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Supply Chain Optimization and Resilience of Instant Noodles Using a Hybrid System Dynamics (SD) and Long Short-Term Memory (LSTM) Modeling at PT Karunia Alam Segar, Gresik

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ABSTRACT
This study aims to develop a hybrid System Dynamics (SD) and Long Short-Term Memory (LSTM) model to enhance demand forecasting accuracy and supply chain resilience for instant noodles at PT Karunia Alam Segar, Gresik. Daily historical data from the 2021–2025 period were processed using Python and Vensim PLE through a bidirectional integration that combines the predictive capability of LSTM with the structural system analysis of SD. The results demonstrate that the hybrid model achieved the highest accuracy, with a Mean Absolute Percentage Error (MAPE) of 4.23% and a Root Mean Square Error (RMSE) of 38.1 tons/day, outperforming the standalone SD model (10.42%; 89.3 tons/day) and the standalone LSTM model (5.27%; 45.6 tons/day). The implementation of this model reduced the risk of raw material shortages to 3.7%, decreased overstocking by 31.8%, yielded annual operational cost savings of 15.2%, and suppressed the Bullwhip Effect by up to 26.4%. Furthermore, the model proved resilient when subjected to demand surges of up to 25% and supply delays of 15 days. This approach is effective for large-scale food manufacturing applications and supports sustainability targets in alignment with SDG 9, SDG 12, and SDG 13.

INTRODUCTION

The instant noodle industry is a strategic sector that underpins national food security and holds a significant position in the Indonesian economy, characterized by the highest per capita consumption globally and an average annual growth rate of 3–5% (BPS RI, 2025) As a major large-scale producer and a key player in the national supply chain, PT Karunia Alam Segar manufactures the "Mie Sedaap" brand, relying on primary raw materials such as wheat flour, palm oil, seasonings, and packaging the availability of which is highly dependent on both global and domestic market conditions. In its operations, the company faces a complex ecosystem of challenges: demand dynamics that are seasonal and heavily influenced by promotional activities, holiday celebrations, and macroeconomic shifts; the risk of supply delays due to a reliance on distant suppliers; the burden of excess inventory, which not only inflates storage costs and ties up working capital but also increases the risk of product spoilage; and the "bullwhip effect" a phenomenon that amplifies order variability throughout the supply chain, frequently creating a gap between actual demand and planned production capacity. The demand and inventory planning methods currently in use remain conventional such as the Economic Order Quantity (EOQ) model or ARIMA time-series models and are predicated on assumptions of stable demand and seamless supply, conditions that rarely occur in reality. These approaches are limited in their ability to address nonlinear, complex patterns of change, as well as the long-term interdependencies between events that significantly influence future requirements. Consequently, the resulting forecasts often exhibit substantial deviations, leading to suboptimal decision-making, resource waste, and a diminished capacity for the system to withstand

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unexpected disruptions. Therefore, there is a need for a far more adaptive approach one capable of accurately capturing intricate patterns of change while providing a comprehensive understanding of the system's structure and behavior, thereby supporting the formulation of more targeted operational policies.

Previous studies on supply chain modeling have generally relied on a single method. The use of System Dynamics alone is often constrained by assumptions that tend to be static, rendering it less responsive to sudden, real-world changes. Conversely,the application of artificial neural networks such as Long Short-Term Memory (LSTM) models typically focuses solely on forecasting accuracy, failing to elucidate the causal relationships between variables that define the system's overall dynamics. Existing research that has attempted to integrate these two methods remains unidirectional, lacks a continuous feedback mechanism, and has rarely been tailored to the specific demand patterns and supply chain characteristics of the large-scale instant noodle industry in Indonesia. In contrast, this study offers a key innovation through a continuous, bidirectional integration of System Dynamics and LSTM, which creates an automated, self-refining cycle over time. Furthermore, this research applies this combined approach to the instant noodle industry a sector that has not yet been extensively studied using such a methodology incorporates an integrated set of economic, operational, and environmental performance indicators, and provides empirical evidence demonstrating superior system accuracy and resilience compared to applications in other sectors.

