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A Practical Multiagent Model for Resilience in Commercial Supply Networks

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Abstract. As commercial supply chains grow into complex global supply networks, more and greater risks are introduced for cooperating and competing companies alike. These networks can be affected by events such as natural disasters, terrorism, and of late, economic downturn. Supply industry leaders, such as IBM, have announced a need for methods to identify and prevent risks in these ever-growing complex networks. Multiagent-based simulation lends itself perfectly to supply network modeling due to its autonomous nature. Our research illustrates a multiagent supply network formation technique using greedy supply agents and limited resource allocation. Using these formations, the resilience of each network is compared with others and assessed so that we may ascertain the characteristics of risky supply network structure. Our results show that an increase in relationship resources results in a more resilient network; however, as the amount of available resources increases, the risk of the most vulnerable agent in the network decreases by a smaller margin.

1 Introduction

The need for resilience in supply networks is a concern for many. During combat, the military is concerned because convoys and supply stations are highly susceptible to enemy attack and disruption [12, 9]. More recently, with the rough global economy, we are seeing businesses declaring bankruptcy and going out of business at an alarming rate; from the end of the year 2007 to the end of 2008, business bankruptcies rose 54%, and are continuing to rise[1]). These closures cause disturbances and possible breaks in supply networks, especially as the world's leading manufacturers, like in the automotive industry, are starting to fail. Other global factors such as terrorism and severe weather conditions also have been known to cause commercial supply networks to come to a halt [4, 9]. As the globalization of supply networks becomes more common, these networks also become more complex and thus increase the chances of global factors affecting larger number of businesses [4].

Methods such as just-in-time (JIT) inventory to improve efficiency in supply chain management have been geared towards making a company the most profit with the least amount of inventory on hand. This approach unfortunately creates

[1] `www.bankruptcyaction.com`

weaknesses in the supply network's reliability [9]. Since the terrorist attacks of September 11th, 2001 and the current downturn in the economy, efforts have shifted to try and improve reliability in supply networks [4].

Our long-term goal is to build dynamic agent-based model of these supply networks so that we may study how they handle disturbances: missing nodes, broken routes, order delays, etc. We hope to model both the current human-made supply networks, where all the decisions about who to buy from and what to buy are made by humans, as well as the emerging agent/human networks where some of these decisions are made by automated agents. This paper presents our first steps towards that goal. We use an agent-based model of human-formed supply networks, based on [6], to generate supply networks and analyze these networks to determine their resilience to various types of attacks. Our test results provide quantitive measures of the resilience of networks formed by humans given different capacities to form social ties.

1.1 Previous Research

IBM and several other sources have noted the importance of maintaining a reliable supply network [2, 9]. Several examples exist of major losses of profit and business due to supply chain disruptions. Because of this, there is a need to reconsider how supply networks are setup, as well as the processes involved in these networks.

Several examples exist of multiagent supply network formations as simulating the day to day operations of supply networks [13, 10], but neither assess the reliability of the network as a whole. As recent research has shown, however, complex networks need to cooperate with other agents in the network, even with competing agents to some extent [5]. Using the customer lifetime value equation developed by V. Kumar, Chuan and Yun developed a multiagent market that models how consumers interact with suppliers [6, 3]. In this paper we will extend this method to an entire supply network.

A topological method for developing a reliable supply network for military settings was developed to ensure that suppliers could get goods to troops, even in the event of random or planned attacks [12]. This model resulted in a high level of redundancy between suppliers and their consumers. However, as the authors of [12] noted, such large amounts of interconnectivity are not practical in a commercial market. In order to accrue decent profit and maintain a competitive market, partnerships must be selective. Making such a large amount of connections and trade agreements takes a considerable amount of management time, and often decreases the quality of business relationships and profit. Reducing the similar property of interaction costs in auctions was recently studied [15]. Agents in our model consider these costs in network formation, and the reduction of these costs will undoubtedly be an incentive in our future work. This behavior of resource management can also be related to personal social management [2][13] [10], and will be compared throughout the paper. This paper presents a topological approach similar to that of [12], but geared towards identifying resilient network structures in a competitive, commercial market.

