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Optimizing Emergency Logistics Identification: Utilizing A Deep Learning Model in the Big Data Era

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Abstract

This study investigates the dynamics of commodity flow across different facilities and settings, evaluating the performance of Simulation and Feed Forward Neural Network (FFNN) methods in optimizing these flows. Analyzing data from various configurations, the research reveals significant variations in commodity distribution patterns. At Facility_1 from the K1 disposer market, the flow of Commodity_1 increased from 770 units to 830 units, while Commodity_2 decreased from 192 units to 166 units. At Facility_2, Commodity_1's flow decreased from 851 units to 793 units, and Commodity_2's flow slightly increased from 139 units to 148 units. Similar trends are observed at facilities from the K2 disposer market, reflecting the complex impact of different settings on commodity flow. The comparative analysis of Simulation and FFNN methods demonstrates their relative strengths. In Setting I, the Simulation method achieved an objective value of 1,800,574.36 Rs with a computation time of 46.78 seconds, while the FFNN method yielded a slightly lower objective value of 1,800,352.24 Rs in 42.01 seconds. In Setting II, the Simulation method provided an objective value of 1,801,025.36 Rs with a computation time of 103.86 seconds, whereas FFNN achieved a comparable objective value of 1,800,847.27 Rs in 63.05 seconds. In Setting III, Simulation resulted in an objective value of 1,801,527.36 Rs with a computation time of 61.12 seconds, while FFNN produced a higher objective value of 1,806,997.32 Rs in 50.03 seconds. The results highlight the trade-offs between solution quality and computational efficiency. The Simulation method consistently delivers higher objective values but requires more time, making it suitable for applications where result accuracy is crucial. Conversely, the FFNN method offers faster computation with competitive or superior objective values, making it advantageous for scenarios where time constraints are significant. This study underscores the importance of selecting appropriate computational methods based on specific operational needs, optimizing both the efficiency and effectiveness of commodity flow management.

Keywords: Logistic Identification, Deep Learning, Feed Forward, Big Data, Mapper, Reducer, Neural Network

1. Introduction

The logistics domain, particularly in emergency situations, has experienced significant evolution due to the rise of big data and the integration of advanced technologies such as deep learning models [1]. Efficient management of emergency logistics is crucial for prompt responses, resource allocation, and overall disaster mitigation [2]. In today's era, characterized by vast and diverse data sources, leveraging big data analytics and deep learning is essential for optimizing emergency logistics operations [3]. Emergency logistics involves the strategic coordination, synchronization, and execution of activities aimed at addressing unforeseen events such as natural disasters, accidents, or public health crises [4]. The challenges in emergency logistics are multifaceted and complex, including rapid decision-making, resource allocation, and distribution [5]. Traditional approaches often struggle to handle the complexity and dynamic nature of these situations, leading to the adoption of big data analytics and deep learning models as transformative solutions [6].

The advent of the big data era has resulted in an overwhelming influx of information from sources such as social media, sensors, and satellite imagery [7]. While this data is valuable, managing its volume and extracting meaningful insights presents challenges [8]. Big data analytics provides the tools and techniques necessary to analyze large datasets effectively and derive actionable information [9]. Deep learning, a subset of machine learning, has shown remarkable capabilities in processing complex and unstructured data [10]. Its ability to autonomously learn hierarchical

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representations makes it well-suited for tasks like image recognition, natural language processing, and pattern recognition—crucial for efficient emergency logistics [11].

Optimizing emergency logistics involves several key aspects. First, it is essential to swiftly and accurately assess the nature and severity of the situation [12]. Big data analytics facilitates real-time monitoring and analysis of diverse data streams, allowing organizations to gain timely insights [13]. Understanding the circumstances, whether a disaster, epidemic, or transportation incident, is the first step toward effective logistics management [14]. Resource allocation is another critical component of emergency logistics optimization [15]. This involves distributing personnel, vehicles, medical supplies, and other essential resources. Big data analytics enables predictive modeling and simulation to anticipate resource needs based on changing conditions [16]. Deep learning models can enhance prediction accuracy by analyzing historical data and trends, enabling proactive rather than reactive responses [17].

