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An Agent-Based Network Analytic Perspective on the Evolution of Complex Adaptive Supply Chain Networks

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Abstract – **Supply chain networks of modern era are complex adaptive systems that are dynamic and highly interdependent in nature. Business continuity of these complex systems depend vastly on understanding as to how the supply chain network evolves over time (based on the policies it adapts), and identifying the susceptibility of the evolved networks to external disruptions. The objective of this article is to illustrate as to how an agent-based network analytic perspective can aid this understanding on the network-evolution dynamics, and identification of disruption effects on the evolved networks. To this end, we developed a 4-tier agent based supply chain model and simulated the evolution of the supply chain network based on two different partner selection scenarios. Network-evolution diagrams, change in structural characteristics over time and effect of disruptions on the critical nodes for the two different partner selection scenarios are presented. The network-evolution characteristics (social network analysis based node/network level metrics) over time have been quantified and the vulnerability of the evolved networks, due to disruptions that result in reduction in production of the network's critical producer node, has been identified.**

Keywords – **Complex adaptive supply network, supply chain, adaptive systems, network evolution, structural characteristics of supply network, agent-based model**

I. Introduction

Today's supply chain networks are complex and highly interdependent in nature [1]. The inter-dependency among the entities, outsourcing across international borders, and partner selection based on competitive merits have resulted in dynamic evolution of these complex adaptive systems [2]. A complex adaptive supply chain network is a collection of entities that exchange materials or information so as to maximize their individual revenue/goals [3]. Hence, the interactions among entities in the supply chain network determine the evolution of the network and its response to disruptions [4].

With the supply chain network structure being the fundamental aspect of risk management [5], it is hence critical to study the evolution of the network structure over time [6]. Modeling supply chain network as complex adaptive systems and investigating the supply chain network's structural characteristics via social network analysis [7] provides a better opportunity to achieve our objective – to understand as to how does a supply chain network evolves over time (based on the policies it adapts), how does the network characteristics change with time, how does this change affects the network if there is a disruption, and identify the risk-related-vulnerability of the evolved networks to external disruptions. In particular, understand as to how the supply chain network characteristics (Network density, In-degree centralization, Out-degree centralization and Maximum out-degree centrality) vary over time and how varying degrees of disruption of the critical producer node affects each network after their evolution.

To this end, we developed a 4-tier agent-based supply chain network model that models the laptop manufacturing network. The supply chain network includes pre-defined entities of 6 suppliers, 4 producers, 8 distribution hubs and 20 retailers. In our model, Quality of Service (QoS) was used as the performance measure. If the quality of service falls below the expected delivery time, the agent will search for alternative partners. The results on the comparative performance of the 2 switching scenarios ('QoS' based switch or 'Most Inventory' based switch), the evolution of the networks and variation in the network characteristics over time for each scenario are presented.

II. Methodology

A. Agent-based supply chain network modeling

Agent based modeling in supply chain involves entities, called agents, which exchange materials and information with one another in a simulated environment. The 4-tier agent-based supply chain model used in our study models the laptop manufacturing network. The supply chain network includes pre-defined entities of 6 suppliers (2 different sources for the supply of each of the 3 laptop component), 4 producers (that assemble a laptop using the 3 components with a 'bill of materials' of 1:1:1), 8 distribution hubs and 20 retailers.

The supply chain network topology at the start-up of the simulation, with the material exchange details between the nodes, is shown in Figure 1. The color and the thickness of the bridges show the varying degrees of material-exchange among the nodes. Producer agents are the direct downstream entities in our supply chain network. In our model, producer agents order and receive the laptop components from the suppliers, assemble them and then deliver the assembled laptops to the distributors. Distributor agents will then send these laptops to the retailer agents. Agent's attributes like the inventory level and the amount of goods the agent has shipped in/out describe its states at any given instant of time. These attributes are dynamic and hence, change over time

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responding to shipment from other agents. Here it has to be noted that all agents use the distance as a measure to choose their upstream supplier. The (s, S) inventory policy is used in the model. Agent's parameters like fleet size and production capacity determine the ability of an agent in producing and delivering the goods to other agents.

