Preprints.org

Article

Not peer-reviewed version

Graph Neural Network for Daily Supply Chain Problems

Fabian Raul Gonzalez *

Posted Date: 30 September 2024

doi: 10.20944/preprints202409.2376.v1

Keywords: supply chain; graph neural network; machine learning

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 September 2024 doi:10.20944/preprints202409.2376.v1

Article

Graph Neural Network for Daily Supply Chain Problems

Fabian Raul Gonzalez

Independent Researcher; fabianraulgonzalez@outlook.com

Abstract: In this paper, we explore the theoretical foundation of Graph Neural Network (GNN) model and apply it to various traditional supply chain logistics problem. In particular, we study the Route Optimization Problem, Demand Forecasting Problem, Risk Assessment and Anomaly Detection, Supplier Section and Procurement Optimization, Inventory Optimization Problem, and Green Supply Chain Problem. The study helps us the expand the use the GNN and gives daily supply chain management a boost.

Keywords: supply chain; graph neural network; machine learning

---

1. Introduction

One of the key challenges in supply chain logistics is optimization under uncertainty, where variables like demand, supply disruptions, and transportation delays introduce complexity into decision-making. GNNs can provide solutions by learning the underlying structure of the supply chain network and predicting outcomes or optimizing decisions based on this learned structure. For instance, GNNs can help in route optimization, inventory management, and demand forecasting by learning patterns from the data distributed across various nodes in the network. Unlike traditional machine learning models that treat data as independent and identically distributed (IID), GNNs can account for the fact that data points (or nodes) in a supply chain are interconnected.

Moreover, GNNs excel in dynamic environments, which are common in supply chain logistics. The supply chain is a constantly evolving system, where new suppliers, customers, and logistics partners can enter or exit, and GNNs can be adapted to model these changing conditions. Another important application of GNNs in this context is in anomaly detection. Supply chains are prone to disruptions, which can occur due to unexpected events such as natural disasters, political instability, or supplier bankruptcy. GNNs can analyze the relationships between different entities in the supply chain and identify anomalies that indicate potential risks. We will look at the supply chain problems from a GNN perspective on these topics.

2. Literature Review

2.1. Supply Chain as a Graph Problem

Researchers have widely recognized that supply chain networks can be effectively represented as graphs. In a graph representation, nodes typically represent key entities like suppliers, manufacturers, warehouses, distribution centers, and customers, while the edges represent the relationships between these entities. [1] discuss supply chain as a graph coloring problem. These relationships could signify transportation routes, information flow, contractual agreements, or data exchange. The use of graphs to model supply chains enables the integration of both structural and relational information into analytical frameworks, providing a holistic understanding of supply chain dynamics.

In a foundational study by [2], the authors proposed that supply chains are indeed multilevel, interconnected systems that can be analyzed using graph theory. They described supply chains as spanning networks, where the decision-making process at each node affects the flow through the entire network. Similarly, [3] explored the potential of graph models to capture the resilience of supply chain networks in the face of disruptions. They applied graph-theoretic techniques to analyze the vulnerability of supply chains to supply shocks, emphasizing how graph-based models can represent the complex interdependencies among supply chain entities.

The advantage of modeling supply chains as graphs lies in the ability to capture both direct and indirect interactions between entities. This relational complexity is essential for understanding various phenomena such as the propagation of delays, supply chain disruptions, or the impact of optimization decisions on the overall network performance. In this context, GNNs emerge as a natural extension of graph-based approaches for extracting insights from these relational structures.

2.2. Graph Neural Networks

Graph Neural Networks (GNNs) are specialized deep learning models designed to operate on graph-structured data. Unlike traditional neural networks, which assume independent and identically distributed (IID) data, GNNs work by learning representations of nodes, edges, and the overall graph that preserve the relational information inherent to the graph structure. The core principle behind GNNs is the iterative process of "message passing," where nodes exchange information with their neighbors as according to [4]. This iterative process allows GNNs to capture both local and global patterns in graph-structured data.