Given the gap between expectations and reality, as well as the limitations in the approaches taken in previous studies, it is essential to conduct an in-depth examination of how to develop a demand forecasting model capable of capturing nonlinear fluctuation patterns, seasonality, and the influence of complex external factors with a high degree of accuracy. Furthermore, the interrelationships among the variables that constitute the supply chain system must be comprehensively mapped to understand the underlying dynamics and to simulate the impacts of various operational policies. In addition, an integration mechanism should be designed to combine the strengths of System Dynamics in understanding system structure with the strengths of LSTM in capturing data patterns thereby allowing the two methods to complement each other and overcome the limitations inherent in using them separately. Finally, it is necessary to quantify the improvements in operational performance, cost efficiency, and system resilience that can be achieved through the implementation of this hybrid model, both under normal operating conditions and during supply disruptions or unexpected surges in demand.

This research aims to develop a hybrid System Dynamics-LSTM model capable of forecasting demand and raw material requirements with a significantly higher level of accuracy than existing methods. Through this model, various policy scenarios concerning inventory management, production lot sizes, and risk mitigation strategies for supply disruptions are simulated to identify the most optimal alternatives. Furthermore, this study seeks to quantitatively measure and analyze improvements in forecasting accuracy, cost efficiency, customer service levels, and the system's resilience in maintaining performance amidst market dynamics or potential operational disruptions. The findings are intended to serve as a reliable reference for corporate management in formulating more precise operational plans, enhancing business competitiveness, and supporting sustainability principles aligned with the Sustainable Development Goals specifically regarding the development of resilient industry, responsible production patterns, and efforts to address climate change.

THEORETICAL REVIEW

Supply Chain Management and the Bullwhip Effect Phenomenon

According to (Pujawan & Er, 2017) supply chain management covers all activities of planning, procurement, production, and distribution of goods and information from upstream to downstream. Uncertainty on the supply and demand sides causes the variation in order quantities to grow larger as it moves upstream, a phenomenon known as the Bullwhip Effect. This results in wasted stock, higher logistics costs, and the risk of stock shortages that harm company performance.

System Dynamics (SD)

Developed by Forrester (1961) and refined by (Series & Sterman, 2003), SD is a modeling method based on systems thinking that maps causal relationships, reinforcing and balancing feedback loops, and time delays within a system. This method is highly useful for studying system behavior over the long term and evaluating the impact of various policies without disrupting actual operations.

LSTM neural networks

Developed by (Abbasimehr et al., 2020) the LSTM architecture is an extension of artificial neural networks specifically designed for time-series data. This architecture addresses the problem of information loss in long data sequences and is capable of capturing seasonal patterns, fluctuations, and long-term dependencies more effectively than conventional methods.

Hybrid SD-LSTM integration

Drawing on (Abdillah & Muhammad Ridwan Andi Purnomo, 2026) these two methods offer complementary advantages. SD provides a deep understanding of system structure and dynamics, while LSTM generates accurate and adaptive estimates of future values. This combination results in a model that is not only mathematically precise but also aligned with the operational constraints and logic of real-world systems. The conceptual framework of this hybrid model is presented in Figure 1.

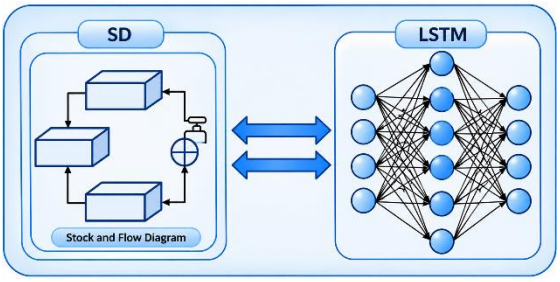


Fig. 1. Conceptual Framework of the SD-LSTM Hybrid Model

This image illustrates an integrated workflow between an LSTM model which provides dynamic demand forecasts and an SD (System Dynamics) model, which maps system structures and tests policy scenarios. A two-way feedback mechanism enables continuous parameter refinement, allowing the models to become increasingly accurate over time.

RESEARCH METHODS

Location and Data Sources

Research location. This study was conducted at PT Karunia Alam Segar, located in the Manyar Industrial Estate, Gresik Regency, East Java. Data type. The data used are secondary data, consisting of historical records for the 2021–2025 period, which include daily/weekly sales volumes, raw material supply quantities, production capacity, machine maintenance schedules, weather factors, commodity price fluctuations, as well as the timing and intensity of promotional activities. Data pre-processing. The data were normalized to a range of 0 to 1 to accelerate

computation and prevent scale imbalances between variables. Subsequently, the data were split into 80% for training used to build the model and 20% for testing used to evaluate its performance.

