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Complexity in road freight transport outsourcing networks. TRANSOPE: An agent-based dynamic model

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ABSTRACT

This paper proposes a dynamic agent-based model (TRANSOPE) to simulate outsourcing among transport companies where, for the first time, accumulated knowledge is included as a variable to select service providers. The model consists of two main procedures. Firstly, the model simulates the decision-making of the professionals that contract transport service providers and the formation of outsourcing chains. Secondly, the model simulates the direct learning of participating companies and the transfer of knowledge towards their environment. Imperfect competition is replicated in three different scenarios, which involve the demand for transport services, regional distances and the intensity of knowledge transfer. The model is based on expert consultations and a survey conducted in an environment with a high concentration of transport companies in the Basque Country, Spain. The results indicate significant imbalances in the distribution of outsourcing, particularly in situations of low transport service demand, where 30% of transport companies do not secure any contracts. However, such situations led to strong regional interdependence. The dynamics of outsourcing reveals that over 75% of the contracted companies participate in all simulated scenarios from the first day. A strong hierarchy is also observed in the network, where certain transport companies act as connector hubs (with z-score values higher than 2.5 and participation coefficient values between 0.3 and 0.75), indicating a greater capacity for interaction and leadership in the transfer of knowledge. This feature allows the collaboration network to be identified as a scale-free network. The model has a low computational cost since the distances between agents remain constant. Finally, the formalisation of outsourcing decision-making in the model underpins its validity in forecasting the conduct of a freight transport system under shifting scenarios.

1. Introduction

Due to the growing outsourcing of freight distribution needs experienced in recent decades (Gavaud, Brehier, Guilbault & Niérat, 2013; Cruz, 2013; Stojanović, 2017), service providers in the Road Freight Transport (RFT in the following) sector are increasingly more decisive in the supply chains thanks to greater specialisation and personalisation of the service they offer (Jharkharia & Shankar, 2007; Marasco, 2008). This specialisation allows companies to collaborate in undertaking a transport operation by performing a specific role, which involves a defined set of responsibilities and a certain decision-making capacity (Holmgren, Ramstedt & Davidsson, 2009). When this collaboration involves more than two companies, transport outsourcing chains are formed (Salas, Cases & García-Palomares, 2019), whereby each of these companies has a certain impact on the other agents in the chain (Rühl et al., 2013), since each agent has, in turn, a series of specific objectives (Rühl & Boltze, 2017) that must align with the overall objective of realizing transportation in accordance with the customer's requirements.

Outsourcing is the result of the decision by a company to outsource certain processes or activities. In the case of such complementary processes as transport, outsourcing is not only possible, but may also prove to be highly beneficial (Barthélemy, 2003). On a local or regional scale, the succession of transport outsourcing chains generates the formation of complex collaboration networks between companies. The complexity of the organisation of these chains not only affects the physical

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movement of goods, but also the way in which the agents involved in each transport operation interact and conduct relations with each other, transferring information and knowledge (Coccia, 2008; Brekalo & Albers, 2016). This communication flow is closely tied to the type of organisational structure of each Transport Outsourcing Chain (TOC, hereafter) and also affects the decision-making capacity of the expert agents that comprise them. Given that the most common outsourcing chains are hierarchical, the capacity to communicate and exchange ideas between pairs of agents is limited (Daugherty et al., 2011). However, this exchange not only takes place explicitly (Blumenberg, Wagner & Beimborn, 2009), but also indirectly. Thus, according to Giuliani (2007), although mere geographical proximity does not necessarily trigger this phenomenon, the involvement of agents in local networks leads to collective learning and the dissemination of knowledge.

Agent-based modelling (ABM) allows phenomena to be analysed through the modelling of the heterogeneity of the agents and the observance of the way in which they interact and organise themselves (Macal & North, 2010). ABM enables the representation and analysis of complex systems, allowing for the exploration of potential scenarios through the simulation of dynamic processes to optimize them. However, certain gaps still exist in relation to freight transport. First, the collaboration mechanisms that give rise to outsourcing chains within a single transport operation under different conditioning factors have not been modelled in the literature to date. Second, the impact of direct learning through experience and the transfer of knowledge in the decision-making of professionals has not been included as a variable in the selection of service providers under any known model. Third, according to de Bok and Tavasszy (2018), robust models need to be constructed based on the search for relationships of interdependence between empirical agents, basing them on real performance data on the decision-making processes in the freight transport chain. The individual characterisation of each agent must be integrated into the spatial interaction processes using geographical analysis tools like GIS. Lastly, the collaboration processes between transport companies, driven by the transfer of knowledge, need to be simulated from the perspective of complex social media in order to identify, analyse and predict potential emerging phenomena.

To aid professionals in decision-making and the development of policies that improve the competitiveness of local and regional transport systems, we propose the TRANSOPE (TRANSport OPErations) agent-based freight transport model. TRANSOPE allows expert decisions on outsourcing and operational collaboration between companies to be simulated according to a series of rules, conditions and limitations. The model is based on data collected from interviews and an SP survey of RFT professionals. Each agent is characterised by attributes such as confidence in their professional performance, competitiveness in transport pricing, and service availability. Additionally, the topological variables measure the distance between the service providers and their potential clients, as well as the relational distance from companies in their area. The model reproduces imperfect competition in scenarios with different transport service demand situations, the distance between regions and the intensity of knowledge transfer. We are unaware of any other model that simulates expert decision-making in the formation of TOCs based on both the aptitudes and location of agents and on the transfer of knowledge among them. TRANSOPE analyses the development and heterogeneity of interactions between RFT agents as a complex network, the dynamics of which may deviate from the predictions of aggregate behaviour (Crooks & Heppenstall, 2012), and may give rise, in turn, to patterns and structures that are not explicitly programmed in the model (Macal & North, 2010).

This paper fits the scope of the journal, as it analyses through a multi-agent model how an expert system adapts to different scenarios using network collaboration and knowledge transfer.

The paper is divided into the following sections. First, the background section describes the reference models for this work. Section 3 outlines the methodological aspects of the research by describing the TRANSOPE model. The model is then applied to a case study in section 4. Section 5 outlines the results relating to the distribution and dynamic of the participation of agents in the TOC and the self-organisation of the agents in the network. Lastly, the results are discussed, and conclusions are offered.

2. Background

This section describes some of the most significant agent-based freight transport models produced in recent years. Table 1 compares various aspects of these models and TRANSOPE. Lastly, as regards the gaps expressed in the previous section, the contributions and novel aspects of our model are listed.

A series of agents exist in all transport systems involved in their organisation that control a part of their management, although none of them totally controls or is familiar with the decision-making process of the others (Roorda, Cavalcante, McCabe & Kwan, 2010). Considering ABM from a decentralised perspective (Ramstedt & Woxenius, 2006), a transport system is the product of the operational decision-making of each agent and of their capacity to interrelate. Accordingly, the agents, as well as being autonomous, are also reactive to the changes that take place in their environment and may take proactive initiatives at an operational level (Wooldridge & Jennings, 1995). Furthermore, in ABM, the agents are able to adapt to the demand needs for transport services and to economic changes at a local, regional and global level.

A great many models have been developed with different approaches and orientations. Holmgren (2008) and Ramstedt (2008) propose hybrid models involving approaches based on agents and mathematical optimisation techniques through the TAPAS platform (Davidsson, Holmgren, Persson & Ramstedt, 2008). TAPAS takes into account such aspects of the chain as its adaptability, organisational variety, hierarchy and time lags in decision-making, to then use in two levels of interconnected simulations: a physical simulation level, in which the agents are passive, and a second decision-making simulation level, in which the agents behave autonomously and proactively. In the first level, the travel time values, the production size and time and the loading/unloading times are calculated stochastically according to a probability distribution. The roles of each agent are then established and their interactions are considered from the final client's order through to the delivery of the product following a criterion of negotiation based on the calculation of the minimum cost.

Baindur & Viegas (2011) use the interaction between agents in a transport market to explain modal decision-making at an operational level by transport companies, validated by discrete choice models. In this model, the exchanges between two regions are described, structured in three layers of action: a) regulatory layer, b) market layer and c) physical layer. However, the selection of transport operator is based on stochastic methods like Nested Logit, taking into account four variables: price, delivery time, delays and the expected damage rate which, while amplifying the resolution and heterogeneity of agents, diminishes the verifiability of the model.

In the work by Cavalcante (2013) and Cavalcante & Roorda (2013), only two types of structural agents in the transport market are considered – shippers and carriers – who interact through contracts concluded according to the price of the transport and the level of service. Each agent maintains its aim of maximising unit profit, seeking to optimise its logistics decisions in the case of the carrier and evaluating the service offered to select an operator in the case of the shippers. Accordingly, a market can be modelled under conditions of imperfect competition, simulating the competition between carriers and even processes to create new transport companies.

Démare (2016) and Démare, Bertelle, Dutot & Lévêque (2017) model a logistics system in which the modal infrastructures and the communications network display a certain conduct thanks to a series of attributes, the values of which vary according to the interaction with the other system agents. The authors use the GAMA platform, which

Table 1
Overview of significant agent-based freight transport models and TRANSOPE.

Model features		TAPAS	Baindur & Viegas (2011)	FREMIS	Démare et al. (2017)	Reis (2018)	SYMBIT	CRISTAL	TRANSOPE
Modeled agents	*Shippers*	•	•	•	•	•		•	
	Recipients				•			•	•
	Transport Companies	•		•				•	•
	Carriers/Drivers		•			•		•	•
	Assets	•				•	•	•	
Data source	*Interviews*	•				•			•
	survey		•	•					•
Planification level	*Strategic*	•		•	•			•	
	Tactical	•		•	•	•		•	
	operational	•	•	•	•	•	•	•	•
Interaction with the environment				•		•		•	
Simulated processes	*Mode choice*	•	•	•		•	•	•	
	TPS selection		•	•		•		•	•
	Transport chains	•			•	•		•	•
	Information exchange				•	•	•	•	•
	Knowledge transfer								•
	Collaboration networks								•
Applications	*Public policy support*	•		•				•	•
	Freight Transport Market		•	•		•		•	•
	Integration with GIS				•		•		•

provides a complete modelling environment to create spatially explicit simulations (Taillandier, Vo, Amouroux & Drogoul, 2010) which allow GIS and ABM to be effectively integrated in the modelling of transport systems. Accordingly, they seek to understand the collective organisation of agents based on existing infrastructure to manage the freight flows, subject to a series of spatial and temporal frictions that may also be modelled.

Reis (2018) structures his model into two interrelated layers: the physical layer and the administrative layer. In this model, the authors simulate the outsourcing decision-making process between shippers, freight forwarders and carriers by means of a Random Fuzzy Logic Inference Mechanism. This process involves the experiences of the agents and their perception of the conduct of other agents (Reis, 2018). The model also considers the dynamic market pricing strategies of transport service buyers in the bid process to select the best option.

