# Augmenting Multi-Agent Negotiation in Interconnected Freight Transport Using Complex Networks Analysis

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**Abstract.** This paper proposes the use of computational methods of Complex Networks Analysis to augment the capabilities of broker agents involved in multi agent freight transport negotiation. We have developed an experimentation environment that enabled us to obtain compelling arguments suggesting that using our proposed approach, the broker is able to apply more effective negotiation strategies for gaining longer term benefits, than those offered by the standard Iterated Contract Net negotiation approach. The proposed negotiation strategies take effect on the entire population of biding agents and are driven by market inspired purposes like for example breaking monopolies and supporting agents with diverse transportation capabilities.

**Keywords:** Complex Networks Analysis · Automated Negotiation · Multi Agent Systems · Iterated Contract Net

## 1 Introduction

This paper proposes a new computational approach to endow negotiation brokers with novel and controllable instruments aiming to better impact their business environment, by providing quantitative feedback on their decisions. In general, the majority of negotiation protocols only consider short-term advantages of participants, like for example monetary benefits, by aiming to increase the profit per negotiation of the broker and/or other participant agents. However, we consider this is a limited vision as the business world is far more complex and with many facets of the longer-term benefits one might gather by engaging in negotiations.

Let us consider a well known fact in economy: monopolies are bad for an open market since the broker and the entire market environment is at the hand of a single actor. The monopoly holder establishes the monetary value and the pace of evolution, see for example the case of Standard Oil [21]. Hence, brokers/markets need to prevent the rise of monopolies. This phenomenon can be controlled either through regulatory bodies and/or through active preemptive strategies, the latter approach being considered in this paper. Since, monopoly hindering strategies that involve only adjustments to the monetary value are ineffective, as a monopoly will diminish the value of goods/services in order to hinder potential competition in the short term and to gain monopoly in the medium to longer term [28], a need for a broader set of actions emerges.

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Hence, our motivation is to design an enhanced negotiation protocol that enables the broker to easily employ complex dynamic negotiation strategies of domain specific (transport and logistics in our case) and social inspiration. For example, a strategy for hindering monopolies might consider favouring smaller / less important transporters over larger / more important transporters when their bids are the same or marginally different. Also, sometime might be better to encourage transporters that have multiple transport capabilities in order to reduce the dependence of rather few and highly specialised transporters.

This work heavily relies on experimental evaluation of negotiations, thus we have successfully created an agent-based simulation environment by using concepts and computational methods borrowed from the fields of Complex Networks Analysis (CNA in what follows) [32] and Multi-Agent Systems (MAS in what follows) [9]. CNA is an interdisciplinary research domain inspired by Graph Theory, Statistics and Computer Science that seeks to represent and extract knowledge from complex interconnected environments where non-trivial phenomena arise. The use of MAS is justified by the requirement for developing and analysing automated negotiation models involving self-interested agents.

The results included in this paper represent a progress of our work described in previous research publications on multi-agent systems for freight transportation brokering. The initial proposal and general architecture of an agent-based system for brokering of logistics services and of semantic modelling of freight information were introduced in [16] & [17]. The details of agents' interaction protocols were defined in [19]. As per [18], the authors were able to develop and validate multiple ontologies to be used by the transportation broker for matching the cargo transportation requirements with the appropriate transport vehicles. In [20], an automated negotiation framework based on Iterated Contract Net protocol [13] was developed and experimentally analysed. The results have shown that agents using this protocol tend to behave realistically by manifesting features typically encountered in human-conducted negotiations.

The ultimate goal of our work is to develop a MAS framework for transport and logistics services – MAFTLS in what follows. The architecture of MAFTLS includes three types of actors: cargo owners, transport providers and broker. The focus of this paper is set on the broker and its capabilities to match the appropriate transport providers and transport vehicles for solving each specific transportation request. Note that transportation contracts can only be established through the broker, by employing an appropriate negotiation protocol.

