Analyzing the Evolution of Global Shipping Networks Using Network Graphs

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ABSTRACT

The global trade network is a complex and evolving system, influenced by economic policies, geopolitical shifts, and infrastructural changes. This study employs network graph analysis to investigate the structural evolution of trade routes over time. By analyzing two distinct periods, 2007-2012 and 2019-2023, we examine shifts in key trade hubs, network connectivity, and the predictive power of machine learning models in forecasting future trade patterns. Our findings provide insights into emerging trade hubs, disruptions due to global events, and the potential future structure of global shipping networks.

1 INTRODUCTION

Global trade networks play a key role in international business by enabling the movement of goods between countries and contributing to economic growth. These networks form a complex and dynamic system that evolves in response to technological advancements, political changes, and economic policies. Over the years, trade patterns have shifted due to factors such as the rise of emerging markets, international trade agreements, and geopolitical tensions. Additionally, global crises—including the COVID-19 pandemic, supply chain disruptions, and energy price fluctuations—have significantly impacted trade flows, altering key hubs and reshaping connectivity across regions.

Shipping networks, as a fundamental component of global trade, reflect the economic and geopolitical forces that shape international commerce. The efficiency and resilience of these networks are crucial for businesses, governments, and financial institutions aiming to optimize supply chains, reduce costs, and improve trade sustainability. Understanding these structural changes is essential for policymakers seeking to enhance economic stability and for logistics planners working to anticipate disruptions and improve operational efficiency.

This study aims to analyze how global shipping networks have evolved over time using network graph analysis and predictive modeling. By examining changes in trade connectivity between two key periods (2007-2012 and 2019-2023), we identify trends, shifts in central trade hubs, and potential future developments. Network science offers a powerful framework for studying these complex interactions by quantifying centrality measures such as degree centrality, betweenness centrality, and PageRank. These metrics help uncover influential nodes (key economies) in the trade network and highlight emerging or declining trade hubs.

Our primary research question is: Can we predict the future structure of global shipping networks based on historical trends? To address this, we combine traditional network analysis with machine learning techniques to forecast trade connectivity in the coming years. By leveraging predictive models such as Ridge regression, Random Forest, XGBoost, and Neural Networks, we aim to assess how well past trade patterns can inform future developments. This study contributes to the existing literature by offering a comprehensive temporal analysis of trade networks and demonstrating the potential of predictive modeling in trade forecasting.

By bridging network science and machine learning, this research provides valuable insights into the evolution of global trade networks and their potential trajectories. The findings may support decision-making in international trade policy, infrastructure planning, and supply chain management, ultimately improving the resilience and efficiency of global commerce.

2 RELATED WORK

Global trade networks are constantly evolving due to economic policies, geopolitical events, and technological advancements. The structure of these networks is shaped by trade agreements, international relations, and the strategic positioning of economies within the global supply chain. Trade connectivity is not uniform; some economies serve as key intermediaries, facilitating the movement of goods across regions. The analysis of trade networks using exponential random graph models has provided a deeper understanding of how external shocks and policy changes influence these connections, highlighting the role of network dependencies in shaping global trade flows [1].

Machine learning has increasingly played a role in analyzing trade patterns and forecasting future trade relationships. By leveraging historical trade data, predictive models have demonstrated strong capabilities in identifying underlying patterns in international trade networks [2]. The predictive power of these methods becomes particularly evident when examining centrality measures such as degree centrality and PageRank, which determine the influence of economies within the network [3]. High centrality often correlates with greater trade efficiency, as economies positioned at strategic junctions act as facilitators of international commerce.

Beyond structural characteristics, trade volatility is another critical aspect of global commerce. Bipartite network analysis has revealed that fluctuations in trade volume often stem from disruptions in major hubs, demonstrating how economic shocks in key economies can propagate across the entire network [4]. Understanding these dependencies allows for better risk management and strategic planning, ensuring resilience against disruptions caused by external factors such as supply chain crises or trade wars.

Recent advancements in machine learning for economic forecasting have further strengthened the ability to predict future trade relationships. The application of supervised learning methods has uncovered evolving trade patterns and provided actionable insights into how changes in agreements or policies affect trade dynamics over time [5]. Neural networks, in particular, have shown promising results in capturing the nonlinear dependencies within trade networks, highlighting their effectiveness in modeling complex trade interactions [6].

