Order Sensitivity of Integrated Electronics Supply Networks in Emergent Customer and Market Conditions

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***Abstract*—Network modeling of supply chains gives insights into the structure, risks, and resilience of the system, aiding in supply chain management decision-making. Through mapping dependencies between supply chain organizations, materials, equipment, and locations, the priority of supply chain entities can be analyzed. This paper applies a system ordering methodology to supply chain network nodes through calculating centrality measures. PageRank measures the importance of a node based on its connections to other influential nodes. Personalized PageRank scores allow for centrality scores to better represent different perspectives on system order of the supply chain including customers, material suppliers, and geopolitical influences. The system order and its sensitivity to disruption by scenarios are analyzed for a synthetic semiconductor supply chain for each centrality metric, providing insights into the network structure, robust nodes, and the most disruptive scenarios.**

***Index Terms*—network modeling, systems engineering, resilience, topological analysis, personalized PageRank**

I. Introduction

Semiconductors are ubiquitous inputs in commercial products ranging from laptops to automobiles as well as defense applications including communication and encryption technologies [1]. However, semiconductor supply chains are prone to disruption. Semiconductor supply chains are complex with multiple tiers of entities specializing in design, manufacturing, assembly, and testing of the semiconductors [2]. The distributed nature, geographical clustering, and raw material-intensive nature of these supply chains make them susceptible to disruptions ranging from natural disasters to geopolitical tensions [3].

Resilience modeling of semiconductor supply chains can help reduce the impact of disruptions. Discrete event simulations have been applied to model the impact of disruptions on notional semiconductor supply chains [4]. Machine learning methods can improve supply chain management tasks, but also struggle with data availability for training these methods [5]. Recognizing the need for improved understanding of supply chain resilience, [6] describes metrics for assessing supply chain resilience to identify vulnerabilities and quantify risks, with a focus on cybersecurity.

II. Background

Recognizing that systems can be characterized by the rank order of system components, order-based risk methodologies quantify the disruptiveness of scenarios by analyzing relative changes in rank order and system priorities [7]. The approach has been applied to a variety of domains, including prioritization of critical infrastructure projects under worst case hazards and critical sector outages [7], socio-technical initiatives for economic development under environmental, societal, and technological disruptions [8], national and international water policies under changes in technological, political, and societal

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conditions [9], alternative fuel supply chain components under political, technological, societal, environmental, and market changes [10], and disaster detection and monitoring technologies under environmental and societal disruptions [11]. In each application, the focus on system order enables the identification of disruptive scenarios and changes in system priorities that may otherwise be overlooked, providing insights for system managers and decision-makers.

Networks, at their simplest, are a collection of entities called nodes connected to one another through various relationships called edges. Networks have been used to analyze a wide range of systems from social network analysis of people and their personal relationships to the internet with its websites and links [12], [13]. When a supply chain is modeled as a network, the structural characteristics can provide a basis for a resilience assessment [14]. Common features of network analysis include diameter as the shortest path between nodes, degree as the number of links associated with a node, centrality as a measure of the positional significance of a node in the network, and clustering as the tendency for nodes to form groups [14]. Graph centrality metrics have been used to prioritize nodes in a dependency graph when applying risk mitigation controls [15]. Using multiple centrality and other network assessment measurements, [12] develops a multi-attribute supply chain resilience assessment. Furthermore, betweenness and closeness centrality metrics of dependency graphs have been used to enhance resilience of cyber-physical systems [16].

Network centrality measures have also been used to calculate system order on network nodes under disruptive conditions. Loose et. al analyze the resilience of critical infrastructure sectors and compared different centrality metrics including eigenvector, degree, closeness, and betweennesss centrality [17], [18]. This methodology has also been applied to multimodal logistics to compare how the graph structure of an abstracted supply chain influences the system order of supply chain components and the resilience of the network to disruptions [19]. This work extends prior methodologies by incorporating analysis of PageRank and personalized PageRank for system order prioritization of networks from diverse, relevant perspectives. The methodology is novelly applied to synthetic semiconductor supply chain data to determine the relative importance of nodes in the network based on the network structure, compare the sensitivity of system components to disruption, and quantify the disruptiveness of scenarios to the network.

