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A Reverse Logistics Network Model for Handling E-commerce Returns

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Abstract: E-commerce supply chains are becoming more complex due to increasing global sales, and product returns from these sales are alarmingly high, highlighting the importance of effective return management. This paper proposes a reverse logistics network model to optimize return management. The proposed model applies ward-like hierarchical clustering with geographical constraints to detect return tendencies and utilizes mixed integer linear programming to optimize the network. The decision variables of the model include selection of Initial Collection Centers (ICCs), allocation of customer markets to ICCs, and optimal return volumes to be sent to each fulfillment center and recycling center from ICCs. The validity of the proposed model is established through a case study conducted in the consumer electrical and electronics sector of an e-commerce firm, providing 39.9% cost savings on average compared to the current Reverse Logistics (RL) network operation. This study contributes to the literature by integrating industry 4.0 technologies into the assessment of RL and facility planning with network optimization. The proposed RL network model serves as an operational planning tool, providing directions to e-commerce firms on optimizing RL networks and utilizing partner networks with integrated decision making for product returns.

Keywords: Supply chains and networks, Industry 4.0, Operations research, Facility planning and materials handling, Logistics in manufacturing, Sustainable Manufacturing

1. INTRODUCTION

The E-commerce industry is growing at a rapid pace and is increasingly popular among consumers, with a staggering 228% growth recorded between 2014-2020 in worldwide retail e-commerce sales (Statista, 2021). Currently, e-commerce firms are paying greater attention to their return policies, recognizing their importance as a key success factor in this competitive industry and a way to attract more customers. In recent times, product returns from e-commerce sales have shown a quick growth of at least 30% (Dennis, 2018). To successfully address this challenge, e-commerce firms need to focus on identifying effective strategies for return management. According to Rogers et al. (2002), return management involves managing the activities related to returns, evacuation, and avoidance at the enterprise level and at the levels of key stakeholders in the supply chain.

An e-commerce firm's ability to manage returns effectively depends on a well-designed Reverse Logistics (RL) network. Hawks (2006), defines RL as the planning, implementation, and control of the flow of raw materials, inventory, finished goods, and related information. The process must maintain efficient and cost-effective practices from end to beginning to recover value or dispose of items correctly (Bocewicz *et al.*, 2019).

However, only a few studies have focused on RL network design of an e-commerce firm that supports effective returns management (Chang and Zheng, 2014; Li, Lu and Liu, 2014; Liu, 2014; Das, Kumar and Rajak, 2020; Dutta *et al.*, 2020). This indicates the need for more quantitative and realistic studies in this domain (de Araújo *et al.*, 2017; Das, Kumar and Rajak, 2020).

This paper is structured as follows: Section 2 provides a literature review of the background stated above. In Section 3, we present the methodology of the proposed RL network model, including the RL network model, sequencing steps, assumptions, decision variables, parameters, and constraints in the mathematical model. Section 4 and 5 contain the case study, results and discussion, along with a sensitivity analysis of the proposed model. Finally, in Section 6, we provide a conclusion to the study, highlighting implications and future research directions.

2. LITERATURE REVIEW

Returned products can come in different conditions and quantities (Bernon, Tjahjono and Ripanti, 2018). Therefore, there should be options in the RL network of an e-commerce firm to effectively face these different situations (de Araújo *et al.*, 2017). Peck et al. (2020) mentioned that the proper utilization of resources, technologies, and partner network capabilities are key to sustainable manufacturing.

Li, Lu and Liu (2014) developed an algorithm in the form of two stages to optimize a location and inventory problem model in e-commerce returns. The model determines the optimal quantity, locations, order times, and order size of MCs for both forward and reverse logistics networks. Liu (2014) also proposed a generic algorithm that incorporates storing,

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reprocessing, remanufacturing operations, and a suppliers' module. This research provides valuable insights for strategic decisions on facility count, location, capacity, and material flow, with a focus on utilizing remanufacturing to gain a competitive advantage (Sung, Nam and Lee, 2013).