Resilience, as opposed to reliability, refers to a network's ability to respond to attacks or disabled nodes.

The multiagent community has studied the problem of how automated agents should make decisions in is supply chain, especially in the context of the Trading Agent Competition Supply Chain Management (TAC SCM) game[2][1, 8]. However, we are interested in studying the reliability of human-formed networks which we assume to be static, for now. In our future work we will expand the model to include dynamically trading agents as well as allow agents to dynamically find new partners when necessary.

2 The Model

We are interested in investigating the resilience of supply networks that are formed by selfish agents. We start by identifying the various types of agents in a supply chain (section 2.1). We then explain the various types of ties that can exist between these agents (section 2.2) and use proven models of supply-chain tie formation to create our networks (section 2.3). Finally, we formally describe how we measure resilience in a supply chain network.

2.1 Agent Composition

We model five different types of business agents: suppliers, manufacturers, distributors, retailers, and consumers. Each agent's identity determines who they interact and exchange product with. At any time, an agent has one of two roles: a local supplier or a local customer. A local supplier is one who is supplying a product while a local customer is one who is purchasing a product. All agents, except for the suppliers and the consumer, can take on both of these roles. The suppliers can only take on the supplier role, and the consumer can only take on the customer role. A very simple supply chain is shown in figure 1. Along with their roles, each agent also has a number of properties that describe its capabilities. Table 1 shows these properties along with their descriptions.

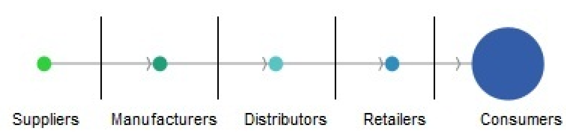

Fig. 1. Organization of a supply network.

Once an agent (except for suppliers) is initialized, their price, profit, reliability, quality, supply and demand are set to zero. The values stay at zero until

[2] `http://www.sics.se/tac/page.php?id=13`

Table 1. Properties of Business Agents

Price	The selling price of this agent's product
Quality	Quality of this agent's product
Reliability	Reliability of this agent's product
Profit	The amount of the selling price that goes towards profit
Customer List	A CLV-ordered list of this agent's customers
Score List	An ordered list of desired suppliers
Supply	The amount of product coming in to this agent
Demand	The amount of product desired by this agent
Relationship Resources	Amount of relationship resources available to this agent (discussed in section 2.2)

relationships are formed. Suppliers' price is set to the raw good price, and their profit, quality, reliability, supply and demand are set randomly. Their customer and score list is set to empty until negotiations begin, which we discuss later in section 2.3. Relationship resources are set by the user before the model is initialized. Notice that since supplier and consumer agents only take on one of the two roles available, they only have the properties necessary to satisfy these roles. That is, suppliers do not have a score list and consumers do not have a customer list, price or profit.

The number of agents can vary from run to run, to provide varying network structures. We only model one consumer agent. The reason for this is that supply networks usually make relationships based on contracts, whereas consumers often make one-time purchases. The interaction between an individual consumer and a market is discussed in [3], and our work could be extended to include that research. However, the focus of this paper is on resilience of the supply network so we opted not to model individual customer behavior.

Relationships are formed based on maximization of each agent's utility. This utility function differs depending on the current role the agent is playing. If an agent is in the supplier role the we use Equation (2) as the utility function. If an agent is in the customer role, the agent with the highest combination of price, reliability and quality wins. The determination of how strong the relationship will be, and what this strength implies, is discussed in the next section.

2.2 The Importance of Ties

Managing relationships between business agents can get costly depending on the number and strength of each tie. In social relationships, on average, the human brain can manage 150 strong relationships determined by age, frequency of interaction, emotional attachment, reciprocity, and kinship [11]. This limited amount of relationship resources can be reflected to supply network management in different units, like time and money [7]. In commercial networks the proper distribution of these limited relationship resources among an agent's strong and weak ties is critical for maintaining high profitability and reliability.