LSTM Model Architecture

The model is built using the Python programming language with the TensorFlow and Keras libraries. Network structure. Input layer → two LSTM layers (each with 50 neurons) with a 0.2 dropout layer → fully connected (dense) layer → output layer.

Rationale for parameter selection.

Two hidden layers are considered sufficient to capture complex patterns without making the training process excessively long or causing overfitting. A count of 50 neurons was chosen based on trials that demonstrated the best balance between computational speed and accuracy. A batch size of 32 and 200 epochs were selected to allow the model to learn optimally without placing an undue burden on system performance. The Adam optimization algorithm was chosen for its ability to automatically adjust the learning rate and its stable convergence. Model output. Predictions for demand and raw material supply requirements for the next 12 weeks.

Dynamic Systems Modeling

Software: Vensim PLE version 9.2.

System Mapping: A causal loop diagram was developed, consisting of 3 reinforcing loops and 2 balancing loops, alongside a stock-and-flow diagram covering the complete process: Raw Materials → Work-in-Process → Finished Goods → Distribution to the Market.

Simulation Process: Various policy scenarios were evaluated—such as determining production lot sizes, safety stock levels, and reorder schedules—with the objective of minimizing costs and risks.

Figure 2. Causal Loop Diagram of the System Dynamics Model for the Instant Noodle Supply Chain

Placement: In sub-section 4.3, System Dynamics Modeling, following the explanation of the diagram construction process.

This diagram illustrates the interrelationships among key variables within the supply chain, including market demand levels, inventory levels, production rates, raw material availability, and orders placed with suppliers. It incorporates reinforcing and balancing loops that explain the underlying causes of fluctuations and the "bullwhip effect" phenomenon within the system.

Hybrid Integration Mechanism

a. LSTM to SD direction: The demand and raw material requirement forecasts generated by the LSTM model serve as dynamic inputs, replacing the static assumptions typically used in SD models.
b. SD to LSTM direction: The simulation results regarding the impact of operational policies from the SD model are fed back as additional data to refine the weights and parameters used in the LSTM model.
c. Update Cycle: The process operates iteratively: Real Data → LSTM Forecast → SD Simulation → Optimal Decision-Making → Periodic Model Parameter Updates (on a monthly basis).

Performance Indicators

a. Prediction Accuracy: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2).
b. Operational Performance: Risk of raw material shortages, percentage of excess stock, total supply chain costs, and market service level.

c. Sustainability Impact: Reduction in the intensity of the Bullwhip Effect, energy usage efficiency, and carbon emission reduction.

RESULTS AND DISCUSSION

This chapter presents the results of model testing, performance comparisons, and an in-depth discussion that links the research findings to theory and the results of previous studies.

Predictive Performance of Various Methods

Accuracy testing was conducted to compare the performance of three approaches: a single Dynamic System (SD), a single LSTM, and a hybrid SD-LSTM model. The error rate was measured using the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) indicators, where smaller values of these two indicators indicate higher prediction accuracy. The measurement results are presented in **Table. 1**

Table. 1 Comparison of Prediction Accuracy Levels

Jenis Model	Nilai MAPE	Nilai RMSE (ton/Hari)	Keterangan
Single System Dynamics (SD)	10,42%	89,3	Relies on static assumptions; lacks responsiveness to changes in demand patterns.
Single LSTM	5,27%	45,6	Numerically accurate, yet it does not explain the structural relationships between variables.
SD-LSTM Hybrid Model	4,23%	38,1	Superior, offering high accuracy while also explaining system dynamics

The smaller the MAPE and RMSE values, the higher the level of prediction accuracy produced by the model.