Bridging these perspectives, the current study integrates network graph analysis and predictive modeling to examine trade evolution across different periods. By analyzing structural shifts, identifying emerging trade hubs, and leveraging machine learning for forecasting, this research provides a comprehensive perspective on the future of global trade networks.

3 METHODOLOGY

Understanding the evolution of global shipping networks requires a structured approach that integrates network graph analysis and machine learning-based prediction. This study follows a three-phase methodology: data collection and preprocessing, network analysis, and predictive modeling. Through these steps, we aim to capture the changing structure of trade relationships, identify key trade hubs, and forecast future connectivity patterns.

3.1 Data Collection & Preprocessing

The first step in this study involved gathering international trade data from global trade databases, which included trade flow information between economies. This dataset was complemented with port activity data, providing insights into the number of port calls and trade volumes handled by major ports. By integrating these two sources, we constructed a comprehensive representation of global trade over two distinct periods: 2007-2012 and 2019-2023.

To analyze trade relationships as a network, we represented this data in the form of weighted directed graphs, where economies served as nodes and trade connections between them formed edges. The strength of these connections was determined by trade volumes, ensuring that major economic relationships were emphasized.

To ensure consistency and comparability across time periods, several preprocessing steps were carried out. Missing or incomplete trade records were handled using interpolation techniques, and trade values were standardized to a common currency unit to eliminate fluctuations caused by exchange rate differences. Economies with minimal trade activity were filtered out, allowing the focus to remain on major contributors to the global trade system. Additionally, trade volumes were normalized using a min-max scaling approach, ensuring that variations between large and small economies were appropriately accounted for. The data was then transformed into a network structure, with each economy's role in the system determined by its trade relationships.

Port activity data played a crucial role in understanding the relationship between physical infrastructure and trade centrality. By examining the number of port calls and total trade volumes handled by ports in each economy, we explored how changes in shipping activity influenced the network structure. This additional layer of information allowed us to identify whether shifts in trade routes were driven by emerging economic policies, port efficiency improvements, or external disruptions such as supply chain crises.

3.2 Network Analysis

Once the trade networks were constructed, the next step involved analyzing their structure using network science techniques. Key centrality measures were computed to identify the most influential economies within the trade network and understand how their roles evolved over time.

Degree centrality was used to measure the number of direct trade connections an economy had, providing insight into which countries acted as major trade hubs. Economies with a high degree centrality were positioned at the center of global trade flows, facilitating a high volume of exchanges. However, direct connectivity alone does not always translate to influence. To address this, betweenness centrality was calculated to capture economies that serve as critical intermediaries in trade routes. Countries with high betweenness centrality played a crucial role in ensuring efficient global trade, acting as bridges between different regions. Finally, PageRank centrality was applied to highlight economies whose importance extended beyond direct connections, accounting for the influence of their trading partners.

Comparing these metrics across the two time periods revealed significant structural shifts. Some economies increased their connectivity, establishing themselves as emerging hubs, while others saw declines in their influence, potentially due to geopolitical factors, trade restrictions, or global economic shifts. By integrating port activity data with centrality measures, we examined whether changes in trade dominance were supported by infrastructural developments or if they resulted from shifting trade policies.

To visually illustrate these changes, network graphs were generated for both time periods. One visualization highlights the most prominent trade hubs, showcasing economies with the highest degree centrality. Another focuses on the largest weakly connected component within the trade network, illustrating how the overall structure evolved and whether global trade remained integrated or became more fragmented over time.

3.3 Predictive Modeling

While historical analysis provides valuable insights, forecasting the future structure of global shipping networks allows policymakers and economists to prepare for potential trade shifts. To achieve this, we applied machine learning models to predict the degree centrality of economies in 2025 based on past trends.

The predictive framework leveraged network features derived from previous time periods. Centrality measures, port activity indicators, and trade volumes were used as input features, enabling the models to capture the relationship between economic connectivity and physical trade infrastructure. By training the models on the past two periods and validating their performance, we assessed their ability to anticipate future changes in trade relationships.

