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Decision Trees to Model the Impact of Disruption and Recovery in Supply Chain Networks

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Abstract – **Increase in the frequency of disruptions in the recent times and their impact have increased the attention in supply chain disruption management research. The objective of this paper is to understand as to how a disruption might affect the supply chain network – depending upon the network structure, the node that is disrupted, the disruption in production capacity of the disrupted node and the period of the disruption – via decision trees. To this end, we first developed a 5-tier agent-based supply chain model and then simulated it for various what-if disruptive scenarios for 3 different network structures (80 trials for each network). Decision trees were then developed to model the impact due to varying degrees of disruption, and the recovery time from these disruptions. Visual outputs of the developed decision trees are presented to better interpret the rules. Supply chain managers can use the approach presented in this work to generate rules that can aid their mitigation planning during future disruptions.**

Keywords – **Disruptions in supply chain, network structure, impact due to disruption, recovery time, decision tree, agent-based model.**

I. INTRODUCTION

Supply chains of modern era are dynamic, complex and highly interdependent in nature [1]. With the introduction of increased product/service/process complexity, inter-dependency among the entities and outsourcing of supply networks across international borders, risk associated with supply chain management due to disruptions is growing [2] [3]. Disruptions, a type of risk, comprise the deletion of ties/nodes from the network (permanently or temporarily) as a consequence of some unexpected event like an earthquake and have the potential to disrupt the whole supply chain network if ill-managed [4]. Hence, there is a need for understanding the effect of disruptions for a given network structure and evaluating as to how the disruption effect varies for different network structures [5].

The structure of a supply chain network plays a vital role in both the evolution of the network and its response to disruptions [6]. The network structure's influence in determining the severity of a disruption, and the time taken by the network to recover are key components to be addressed in risk management associated with disruptive events. Greening and Rutherford (2011) summarized as to how a network will respond to disruption, and the time it takes for the network to recover through a conceptual framework and hypothesized that each of the network attributes has a specific implication in the way the networks respond to disruption. Such assessment process typically asks the following questions: (i) what are the consequences if the disruption occurs, the "impact"? , and (ii) how long does the supply chain network take to recover from the disruption, the "recovery time"?

The objective of this paper is to quantify the effect of disruptions for a given network structure and differentiate the impact that a disruption has on various network structures, via decision trees. In particular, understand as to how a disruption, as and when it happens, affects the supply chain network – depending upon the network structure in which the disruption is simulated, the node that is disrupted during the disruption, the disruption in production capacity of the disrupted node and the period of the disruption. To this end, we developed a 5-tier agent-based supply chain model, hypothetically simulated various disruptive scenarios for each of the 3 different network structures, and developed decision trees for the impact due to varying degrees of disruption and the recovery time.

II. METHODOLOGY

2.1. Agent Based Simulation Model

A 5-tier agent-based supply chain model was developed in AnyLogic. The model was then simulated for various what-if scenarios to aid our understanding in predicting the impact and recovery time during a disruption for a given supply chain network.

2.1.1. Agent-based model design

Agent based modeling involves entities, called agents, which communicate and transfer goods with one another in a virtual environment. The 5-tier agent-based supply chain model used in our study models the laptop manufacturing network. The supply chain network includes pre-defined entities of laptop component suppliers (Tier II and Tier I), assembly plants (producers), distribution hubs, retailers and consumers (the number of entities in each tier varying for the 3 different networks considered). Producer agents are the direct downstream entities in the network. In our model, producer agents order and receive the laptop components before assembling them and then delivering the laptops to the distributors. Distributor agents are responsible for sending these laptops to the retailer agents, which in turn sell the laptops to the consumers.

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The individual agent's attributes describe its states at any given instant of time. These attributes include the inventory level, the expected quantity of goods destined for arrival and the amount of goods the agent has shipped in and out. These attributes are dynamic and hence, change over time responding to shipment from other agents. Every agent has its own parameters, such as fleet size and production capacity. This will define the characteristics of the entity in its ability to produce and deliver the goods with respect to time. Agent interactions refer to the communication mechanism between the agents. These communications come in the form of "messages", which may either be an order or a shipment. These messages trigger events that will then change the agent's attributes which in turn reacts accordingly and propagate the changes downstream throughout the network. The goal of each agent is to be able to meet the demand of its downstream entities and all goods eventually end up with the consumer agents on time. In our model, all entities use the distance as a measure to decide their upstream supplier. The (s, S) inventory policy is used in the model.