III. METHODOLOGY

The resilience assessment methodology includes (1) defining a network graph of semiconductor supply chain entities and their relationships, (2) calculating centrality measures for baseline rankings of each entity, (3) applying disruptive scenarios to adjust network construction and recalculate rankings, and (4) analyzing changes in system order to quantify disruptiveness.

A. Construct Network Representation

Let $G = (V, E)$ be a graph of a semiconductor supply chain where V is the set of nodes corresponding to semiconductor supply chain entities and E is the set of edges between nodes representing relationships and functional dependencies between supply chain entities. The supply chain entities are heterogeneous in nature, representing diverse capabilities and specializations. The network nodes V include organizations such as fabless design firms, foundries, electronic design automation (EDA) and intellectual property (IP) providers, and distributors, as well as equipment, materials, and infrastructure. The network edges are directed allowing for one-way dependencies reflecting the asymmetrical nature of supply chain dependencies.

B. Centrality Measures

PageRank (PR) is a network centrality technique, originally used by Google to determine the importance of webpages, that ranks nodes by the steady state probability of the node being visited on a random walk through the network [13]. Let q_i be the number of outgoing edges from node v_i, then $\mathbf{S}$ is a square matrix of size equal to the number of nodes in the network where each value s_{ij} is $1/q_i$ if there is an link from node v_i to node v_j, otherwise $s_{ij} = 0$. To account for dangling nodes without outgoing edges, the corresponding row of $\mathbf{S}$ is replaced by a uniform probability vector representing the equal likelihood of moving to any other node in the network. The PageRank vector $\mathbf{R}$ containing the PageRank scores for each node is given by the equation:

$$\mathbf{R} = \alpha \mathbf{RS} + (1 - \alpha)\mathbf{u} \tag{1}$$

where α is a damping factor normally set at 0.85, and $\mathbf{u} = \mathbf{1}/|V|$ is a uniform probability vector representing equal likelihood of returning to any other node.

The PageRank score of a node is based on the endogenous factor of $\mathbf{RS}$ based on the topological structure of the graph and the exogenous factor of u that assigns a uniform probability of teleportation to each node ensuring a minimum status for each node independent of network topology [13]. PageRank scores are normalized so that the sum of the scores for all nodes is equal to 1. Higher PageRank scores indicate that the node is more connected to other highly connected nodes within the graph.

A personalized PageRank (PPR) approach is also taken, which modifies the random walker to now follow a more personalized path through the network. Personalized PageRank modifies the exogenous component of (1) to follow a personalization vector that prioritizes certain starting locations for the random walker [13]. Personalized PageRank is calculated as:

$$\mathbf{R} = \alpha \mathbf{RS} + (1 - \alpha)\mathbf{p} \tag{2}$$

where $\mathbf{p}$ is the personalization vector defining the probability of teleportation to each node. To continue the benefits of the minimum status with PageRank, a hybrid personalization vector is created, which prioritizes teleportation to a focused subset, $F \subset V$, while ensuring every node a nonzero probability. The hybrid approach maintains relevance for nodes and topological structures disconnected from the focused subset. The hybrid bias is parameterized as β. Thus, the personalization value for a particular node v_j is defined as:

$$p_j = \beta \frac{\delta(v_j \in F)}{|F|} + (1-\beta)\frac{1}{|V|} \tag{3}$$

where $\delta(v_j \in F)$ is 1 if $v_j \in F$ and 0 otherwise. PPR allows for the calculation of centrality metrics based on dependency flow focused on particular starting regions or node types of interest for more nuance in overall scores.

Each node v_j can be ranked according to its PageRank or personalized PageRank score to create a ranked system order of semiconductor supply chain entities.