The aim of this paper is to experimentally investigate if the proposed augmented negotiation protocol – Augmented Iterated Contract Net or AICNET in what follows, is able to provide the broker with the capabilities required for the dynamic selection and application of various market strategies of social inspiration in order to obtain longer-term benefits. Our approach relies on agent-based computational modelling and simulation. The novelty of our proposal is supported by the use of CNA for capturing and extracting knowledge from the negotiation environment and its further incorporation it into negotiations through an augmentation process. This enables the broker agent using AICNET to easily adapt and control its negotiation strategy for achieving higher level goals, possibly on a longer time horizon.

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## 2 Background & Related Work

### 2.1 Negotiations in Freight Transport Multi Agents Systems

As early as 1998 ([7]) freight transportation approaches based on cooperating agents have been proposed. The aforementioned paper describes a *Holonic* MAS approach called *TeleTruck*, where transportation agents could bid for the "whole" freight to be transported or only for parts of it. In [1], Adler et al. have focused on the efficient reallocation of network capacity over time and space without seriously violating any individual users preferences for mode, routing, departure, and/or arrival time. Neagu et al. ([25]), have developed an agent based solution to support human freight transport dispatchers, which was considered business-fit and therefore it was adopted by a multinational logistics company. A recent MAS related approach to freight transportation, presented by Mes M. et al. [22], tackled the problem of real-time scheduling of time-sensitive full truckloads pickup-and-delivery jobs. Among the many related papers it is also noteworthy to mention a recent work by Wang Y. et al. [34] sharing many of our research goals, that proposes a promising new *gradient knowledge* policy for matching shippers with carriers through brokering.

Note that MAS provides the perfect setting for simulating freight transport negotiation models. We argue that such models are highly interconnected due to the continuous exchange of messages between the involved agents, with the goal of establishing transport agreements. Such contracts can be reached by letting agents use a shared language and a shared set of negotiation rules that we have addressed in paper [19].

A negotiation can be defined as a complex dynamic process by which two or more parties seek a compromise to a non-trivial negotiation subject. In the context of transportation networks, large scale automated negotiations involving a large number of participant agents, fit best our model. One of first prototype mass negotiation systems was introduced by Picard W. [27] and it used a multi-facet analysis mechanism.

According to [14], a negotiation brings together three elements: *negotiations protocols*, *negotiation subject* and *negotiation strategies*. This paper builds upon the Iterated Contract Net as *negotiation protocol*. It allows multiple rounds of bidding before reaching an agreement among the participant agents regarding the *negotiation subjects* represented by specific freight transportation requests. Our contribution is the introduction and experimental validation of new *negotiation strategies* of the broker agent.

An overview of existing models of automated negotiation in multi-agent systems with a special focus on complex negotiations involving non-linear utility functions has been presented by Scafes M. et al. [30]. However, the lack of a critical mass of research papers related to our negotiation scenario can be seen. This observation is also supported by the authors of paper [5] which have formally defined and designed a conceptual software architecture of a multi-strategy negotiation agent-based system.

### 2.2 Multi-Agent Framework for Transport Logistic Services

MAFTLS is a MAS framework that captures each transportation actor as an agent: cargo owner as *aCAgent*, transport provider as *aFTPAgent*, freight broker's registry as *aFBRAgent*, and freight broker as *aFBAgent*. The focus of our research is on the freight

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broker agent. It has a unique intermediate position between buyer and seller of transportation services. It is a self-interested agent with the goal to sell freight transport services at the highest possible value (*oval*) to cargo owners and to buy freight transport services from transport providers at the lowest possible value (*tval*). The business model of the broker implies a positive difference between $oval - tval$ in order to support broker's operating costs and produce its profit.

For the description of MAFTLS we are using the agents' communication diagram depicted in Figure 1. This diagram presents the workflow of MAFTLS triggered by receiving a transport request from a cargo owner. The *aCAgent* representing the requesting cargo owner forwards the request to the broker, which queries the *aFBRAgent* to obtain a list of pre-registered vehicles suited to the transport requirements of the cargo. Both the transport request and the process of determining if a vehicle is suited for specific transport requirements are using ontological demarcated information. If the matching is successful, the broker will start a one to many negotiation process with the *aFTPAgents* owning the vehicles (right-hand negotiation). If the negotiation process is successful, a winner transporter is established together with the *tval*. Based on *tval* the broker will engage in a second (one to one) negotiation with the requesting cargo owner (left-hand negotiation). If an agreement is reached with the cargo owner, then a contract between the winning transporter and the cargo owner is set. If any of the above fail then the contract is not set and all actors involved are informed accordingly. Broker strategy is based on the *list order algorithm* that is captured as a "black-box" in Figure 1. It enables the broker to dynamically configure and adapt its strategy by possibly introducing other criteria that govern the selection of the winner transporter. We will focus on such criteria in the following sections of the paper.