Dutta et al. (2020) developed a logistics network model for the Indian e-commerce market that accounts for product returns. The proposed model includes customer markets, warehouses, delivery hubs, landfills, incineration centers, and recycling centers as nodes in the supply chain. Multi-objective Mixed Integer Linear Programming (MILP) with weighted goal programming was used to develop the RL network model. In a similar vein, Das, Kumar and Rajak (2020) proposed an RL network model for an e-commerce company that specializes in fashion goods. Their study introduces Initial Collection Centers (ICCs) to collect and store the returned products before sending them to warehouses, with the goal of minimizing logistics costs. They also suggest replicating their study for e-commerce firms in the consumer electronics industry as a future research direction.

Agrawal and Singh (2019) have highlighted novel research directions in RL applications that incorporate Industry 4.0 technologies, including big data analytics and machine learning. Moreover, existing literature has several drawbacks and gaps, including the lack of connectivity between different parties in an e-commerce RL network, the lack of industry 4.0 applications in RL, and the lack of practicality to apply in the actual industry. To address these gaps, our study considers the research objective of developing a RL network model that utilizes industry 4.0 technologies and integrated decision-making among different parties to effectively manage e-commerce product returns.

3. METHODOLOGY

We consider locating ICCs with integrated decision-making to effectively manage e-commerce product returns. As a first step, we implemented hierarchical clustering with geographical constraints on return data to identify better locations to place ICCs. This will address the literature gap of utilizing industry 4.0 technologies in RL operations. Afterwards, we developed a Mixed Integer Linear Programming (MILP) model to optimize the RL network. An e-commerce firm can have multiple sellers, and the expertise required for remanufacturing, repairing, and refurbishing particular products may differ from seller to seller. Therefore, we propose communicating with sellers at the ICCs to decide which products are in a condition for remanufacturing, repair, refurbishment, and which products cannot be reused by any means.

After going through the decision-making process, the e-commerce firm can retrieve the set of products that are suitable for remanufacturing, repairing, and refurbishing to its fulfillment centers. At this stage, the sellers can take them back to their facilities to proceed with the chosen operations. Any products that cannot be reused will be transported to recycling centers by the e-commerce firm.

In order to address the challenge of optimizing e-commerce RL networks, we developed a MILP model from various perspectives. Our model formulation considered cost elements, such as fixed costs of ICCs, inventory holding costs, and transport costs. However, we excluded communication costs between sellers and ICCs from the RL network model to maintain the simplicity of the model. The nodes in our e-commerce RL network model consist of four types: customer markets, ICCs, fulfillment centers, and recycling centers.

3.1 Hierarchical clustering with geographical constraints

We utilized the ClustGeo package (Chavent *et al.*, 2018) in R Studio (RStudio Team, 2019) to perform a ward-like hierarchical clustering method with geographical constraints to identify clusters of customer markets. Chavent et al. (2017) introduced this method as a means of generating geographically compact clusters while considering other socio-economic factors. As a novel approach to capture the geographical proximity between customer markets, we adopted this method in our study to obtain more precise clusters. These clusters will aid in identifying return patterns and determining optimal ICC locations to optimize the RL network. Figure 1 illustrates the steps used in the proposed model.

We developed two dissimilarity matrices (D_0, D_1) in the hierarchical clustering process, which compare similarity pairs between two sets. Our research addresses a gap in e-commerce RL network design by incorporating data on volume, frequency, and price of returns in clustering (Das, Kumar and Rajak, 2020). D_0 initially performed hierarchical clustering using these data as variables within the dissimilarity matrix. D_1 incorporated geographical proximity between customer markets as a constraint. To avoid suboptimal clustering, we did not use Euclidean distances (Fernando *et al.*, 2022). We combined D_1 into the initial hierarchical clustering based on D_0 using the mixing parameter alpha (α), chosen based on the relative importance of D_0 and D_1. Finally, we derived clusters capturing all variables and geographic constraints on returns data.

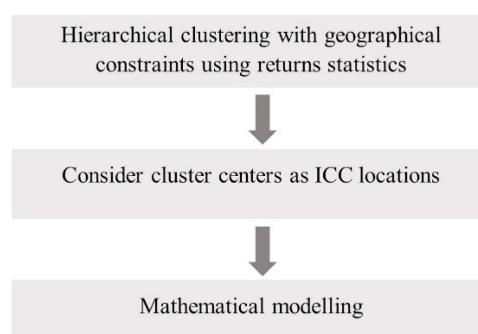

Fig. 1. Conceptual framework of the proposed model.