C. Disruption

After the centrality measures are used to calculate a baseline system order, disruptive scenarios, $s_k \in S$ are applied by removing selected sets of nodes, $V^{(s_k)} \in V$ and their corresponding edges $E^{(s_k)}$ in the graph. The disrupted graph for scenario s_k is $G^{(s_k)} = (V', E')$ is constructed where $V' = V \backslash V^{(s_k)}$ and $E' = E \backslash E^{(s_k)}$. The centrality measures for each node in the new graph $G^{(s_k)}$ are recomputed to prioritize each node in the disruptive scenario. The change in the rank of each node v_i under scenario s_k reflects how much the scenario disrupts the system and its order. Spearman's rank correlation coefficient is used to quantify the disruptiveness of each scenario by measuring the non-parametric, monotonic agreement between two ranked lists. Spearman's ρ for scenario s_k is calculated as

$$\rho_k = 1 - \frac{6\sum d_i^2}{N(N^2-1)} \tag{4}$$

where d_i is the difference in the ranking of node v_i between the baseline scenario and scenario s_k, and N is the number of nodes to compare. ρ can assume values [-1, 1], with values near 1 indicating monotonic agreement between the ranks and thus low system order disruptiveness from the scenario, and values near -1 representing a complete reversal of rankings and thus high system order disruptiveness from the scenario [18].

IV. Case Study

The methodology is applied to a case study on synthetic semiconductor supply chain data.

A. Case Study Data

Synthetic data for this case study was generated following the framework defined in [20], [21] using knowledge graphs and multi-stage data validation for LLM generated synthetic data. The synthetic data was generated as a JSON file using Gemini 2.5 flash following the best practices and including the knowledge graph structure of [20]. The synthetic data was validated structurally for formatting, type, and missing data errors [20]. The synthetic data was validated semantically to ensure internal self-consistency and plausibility of data values [21]. An additional semantic validation rule enforced that all nodes were referenced in at least one relationship, ensuring that the graph contained no orphan nodes. The synthetic data was converted from a JSON file to a heterogeneous network, as shown in Fig. 1, with 128 nodes and 209 edges including a representative sample of entity and relationship types.

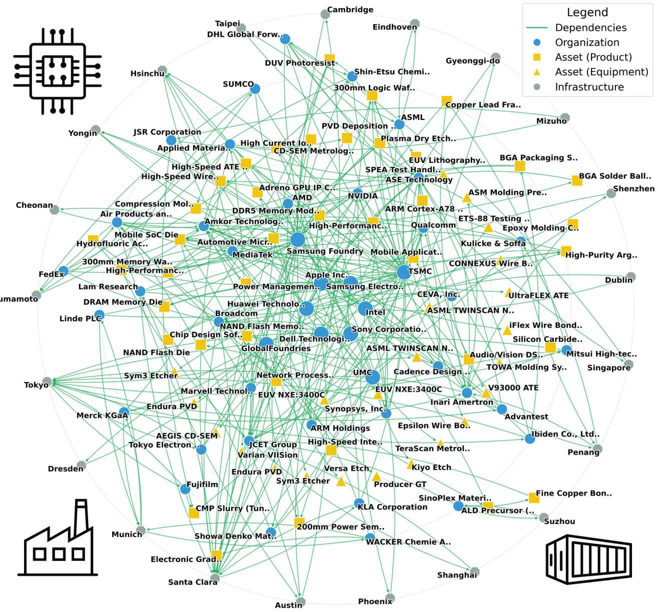

Fig. 1. Heterogeneous network of synthetic semiconductor supply chain data including 128 nodes with 209 edges.

The nodes V in the graph $G = (V, E)$ represent the semiconductor supply chain entities. The nodes are divided into the three subsets of organizations, assets, and infrastructure nodes: $V_o, V_a, V_i \subset V$. V_o represents the organizations like foundries, IP providers, and distributors. V_a represents the assets within the supply chain including products and materials as well as equipment. V_i represents the physical location of the supply chain entities.

The edges E represent functional dependencies in the supply chain. An edge $u \to v$ implies that node v depends on node u. The edges are generated based on the relationships between entities in the synthetic supply chain data set including relationships of supply, services, IP licenses, partnerships, equipment utilization, and location.

B. Baseline Priority

The centrality measures of each node are calculated using (1) and (2) to determine a baseline system order with higher scores indicating higher ranking. Three different personalization vectors are implemented to compare how different focuses change the system order hierarchy. The three focuses are demand, supply, and infrastructure. The demand personalization vector focuses on how consumer demand influences the network and prioritizes the customer nodes. The supply personalization vector focuses on raw material and equipment suppliers and their influence on the network with a focused subset of manufactures as the personalization vector. The infrastructure personalization vector focuses on the impact of geographic location on the supply chain with a focus set of infrastructure nodes. A summary of the different personalized PageRank approaches and focus subsets F is included in Table I.