Optimizing transportation routes is vital for effective emergency logistics [18]. Ensuring timely and efficient transportation of resources to and within affected areas is crucial for a successful response. The integration of big data analytics and geographical information systems (GIS) allows for route optimization using real-time data and traffic conditions. Deep learning models continuously adapt to dynamic situations, improving route optimization. Efficient management of medical supply chains is also crucial in emergency healthcare logistics. Big data analytics enables monitoring of inventory levels, consumption patterns, and demand forecasts. Deep learning models aid in forecasting medical requirements based on the nature of the emergency and demographic factors, ensuring the proper placement of medical supplies for rapid deployment [19].

Integrating technology, particularly Internet of Things (IoT) devices, adds another dimension to enhancing emergency logistics efficiency. Sensors and IoT devices provide real-time information on environmental conditions, infrastructure status, and vital facilities. Big data analytics processes this data flow effectively, offering valuable insights for decision-makers. Deep learning models improve forecast accuracy and decision support by adapting to changing data patterns.

2. Literature Review

The incorporation of big data technology in logistics optimization has significantly transformed the management of large and complex datasets related to supply chain operations. Technologies such as Hadoop and Apache Spark address the fundamental challenge of managing extensive datasets by providing scalable methods for processing and analyzing data on a massive scale [15]. Big data analytics enables logistics managers to monitor the entire supply chain in real-time, optimizing routes, resources, and overall responsiveness. This facilitates enhanced real-time monitoring and decision-making capabilities [16].

Predictive analytics, a core component of big data, enables accurate demand forecasting by identifying patterns in historical data. This capability helps optimize inventory levels and ensures product availability [17]. For instance, recent studies have shown that predictive models can significantly reduce stockouts and overstock situations by improving inventory management [18]. Route optimization, another crucial aspect, leverages geographical information systems (GIS) and real-time data to navigate through traffic conditions efficiently, thereby reducing transportation costs and delivery times [19]. Research by [20] demonstrated that incorporating real-time traffic data into routing algorithms can reduce delivery times by up to 15% [20].

Warehouse optimization is achieved through the analysis of data related to product movement, order frequencies, and seasonal trends. This analysis prevents issues of overstocking or stock shortages, thereby improving supply chain efficiency [21]. For example, research by [22] found that data-driven approaches to warehouse management could enhance inventory turnover rates and reduce holding costs [22]. Moreover, big data enhances customer experience in logistics by enabling service customization, providing real-time shipment tracking, and delivering precise delivery forecasts [23]. A study by [24] highlighted how real-time tracking systems improve customer satisfaction by providing accurate delivery estimates and timely updates [24].

Several studies have explored the impact of big data on logistics optimization. For example, research [25] examined how big data analytics can be utilized for dynamic route planning and its effects on reducing operational costs [25]. Additionally, research by [15] focused on integrating big data with IoT devices to enhance real-time monitoring and predictive maintenance in supply chain management [15]. Another significant contribution is by [16], who investigated the use of machine learning algorithms for optimizing inventory levels and minimizing supply chain disruptions [16]. These studies collectively underscore the transformative potential of big data technologies in various aspects of logistics, from route optimization and warehouse management to customer experience enhancement. The integration of big data solutions has become essential for achieving maximum efficiency and optimization in logistics operations.

By leveraging these advanced technologies, organizations can continuously improve their logistics strategies and operations [17], [18], [19].

3. Flow Control and Emergency Logistic Identification using Deep Learning

Using a Feed Forward Neural Network (FNN) for flow control entails systematically processing input properties through layers of nodes to capture complex relationships within data, resulting in optimal allocation of commodities. The input nodes in the system reflect factors such as commodity types, current facility availability, and historical usage patterns. The hidden layers of the system do calculations using weighted connections and activation functions to identify complicated patterns. The FNN, which has undergone training using a dataset consisting of historical or simulated scenarios, is capable of making real-time judgments regarding the optimal distribution of commodities across service facilities [26].

Forward propagation consists of calculating weighted sums and applying activation functions, while backpropagation adjusts weights and biases to minimize the discrepancy between projected and actual results. Similarly, in the context of emergency logistic identification, the FNN uses input features such as severity, geography, and previous response data to forecast the most effective reactions to emergencies. The FNN's ability to acquire knowledge from varied datasets makes it a potent tool for making data-based decisions in dynamic logistic scenarios and emergency response circumstances [27].