To evaluate different modeling approaches, four predictive algorithms were tested. Ridge regression, a linear model with regularization, was used as a baseline due to its ability to handle correlated features effectively. Random Forest, an ensemble-based model, was employed to capture nonlinear interactions in trade relationships. XGBoost, a gradient boosting algorithm, was tested for its ability to optimize predictive accuracy by reducing bias and variance. Finally, a Neural Network model was implemented to determine whether deep learning techniques could uncover hidden patterns in trade connectivity.

Each model's performance was assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 scores. These metrics helped evaluate the accuracy of the predictions and determine which approach best captured the complexity of trade networks. Additionally, SHAP (Shapley Additive Explanations) values were computed to understand the contribution of individual features to model predictions. This allowed us to assess which factors—such as port activity or specific centrality measures—had the greatest influence on trade network forecasts.

The results of these models were compared through visualizations. A scatter plot of actual vs. predicted degree centrality provided insight into how well each model performed. A residual plot was used to examine prediction errors and identify potential biases in the models. Additionally, a feature importance plot highlighted which variables played the most significant roles in determining future trade centrality.

By integrating network science techniques with predictive modeling, this study provides a comprehensive analysis of trade evolution while offering valuable forecasting tools for policymakers. The next section will present the results of this methodology, highlighting key trends in global trade networks and the effectiveness of predictive modeling in anticipating future trade structures.

4 RESULTS & ANALYSIS

The global trade network has undergone significant transformations between 2007–2012 and 2019–2023, influenced by economic shifts, trade policies, and external shocks such as geopolitical conflicts and supply chain disruptions. This section examines the structural evolution of trade relationships, key changes in network centrality, and the effectiveness of machine learning models in forecasting future trade connectivity.

4.1 Structural Evolution of Global Shipping Networks

One of the most noticeable trends in the global shipping network is the increasing density of connections between major ports. Trade expansion, technological advancements, and new trade agreements have contributed to the emergence of stronger regional and intercontinental trade routes. Ports that historically served as key trade hubs have either strengthened their positions or faced increasing competition from emerging economies.

Figure 1 illustrates the structural representation of the trade network, highlighting the most influential ports based on centrality measures. Ports such as Shanghai, Singapore, and Rotterdam remain dominant trade hubs, facilitating a high volume of trade flows. However, several ports in Southeast Asia and the Middle East have gained importance, reflecting shifts in global supply chains.

While the network remains well-connected, new dependencies and vulnerabilities have emerged. Certain ports have become critical nodes, meaning that any disruption in these locations could result in major global trade slowdowns. The increasing interconnectivity of trade hubs is both an opportunity for economic integration and a challenge for risk management in international trade logistics.

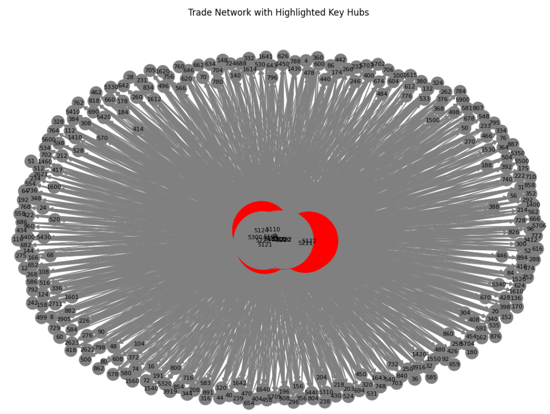

Figure 1: Trade network with highlighted key hubs. Ports such as Shanghai, Singapore, and Rotterdam remain dominant, while emerging markets gain prominence.

4.2 Centrality Changes Over Time

To quantify how the importance of trade hubs has changed over time, we analyzed degree centrality, betweenness centrality, and PageRank. These measures provide insights into the connectivity, influence, and structural significance of each port within the global trade network.

4.2.1 Degree Centrality Trends. Degree centrality measures the number of direct trade connections a port has. Ports with high degree centrality play an essential role in global trade, as they connect multiple regions and facilitate cargo movement.