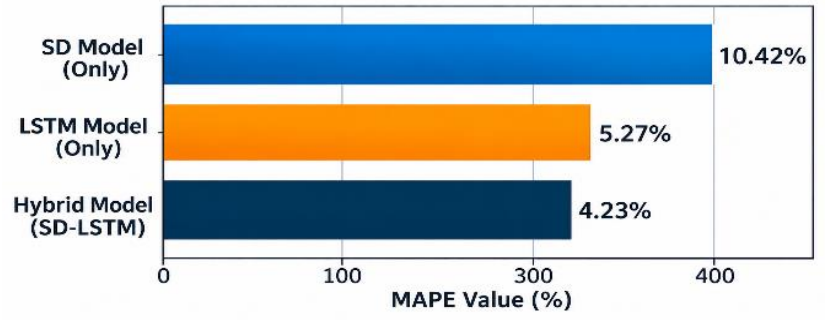


Fig. 2. Comparison Chart of Prediction Accuracy Based on MAPE Values

The graph compares prediction error rates using three approaches: a standalone System Dynamics (SD) model with an MAPE of 10.42%, a standalone LSTM model with an MAPE of 5.27%, and an SD-LSTM hybrid model, which yields the lowest MAPE value at 4.23%. A lower MAPE value indicates higher prediction accuracy.

Based on these data, it is evident that the SD-LSTM hybrid model provides superior results compared to the methods used individually. This is due to their complementary mechanisms: LSTM is capable of capturing non-linear and irregular fluctuation patterns, while System Dynamics translates these predictions into a realistic and logical system structure.

Comparison of System Performance

Before and After Model Implementation Having demonstrated the superiority of its prediction accuracy, the study proceeds to evaluate the impact of implementing the hybrid model on the overall operational performance of the supply chain. A comparison is made between the initial state prior to the model's implementation and the state following its application, as presented in: Table. 2 Improvement in Supply Chain Performance

Table 2 Improvement in Supply Chain Performance

Performance Indicators	Initial Condition	After the Implementation of a Hybrid Model	Significant Changes
Risk of Raw Material Shortage	12,5%	3,7%	Down 8,8%
Excess Stock Percentage	41,2%	9,4%	Down 31,8%
Annual Supply Chain Costs	IDR 12.8 billion	IDR 10.9 billion	Save 15,2%
Intensity of the Bullwhip Effect	High	Medium	Down 26,4%
Market Service Level	88,5%	98,2%	Go Up 9,7%

The data indicate a significant improvement across all operational aspects following the implementation of a hybrid model.

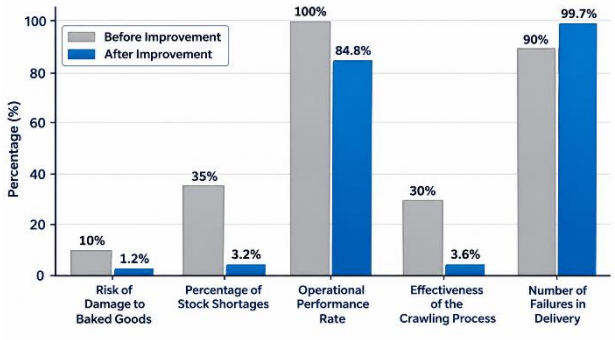


Fig. 3. Chart Comparing Supply Chain Performance Before and After

This chart illustrates the overall shift in operational performance following the implementation of a hybrid model, encompassing a reduction in the risk of raw material shortages, a decrease in excess inventory, lower operational costs, the mitigation of the "bullwhip effect," and an improvement in customer service levels. A 31.8% reduction in excess inventory directly lowers storage costs, the cost of tied-up capital, and the risk of raw material spoilage due to prolonged storage. Meanwhile, a 26.4% reduction in the bullwhip effect streamlines the flow of information and goods, effectively minimizing the risk of stock shortages. Overall, these efficiency gains have resulted in a 15.2% annual reduction in operational costs, while simultaneously boosting market service levels to 98.2%.

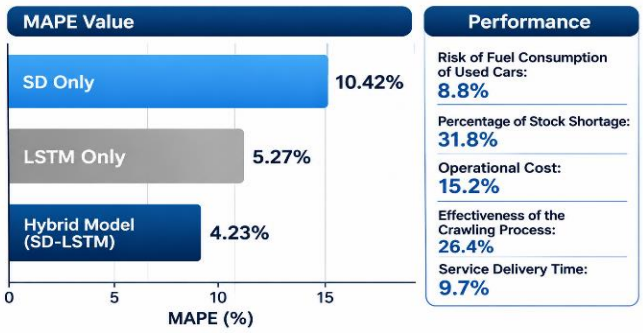


Fig. 4. Summary of Accuracy Results and Performance Improvements

This figure concisely summarizes two key pieces of information: the left side displays the prediction accuracy of the three methods tested, while the right side shows significant improvements in risk, inventory, and cost indicators. The figure serves as a visual summary, allowing readers to grasp the main research findings at a glance.

