Computing Ripple Effects in Supply Chain Networks Using Dynamic Causal Graphs

Abstract

A supply chain is a complex network of entities, including producers, suppliers, warehouses, transportation providers, distribution centers, and retailers, that collaborate to manufacture and deliver products to consumers. The strength of any economy is contingent on the robustness and resilience of its supply chains. This work models supply chain interactions using a Dynamic Causal Bayesian Network and employs it to compute ripple effects, which is an important query in the supply chain domain. The particle filtering algorithm is then used to quantify the ripple effects of disruptive events on key outcome variables. Empirical evaluations demonstrate the effectiveness of this technique and provide a strong foundation for building resilient supply chain systems grounded in causal principles.

I. Introduction

A supply chain (SC) is a network of entities, processes, and resources involved in the production, transportation, and delivery of goods and services from suppliers to end consumers [10]. It includes multiple components such as raw material suppliers, manufacturers, logistics providers, warehouses, retailers, and customers. Effective supply chains ensure the smooth flow of products, information, and finances across the network.

II. Purpose of Supply Chains

The primary purpose of a supply chain is to efficiently manage the production and distribution of goods and services. Its key functions include: [3]

- **Ensuring Product Availability:** Facilitates the continuous supply of goods to meet consumer demand.
- **Cost Optimization:** Reduces production, transportation, and inventory costs through efficient management.
- **Enhancing Efficiency:** Streamlines operations to minimize waste, optimize resources, and improve overall productivity.
- **Risk Management:** Identifies and mitigates potential disruptions to maintain business continuity.
- **Customer Satisfaction:** Ensures timely delivery and availability of quality products to end consumers.

III. Disruption of Supply Chains During COVID-19

The COVID-19 pandemic exposed vulnerabilities in global supply chains, leading to widespread disruptions across industries [2]. Some notable events include:

A. *Shutdown of Manufacturing Facilities*

Many factories, especially in China, were forced to shut down due to lockdowns and worker shortages. This led to delays in the production of essential goods, including electronics, automotive parts, and pharmaceuticals.

B. *Global Shipping Crisis*

The pandemic caused port congestions and shipping delays due to labor shortages and changing regulations. The blockage of the Suez Canal in March 2021 further exacerbated delays, impacting global trade and supply chain operations.

C. Shortages of Critical Medical Supplies

At the height of the pandemic, supply chains struggled to meet the demand for personal protective equipment (PPE), ventilators, and vaccines. Many countries faced export restrictions and hoarding, further straining medical supply chains.

D. Semiconductor Chip Shortage

A surge in demand for electronics combined with factory shutdowns led to a severe semiconductor chip shortage, impacting industries such as automotive, consumer electronics, and telecommunications.

E. Food Supply Chain Disruptions

Labor shortages, transportation bottlenecks, and changing consumer behaviors led to food supply issues. Meatpacking plants in the U.S. faced closures due to COVID outbreaks, causing meat shortages and price increases.

F. Panic Buying and Inventory Shortages

Consumer panic buying led to shortages of household essentials like toilet paper, sanitizers, and groceries. Retailers struggled to restock shelves, exposing weaknesses in demand forecasting and inventory management.

IV. Modeling Supply Chains Using Causal Dynamic Graphs

When considering the semiconductor industry, disruptions can create ripple effects throughout the supply chain, significantly impacting performance. [4].

V. Raw Materials

The semiconductor supply chain relies on critical raw materials, including:

- **Silicon**: The primary material for semiconductor wafers.
- **Recycled Silicon**: Reprocessed silicon from defective or excess wafers, reducing material waste.
- **Gallium Nitride (GaN)**: A key compound used for high-performance and power-efficient semiconductor devices, particularly in power electronics and RF applications.

