Supply Chain Resilience in the Face of Disruptive Events: An Operations Research Perspective

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Abstract

In today's ever-changing world the ability of supply chains to withstand disruptions is crucial for businesses to maintain operations. This paper focuses on supply chain resilience, from an Operations Research perspective exploring how theoretical frameworks and practical applications work together to strengthen supply chains against events. By analyzing a dataset related to Makeup product supply chains this study demonstrates the effectiveness of Long Short-Term Memory (LSTM) networks in capturing time patterns and highlights the importance of data normalization in improving accuracy. Comparing models trained on normalized and unnormalized data provides insights into the significance of preprocessing techniques in predicting outcomes within the Fashion and Beauty industry. Additionally, this study combines theory with real-world case studies underscoring the importance of risk management, adaptive decision-making, and resilient network design. With the integration of methodological consistency, and applicability, we demonstrate the significance of our approach in sustaining supply chain resilience against disruptive events.

Keywords: Operation Research; Supply Chain; Business Intelligence; Operational Management; Decision-Making.

1. Introduction

In today's changing landscape the ability of supply chains to withstand challenges is crucial for businesses to maintain sustainability and continuity. With markets becoming interconnected and events occurring more frequently and severely it is vital to strengthen supply chains against potential disruptions. These disruptions can range from disasters and political tensions to pandemics and technological failures covering a range of possibilities [1-4]. Consequently, it is essential to explore and enhance the resilience of supply chains through the lens of Operations Research (OR). Taking an approach, within the domain of operations research becomes crucial in understanding the complexities involved in supply chain resilience [5]. By combining models, optimization techniques, and analytical frameworks we gain a toolkit for not only identifying vulnerabilities, within supply chains but also developing proactive strategies to mitigate risks [6-7].

Furthermore, the changing landscape of trade and the integration of information technology, into supply chain operations have caused a shift in how disruptions are perceived and managed. Traditional methods of supply chain management are being redefined, leading to a need for risk identification decision-making and innovative resilience strategies [8-10]. Operations research plays a role in guiding industries towards enhancing supply chain resilience by offering methodologies. Of relying on reactive measures this research aims to provide an understanding and practical strategies to fortify supply chains against uncertainties, in today's dynamic business environment [11-12].

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The residual part of this research is structured as follows. First, the related literature studies are reviewed in section 2. The case study of this work is explored in section 3. The methodology of this work is given in section 4. The result of our work is discussed in section 5. The conclusions are derived in section 6.

2. Related Studies

In this section, we provide a deep dive into the related studies from the current literature to provide a panoramic view of their contributions, and gaps, which shaped the motivation of the current study. The concept of supply chain resilience has garnered significant attention in recent years due to its pivotal role in mitigating disruptions and ensuring sustainable operations. The researchers, in [2], have provided a foundation for understanding supply chain resilience by identifying its key components. Their work has helped define the concept and has presented a framework that captures the complex nature of resilience in supply chains. In [5], the authors examined perspectives on the effects caused by disruptions. This compilation serves as a resource offering insights into how disruptions can affect supply chains and suggesting strategies to mitigate these effects. In [6], researchers introduced an approach to evaluate supply network disruptions and resilience. Their study shed light on the dynamics within supply chains emphasizing the importance of network structures in enhancing resilience, against disruptions and contributing to an understanding of supply chain network resilience.

The authors of [9] contributed significantly by developing a scale to measure a firm's resilience to supply chain disruptions. Through empirical examination, their work not only provided a quantifiable measure of resilience but also shed light on factors that contribute to firms' ability to withstand and recover from disruptions effectively. The authors of [13] critically reviewed the design of robust value-creating supply chain networks, offering insights into strategies for creating resilient networks capable of withstanding various disruptive events. Their work provided a critical evaluation of the design aspects crucial for fostering resilience in supply chain networks. The severity of supply chain disruptions and the mitigation capabilities thereof were investigated by Craighead et al. [15]. Their research explored the relationship between supply chain design characteristics and the severity of disruptions, unveiling mitigation strategies to alleviate the impact of disruptions on supply chain operations. Moreover, the authors of [19] delved into the structural drivers of upstream supply chain complexity and its correlation with the frequency of disruptions. Their study highlighted the intricate relationship between supply chain complexity and the vulnerability to disruptions, offering insights into structural aspects that influence supply chain resilience.

