseini et al., 2016).

Developments based on integrating these two modeling paradigms can offer great potential for systems analysis and its modeling methodology (Boman and Holm, 2004; Parikh et al., 2017). It allows simultaneous representation of the amount of data, stochastic activities of agents, and their interactions, with the possibility to communicate and generate coherent behaviors in which coordination between agents can improve responses to events both internal and external to the system.

Some researchers expose multi-agent microsimulation focused on behavior definition and communication processes of agents employing rules and protocols. The generation of changes in these behaviors and communication are defined by probabilistic distribution processes (Kammoun et al., 2014; Kickhöfer and Nagel, 2016; Mastio et al., 2018), but so far, no studies have been found in the literature that combines the individualization of these behaviors and changes within the communication processes, architectures, and agent types that characterize MAS.

3 Framework for integrating multi-agent system and microsimulation

To integrate the multi-agent system and the microsimulation, it is necessary to transmit the different micro-changes that occur in the real-time operation of a system (Gómez-Marín et al., 2020) and search for efficient responses to these changes. For successful integration of these two modeling methods, an architecture that allows communication between them is proposed. This architecture uses two agents to perform these functions. These agents send and receive messages with different micro changes and the system responds to them.

The proposed structure for integrating these two modeling tools is presented in Fig. 1. This framework is divided into two parallel modules. The first one – the microsimulation module – simulates the real-time data, representing the analysis units by individual entities, with behaviors from statistical data and their interactions. It simulates different micro-changes occurring to customers and road segments' travel time during the simulation. The second module – the multi-agent system – replicates the entities as decision-making agents with resources, capabilities, objectives, and intentions reacting to the received information. Furthermore, it shows the creation of the two communicator agents that connect the two modules by sending and receiving data from entities and agents using a FIPA communication protocol, one for the microsimulation and the

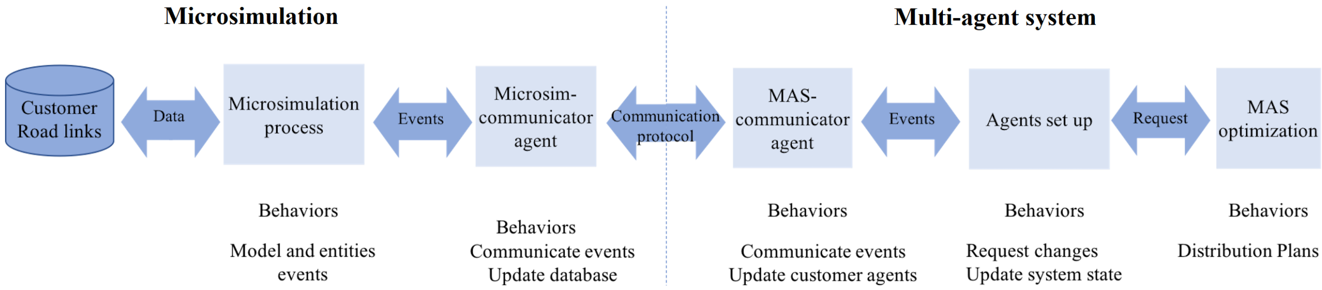

Fig. 1 Architecture for integrating multi-agent system and microsimulation

other for the MAS. These agents transfer the required information to the different types of MAS agents and microsimulation entities. Finally, the MAS optimizes the common objective, updates, and records in real-time the changes in the operating context, the response to those changes with the respective index, and broadcasts these actions to the microsimulation module as feedback information.

The microsimulation process uses customer and urban road network databases with information on the demand and travel times. It generates the micro-changes behaviors to simulate the daily operation of urban freight transport on customer demands and road segments' travel time. These micro-changes are related to demand changes (new orders, cancellation orders, quantity changes) and time changes (travel time changes, service time changes). Each micro change is communicated to the Microsim communicator agent. It considers each of them and sends them to the multi-agent system using a Subscription protocol (FIPA, 2015) for the message interchange between the two agents.

To receive the different micro-changes, the MAS has a communicator agent. This agent establishes permanent communication with the Microsim communicator agent using the same FIPA Subscription protocol to settle the information and send it to the agents in the MAS. Fig. 2 shows the Subscribe Protocol used to send inter-platform messages, and how the different events are received and reported. Each agent searches related micro-changes to identify the different types of messages, so each micro-change informs one message and triggers behaviors in a cyclic, repetitive, or one-time frequency. Fig. 3 presents the communicator agent's behaviors. Both agents should subscribe to a communication process to send and receive inform messages from the microsimulation entities to multi-agent computational agents and vice versa. Each inform message contains the occurring change, the entity affected, and the characteristics of the change.