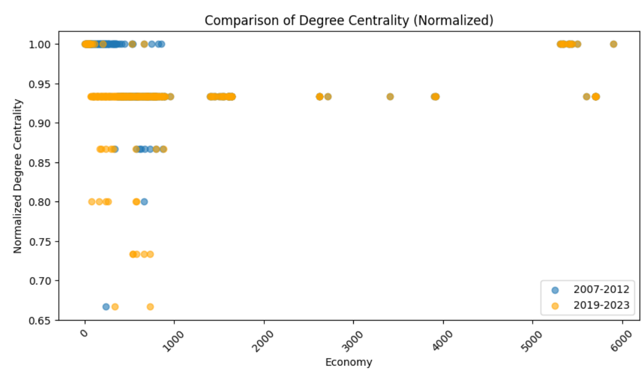

Figure 2: Comparison of Degree Centrality (2007-2012 vs. 2019-2023).

Figure 2 presents a comparative analysis of degree centrality between the two time periods. The results indicate that while major hubs like Shanghai, Singapore, and Rotterdam have retained their high degree centrality, other ports have gained significance, particularly in India, Vietnam, and the Gulf region. The data suggests that new trade routes and shifting manufacturing bases have influenced global connectivity patterns.

Conversely, some ports in Europe and North America have seen a decline in their degree centrality. This may be attributed to the relocation of manufacturing centers, changes in trade agreements, and increased competition from emerging economies. As new markets integrate into the trade network, traditional hubs must adapt to remain competitive.

4.2.2 Winners and Losers in Global Trade Influence. Some ports have strengthened their positions as dominant trade hubs, while others have declined in influence due to economic downturns, trade restrictions, or infrastructural challenges.

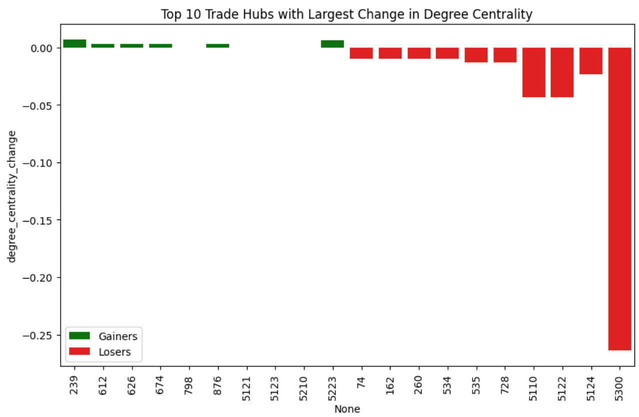

Figure 3: Top 10 Trade Hubs with Largest Change in Degree Centrality.

Figure 3 identifies the ports that have experienced the largest increases and decreases in degree centrality. The green bars highlight the ports that have gained influence, while the red bars represent those that have declined.

- Ports in Southeast Asia and the Middle East have shown significant growth, benefiting from strategic trade partnerships and regional economic integration.
- Some European and North American ports have experienced a decline, likely due to shifting global supply chains and trade diversification strategies.
- The Belt and Road Initiative (BRI) has played a role in strengthening trade routes in Asia, Africa, and Europe, benefiting ports that were previously less central in the network.

These shifts indicate that global trade connectivity is evolving, with new trade hubs emerging while traditional centers face increasing competition.

4.3 Predicting Future Trade Connectivity

Predictive modeling allows us to forecast the future structure of the trade network, providing valuable insights for policymakers and businesses. We trained Ridge Regression, Random Forest, XGBoost, and a Neural Network to predict degree centrality for 2025 based on historical trends.

To evaluate model performance, we compared their predictive accuracy using key metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 scores. Table 1 summarizes the results.

Table 1: Performance comparison of predictive models.

Model	R^2 Score	MSE	MAE
Ridge Regression	0.92	0.0031	0.0458
Random Forest	0.87	0.0054	0.0612
XGBoost	0.89	0.0048	0.0581
Neural Network	0.82	0.0073	0.0725