3.2 Mathematical Model

Using MILP for the mathematical formulation, we have incorporated certain components of the mathematical model introduced by Das, Kumar and Rajak (2020) making suitable adjustments to satisfy the requirements of the extension we propose in this study.

When developing our proposed mathematical model, we made several assumptions. Firstly, we assumed the availability of past data related to the daily product returns of each customer market. Additionally, we assumed that returns from a particular customer market are assigned to a single ICC and that a single ICC has the capacity to accommodate returns from several customer markets. We also determined the percentage of returns sent to formal recycling centers and fulfillment centers based on past data and existing literature on product returns. Further, we assumed that the firm is aware of the locations of the fulfillment and recycling centers. The fixed costs of ICCs were determined based on current rates for annual rental and maintenance costs in the region, and transportation costs per km per item were extracted from secondary source. Table 1 indicates the set of indexes, different parameters used, and the decision variables.

Table 1. Notation table

Sets		
M	-	Set of Customer Markets indexes, $m \in M$
H	-	Set of Initial Collection Centers, $h \in H$
W	-	Set of Fulfillment Centers, $w \in W$
R	-	Set of formal Recycling Centers, $r \in R$
Parameters		
C	-	Cost per km per item
D_{mh}	-	Distance between customer market 'm' and ICC 'h'
D_{hw}	-	Distance between ICC 'h' and Fulfillment center 'w'
D_{hr}	-	Distance between ICC 'h' and Formal Recycler 'r'
F_h	-	Fixed cost of establishing ICC 'h'
h	-	Inventory carrying cost per unit of returned item on a daily basis
T	-	Total number of annual working days
t	-	Holding time of returned item in an ICC in days
P	-	Maximum number of returned items that could be accommodated in an ICC in case it is selected
L	-	Minimum number of returned items that need to be kept in an ICC in case it is selected
Q_m	-	Daily returned product quantity of customer market 'm'
R_w	-	Average percentage rate of total returned products, sending for Fulfillment centers
R_r	-	Average percentage rate of total returned products, sending for recycling
Decision Variables		
Y_h	=	$\begin{cases} 1, & \text{if ICC 'h' to be opened} \\ 0, & \text{otherwise} \end{cases}$
A_{mh}	=	$\begin{cases} 1, & \text{if customer index 'm' is allocated to ICC 'h'} \\ 0, & \text{otherwise} \end{cases}$
Q_{hw}	-	Quantity of returned products sending from ICC 'h' to Fulfillment Center 'w'
Q_{hr}	-	Quantity of returned products sending from ICC 'h' to Formal Recycling Center 'r'

Objective Function

$$\text{Minimize } Z = \sum_h Y_h F_h + T\sum_m\sum_h CQ_m D_{mh} A_{mh} + hT\frac{(t+1)}{2}\sum_m\sum_h Q_m A_{mh} + T\sum_h\sum_w CQ_{hw} D_{hw} + T\sum_h\sum_r CQ_{hr} D_{hr} \quad (1)$$

Subject to

$$\sum_h A_{mh} = 1 \quad \forall\ m \quad (2)$$

$$\sum_m A_{mh} <= MY_h \quad \forall\ h \quad (3)$$

$$t\sum_m Q_m A_{mh} <= PY_h \quad \forall\ h \quad (4)$$

$$t\sum_m Q_m A_{mh} >= LY_h \quad \forall\ h \quad (5)$$

$$\sum_w Q_{hw} = \sum_m A_{mh} Q_m R_w \quad \forall\ h \quad (6)$$

$$\sum_r Q_{hr} = \sum_m A_{mh} Q_m R_r \quad \forall\ h \quad (7)$$

$$A_{mh} = 0 \text{ or } 1 \quad (8)$$

$$Y_h = 0 \text{ or } 1 \quad (9)$$

$$Q_{hw}, Q_{hr}\ \varepsilon\ I \quad (10)$$

$$\sum_h Y_h = 2/3/4 \quad (11)$$

We have indicated the objective function of the mathematical model as (1) and the reverse logistics cost components included in that are as follows:

The first cost component reflects the annual rental and maintenance costs for ICCs. The second component captures the annual transport cost to transport returned items from customer markets to ICCs. The annual inventory holding cost of the returned products in ICCs are captured as the third cost component. The fourth component denotes the annual transport costs from ICCs to fulfillment centers and finally, the fifth component reflects the transport costs from ICCs to recycling centers (Nanayakkara *et al.*, 2022).