Ambra et al. (2019) and Ambra & Macharis (2020) introduce the concept of Digital Twins in the SYMBIT model to explore its potential in synchro-modal transport. The model creates a digital environment based on a GIS database in which the assets are represented as agents that can exchange information. More recently, Stinson & Mohammadian (2022) proposed the CRISTAL model, which models the flow of shipments and includes, for the first time, the exchange of information between agents participating in the supply chain. The model simulates decision-making at three levels of action (strategic, tactical and operational) in which four types of agents are involved: trade agents, logistic agents, rule-makers and carriers. In CRISTAL, the exchange of information between agents takes place by simulating Pull demand systems, in which just-in-time unloading systems predominate.

Other research papers, such as those by Liedtke (2009), Schröder, Zilske, Liedtke & Nagel (2012), Matteis, Liedtke & Wisetjindawat (2016), Alho et al. (2017) and Renna, Petrelli, Carrese & Bertocci (2021) provide new approaches to the analysis of the interactions between transport agents.

Bearing in mind the models described above and the gaps mentioned in Section 1, this paper contributes to the literature by gathering the following contributions in a single model:

1) Modelling of outsourcing chains under different transport service supply and demand conditions and regarding the distance between companies.
2) Simulation of the direct learning of companies as a result of their operational activity and the transfer of knowledge to other companies in their spatial environment.

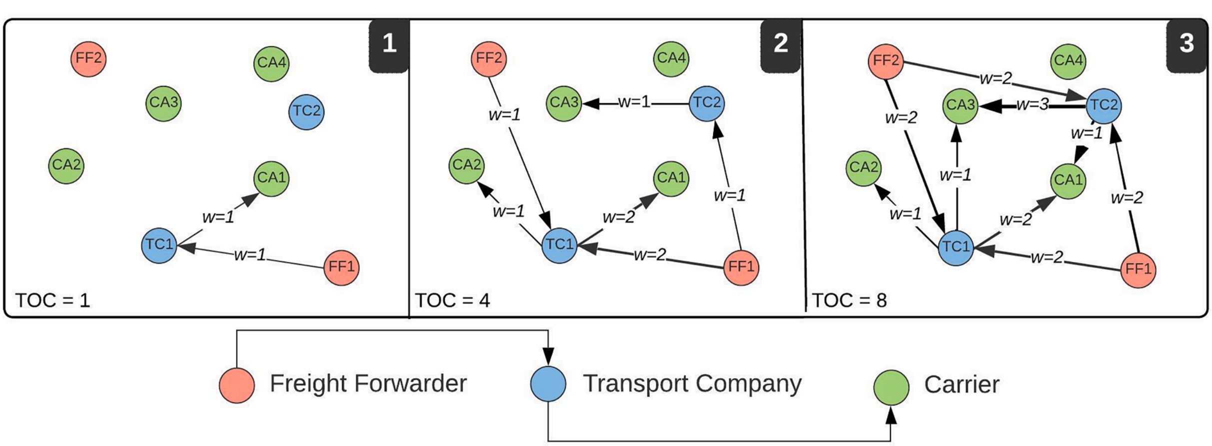

Fig. 1. Sequence in an outsourcing process. Picture 1 shows a first TOC, where w = 1 for all three agents. In picture 2 FF1, TC1 and CA1 form a new TOC between them, so w = 2. Picture 3 shows 8 TOCs with different outsourcing distributions, where w = {1,2,3}.

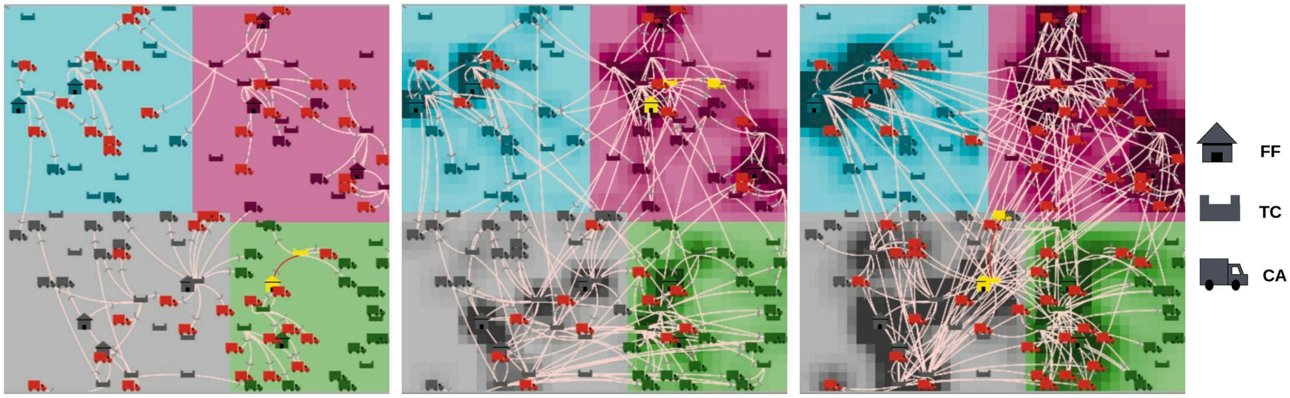

Fig. 2. Three moments in the evolution of the graph during the simulation. Shaded areas indicate knowledge accumulation environments.

3) Replication of outsourcing practices and expert decision making based on rules explicitly stated by RFT experts.
4) Analysis of the formation and dynamics of complex networks resulting from collaborations between RFT companies and direct and indirect knowledge transfer.
5) The model can simulate interactions between real companies in local geographic environments by coupling with Geographic Information Systems.

However, the TRANSOPE model can be improved by the incorporation of new modules such as modal choice, the participation of assets and other agents with decision-making capacity and the inclusion of tactical and strategic levels in transport planning. The model is available to be replicated and improved on in the CoMSES repository (Salas-Peña & Cases, 2022).

3. Method: TRANSOPE model description

TRANSOPE is an agent-based model developed in the NetLogo environment, version 6.0.2 (Wilensky, 2017), which allows outsourcing among RFT companies to be simulated in different scenarios to study the collaboration networks and spatial environment where a high level of information and knowledge is exchanged between these companies. The model seeks to reproduce situations of imperfect competition between a certain set of agents that operate in a territory made up of four zones of different sizes and densities of companies. To analyse the effect of the distance in collaboration between companies, the model allows the separation between the four zones from 0 to *n* km to be simulated.

The agents comprise three types of companies: Freight Forwarder (FF), Transport Company (TC) and Self-employed Carrier (CA), located in a fixed position in the territory. The outsourcing chain is the basic structure of collaboration between these companies; in other words, a hierarchical sequence FF_i -> TC_j -> CA_k in which each agent outsources to the next agent according to their function and decision-making power. The model also allows four agents' TOCs to be simulated (FF_i -> TC_{j1} -> TC_{j2} -> CA_k). The TOC are directed graphs in which each *node* is a RFT company and each *arc* represents the outsourcing from *A* to *B* with weight (w), equal to the number of contracts concluded between them (Fig. 1). The aggregation of all the TOC over the course of the simulation produces a complex network.

The companies that outsource choose their suppliers using various selection criteria. As the simulation advances, the agents are able to learn from it. The model simulates the acquisition of knowledge by agents through experience and their spatial transfer towards other agents, allowing them to identify environments with an intense exchange of information (Fig. 2).

Each simulation in TRANSOPE covers a certain period of *n* days, established at the start. A number of TOCs equal to a determined number of transport operations must be completed each day. The simulator takes into account the travel times of self-employed carriers (CA) according to the distances they must cover on each trip and their return to the point of origin. The aim of the model is to complete all the scheduled operations for a period of *n* days. The number of operations per day is calculated according to the number of RFT agents with an existing operating capacity in the system and the situation of the transport market.

3.1. The agents

In the development of an ABM, the agents are autonomous entities with decision-making capacity (Bonabeau, 2002), which may represent a huge range of entities and spatial phenomena (Torrens, 2010). According to Gilbert & Troitzsch (2005), agents are presupposed to have intentionality, and their actions are based on knowledge of their environment. In addition, they have the capacity to learn and adapt according to their experiences (Macal & North, 2008), forge new knowledge and convey this to other agents according to their geographical location. Three types of agent intervene in TRANSOPE: freight forwarders, transport companies and self-employed carriers. Those agents involved in the chain supply but not exclusively engaged in transport management are excluded from the model: shipper and recipient (Fig. 3).

The agents that take part in TRANSOPE, ordered from the top to the bottom of the hierarchical range, are the following:

- *Freight Forwarders (FF)*. Companies engaged in logistics and warehousing without their own lorries, and hence outsource to RFT companies to cover their transport needs. They tend to be large multinational companies with a high market control capacity. According to Reis (2014), FF organise the transport chain at an administrative level and manage it at an operational level. All the TOCs start with them in TRANSOPE.
- *Transport companies (TC)*. These tend to be small- and medium-sized enterprises with a fixed fleet of their own lorries (Baindur & Viegas, 2011), which also outsource to other self-employed carriers when their own resources are unable to cover their transport needs. These are local or national companies that are deeply entrenched in their geographical environment. In TRANSOPE, these agents are intermediate cogs in the chain.
- *Self-employed carriers (CA)*. These are transport microcompanies, mostly with just one truck, where the business owner is generally the driver as well. Their transport capacity, in accordance with prevailing legislation, is limited. In TRANSOPE, they occupy the last place on the TOC.

The decision-making capacity decreases as one goes down the outsourcing chain, as does the profit margin for each operation. Within

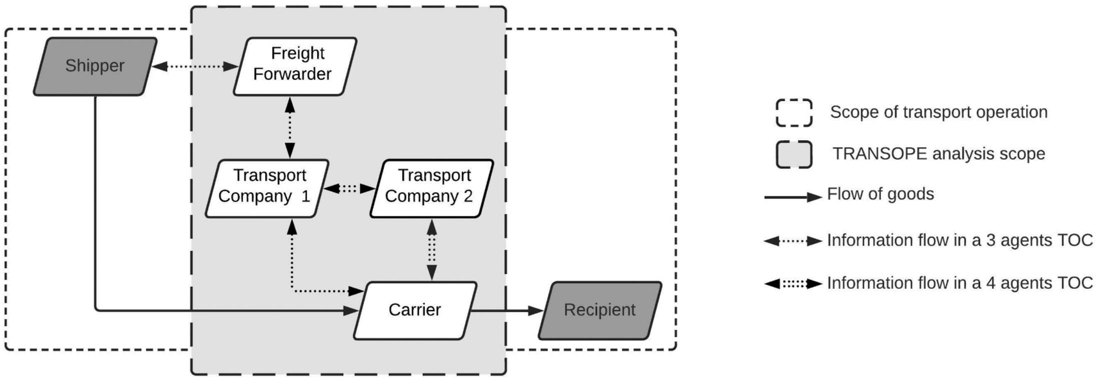

Fig. 3. Goods flows and information flows follow different paths within a transport operation. TRANSOPE is concerned with information flows between RFT agents based on the formation of TOCs.