As already mentioned, we adapted the Iterated Contract Net negotiation protocol for our transport scenarios ([20]), while also introducing basic negotiation personalities of the participant agents ([20]). Experiments conducted using Java Agent Development Framework (version 4.4) [3] were successful, with a rate of less than 7% of negotiation failure and with a rather fast agreement reaching in 5.7 negotiation rounds on average. From the business point of view, the experiments were successful too, as the broker would receive an average commission of about 10% from *oval*. Results regarding the agents' personalities have shown that the negotiation protocol has favoured transport providers asking an initial low price and which are flexible during the negotiation process (Low Price Lenient personality). Also, the distribution of the *oval* prices has a Gaussian bell-like shape, as one might expect to happen in human driven negotiations.

In this paper we build our experimental evaluation on this setting, by augmenting the right-side negotiation process with new information representing social insight obtained using computational methods of Complex Networks Analysis.

### 2.3 Complex Network Analysis

The establishment of transport contracts between *aCAgents* and *aFTPAgents* enables them to interconnect into a large social network of transport stakeholders. As new transport requests are processed by the broker, a highly interconnected network emerges. Hence, we can use some of the information related to this inter-connectivity of agents

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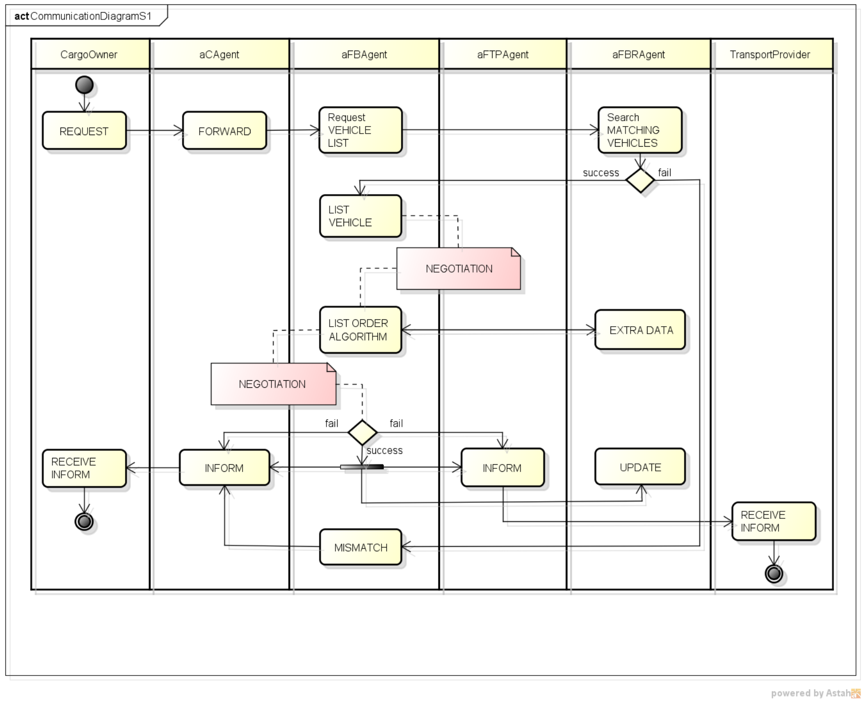


**Fig. 1.** Agents' communication diagram in MAFTLS

to provide additional leverage for the broker during the negotiation processes. The interconnectivity emerging between pairs of agents is called *social behaviour*, since the behaviour on one agent can influence the other agent.