VI. Key Metrics

- **Manufacturing Capacity (MC)**: The number of wafers a fabrication facility can produce per month.
- **Demand (D)**: The market requirement for semiconductor components, fluctuating based on consumer electronics, automotive, and industrial needs.
- **Total Quantity Produced (Q)**: The actual output of semiconductor wafers, factoring in production efficiency and constraints.
- **Shipping Rate (SR)**: The rate at which semiconductor products are transported from fabrication plants to customers.

VII. Supply Chain Dynamics

A. Production Process

Raw materials are processed into semiconductor wafers at fabrication plants, constrained by *MC*.

B. Demand-Supply Balance

The ability to meet *D* depends on *Q*, which is influenced by available raw materials and fabrication efficiency.

C. Logistics & Shipping Impact

- Shipping rate at time *t* (SR_t) directly affects demand at time *t+1* (D_{t+1}).
- If SR_t is low due to logistics bottlenecks, inventory shortages may increase, leading to higher demand (D_{t+1}).
- If SR_t is high, excess inventory may cause D_{t+1} to stabilize or decline.

VIII. Challenges & Risks

- **Raw Material Shortages**: Limited availability of high-purity silicon and GaN can constrain production.
- **Manufacturing Constraints**: Capacity limitations and high fabrication costs restrict output scalability.
- **Shipping & Logistics Disruptions**: Supply chain bottlenecks can delay shipments, impacting global demand patterns.
- **Market Volatility**: Changes in consumer demand for electronics, electric vehicles, and AI-driven technologies impact semiconductor demand.

IX. Strategies for Resilience

- **Diversification of Suppliers**: Reducing dependency on a single supplier for raw materials.
- **Capacity Expansion**: Investing in new fabrication facilities to increase *MC*.
- **Supply Chain Digitalization**: Leveraging AI for predictive demand analysis and logistics optimization.
- **Recycling & Sustainability**: Enhancing the use of recycled silicon to mitigate material shortages.

This supply chain framework highlights the interdependencies of raw materials, production capacity, shipping logistics, and market demand, ensuring a strategic approach to managing semiconductor supply chain disruptions.

The figure 1 represents a causal model of the semiconductor supply chain, highlighting dependencies between raw materials, manufacturing capacity, production, demand, shipping, and availability.

A. Ripple Effects

Disruptions are considered high-impact, low-frequency events (e.g., fire, tsunami) that change the supply chain's structural design. The propagation of a disruption through a supply chain and its associated impact is called the *ripple effect* [3]. The ripple effect manifests when the impact of a supply chain disruption cannot be localized or contained to one part of the supply chain and cascades downstream, resulting in high-impact effects on performance.

A ripple effect is distinct from the well-known *bullwhip effect* [3]. While the ripple effect considers structural network dynamics in the supply chain, the bullwhip effect characterizes the oscillations in operational parameters. The ripple effect is initiated by a severe disruption and describes its propagation downstream, often resulting in demand fulfillment downscaling. In severe cases, it can lead to temporary shutdowns of supply chain nodes due to material shortages. On the contrary, the bullwhip effect is triggered by small operational deviations and tends to amplify in the upstream direction.

X. Particle filtering for Computing Ripple Effects

The particle filter algorithm used for the experiment is shown below, with insights derived from [8] and [9].

Algorithm 1 PARTICLE-FILTERING

Require: e, the new incoming evidence
Require: N, the number of samples to be maintained
Require: dbn, a DBN defined by $P(X_0)$, $P(X_1|X_0)$, and $P(E_1|X_1)$
persistent: S, a vector of samples of size N, initially generated from $P(X_0)$
local variables: W, a vector of weights of size N
for $i = 1$ to N **do**
  $S[i] \leftarrow$ sample from $P(X_1|X_0 = S[i])$ ▷ Step 1
  $W[i] \leftarrow P(e|X_1 = S[i])$ ▷ Step 2
end for
$S \leftarrow$ WEIGHTED-SAMPLE-WITH-REPLACEMENT(N, S, W) ▷ Step 3
  return S

