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Measuring Supply Chain Resilience with Foundation Time-Series Models

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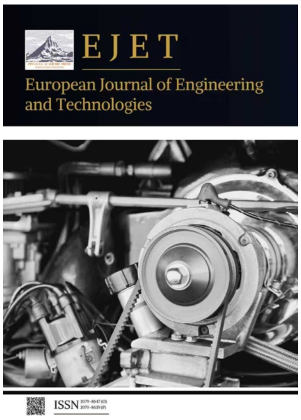

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Abstract: This study addresses the critical need for quantifying and assessing supply chain resilience by developing an advanced, data-driven measurement approach. We integrate Long Short-Term Memory (LSTM) networks with the Hybrid Foundation framework to construct a dynamic resilience index that captures both shock absorption and recovery capabilities across complex supply chains. The analysis leverages monthly operational data from 15 manufacturing enterprises collected between 2020 and 2024, encompassing key performance indicators such as order fulfillment rate, inventory turnover days, and transportation delay rate. The proposed model demonstrates exceptional predictive performance, achieving a mean squared error (MSE) of 0.0019 and a mean absolute percentage error (MAPE) of 4.32% in stability tests. Notably, it maintains high accuracy and robustness even under challenging conditions, including 5% missing data and ±10% noise perturbations, which reflects its resilience in real-world scenarios characterized by incomplete or uncertain information. By accurately simulating the temporal dynamics of supply chain disruptions and recoveries, the model provides a reliable and granular quantitative tool for resilience evaluation, supporting informed decision-making for supply chain managers. Furthermore, the methodology offers a scalable and adaptable framework applicable to diverse industrial contexts, enabling systematic monitoring, early-warning detection, and targeted strategic interventions to enhance overall operational stability and responsiveness. The findings underscore the value of combining deep learning with hybrid modeling techniques to achieve a nuanced understanding of supply chain behavior under both routine and stress conditions, contributing to the advancement of resilience analytics in contemporary supply chain management.

Keywords: supply chain resilience; time series model; LSTM; Hybrid Foundation; resilience index

1. Introduction

Supply chain resilience has become increasingly critical in the context of globalization, heightened market volatility, and growing interdependence of production networks. As supply chains become more complex and globally integrated, the ability to withstand disruptions and recover efficiently from shocks has emerged as a central concern for both researchers and practitioners. Resilience indices have been widely recognized as essential tools for evaluating a supply chain's capacity to recover after disturbances, and they are applied across diverse industries and geographic regions to guide strategic planning and operational decision-making. Traditional methods for measuring resilience, however, often rely on static analyses that fail to capture the dynamic evolution of supply chain performance under sustained or repeated disruptions. Recent advancements in predictive modeling, particularly those based on time-series data, offer promising avenues for addressing this limitation. Among these, Long Short-Term Memory (LSTM) networks have demonstrated considerable efficacy in modeling complex nonlinear relationships and temporal dependencies within supply chains [1]. By capturing dynamic fluctuations and sequential patterns in operational metrics, LSTM models enable a more realistic and adaptive assessment of system resilience. In parallel, other time-series-based approaches, such as those incorporating wavelet energy entropy and the Hybrid Foundation framework, provide additional analytical perspectives by integrating energy-level evaluations and information-theoretic metrics, thereby facilitating a nuanced understanding of stability and systemic risk [2,3]. Building on these methodological developments, this study proposes a composite resilience measurement system that combines LSTM with the Hybrid Foundation structure, allowing for comprehensive quantitative analysis of supply chain recovery processes under multidimensional time-series inputs. The model is designed to systematically reflect both short-term perturbations and long-term adaptive responses, thereby offering a robust framework for resilience assessment. By doing so, the study aims to contribute to the theoretical understanding of supply chain dynamics while providing practical guidance for risk assessment, strategic planning, and decision support systems, ultimately enhancing the operational robustness and responsiveness of contemporary supply chains.