To the best of our knowledge we are not aware of any previous studies that augment an automated negotiation protocol with information extracted from the resulting interconnected world of the actors involved. Nevertheless, we could find some related studies, as follows. Van Doosselaere was able to infer the social rules that brought the rise of capitalism by analysing the link between commercial agreements and social processes ([33]). Further more, Money R. B. has shown that social activity influences human based multilateral commercial negotiations ([23]). Nan S. A. highlighted the potential impact of using social structures (networks) in conflict resolution processes through negotiation ([24]). Thus, we argue there is sufficient evidence to motivate a research study into social automated negotiation, which is the purpose of this paper.

In order to better understand complex interconnected systems, the research field of *Complex Networks Analysis* has evolved from synergies of graph theory, social sciences, physics, statistics, and computer science ([15]). This field of research studies overlapping non-trivial complex phenomena that can not be explained either by more "classic" approaches of lattice theory, random graphs, or statistics. CNA has matured during the last five decades and several branches have emerged, with Social Network

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Analysis (SNA) standing out as triggered by the rapid evolution of synergies between Computer Networks and Social Sciences ([31]).

SNA techniques and methods have proven their utility in many business related studies. According to [6], SNA can be used to support strategic collaborations. Greve A. et al. have used SNA to discover that social capital is the most important factor in productivity ([11]). The authors of [8] have made a marathon in their textbook to support the utility of SNA/CNA in various areas including: game theory, auctions, bargaining, etc. In our study we are using dedicated CNA/SNA computational tools (*Gephi* ([2]) graphical environment and *NetworkX* [12] Python library) for analyzing social networks, as well as the Python programming language and its relevant libraries.

## 3 System Design

We have developed a simulation system using Python programming language, for experimental evaluation of our proposals, publicly available on *Github*[1] under MIT license. The following subsections introduce the conceptual model of our experiments and the supporting experimental system (ES).

### 3.1 Conceptual Model

In order to analyze social characteristics of agents involved in MAFTLS, we introduce the methods used for representing the agents' social environment. CNA defines the structures used to represent such environments as networks, while SNA often refers to them as sociograms. However, both are essentially graphs (as in graph theory) augmented with specific information. Hence, we are using these terms interchangeably. Graphs have two types of constituent elements: nodes/vertices and links/edges; nodes are the portrayal of environment actors, while links are depicting relations among the actors. In our scenario we model each *aCAgent* and *aFTPAgent* by a separate node. Links are formed among nodes that have established a transport contract. Hence, we obtain a social bipartite graph of cargo owners and transport providers, where the social relationship is based on prior commercial agreements. The broker and the broker registry are not included since they are only environment artefacts, acting as match makers, with no active role in the social relationship formation and development. As a freight transport contract does not imply a leadership/direction, we use undirected graphs in our modelling. Also, as multiple contracts can be established between the same freight transporter and cargo owner, it is natural to augment our model with link weights.

As already mentioned, the broker is involved in two types of negotiation processes: one with the cargo owner (left negotiation in Figure 1) and the other with the freight transport providers (right negotiation in Figure 1). Since the *left negotiation* is one to one, we consider that social factors are less important here. So, for this study, we will focus only on the *right negotiation* type, where the broker is involved in one to many negotiations. Here the social characteristics of each freight transporter will be explicitly considered to differentiate between them. We are now considering possible social features for characterising freight transporters.

[1] https://becheru.github.io/aicnet/

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*Centrality measures* are indicators of the most important/influential nodes in a social graph. The *PageRank* ([26]) is a highly utilised centrality measure in SNA studies. It stands out as the underlying algorithm of *Google*'s search engine. The algorithm for computing this measure takes into consideration the number of links of a node (similarly with *Degree* measure) and their respective *quality*. Simply put, it is important to have as many connections as possible with nodes that are also highly connected. In our scenario, a freight transporter with high *PageRank* established many transport contracts with cargo owners that in their turn have established a significant number of contracts with other highly successful transporters. From an economic point of view, a highly rated transport provider according to *PageRank* serves the transport needs of the most active cargo owners, i.e. those cargo owners which are making most transport requests. Hence, such transport providers represent a crucial factor for the success of MAFTLS, as the revenue increases with each established transport contract.

Another measure of centrality that we are considering in our work is *Betweenness*, initially proposed by Freeman L. C. in [10] and further developed by Brandes U. in [4]. It emphasises the nodes that act as bridges between graph communities, by representing the weak ties in a social graph, as described in [29].