TABLE I
PERSONALIZED PAGERANK APPROACHES FOR SYSTEM ORDER SENSITIVITY OF SEMICONDUCTOR SUPPLY CHAIN NODES

Index	Perspective	Explanation	Focus Set
p.01	Standard	Represents holistic system dependencies	Empty set $\emptyset$
p.02	Demand	Focuses on customer demand at the end of supply chain	Customers and fabless designers
p.03	Supply	Focuses on the inputs at the beginning of the supply chain	Raw materials and IP providers, equipment manufacturers
p.04	Geopolitical	Focuses on geographic concentration	Any node within a specific country

A hybrid bias parameter β of 0.75 is set, indicating a 75% chance of the PageRank teleportation to a node in the focus set; however, a sensitivity analysis on this parameter is performed. The centrality scores for each node in the network are calculated with all four PageRank methods and a baseline system order using each scoring method is created by ranking each node.

C. Disruptions

To disrupt the baseline system order, scenarios are applied to the graph which strategically remove nodes and edges to determine how the network system order is shifted. The scenarios, summarized in Table II, include a diverse selection of global or regional impacts and market conditions at different levels of the supply chain.

TABLE II
DISRUPTIVE SCENARIOS OF SEMICONDUCTOR SUPPLY CHAIN NETWORKS

Index	Scenario	Network Impact
s.01	Regional Blockage	Remove organization and location nodes in Taiwan
s.02	Equipment Shock	Remove ASML organization and its products
s.03	IP Blockage	Remove three common EDA and IP providers
s.04	Global Material Shortage	Remove a photoresists raw material and suppliers
s.05	Regional Material Shortage	Remove material suppliers located in Japan
s.06	Commodity Shortage	Remove three intermediate goods
s.07	Logistics Freeze	Remove logistics providers
s.08	Tier 3-4 Insolvency	Remove 30% of Tier 3 and 4 organizations
s.09	Obsolescence	Remove legacy and older products

D. System Order Sensitivity Results

The system order results for the standard PageRank are displayed in Fig. 2. The nodes are sorted by their baseline system order, shown as the black diamond. The red bar represents how far the node can fall in system order while the blue bar represents how far a node can rise in system order under the disruptive scenarios.

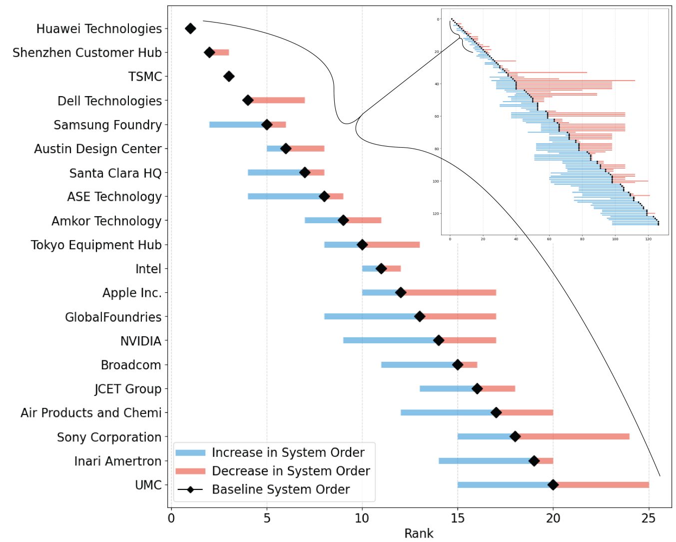

Fig. 2. Disruption of system order of a semiconductor supply chain graph evaluated by PageRank.

The nodes near the top of the system order do not decrease or increase in system order dramatically under the scenarios. Outside of the top 20 nodes, the sensitivity of the rank of the nodes increases, and thus their robustness to the disruptive scenarios is lesser compared to the relatively stable top 20. Nodes of many different types are highly ranked in the system order including customers, foundries, infrastructure locations, fabless designers, and material suppliers.