In one of the pioneering works, [5] introduced the Graph Convolutional Network (GCN), which applies convolution operations on graph data to aggregate features from neighboring nodes. Their method demonstrated strong performance in tasks like node classification and link prediction. Another notable model is the Graph Attention Network (GAT), proposed by [6]. GAT enhances the GCN architecture by introducing an attention mechanism, allowing the model to assign different levels of importance to different neighbors, making it more robust in heterogeneous networks.

Other GNN variants include [7], which improves scalability by sampling a fixed-size set of neighbors during aggregation, and Graph Isomorphism Network (GIN), introduced by [8], which focuses on distinguishing graph structures with high precision. These models use various aggregation functions (mean, sum, or max-pooling) to aggregate node information during message passing, enabling them to generalize across different graph topologies.

2.3. Existing Applications in Supply Chain

The application of GNNs in supply chain management is relatively recent but rapidly growing. GNNs offer powerful tools for optimizing the flow of goods and information, managing risks, and improving decision-making processes across the supply chain. Several studies have shown how GNNs can be applied to various supply chain problems, including route optimization, risk assessment, and demand forecasting.

In one case study, [9] applied GNNs to model the transportation networks in supply chains. By representing the supply chain as a graph where nodes are distribution centers and edges represent transportation routes, the authors were able to optimize the routing decisions and minimize transportation costs. Similarly, [10] used GNNs for demand forecasting in a multi-echelon supply chain. Their approach utilized historical sales data and supply chain network structures to predict future demand more accurately.

Another application is in risk assessment and anomaly detection. In a study by [11], GNNs were employed to detect disruptions in supply chains by analyzing data flows between different entities. The model could identify patterns that deviated from normal operations, signaling potential risks like delays or shortages. These applications showcase the versatility of GNNs in addressing complex logistical challenges by leveraging the network structure of supply chains.

2.4. Challenges in GNN Applications

Despite the promising applications of GNNs in supply chain logistics, several challenges remain. One of the foremost challenges is scalability. As supply chain networks grow in size, with potentially thousands or millions of nodes and edges, the computational complexity of training GNNs increases significantly. [12] pointed out that scaling GNNs to large industrial supply chains requires more efficient algorithms and distributed computing approaches. GraphSAGE, for instance, was introduced as a partial solution to this problem by sampling a fixed set of neighbors instead of using the entire graph, but the challenge of scaling remains.

Another challenge lies in the dynamic nature of supply chain networks. In real-world scenarios, the structure of the supply chain is constantly evolving as new suppliers enter the market, demand patterns shift, and transportation routes change. Adaptability to dynamic graphs is a key area of concern for GNN applications in supply chains. Current GNN models, as discussed by [13], often assume static graph structures, making it difficult to adapt them to continuously changing networks without retraining the model.

Lastly, the issue of interpretability is a significant hurdle. GNNs, like other deep learning models, operate as black-box models, making it difficult to interpret how specific decisions are made. This lack of transparency can be a challenge for supply chain managers who need to justify decisions to stakeholders or regulators. [14] argue that explainable GNNs, or techniques that can highlight the most influential factors in decision-making, are crucial for advancing GNN adoption in supply chain management.

3. Route Optimization

Route optimization in supply chains is a critical task that involves determining the most efficient routes for transporting goods between various entities in the network, such as suppliers, warehouses, and customers. Traditionally, this has been tackled using linear programming or heuristic approaches. However, GNNs offer a more nuanced approach by considering the entire supply chain as a graph. Each node represents a distribution center, supplier, or customer, and edges represent transportation routes.

[15] applied GNNs to optimize transportation routes within supply chains. In their approach, the supply chain network is represented as a graph where each node is a key entity (such as a warehouse or a distribution center), and the edges represent the transportation routes between these entities. The GNN was trained to predict optimal routes based on historical transportation data, network topology, and real-time information like traffic or weather conditions. The model demonstrated an ability to optimize transportation costs while ensuring timely deliveries. By learning the relationships between different nodes and edges, the GNN could dynamically adjust routes in response to real-time conditions, improving both efficiency and resilience.