Note that all the metrics are able to assign a quantifiable measure to each node of the social graph, hence enabling their comparison by an appropriate ranking.

Now that we have the means to determine the social welfare of each transport provider, we must establish the goal(s) of using them. We group one or more goals into *strategies*, for a better business alignment. The broker is the agent capable of selecting and applying various strategies, according to its business and/or social interests.

It is not possible to cover all the possible strategies, even in a larger paper. Hence we will focus on few of them that we consider more relevant. We are aware that a strategy can involve more SNA metrics. However, in this work we consider only strategies that can be at least partly satisfied by a single metric. The simultaneous intertwining of multiple metrics to adhere to a specific strategy will be addressed in future works.

In the introduction we discussed that the existence of the monopoly might negatively impact a market. Hence, being able to apply a strategy to hinder/disrupt monopolies can be of great value for the broker. One such strategy may rely on increasing competitiveness by providing an advantage to transport providers that have this trait. Let us call this strategy *Competitiveness Advantage* (*sCA*). As already mentioned, such transport providers can be highlighted using the *Betweenness* metrics. Hence, the transport provider with the highest *Betweenness* will be awarded contracts with *sCA*. The second strategy, let us call it *Page Rank* (*sPR*), will use *PageRank* centrality measure to identify nodes that represents potential monopolies. The freight transporter with the lowest *PageRank* coefficient will be selected as winner.

Having fixed those SNA metrics that we intend to utilize as negotiation factors, we now present some details of the winner selection in negotiation protocol (we assume the reader familiarity with ICNET – a standard task allocation protocol in MAS).

The simplest solution would be to directly (i.e. in one negotiation round) select based on the metric value. However, this approach would not imply really a negotiation. Therefore, we decided to slightly update ICNET to better support the use of our metrics.

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This is actually a natural development of our previous results that discussed negotiation processes in MAFTLS ([20]), as we can use those results as comparison benchmarks.

ICNET implies that the negotiation proceeds as a series of negotiation rounds until one or more freight transport providers will agree with the broker's offer or the maximum number of iterations is reached (negotiation failure). During each round the broker proposes a monetary value in exchange for the transport service that the freight transporters can: accept – thus finishing the negotiation (negotiation success), reject but continue to the next round and reject and withdraw of the current negotiation. The accept is given when the broker bid is higher than transporter bid ceiling, while the reject is given when the broker bid is lower than the transporter bid floor. In between the bid ceiling and bid floor the transport will reject the current bid, but it will proceed to the next round of negotiation. In standard ICNET, if multiple transport providers accepted the offer in the current round then the one with lowest price would win. In our variant, AICNET, the accepting transport providers would be ranked based on a SNA metric and the winner would be the highest/lowest ranked depending on the strategy used.

### 3.2 System Architecture

We now provide some of the details of our experimental system – ES. An experiment is organised as a series of simulation rounds. Each simulation round deals with solving of multiple transport requests. Each transport request can be satisfied by a negotiation process that usually takes several negotiation iterations, with a maximum threshold established. The negotiation protocol (ICNET or AICNET), number of experiments, rounds and iterations are defined by the user at the start of the experiment and they are fixed for the whole duration of the experiment. It is noteworthy to mention that a series of simulation rounds can be continued by another as the data is not lost between rounds, unless this is explicitly requested by the user. These experiments produce and record results and information that can be obtained by querying the ES's statistical module.

The population of participant agents is automatically generated at the start of each simulation round. Currently each cargo owner is only characterised by its ID, since cargo owners are not involved in the *right side* negotiation. The broker and the transport providers have a more complex structure since they are endowed with "personalities". The details on the personalities have been discussed in our previous paper [20]. The personalities influence the initial and reserve values (High Price or Low Price) and the level of flexibility of the agents during a negotiation (Conservative or Lenient). Transport providers change their personalities autonomously, between consecutive transport requests, as they reach specific thresholds or randomly. The broker personality is explicitly set by the user, while transporter personalities are set at the start of each experiment, by random selection from 4 available options.