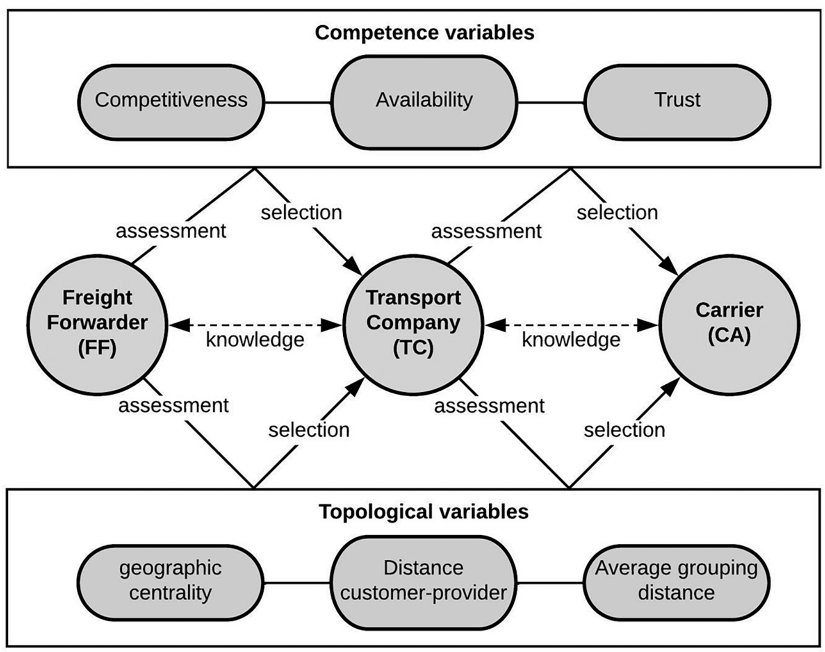

Fig. 4. Decision-making process in a Transport Service Provider selection.

the general aim of carrying out transport operations, each type of agent has a concrete function in the TOC. Each one has its individual scope of decision-making which, in the case of CA agents, may mean they do not participate in a TOC as it is not profitable. Finally, the limitations on the availability of resources, in the case of the TC, and of driving, in the case of the CA, may impede the timely participation of agents in the TOC.

3.2. Agent variables

In the ABM models, each agent has a series of properties that serve to characterise each individual and distinguish them from the others. These properties may vary during the course of the simulation as a result of the decisions and actions of each agent and also due to their interactions (Crooks, Malleson, Manley & Heppenstall, 2019). In our model, the decisive variables in the conduct of the agents (Fig. 4) can be divided into two groups:

a) *Competence variables*. These characterise each agent according to their aptitude to offer a transport service in line with market needs. These correspond to selection criteria assessed in the survey of the transport professionals. Their calculation introduces randomness through a floating-point number of a gamma distribution, with parameters $\alpha = 1$ *and* $\lambda = 9$, to achieve variability in the values of each agent: There are three of them:

- *Competitiveness (C)*. Capacity of an agent to offer better prices than their competitors. They offer a price value (P) in EUR that each agent is willing to work at to perform the transport operation. Each type of agent calculates their price differently. FF agents maintain an unvaried price throughout the simulation. In turn, the price of the TC will be subject to changes depending on the price of the FF that contracts them and of the market situation at that time. Lastly, the transport price of the CA agents is calculated taking into account the fixed and variable costs of the transportation.[1] The cost-profit ratio will determine the availability of the CA to be selected by the TC.
- *Availability (D)*. The capacity of agents to perform transport services is not unlimited, except for the FF, who have permanent availability as long as operations to be undertaken exist. For their part, the TC do not have an infinite number of suppliers, hence their D value will

[1] OTEUS – Transport Observatory of Regional Government of the Basque Country: https://www.euskadi.eus/oteus-herramientas/web01-a1oteusn/es/.

depend on the number of carriers available to outsource the work. The CA, according to prevailing legislation[2,3] may only drive for nine hours a day (the maximum distance estimated that a truck can drive per day is 600 km). Hence, a CA may be unable to perform a transport service if they have used up their daily *km*.

- *Trust (T)*. Trust in the professionalism of the agent to be contracted. In TRANSOPE, it is presupposed that all transport operations are performed as scheduled; hence, whenever an agent takes part in a TOC, its value does not decrease. Furthermore, in the same way as with the two previous variables, T has no effect on the FF agents because their professionalism is evaluated by their clients, which do not take part in the model.

b) *Topological variables*. This group of variables includes those related to the location of each agent in the system. TRANSOPE, like a good number of spatial analysis mathematical models (Entrikin & Tepple, 2006), is modelled on an isotropic, homogeneous virtual space without more spatial elements than the agents themselves. All the distance measurements are thus Euclidian and expressed in kilometres. The model includes three topological variables for agents that will be used to calculate their relative position and their centrality.

- *Client-supplier distance (δ)*. During the simulation, each potential supplier that may be chosen by a client calculates the Euclidian distance that separates them. For example, when an FF chooses a TC, it calculates the distance from the latter.
- *Geographical centrality (Cg)*. This consists of the sum of the distance between one agent and the other agents in their region, divided among the number of agents less one. This is prepared based on closeness centrality (Bavelas, 1950), although in our model it is calculated according to the real distance separating the nodes from each other and not based on the number of arcs that separate one agent from the others. Another important difference lies in the fact that the Cg is calculated for each zone (*reg x*) separately. Furthermore, the reverse mode is used; in other words, using the arithmetic mean instead of the harmonic mean. The lower the Cg value the greater the centrality.

$$Cg_{i_{(regx)}} = \frac{\sum_j d(i,j)}{n_x - 1} \tag{1}$$

- *Average grouping distance (Dg)*. This metric provides a unique value for the whole set of agents in a region. It is calculated as a Euclidian matrix distance between all the vertices on a graph (Herring, Namikis, Chemmangattuvalappil, Roberts & Eden, 2012). It endeavours to represent the theoretical cohesion value between all the agents in a region in the event that they were all connected to each other by undirected links. It is thus a potential cohesion metric for each region of the model, based on the geodesic distance mean (Newman, 2003):

$$Dg_{(regx)} = \frac{\sum_{i>j} d(i,j)}{n_x {}^{*}(n_x - 1)/2} \tag{2}$$

where the distances from one to the other are divided among the number of possible pairings. The lower the Dg value, the greater the cohesion between the agents in region x.

[2] Regulation (EC) 561/2006: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006R0561.

[3] Regulation (EU) 2020/1054: https://eur-lex.europa.eu/eli/reg/2020/1054/oj.

3.3. Decision-making: transport service provider selection

In TRANSOPE's simulated outsourcing operations, customers select a Transport Service Provider (TSP, hereafter) based on specific selection criteria related to competence and topological variables, as described in the previous section. The only criterion that requires physical transport material is Availability (D), which decreases in value with each participation in a TOC. Without it, the other two competence variables become irrelevant.

As regards the topological variables, both the distance between provider and client (δ) and the centrality by geographical closeness (Cg) take on particular importance in TRANSOPE. The lower their values, the more benefits the TSP will have if selected. K_j should be added to these variables, which is the value of the knowledge acquired by a TSP as a result of its own learning, thanks to its participation in transport operations, and also the information and learning that have been transferred thereto outside the contractual scope due to the proximity to other agents. Hence the decision to select the TSP by a client is effected by means of the expression

$$S_{ij} = \frac{(T_j + C_j)D_j^2}{\left(\delta_{ij}\cdot\sqrt{Cg_j\cdot Dg_{(r_j)}}\right)^2} + K_j \tag{3}$$

where S_{ij} is the value of the potential selection of the TSPj for client i. In TRANSOPE, this expression is used by both FF and TC agents to select their suppliers. They both look for the TSP with the best transport aptitudes at a relatively short distance and with the possibility to benefit from the local advantages thanks to the proximity to other agents and to their centrality *vis-à-vis* them.

3.4. Interaction between agents

Interactions between agents constitute the true purpose of the study of complex social systems. In TRANSOPE, these interactions may be of two types:

- *Direct interactions.* These are the result of outsourcing and are represented by means of directed arcs. In direct interactions, the arcs act as primordial elements in the formation of graphs based on two fundamental attributes: weight (w) and length (l). Both attributes are key for measuring the structure and the dynamic of the resulting graph. Thanks to these direct interactions, a learning process takes place as a result of the experience (Blumenberg et al., 2009), whereby this is initially considered at an individual level, although always within a determined geographical and time framework (Argote & Miron-Spektor, 2011). The more times an agent participates in the operations, the more they will learn, thus generating a value that accumulates operation-by-operation. This is calculated taking into account the number of times an agent has been contracted for a transport service. Hence,

$$DL_j = \sum_{m=1}^{n} \frac{kt}{V_{TOC_m^j}} \tag{4}$$

where DL is the direct learning by the agent j, $V_{TOC_m^j}$ is the value generated for the TOC in which agent j has participated, and kt is a controller of the level of knowledge transfer with values between (0, 1].

- *Indirect interactions.* These take place due to the proximity of the agents to a zone of information and knowledge transfer. Following the principle of Tobler (1970), in the model it is assumed that the agents have more possibilities of making contact and exchanging information the closer they are to each other. Every time that an agent is selected in a TOC, it transfers knowledge of the learning acquired to its immediate environment (Argote & Miron-Spektor, 2011). In TRANSOPE, each *patch* of territory has the ability to retain part of the learning accumulated by the agents located in a radius *r*. Resident agents in areas of learning will increase their chances of being chosen for subsequent TOCs thanks to the acquisition of knowledge received indirectly. This phenomenon is based on a series of assumptions regarding the conduct of agents: *i*) all agents intend to convey information; *ii*) all agents accept the information transferred to them and incorporate it in their internal mechanisms as new knowledge, *iii*) the information conveyed is always of sufficient quality and quantity to be considered valuable, *iv*) the dissemination of the information and knowledge takes place due to proximity, without considering the presence of physical barriers.