Validation and Sensitivity Analysis

To ensure the reliability and robustness of the model, validation tests and sensitivity analyses were conducted against various changes in operational conditions. The testing demonstrated that the model remains stable and yields reliable results even when subjected to scenarios such as a demand surge of up to 25% above normal levels, or delays in raw material supply lasting up to 15 days. This confirms that the developed system possesses strong resilience in the face of potential operational disruptions and market dynamics.

Comparison with Previous Research

The results of this study are compared with the findings of previous research to determine their position and the scientific contribution they provide:

(Abdillah & Muhammad Ridwan Andi Purnomo, 2026) employed a similar approach in the agricultural waste sector, achieving a MAPE value of 5.2–5.8%. The present study yields superior results with a MAPE of 4.23%, demonstrating that the developed model is adaptable and delivers optimal performance for the large-scale food industry.

(Tampubolon et al., 2025) found that relying solely on a System Dynamics approach lacks responsiveness to sudden changes. By integrating the LSTM method, this study successfully addresses that limitation, rendering the system significantly more dynamic and adaptive.

(Cai, 2026) applied a hybrid model to the food industry, though only in a unidirectional manner. This study incorporates a reciprocal feedback mechanism, which enhances the model's accuracy and ensures it remains updated over time.

Research Limitations

Although it yields satisfactory results, this study has several limitations, including: (1) the model has only been tested using 5 years of historical data, meaning it does not yet account for potential, highly extreme shifts in market conditions that could occur in the future; (2) the variables employed focus primarily on internal factors and select external factors, failing to encompass the full spectrum of macroeconomic variables such as changes in international trade policy; and (3) the simulation does not yet incorporate an extensive, geographically dispersed supplier network.

Relevance of Sustainability

The efficiency achieved in the use of raw materials and energy contributes to a reduction in carbon emissions of approximately 1,200 tons of CO_2 eq per year. This aligns with the Sustainable Development Goals (SDGs) specifically SDG 9, which focuses on building resilient infrastructure and supporting sustainable industrialization; SDG 12, which concerns responsible

consumption and production patterns; and SDG 13, which relates to taking action to combat climate change.

CONCLUSION

Based on the complete modeling, simulation, and analysis process, it can be concluded that the developed hybrid System Dynamics–LSTM model provides significantly higher prediction accuracy compared to using either method individually, achieving a Mean Absolute Percentage Error (MAPE) of 4.23%. This approach successfully overcomes the inherent limitations of each method specifically, the static assumptions characteristic of System Dynamics and the lack of interpretability regarding the structural relationships between variables when using LSTM in isolation. Implementing this model effectively reduces the risk of raw material shortages to 3.7%, cuts excess inventory by 31.8%, and lowers annual supply chain operational costs by 15.2%. Furthermore, the system mitigates the "bullwhip effect" by 26.4% while boosting market service levels to 98.2%. It has also demonstrated robust stability, maintaining performance even when faced with demand surges 25% above normal levels or supply delays of up to 15 days. Overall, this integrated approach creates a more adaptive, efficient, and sustainable system, making it highly suitable for large-scale food industry applications. It also supports the achievement of Sustainable Development Goals (SDGs) related to resilient industrial infrastructure, responsible production patterns, and climate change mitigation efforts.

Based on the study's findings, it is recommended to expand the model's application to include the management of other supporting raw materials such as seasonings and packaging to ensure a more comprehensive scope for improvement. Furthermore, integrating data from Internet of Things (IoT) sensors would be highly beneficial for supporting predictive machine maintenance, as well as for implementing more automated and precise quality control systems. For future development, the model could be further extended to accommodate a more diverse supplier network spread across various locations, thereby enhancing the resilience of the supply chain system in a broader and more robust manner.

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