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RESEARCH ARTICLE

Retail reverse supply chain optimization under profit–loss budgetary limitation

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ABSTRACT

Retailers increasingly need decision-support tools to manage unsold inventory under operational and fiscal constraints. In this paper, we develop a reverse supply chain (RSC) model for retailers under profit–loss budgetary limitation. The retail RSC consists of multiple stores, a warehouse, and multiple vendors. Each store carries inventory that is not selling as hoped, and they want to get rid of these unwanted products to replace the space with more productive items. Our model considers two options for how a store can get rid of these products: the retailer can send the products to its warehouse if there is demand at other stores, or send them back to their vendor if there are available vendor funds. However, the retailer operates under a predetermined profit–loss budget that should be utilized as closely as possible within the fiscal cycle. The budgetary limitation is the result of profit–loss that will be incurred due to relocating products within and out of its supply chain system. This budgetary limitation, also known as the "P&L effect" in industry, is decided a year prior to an RSC activity for financial, planning, and/or taxation reasons. We model this problem as a mixed integer linear program and solve test problems using CPLEX. We then develop a heuristic solution algorithm and compare the CPLEX solution results and times with our heuristic. We summarize useful insights into our heuristic and how it can be further developed for similar optimization problems with budgetary constraints. Eventually, we outline future research topics and suggestions for RSC models for retailers.

1. Introduction

Reverse logistics concerns the upstream movement of goods and information from points of consumption back to points of origin for value recovery or proper disposal. In practice, this encompasses the collection, transportation, and redistribution of used, new, recyclable, or scrap items from end-collection points (e.g., consumers, business customers, stores, warehouses, collection centers, and municipal bins) to producers/manufacturers/suppliers or to disposal facilities, such as incinerators or landfills. The Reverse Logistics Executive Council offers a widely cited definition: "The process of planning, implementing, and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods, and related information from the point of consumption to the point of origin for the purpose of recapturing value or of proper disposal." [1(p2)]

Whereas forward supply chains typically exhibit a divergent "few-to-many" structure (from factories or vendors to numerous demand points), reverse supply chains (RSCs) are characteristi-

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cally convergent "many-to-few" networks that channel returns from many collection points to comparatively few processing centers (e.g., vendors, plants, specialized facilities). This structural asymmetry has modeling implications that distinguish reverse problems from their forward counterparts.

Within this general setting, retail organizations operate their own internal forward and reverse networks after purchasing products from manufacturers or wholesalers. The manufacturer's universal reverse network may include echelons such as repair, disassembly, remanufacturing, or recycling, but a product re-enters that network only when it (or its components/materials) is routed back to one of those echelons via the retailer, third parties, liquidators, municipal programs, or end consumers. Retailers themselves typically do not alter the physical characteristics of products they do not produce; therefore, the retailer's reverse network focuses on commercially viable routes within its sphere of control—principally stores, distribution centers/warehouses, and vendors.

A salient feature of retail practice is the recognition that some items ordered from vendors—particularly spare parts, specialized equipment, and seasonal products—may not be sold to end customers within the fiscal year (and sometimes over multiple years). Nevertheless, when the retailer purchases goods and "sells" them internally to its stores (including company-owned outlets, dealers, or franchisees), the associated profit margins are recorded in the current period's financial statements. If some of those store-level sales do not translate into end-customer sales, part of the recognized margin is economically unrealized and must be reversed when the items are returned or reallocated. This accounting reality motivates a budgeting mechanism that is distinct from classical cost caps in reverse logistics.

Specifically, retailers set aside a deterministic profit–loss budget B at the start of the fiscal cycle to cover expected margin reversals and related return costs. Operationally, B is not merely an upper bound on spending; it is a period spending target tied to profit–loss timing and tax recognition. Under-consuming B can be detrimental: unrealized returns are insufficiently recorded, tax shields associated with write-downs are foregone in the current period, and future allocations to reverse operations may be rolled back in the next budgeting cycle. Over-spending B, in contrast, would exceed the intended margin reversals and induce avoidable costs. Hence, the managerial objective is twofold: (i) minimize realized loss from return and reallocation actions, while (ii) consuming B judiciously within the fiscal window.