As this paper is focused only on the *right-negotiation*, the simulation of a transport request issued by a cargo owner is simply reduced to: i) randomly selecting a cargo owner as transport request issuer, and ii) generating a random monetary values between 1 and 10000 that represents the estimated-transport-cost. In MAFTLS, the broker-estimated-cost is computed by the broker based on the details of the transport request, to determine the broker initial bid. The broker bid for each negotiation iteration is computed based on the previous bid value and the broker personality.

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During each negotiation iteration, the transporters receive the transport request from the broker, and consequently they compute their own transporter-cost-estimation. In a realistic market we would expect that the transporter-cost-estimation of transporters is randomly distributed around the broker-estimated-cost. Hence, we compute the transporter-cost-estimation for each transport provider using Gaussian distribution, as follows. The *mean* is computed by adding the broker-estimated-cost with a *displacement* (a parameter set by the user for each experiment). It models the estimation error of the transporters, for the broker-estimated-cost, as in a real setting this value is private to the broker, so transporters do not know it exactly. The *standard deviation* is given as *displacement* over *deviation* (user defined scaling parameter).

After determining its private cost estimation, each transporter proceeds to compute the bid ceiling and bid floor, based on its personality. Bid floor and bid ceiling are updated in each negotiation iteration. Then the negotiation proceeds according to the negotiation protocol, until termination is reached. If the negotiation terminates with success then the social graph is updated by creating a new link between the cargo owner and the transport provider.

## 4 Experimental Results

### 4.1 Experimental Setup

ES has been developed as an object oriented program in Python which makes it very easy to use and/or adapt. The user can easily interact with ES using two classes: *Environment* and *Statistics*. The *Environment* class makes the necessary initialisation and controls the execution of the negotiation processes. The *Statistics* class is in charge of gathering data during the negotiation and presenting various statistics to the user.

ES provides the user with a wide experimentation perspective, by suitable setting of the various parameters. Because of the limited space, we focus here only on experiments with the following settings of the simulation parameters: broker personality set to Low Price Lenient, 50 transport provider agents, 1000 cargo owner agents, a threshold of maximum 12 iterations per negotiation, displacement 10 and deviation 10.

The experiments are focused on two broker strategies (*Competitiveness Advantage* (*sCA*) and *Page Rank* (*sPR*), see Section 3.1), aiming to provide compelling evidence that AICNET can satisfy the goal of each strategy. Since we are restricted regarding the length of the paper, the details of using ES to run these experiments are mentioned on the GitHub page of the tool. For each parameter setting, we first run 1000 rounds of ICNET, to avoid the cold start problem for computing graph metrics, and then we run another 1000 rounds of AICNET (with ICNET in parallel), to be able to draw conclusions about the effectiveness of AICNET and compare it with ICNET. Concluding, after 2000 rounds we are able to compare the results of running ICNET (2000 rounds) with those of running 1000 rounds of ICNET followed by 1000 rounds of AICNET.

### 4.2 Results & Discussions

Table 1 presents some results obtained with ICNET and AICNET in the context of the broker strategies. Regarding negotiation related metrics, we can observe one major

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advantage of AICNET: the number of iterations per negotiations is slightly smaller, which translates in less waiting time for the cargo owner.

The gain per negotiation of the winning transporter is computed as the winning price over the initial estimate of the broker. Hence, from a business perspective there are no or minor differences between ICNET and AICNET, which we consider to be a major incentive for using AICNET. Some differences still arise, albeit not major, when we take into account the personalities of the winning transport providers. However, as stated before there is almost no impact on the negotiated monetary value. Our interpretation is that transporter providers that are more conservative and give higher initial prices have better chances to participate with success in AICNET than in ICNET, resulting in a slightly more inclusive negotiation protocol.

Regarding negotiation failures, both protocols act well. Although, as shown in [20], when the implementation is done in a distributed MAS framework (like Jade), some failures may arise because of communication problems between agents distributed on different machines. Based on our obtained results, we can speculate that AICNET has a slight edge over ICNET.