2.2. Supply Chain Network characteristics

The node-level and network-level metrics for the 3 agent-based supply chain network structures used in our study were calculated based on the literature [5], as shown in Table I, and the values are summarized in Table II :

TABLE I
NODE-LEVEL AND NETWORK-LEVEL METRICS USED TO DEFINE THE NETWORK

Metric	Formula used
Network density	$\frac{Number\ of\ Ties\ in\ the\ Network}{Network\ Size\ \times (Network\ Size - 1)}$
In-degree centrality	$\frac{Number\ of\ Ties\ to\ Upstream\ Nodes}{Network\ Size - 1}$
Out-degree centrality	$\frac{Number\ of\ Ties\ to\ Downstream\ Nodes}{Network\ Size - 1}$
Average degree centrality	$In - Degree = \frac{\sum In - Degree\ Centrality}{Network\ Size}$ $Out - Degree = \frac{\sum Out - Degree\ Centrality}{Network\ Size}$
Centralization	$In - Degree = \frac{\sum(MAX\ InDeg\ Centrality - InDeg\ Centrality)}{(Network\ Size-1)(Network\ Size-2)}$ $Out - Degree = \frac{\sum(MAX\ OutDeg\ Centrality - OutDeg\ Centrality)}{(Network\ Size - 1)(Network\ Size - 2)}$

From Table II, it can be seen that Network 3 is the biggest, followed by Network 2 and Network 1. For all 3 networks, the number of ties in the network is approximately the same as the network size. However, there is a significant difference in network density with Network 1 being the densest. The differences in density are also evident in the average centralities. A distinct feature of Network 1 is that it has a low In-Degree Centralization of 0.0762, but, a fairly high Out-Degree Centralization of 0.3048. This shows that all nodes receive materials from approximately the same number of sources but there is a common node that provides materials to many of the downstream nodes. Network 2 is a very balanced network with an equal value for both in-degree and out-degree centralization. This implies that the nodes in the network have approximately the same number of ties. The same can also be said for Network 3, although the out-degree centrality is slightly higher than the in-degree centralization. The topologies of the supply chain networks used in our study are shown in Figure 1.

TABLE II
NETWORK CHARACTERISTICS OF THE 3 SUPPLY CHAIN NETWORK USED IN THE STUDY

Metric	Network 1	Network 2	Network 3
Number of Firms (Network Size)	16	24	32
Number of Linkages	16	26	33
Network Density	0.0667	0.0471	0.0333
Average In-Degree Centrality	6.6667	4.7101	3.3266
Average Out-Degree Centrality	6.6667	4.7101	3.3266
Maximum In Degree Centrality	2	4	3
Maximum Out Degree Centrality	5	4	4
Centralization (In-Degree)	0.0762	0.1383	0.0677
Centralization (Out-Degree)	0.3048	0.1383	0.1022

2.3. Simulation of disruption

The disruption was introduced in each of the 3 networks based on the following 4 parameters:

- Starting time of a disruption
- Period of the disruption
- Producer node(s) that will be disrupted, and
- Percentage that the disrupted node(s)'s capacity will be restricted to

A control run in which no disruption occurs is then used as the baseline scenario for comparing the impact and recovery time due to the disruption. Multiple simulation trials (80 trials) were then run for each network type, for varying disruptive parameters. The data samples collected were then used to develop decision trees to model the impact and recovery time based on these predictors.

2.4. Decision trees

Modeling with decision trees results in a pictorial representation comprising of a series of *if-then* rules to predict the impact and recovery time due to disruption. Construction of such decision trees can aid in the illustration of certain "rules" governing the impact and recovery time for varying degree of disruptions. Supply chain managers can use these rules as the basis to strategize mitigation planning for future disruptions.