The definitions of strong and weak ties are very similar for social and supply networks [7]. In commercial supply networks, strong ties indicate a day-to-day relationship. Businesses linked by strong ties engage in frequent orders and shipments, thus undergoing more reliable and predictable transactions as a result. They can also show a parallel in business practices and ideas. Businesses linked by weak ties acknowledge each others' product needs, but are not regularly involved in transactions. These ties exist as bridges for possible future needs. If a weak tie is made, these transactions will not be as reliable, predictable, or cheap in price as those between two businesses with a strong tie due to the unfamiliarity and higher cost in planning.

In our model, business agent relationship resources are a user-controlled variable which allows us to set up different kinds of networks. An agent establishes relationships with other agents by using these resources. Relationships in the simulation can run from a range of 0 to 10, where 0 is a nonexistent relationship and 10 is the strongest relationship. Relationships in the range of 0 – 4 are considered weak ties and are represented by a thin gray directed arrow. Relationships from 5 – 10 are considered strong and are represented by a thick black directed arrow, as shown in Figure 2. For example, if an agent has 5 available relationship resources, it may form one strong relationship of 5 with a customer, or it could form 5 weak relationships of 1 with 5 customers. These relationships form during the negotiation stages of network formation.

2.3 Communication and Negotiation

Once the agents are initialized, communication between the different tiers of the network begins. A weak tie is temporarily established between all the agents to exchange product and company information, so each agent playing the customer role can evaluate their potential suppliers. Customers assign each supplier a score using the formula

$$\text{quality} + \text{reliability} + \left(\frac{\text{mean price} - \text{price}}{\text{price}} \times 100\right), \tag{1}$$

where quality, reliability and price are as defined in Table 1. This formula was established to ensure that if a price is below the mean price of all suppliers, a negative score is produced, unless quality and reliability are enough to offset it. These scores are then translated to desired relationship strengths, in the range of 1– 10. These desired relationships are stored in the score list agent property.

After the communication stage, negotiations begin. The first stage involves the customer agents sending their supplier assessment to each supplier. Generally, this information is not broadcast like this, but since there are no past interactions to evaluate, suppliers need a way to know how customers assess their service.

Suppliers then assess the customers using V. Kumar's [6] customer lifetime value formula

$$CLV = \sum_{y=1}^{T_i} \frac{CM_{i,y}}{(1+r)^{\frac{y}{f_i}}} + \sum_{i=1}^{n} \frac{\sum_m c_{i,m,l} \times x_{i,m,l}}{(1+r)^{i-1}}, \tag{2}$$

where CLV stands for the customer lifetime value of the current agent, T_i is the predicted number of purchases for customer i in a given time interval, $CM_{i,y}$ is the contribution margin of customer i during purchase y, r is the discount rate, f_i is the predicted purchase frequency for customer i, n is the number of years predicted for the relationship, $c_{i,m,l}$ is the marketing cost for customer i in market m during year l and $x_{i,m,l}$ is the number of other suppliers customer i is in a relationship with in market m during year l.

This formula is reduced in our experiments, since there is no past purchase history, the discount rate (r) is zero. Also, since there is only one consumer base, there is only one channel. The reduced CLV formula is

$$CLV = \sum_{y=1}^{T_i} CM_{i,y} - (c_i \times x_i). \tag{3}$$

The number of predicted purchases a customer makes (T_i) is determined by their desired relationship with the supplier. The marketing cost (c_i) is the maximum possible relationship value (10 for this model) minus the desired relationship with the supplier. The current number of other suppliers (x_i) is the count of all those with higher desired relationships. The corresponding CLVs for each customer are stored in the supplier's customer list. Only those with positive CLVs are kept in this list. Since negative values indicate a predicted profit loss, they are not beneficial to the supplier. These CLVs are then translated to desired relationship values based on the mean CLV and the number of resources available (similar to the customer's relationship conversion described above).

