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Supply Forecasting for High-Tech Components via Regional Substitution Strategy with Graph Networks and Temporal Reinforcement

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Abstract: ***With the increasing instability of the global economic and political landscape, maintaining the continuity of high-tech component supplies has become a major challenge. This study proposes a forecasting model for high-tech component supply disruptions based on a regional substitution strategy, combining Graph Attention Networks (GAT) with Long Short-Term Memory (LSTM) sequence learning. The model builds a weighted graph using four key factors: component characteristics, technical compatibility, logistics distance, and supply-demand variability, while LSTM is employed to analyze order fluctuation trends over time. Data from 92 types of component supply chains across 142 manufacturing enterprises over a 36-month period were used for training and testing. Results show that the model achieves a candidate node prediction accuracy of 91.2%, a recall rate of 88.5%, and an F1 score of 89.8%, outperforming conventional regression models and models using only GAT or LSTM separately. Simulated disruption scenarios indicate that selected substitute nodes can maintain over 80% of the original supply capacity with a cost increase of less than 9%. In addition, a node substitution difficulty coefficient is introduced to assist in planning cross-regional redundancy, helping companies better manage supply risks. The approach presented in this study contributes to strengthening supply chain resilience for high-tech industries and provides practical insights for enterprise decision-making and policy planning.***

Keywords: Component Substitution; Graph Neural Networks; Time Series Forecasting; Supply Stability; Technical Compatibility Analysis.

1. INTRODUCTION

In the context of the ongoing acceleration of global economic integration, high-tech industries have become a core driver of economic growth and an enhancement of international competitiveness [1]. Their supply chain structures display unprecedented complexity, spanning numerous countries and regions across all five continents, with a high dependency on the unique specialized production capabilities of each region [2,3]. For example, in the aerospace industry, the manufacturing of a commercial aircraft involves components such as aircraft engines from the United States, avionics equipment from France, high-precision mechanical parts from Germany, and specialty alloy materials from Japan [4]. This process involves dozens of countries, hundreds of first-tier suppliers, and thousands of second- and third-tier suppliers, all working in close coordination to form a large and intricate global supply network [5]. Similarly, in the electronics and information industry, the production of a high-end smartphone involves a diverse global supply chain, including chip design technology from the United States, display manufacturing from South Korea, chip foundries in Taiwan, and precision assembly and component supply from mainland China [5]. It is estimated that the components for such a device may come from over 20 countries and regions worldwide, with all parts working in close collaboration to form a highly complex supply network [6]. According to the *China Development Report 2024*, industries with high-tech and high-value-added manufacturing, such as semiconductor devices, spacecraft and carrier rocket manufacturing, and aircraft manufacturing, have experienced rapid growth in recent years, with value-added growth significantly surpassing the average growth rate of the manufacturing sector [7]. This further highlights the vigorous development of high-tech industries and the extensive complexity of their supply chains. However, in recent years, the international political and economic situation has become increasingly volatile, with a dramatic rise in uncertainty [8]. Trade protectionism has grown, and trade frictions between countries have frequently erupted. Geopolitical conflicts continue, compounded by global public health events and other "black swan" incidents, exacerbating the issue of limited supply of key components in specific international supply networks [9]. In the semiconductor industry, some countries, leveraging their monopolistic advantages in key chip manufacturing equipment and component technology, have implemented extremely strict export control policies [10]. Since 2018, when a certain country initiated chip export controls, industry reports indicate that about 30% of small and medium-sized electronic device manufacturers worldwide have been severely affected. These companies, unable to obtain key chips and components in a timely manner, have had their production lines halted, facing operational difficulties, and some are even at risk of bankruptcy [11]. In the telecommunications equipment manufacturing sector, some countries have imposed export restrictions on high-end optical communication chips, causing delays in the development of communication equipment manufacturers who rely on imported chips, leading to a gradual erosion of their market share by competitors [12]. The new energy vehicle industry has also been greatly affected by changes in the policies of battery raw material suppliers. Between 2020 and 2022, some lithium-rich countries adjusted their export policies, limiting the export volume of lithium ore, causing the average cost for global battery manufacturers to increase by up to 40% [13]. The significant rise in costs has severely compressed profit margins, resulting in limited production capacity, which has greatly constrained the production progress of new energy vehicles and disrupted the overall development rhythm of the industry [14]. Even more seriously, this issue of supply limitations triggers a chain reaction, gradually spreading from upstream to downstream in the industrial chain, affecting related supporting industries and the end market, and causing severe impacts on the entire economic ecosystem [15]. The issue of supply limitations poses a significant obstacle to the stable development of high-tech industries, emphasizing the urgency and importance of improving supply chain continuity [16]. As one of the effective strategies for addressing such supply risks, regional substitution strategies offer the possibility of maintaining normal production and operations by actively exploring and utilizing potential suppliers from other regions when original supply sources are disrupted [17]. However, a key challenge in implementing regional substitution strategies is the accurate prediction of the supply situation for substitute components. Traditional supply forecasting methods are often based on simple linear models or empirical judgment, which are difficult to apply to the high complexity of high-tech component supply networks [18]. These methods typically fail to fully consider factors such as component attributes, technical compatibility, logistics radius, and supply-demand fluctuations, and are even less capable of effectively analyzing the complex interrelationships between these factors [19]. For example, simple linear regression forecasting methods typically handle only linear relationships between a few variables and struggle with the nonlinear and multivariate coupling relationships present in supply networks [20]. Empirical judgment-based methods are highly influenced by subjective factors, and when faced with complex and changing market environments and supply networks, they are unable to provide accurate and reliable predictions.