Forward propagation is the transmission of information from the input layer to the output layer in a neural network. Every individual unit inside a given layer of a neural network receives input signals, which are then manipulated using weighted connections and activation functions [28]. The resulting output is subsequently transmitted to the subsequent layer. The mathematical expression for forward propagation is given by:

$$a_j^{(l+1)} = \sigma\left(\sum\nolimits_i w_{ij}^{(l)} \cdot a_i^{(l)} + b_j^{(l)}\right) \tag{1}$$

where $a_j^{(l+1)}$ is the activation of node j in layer l+1, $w_{ij}^{(l)}$ is the weight between node i in layer l and node j in layer l+1,$a_i^{(l)}$ is the activation of node i in layer l,$b_j^{(l)}$ is the bias term for node j in layer l, andσ is the activation function.

The loss function quantifies the difference between the anticipated output of the neural network and the true output (ground truth). The inaccuracy in the model's predictions is quantified by a single scalar value, which the training process aims to minimize. diverse loss functions may be utilized by different types of tasks, such as classification and regression, as well as by diverse network designs. Mean Squared Error (MSE) is frequently employed in regression tasks, but Cross-Entropy Loss is prevalent in classification challenges. The loss function is formulated as:

$$\mathrm{L} = \mathrm{Loss}(\text{predicted output}, \text{actual output}) \tag{2}$$

Backpropagation is an optimization strategy employed to decrease loss by altering the weights and biases within a neural network. The process entails calculating the gradient of the loss in relation to the weights and biases, and then modifying these parameters using a method known as gradient descent. The backpropagation algorithm proceeds through the following steps:

$$\text{Loss Gradient} = \frac{\partial \mathrm{L}}{\partial \mathrm{w}_{\mathrm{ij}}^{\mathrm{l}}} \text{ and } \frac{\partial \mathrm{L}}{\partial \mathrm{b}_{\mathrm{j}}^{\mathrm{l}}} \tag{3}$$

Weight update and biases are given as

$$w_{ij}^{(l)} \quad = w_{ij}^{(l)} - \alpha \frac{\partial L}{\partial w_{ij}^{l}} \tag{4}$$

$$b_j^l = b_j^l - \alpha \frac{\partial L}{\partial b_j^l} \tag{5}$$

The symbol α represents the learning rate, which is a hyperparameter that determines the magnitude of the optimization step. Through the repeated process of forward propagation and backpropagation across numerous epochs, the neural network acquires the ability to generate increasingly precise predictions by modifying its parameters in order to minimize the loss function.

In the architecture of a FNN, the input layer serves as the initial stage where nodes represent crucial features or variables associated with commodities and facilities. In the context of flow control, these input nodes encompass information about various aspects such as the types of commodities, their current availability across different facilities, and historical usage patterns. As the data progresses through the network, hidden layers undertake the task of processing it through weighted connections and activation functions. These layers excel at capturing intricate relationships and patterns within the data, acquiring optimal representations for effective decision-making. Subsequently, the output layer generates the final results, signifying the recommended allocation of commodities to specific facilities.

The output values are determined by the network's learned weights and biases, refined during the training process. Training the FNN involves exposing it to a dataset containing examples of optimal commodity allocations derived from historical or simulated scenarios. Throughout this training phase, the network dynamically adjusts its weights and biases to minimize the disparity between predicted and actual outcomes. Once successfully trained, the FNN transforms into a powerful tool capable of making real-time decisions on the optimal flow of commodities, thereby enhancing resource utilization and service levels in the realm of flow control.

4. Result and Discussion

The environmental configuration for this project includes the necessary hardware, software, and networking components to ensure its smooth functioning. The hardware requirements encompass a range of machines or devices, spanning from PCs to servers, which must meet the minimum specifications necessary for the operations being performed. The user highlights the importance of a dependable internet connection when utilizing external resources or cloud services, specifically focusing on the networking architecture, which encompasses routers and switches. The software aspect emphasizes the specified operating systems, programming tools, frameworks, and libraries, assuring compatibility and correct installation.

This discusses both relational and NoSQL database systems, as well as relevant virtualization or containerization solutions. Security measures, such as firewalls and access controls, are put in place to protect against potential threats. The documentation includes details on dependencies on external services or APIs, as well as any integrations with cloud providers such as AWS or Azure. Incorporating testing and quality assurance tools ensures a consistently high level of performance and reliability. The entire setup process is thoroughly documented to offer explicit instructions and address any potential issues that may arise. The careful establishment of this environmental setup creates a stable base for the project's development, testing, and deployment stages, promoting a consistent and dependable operational environment.