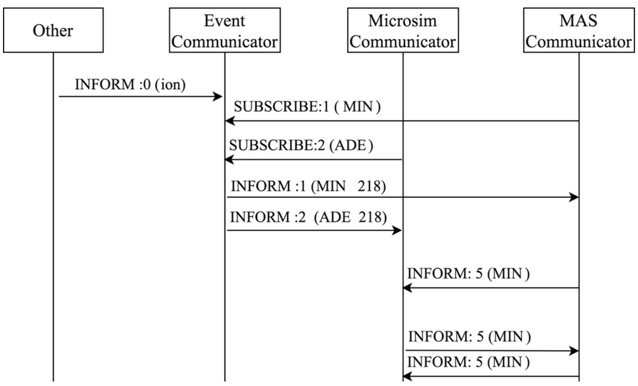

Fig. 2 Subscribe protocol between communicator agents of simulation platforms

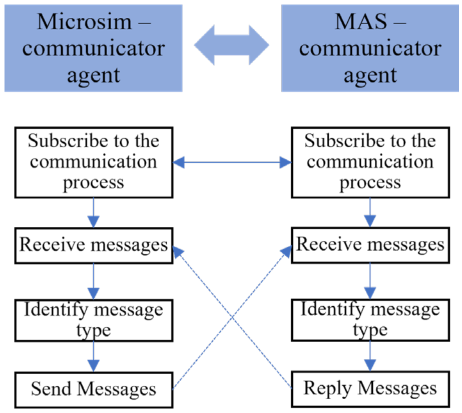

Fig. 3 Communicator agent's behaviors

Once the microsimulation begins, these changes are generated as events from the dynamic environment in the system. The communicator agents broadcast and receive the messages, and the multi-agent system reacts with different behaviors for each micro-change. The MAS uses a FIPA *Brokering* protocol to send messages to the different types of agents in the system. The agents perform their behaviors to optimize the distribution plans and send them back until the microsimulation module.

To implement the proposed integration framework, we use two existing programming tools developed in Java. The microsimulation platform Jas-Mine allowed us to characterize each different behavior using distribution probabilities and interact with multiple events from an internal event generator engine. The platform Jade for the Multi-agent system allowed the creation of the different agent types with their behaviors and the use of the communications protocols. These platforms were chosen because of their available documentation and the academic communities that use them.

4 Results and discussion

4.1 Architecture integration in urban freight transport

The microsimulation module starts the simulation by creating the customer and road segment entities according to the statistical data from the database. Depending on the instances, the number of initial customers varies. In this initialization, all agents (customers and vehicles) are generated in the MAS, including communicator agents. Once the simulation is running, this module generates micro-changes using the Jasmine microsimulation engine.

Each time a micro-change appears, the Microsim communicator agent sends an inform message with the type of change to the MAS communicator agent. This agent searches for the receiver agent and sends the message.

The type of change triggers the behaviors in the MAS optimization searching for the best distribution plan that accomplishes the micro-change.

4.2 Benchmark instances generation

The operating context for the benchmark is the city of Medellín, Colombia. The authors use an Open Street Map API to obtain the road network distances and travel time. The scenarios have a homogeneous fleet of vehicles. An individualized probability distribution sets each customer's demand behaviors and possible travel and service time changes.

The following instances were generated based on the above features to test the multi-agent microsimulation integration process. Instance nomenclature identifies the number of total customers and the level of dynamism measured as the number of initially known customers and the number of potential new customers requesting a service. In all instances, the number of total customers is 200.

The initial Benchmark Instance (B1-40-160) has 40 known customers, and the maximum number of new customers is 160. The number of initial customers changes with an increase of 10 customers per instance while reducing the number of potential new customers. Table 1 presents instances where the communication tests between the platforms take place.

4.3 Simulation results

Each instance was simulated 30 times for a total of 330 simulations. From these simulations, Throughput and Latency are calculated as the indicators of interest for integrating these simulation tools. Throughput determines the time a response to an event takes in the communication processes between the agents. Latency measures the time delay between the occurrence of an event and the system's response to it.

Table 1 Cross-platform communication instances

Instance	Description
B1-40-160	40 initial customers – 160 possible new customers
B2-50-150	50 initial customers – 150 possible new customers
B3-60-140	60 initial customers – 140 possible new customers
B4-70-130	70 initial customers – 130 possible new customers
B5-80-120	80 initial customers – 120 possible new customers
B6-90-110	90 initial customers – 110 possible new customers
B7-100-100	100 initial customers – 100 possible new customers
B8-110-90	110 initial customers – 90 possible new customers
B6-120-80	120 initial customers – 80 possible new customers
B7-130-70	130 initial customers – 70 possible new customers
B8-140-60	140 initial customers – 60 possible new customers

Every time an event occurs in the urban freight transport process, the Microsim communicator agent transmits it, then the MAS communicator agent receives and processes it. When an event occurs, the procedure calculates the Throughput and Latency values; at the end of the 30 runs, the average of these variables is calculated.

The authors decided to use throughput (message/millisecond) and latency (milliseconds) metrics to verify the impact on message transmission between MAS agents and the microsimulation engine. In the literature, other authors evaluated latency and throughput as metrics to show the impact of their proposals on a specific process e.g., complex event processing (Dantas et al., 2020; Jang et al., 2020; Jayaram et al., 2013).