3. Case Study and Exploration

This section provides detailed information about the case study used to prove the concept in this study for resilience strategies in the face of disruptive events. Our case study focuses on an analysis that comes from a dataset obtained from a fast-growing startup, in the Fashion and Beauty industry. Specifically, we delve into the workings of their Makeup product supply chain examining aspects that make this industry unique. The dataset provides information, including product types of details about each SKU, pricing, and availability. This gives us an understanding of the products offered. Additionally, we gain insights into performance metrics such as sales volume, revenue generated, and customer demographics. These metrics help us understand consumer behavior and market trends. The dataset also covers elements like stock levels, lead times for orders quantities ordered, shipping processes, and associated costs. By examining these factors, we shed light on the operations and financial aspects of the supply chain. Furthermore, it uncovers information about supplier's networks including their locations, production volumes/capacity along with manufacturing costs; inspection results are also documented to highlight quality control measures implemented by suppliers. Notably, transportation modes, routes, and associated costs encapsulate the final leg of this comprehensive dataset, offering insights into the logistical strategies and cost dynamics entwined with product distribution. This rich repository of information allows for a multifaceted exploration, enabling the identification of critical nodes, potential vulnerabilities, and opportunities for enhancing resilience within the Makeup product. A summary of the statistical characteristics of our case study is given in Table 1.

Table 1: Central tendency measures for different variables in our case study.

	count	mean	std	min	Q1	Q2	Q3	max
Price	100.0	49.5	31.2	1.7	19.6	51.2	77.2	99.2

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Availability	100.0	48.4	30.7	1.0	22.8	43.5	75.0	100.0
Number of products sold	100.0	461.0	303.8	8.0	184.3	392.5	704.3	996.0
Revenue generated	100.0	5776.0	2732.8	1061.6	2812.8	6006.4	8254.0	9866.5
Stock levels	100.0	47.8	31.4	0.0	16.8	47.5	73.0	100.0
Lead times	100.0	16.0	8.8	1.0	8.0	17.0	24.0	30.0
Order quantities	100.0	49.2	26.8	1.0	26.0	52.0	71.3	96.0
Shipping times	100.0	5.8	2.7	1.0	3.8	6.0	8.0	10.0
Shipping costs	100.0	5.5	2.7	1.0	3.5	5.3	7.6	9.9
Lead time	100.0	17.1	8.8	1.0	10.0	18.0	25.0	30.0
Production volumes	100.0	567.8	263.0	104.0	352.0	568.5	797.0	985.0
Manufacturing lead time	100.0	14.8	8.9	1.0	7.0	14.0	23.0	30.0
Manufacturing costs	100.0	47.3	29.0	1.1	23.0	45.9	68.6	99.5
Defect rates	100.0	2.3	1.5	0.0	1.0	2.1	3.6	4.9
Costs	100.0	529.2	258.3	103.9	318.8	520.4	763.1	997.4

In Figure 1, we analyze the Supply Chain by looking at the relationship between the price of the products and the revenue generated by them. It is notable that the company derives more revenue from skincare products, and the higher the price of skincare products, the more revenue they generate. In Figure 2, we visualize the Sales distribution according to Product Type. It is worth noting that 45% of the business comes from skincare products, 29.5% from haircare, and 25.5% from cosmetics. Similarly, in Figure 3, we visualize the Sales distribution according to customer Type. It is worth noting that 27 of the business comes from females, 16% from males, and 23 from non-binary type.