Once suppliers calculate their desired relationship, they ask their customers for this relationship. Customers receive the request, and first see if there are enough relationship resources available to accept the proposed relationship. If there are, the relationship is accepted and formed. However, if the relationship would cause the customer to exceed their available relationship resources, a pruning process ensues. The inquiring suppliers score is compared with the score of those suppliers who are currently in a relationship with the customer. Those suppliers who are ranked lower have their relationship reduced until there are enough relationship resources available for the inquiring supplier, or until the relationship dies. If there are still not enough relationship resources to include the inquiring supplier, the proposed relationship is reduced until the relationship can be made. The weight of this relationship determines how much product, by percent, is sent to the customer. For example if 50% of a suppliers resources are allocated to a customer, that customer will get 50% of the supplier's product.

When the negotiation process has ended, the customers calculate their price, reliability and quality based on the weighted average of all its suppliers. Their demand and initial supply are set to the total number of incoming product from their suppliers. This negotiation process is repeated down to the consumer agent.

Once the consumer agent is reached, the supply/demand ratio is set to 1 initially, since the supply is equal to demand. The importance of this value is discussed section 2.4. The entire negotiation process described is highlighted in Table 2.

Table 2. Steps for Agent Negotiation

Step	Task
1	Customers evaluate suppliers
2	Customers send evaluations to suppliers
3	Suppliers evaluate customers using CLV
4	Suppliers request relationship with customers
5	Customers accept, deny, or reduce relationships accordingly

We note that this negotiation process sometimes results in isolated agents who have no suppliers or customers. This is the result of a saturated market, and the isolated agents are those unfit for competition. Figure 2 shows the result of a completely formed network using the methods described above.

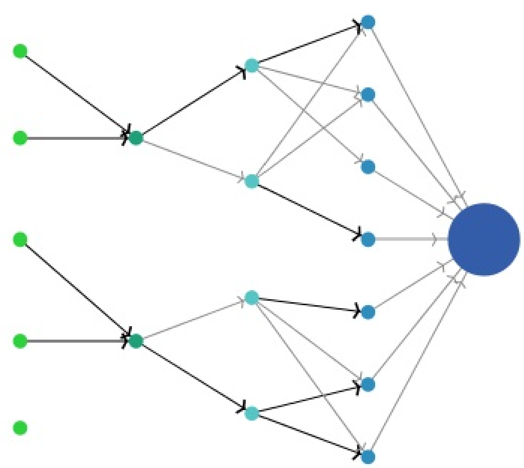

Fig. 2. Complete network formation after agent negotiations.

2.4 Resilience

After the network is established, it is tested for resilience. Testing for resilience simulates the attack or disabling of a single agent. We then measure the effect of its removal on the entire supply network. The method begins by eliminating an agent and its relationships. The effects of this elimination are then propagated down the network until the consumer is reached. The resulting supply is compared to the consumer's demand and measured as the supply/demand ratio. That is, the **supply/demand ratio** of agent i in network N is given by

$$r_i(N) = \frac{\text{amount of product arriving to the consumers in } N - i}{\text{amount of product demanded by the consumers in } N}. \tag{4}$$

The lower the ratio, the harder it will be for the network to recover from the attack. The agent is then placed back in the network, and the network is returned to normal. Once all agents have been tested for resilience, the agent with the lowest $r_i(N)$ is saved along with its corresponding ratio value. We define the **resilience** of a network as the supply/demand ratio of the agent with the lowest supply/demand ratio in the network. That is, the resilience of network N is given by

$$r(N) = \min_{i \in N} r_i(N). \tag{5}$$

We also save the the **variance of the supply/demand** ratio across all agents, which we denote as $\sigma^2(r_i(N))$. A higher variance in the supply/demand ratio means that there are some nodes which are much more important to the well-being of the supply network than others. Thus, these nodes might be more at risk for an attack by an enemy.