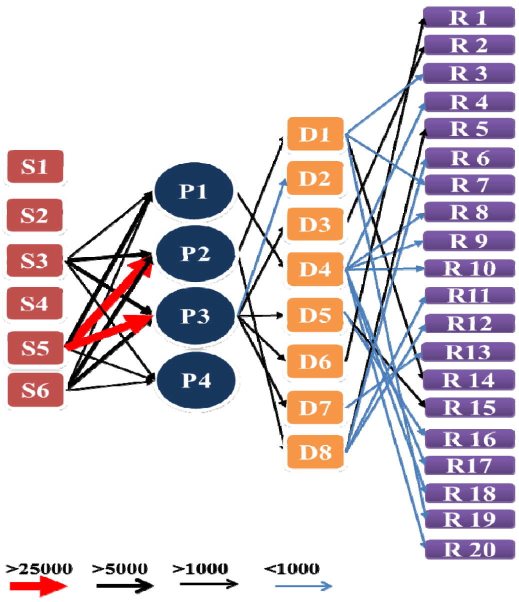

Figure 1. Supply chain network topology used in the study;
S – Suppliers, P – Producers, D – Distributors and R – Retailers

Interactions among the agents occur via the communication mechanism, in the form of "messages", which may either be related to an order or a shipment. These messages trigger events that will then alter the agent's attributes, resulting in the agents adapting to the requirements. This adaption mechanism then propagates downstream throughout the supply chain network. The objective of each agent, hence, is to satisfy the demand of its downstream agents.

B. *Network characteristics of the supply chain*

The node-level and network-level metrics for the agent-based supply chain network structure used in our study were calculated based on the literature [7], and the values are summarized in Table I. From Table I, it can be seen that the network used in our study is fairly dense, with more ties to the downstream nodes. The network has a low in-degree centralization of 0.0556, compared to its out-degree centralization of 0.1697. This shows that the network used in our study is generally balanced, with many nodes receiving materials from approximately the same number of sources. However, there are some nodes that provide more materials to many of the downstream nodes.

C. *Quality of service check and the switching scenarios*

In our model, Quality of Service (QoS) was used as the performance measure. QoS was measured by the average delivery time of materials of the respective agents. QoS values of each agent were constantly updated during the simulation. Producers, distributors and retailers have access to the quality of service of all suppliers, producers and distributors respectively.

If the quality of service falls below the expected delivery time, the agent will search for alternative partners. This switch on seeking alternative partners shall be either (i) 'QoS' based switch, or (ii) 'Most Inventory' based switch. For switching via 'QoS mode', a new agent was randomly selected from a pool of agents with better quality of service in the same tier i.e. shorter delivery time than the current one. For switching via 'Most Inventory mode', the agent with the most inventory and has a better quality of service than the current agent was selected.

TABLE I. Network characteristics of the supply chain used in the study based on the literature [7]

Metric	Formula used	Values
Network Density	$\frac{\text{Number of Ties in the Network}}{\text{Network Size} \times (\text{Network Size-1})}$	0.0285
Average In-Degree Centrality	$\text{In-Degree} = \frac{\sum \text{In-Degree Centrality}}{\text{Network Size}}$	2.8445
Average Out-Degree Centrality	$\text{Out-Degree} = \frac{\sum \text{Out-Degree Centrality}}{\text{Network Size}}$	2.8445
Maximum In –Degree Centrality	$\text{Max}(\frac{\text{Number of Ties to Upstream Nodes}}{\text{Network Size-1}})$	3
Maximum Out-Degree Centrality	$\text{Max}(\frac{\text{Number of Ties to Downstream Nodes}}{\text{Network Size-1}})$	7
Centralization (In-Degree)	$\text{In-Degree} = \frac{\sum (\text{MAX InDeg Centrality- InDeg Centrality})}{(\text{Network Size-1})(\text{Network Size-2})}$	0.0556
Centralization (Out-Degree)	$\text{Out-Degree} = \frac{\sum (\text{MAX OutDeg Centrality- OutDeg Centrality})}{(\text{Network Size-1})(\text{Network Size-2})}$	0.1697

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D. Simulation experiments

Setting a fixed seed to simulate reproducible runs, the simulation trials were performed for a period of 2 years. Service checks for satisfactory performance were conducted every 3 months. A control run whereby no switching occurs was also performed, to be used as the baseline scenario for comparing the performance of the two switching scenarios as well as to understand the evolution of the network structures for these scenarios.

The total amount of goods received at the retailer's level was used as a performance measure to determine and compare the performance of the various scenarios. The next section will present the results on the comparative performance of the 2 switching scenarios, the evolution of the networks and variation in the network characteristics over time for each scenario.