SEQUENTIAL IMPORTANCE SAMPLING

Initialization

1) Draw N samples from the prior distribution $P(X_0)$:

$$x_0^{(i)} \sim P(X_0), \quad i = 1, \ldots, N$$

2) Assign equal weights to all particles:

$$w_0^{(i)} = \frac{1}{N}, \quad \forall i = 1, \ldots, N$$

Recursive Steps for Each Time Step $k = 1, \ldots, T$

3.1 Sample New Particles Using Importance Sampling

- Draw $x_k^{(i)}$ from the importance distribution:

$$x_k^{(i)} \sim \pi(x_k | x_{0:k-1}^{(i)}, y_{1:k}), \quad i = 1, \ldots, N$$

3.2 Compute New Weights

- Update weights using the importance weight formula:

$$w_k^{(i)} = \frac{w_{k-1}^{(i)} \cdot p(y_k | x_k^{(i)}) \cdot p(x_k^{(i)} | x_{k-1}^{(i)})}{\pi(x_k^{(i)} | x_{0:k-1}^{(i)}, y_{1:k})}$$

- Normalize the weights to sum to unity:

$$\tilde{w}_k^{(i)} = \frac{w_k^{(i)}}{\sum_{j=1}^{N} w_k^{(j)}}$$

RESAMPLING STEP

1) Interpret each weight $w_k^{(i)}$ as the probability of selecting the sample index i in the set $x_k^{(i)}$, where $i = 1, \ldots, N$.
2) Draw N samples from the discrete distribution defined by the weights $w_k^{(i)}$ and replace the old sample set with the newly drawn samples.
3) Set all weights to a constant value:

$$w_k^{(i)} = \frac{1}{N}, \quad \forall i = 1, \ldots, N.$$

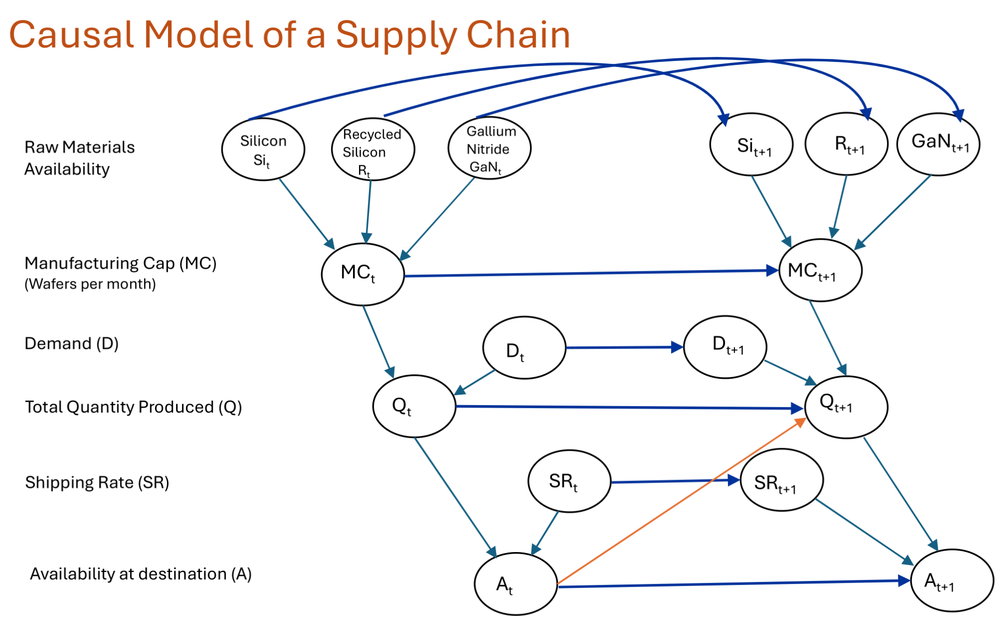

Fig. 1: Supply Chain Model in Semiconductor Industry

A. Exact Inference Algorithm

Exact inference in probabilistic graphical models, such as Bayesian networks, involves computing the exact posterior distribution of variables given observed evidence. One of the primary methods for exact inference is variable elimination, which systematically marginalizes out irrelevant variables to compute conditional probabilities. Another efficient method is belief propagation, which distributes computations across the network structure, reducing computational redundancy.