The procedure for the transfer of knowledge is as follows: the agents that have taken part at least once in a TOC establish a zone of influence in a radius *r*. In turn, each *patch* within this radius computes the number of contracts performed by the agents located within the radius *r* and calculates a value of indirect learning (*IL*),

$$IL_{(p_i)} = kt\frac{\sum_{j=1}^{m} contracts_{j_{(r_{p_i})}}}{n_{(r_{p_i})}} \tag{5}$$

where *n* is the number of agents, r_{p_i} is the radius of *patch i*, and *contracts* is the number of contracts that an agent has managed to conclude. In this case, *contracts* computes the contracts of all the agents located in r_{p_i}. These values are updated at the end of each day. Hence, each unit of land transfers information to its neighbouring patches (*v*), distributing a percentage of their *IL* between them according to the controller *kt*,

$$IL_{(p_i)} = IL_{(p_i)} - \left(IL_{(p_i)} \cdot kt\right) + kt\sum_{u=1}^{w}\frac{IL_u}{n_{v_u}} \tag{6}$$

Finally, each agent receives knowledge from the patch in which the *IL* value is located, which adds to its direct learning. During the simulation, the amount of knowledge in the system increases as more TOCs are generated (Fig. 5). Hence, the knowledge accumulated by one agent is due to both its participation in the TOC and to its proximity to the zone of knowledge transfer.

4. Model application: A case study

Peer-to-peer relations between agents, as shown above, often take place confidentially, even within a single transport operation. Accordingly, the accumulation of successive outsourcing operations between RFT companies gives rise to complex outsourcing networks at a local and regional level that are not easily detectable. TRANSOPE allows the formation of these networks to be simulated by introducing values extracted from real transport systems for their subsequent analysis.

4.1. Model adjustment to empirical data

The application of the model is carried out in the area of Donostialdea-Bidasoa Beherea (DABB), located in the Basque Country, in the border area between France and Spain. This area has a high concentration of transport companies and an intense flow of goods within the framework of the European Atlantic Axis. In 2019, thanks to the collaboration with the local transport association Guitrans Fundazioa Foundation, a survey was carried out on a wide range of transport company operators (Salas-Peña, 2021). The results allowed the parameters of the model to be adjusted with empirical values with a view to simulating the formation of outsourcing networks:

- *Number of agents of each type*: Given the lack of official directories of companies, the registers of the *Guitrans Fundazioa Foundation* were used to identify the number of agents of each type and the values to be considered in TRANSOPE (Table 2).
- *Competence values:* The survey asked RFT service demanders to rate the importance of skills used to select transport service providers. Table 3 shows in each row the value of the variables when the requirement of one of them is the highest. Trust was rated higher than competitiveness and availability. These values represent the output parameters for each competence, although some randomness is subsequently introduced to differentiate each agent.
- *Prices and costs*: access to data sources that allow the adjustments to the economic parameters is not straightforward. The adjustments to the model are based on consultations with experts, mainly managers or supervisors of transport companies and self-employed carriers. Their values were averaged out and compared with the estimates provided by the price and cost observatory of the Ministry of Public Works and the Department of Economic Development and Infrastructure of the Regional Government of the Basque Country.
- *Structure of the TOC*: according to the results of the survey, the structure with three agents is considered to be the most typical TOC

Table 2
Proportion of agents according to their type.

Data processing	Agent type		
	FF	TC	CA
Registered data	44	191	329
Ratio of agents	1	4,34	7,47
Agents in TRANSOPE	10	40	80

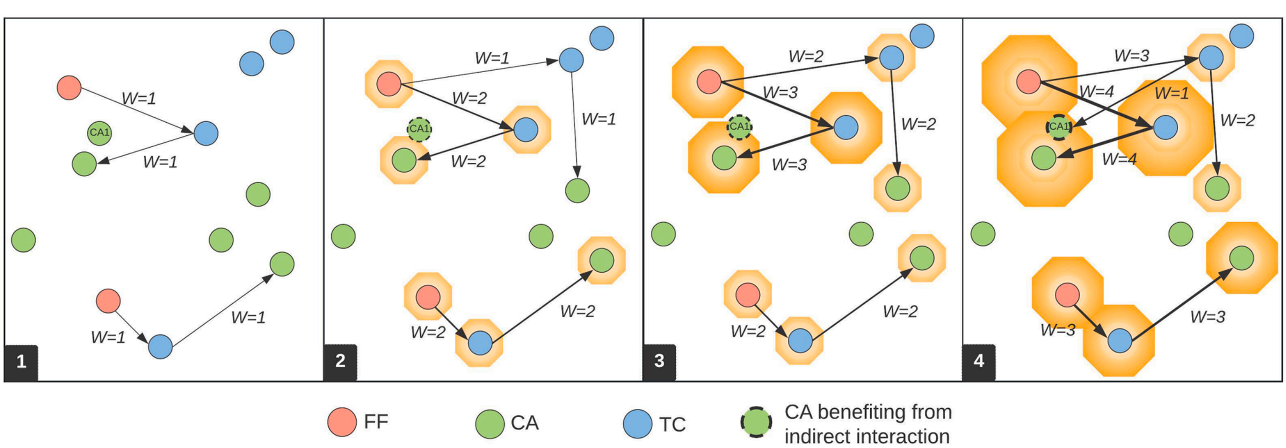

Fig. 5. Functioning of the indirect interaction in TRANSOPE. Carrier CA1 is not selected in the first three ticks as its potential selection value is lower than other competitors. In tick 4 CA1 gains an advantage by acquiring indirect learning and is selected by a TC.

Table 3
Relationship between competence variables.

Functions	Competitiveness	Trust	Availability
F (max. *competitiveness*)	1	0,82	0,79
F (max. *trust*)	0,78	1	0,80
F (max. *availability*)	0,82	0,86	1

in a normal situation. Accordingly, this type of TOC structure is always maintained in the simulation.

- *Length of the trip*: the most frequent type of transport service is performed with heavy goods vehicles on short trips. This type of transport may fluctuate, on average, between 100 and 200 km from origin to destination (*OD*), with the ensuing return trip to the point of origin. To avoid too large a number of analysis scenarios, a single average value is proposed consisting of $OD\{150\}$, which implies a return trip of the same distance and, taking into account the maximum estimate travelled of 600 km per day - a maximum number of two daily trips by each CA.
- *Number of operations per day*: this depends on the situation of the transport market, the distance of the trips to be made and the number of CA agents. The starting point is established whereby, in a situation of market balance ($TMS = 1$), each CA should be able to carry out at least one transport operation per day. Accordingly, the relationship between these elements is set out in the following way:

$$O_{day_i} = 1 + n_{(TA)}\frac{K_{\max}}{km}\cdot\frac{SMT}{2n_{(OD+DO)}} \tag{7}$$

where O_{day_i} are the transport operations in one day, K_{max} is the maximum distance that a CA can travel in one working day, estimated at 600 km, *km* is the trip distance to be travelled,$n_{(TA)}$ is the number of self-employed carriers in total and $n_{(OD+DO)}$ is the number of trips carried out by each CA until they become available again; in other words, a trip from origin to destination (*OD*) and another return trip (*DO*).

4.2. Simulation scenarios

In order to analyse the conduct of the model and the structures resulting from the formation of the TOC under different conditions, the agents are randomly distributed in the space and three parameters are chosen that may significantly alter the RFT system: the distance between zones (δ), the transport market situation (*TMS*) and the level of knowledge transfer (*kt*):

- δ seeks to discover how distances influence the conduct of the agents when collaborating among themselves. This parameter considers the values δ {0, 5, 25}.
- The transport market may suffer changes in demand due to the macroeconomic context, the supply strategies of shipping companies and holiday periods. Accordingly, the *TMS* permits the comparison of collaboration structures that arise in times in which the supply of transport services does not adapt to demand. Three situations are proposed with *TMS* values {0.5, 1, 1.5}, where $TMS = 1$ indicates a balance between the supply and demand of transport services.
- *kt* fluctuates between 0 and 1, which means that a *patch* is able to transfer between 0 and 100 % of its accumulated knowledge based on the learning of agents in its environment. Accordingly, three scenarios are proposed in which the transfer of knowledges acquires the *kt* values {0.2, 0.5, 0.8}.

Three different scenarios have been designed to reproduce complex and disparate situations that can occur in real local transport systems, based on these parameters:

a) Scenario 1 (S1) represents balanced conditions between the supply and demand for transport services ($TMS = 1$). It occurs in a single region as there is no distance between areas. Additionally, knowledge transfer is $kt = 0.5$, indicating that only half of the acquired learning is transferred to the environment.
b) Scenario 2 (S2) presents a scant number of transport operations ($TMS = 0.5$), although the transfer of knowledge is intense ($kt = 0.8$). In this scenario, the four zones are 5 km apart from each other.
c) Scenario 3 (S3) involves numerous operations (TMS = 1.5), but with limited information exchange between agents (kt = 0.2). The four zones are separated by a distance of 25 km in this scenario.

4.3. Model performance indicators

In order to assess the functionality of the preferential relationship network that structures the system, it is crucial to consider the temporal development of contracting. The analysis of contracting activity dynamics involves two indicators:

- *Percentage of new operations contracted per day*. This corresponds to the value of the median of 30 repetitions per day and scenario analysed. It should be noted that this indicator only refers to the agents that take part in each scenario at some time. Hence, the percentages do not include excluded suppliers.
- *Average distance between client and supplier per day*. This is obtained by taking the average value of the distance from the arcs of the 30 repetitions in each scenario at time t_n. Since the arcs are always ordered according to the scheme FF → TC → CA at time t_n the same type of relationship always occurs (whether FF → TC or TC → CA) in all the repetitions. Furthermore, depending on the TMS, we will have a larger or a smaller number of contracts to be performed, and hence a different number of arcs. For $TMS = 0.5$, the daily operations number 41 and the total arcs number 410; for $TMS = 1$ the operations number 81 and the arcs 810; and finally, for $TMS = 1.5$, the daily transport operations number 121 and the total arcs 1210.

Furthermore, to analyse the collaboration networks stemming from outsourcing between RFT companies, local metrics on centrality for each scenario were extracted. The data were obtained by averaging out the metrics of all the repetitions of the experiment for each scenario with the help of *Igraph* packages (Csardi & Nepusz, 2006) and *fastnet* packages (Dong, Castro & Shaikh, 2020), implemented in RStudio. The set of local metrics that evaluate the centrality of each node (Freeman, 1978) are formed by the following:

- *Degree centrality*. The degree of the node indicates the number of arcs connected to this node which, in the case of directed graphs, may be both entry and exit (Newman, 2003). In our case, the degree calculated does not take into account the weight of the arcs, but only computes the different connections of each agent. This aspect is important for measuring the diversity of the connectivity beyond the volume of the connections. Furthermore, the value of the median degree is obtained by averaging out the total number of repetitions in the experiment for each agent and scenario.
- *Closeness centrality*. This is the reverse of the sum of the geodesic routes (or shortest routes) between one node and the rest of the nodes in the network (Latora & Marchiori, 2007). It does not consider the spatial distance between two agents, but is based on the minimum number of connections that an agent must travel to reach another in the network.
- *Betweenness centrality*. This is defined as the number of geodesic routes between pairs of nodes that pass through a specific node (Chen, Gao, Lü & Zhou, 2013). This metric obtains information on the performance of the connectivity roles between agents in the network (Barthélemy, 2004). Applied to our model, the betweenness centrality is an attribute that is exclusive to the group of agents

formed by the TC, given that they are located at the centre of the TOC.