III. Results And Discussion

A. Evolution of the supply chain network

The variation in total production at the retailer's level for different scenarios, over time, is shown in Figure 2. From the figure, it can be inferred that for the first 13 months, 'QoS' based switching results in higher production when compared with other scenarios. However, from then on, till 24th month, 'Most Inventory' based switching results in higher production.

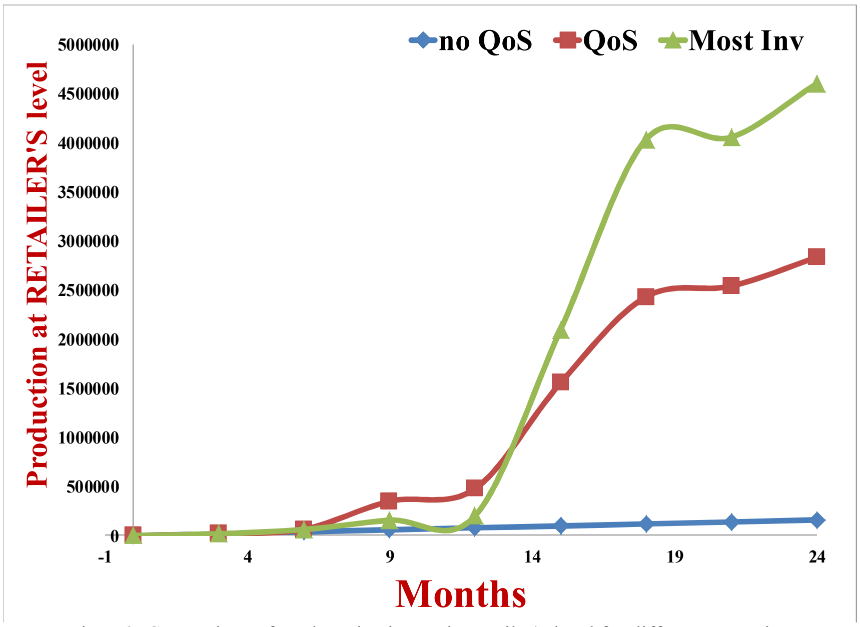

Figure2. Comparison of total production at the retailer's level for different scenarios

From Figure 2, an obvious inference is that throughout the simulation period of 24 months, 'QoS' and 'Most Inventory' based switching achieve better performance than 'No QoS'. The evolutions of the supply chain network over time, based on the switching algorithms used, are different as shown in Figure 3-6. These changes in the network structure have been further studied using the following 4 parameters: Network density, In-degree centralization, Out-degree centralization and Maximum out-degree centrality, as described in Table 1. The network diagrams for 'QoS' and 'Most Inventory' based switching for the following months – 6, 12, 18 and 24 – are shown in Figure 3-6 respectively.

From Figure 3, it can be seen that the total production for the 6th month (3 months after the activation of the service check and switching partners if the offered service is not satisfactory) is almost similar in both the scenarios, however, with different network structures. The network structure for 'QoS' based switching appears to be more balanced, utilising most of the agents in the network. 'Most Inventory' based switching, on the other hand, has fewer active agents who send out or receive goods in the network. Considering the 12th month (Figure 4), the total production for 'QoS' based switching more than doubles the amount when compared with 'Most Inventory' based switching. 'QoS' based switching supply chain network engages all 4 producers while 'Most Inventory' only engages 2 out of the 4 producers in the network.

For the network structure corresponding to 18th month (Figure 5), 'Most Inventory' achieves a much better performance than 'QoS'. A distinct difference in the network structure is that only 1 producer is active in the production for 'Most Inventory', whereas 3 out of 4 producers are still active for 'QoS'. Another key difference is that 15 out of 20 retailers are active for 'Most Inventory', whereas only 8 retailers are active for 'QoS'. For the network structure corresponding to 24th month (Figure 6), 'Most Inventory' continues its superior performance over 'QoS' (1.6 times higher). 5 out of 8 distributors are active in the network for 'QoS', while only 2 out of 8 distributors are active in the network for 'Most Inventory'.

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The varying degrees of evolution in the supply chain network topology based on the switching preferences are clearly evident from Figure 3-6. The initial stages of the evolution shows more balanced topology with even distribution of goods among the agents with only a considerable increase in performance when compared with 'no QoS' scenario. However, with time, there is a remarkable increase in total production for 'QoS' and 'Most Inventory' based switching. The supply chain networks tend to focus the production and delivering of goods to a few central agents (producers and distributors in particular), that demonstrate a superior service over time.