Here, the constraints of the mathematical model can be mentioned from (2) to (11), and the enforcement of the constraints are as follows. Defining constraint (2), we ensure that returns from one customer market each representing states in Brazil, is allocated only to a particular ICC. Using constraint (3) we have restricted the allocation of customer markets to a closed ICC. Here, a large number denotes by M is included in the constraint. Using constraint (4), we have defined the maximum number of returned items that can be handled at a particular ICC if it is decided to be opened. Further, to ensure the increased space utilization we have indicated the constraint (5) to capture the minimum requirement of a returned products volume that should be allocated to a particular ICC if it is to be opened.

Constraint (6) determines approximate returns volumes to be sent from ICCs to fulfillment centers. Similarly, constraint (7) determines returns volumes to be sent to recycling centers. Constraint (8) uses binary decision variables to allocate customer markets to ICCs. The model uses constraint (9) to indicate the binary decision variables for opening ICCs. Constraint (10) determines the product returns volume to be dispatched from ICCs to fulfillment and recycling centers in the form of integers. Additionally, while not included in the original model, decision makers can provide the number of ICCs to be opened with constraint (11)

4. CASE STUDY

We used the "Brazilian E-Commerce Public Dataset by Olist" from Kaggle (Olist, Dabague and Magioli, 2018) to validate the proposed model, filtering data related to sales of electronic and electrical equipment (EEE) in 2484 cities across 26 Brazilian states. These 26 states were considered as consumer markets in our mathematical model. We considered three fulfillment centers that belongs to the e-commerce firm, and two recycling centers per each cluster as the nodes in this RL network, apart from customer markets and ICCs. Considered three fulfillment center state locations are shown in Table 2.

We made modifications to the volume of returns to enhance the competency of the e-commerce firm. Our estimation revealed that the approximate daily return volume from all customer markets would be 680. We employed the same method of estimation as Das, Kumar and Rajak, (2020), which also utilized Flipkart's real-world estimation for their fulfillment center. The largest fulfillment center of Flipkart processed 0.12 million units daily on an area of 2.2 square feet. Our findings indicate that approximately 5,200 square feet of total area would be needed in all ICCs to accommodate returns for up to 4 days and allocate buffer space to increase future returns by 3%. The allotment of space to each ICC would differ based on the optimal number of clusters and taking into account the skewed distribution of return rates in the clusters.

5. RESULTS AND DISCUSSION

5.1 Results of hierarchical clustering

Following the model in Fig. 1, we performed hierarchical clustering on returns data with respect to 2,484 cities in Brazil, incorporating geographical constraints. Fig. 2 displays the initial clustering results using the dissimilarity matrix D_0. To enhance the geographical compactness of clusters, we introduced the D_1 matrix containing geographical constraints into the initial clustering in Fig. 2. We used a mixing parameter α of 0.7 to enhance the geographical cohesion of the 4 clusters found previously while minimizing the decline of cohesion among other variables, as shown in Fig. 3.

The final hierarchical clusters are shown in Fig. 4, and the desired clusters based on return patterns are shown in Fig. 5. To obtain the cluster centers and treat them as ICC locations under the proposed model, we used the return volume and customer locations in each of the output clusters following the center of gravity method. Current ICC selections were obtained referring to the secondary sources related to the firm.