The Shenoy-Shafer algorithm is a message-passing approach used for exact inference in junction trees. It organizes the network into a tree structure, where each node (cluster of variables) sends and receives messages containing probability distributions. The messages are computed using local updates, enabling efficient belief updating across the network. This method ensures that all conditional probabilities are updated systematically, reducing redundant calculations. [11]

In SamIam, a widely used Bayesian network tool, the Shenoy-Shafer algorithm is implemented to perform exact inference. Users can construct Bayesian networks, define conditional dependencies, and run inference queries. By leveraging the Shenoy-Shafer approach, SamIam computes posterior distributions precisely, making it an essential tool for validating probabilistic models, such as those used in supply chain causal analysis. [12]

B. Backdoor Criterion (Pearl's Criterion)

This adjustment has been used to apply causal queries in the experiment. [1] [7] [5] A set of variables Z satisfies the backdoor criterion relative to an ordered pair of variables (X, Y) if:

(1) No node in Z is a descendant of X.

(2) Z blocks every backdoor path between X and Y.

Then, the causal effect of X on Y can be expressed using the Backdoor Adjustment Formula as:

$$P(Y \mid do(X = x)) = \sum_z P(Y \mid X = x, Z = z) P(Z = z)$$

C. Experiments

For all experiments in the approximate inference column of Table 1, the Conditional Probability Distributions (CPDs) were calculated using a sample size of 1000, with a timeslice of 2 and intervention queries were calculated using a sample size of 1000, with a timeslice of 4.

The code for the particle filtering algorithm specific to the supply chain in figure 1 provided is available at: GitHub Repository

TABLE I: Experiments on Causal Inference in Supply Chain

Experiment	**Exact Inference**	**Approximate Inference**
$P(Q_{t+1}\|Si_t = 0)$	Quantity when raw material Si is not available at t : 49.47	for condition $Si_t = 0$ is 0.568, and for $Si_t = 1$ is 0.555
$P(Q_{t+1}\|Si_t = 1)$	Quantity when raw material Si is available at t: 49.79	
$P(Q_{t+1}\|A_t = 0)$	Quantity at $t + 1$ when availability $A_t = 0$: 50	
$P(Q_{t+1}\|A_t = 1)$	Quantity at $t + 1$ when availability $A_t = 1$: 50	for condition $A_t = 0$ is 0.548, and for $A_t = 1$ is 0.564
$P(A_{t+1}\|SR_t = 0)$	Availability of product at $t + 1$ when shipping rate $SR_t = 0$: 50	
$P(A_{t+1}\|SR_t = 1)$	Availability of product at $t + 1$ when shipping rate $SR_t = 1$: 50	for condition $SR_t = 0$ is 0.587, and for $SR_t = 1$ is 0.541
$P(Q_{t+1}\|D_t = 0)$	Quantity at $t + 1$ given demand $D_t = 0$: 52.86	
$P(Q_{t+1}\|D_t = 1)$	Quantity at $t + 1$ given demand $D_t = 1$: 49.34	for condition $D_t = 0$ is 0.568, and for $D_t = 1$ is 0.548
$P(Q_{t+1}\|Si_t, GaN_t, RS_t)$	$P(Q_{t+1} = 0\|Si_t = 0, GaN_t = 0, RS_t = 0) = 49.55$	0.45 when $Si_t, RSi_t, GaN_t = 0$
	$P(Q_{t+1} = 0\|Si_t = 1, GaN_t = 1, RS_t = 1) = 49.7$	0.41 when $Si_t, RSi_t, GaN_t = 1$