3 Results

The results gathered for this experiment are from over 400,000 different network structures with varying number of agents, relationship resources, and raw good price. Agents were varied (1 – 15 of each) to see how different relationships and market competition would affect resilience. Relationship resources were varied (5, 10, 20, and 50) to see how selectivity and the number of relationships each agent has affect resilience. Raw good price was varied to see if more expensive products, where the cost of relative distance is relatively small compared to product cost, affect network formation and resilience. Figures 3–5 show the difference in network formation and resource allocation with different variable settings.

Figure 3 shows two networks with varying numbers of agents. Though the total number of agents in the network is equal, the networks formed are very different, and undoubtedly result in different resilience factors. Figure 4 illustrates the critical difference between resource availabilities. The network with 50 resources clearly results in a more connected network, and, in this particular case, a more resilient network. Figure 5 shows how the price of the product does not greatly impact the network structure. This example also suggests that locality of customers may matter less as product price increases, but it is not significant.

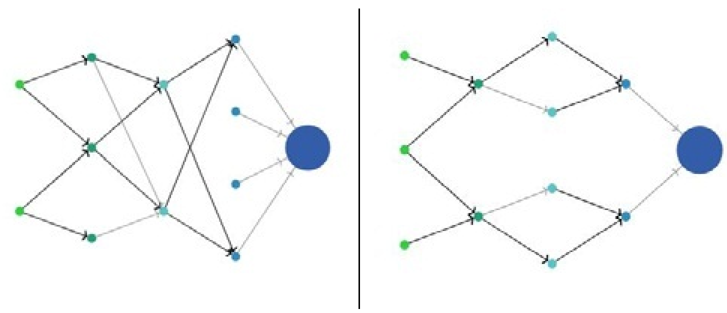

Fig. 3. Varying the number of agents in supply networks

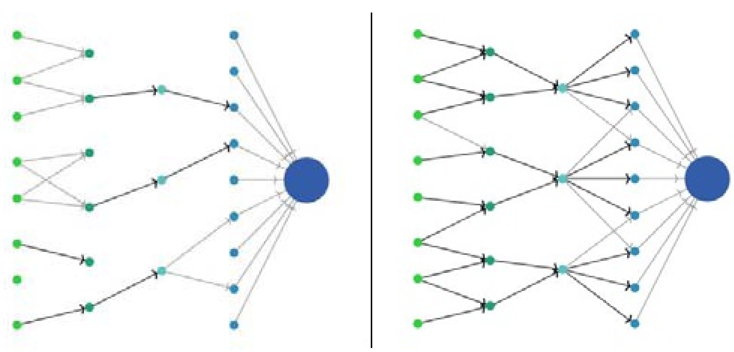

Fig. 4. 5 Relationship Resources vs. 50 Relationship Resources

Our experiments focus on overall network resilience, on the variance of the individual risks of each agent in a supply network, and on the lowest of the individual risks of each agent in a supply network. We pay special attention to the structure with least available resources to each agent since we are interested in resilience in limited-resource commercial domains.

3.1 Model Validation

Our test results show a clear distinction between the most and least resilient network structures, which validates the supply network formation methods implemented by our model. The network structure that produced the least resilient

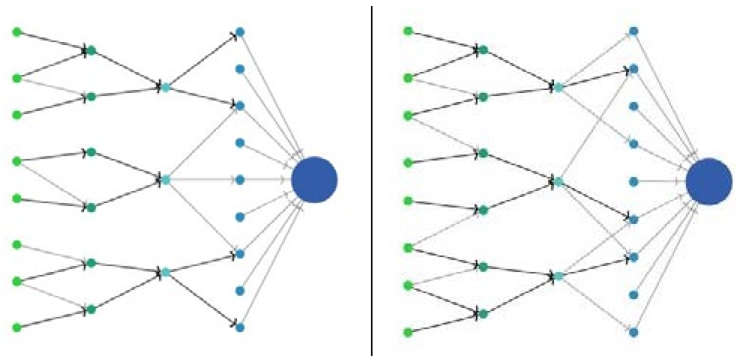

Fig. 5. Raw good price of 5 vs. 1000

supply network was that of a single, simple supply chain. This is true for all resources and raw good values. Since removing any of the agents from a simple supply chain results in complete disruption of the network, it is easy to understand why this is the least resilient network. Intuitively, the most resilient network is practically 15 separate supply chains directed to one consumer. If an agent is removed, only one of the supply chains is disrupted, leaving 14 other paths for goods to flow to the consumer.