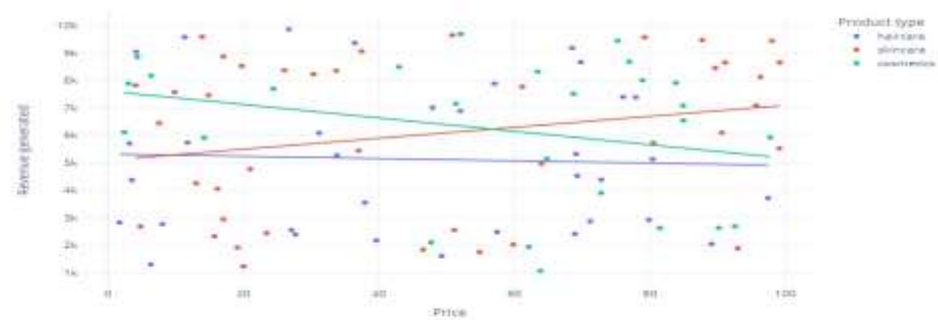

Figure 1: visualization of relationship between the price of the products

4. Methodological approach

This section delineates the structured methodology employed to dissect and analyze the Makeup product supply chain dataset, bridging the chasm between theoretical constructs and real-world applications. To discern intricate temporal patterns and forecast future trends within the Makeup product supply chain dataset, Long Short-Term Memory (LSTM) neural networks were employed. LSTM, a subtype of recurrent neural networks (RNNs), excels in capturing and learning from sequential data, making it an apt choice for modeling the temporal dependencies embedded within supply chain dynamics. Leveraging the sequential nature of the dataset, LSTM architectures were adeptly trained and fine-tuned to comprehend the nuanced relationships between various supply chain attributes across time. This approach facilitated the extraction of latent patterns and intricate dependencies inherent in the historical data, enabling the formulation of predictive models capable of forecasting key metrics critical for supply chain resilience assessment,

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such as stock levels, lead times, and consumer demand patterns. The structural building of the LSTM model is composed of three main gates: the forget gate (f_t), the input gate (i_t), and the output gate (o_t), each of which contributes to the control of the flow of information through the cell state C_t. The working mechanism of each gate can be expressed as follows:

$$f_t = \sigma\left(W_f + [H_{t-1}, X_t] + b_f\right) \quad (1)$$

$$i_t = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh\,(W_c \cdot [H_{t-1}, X_t] + b_c) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (4)$$

$$o_t = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o) \quad (5)$$

$$H_t = o_t \cdot \tanh\,(C_t) \quad (6)$$

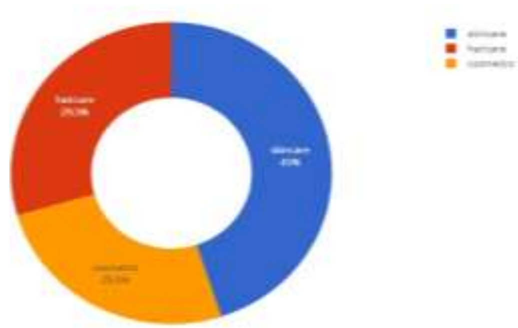

Figure 2: visualization of sales by product type.

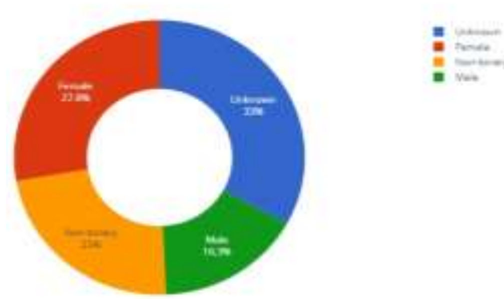

Figure 3: visualization of sales by customer type.

The above expressions use $[H_{t-1}, X_t]$ to denote the concatenation of the previous hidden state H_{t-1} and the current input X_t. Also, they used W_f, W_i, W_r, W_o to symbolize weight matrices specific to each gate, while b_f, b_i, b_c, b_o