Thus, the expectation is that throughput decreases as the number of available clients increases. Likewise, an inverse behavior is expected from latency i.e., latency increases as the number of available clients also increases. Since the authors expect both metrics to behave this way, what is interesting is to know the trend of these metrics. This will let us know how fast throughput decreases and how fast latency grows concerning the number of available clients.

When a simulation begins, the communicating agents of the two platforms send a message using a Subscribe Protocol (Fig. 2). With this protocol the communicator's agents interact with an event communicator agent that manages the subscription to the communication process between both agents, Jade and Jas-Mine, this allows sharing of information about each event in the simulation. Table 2 shows the Throughput and Latency data for each of the instances.

With the throughput and latency results from different simulation runs, a linear regression statistical analysis is

Table 2 Mean throughput and latency in simulations

Instance	Throughput (message/millisecond)		Latency (milliseconds)	
	Mean	Standard deviation	Mean	Standard deviation
B1-40-160	0.01395	0.02729	0.02072	0.05879
B2-50-150	0.01420	0.02663	0.01271	0.02446
B3-60-140	0.01438	0.02770	0.02057	0.04445
B4-70-130	0.01264	0.02575	0.01665	0.03213
B5-80-120	0.01266	0.02443	0.02612	0.07226
B6-90-110	0.01422	0.02872	0.02517	0.07157
B7-100-100	0.01270	0.02435	0.02257	0.06820
B8-110-90	0.01274	0.02476	0.02440	0.06972
B6-120-80	0.01193	0.02223	0.02242	0.05223
B7-130-70	0.01124	0.01685	0.02851	0.05353
B8-140-60	0.01044	0.01492	0.02800	0.05151

performed to identify how these values are explained based on the instance's number of initial customers. Figs. 4 and 5 show the behavior of these two variables and their coefficient of determination of their linear regressions. The 72.97% of the throughput values can be predicted by the number of initial customers and possibly new customers entering the simulation when sending requests to the urban distribution system.

In the case of latency, this coefficient of determination has a lower value. It assumes that latency can only be explained by 54.86% by the number of initial customers and possibly new customers. The metrics behave as expected: throughput decreases as the number of initial customers increases, while latency increases as the number of initial customers also increases.

Additionally, following the results of the linear regressions, the throughput decreases with a negative slope of 0.0613 (i.e., for each new customer considered in the microsimulation, the throughput is expected to reduce by 0.0613 messages/milliseconds), having a confidence of 72.97%. Similarly, latency increases with a slope of 0.00011 (i.e., for each new client considered, latency is expected to grow by 0.00011 milliseconds), with a confidence of 54.86%.

For the first approximation to this kind of integration, the goodness of fit of these two regressions could be a good initial result. The other 45.14% in latency and the 27.3% in throughput of the results could be justified by the types of changes in the dynamic context. Each type of change could affect these differently, in this case, latency is affected more than throughput.

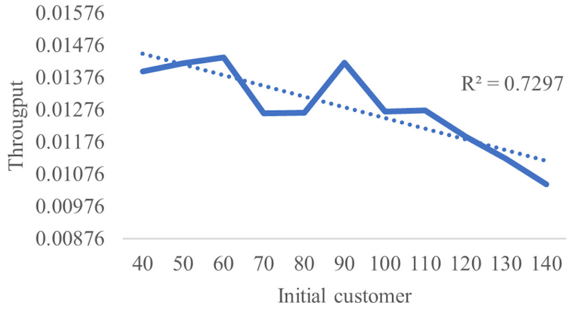

Fig. 4 Throughput results

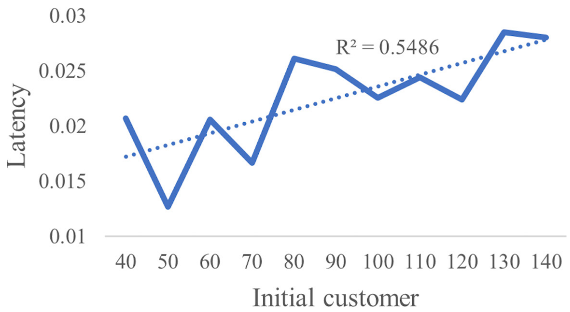

Fig. 5 Latency results

5 Conclusions

A multi-agent system and microsimulation integration takes advantage of large data amounts from the urban freight transport actors and operations, sharing this information to achieve the higher overall performance of the urban supply chain and the principles of autonomy from each actor, responding to an operational context with different dynamic scenarios.

The proposed integration framework produces a satisfactory communication process between multi-agent systems and microsimulation as modeling methods. The integration is measured by throughput for the capacity to share different micro-changes and latency for the time that the system takes to react to the shared events. The integration allows reacting appropriately regardless of the number of requests due to dynamic context conditions. The application of this integration to urban freight transport was successfully implemented showing it is possible to apply in a dynamic context. These conditions make it possible to characterize this integration framework for its robust results in the different responses to dynamic scenarios and the possibility to react to the different changes while it also searches for optimum solutions. In future research, it is possible to extend the integration to another dynamic context in a different context.

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