2. Research Foundation

The study of supply chain resilience is fundamentally grounded in system stability theory and dynamic recovery mechanisms, focusing on the quantification of performance degradation and the capacity for recovery when supply chains are subjected to various internal and external disturbances. Traditional resilience assessment methods primarily rely on static indicator frameworks or expert-driven weighting approaches, which often fail to capture the temporal evolution and complex interdependencies inherent in supply chains. Such static methods are limited in their ability to accurately model responses to sudden disruptions or long-term fluctuations, making the prediction of dynamic recovery processes challenging [4]. With the rapid advancement of big data analytics and computational resources, time series analysis has emerged as a critical tool for resilience evaluation. By modeling temporal sequences of key operational metrics-such as inventory turnover, transportation timeliness, and order fulfillment rate-time series methods effectively reveal both long-term trends and short-term volatility, as well as lag effects, providing insight into the system's adaptive responses during periods of disruption and subsequent recovery [5]. The Foundation Time-Series Models framework integrates the interpretability of traditional statistical approaches with the predictive strength of deep learning techniques, enabling precise modeling of multidimensional, heterogeneous time-series data. This hybrid approach not only uncovers underlying structural patterns within complex datasets but also establishes a quantitative foundation for calculating resilience indices and forecasting future recovery trajectories. Consequently, it enhances the ability of supply chain managers to implement proactive risk mitigation strategies, optimize operational decisions, and strengthen overall supply chain robustness and adaptability in dynamic and uncertain environments.

3. Time Series Model Measurement Methods

3.1. Data Preparation and Feature Extraction

This study utilizes operational data from manufacturing supply chains in Eastern China spanning 2020 to 2024. Monthly core indicators from 15 representative enterprises were collected, including order fulfillment rate, inventory turnover days, transportation delay rate, capacity utilization rate, and supply cycle volatility, resulting in a total of 720 valid time-series datasets. Data sources included enterprise ERP systems, port logistics platforms, and the National Bureau of Statistics' industry operation monitoring database. Initial preprocessing involved imputing missing values, removing outliers, and eliminating short-term noise through sliding window smoothing. Min-Max normalization was then applied to ensure consistency across measurement scales for all indicators.

To capture resilience-related characteristics, both temporal and structural features were extracted. Temporal features included trend, seasonality, and volatility patterns, while structural features reflected upstream-downstream coordination and lagged response characteristics within the supply chain network. To enhance the temporal expressiveness of model inputs, a seven-period rolling window was employed to construct dynamic sample sequences, ensuring that each time slice contained comprehensive state information before, during, and after disruptions. The resulting multidimensional feature matrix provided a robust foundation for subsequent modeling within the Foundation Time-Series framework, enabling detailed characterization of the dynamic evolution of supply chain resilience.

3.2. Model Construction

Building upon the constructed feature matrix, a supply chain resilience measurement model based on the Foundation Time-Series framework was established. The model accepts a seven-period rolling window multidimensional time-series feature vector as input and outputs the predicted recovery rate of the supply chain state. It consists of a multi-layer architecture comprising a temporal encoding layer, a deep memory layer, and a predictive regression layer, as illustrated in Figure 1.

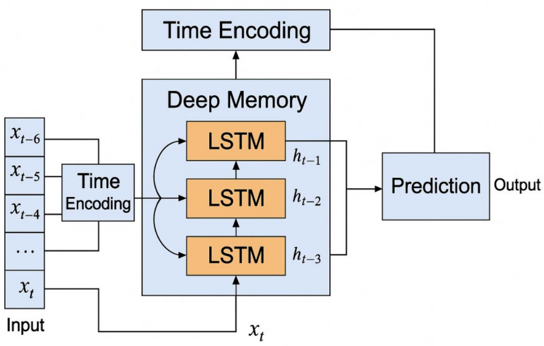

Figure 1. Model Structure.