**Table 1.** Negotiation's results and graph related metrics.

| Metric/Strategy | *sCA* | | *sPR* | |
|---|---|---|---|---|
| | ICNET | AICNET | ICNET | AICNET |
| Negotiation related metrics | | | | |
| Avg. No. of iterations per negotiation | 3.186 | 2.084 | 2.268 | 1.633 |
| Avg. Gain of the transporters | 1.185 | 1.195 | 1.205 | 1.217 |
| No. wins LOW PRICE LENIENT | 1628 | 1544 | 1406 | 1292 |
| No. wins LOW PRICE CONSERVATIVE | 341 | 405 | 403 | 378 |
| No. wins HIGH PRICE LENIENT | 13 | 13 | 87 | 120 |
| No. wins HIGH PRICE CONSERVATIVE | 18 | 38 | 104 | 210 |
| No. failed negotiations | 0 | 0 | 0 | 0 |
| Graph related metrics | | | | |
| Avg Weighted degree | 3.810 | 3.808 | 3.810 | 3.808 |
| Avg path length | 3.780 | 3.602 | 3.771 | 3.786 |
| Diameter | 6 | 6 | 6 | 6 |
| No. communities | 155 | 156 | 158 | 160 |

Analyzing the graph related metrics for *sPR*, they might superficially suggest that they only display minor differences, and thus supporting the idea that both graphs are in fact almost identical. However, this is not true, as clearly shown in Figure 5. We can observe on that figure that the graph produced using AICNET is slightly more connected at the graph periphery, thus supporting the inclusion supposition. A major difference can be seen by looking at the nodes representing the transport providers (shown in purple). With ICNET, the diameter of the nodes varies more than with AICNET. Note that the diameters are proportional to the *PageRank* coefficient. Hence, we could argue that AICNET with *sPR* has successfully hindered the rise of monopolies. This statement is further supported by the plots in Figure 2. Both the number of wins and the *PageR*-

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*ank* coefficients are flatten out in AICNET. Hence *sPR* is proven to be highly effective in hindering the rise of monopolies, while having no negative impact on the monetary values and other relevant metrics.

We obtained rather similar values of graph related metrics with *sCA*. However, as shown in Figure 4, we can observe different results than with *sPR*. The ICNET graph is by far more connected and there is clear evidence in the AICNET graph that at least two monopolies have risen, purple node at the top and the one at the right bottom part. Moreover, the distribution of the transport provider's wins and their associated *PageRank* coefficient are similar to power-law distributions, see Figure 3. Hence, this strategy does not hinder monopolies, rather it encourages their rise. Hence, we can conclude that *sPR* is a good strategy for hindering monopolies, while on the contrary, *sCA* is facilitating them.

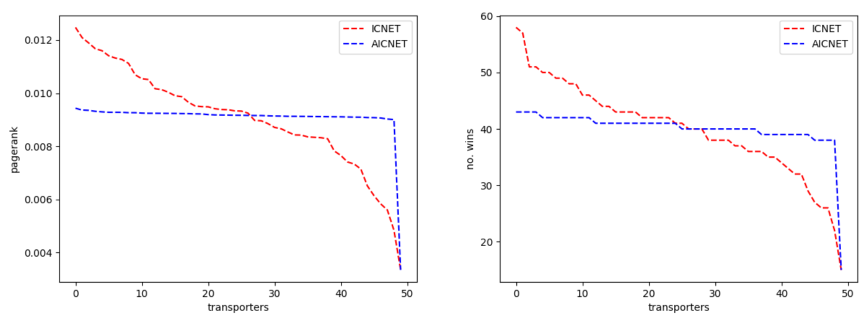


**Fig. 2.** Plots of results obtained by applying *sPR*. On the left side you can see the values of *PageRank* coefficient for each transporter, while on the right the total number of wins per each transporter is depicted.

## 5 Conclusions & Future Work

In this paper we proposed a new computational method based on CNA to augment the capabilities of a broker involved in multi agent freight transport negotiation. Our experiments have shown that using this approach the broker is able to apply negotiation strategies of social inspiration for gaining longer term benefits, like for example hindering monopolies and supporting agents with diverse transportation capabilities. Currently, our experimental strategies involved a single SNA metric. We plan to strengthen our results by considering strategies involving more metrics, possibly in larger scale experiments. Moreover, we plan to experimentally investigate in more detail the impact of several parameters onto the negotiation outcomes.