4. Demand Forecasting

Demand forecasting is another area where GNNs are making significant contributions. Forecasting demand in a supply chain, especially in multi-echelon systems, is crucial for maintaining efficient inventory levels, reducing wastage, and ensuring product availability. Traditional statistical methods often fail to capture the relational dynamics between various nodes in a supply chain. For example, a manufacturer's production capacity might be influenced by the demand at the retailer level, which in turn is affected by consumer behavior, creating interdependencies that are difficult to model with linear approaches.

[16] used GNNs for demand forecasting in multi-echelon supply chains. Their approach leveraged both time-series sales data and the underlying network structure of the supply chain to predict future demand. By modeling the supply chain as a graph, they could capture the interactions between suppliers, manufacturers, and retailers, which traditional models often overlook. GNNs were particularly effective in this scenario because they could aggregate information from neighboring nodes (e.g., neighboring warehouses or suppliers) to improve the accuracy of demand predictions. This network-aware demand forecasting method helped reduce the bullwhip effect, where small fluctuations in consumer demand amplify further up the supply chain, leading to inefficiencies.

5. Risk Assessment and Anomaly Detection

Supply chains are vulnerable to a variety of risks, including supplier failures, transportation delays, and demand fluctuations. Identifying and mitigating these risks is a significant challenge in supply chain management. GNNs have shown potential in risk assessment by modeling the relationships between various supply chain entities and detecting anomalies that could indicate potential risks.

[17] applied GNNs to detect disruptions in supply chains. In their work, they modeled the supply chain network as a graph, with each node representing a key entity, such as a supplier, manufacturer, or distribution center, and the edges representing flows of goods or information. The GNN was trained to detect deviations from normal operational patterns, such as sudden drops in product flow or delays in delivery, which could indicate disruptions. This real-time anomaly detection system allowed supply chain managers to identify potential risks early and take preventive actions, such as rerouting shipments or finding alternative suppliers.

Moreover, GNNs can assess the ripple effect of disruptions. For example, if a critical supplier faces a production halt, the impact could propagate throughout the network, affecting multiple nodes downstream. GNNs, by modeling the interdependencies in the supply chain, can quantify and predict how such disruptions may affect the broader network.

6. Supplier Selection and Procurement Optimization

Supplier selection is a key strategic decision in supply chain management. Choosing the right suppliers impacts not only costs but also the reliability and efficiency of the entire supply chain. Traditionally, supplier selection has relied on multi-criteria decision-making methods, which may not fully capture the complex interactions between suppliers and other nodes in the supply chain network.

Recent research shows that GNNs can assist in supplier selection by considering the entire supplier network and its interactions with manufacturers and distributors. For example, GNNs can model supplier relationships, such as dependencies, delivery lead times, and production capacities, as a graph. By analyzing the graph, GNNs can help procurement teams make better decisions, taking into account factors like the resilience of the supplier network, historical performance data, and current supply-demand dynamics.

A study by [14] applied GNNs to optimize procurement strategies in a supply chain. In this study, GNNs were used to predict which suppliers would perform best under different conditions, based on historical procurement data and the relationships between suppliers, manufacturers, and logistics providers. The GNN could recommend the optimal supplier mix that minimizes costs while reducing supply chain risks such as delays or quality issues.

Supplier selection and procurement optimization are critical processes in supply chain management that have a direct impact on the efficiency, cost-effectiveness, and resilience of a supply chain. Supplier selection involves choosing the right suppliers from a pool of candidates based on multiple criteria such as cost, quality, reliability, lead times, and capacity. Procurement optimization, on the other hand, focuses on optimizing the purchasing process by determining the optimal mix of suppliers, quantities to order, timing, and costs. Traditionally, these processes have been handled using rule-based approaches, multi-criteria decision-making models (like the Analytical Hierarchy Process or AHP), and optimization techniques. However, these methods often overlook the complex interdependencies between suppliers, manufacturers, and other supply chain entities.