Table 1 provides a comprehensive analysis of the complex patterns governing the flow of commodities across various settings and facilities. This dataset is pivotal for understanding the dynamic nature of distribution patterns and the intricate interactions between different locations and commodities. The table categorizes commodity flow at two distinct facilities from two different disposer markets (K1 and K2), under three different configurations (Setting_1, Setting_2, and Setting_3).

Table 1. Variated configurations for commodity flow.

Commodity	Setting_1	Setting_2	Setting_3
Flow at facility_1 from (K_1) Disposer market			
Commodity_1	770	825	830
Commodity_2	192	172	166
Flow at facility_2 from (K_1) Disposer market			
Commodity_1	851	788	793
Commodity_2	139	150	148
Flow at facility_1 from (K_2) Disposer market			
Commodity_1	832	799	795
Commodity_2	180	165	160

Flow at facility_2 from (K_2) Disposer market			
Commodity_1	785	816	819
Commodity_2	166	187	180

At Facility_1, which sources from the Disposer Market K1, the flow of Commodity_1 exhibits a significant increase, rising from 770 units in Setting_1 to 830 units in Setting_3. This upward trend suggests a possible surge in demand or supply, reflecting changes in the market conditions or operational adjustments. Conversely, Commodity_2 shows a consistent decline in flow, decreasing from 192 units in Setting_1 to 166 units in Setting_3. This reduction indicates a corresponding drop in demand or supply, highlighting how various settings influence the flow of goods even within the same facility. The analysis of Facility_2, also sourcing from K1, reveals a different pattern. Here, Commodity_1 experiences a decrease in flow from 851 units in Setting_1 to 793 units in Setting_3. This downward trend could be attributed to shifts in market dynamics or logistical constraints specific to this facility. In contrast, Commodity_2 demonstrates a slight increase in flow from 139 units in Setting_1 to 148 units in Setting_3, suggesting a minor but notable adjustment in demand or supply.

Turning to Facility_1 from the Disposer Market K2, the flow of Commodity_1 exhibits fluctuations, starting at 832 units in Setting_1 and decreasing to 795 units in Setting_3. This variability underscores the complexities of demand and supply dynamics in this market. Similarly, Commodity_2 shows a decline in flow from 180 units to 160 units, reflecting a parallel reduction in demand or supply under different settings. At Facility_2 from K2, the flow patterns differ again. Commodity_1's flow increases from 785 units in Setting_1 to 819 units in Setting_3, indicating an improvement or rise in demand or supply. Commodity_2's flow also rises from 166 units to 180 units, further highlighting the diverse effects of different settings on commodity distribution. Figure 1 visually captures these intricate flow dynamics, offering a clear and intuitive representation of how commodity flows vary across different facilities and settings. This graphical representation aids in swiftly interpreting and comparing the data.