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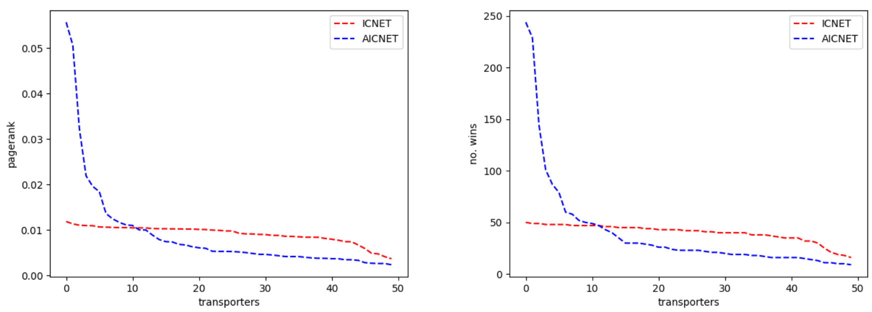


**Fig. 3.** Plots of results obtained by applying *sCA*. On the left side you can see the values of *PageRank* coefficient for each transporter, while on the right the total number of wins per each transporter is depicted.

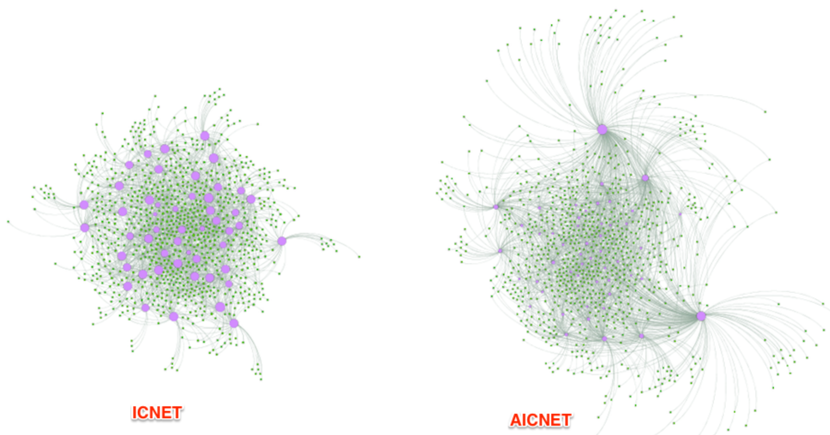


**Fig. 4.** Plots of social graphs results obtained by applying ICNET (left side) and AICNET with *sCA* (RIGHT SIDE). Green nodes represent cargo owners while purple nodes represent transport providers. The diameter of the nodes is proportional to their respective PageRank coefficient. For plotting we used *ForceAtlas 2* algorithm included in *Gephi*.

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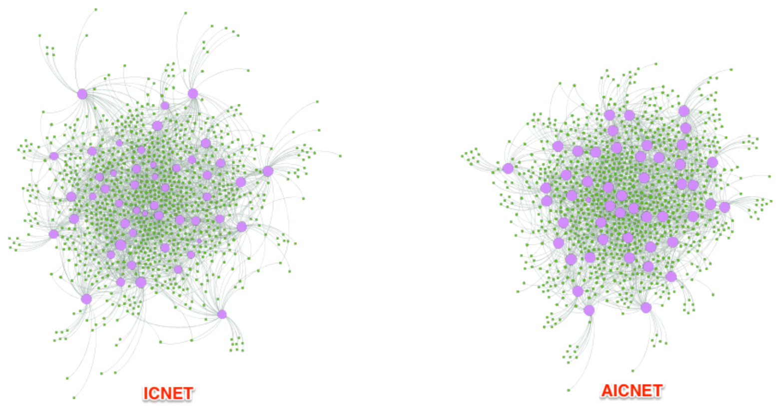


**Fig. 5.** Plots of social graphs results obtained by applying ICNET (left side) and AICNET with *sPR* (RIGHT SIDE). Green nodes represent cargo owners while purple nodes represent transport providers. The diameter of the nodes is proportional to their *PageRank* coefficient. For plotting we used *ForceAtlas 2* algorithm included in *Gephi*.

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