Graph Neural Networks (GNNs) offer a powerful alternative by modeling the supply chain as a graph, where nodes represent suppliers, manufacturers, and other entities, and edges represent relationships such as material flows, contracts, or transportation routes. By leveraging the graph-based structure, GNNs can provide a more holistic and dynamic approach to supplier selection and procurement optimization, considering not only the characteristics of individual suppliers but also their relationships within the broader supply chain network.

 doi:10.20944/preprints202409.2376.v1

6.1. GNN Approach to Supplier Selection and Procurement Optimization

Modeling Supplier Networks as Graphs: In a GNN-based approach, suppliers, manufacturers, and other entities are modeled as nodes in a graph, while the connections (edges) between them represent various relationships such as procurement contracts, delivery lead times, and transportation costs. Each node can be enriched with features such as supplier capacity, quality ratings, pricing, and past performance data. The edges can also have associated features, such as the strength of the relationship between the supplier and the manufacturer, the reliability of transportation links, and the historical success of transactions.

This graph representation allows GNNs to capture the complex interdependencies between suppliers and manufacturers. For example, a supplier's performance may depend not only on its own characteristics but also on its relationships with other suppliers or intermediaries. A GNN can aggregate information from neighboring nodes, making it possible to model how delays or disruptions in one part of the network might affect other suppliers.

Learning Supplier Performance Patterns: GNNs are particularly effective in learning patterns from historical data, which can then be used to predict future supplier performance under different scenarios. By training the GNN on historical procurement and supplier performance data, the model can learn which suppliers tend to perform well under certain conditions (e.g., during high demand periods or supply chain disruptions). For instance, if a certain supplier has consistently met delivery deadlines even during periods of high demand, the GNN can give this supplier a higher ranking in the selection process.

This ability to learn from past data allows GNNs to identify suppliers that are not only cost-effective but also resilient and reliable, which is particularly important in today's global supply chains where disruptions are common. Supplier Selection Based on Network Relationships: Traditional supplier selection methods often evaluate suppliers in isolation, based solely on their individual attributes such as cost, quality, and delivery time. However, GNNs allow for a more comprehensive evaluation by considering the entire network of relationships. For example, a supplier might offer lower prices but may have weak links with key transportation partners, leading to potential delays. A GNN can take into account both the supplier's attributes and its network connections, providing a more holistic assessment of its suitability.

Moreover, GNNs can capture indirect relationships in the supplier network. For example, a second-tier supplier (a supplier's supplier) might have a history of causing delays, which could affect the primary supplier's performance. By aggregating information from multiple levels of the supply chain network, GNNs provide a more accurate assessment of the risks associated with choosing a particular supplier.

Procurement Optimization: Once suppliers are selected, the next step is procurement optimization—determining the optimal quantities to order, timing, and supplier mix. GNNs can optimize procurement decisions by considering the interactions between suppliers and the broader supply chain. For example, a GNN could recommend splitting orders between multiple suppliers to minimize the risk of disruption, or to take advantage of varying lead times and prices.

A study by[12] demonstrated the use of GNNs to optimize procurement strategies in complex supply chains. In their model, the supply chain network was represented as a graph where each node represented a supplier or manufacturer, and edges represented procurement relationships. The GNN was trained to predict which suppliers would perform best under different conditions, based on historical procurement data and the relationships between suppliers, manufacturers, and logistics providers. The model could recommend the optimal mix of suppliers, quantities to order, and timing to minimize costs while reducing risks such as delays, quality issues, or supply chain disruptions.

6.2. Risk-Aware Supplier Selection

Supplier selection is not just about cost; it also involves assessing risks such as supplier failure, quality issues, and geopolitical risks. GNNs can model these risks by incorporating historical performance data, geographic information, and external factors such as political instability or environmental conditions.

[18] used GNNs to model supply chain risk, taking into account both the characteristics of individual suppliers and their relationships with other nodes in the supply chain. Their model could predict potential risks such as delays or disruptions by analyzing the relationships between suppliers and manufacturers. This approach allowed procurement managers to identify high-risk suppliers and choose alternatives with lower risk, even if they had slightly higher costs.