Finally, based on the outsourcing relationships, it is possible to analyse to what degree the companies are integrated in the system and the type of role they play in it. To achieve that, we will use modularity indicators (Guimerà & Amaral, 2005) to analyse connectivity in complex networks. The roles of each agent in the network will be established according to the classification proposed by the authors:

- The *within-module degree* or *z-score* measures the intensity of the connections between one agent and the rest of the agents in their zone, thus offering information on their degree centrality in the network. This indicator is expressed as

$$z_i = \frac{k_i - \overline{k_{s_i}}}{\sigma_{k_{s_i}}} \tag{8}$$

where k_i is the number of contracts concluded by agent i with other agents in the same zone, $\overline{k_{s_i}}$ is the average k in zone s_i, and $\sigma_{k_{s_i}}$ is the standard deviation of k in s_i. Taking into account that a limited number of contracts to be concluded each day exists in our model and that the distribution of these evolves according to a criterion of ties or preferential choice (Albert & Barabási, 2002), a number n of agents will present negative values in this indicator depending on the scenario. Furthermore, the type of resulting graph shows a modular or community structure (Newman, 2003), which means that the density of contracts between the agents in one zone is higher than between the agents on other areas. The value of k_i is obtained by averaging out the 30 repetitions of the model for each agent and scenario.

- The participation coefficient (*P-coefficient)* indicates the level of collaboration between one agent and the companies in other zones (Guimerà & Amaral, 2005; Beckers, Thomas, Vanoutrive & Verhetsel, 2018), and is defined as

$$P_i = 1 - \sum_{s=1}^{M_N} \left(\frac{k_{is}}{k_i}\right)^2 \tag{9}$$

where k_{is} is the number of contracts closed by agent i with the agents in zone s and k_i is the total number of contracts closed by agent i. The values close to 1 indicate a uniform distribution of the contracts between all the modules while the lack of contracts with agents in other zones will give a resulting value of 0. In the same way as with the intramodular degree, the distribution of contracts responds to a density function *f(x)*, such that an indeterminate number of suppliers will obtain $P_i = 0$ as a result of not being selected by any client.

5. Results

The results set out below give the average of 30 repetitions of the simulation for each scenario posed and refer, on the one hand, to the structure and dynamic of the interactions and, on the other hand, to the formation of complex outsourcing networks. The indicators set out in the previous section are analysed below:

5.1. Participation of agents in a TOC

Table 4 displays the relative frequencies of participation in at least one TOC by the agents TC and CA in successive repetitions for each scenario. The FF data is irrelevant since these agents participate in all simulations without needing to be selected.

The frequency results show a very irregular distribution of participation between scenarios and agents (Fig. 6). For example, in Scenario 2, with a transport market with scant transport operations (holiday periods, periods of economic instability, etc.), the percentage of agents that do not participate ever or with a low level of participation is 57 % in the case of the TC and 45 % in the case of the CA. The results show a very pronounced concentration of activity in a very small number of agents in situations of a lack of work. In contrast, in Scenario 3, with a high need for transport ($TMS = 1.5$), the percentage of agents with a very high or constant participation in all the tests of the experiment stands at 85 % for the TC and at 100 % for the CA. Hence, the model reproduces the conditions of imperfect competition inherent to the transport market.

5.2. Outsourcing dynamic

A dynamic graph equates to a discrete sequence of static graphs (Harary & Gupta, 1997). Hence, a network evolves over time and space to the extent that the interactions between nodes takes place. This fact offers a huge quantity of information on patterns originating in these structures that must be efficiently analysed (Held, Moewes, Braune, Kruse & Sabel, 2013):

Percentage of new operations contracted per day. A high percentage of suppliers that end up participating in the network are outsourced for the first time during day 1 (Fig. 7). The fact that the FFs select almost all of the TCs that they will trust all their shipments to on the first day of the week is particularly striking. This circumstance indicates that, with similar levels of trust, competitiveness and availability of vehicles, the learning accumulated by the TCs is sufficient to continue assigning them new transport operations over those that have still not been outsourced operations. In the case of the CA agents, the situation is different in Scenario 2, where $TMS = 0.5$. Despite the fact that those outsourced at least once mainly takes place on the first day, new agents are also outsourced operations in the following days as a result of the accumulation of knowledge ($kt = 0.2$). In both cases, the management of the knowledge generated reinforces the outsourcing network created on the first day of the week, preventing the extension of this to other agents on subsequent days and propitiating the accumulation of activity in the hands of the agents selected on day 1.

Average distance between client and supplier by day. In Fig. 8, each point on the graph represents the average distance $\overline{d_{ij}}$ that exists between two agents that conclude a contract at time t_n in each scenario. The shade of each point represents the weight of each arc in regard to time t_n, expressed as the median of the 30 repetitions of each time for each scenario. This means that, depending on the colour, a contract with $\overline{d_{ij}}$ will have been formalised n times at time t_n.

To verify the correlation between variables, the following steps were taken. Firstly, the normal distribution of the “distance” variable was calculated by applying the Shapiro-Wilk test in Rstudio (Shapiro & Wilk, 1965). By rejecting the normality of the variable (*p-value* < 0.05), it was opted to apply the Spearman correlation coefficient for a level of significance of *p-value* < 0.05.

In all scenarios, the trend lines indicate that the average distance between customers and their suppliers tends to increase as the week progresses. This, combined with the effects of the exclusion of TSP and the distribution of new recruits during the week, highlights the existence of inter-zonal collaboration between agents who have primarily excelled in intra-zonal collaboration. In other words, collaboration between officers from different zones is more intense during the last few days.

Furthermore, other important aspects exist that are worthy of mention. In a balanced system (S1), the trend for the distance to increase between clients and suppliers over time is constant and predominates contractual relations that are repeated between one and three times. In situations with a low demand for operations, but a high transfer of knowledge (S2), there is an intensification to resort to agents from other zones as from the third day. The distribution of the operations among the few agents that participate in them shows very balanced levels. Finally, in those scenarios with a high number of operations to be carried out (S3), the conduct of the outsourcing is very complex. An accumulation of client-supplier arcs is observed with a higher weight below the trend line

Table 4
Percentages of participation of TCs and CAs in the 30 simulations carried out with each scenario.

Scenario	Agent	never	low (1–25 %)	medium (25–50 %)	high (50–75 %)	very high (75–99 %)	always
S1	**TC**	2.5	12.5	15	10	37.5	22.5
	CA	1.25	10	16.25	7.5	31.25	33.75
S2	**TC**	30	27.5	17.5	12.5	12.5	0
	CA	8.75	37.5	11.25	20	22.5	0
S3	**TC**	0	0	7.5	7.5	25	60
	CA	0	0	0	0	16.25	83.75

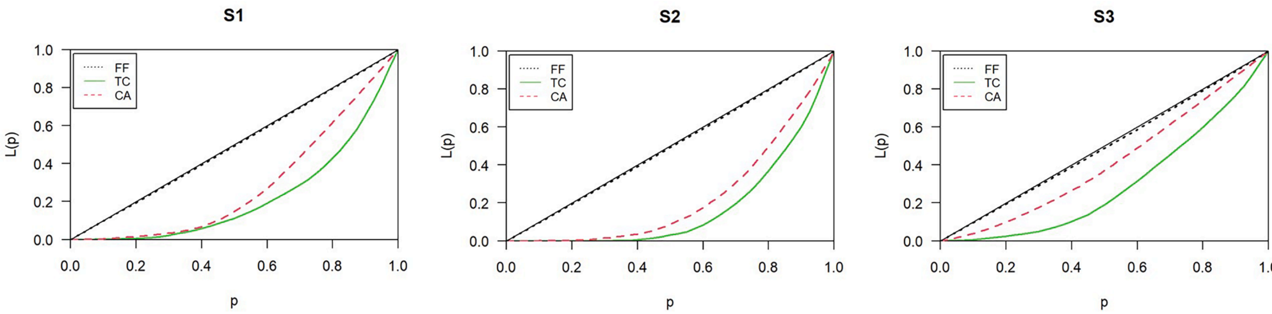

Fig. 6. Lorenz curve for each type of agent and scenario.

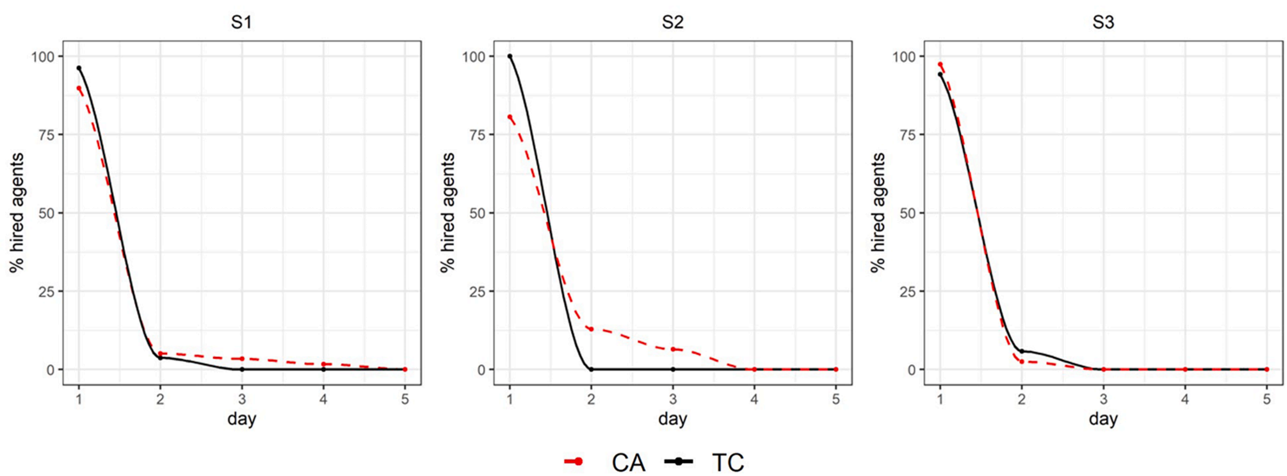

Fig. 7. Relative hiring frequencies by work day.

and arcs with a lower weight above it, which indicates the strength of interzonal collaborations. Less knowledge transfer *(kt = 0.2)* does not enhance interzonal collaboration, as shown by the tenuous growth in the average distance of the arcs.

5.3. Self-organisation of network agents

In this section, the analysis focuses on finding out how agents organise themselves in the model in relation to distance and centrality and in determining the type of role played by each agent in the outsourcing network.