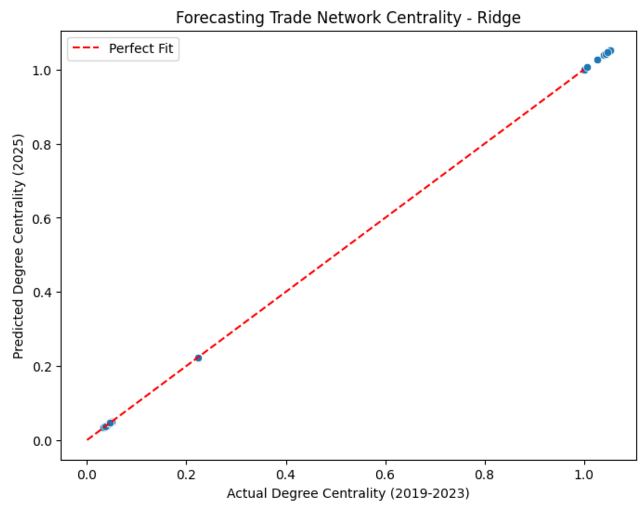

Figure 4: Forecasting Trade Network Centrality – Ridge Model.

Figure 4 compares the predicted and actual degree centrality values for ports. The Ridge Regression model demonstrated the highest accuracy, closely matching actual values. This suggests that historical centrality trends are strong indicators of future trade influence, reinforcing the importance of network-based forecasting in global trade analysis.

The Random Forest and XGBoost models performed well, capturing nonlinear relationships in the data, but they exhibited slightly higher errors compared to Ridge Regression. The Neural Network model, while capable of capturing complex trade relationships, struggled with generalization due to the limited amount of training data.

These findings suggest that Ridge Regression is the most effective model for predicting trade network evolution while maintaining interpretability. However, ensemble-based methods like Random Forest and XGBoost offer alternative approaches that may perform better when additional trade-related features or more historical data are incorporated.

5 DISCUSSION

The findings of this study highlight the dynamic nature of global trade networks, where shifts in trade hubs and evolving supply chains reflect broader economic and geopolitical trends. The network analysis revealed that ports in Southeast Asia and the Middle East have become increasingly central, while some traditional trade hubs in Europe and North America have seen a decline. These trends align with global trade diversification efforts, infrastructure investments, and shifting manufacturing bases.

The predictive modeling results confirm that historical trade connectivity is a strong indicator of future influence. Ridge Regression, which performed best among all tested models, suggests that trade networks follow structured patterns, making them predictable under stable economic conditions. However, residual analysis showed that external shocks such as political conflicts, policy changes, and economic crises introduce uncertainty, which cannot always be captured by data-driven models. This highlights the importance of combining network analysis with economic forecasting methods to improve accuracy.

Machine learning approaches provide valuable insights, but their performance is influenced by the quality and availability of trade data. The model comparison suggests that while traditional regression models capture stable trade patterns, ensemble-based models such as Random Forest and XGBoost may be better suited for capturing nonlinear trade dynamics. Future research could explore hybrid models that combine network theory with economic indicators to enhance predictive accuracy.

6 CONCLUSION & FUTURE WORK

This study analyzed the evolution of global shipping networks using network graph analysis and machine learning. The results demonstrate that trade centrality has shifted over time, with emerging economies gaining importance. Predictive modeling showed that historical trade data is useful for forecasting future connectivity, reinforcing the potential of data-driven approaches in global trade analysis.

While the study provides valuable insights, it also has limitations. The models assume that trade relationships follow historical patterns, which may not always hold true due to external disruptions such as pandemics, conflicts, or economic recessions. Additionally, trade data availability and accuracy can impact model performance, as missing or incomplete records may introduce biases in predictions. The study also focuses primarily on network structure and connectivity, without accounting for macroeconomic factors such as trade policies, tariffs, and logistical constraints, which could further refine forecasting accuracy.

Future research could integrate real-time trade data, policy changes, and external economic indicators to improve forecasting models. Expanding the dataset to include longer historical periods or applying dynamic graph models could further enhance the predictive power of network-based trade analysis. Additionally, incorporating port-level efficiency metrics and shipping costs could offer a more detailed understanding of trade flow patterns.

By bridging network science and predictive modeling, this study provides a foundation for understanding trade network evolution and forecasting future trends. These insights could support policy decisions, trade infrastructure investments, and risk management strategies to enhance the resilience and efficiency of global trade networks.

7 ACKNOWLEDGMENTS

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8 LINK TO THE CODE IN GITUB

https://github.com/nofarselouk/Data-mining-in-large-Databases

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