Table 2. State locations of the fulfillment centers

Fulfillment Center	State
w1	Minas Gerais
w2	Bahia
w3	Santa Catarina

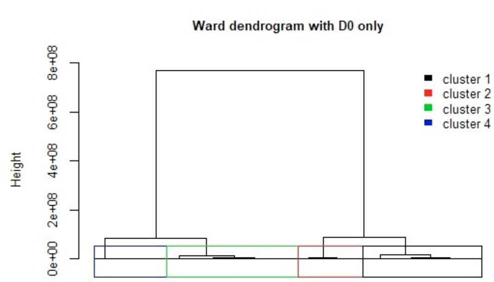

Fig. 2. Ward dendrogram considering only D_0

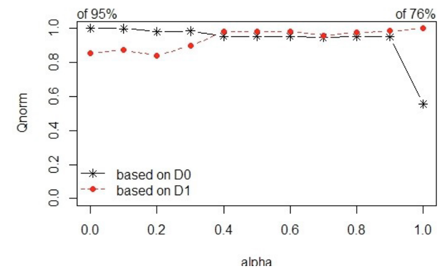

Fig. 3. Choice of α

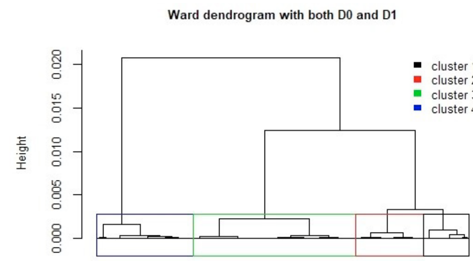

Fig. 4. Ward dendrogram considering both D_0 and D_1

Space allocations of 5,200 square feet for ICC locations are shown in Table 3 and the space varied based on the skewed distribution of returns volume in clusters.

Table 3. ICC locations and space allocation

ICC Selections	ICC state location	Space (square feet) in order
Current	Goiás, Rio de Janeiro, Bahia, Piaui	1900,1100,1100,1100
Proposed	Tocantins, Sergipe, Paraná, Minas Gerais	1100,1100,1100,1900

5.2 Results of the proposed MILP model

The total RL costs incurred in the network were compared with the current selections of ICCs in the firm and the selections of ICCs according to the proposed model. We chose IBM ILOG CPLEX Optimization Studio (IBM Corporation and other(s) 1987, 2019) software, which is widely used in existing literature and applicable to this study, to find the optimum solution to the MILP problem (Sung and Lee, 2018).

The mathematical model provides valuable insights for the e-commerce firm. After comparing the optimal RL cost derived from the current ICC selections of the firm and the proposed model, it was discovered that the proposed model provided the most cost-effective solution with an optimal cost of BRL 9,843,608 per year. The results are presented in Table 4. The baseline cost of BRL 16,262,723 per year got generated via the MILP model considering the current ICC locations, while optimal solution considered the proposed ICC locations. This indicates that the proposed model can offer significant cost savings for the firm, resulting in a margin of 39% compared to the current ICC selections. Both the current and proposed selections identified that opening ICCs in three of the four locations was the optimal solution. Specifically, the proposed model identified Sergipe, Paraná, and Minas Gerais states as the optimum locations for ICCs, as illustrated in Fig. 5.

The proposed MILP model assigns each customer market to a designated ICC and optimizes the daily volume of returned items to be sent from the ICC to fulfilment centers based on distance. Additionally, the model determines the number of daily returns to be sent from ICC to selected recycling centers (Nanayakkara *et al.*, 2022). Furthermore, the model outputs a breakdown of how each cost component of the RL contributed to the total RL cost, offering valuable insights to the firm. Fig. 6 shows the cost contribution of each reverse logistics cost component considering the current and proposed ICC selections in the RL network design. We can clearly identify proposed ICC selections have led to incur lower costs in all the elements of RL except for inventory holding costs.

Table 4. Optimum solutions under each ICC selection

ICC Selections	Optimum Cost (BRL) per annum	Optimum number of ICCs to be opened	Optimum State Location
Current	16,262,723	3	GO, RJ, BA
Proposed	9,843,608	3	SE, PR, MG