5.3.1. Proximity and centrality

In Fig. 9, the values of the centrality metrics are represented for each node through their size. The thickness of the arc is proportional to their weight. The graphs correspond to repetition number 30 of the total of the 30 simulations carried out for each scenario. Accordingly, absolute values, rather than averaged values, are represented.

When looking at the graphs, it can be seen how some TCs are the agents that present a greater degree centrality in all the scenarios. This fact is due to more diversified connectivity, since their collaborations imply a large number of both FFs and CAs, both in their own zone and in others. The most influential agents in the network, however, are identified with greater clarity in betweenness centrality. In S2, where the number of operations to be carried out is lower, the TCs with the greatest roles in the network are fewer in number, but more influential. In contrast with the other two local metrics, the closeness centrality is not decisive in determining the importance of the nodes that participate in the TOC, since no discernible differences exist between the connected nodes in any of the three scenarios. The centrality metrics thus show us an unequally distributed outsourcing network in which some TCs show a great capacity for leadership within the network, while others are barely active.

Furthermore, the links show major differences between scenarios regarding collaboration preferences according to zone. In the case of outsourcing to TCs by FFs (Fig. 10), the scant number of transport operations in S2 leads to an intense interdependence between zones, facilitated by the short distance between them ($\delta = 5$) and increased by

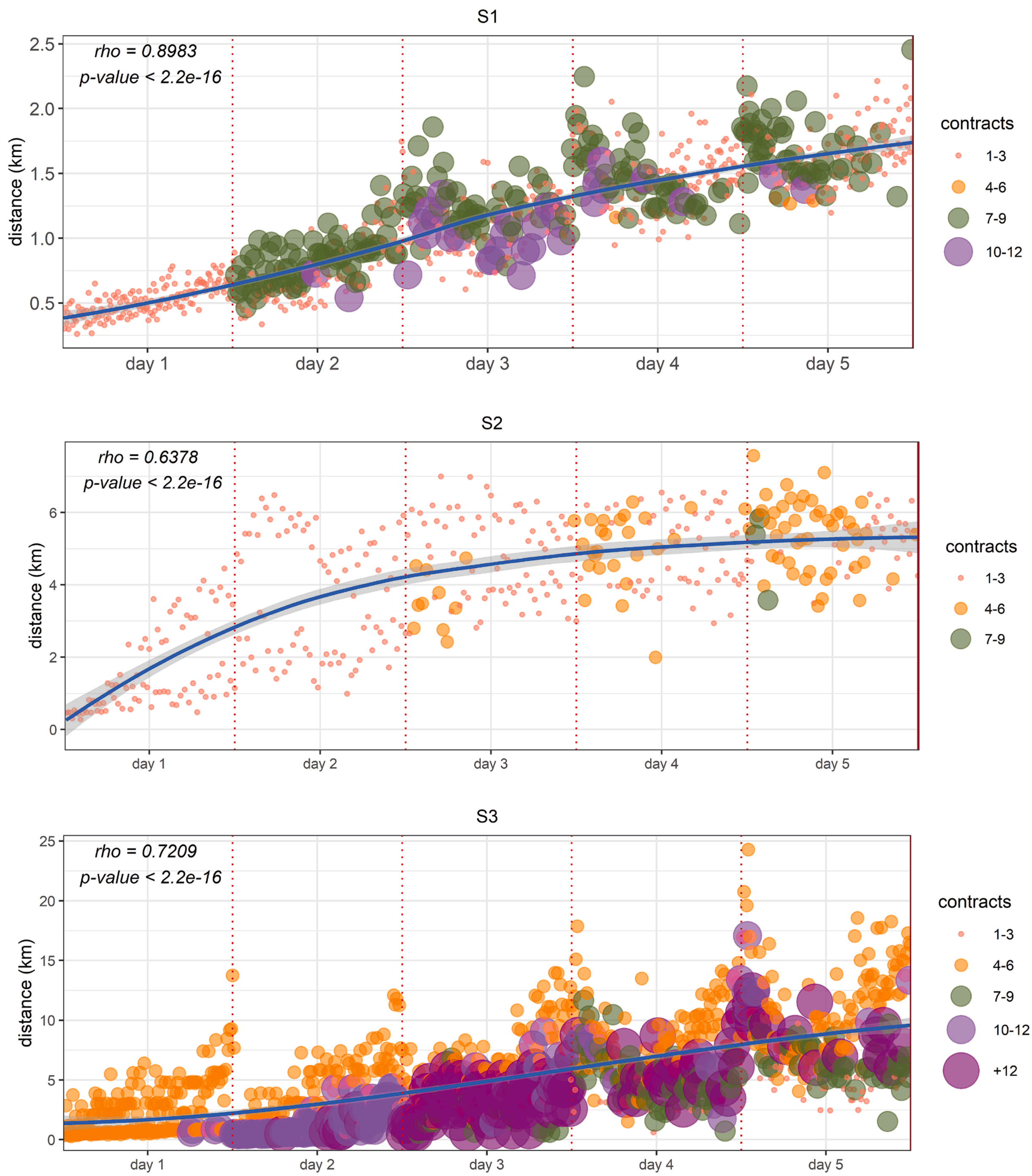

Fig. 8. Evolution of contracts based on distance between customers and suppliers.

greater knowledge transfer between active agents ($kt = 0.8$). In contrast, in S3 we can observe that, for simulations with an abundance of operations to be performed and where, moreover, $\delta = 25$ and $kt = 0.2$, outsourcing between the FFs and TCs are almost always interzonal. This same effect can be observed in the case of the outsourcing by TCs to CAs (Fig. 11), although in a much more tenuous manner, due to the higher number of CAs available in each zone.

Lastly, the geographical centrality (Cg) has been employed in the simulation as a variable in the selection of the TSP. To verify the conduct in relation to the local centrality metrics, all the agents that participate in at least one TOC in one or more of the 30 repetitions for each scenario are represented in Fig. 12, according to their centrality functions, which correspond to the average of all the repetitions. The first line shows the geographical centrality values in relation to the three local centrality metrics, while the following line shows the relationship between these three metrics. The symbols represent the different scenarios.

The first detectable trait is the noteworthy dispersion of the values in the relationship between geographical centrality and local centrality metrics, which expresses the level of importance of the agents in the network. Lacking more conclusive statistics, the Spearman *rho* coefficient reveals a low correlation between this centrality and the local centrality metrics, with a statistical significance of 95 %. This circumstance questions the role of geographical centrality in complex outsourcing networks, since it has an irrelevant effect on the establishment of collaboration relations between the transport system agents. In addition, the dispersion of the values does not show significant

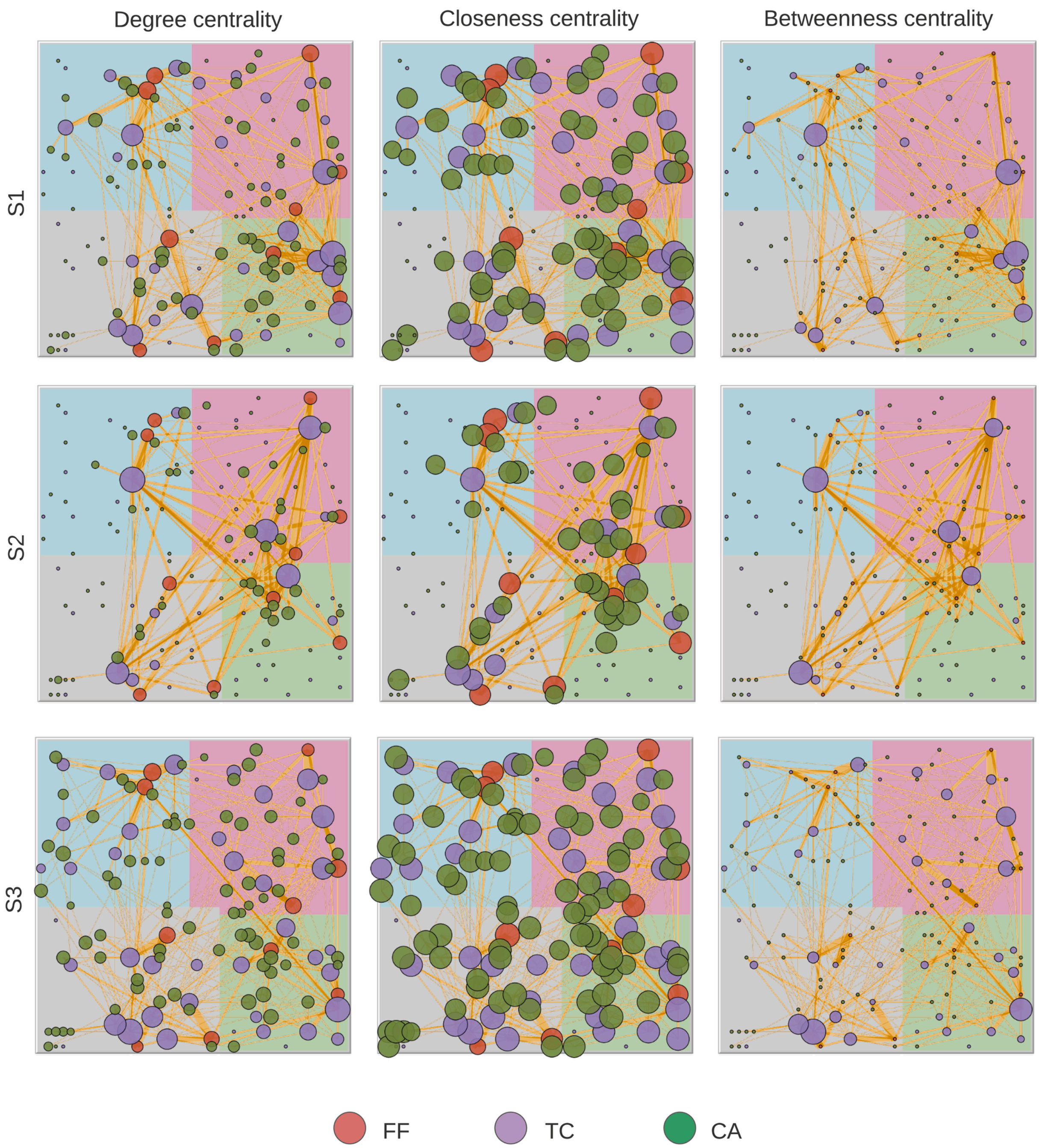

Fig. 9. Representation of local centrality metrics for each scenario.