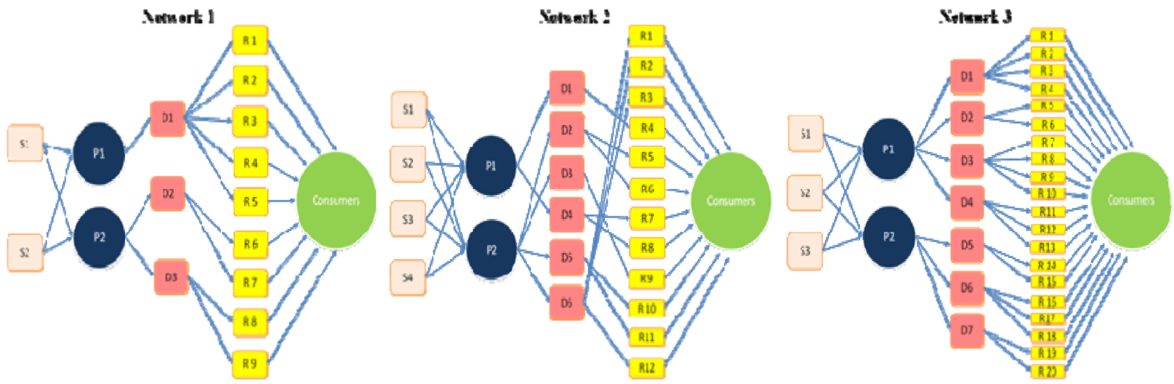

Fig. 1. Topologies of the supply chain networks used in the study

The three basic steps of building a decision tree are: (1) the overall study group is divided into two subgroups using the most dominant predictor of the response variable, (2) this division into two groups is repeated within the subgroups until no further significant splits are found. At this point, a terminal node is created, and (3) the results are then presented in the form of a binary tree structure, which can be pruned to obtain the optimal tree with the least misclassification. Here, we have used '% reduction in production due to disruption' and 'recovery time' as the target variables and built decision trees using the predictors. The 10-fold cross-validation method was used as the tree testing option to select the best tree [7]. Pruning was done to avoid over-fitting. The procedure described here was coded in MATLAB 7.8.0 (R2009a). 80 samples were used for developing the decision trees for the individual networks and 240 samples were used for developing the decision trees for understanding the effect of network structure on the impact and recovery time, in addition to the predictors used for the individual network's analysis.

III. Results And Discussion

This section will present the decision tree on the impact of disruption (% reduction in overall production of the supply chain at the retailer's level), and recovery time due to the disruption, first for one of the 3 networks used in the study (Network 1) and then the decision trees developed including the network structure as a predictor as well. The % reduction in overall production of the supply chain at the retailer's level is calculated by taking the sum of the difference in the number of units received at the retailer's level between the disrupted and undisrupted scenarios divided by the sum for the disrupted scenario, over the recovery period. The formula used is:

$$\% \, Reduction = \frac{\sum Qty\,(Undisrupted\ scenario) - Qty\,(Disrupted\ scenario)}{\sum Qty\,(Disrupted\ scenario)} * 100.$$

3.1. Decision trees for 'Network 1'

The decision tree for % reduction in overall production at the retailer's level due to the disruption for 'Network 1' is shown in Figure 2. From Figure 2, it can be inferred that the first variable selected for splitting is the working production capacity of the node disrupted during disruption. Among the simulation trials included in the analysis, for those which are disrupted completely (0%), a further split was observed depending upon the nodes disrupted.

The simulation trials with both nodes being disrupted have the greatest reduction in production levels, 221.90%. For those with either node 1 or 2 disrupted, an additional split according to the period of the disruption was observed. When either of the nodes is disrupted at 0% for 14 or 28 days, there is a reduction of 54.72%. When the disruption period is longer (45, 60 or 90 days), the reduction increases to 93.67%. From Figure 2, it can also be seen that when the production capacity is 25% and the disruption period is 7 or 28 days, there is a reduction of 15.24%. When the disruption period is longer for node 1 (45 or 90 days), it results in a reduction of 16.79%. Whereas, when the disruption period is longer for either node 2 or both nodes (45 or 90 days), it increases the reduction by over 4 times, to 66.98%.

The decision tree for recovery time due to the disruption for 'Network 1' is shown in Figure 3. In total, there are 9 terminal nodes, and they range from 0.33 weeks to 13.6 weeks. From Figure 3, it can be inferred that the first variable selected for splitting is the period of disruption. Among the simulation trials included in the analysis, those which are disrupted from 45 to 90 days, a further split was observed with respect to the working production capacity of the node disrupted. Trials with a capacity of 75% and 80% have a recovery time of 3.17 weeks. On the contrary, those with a capacity of 0% or 25% and disrupted for 90 days have a maximum recovery time of 13.6 weeks. If the period of disruption is 7 or 14 days and the working capacity is 50%, 75% and 80%, the recovery time is almost negligible, at 0.33 weeks. From the results, the disruption period seems to be a critical factor in determining the length of recovery period.

Similar qualitative trends were observed for 'Network 2', however, with a quantitative difference. For Network 2, the % reduction ranges from a minimum of 3.41% when the capacity is more than 50% to a maximum of 181.19%, when node 2 or both nodes is disrupted completely for more than 45 days.