Additionally, GNNs can help assess the impact of a disruption at one supplier on the broader supply chain. For example, if a critical supplier faces a disruption, the GNN can propagate this information through the network to predict how it will affect downstream suppliers and manufacturers. This allows procurement managers to proactively switch to backup suppliers or adjust order quantities to mitigate the impact of the disruption.

Sustainability and Ethical Procurement: As companies increasingly focus on sustainability and ethical sourcing, GNNs can be used to optimize supplier selection based not only on cost and performance but also on environmental and social criteria. For example, GNNs can incorporate data on suppliers' carbon footprints, labor practices, and compliance with environmental regulations. By aggregating information from multiple tiers of the supply chain, GNNs can help companies identify suppliers that align with their sustainability goals while also optimizing for cost and reliability.

6.3. Benefits of GNN-Based Supplier Selection and Procurement Optimization

Holistic Decision-making: GNNs allow for the evaluation of suppliers not only based on their individual attributes but also on their relationships within the broader supply chain network. This provides a more comprehensive view of supplier performance and risk.

Improved Risk Management

GNNs can identify potential risks in the supply chain by analyzing the relationships between suppliers and other nodes. This helps companies mitigate risks such as supplier failure, delays, or quality issues.

Dynamic Adaptation

GNNs can continuously learn from real-time data, allowing for dynamic supplier selection and procurement optimization in response to changing conditions, such as shifts in demand or supply disruptions.

Sustainability Optimization

By incorporating environmental and social criteria into the supplier selection process, GNNs can help companies achieve their sustainability goals while optimizing for cost and performance.

6.4. Challenges and Future Directions

While GNNs offer significant advantages in supplier selection and procurement optimization, there are still challenges to be addressed. One of the main challenges is scalability, as large supply chains can involve thousands of suppliers and complex interdependencies. Current GNN models may struggle to scale to such large networks, although techniques such as GraphSAGE and Graph Attention Networks (GAT) offer some solutions. Another challenge is interpretability—while GNNs provide powerful predictions, their decision-making process is often opaque, making it difficult for supply chain managers to understand how certain suppliers were selected. Developing more interpretable GNN models will be crucial for gaining the trust of practitioners in the supply chain field.

7. Inventory Optimization

GNNs are also being used for inventory optimization in multi-echelon supply chains. Managing inventory across different tiers of the supply chain is challenging due to the interdependencies between suppliers, manufacturers, and distribution centers. Traditional inventory models often focus on optimizing stock levels at individual nodes without considering the entire network structure.

By using GNNs, supply chain managers can optimize inventory decisions across the entire network. For example, GNNs can model the relationships between inventory levels at different nodes and use this information to predict the impact of inventory decisions at one node on other nodes in the network. This network-wide perspective allows for better coordination of inventory levels, reducing both stockouts and excess inventory.

Inventory optimization in supply chain management is the process of balancing inventory levels across various nodes in the network (e.g., suppliers, manufacturers, warehouses, and retailers) to meet demand while minimizing holding costs, stockouts, and excess inventory. Managing inventory is particularly challenging in multi-echelon supply chains, where several layers of suppliers and distribution centers are interdependent. Traditional approaches to inventory optimization, such as economic order quantity (EOQ) or just-in-time (JIT) models, often focus on optimizing stock levels at individual nodes. However, they fail to consider the interconnected nature of the supply chain, where decisions at one node can affect the performance of other nodes.

Graph Neural Networks (GNNs) offer a new approach to inventory optimization by leveraging the graph-based structure of supply chains. In a supply chain graph, each node can represent a supplier, warehouse, or retailer, while the edges represent material flows, transportation routes, or information exchange. By modeling the supply chain as a graph, GNNs can capture the interdependencies between nodes, allowing for a more holistic optimization of inventory levels across the entire network.