Another result that validates our model with the results of [12] is shown in Figure 6. This chart also confirms that our model complies with the statement that redundancy increases network resilience [9]. This chart will be further discussed in section 3.2.

3.2 Analysis of Results

The first measure we look at is the variance in supply/demand ratio $\sigma^2(r_i(N))$ for a given network N. A high variance indicates that some agents are far safer from risk or far more at risk. High variance could leave a supply network more susceptible to planned attacks. The most imbalanced networks in our test results occurs when there is a large number of suppliers and only one of each other agent. In it, the agents that incur the least amount of risk are the suppliers, while removing any agent from the other tiers would result in a complete disruption. The least imbalanced network we found is also the most resilient network of 15 supply chains directed to one customer. It is the least imbalanced for the same reasons that give it high resilience: there are several supply chains, each of which has close to equal resilience.

We also learned that varying the number of relationships resources affects network resiliency. Figure 6 shows how as we increase the number of relationship resources the supply/demand ratio of the most vulnerable agent generally increases. Figure 7 shows how the variance of the supply/demand ratio $\sigma^2(r_i(N))$ decreases as we increase the amount of relationship resources. We note that a

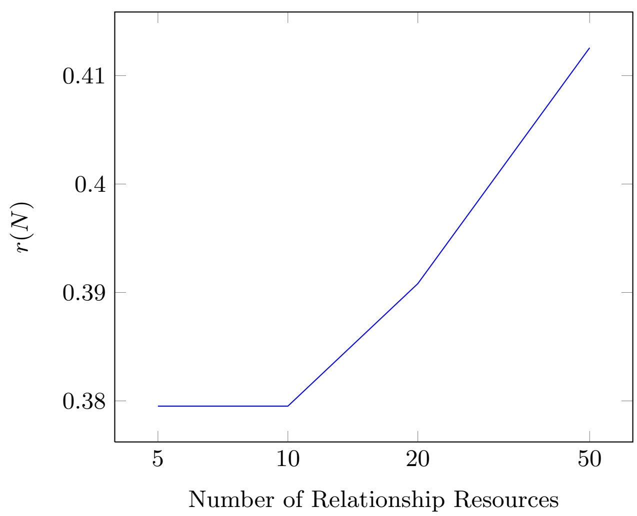

Fig. 6. Chart illustrating the average resiliences $r(N)$ of the networks formed using varying relationship resources.

slight anomaly occurs in Figure 6 when agents have 10 available resources. This could be due to the semi-random generation of the market when the agents are initialized. In general, however, these charts show how the resilience of a network increases as available relationship resources increases, as expected. This is because each agent has more opportunity to divide its product and create fewer dependencies in the supply network. It is also important to note that the most vulnerable node of a network with 5 relationship resources is only slightly lower than that of one with 50 relationship resources. Thus demonstrating that while having unlimited relationship resources may help slightly; it would probably not be worth the cost of having to manage all of the relationships.

Figure 8 shows that the number of agents involved in a single consumer based network with only 5 relationship resources available affects the network up to a certain point as well. Specifically, we see that the variance in supply/demand ratio is high for small numbers of agents (up to 10) but then drops after that and stays at nearly the same value for more than 10 agents. This happens because as more agents are involved in a single network, then more sub-networks are formed, thus increasing resilience. Another anomaly occurs when the total number of agents is 10. The variance is considerably higher. This is probably due to the type of structures that can be formed with 10 agents, or again, the semi-randomness of the agent initialization.