This highlights the self-optimization of the network, in selecting the most-apt agents by the downstream entities, based on the switching scenario considered. 'Most Inventory' takes a longer time to demonstrate a substantial improvement in performance as compared to 'QoS', which shows considerable improvement quickly. However, 'Most Inventory' based switching is able to establish its ability to sustain the superior performance with its counterpart.

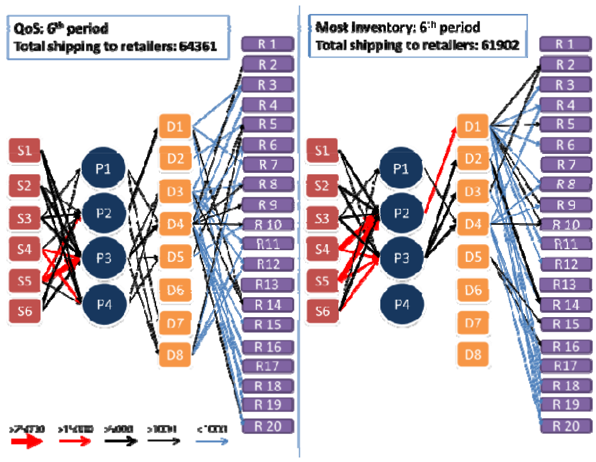

Figure 3. Network topologies for 'QoS' and 'Most Inventory' based switching for 6th month

The varying degrees of evolution in the supply chain network topology based on the switching preferences are clearly evident from Figure 3-6. The initial stages of the evolution shows more balanced topology with even distribution of goods among the agents with only a considerable increase in performance when compared with 'no QoS' scenario. However, with time, there is a remarkable increase in total production for 'QoS' and 'Most Inventory' based switching. The supply chain networks tend to focus the production and delivering of goods to a few central agents (producers and distributors in particular), that demonstrate a superior service over time. This highlights the self-optimization of the network, in selecting the most-apt agents by the downstream entities, based on the switching scenario considered. 'Most Inventory' takes a longer time to demonstrate a substantial improvement in performance as compared to 'QoS', which shows considerable improvement quickly. However, 'Most Inventory' based switching is able to establish its ability to sustain the superior performance with its counterpart.

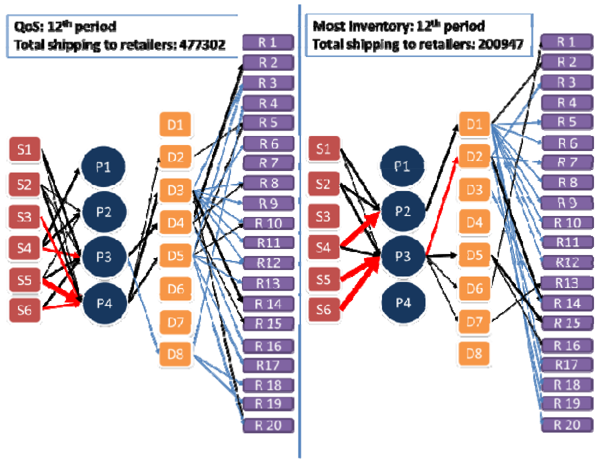

Figure 4. Network topologies for 'QoS' and 'Most Inventory' based switching for 12th month

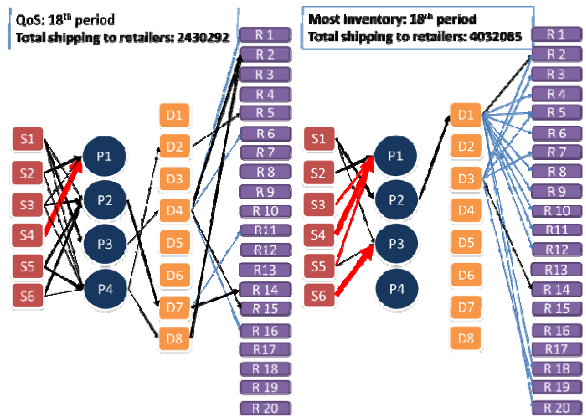

Figure 5. Network topologies for 'QoS' and 'Most Inventory' based switching for 18th month