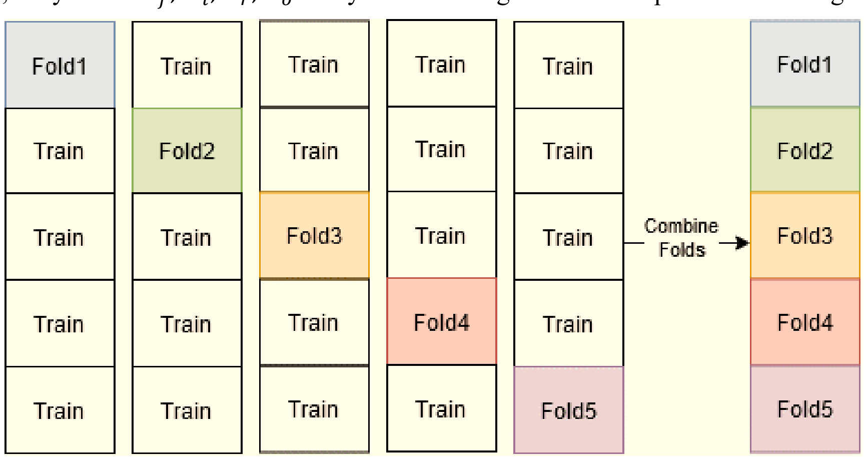

Figure 4: visualization of k-fold cross-validation

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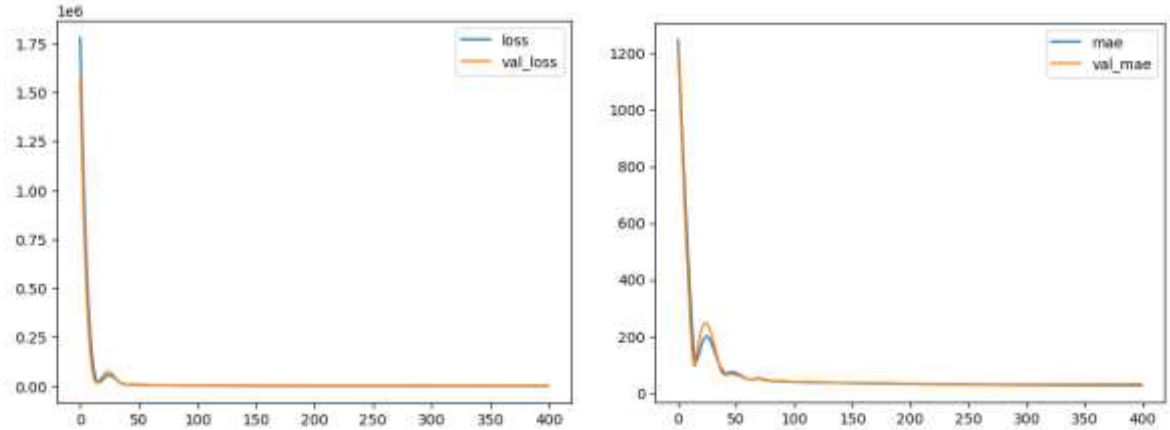