TABLE II: Absolute Errors Table

Experiment	EXACT	N_5000	N_1000	N_10000	N_20000	N_50000	N_1000000
$P(Q_{t+1} \| Si_t = 0)$	0.49	0.03	0.03	0.01	0.04	0.02	0.02
$P(Q_{t+1} \| Si_t = 1)$	0.49	0.01	0.04	0.00	0.04	0.02	0.02
$P(Q_{t+1} \| A_t = 0)$	0.50	0.01	0.06	0.01	0.03	0.01	0.01
$P(Q_{t+1} \| A_t = 1)$	0.50	0.01	0.04	0.01	0.03	0.01	0.01
$P(A_{t+1} \| SR_t = 0)$	0.50	0.02	0.05	0.03	0.01	0.02	0.01
$P(A_{t+1} \| SR_t = 1)$	0.50	0.01	0.03	0.03	0.00	0.01	0.01
$P(Q_{t+1} \| D_t = 0)$	0.52	0.03	0.08	0.04	0.01	0.02	0.02
$P(Q_{t+1} \| D_t = 1)$	0.49	0.02	0.04	0.01	0.04	0.02	0.02
$P(Q_{t+1} = 0 \| Si_t = 0, GaN_t = 0, RS_t = 0)$	0.50	0.06	0.04	0.09	0.03	0.04	0.02
$P(Q_{t+1} = 0 \| Si_t = 0, GaN_t = 0, RS_t = 0)$	0.50	0.01	0.04	0.01	0.05	0.02	0.02

Where N_5000, N_1000, N_10000, N_20000, N_50000, N_1000000 are absolute error values for different N

D. Causal Experiment

Experiment 1: $P(A_{t=3} \mid do(Si_{t=2} = \text{low})) = \sum_{Si_{t=1}} P(A_{t=3} \mid Si_{t=2} = \text{low}, Si_{t=1})P(Si_{t=1})$ is 0.533.

The Causal Probability Formula used, given the system satisfies the backdoor criterion, the adjustment can be made to confounding variable Z :

$$P\left(Y_{t_y} \mid \text{do}(X_{t_x} = x)\right) = \sum_{z \in Z_{t_z}} P\left(Y_{t_y} \mid X_{t_x} = x, Z_{t_z} = z\right) P(Z_{t_z} = z)$$

The terms:

- Y_{t_y} is the target variable whose probability we aim to estimate at a specific future time t_y. - X_{t_x} represents the intervention variable on which the causal intervention is performed, at time t_x. The intervention sets this variable explicitly to a specific value x, independent of its usual causal dependencies. - Z_{t_z} is the marginalized variable at an earlier time t_z. This variable is summed out (marginalized) to account for its distribution before the intervention, ensuring the correct causal ordering.

The Intuition:

This formula reflects the concept of causal inference under intervention: [**?**]

1. Marginalization: Start by enumerating all possible values of the marginalized variable Z_{t_z}. 2. Conditional Probability: For each value of $Z_{t_z} = z$, calculate the probability of the target variable Y_{t_y} given that the intervention variable X_{t_x} is set to x and the marginalized variable is fixed at z. 3. Marginal Probability: Weight these conditional probabilities by the marginal probability of each $Z_{t_z} = z$. 4. Summation: Finally, these products are summed across all possible values of Z_{t_z} to yield the final causal-do probability.

Explanation of the experiment:

$$P\left(A_{t=3} \mid \text{do}(Si_{t=2} = \text{low})\right) = \sum_{Si_{t=1}} P\left(A_{t=3} \mid Si_{t=2} = \text{low}, Si_{t=1}\right) P(Si_{t=1})$$

Here:

- $A_{t=3}$ is target variable at time $t = 3$. - $Si_{t=2}$ is intervention variable, explicitly set to ”low” at time $t = 2$. - $Si_{t=1}$ is marginalized variable, summed over its possible states at $t = 1$.

XI. Conclusion

The exact inference results computed using SamIam and the Shenoy-Shafer algorithm serve as a baseline for validating the approximate inference techniques such as Particle Filtering. The results from Table I will be compared against particle filtering outcomes to analyze the accuracy of the approximation methods.

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