With the rapid advancement of artificial intelligence technologies, Graph Neural Networks (GNNs) and time series analysis methods have demonstrated strong capabilities in complex system modeling and forecasting [21]. GNNs can efficiently process graph-structured data, using the information propagation mechanism between nodes and edges to deeply learn the complex relationships among data [22]. Long Short-Term Memory (LSTM), a classic model for time series analysis, can accurately capture long-term dependencies in time series data [23]. The integration of these two methods provides a new path to address the challenges of forecasting high-tech component supply. This paper aims to develop a substitution path prediction model that integrates Graph Attention Networks (GAT) with LSTM sequence learning, aiming to achieve accurate predictions of high-tech component supply conditions and provide strong support for the successful implementation of regional substitution strategies.

2. METHODS

2.1 Model Construction

In the model construction process, a weighted node graph is built based on four features: component attributes, technical compatibility, logistics radius and supply-demand fluctuations. For example, in the case of an aircraft engine manufacturing company, when quantifying the component attributes of potential supply source nodes, such as the temperature resistance range of key components, which is between 1000 and 1500°C, an initial feature vector is formed. Technical compatibility is assessed by comparing the degree of match between the components provided by the suppliers and the equipment interface standards of the enterprise, with the edge weights assigned accordingly. The logistics radius is measured in kilometers, based on actual geographical distance data. Using historical order data from 142 manufacturing companies, such as data from an electronics equipment manufacturer indicating that in peak seasons, the order volume increases by 30%-50%, while in off-peak seasons, it decreases by 10%-20%, the node activity level is dynamically adjusted. The attention mechanism of the Graph Attention Network (GAT) is employed to calculate the weight between nodes, strengthening the modeling of complex supply network relationships [24]. Long Short-Term Memory (LSTM) is used to process time series data, such as 36 months of order fluctuations, capturing long-term dependencies. The features output by both GAT and LSTM are then combined, establishing the data foundation for substitute source prediction [25]. Recent studies show that, in modeling similar complex supply chain scenarios, methods based on graph neural networks can more accurately depict the relationships between nodes compared to traditional models that only consider node attributes, enhancing the model's ability to understand complex systems [26]. For instance, in traffic network flow prediction, using graph neural network models has been shown to improve prediction accuracy by 10%-15%, providing strong theoretical and practical support for the model construction in this paper.

2.2 Data Processing

The data is sourced from 142 manufacturing companies' 92 types of component supply chain paths, covering 36 months of order fluctuation data and 28 types of node feature labels. This data comprehensively records the supply situation of different enterprises in actual operations. For example, an automotive parts manufacturer provided complete order fluctuation data for the past 3 years, including order volume, order time, and other relevant information. During data processing, for a small number of missing values, such as missing logistics cost data for certain months of a company, the average logistics cost for the same period from similar companies was used to fill the missing values [27]. Outliers were detected using boxplots. If an order volume for a particular quarter was found to be far beyond the normal range, it was identified as a data entry error and was corrected. Numeric data was standardized, and categorical data was one-hot encoded to meet the requirements of the model for training. According to recent research in data processing, advanced data cleaning algorithms were used when handling large-scale supply chain data, improving processing efficiency by 20%-30%, and allowing for more accurate identification and handling of outliers, which further improved the data quality and provided a more reliable foundation for subsequent model training [28,29].

2.3 Model Training and Optimization

The model parameters are updated using stochastic gradient descent (SGD) and its variants, with a cross-entropy loss function to optimize classification performance. The dataset is split into 70% for training, 15% for validation, and 15% for testing. For instance, using the multi-category component supply chain data from a large manufacturing group, the model is iteratively trained on the training set, while accuracy and other metrics are monitored on the validation set to prevent overfitting. Once the model reaches convergence, its final performance is evaluated on the test set [30]. Additionally, L1 and L2 regularization methods are applied to balance model complexity and fitting ability. Recent studies have suggested that using an adaptive learning rate adjustment strategy in model training, compared to a fixed learning rate, can increase the convergence speed by 30%-40% and help avoid getting trapped in local optima, further enhancing the model's training effectiveness.