The system order graphs using each of the different PageRank approaches can also be compared. The personalized PageRank system orders are overlayed on the standard PageRank for the highest ranked nodes in Fig. 3. The demand PPR

Fig. 3. Comparison of standard and personalized PageRank methods for disruption of system order of a semiconductor supply chain graph.

system order appears most similar to the standard PR system order, with similar sensitivity of system order to disruptions. Under demand PPR, the system order scores for several key customer and fabless companies (Intel, NVIDIA, and Sony) and consumer hub locations (Santa Clara and Austin) are slightly higher than when ordered by standard PR, and foundries and outsourced semiconductor assembly and test (OSAT) facilities (TSMC, ASE, Amkor, Inari) are ranked slightly lower than when ordered by standard PR. The supply and geopolitical PPR have significantly higher sensitivity of system order to disruptive scenarios as shown by the wide bars in Fig. 3.

The disruptiveness for each scenario was calculated using (4) with rankings under each of the standard and personalized PageRank measures. The scenario disruptiveness is shown in Fig. 4. The most disruptive scenario is *s.01 Regional Blockage* when scoring with geopolitical or demand PPR, but *s.08 Tier 3-4 Insolvency* is most disruptive when scoring with supply PPR and standard PR. The set of the three most disruptive scenarios is the same across all three metrics: *s.01 Regional Blockage*, *s.08 Tier 3-4 Insolvency*, and *s.05 Regional Material Shortage*. Additionally, supply and demand PPR increase disruptiveness of *s.03 IP Blockage*. *s.04 Global Material Shortage* is more disruptive in standard PR and supply PPR as the fourth and fifth most disruptive, respectively, compared to seventh most disruptive when using the other PPR measures. The differences in the most disruptive scenario by metric allow supply chain managers to consider the impact of disruption from various perspectives while the general agreement on most disruptive scenarios highlights impactful scenarios across all perspectives.

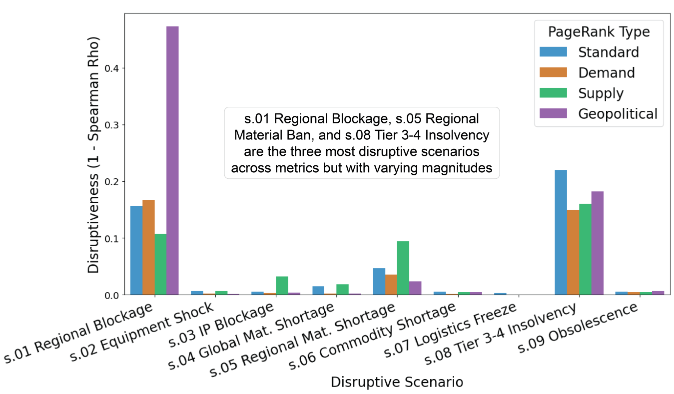

Fig. 4. Degree of order disruption for each scenario based on four PageRank and personalized PageRank centrality measures.

To compare the correlation between the different PageRank measures for each scenario, Spearman's rank correlation coefficient was calculated on the system order lists of nodes using (4). The correlation coefficient for each of the measures is shown in a modified heatmap in Fig. 5. The correlation coefficients in the baseline scenario are shown below the diagonal of the heatmap, the correlation coefficients in *s.01 Regional Blockage* are shown above the diagonal, and the diagonal are the scenario ρ values from comparing the scenario to the baseline using the same metric. Comparing the correlation coefficients