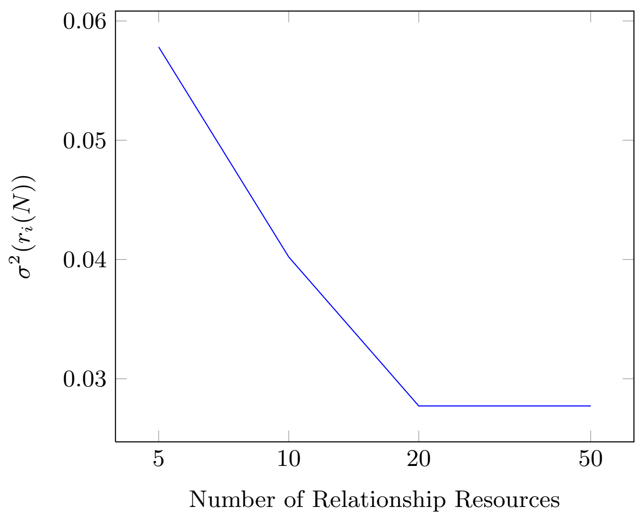

Fig. 7. Chart illustrating the average variances in the supply/demand ratio $\sigma^2(r_i(N))$ of the networks N formed as relationship resources vary.

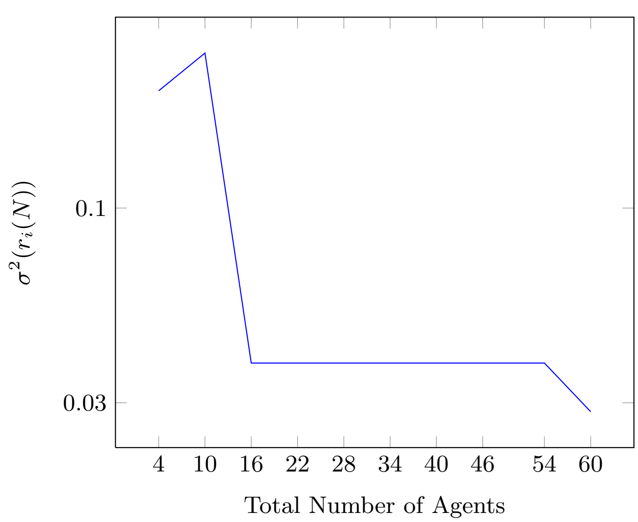

Fig. 8. Chart illustrating the average variances of the supply/demand ratio as the size of the network increases.

4 Conclusion and Future Work

The selfish-agent limited-resources supply network formation implemented by our model has produced results that are confirmed by previous research [12]. We have shown that the number of relationship resources available to business agents directly affects the resilience of the network. We have also shown that as relationship resources increase, the risk of the most vulnerable agents shows diminishing returns. Though the relationship resources in this experiment can be interpreted as any combination of time, money or any other overhead needed to maintain a contractual relationship, there is no doubt these additional relationship resources increase the cost to agents in a commercial supply network. Our results show that it is not cost effective to increase these relationship resources past a certain point (in Figure 6, this point is 20 relationship resources). These factors must be considered when constructing a commercial supply network.

The analysis of all the network topologies identify networks with low and high resilience. Although available resources seem to have the biggest impact on resilience, different structures also have a substantial effect on resilience. More specifically, the more opportunities agents have to form relationships, the more resilient the network. These observations will be useful in our future work.

While our current model does not fulfill the need of making supply networks more resilient, it identifies possible weaknesses in commercial supply networks and illustrates the reasons for these weaknesses. This is a significant step towards a solution. Our model also implements a new method for forming multiagent supply networks using current supply network management techniques [9][6][3]. The network formation and results from testing resilience will be improved and expanded in a number of different ways.

The greedy agent limited resource network formation method implemented in this paper will be used to create a dynamic market in which agents are actively trading goods. We will combine this model with our previous study of robustness, responsiveness and dynamism of supply networks during attacks [14]. This addition will give more intuition as to how the resilience of a particular network structure affects the way agents trade with each other and how trading agents will respond to the disruption of their supply network. The next step will be to offer certain incentives to agents and see if they cause the agents to form resilient supply networks.

Our research and results presented in this paper are a good foundation for developing methods that cause competing agents to be cooperative, but still selfish, as suggested by supply network management research [5].

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