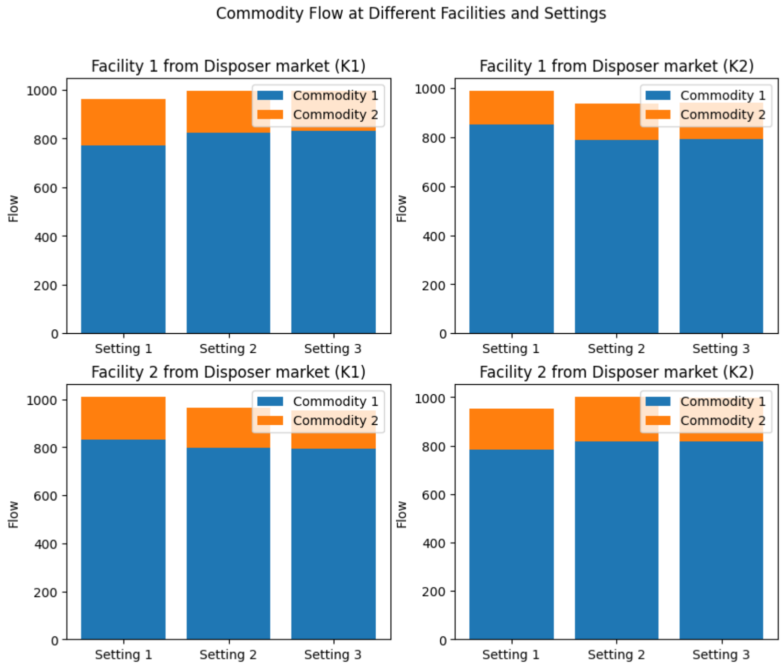

Figure 1. Diverse setting for flow commodity

Table 2 provides a comparative analysis of the computational results obtained using Simulation and Feed Forward Neural Network (FFNN) methods across three distinct settings. The table details both the objective values (in Rs) and the computation times (in seconds) for each method. In Setting I, the Simulation method achieves an objective value of 1,800,574.36 Rs with a computation time of 46.78 seconds, whereas the FFNN method yields a slightly lower objective value of 1,800,352.24 Rs and requires only 42.01 seconds of computation time. This indicates that the FFNN method provides a marginally better result in a shorter time frame compared to Simulation. In Setting II, the Simulation method results in an objective value of 1,801,025.36 Rs and takes 103.86 seconds to compute, while the FFNN method produces a slightly better objective value of 1,800,847.27 Rs with a reduced computation time of 63.05 seconds. This suggests that, despite achieving a slightly superior objective value, the FFNN method is more efficient in terms of computation time in this setting. Conversely, in Setting III, the Simulation method yields an objective value of 1,801,527.36 Rs with a computation time of 61.12 seconds, whereas the FFNN method results in a higher objective value of 1,806,997.32 Rs but with a shorter computation time of 50.03 seconds. This scenario illustrates a trade-off where the FFNN method is faster but provides a less favorable objective value. Overall, the table underscores the trade-offs between computational efficiency and solution quality. The choice between Simulation and FFNN methods should be guided by the specific needs of the problem, balancing the desire for quicker computation times with the pursuit of optimal objective values.

Table 2. Result of Computation

Setting	Simulation		FFNN	
	OBJ value (Rs)	**Time (sec)**	**OBJ value (Rs)**	**Time (sec)**
I	1800574.36	46.78	1800352.24	42.01
II	1801025.36	103.86	1800847.27	63.05
III	1801527.36	61.12	1806997.32	50.03

Figure 2 illustrates a comparative analysis of computation performance between the Simulation and FFNN methods across three different settings. The figure visually represents key metrics: the objective values (in Rs) and computation times (in seconds) for both methods.

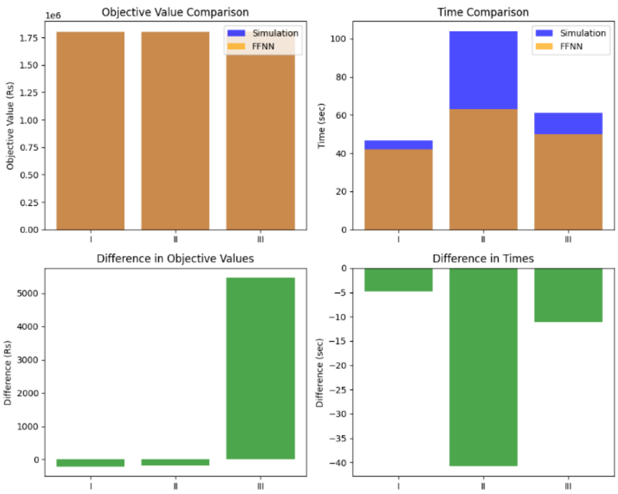

Figure 2. Comparison of Computation

The analysis presented in table 1 and figure 2 provides valuable insights into the dynamics of commodity flow and the performance of different computational methods. The data reveals several key observations about the impact of varying settings on commodity flow patterns and the trade-offs between different computational techniques.

Table 1 illustrates the fluctuations in commodity flow across different facilities and settings from two distinct disposer markets, K1 and K2. At Facility_1 sourcing from K1, we observe that Commodity_1 shows a significant increase in flow from 770 units in Setting_1 to 830 units in Setting_3, which may suggest an increase in demand or improved supply conditions. Conversely, Commodity_2 exhibits a steady decline, reflecting a reduction in demand or supply. These findings indicate that different settings can substantially influence the flow of goods, even within the same facility. At Facility_2, the flow patterns reveal a different dynamic. Commodity_1's flow decreases from 851 units in Setting_1 to 793 units in Setting_3, while Commodity_2's flow slightly increases. These contrasting trends emphasize the complex interplay between different factors affecting commodity distribution. Similar complexity is observed in Facility_1 and Facility_2 sourcing from K2, where Commodity_1 and Commodity_2 show variable trends, further highlighting the impact of different settings on flow patterns.