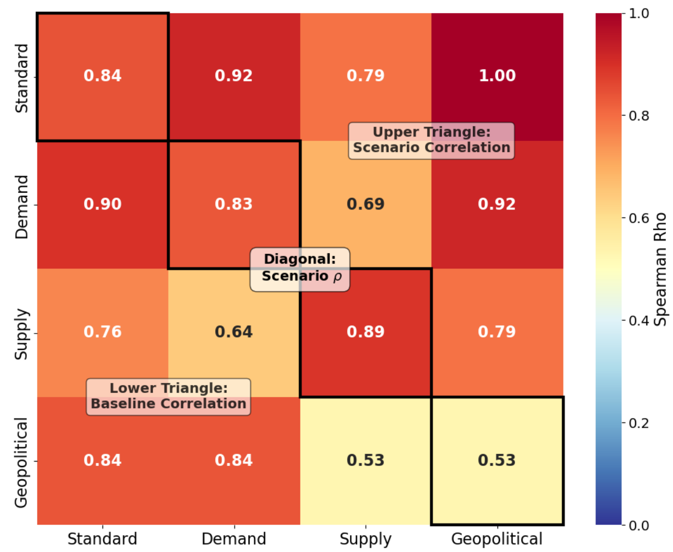

Fig. 5. Spearman's rank correlation coefficient comparison of system order using standard and personalized PageRank in the baseline and a highly disruptive scenario, *s.01 Regional Blockage*.

across the diagonal, i.e. comparing the correlation between the same two metrics in the baseline and disruptive scenario, reveals relatively similar behavior indicating similar correlation between centrality measures across disruptive scenarios. The largest discrepancy in correlation value between the baseline and disruptive scenario occurs when comparing supply and geopolitical PPR. By observing the diagonal value of each of these PPR measures, we notice that the scenario is far more disruptive with the geopolitical-focused scoring and less disruptive with the supply-focused PPR. Interestingly, different metrics are often more correlated in the disruptive scenario than in the baseline highlighting similar system prioritization under disruption across metrics. In particular, geopolitical and standard PageRank become perfectly correlated in the disruptive scenario. The behavior shown in this heatmap is representative of other scenarios: high correlation between standard, demand, and geopolitical measures and lower correlation values with supply PPR.

A sensitivity analysis of the scenario disruptiveness scores to changes in hybrid bias β was conducted. For values of β between 0.1 and 0.9, the value of the disruptiveness score changed, but the ordering of most to least disruptive scenario for each centrality measure remained the same. Intuitively, as β decreased, the PPR disruptiveness scores converged towards the PR scores since when $\beta = 0$ in (3), the method is equivalent to standard PageRank. On the other hand, when β increased, any existing difference between the PPR method and the standard PageRank was magnified.

V. Conclusions

This paper has analyzed semiconductor supply chain network system order using different personalized PageRank approaches on a synthetic supply chain dataset. The case study results show that the system order of nodes ranked highly in the baseline are more robust to disruption and shows the volatility of the middle ranked baseline nodes, demonstrating the large range of lower ranked entities that become more highly prioritized under disruptive scenarios. Additionally, the different PPR scoring approaches impact which scenario is most disruptive, either *s.01 Regional Blockage* or *s.08 Tier 3-4 Insolvency*, as focusing on different aspects of the supply chain influences the sensitivity of system order. Further, certain PPR scoring methodologies increase the disruptiveness of certain scenarios compared to others, such as supply PPR increasing disruptiveness of *s.03 IP Blockage* and *s.04 Global Material Shortage*, highlighting scenarios that might be overlooked otherwise. The similarities and differences in scenario disruptiveness between different metrics enable supply chain managers to consider the impact of a disruption from different perspectives. The correlation between metrics in scenarios and between scenarios within the same metric show overall similarity of perspectives and how they adjust to become more in agreement or more distinct across disruption. The sensitivity analysis of hybrid PPR parameters shows continuity of relative scenario disruptiveness and the ability to tune personalized PageRank scores aiding decision-support implications.

Limitations of this work include the simplification of network relationships into a single edge type representing a dependency between nodes. Similarly, all edges are given an equal weight, regardless of the perceived criticality or importance of a particular dependency. Additionally, this analysis is conducted on a static snapshot of a network when supply chains vary over time, suggesting a dynamic network model approach to allow for graph changes over time and analysis of recovery time under disruptions. The set of disruptive scenarios can be expanded or altered to reflect compounding failures or specific interests of supply chain managers.

Other future work includes a multiplex network construction to differentiate between diverse relationships and dependencies within a supply chain. Then, system order can be analyzed through multiplex centrality measures including PageRank versatility, which calculates the influence of a node and its ability to serve as a bridge across multiple network layers. Additionally, testing on multiple synthetic datasets can allow for comparison of resilience strategies across networks with different structures and parameters, enabling supply chain managers to evaluate response efforts.

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