The temporal encoding layer extracts local trend features through one-dimensional convolutions. The deep memory layer employs a bidirectional LSTM network to capture temporal dependencies among supply chain indicators. The prediction layer outputs resilience estimates via a linear regression unit. The core computational process of LSTM is:

$$h_t = f(W_x x_t + W_h h_{t-1} + b) \tag{1}$$

Where: h_t represents the hidden state vector, x_t denotes the input feature sequence, W_x and W_h are weight matrices, and bbb is the bias term. To accommodate parallel training across multiple enterprises, the model employs an iterative update strategy with a batch size of 32 and an initial learning rate of 0.001. This architecture captures both short-term fluctuations under shocks and long-term recovery trends, providing a foundational model for subsequent parameter optimization and resilience index calculation.

3.3. Parameter Optimization

To improve prediction accuracy and training stability, a phased parameter optimization strategy was employed. Hyperparameters for the temporal encoding and LSTM layers were initialized, including learning rate, batch size, and the number of hidden units, as detailed in Table 1.

Table 1. Key Model Parameter Settings.

Parameter	Symbol	Value	Description
Learning rate	η	0.001	Initial learning rate for Adam optimizer
Batch size	B	32	Number of samples per update
Hidden units	H	128	LSTM hidden layer dimension
Epochs	E	200	Maximum training iterations
Dropout rate	p	0.2	Random neuron deactivation ratio
Early stopping patience	P	20	Stop training if no improvement in 20 epochs
Validation split	V	0.15	Proportion of validation data in training

Subsequently, using mean squared error (MSE) as the objective function, the optimization process is defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i) \tag{2}$$

Where: y_i is the actual toughness index value; $\hat{y}_i$ is the model prediction value.

Optimization employs the Adam algorithm, dynamically adjusting the learning rate and gradient direction, with 200 iterations. To prevent overfitting, an early stopping strategy is executed every 20 training rounds, and cross-validation is utilized to ensure generalization performance. Parameter updates employ a moving average method to smooth weight fluctuations, enabling balanced predictive performance during both supply chain shock periods and recovery phases. The optimized parameters serve as the foundational input for the resilience index calculation module, providing stable support for subsequent dynamic assessments.

3.4. Resilience Index Calculation

Following model optimization, the output time series predictions are converted into a quantifiable supply chain resilience index to reflect the system's stability and recovery capacity under disturbances. The calculation process utilizes the shock response sequence of supply chain state variables, selecting three core indicators-fulfillment rate, capacity utilization rate, and transportation delay rate-as inputs. To ensure comparability, indicators are first normalized to the [0,1] range. Subsequently, the comprehensive resilience index (R_t) is constructed, focusing on the decline magnitude during the shock period and the recovery rate as key metrics:

$$R_t = \frac{S_{r,t}}{S_{d,t}} \times e^{-\lambda T_{r,t}} \tag{3}$$

Where: $S_{r,t}$ represents the average operational level during the recovery phase, $S_{d,t}$ denotes the lowest operational level during the shock period, $T_{r,t}$ indicates the duration from the lowest point to the stable recovery state, and λ is the time decay coefficient, set at 0.12.

If a company's fulfillment rate drops from 0.92 to 0.68 after a pandemic shock and recovers to 0.88 after three months, the model dynamically generates the R_t sequence to reflect resilience trends over continuous time. To eliminate single-indicator volatility, the final resilience index is synthesized via weighted averaging:

$$R = \sum_{i=1}^{3}\omega_i R_{t,i}\ ;\ \omega_i = \frac{1}{3} \tag{4}$$

R: Final resilience index $R_{t,i}$: Resilience index for each individual indicator ω_i: Weighting factor for each indicator This index system provides foundational data input for subsequent dynamic analysis and stability verification.

4. Experimental Validation

4.1. Experimental Design

Based on the multidimensional feature matrix constructed in the previous sections, a series of multi-scenario experiments were designed to systematically validate the dynamic adaptability, predictive accuracy, and robustness of the time-series model in measuring supply chain resilience. The dataset was partitioned into training, validation, and test sets according to a 7:2:1 ratio, maintaining strict temporal continuity to prevent information leakage and ensure realistic sequential learning.