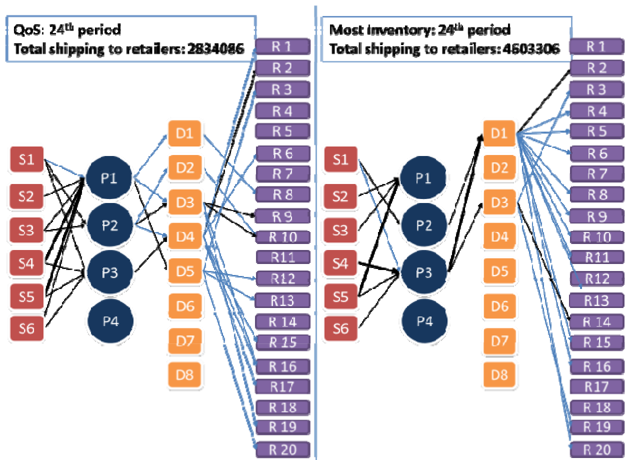

Figure 6. Network topologies for 'QoS' and 'Most Inventory' based switching for 24th month

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B. *Change in network characteristics over time*

The change in network characteristics (Network density, In-degree centralization, Out-degree centralization and Maximum out-degree centrality) over time is shown in Figure 7-10. From Figure 7, it can be observed that 'QoS' based switching generally results in a higher network density than 'Most Inventory' based switching. This suggests that there are more linkages in the network, and that there are a larger proportion of agents who deliver goods to many agents at a particular period of time for 'QoS' based switching.

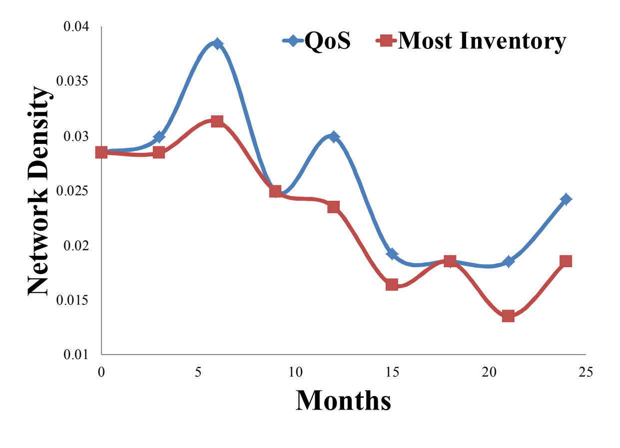

Figure 7. Variation in 'Network Density' over the simulation period

Across the simulation period, both scenarios show a general trend of a decrease in network density. This implies that the networks become less complex, with a decrease in the number of linkages in the networks over time. 'QoS' and 'Most Inventory' based switching have similar In-degree centralization throughout the simulation period (Figure 8). This implies that both scenarios show a similar trend of having a comparable proportion of central sources that provide materials to the other nodes at the front tier of the network.

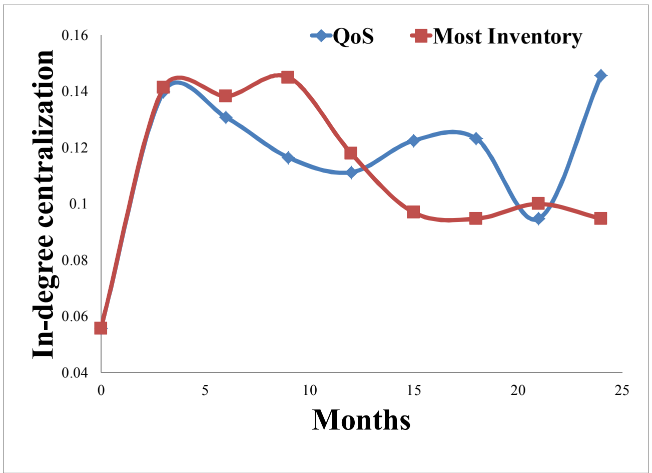

Figure 8. Variation in 'In-degree centralization' over the simulation period

However, 'Most Inventory' based switching has a generally higher value of Out-degree centralization (Figure 9) and Maximum out-degree centrality (Figure 10) throughout the simulation period. This suggests that the network of 'Most Inventory' based switching relies more heavily on a few central agents in delivering the laptops to the other agents downstream.