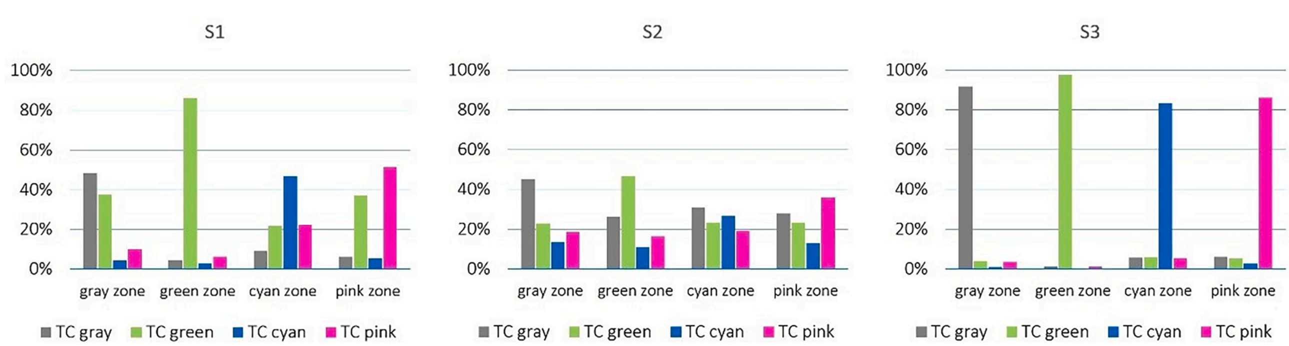

Fig. 10. Outsourcing frequencies of TCs by FFs based on the zone of origin.

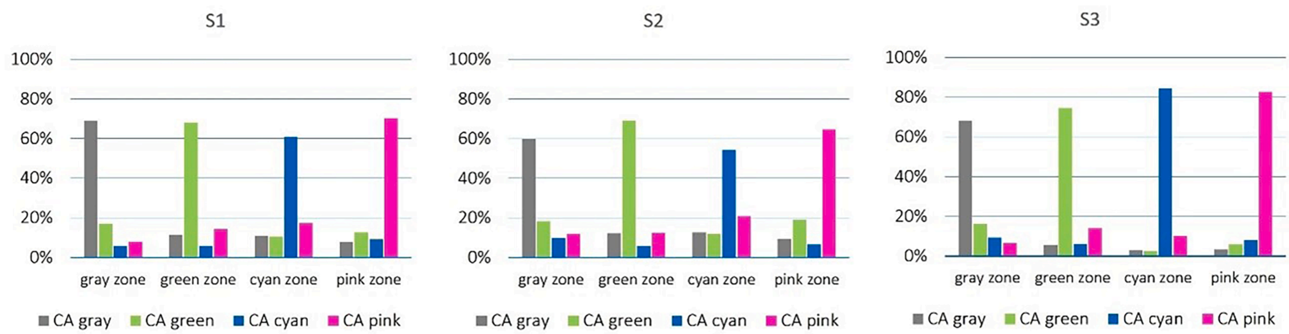

Fig. 11. Outsourcing frequencies of CAs by TCs based on the zone of origin.

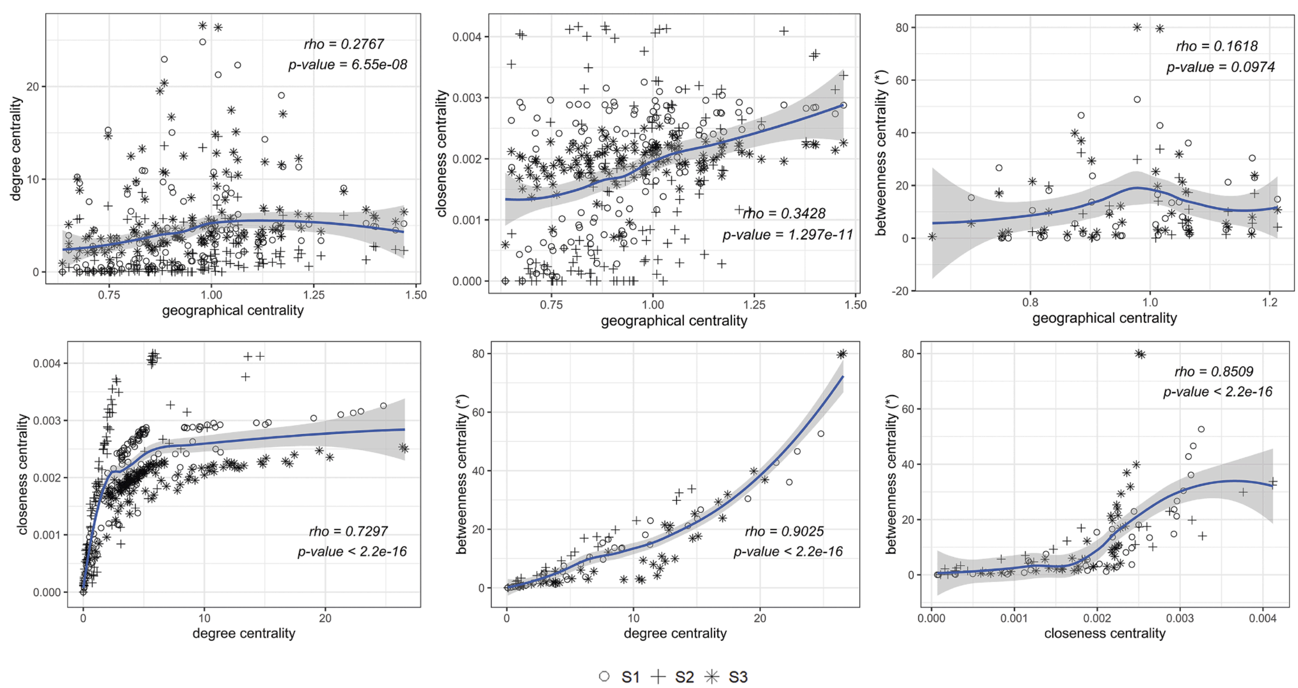

Fig. 12. Correlation of centrality metrics for all scenarios. (*) Only TCs are represented in the calculation of betweenness centrality.

groupings by scenario, which indicates that the scant relationship between centrality and activity are similarly reproduced in different situations.

However, the centrality metrics show an important correlation with each other. For example, the regression line derived from the relationship between degree centrality and betweenness centrality, only applicable to TC agents since the fact that the others are located at the extremes of the TOC, points to a clearly positive correlation, which identifies the agents with the most influence in the network. On a different basis, the relationship between betweenness and closeness centralities, on the one hand, and closeness and degree centralities, on the other, show clean turning points beyond which the trend changes significantly. These circumstances pave the way for future research about the conduct of these complex systems.

5.3.2. Distribution of roles in the RFT system

According to the modularity indictors set out in Section 3.3, the combination of the values contained for each node allow agents to be categorised according to the role they play in the outsourcing network. Following the classification designed by Guimerà & Amaral (2005), seven types of role can be distinguished: *Ultra-peripheral nodes (R1)* with very little intra- and inter-modular connectivity ($z_i < 2.5$ and $P_i < 0.05$), *peripheral nodes (R2)* with a high yet insignificant connectivity ($z_i < 2.5$ and $0.05 < P_i < 0.62$), *non-central connector nodes (R3)* with a significant degree of integration in the network ($z_i < 2.5$ and $0.62 < P_i < 0.8$) albeit not excessively important in their zone (Beckers et al., 2018), *unconnected nodes (R4)* in which the connectivity with other zones is significantly greater than intrazonal ($z_i < 2.5$ and $P_i > 0.8$), *hub zones (R5)* which present a higher degree of internal connectivity but little collaboration with other zones ($z_i > 2.5$ *and* $P_i < 0.3$), *connector hubs (R6)*, very well integrated in both the local network and in the system as a whole ($z_i > 2.5$ and $0.3 < P_i < 0.75$), and finally, *unconnected hubs (R7)*, with an external vocation, despite their intrazonal connectivity ($z_i > 2.5$ and $P_i > 0.75$), which do not strengthen local communities (Beckers et al., 2018).

As regards functionality, the connector hubs (R6) represent the role with a more dynamic value at a local and regional level (Beckers et al., 2018) followed by the non-central connector nodes (R3), which see their lower degree of implementation in their own zone offset by their higher degree of interzonal connectivity.

Fig. 13 shows significant differences between the three scenarios in relation to the distribution of roles. We should remember that the FF agents only show degrees of exit and the CA agents only degrees of entry, while the TC agents show both degrees. A reduced group of TCs exist in S1 as connector hubs (R6) and a larger and more heterogenous group of non-central connector nodes (R3), which play a structuring role in the

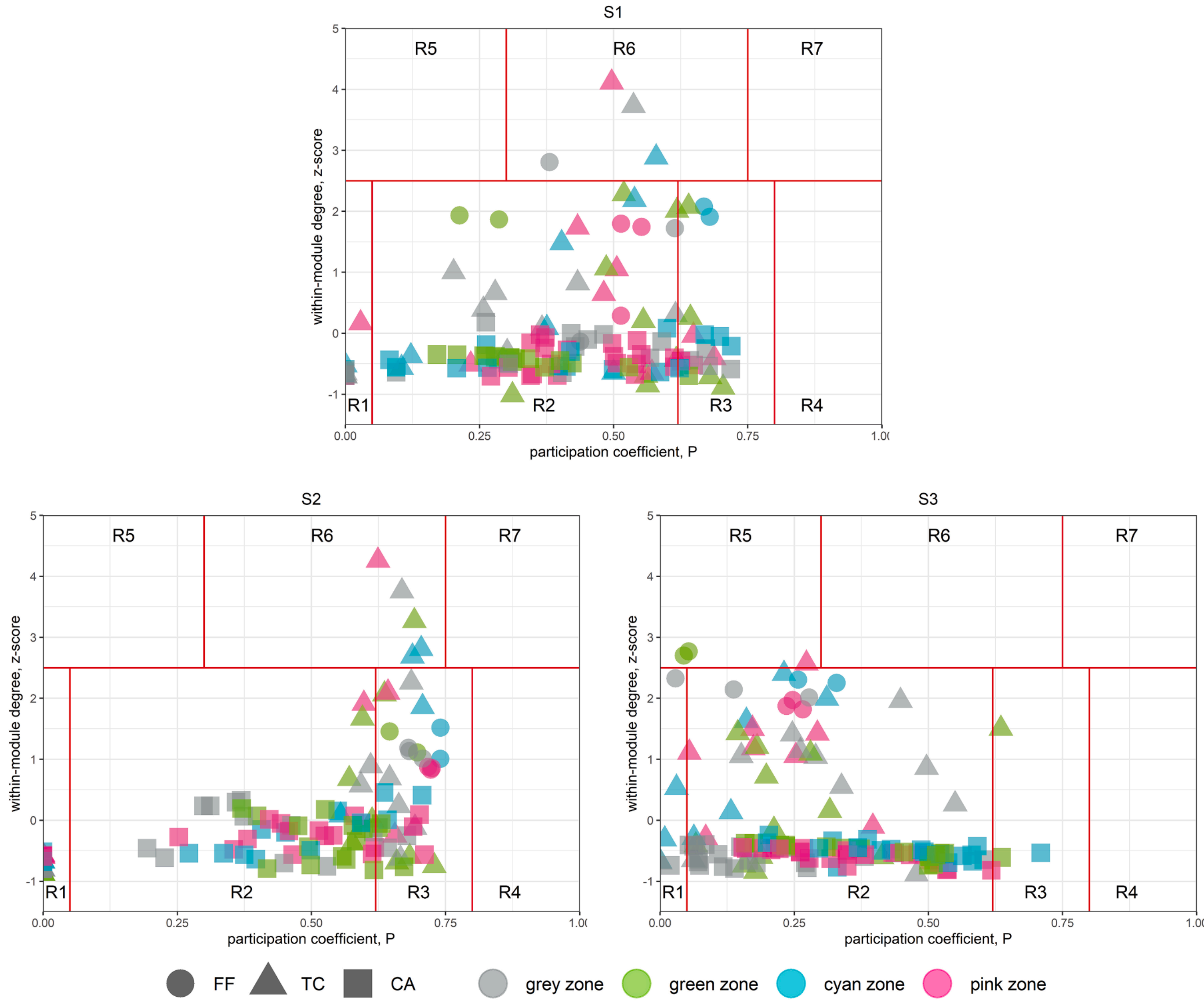

Fig. 13. Distribution of roles in the three scenarios.