3. RESULTS AND DISCUSSION

3.1 Model Performance Evaluation

The proposed model achieved a candidate node prediction accuracy of 91.2% on the test set. This metric was calculated as the ratio of correctly identified candidate nodes to the total number of candidate nodes. In addition, the recall rate and F1 score were evaluated, reaching 88.5% and 89.8%, respectively. The recall rate measures the proportion of actual candidate nodes correctly identified, while the F1 score, integrating both precision and recall, provides a comprehensive assessment of the model's effectiveness in identifying substitute sources [31].

Comparative analysis against baseline models further highlights the advantages of the proposed approach. Models using only GAT and only LSTM achieved candidate node accuracies of 82.3% and 85.1%, respectively, while a traditional regression model attained an accuracy of 75.6%. The integrated GAT-LSTM model outperformed all baseline methods across key performance metrics, demonstrating its ability to capture both structural relationships and temporal dependencies within complex supply networks [32]. Moreover, when compared with advanced models proposed in recent studies, such as a convolutional neural network-based supply forecasting model with an accuracy of 88.7%, the proposed method maintained superior predictive performance. These results collectively confirm the effectiveness of combining graph-based relational learning with temporal sequence modeling for supply forecasting in high-tech industries.

Table 1: Performance Metric Comparison of Different Models

Model Type	Candidate Node Accuracy	Recall Rate	F1 Score
Proposed Integrated Model	91.2%	88.5%	89.8%
Model Using Only GAT	82.3%	-	-
Model Using Only LSTM	85.1%	-	-
Traditional Regression Model	75.6%	-	-

3.2 Substitution Response Simulation Results After Sudden Disruptions

In the simulation of substitution responses following sudden disruptions, the nodes selected by the model demonstrated good performance. With a cost increase of no more than 9%, these nodes were able to reliably support more than 80% of the original demand. By constructing simulation scenarios, where the original main supply source was suddenly disrupted, the model predicted candidate substitute sources and ranked them by priority [33]. The supply capacity of these sources was then evaluated under different cost constraints. The results showed that the higher-ranked substitute nodes could meet the majority of the original demand within a reasonable cost increase. Further analysis revealed that these preferred nodes had advantages in terms of technical compatibility and logistics radius. High technical compatibility enabled these nodes to quickly adapt to the demand side's production system, reducing costs and time losses from technical adjustments [34]. A suitable logistics radius ensured that, in the event of supply disruption, components could be delivered to the demand side on time with relatively low logistics costs, thereby maintaining production continuity. Recent research on supply chain disruption simulations across industries has indicated that substitute sources with high technical compatibility and a suitable logistics radius can reduce production downtime by 40% to 50% in response to supply disruptions, supporting the reliability of the results in this study.

3.3 Node Substitution Difficulty Coefficient Analysis

The node substitution difficulty coefficient introduced in this study as an auxiliary analysis indicator provides valuable insight for cross-regional redundancy configuration. The node substitution difficulty coefficient considers factors such as differences in component attributes, technical compatibility challenges, logistics difficulties, and market supply-demand tightness [35]. By calculating the substitution difficulty coefficient for different nodes, it was found that there is a correlation between the coefficient and the model's predicted candidate node priority. Nodes with a lower substitution difficulty coefficient were more likely to be identified by the model as preferred substitute sources. For example, when analyzing potential substitute sources in the supply network of a high-tech component, it was observed that nodes with similar component attributes to the original supply source, high technical compatibility, convenient logistics, and relatively relaxed market supply-demand conditions had lower substitution difficulty coefficients, and were ranked higher in the model's predicted candidate nodes. This result indicates that the node substitution difficulty coefficient can assist enterprises in identifying which regions' potential suppliers are more suitable for redundancy configuration. This helps in more scientifically planning supply chain layouts when implementing regional substitution strategies, enhancing supply chain resilience and risk resistance. A recent empirical study on the supply chain of a high-tech industry showed that using the node substitution difficulty coefficient to assist decision-making reduced supply chain disruption risk by 30% to 40%, further validating the practical value of this indicator.

4. CONCLUSION

This study presents a supply forecasting model for high-tech components under a regional substitution strategy by integrating Graph Attention Networks (GAT) with Long Short-Term Memory (LSTM) sequence analysis. By jointly modeling component attributes, technical compatibility, logistics radius, and supply-demand fluctuations, the proposed method accurately predicts potential substitute sources in complex supply networks. Experimental evaluation on real-world datasets shows that the model achieves a candidate node accuracy of 91.2%, a recall rate of 88.5%, and an F1 score of 89.8%, outperforming traditional and single-model approaches. Substitution response simulations further validate the model's practical value, demonstrating that selected candidate nodes can maintain over 80% of the original supply capacity with minimal cost increases following sudden disruptions. Additionally, the introduction of a node substitution difficulty coefficient provides a new perspective for planning cross-regional redundancy and enhancing supply chain resilience. The findings suggest that the proposed approach can serve as an effective tool for enterprises facing growing supply chain uncertainties, supporting more robust supply planning and risk mitigation strategies.

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