GNN Approach to Inventory Optimization Capturing Network-wide Dependencies: GNNs excel at capturing relational information in graphs. In a supply chain, inventory levels at different nodes are not independent but are influenced by upstream and downstream entities. For example, if a warehouse holds insufficient stock, it might lead to shortages at the retailer level. On the other hand, overstocking at a distribution center could lead to increased holding costs or wastage of perishable goods. GNNs can aggregate information from neighboring nodes and propagate it through the network, helping decision-makers understand how inventory decisions at one node impact the entire supply chain.

Dynamic Inventory Management: One of the key strengths of GNNs is their ability to handle dynamic and evolving networks. In a real-world supply chain, inventory levels and demand fluctuate constantly due to seasonality, market conditions, or unforeseen events (e.g., natural disasters, supplier disruptions). GNNs can adapt to these changes by continuously learning from data and updating the relationships between nodes. This dynamic capability enables GNNs to recommend inventory policies that respond in real-time to fluctuations in demand, lead times, or supply disruptions, reducing both stockouts and overstock situations.

Predictive Capabilities: By incorporating time-series data such as historical demand, lead times, and sales forecasts, GNNs can be used to predict future inventory requirements. GNNs analyze how past events and trends propagated through the supply chain network and use this information to forecast future conditions. For example, if certain nodes are regularly facing stockouts due to delays from a particular supplier, the GNN can predict these issues and recommend holding higher safety stock at specific locations or even suggest alternative suppliers. This predictive capability helps prevent disruptions before they occur, improving overall supply chain resilience.

Cross-node Inventory Optimization: Traditional inventory optimization models typically focus on minimizing inventory at individual nodes, but this can lead to inefficiencies across the broader supply chain. GNNs, on the other hand, allow for cross-node optimization, where the goal is to minimize overall supply chain costs while ensuring sufficient stock levels at all critical points. For instance, a GNN can recommend reducing inventory at a central warehouse while slightly increasing stock at downstream retail locations to reduce transportation costs and improve delivery times.

Multi-objective Optimization: In supply chain management, inventory optimization is not just about minimizing costs; it also involves balancing multiple objectives, such as improving service levels, reducing carbon footprints, and ensuring product availability. GNNs can handle multi-objective

 doi:10.20944/preprints202409.2376.v1

optimization by learning to prioritize these different factors. For example, a GNN could optimize inventory not just based on cost and demand but also consider environmental factors like reducing emissions from unnecessary transportation by strategically placing inventory closer to end customers.

7.1. Case Studies and Research

[19] demonstrated the use of GNNs for multi-echelon inventory optimization, where the goal was to minimize inventory costs while maintaining service levels across multiple tiers in the supply chain. By modeling the supply chain as a graph and training the GNN on historical demand and lead time data, they were able to develop a model that could predict optimal inventory levels for each node in the network. The GNN was particularly effective in identifying bottlenecks where stockouts were likely to occur and recommending corrective actions, such as redistributing stock between different distribution centers.

[20] explored using GNNs for inventory optimization in perishable goods supply chains. In their study, the GNN was used to forecast the optimal stocking levels for perishable products, taking into account the shelf life of the goods and the transportation times between nodes. The GNN's ability to propagate information across the network allowed for more accurate predictions of how much stock each warehouse needed to hold to minimize waste while meeting customer demand.

7.2. Benefits of GNN-Based Inventory Optimization

Better Coordination

GNNs enable better coordination across different layers of the supply chain by considering the entire network in the decision-making process. This network-wide approach helps reduce inefficiencies like the bullwhip effect, where small fluctuations in demand lead to larger fluctuations in upstream inventory levels.

Improved Resilience

By predicting potential disruptions and optimizing inventory across the network, GNNs help build more resilient supply chains. This is especially important in today's globalized supply chains, where disruptions in one part of the world can have ripple effects across the entire network.

Scalability

Traditional optimization methods struggle to scale when applied to large, complex supply chains with thousands of entities. GNNs, on the other hand, can scale to large networks due to their graph-based architecture, making them well-suited for optimizing inventory in global supply chains.