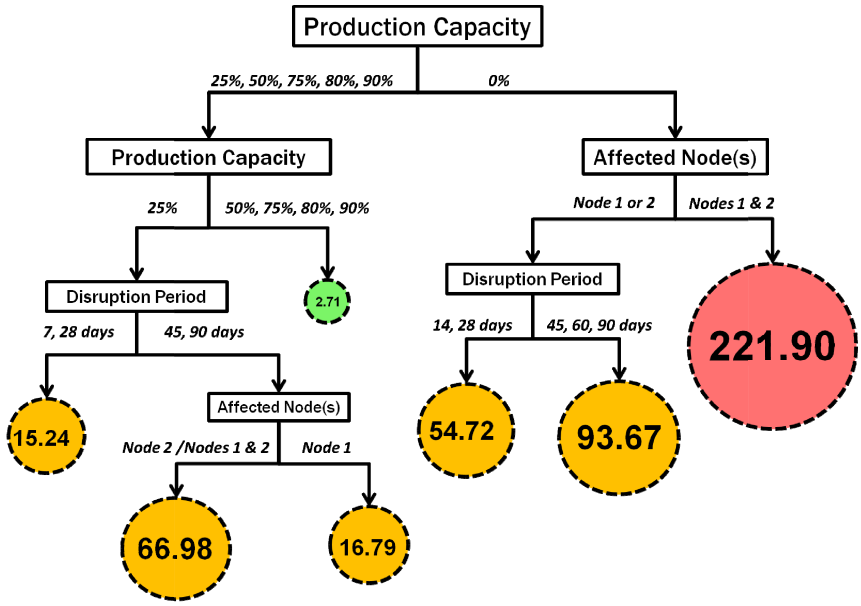

Fig. 2. Decision tree for % reduction in overall production

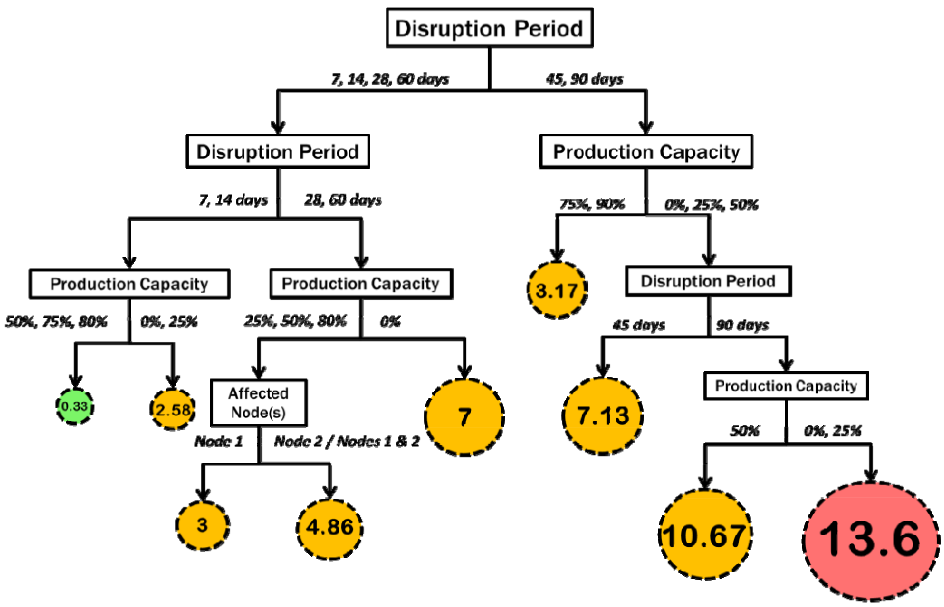

Fig. 3. Decision tree for recovery time for 'Network 1'

The recovery time ranges from a minimum of 0 weeks when the capacity is more than 90% to a maximum of 17 weeks when the capacity is capped at 0% to 25% for more than 90 days. Since the decision trees varied for different networks, we included the network structure as a predictor and developed decision trees for the impact and recovery time.

3.2. Decision trees including the network structure as a predictor

The decision tree for % reduction in the overall production at the retailer's level due to the disruption is shown in Figure 4. In total, there are 8 terminal nodes, and they range from to 2.76% to 165.78%. The first predictor used in splitting is the working production capacity. Among the trials, those which have a working capacity of more than 37.5% have the least impact, a reduction of 2.76%. The trials in which 'node 1' is disrupted, with a working capacity between 12.5% and 37.5% and a disruption period longer than 36.5 days results in a reduction of 14.64%. However, if a similar disruption occurs in node 2 or both nodes are disrupted, the reduction increases significantly to 63.21%. This clearly shows that the effect of disruption on the critical nodes and its subsequent impact on overall production. If the nodes being disrupted are either node 2 or both nodes are disrupted, we observe a further split by the network structure type.