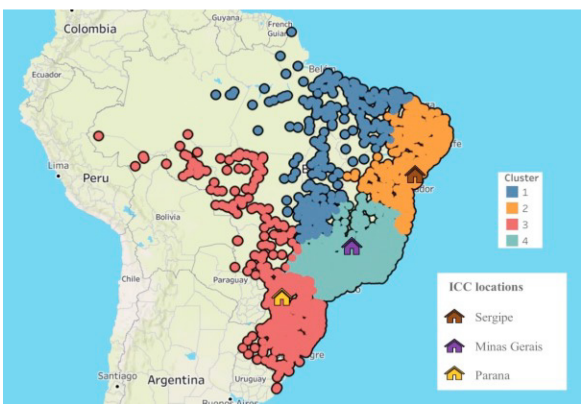

Fig. 5. ICC locations under proposed model

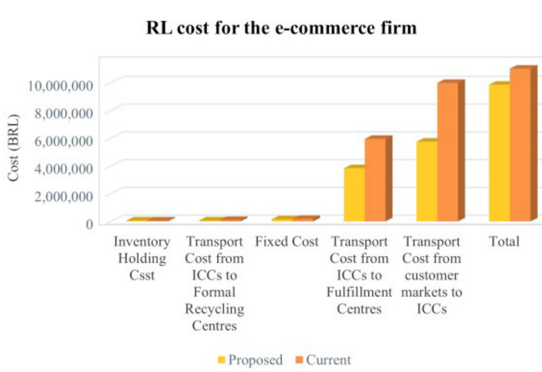

Fig. 6. RL Cost comparison

The total cost of RL is significantly influenced by transportation cost from customer markets to ICCs, as it accounts for approximately 58.3% of the total RL cost. The proposed model provides insight into the contribution of each cost component of RL to the total cost. The transportation cost from ICCs to fulfillment centers is the second most significant component, contributing approximately 38.9% to the total RL cost. The fixed cost of ICCs, including rent and maintenance, represents a relatively small portion of the total RL cost at only 1.5%. Conversely, transportation costs from ICCs to recycling centers contribute minimally to the total cost of RL, accounting for approximately 0.7%. This is due to the assumption that recycling centers are evenly distributed across all states in Brazil, requiring shorter travel distances. Finally, the inventory carrying cost component has the lowest contribution to the total cost of RL, accounting for only around 0.6%. E-commerce firm managers can use these insights to develop appropriate strategies and make cost-effective decisions to optimize reverse logistics networks (Nanayakkara *et al.*, 2022).

5.3 Sensitivity analysis of proposed MILP model

We further validated the MILP model by varying important factors such as the daily volume of product returns and the number of ICCs in the model. This provides a clear understanding of the model's behaviour with respect to varying situations.

We have varied the daily return volume Q_m both in the positive direction and negative direction while considering the fact that there is more probability for growth than decline in e-commerce. First, we individually calculated the total cost of the RL for both current ICC selections and proposed ICC selections. Then we found the total RL cost savings % that can be obtained using the ICC selections under the proposed model for each scenario, as illustrated in Table 5. We can observe that for nearly every change in daily return volume, the proposed model consistently delivers around 40% cost savings. Thus, the proposed model has proven to deliver significant cost savings even as returns volume vary.

Second, we imposed a variation on the number of ICCs that can be specified in the model by one, in both directions. Table 6 illustrates the cost savings in each variation in the number of ICCs. The cost savings for the e-commerce firm using the proposed model increase as the number of selected ICCs to open increases in the order of 4, 2, and 3. The above significant cost savings margins further validate the credibility of the proposed model even with the variation in number of ICCs.

Table 5. Cost savings % under variation in returns volume

Variation in returns volume %	-10%	-5%	Base	+5%	+10%	+15%	+20%
Cost Savings %	40%	40%	39%	40%	40%	40%	40%

Table 6. Cost savings % under variation in number of ICCs

Number of ICCs	2	3	4
Cost Savings %	32%	39%	28%

6. CONCLUSION

This study introduces a novel reverse logistics network model for efficiently managing product returns in e-commerce. It offers valuable insights for decision-makers in e-commerce firms to optimize their RL network. The proposed model serves as a decision support system that provides guidance on the ideal number and location of ICCs, customer market allocation to ICCs, and the optimal returns volume to be directed to each fulfillment and formal recycle center. By comparing the current ICC operations to the proposed model, significant cost savings were achieved with the latter. On average, the proposed model resulted in a 39.9% reduction in RL costs for variations in return volume. Moreover, when varying the number of ICCs, the cost savings obtained ranged between 28% - 40%, further validating the efficacy of the proposed model.

This research has few limitations. First, it assumes deterministic behaviour for daily returns, while the actual nature of returns is uncertain. Second, the RL network design only focuses on consumer electronic and electrical products with the highest return rates for the firm. Therefore, future research can extend the study by applying deep learning to predict return volumes and replicating the research for the complete product range of an e-commerce firm.

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