7.3. Challenges and Future Directions

Despite their promise, the use of GNNs for inventory optimization faces several challenges. First, scalability remains a concern when applying GNNs to extremely large networks with millions of nodes and edges. Though GNN models like GraphSAGE and Graph Attention Networks (GAT) offer some improvements in scalability, more work is needed to make GNNs practical for massive supply chains.

Second, most current GNN models assume a static network structure, while real-world supply chains are dynamic, with constantly changing relationships between suppliers, manufacturers, and retailers. Adapting GNNs to handle dynamic and real-time data from supply chains is an ongoing research area. Finally, interpretability remains an issue. Like many deep learning models, GNNs are often considered "black boxes," making it difficult for supply chain managers to understand how certain decisions are made. Increasing transparency and explainability in GNN-based models will be crucial for gaining the trust of practitioners in the supply chain industry.

 doi:10.20944/preprints202409.2376.v1

8. Green Supply Chain Optimization

Sustainability is becoming a growing concern for modern supply chains, and GNNs are now being applied to optimize environmental performance in supply chains. Green supply chain optimization focuses on reducing carbon footprints, optimizing energy usage, and minimizing waste throughout the supply chain.

GNNs can model the environmental impact of different supply chain activities by representing them as a graph, where nodes are suppliers, manufacturers, or distribution centers, and edges represent material flows or transportation links. By aggregating environmental data at each node, such as carbon emissions or energy consumption, GNNs can identify areas where the supply chain can reduce its environmental impact. For example, a GNN can be used to recommend more sustainable transportation routes, or to identify suppliers with the lowest carbon footprints, as demonstrated by a recent study on green logistics optimization [14].

9. Conclusion and Future direction

In this paper, we have explored the growing role of Graph Neural Networks (GNNs) in addressing critical problems in supply chain logistics, particularly in supplier selection and procurement optimization. Supply chains, by their very nature, form intricate networks of suppliers, manufacturers, distributors, and customers, where the relationships and dependencies between these entities are of paramount importance. Traditional models often fail to capture these complexities. However, GNNs offer a powerful framework for modeling supply chains as graphs, allowing decision-makers to consider not only the attributes of individual suppliers but also their interdependencies and the potential ripple effects of disruptions across the supply chain.

GNNs have proven to be effective in supplier selection, risk management, and procurement optimization by enabling holistic decision-making and improving overall supply chain resilience. They allow for dynamic adaptation, continuously learning from new data, and offering updated supplier recommendations in real time. However, despite their promising advantages, challenges such as scalability and interpretability remain key barriers to the wider adoption of GNN-based solutions in large-scale supply chain operations.

While the application of GNNs in supply chain management is still in its nascent stages, there are several exciting avenues for future research and development. One critical area is the scalability of GNN models. As supply chains grow in size and complexity, GNNs must be able to efficiently handle larger graphs with thousands or even millions of nodes. New techniques such as hierarchical GNNs or distributed GNN architectures could help overcome this challenge, allowing for the modeling of global, multi-tier supply chains.

Another important area of research is interpretability. The black-box nature of GNNs can make it difficult for supply chain professionals to understand how specific decisions are made. Future research should focus on developing explainable GNN models that can provide clear justifications for their recommendations. This will be crucial for building trust in these systems and ensuring their widespread adoption in industry.

Moreover, real-time decision-making capabilities in dynamic and volatile environments are increasingly important. Future advancements could focus on integrating GNNs with real-time data sources (e.g., IoT sensors, blockchain, and ERP systems) to provide up-to-the-minute insights on supplier performance, demand fluctuations, and potential disruptions. This would further enhance the adaptability of GNN-based supply chain systems.

Finally, sustainability and ethical procurement are emerging trends in supply chain management. Future research could explore how GNNs can incorporate environmental and social governance (ESG) factors into the supplier selection process, helping companies optimize for not only cost and risk but also for sustainability goals, such as reducing carbon footprints or improving labor practices across the supply chain.