network, while most of the active agents play a less central role in the network (R1 and R2). This distribution evolves in S2 towards a network made up of less active agents, due to a lower number of operations to be performed, although they are more central, where the TCs take on even more influential roles in the system as a whole, while the rest of the agents benefit from a greater exchange of knowledge ($kt = 0.8$) to secure their position in the network. In S3, there is greater participation of the agents, although it is more evenly distributed which, together with a greater distance between zones ($\delta = 25$) and a lower exchange of information ($kt = 0.2$), leading the central agents to tend to exercise a role more as zonal hubs (R5), by exercising their influence in their own zones and participating more sporadically in the other zones.

In addition, three main aspects can be highlighted in relation to the variables that define the scenarios:

- *The TMS strongly affect the structure of the network*. On the one hand, the scant number of transport operations (S2) leads to a hierarchical structure dominated by a few TCs in the role of connector hubs (R6) and driven by other non-central connector nodes (R3), which boost the collaboration with other poles of the system. In contrast, the abundance of transport operations (S1) means that the FFs exercise a more influential role as zonal hubs (R5) by preferably outsourcing to TCs from their own zone.
- *The transfer of knowledge drives interzonal collaboration*, as can be observed in S2. The learning processes positively affect those agents that maintain a high degree of intrazonal participation, as there are several TCs. In S3, where the distribution of contracts is less concentrated in a select group of agents, the indicators place a good number of the TCs as peripheral nodes (R2).
- *The distribution of roles and the structure of the network vary as the interzonal distance increases*. The relationship between distance and the conduct of the agents may be correlated with greater distances between zones, which fosters greater modularity, and hence, less collaboration between them. However, this relationship needs to be studied in greater depth.

6. Discussion

6.1. Distribution and dynamic of participation in TOCs

The use of variables on the situation of the job market, transfer of knowledge and distance between zones has proven to be effective for the simulation of different scenarios in the performance of the outsourcing network. Firstly, the scant number of transport operations produces major imbalances in the assignation of contracts. Given that in each scenario the number of contracts is limited, the concentration of contracts in certain agents leads to the exclusion of others, which may result in being a very high proportion. The higher levels of knowledge transfer between agents and the reduced distance between zones does not contribute to significantly correct the disadvantageous situations for a good number of the TCs and CAs. At the other extreme, the abundance of transport operations to be carried out results in a high level of participation of all agents, even at a greater interzonal distance. The data align with the trend of operational concentration among agents with greater capacity to compete, leading to the disappearance of small and medium-sized companies in the study area.[4] Despite the gradual increase in tonne-km transported since 2014[5] (except for 2020), this trend persists. In the case of the CA agents, the limitations on transport activity (daily hours of driving) forces them to not accept more operations than they are able to carry out, hence the lack of activity affects them less than the TCs. Secondly, the transfer of knowledge between agents can help improve unfavourable situations, creating cohesive and competitive environments. Accordingly, due to the existence of collaborations based on the exchange of knowledge as a result of experience and learning, the emergence of dynamic environments, such as logistics clusters, fosters the creation and guarantee of more and better contractual relations between sector companies (Rivera, Gligor & Sheffi, 2016).

Furthermore, the analysis of the results of the dynamic show, firstly, the evolution of very unequal outsourcing conditions depending on the transport market situation and, secondly, a growing complexity of the collaborations as the size of the network increases. As regards the spatial aspect, assuming that a high degree of modularity of the network produces a high degree of clusterisation (Strogatz, 2001; Surana, Kumara, Greaves & Raghavan, 2005), the structural and evolutional traits of the model suggest the formation of a dynamic environment in those zones where activity and knowledge achieve higher levels. In short, it is reasonable to place the dynamic of the outsourcing networks of RFT companies in the context of complex adaptive systems in which agents are sensitive, flexible, reactive and proactive to the circumstances of their environment (Nilsson & Darley, 2006).

6.2. Network centrality and geographical centrality in RFT systems

The use of graphs through Fuzzy Cognitive Maps has been employed previously in both the analysis of the collaboration between transport companies (Kayikci & Stix, 2014) and in operational decision-making (Tsadiras & Zitopoulos, 2016; Reis, 2018). However, the results offered by our model shows the complex structure of outsourcing networks given the diverse nature of the agents that comprise them and their different ways of conducting relations with each other through their aptitudes and the exchange of knowledge. In this regard, local centrality metrics, based on the active participation of agents, have shown their validity as instruments to analyse complex networks in conjunction with other methodologies, such as the analysis of roles and dynamic analysis.

Geographical centrality has been introduced in the selection of the TSP since this could constitute an advantage for those agents with better access to information and knowledge flows, according to the principles of proximity and friction of distance (Tobler, 1970; 2004; Han, Tsou & Clarke, 2018). However, based on their contrast with local centrality metrics, it can be deduced that geographical closeness does not constitute a relevant factor in the formation of the TOC. In other words, transport operators collaborate based on preferential attachments rather than location. In contrast to local centrality metrics, geographical centrality does not offer any information on the influence of each agent in the network, since it is an attribute that expresses the centrality of their positioning *vis-à-vis* the other agents in their zone, regardless of their activity. Their presence, in contrast, permits an analysis of the way in which the centrality of the nodes in the network are related to their geographical location in the system and the role they play in both the selective process and in the confirmation of the different outsourcing networks depending on the scenario.

6.3. Knowledge networks vs. knowledge environments?

It has been observed that direct learning (*DL*) through the experience obtained following their first outsourcing is the main facilitator of a succession of new outsourcing contracts. Fig. 7 shows how this conduct is particularly noteworthy for TCs which, in reality, could correspond to the loyalty of one collaborator or to the establishment of strategic alliances between companies (Rinehart, Eckert, Handfield, Page & Atkin, 2004), leading to the accumulation of operations by some agents. Despite this, the information is shared by forming networks for the dissemination of knowledge between agents that have no collaboration among themselves necessarily, but which receive part of this knowledge, thus allowing them to perfect and consolidate the network. However, no definitive evidence has been obtained regarding the effect of indirect learning (*IL*) in the participation of agents in the network. The formation of environments for the transfer of knowledge is related to formal and informal exchanges of information (Phelps, Heidl & Wadhwa, 2012) in spaces where professionals carry on their activity. It is in these environments, headed up by connector hubs (Fig. 13) where the accumulation of knowledge reaches higher levels. The analysis of the relationship between networks and environments for the transfer of knowledge thus constitutes the next step in the research of RFT systems.

7. Conclusions

This paper uses an agent-based dynamic model to examine the collaborative relationships that structure TOCs in the real world. The model is subjected to experimental stresses of simulation, and several novel aspects can be extracted. Firstly, the selection process for suppliers in each link of the chain has been formalised, with contracting experts making decisions based on identified variables. A score is used to preferentially select certain agents over others, with some degree of randomness involved. Among these variables, learning through experience has been shown to play a fundamental role, since it qualifies agents for later operations and allows a spatial transfer of knowledge that benefits third parties outside of the outsourcing chain.

Secondly, as a result of this preferential selection process, the distribution of the activity between TCs and CAs has proven to be highly irregular. The cumulative network resulting from the self-organisation of the system suggests a similar structure to scale-free networks, where the probability of a node interacting with others responds to power laws (Barabási & Albert, 1999; Albert & Barabási, 2002). Furthermore, in our model, new agents join the network according to market needs in accordance with one of the principles of scale-free models. These models consider growth in the number of agents as a necessary component of the algorithm (Albert & Barabási, 2002). Similarly, it has been verified how this network of preferential relationships persists over time. In these relationships, the transfer of knowledge once again plays a vital role in the emergence of the central role of connectors, whose participation in the outsourcing network is even more decisive in situations with a scant number of transport contracts.

The initial attempt to reproduce the complexity of RFT systems by comparing very different scenarios has led to the model showing a series of imbalances and asymmetries in terms of participation and the dissemination of knowledge, which can be identified in two interrelated

[4] MITMA: https://cdn.mitma.gob.es/portal-web-drupal/estudios_transporte/IndicadoresEconomicos_2021.pdf.

[5] OTLE: https://cdn.mitma.gob.es/portal-web-drupal/OTLE/elementos_otle/Informe_anual_2021.pdf.

areas. As regards the agents, beyond the inherent organisational hierarchy of outsourcing models, the emergence of a parallel hierarchy has been shown based on the operating capacity and learning of the agents, in which a small number of TCs take on leadership roles and make the system more dynamic sustained in the positive interaction with their collaborators.

Furthermore, TRANSOPE has been stoked with empirical data with the aim of simulating the decision-making of experts in the field of the outsourcing of transport services. The results are thus sufficiently robust to be applied to future policies to make the sector more dynamic in local and regional environments. In addition, the model allows its application to individual situations with a need to outsource to TSP based on certain criteria, which amounts to an opportunity for its use as a management tool.

Finally, the research should enjoy continuity in the identification of innovative environments for the accumulation of knowledge that explains the spatial organisation of RFT systems at a local and regional level.

CRediT authorship contribution statement

Aitor Salas-Peña: Conceptualization, Data curation, Methodology, Software, Investigation, Resources, Writing – review & editing. **Blanca Cases:** Methodology, Software, Validation, Supervision. **Juan Carlos García-Palomares:** Resources, Validation, 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.

Data availability

Data will be made available on request.

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