Figure 2 and table 2 offer a comparative assessment of the Simulation and FFNN methods across three settings. The Simulation method consistently yields higher objective values compared to the FFNN method, reflecting its ability to achieve potentially more optimal results. However, this advantage comes at the cost of longer computation times. In

Setting I, the Simulation method achieves an objective value of 1,800,574.36 Rs with a computation time of 46.78 seconds, while the FFNN method provides a slightly lower objective value of 1,800,352.24 Rs in less time (42.01 seconds). This indicates that while FFNN is more efficient in terms of computation time, Simulation offers a marginally better result. In Setting II, the FFNN method demonstrates its strength by providing a slightly better objective value of 1,800,847.27 Rs compared to Simulation's 1,801,025.36 Rs, with notably reduced computation time. This efficiency is advantageous for scenarios where time constraints are critical. Conversely, in Setting III, the FFNN method produces a higher objective value (1,806,997.32 Rs) in a shorter computation time compared to Simulation, which highlights the trade-off between computation speed and result quality.

The results underscore the trade-offs between computational efficiency and solution quality. The Simulation method, while providing higher objective values, requires longer computation times, making it suitable for scenarios where optimal results are prioritized over speed. On the other hand, the FFNN method, with its shorter computation times, offers a balance between efficiency and result quality, making it a preferable choice for applications where computational resources or time are constrained.

The findings from table 1 and figure 2 emphasize the importance of selecting appropriate computational methods based on specific requirements and constraints. In practical applications, decision-makers must consider whether they prioritize optimal objective values or computational efficiency, and choose the method that best aligns with their operational goals and constraints.

5. Conclusion

This study provides a comprehensive analysis of commodity flow patterns and evaluates the effectiveness of Simulation and FFNN methods in optimizing these flows. Table 1 demonstrates significant variations in commodity distribution across different facilities and settings. At Facility_1 from the K1 disposer market, Commodity_1's flow increases from 770 units in Setting_1 to 830 units in Setting_3, while Commodity_2's flow decreases from 192 units to 166 units. In contrast, at Facility_2, Commodity_1's flow decreases from 851 units in Setting_1 to 793 units in Setting_3, whereas Commodity_2's flow slightly increases from 139 units to 148 units. Similar patterns are observed at Facility_1 and Facility_2 from the K2 disposer market, indicating the complex interplay of market conditions and facility capabilities on commodity distribution. Table 2 and figure 2provide a comparative analysis of the Simulation and FFNN methods. In Setting I, Simulation achieves an objective value of 1,800,574.36 Rs with a computation time of 46.78 seconds, while FFNN provides a slightly lower objective value of 1,800,352.24 Rs in 42.01 seconds. In Setting II, the Simulation method results in an objective value of 1,801,025.36 Rs with a longer computation time of 103.86 seconds, compared to FFNN's objective value of 1,800,847.27 Rs and a shorter computation time of 63.05 seconds. In Setting III, Simulation yields an objective value of 1,801,527.36 Rs with a computation time of 61.12 seconds, whereas FFNN results in a higher objective value of 1,806,997.32 Rs with a shorter computation time of 50.03 seconds. These findings highlight the trade-offs between solution quality and computational efficiency. The Simulation method consistently provides higher objective values but requires longer computation times, making it suitable for scenarios where optimal results are prioritized. Conversely, the FFNN method offers faster computation times and, in some cases, comparable or better objective values, making it ideal for situations where speed is critical. This research emphasizes the need to balance computational efficiency with solution quality when selecting optimization methods. Organizations should consider their specific operational requirements and constraints to choose the most appropriate method. By doing so, they can effectively optimize commodity flow and improve overall supply chain management.

6. Declaration

6.1. Author Contributions

Conceptualization: V.S., B.L.S., S.S.M., and W.G.; Methodology: S.S.M.; Software: B.L.S.; Validation: V.S. and W.G.; Formal Analysis: B.L.S. and V.S.; Investigation: W.G.; Resources: S.S.M.; Data Curation: S.S.M.; Writing Original Draft Preparation: V.S. and B.L.S.; Writing Review and Editing: S.S.M. and W.G.; Visualization: V.S.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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