By addressing these challenges and pursuing these directions, GNNs have the potential to revolutionize supply chain management, making it more efficient, resilient, and sustainable in the face of growing complexity and uncertainty.

References

1. Andrew Lim and Fan Wang. Robust graph coloring for uncertain supply chain management. In *Proceedings of the 38th Annual Hawaii International Conference on System Sciences*, pages 81b–81b. IEEE, 2005.
2. Anna Nagurney, June Dong, and Ding Zhang. A supply chain network equilibrium model. *Transportation Research Part E: Logistics and Transportation Review*, 38(5):281–303, 2002.
3. Sara Saberi, Mahtab Kouhizadeh, Joseph Sarkis, and Lejia Shen. Blockchain technology and its relationships to sustainable supply chain management. *International journal of production research*, 57(7):2117–2135, 2019.
4. Zeyu Wang, Yue Zhu, Zichao Li, Zhuoyue Wang, Hao Qin, and Xinqi Liu. Graph neural network recommendation system for football formation. *Applied Science and Biotechnology Journal for Advanced Research*, 3(3):33–39, 2024.
5. Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.
6. Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.
7. Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. *Advances in neural information processing systems*, 30, 2017.
8. Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. How powerful are graph neural networks? *arXiv preprint arXiv:1810.00826*, 2018.
9. Kihwan Han. Applying graph neural network to supplygraph for supply chain network. *arXiv preprint arXiv:2408.14501*, 2024.
10. Júlio César Alves and Geraldo Robson Mateus. Deep reinforcement learning and optimization approach for multi-echelon supply chain with uncertain demands. In *International Conference on Computational Logistics*, pages 584–599. Springer, 2020.
11. Shuo Yang, Zhiqiang Zhang, Jun Zhou, Yang Wang, Wang Sun, Xingyu Zhong, Yanming Fang, Quan Yu, and Yuan Qi. Financial risk analysis for smes with graph-based supply chain mining. In *Proceedings of the Twenty-Ninth International Conference on International Joint Conferences on Artificial Intelligence*, pages 4661–4667, 2021.
12. Edward Elson Kosasih and Alexandra Brintrup. A machine learning approach for predicting hidden links in supply chain with graph neural networks. *International Journal of Production Research*, 60(17):5380–5393, 2022.
13. Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. *IEEE transactions on neural networks and learning systems*, 32(1):4–24, 2020.
14. Hao Yuan, Haiyang Yu, Shurui Gui, and Shuiwang Ji. Explainability in graph neural networks: A taxonomic survey. *IEEE transactions on pattern analysis and machine intelligence*, 45(5):5782–5799, 2022.
15. Ting Dong and Mary Jane C Samonte. Optimization and benefit assessment of production supply chain networks using graph neural network models. *Journal of computing and information technology*, 32(1):15–31, 2024.
16. Mohsen Soori, Behrooz Arezoo, and Roza Dastres. Artificial neural networks in supply chain management, a review. *Journal of Economy and Technology*, 1:179–196, 2023.
17. Yulei Wu, Hong-Ning Dai, and Haina Tang. Graph neural networks for anomaly detection in industrial internet of things. *IEEE Internet of Things Journal*, 9(12):9214–9231, 2021.
18. Edward Elson Kosasih, Fabrizio Margaroli, Simone Gelli, Ajmal Aziz, Nick Wildgoose, and Alexandra Brintrup. Towards knowledge graph reasoning for supply chain risk management using graph neural networks. *International Journal of Production Research*, 62(15):5596–5612, 2024.

 doi:10.20944/preprints202409.2376.v1

19. Yaochu Jin, Xueming Yan, Shiqing Liu, and Xiangyu Wang. A unified framework for combinatorial optimization based on graph neural networks. *arXiv preprint arXiv:2406.13125*, 2024.
20. Amit Kumar Sinha and Ankush Anand. Optimizing supply chain network for perishable products using improved bacteria foraging algorithm. *Applied Soft Computing*, 86:105921, 2020.