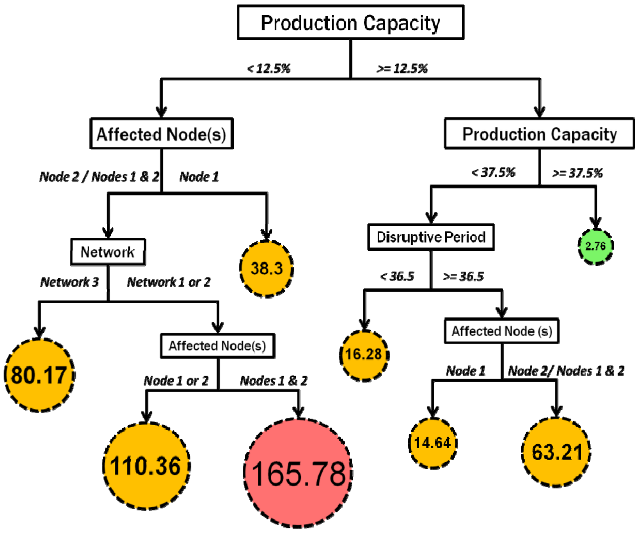

Fig. 4. Decision tree for % reduction including the network structure as a predictor

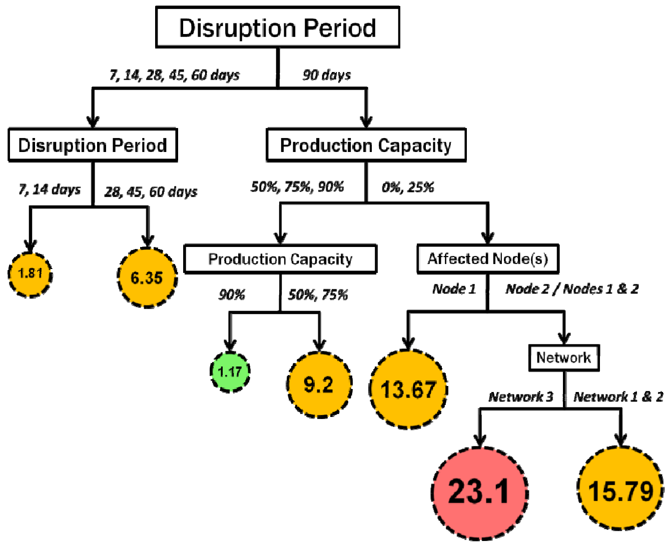

Fig. 5. Decision tree for recovery time including the network structure as a predictor

For network 3, if node 2 or both nodes are disrupted to a capacity less than 12.5%, the reduction is 80.17%. For network 1 or 2, if node 1 or 2 is disrupted to a capacity less than 12.5%, there is a reduction of 110.36%. This reduction increases to the maximum value of 165.78% if both nodes are disrupted. Similar effects of the significance of the node disrupted, type of the network is clearly evident with the recovery time from disruption as well, as illustrated in Figure 5. The first predictor used in splitting the decision tree is the disruption period. For a disruption period of 90 days and a working capacity of 0% or 25%, if only node 1 is disrupted, the recovery period is 13.67 weeks. If node 2 or both nodes are disrupted for network 3, the recovery period is longest at 23.1 weeks. For network 1 and network 2, the recovery period is slightly shorter at 15.79 weeks.

IV. Conclusion

Risk associated with supply chain management due to disruptions is on the rise and has the potential to disrupt the whole supply network if not managed effectively. Hence, there is an immediate need for assessing the effect of disruptions for a given supply chain network structure, to facilitate better supply chain management during future disruptions. To this end, we developed a 5-tier agent-based supply chain model, simulated various disruptive scenarios for 3 different network structures, and developed decision trees for the impact due to varying degrees of disruption and the recovery time. Our study demonstrates the quantification of degree of incapacitation of the node disrupted due to a disruption, period of the disruption, criticality of the node disrupted and the effect of network structure on the impact due to the disruption and recovery time. This comprehensive study provides the decision trees governing the impact and recovery time for varying degree of disruptions for a given supply chain network, a first of its kind. Supply chain managers can use these decision rules as the basis to strategize mitigation planning, depending upon their supply chain network structure, for future disruptions. The capability to understand the implications of network structure in the context of disruptions will enable managers to respond appropriately to disruptive supply chain events. Such efforts would ensure an immaculate supply chain risk management during disruptions.

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