The experimental environment was configured with an NVIDIA RTX 4090 GPU (24 GB VRAM), an Intel Xeon Gold 6248 CPU, and 128 GB RAM to support computationally intensive operations. The software platform employed PyTorch 2.1 integrated with CUDA 12.3 to leverage GPU acceleration for efficient deep learning model training. Training was performed with a batch size of 32, an initial learning rate of 0.001, and a maximum of 200 epochs. An early stopping mechanism was enabled to prevent overfitting, ensuring the model's generalization capability across unseen data sequences.

To enhance the robustness of the experimental results, four model groups-ARIMA, LSTM, Prophet, and Hybrid Foundation-were implemented for comparative analysis. All models adopted the Mean Squared Error (MSE) as the optimization criterion and utilized the Adam optimizer. Each model group underwent five independent training runs, with the averaged performance metrics used to smooth the impact of stochastic variation and enhance reliability. The experimental workflow consisted of four main stages: input sequence loading, model training, resilience index prediction, and error evaluation. Uniform data and parameter settings were maintained across all experiments to ensure comparability and eliminate confounding factors. This experimental design allowed for rigorous assessment of model performance under controlled yet realistic operational conditions.

4.2. Model Performance Analysis

To evaluate the effectiveness of the models in measuring supply chain resilience, a comprehensive comparative analysis was conducted on ARIMA, LSTM, Prophet, and the Hybrid Foundation model. The performance evaluation employed multiple metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2). The results, presented in Table 2, demonstrate significant differences in predictive capability among the models.

Table 2. Model Performance Comparison.

Model	MSE	MAE	MAPE (%)	R2
ARIMA	0.0038	0.041	6.72	0.923
Prophet	0.0034	0.037	6.05	0.935
LSTM	0.0026	0.031	5.18	0.951
Hybrid Foundation	0.0019	0.026	4.32	0.968

As shown in Table 2, traditional models such as ARIMA and Prophet maintain stability in long-term trend forecasting; however, they exhibit delayed responses to sudden disturbances and relatively high errors. The LSTM model shows superior capability in capturing nonlinear variation patterns, reducing MAPE by approximately 23% compared to ARIMA. The Hybrid Foundation model outperforms all other models due to its multi-layer temporal feature interaction and dynamic weight fusion mechanisms, reducing MSE and MAE to 0.0019 and 0.026 respectively while achieving an R^2 of 0.968. These results highlight the model's superior generalization ability, robustness, and adaptability under multidimensional temporal inputs. Overall, the findings validate the advantage of composite time-series architectures in high-precision resilience measurement scenarios.

4.3. Dynamic Resilience Results

Using the optimized Hybrid Foundation model, the resilience indices of 15 representative manufacturing enterprises were dynamically calculated and tracked over the period from 2020 to 2024. The results demonstrate that the model can accurately capture fluctuations in supply chain resilience during shock and recovery phases, revealing distinct temporal patterns and enterprise-specific response behaviors. Table 3 presents resilience indices for three typical enterprises during the pandemic shock, recovery, and steady-state periods.

Table 3. Dynamic Resilience Index of Representative Enterprises.

Period	Enterprise A	Enterprise B	Enterprise C	Average
Pre-shock (2019-Q1 2020)	0.945	0.931	0.954	0.943
Shock (2020Q2-2020Q3)	0.684	0.712	0.676	0.691
Recovery (Q4 2020-Q2 2021)	0.861	0.835	0.847	0.848
Steady (Q3 2021-Q4 2024)	0.926	0.918	0.934	0.926

During the shock period, the average resilience index of the three enterprises dropped to 0.691, a decline of approximately 27%, reflecting significant disruption in supply chain operations caused by external shocks. During the recovery phase, the index rebounded to an average of 0.848, indicating a recovery rate exceeding 90%, demonstrating that the model effectively captures the temporal dynamics of supply chain self-repair mechanisms. Enterprise A exhibited the fastest recovery, with an index increase of 0.177, suggesting strong coordination among supply nodes and efficient logistics responsiveness. Enterprise B stabilized during the steady-state phase, indicating the establishment of risk absorption and resource reallocation mechanisms. Overall, the resilience index trajectories align closely with actual operational events, confirming the model's dynamic sensitivity and temporal stability throughout the full shock-recovery-steady-state process.