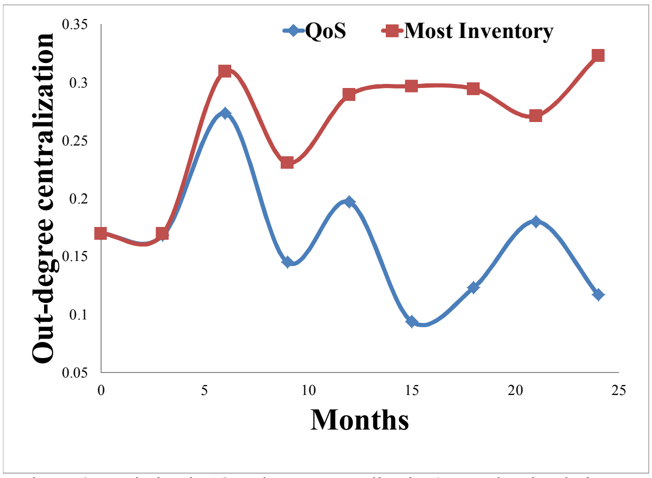

Figure 9. Variation in 'Out-degree centralization' over the simulation period

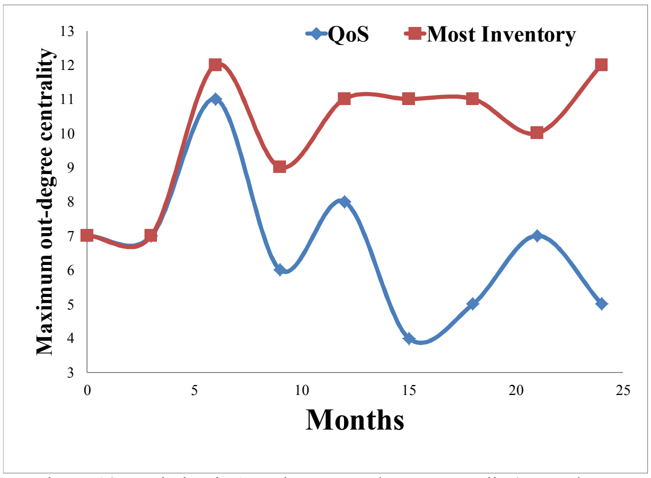

Figure 10. Variation in 'Maximum out-degree centrality' over the simulation period

C. *Impact of a disruption on the evolved networks*

In an effort to understand as to how varying degrees of disruption of the critical producer node affects each network after their evolution, we introduced hypothetical disruptions in both the networks that evolved through 'QoS' and 'Most Inventory' based switching. The disruptions were introduced from 24th month onwards, for a period of 30 days, reducing the % production capacity of the critical producer nodes by 5, 10, 15, 20, 25, 50 and 100%.

From our results, it is evident that the risk associated with the network that has evolved through 'Most Inventory' based switching is three-fold when compared with its counterpart that has evolved through 'QoS' based

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switching. With 'QoS' based switching resulting in a more balanced network, for a reduction in production of the critical producer node by 50%, there is only a 38% reduction in overall production of goods at the retailer's level. Whereas in comparison, similar effects are experienced by the network that has evolved through 'Most Inventory' based switching even for a 15% reduction in production of its critical producer node. The recovery time is also much longer, 14 weeks.

IV. Conclusion

In this work, we have demonstrated as to how the partner-selection at the microscopic level by the individual agents affects the evolution of the network, its structural characteristics and the overall performance at the macroscopic level. In addition, we have shown as to how the disruption at the microscopic level affects the supply chain network's productivity at the macroscopic level, after the self-evolution of the supply chain network based on the partner selection policy it adapts. From our results, it can be inferred that 'QoS' based switching results in higher total production at the retailer's level for the first 13 months, whereas, 'Most Inventory' based switching results in higher production from then on, till the 24^{th} month. It is also evident that the demand load for the 'Most Inventory' is heavily inclined towards one of its producers and a reduction in production of this producer node, hence, results in a larger impact to the overall production. Using hypothetically simulated scenarios, our study demonstrates the evolution of structural characteristics of a laptop manufacturing supply chain network and their influence on the network's response during a post-evolution-disruption. Here, it has to be noted that the results presented in this work are based on a fixed seed that can result in reproducible runs. Further efforts are required to extend this study to accommodate the stochastic effects due to randomization in partner selection and analyze the results based on the average of several repeated trials. The capability to understand the supply chain network structure's evolution over time, identifying the critical nodes that might evolve to be the key players of the supply chain production, and impact of a disruption in these critical nodes will enable decision maker's ability to respond swiftly to effective risk management of these complex adaptive systems.

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