Figure 5: Training Curves of LSTM Model

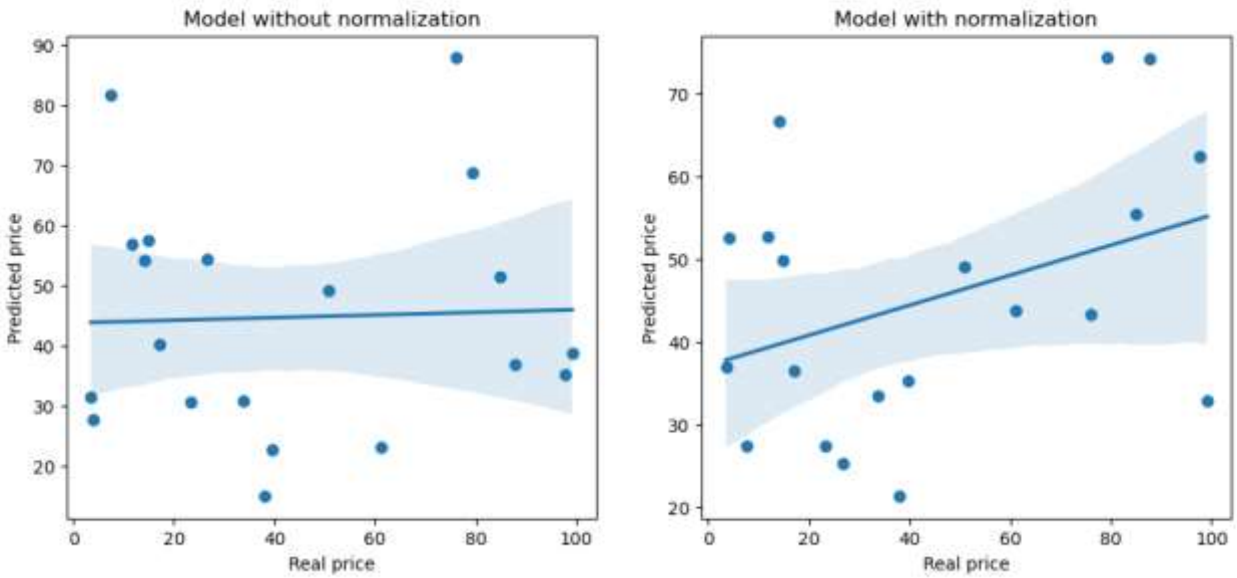

Figure 6: Prediction Plots of LSTM Model

symbolize bias vectors specific to each gate. To ensure the robustness and generalizability of our LSTM modeling approach, a rigorous k-fold cross-validation methodology was implemented, as depicted in Figure 4. This method involved partitioning the Makeup product supply chain dataset into k subsets, leveraging k-1 folds for training the LSTM model, and reserving the remaining fold for validation. This process iterated k times, rotating the validation fold in each iteration to train and validate the model across diverse subsets of the data. The depicted visualization in Figure 4 encapsulates the iterative nature of this technique, showcasing the training and validation cycles across multiple folds.

5. Results and Discussion

This section traverses the terrain of empirical revelations, presenting an array of results stemming from the application of diverse analytical techniques and modeling approaches. The synthesis of these findings aims to illuminate the intricate interplay of variables, unveil emergent patterns, and discern pivotal factors shaping the resilience landscape within the Makeup product supply.

The performance and convergence of the LSTM model trained on the Makeup product supply chain dataset are visually articulated through the training curves depicted in Figure 5. This visualization encapsulates the dynamic

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evolution of key metrics, including loss functions and accuracy, across epochs during the training process. The observed trends unveil the model's learning trajectory, portraying the optimization of the LSTM network's parameters over successive iterations. Figure 5 serves as an insightful representation, illustrating the diminishing trend in the loss function and the corresponding augmentation in accuracy as the model iteratively learns from the temporal dynamics ingrained within the supply chain data.

The predictive efficacy of the LSTM model applied to the Makeup product supply chain dataset is vividly portrayed in the prediction plots illustrated in Figure 6. These plots offer a compelling visual representation of the LSTM model's ability to forecast crucial supply chain parameters, such as stock levels, order quantities, or shipment trajectories, over a specified future horizon. The comparison between the models using normalized and unnormalized data reveals a substantial impact of normalization on predictive performance. The model trained on normalized data exhibited a notably improved performance, explaining 12% of the predictions with an R2-score of 0.129. In contrast, the unnormalized data hindered the model's predictive capability, resulting in an R2 score that indicated an inability to explain any of its predictions. The model utilizing normalized data showcased enhanced predictive accuracy, reflected in its lower Mean Absolute Error (MAE) of 26.290, Mean Squared Error (MSE) of 940.151, and Root Mean Squared Error (RMSE) of 30.662 compared to the unnormalized model's respective values of 34.008, 1482.000, and 38.497. These metrics underline the superior performance of the normalized model in generating predictions closer to the actual observations within the Makeup product supply chain dataset. The stark contrast in R2 scores further underscores the critical role of normalization in improving the model's ability to capture and elucidate underlying patterns within the data, ultimately leading to more reliable and accurate predictions.

6. Conclusion

In navigating the complexities of supply chain resilience within operation research, this study has unveiled pivotal insights derived from a meticulous analysis of the Makeup product supply chain dataset. Our exploration illuminated the significance of methodological rigor, showcasing the efficacy of Long deep networks in modeling temporal dependencies within supply chain data. The comparison between models trained on normalized and unnormalized data highlighted the profound impact of normalization on predictive performance, with the normalized model demonstrating superior accuracy and explanatory power. This underlines the crucial role of data preprocessing techniques in enhancing predictive capabilities and deciphering intricate supply chain dynamics. The comprehensive examination of case studies underscored the practical applications of resilience strategies, emphasizing the importance of proactive risk mitigation, adaptive decision-making, and robust network designs in fortifying supply chains against disruptions. As industries navigate an ever-evolving landscape rife with uncertainties, our study advocates for a holistic approach that leverages advanced analytics, empirical scrutiny, and strategic foresight to fortify supply chains, ensuring sustained operations and fostering adaptability amidst dynamic market environments.

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