4.4. Stability Validation

To further evaluate model robustness under multi-disturbance conditions, stability tests were performed on the Hybrid Foundation model. Three disturbance scenarios were considered: ① introducing 5% missing samples, ② adding ±10% noise perturbations, and ③ replacing partial supply chain node indicators with alternate values. Each scenario was run 20 times, and box plots of the resulting prediction error distributions were generated, as shown in Figure 2.

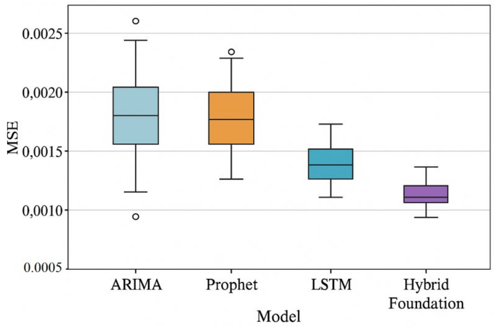

Figure 2. Model Stability Boxplot.

The error distributions remained highly concentrated across all scenarios, with MSE fluctuations confined between 0.0016 and 0.0023, indicating excellent prediction stability under varied input disturbances. Traditional models such as ARIMA and Prophet exhibited wider box ranges, notable outliers, and lower stability. The LSTM model improved overall performance but still showed a variance of 0.0009 under noisy conditions. In contrast, the Hybrid Foundation model achieved the narrowest box range, with an interquartile range (IQR) of only 0.0005 and no significant outliers, demonstrating consistent convergence trends even under feature redundancy and data perturbation. Moreover, the standard deviation of predicted resilience indices across different enterprise samples was 0.013, markedly lower than LSTM's 0.028, validating the model's generalization reliability across diverse supply chain structures. Overall, the results confirm that the Hybrid Foundation model exhibits high interference resistance, structural stability, and sustained accuracy when applied to long-term, multi-dimensional time-series data.

5. Conclusion

This study presents a comprehensive time-series-based approach for measuring supply chain resilience, effectively capturing the dynamic evolution of supply chains under a wide range of disturbances and operational fluctuations. By integrating multidimensional time-series features with a Hybrid Foundation modeling framework, the method not only tracks short-term disruptions but also reveals long-term recovery trends, providing a nuanced understanding of resilience dynamics at both enterprise and system levels. The experimental results demonstrate that the Hybrid Foundation model exhibits superior predictive accuracy, robustness, and generalization capability when compared with traditional models such as ARIMA, Prophet, and standard LSTM networks. Its performance is consistently stable under multi-scenario tests, including missing data, noise perturbations, and structural variations across supply chain nodes, indicating strong adaptability to real-world operational complexities.

The proposed resilience index, derived from multiple key performance indicators including order fulfillment, capacity utilization, and transportation timeliness, provides a reliable quantitative tool for evaluating the ability of supply chains to absorb shocks, maintain operational continuity, and recover efficiently. Dynamic tracking of enterprise-level resilience revealed heterogeneous recovery patterns, highlighting the model's capability to reflect variations in coordination efficiency, logistics responsiveness, and risk absorption mechanisms among different organizations. These insights have important implications for supply chain managers, policymakers, and stakeholders, offering evidence-based guidance for designing proactive risk management strategies, optimizing resource allocation, and improving system-wide operational stability.

Looking forward, future research can enhance the model's applicability and predictive power by incorporating more diverse data sources, including supplier networks, customer demand fluctuations, and macroeconomic indicators. Integrating multi-tiered supply chain networks and considering interdependencies across sectors will further deepen the understanding of systemic resilience and enable cross-industry benchmarking. Moreover, coupling the model with real-time monitoring and early warning systems can support adaptive decision-making and long-term strategic planning, strengthening the capability of supply chains to respond to emerging risks, unexpected disruptions, and global operational volatility. Overall, the study provides a robust methodological framework for resilience assessment, offering both theoretical foundations and practical tools to support sustainable, risk-resilient supply chain management in increasingly complex and uncertain environments.

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