The operational decision, therefore, centers on identifying excess inventory in store stocks and choosing among feasible reverse routes. Products may be reallocated to other stores where demand exists (recovering margin internally) or returned to vendors under contractually specified terms, which may include penalties or fees. Because the retailer cannot perfectly foresee which stock-keeping units (SKUs) will fail to sell through at the store level, all internal transfers are initially booked as sales; B then functions as a planned allowance for subsequent margin reversals. In this work, we model the retailer's problem as a cost-minimization program that explicitly embeds the budget–consumption obligation: the model searches for the "sweet spot" that maximizes internal margin recovery via store-to-store reallocations and minimizes costly vendor returns, subject to meeting the planned consumption of B.

Finally, our heuristic reflects this economics-driven trade-off. When the marginal profit–loss benefit of reallocating an additional unit within the network is high, the procedure prioritizes internal redistributions. As the fiscal horizon narrows and the penalty for under-consuming B becomes material, the search shifts toward budget-utilization moves that complete the planned consumption at the lowest incremental loss. In summary, the proposed formulation and solution approach operationalize retail profit–loss logic within an RSC setting: they account for the convergent network structure of returns, respect the retailer's control over routes (stores–warehouses–vendors), and reconcile loss minimization with the fiscal imperative to fully utilize the profit–loss budget.

2. Literature review

RSC research emerged from end-of-life recovery and waste-management problems and, from its early development, largely focused on reverse network design and location–allocation decisions (e.g., siting collection and processing facilities and allocating returned flows). Since the 2000s, interest has accelerated—spanning reverse logistics, closed-loop supply chains, and product returns management—and recent syntheses provide accessible entry points by mapping themes, modeling choices, and methodological trends.[2–4]

Among these, a recent review is especially useful because it organizes prior studies using structured tables across multiple dimensions (e.g., recovery options, objective structure, waste type, uncertainty treatment, and solution approach), which helps readers quickly identify comparable modeling streams and exposes gaps in a rapidly growing literature.[3]

Despite this substantial body of research in RSCs (and closed-loop supply chains), the retail RSC (RRSC) domain remains comparatively scarce—especially with respect to modeling contributions that address network design, allocation decisions, cost optimization, budget management, or product-return decisions within and/or outside a retailer's own network. In our search, several modeling-oriented studies are among the few that propose explicit frameworks on RRSC activities.[5–7] This scarcity is also highlighted in the RRSC review reported by Dias et al.,[8] which we encourage readers to consult for a targeted synthesis and identification of open questions in this domain. Beyond modeling, additional empirical, conceptual, theoretical, investigative, and qualitative work on RRSCs can be found in numerous studies.[9–30]

Within the more recent RRSC-adjacent retail returns stream, however, research has started to sharpen the picture of what retail returns management entails—often at the level of strategy, process, sustainability, operational policy design, and risk. Frei et al.[31] mapped multichannel retail returns processes in detail and emphasized the operational complexity, prevalence of manual steps and process variations, and the presence of unclear decision rules—elements that help motivate and justify more formal decision-support models. At the strategy and governance level, Karlsson et al.[32] conceptualized retail returns management strategy through an alignment perspective and empirically identified key components that retailers need to coordinate when designing effective returns management systems. From an operations-analytic perspective, Yang et al.[33] examined buy-online-and-return-to-store return operations and connected return policy parameters to inventory decisions, customer response, and expected profit outcomes in omnichannel retailing. On the sustainability dimension, Zhang et al.[34] developed an environmental sustainability framework for multichannel retail returns and synthesized actionable practices aimed at reducing ecological impacts associated with reverse flows. Finally, Zhang et al.[35] addressed a particularly retail-salient concern—fraudulent returns—by identifying enabling factors and outlining mitigation strategies, thereby highlighting that RRSC design and operation are shaped not only by cost–service trade-offs but also by behavioral and control considerations.

Importantly, while previous studies have meaningfully enriched the RRSC landscape, much of this stream is not yet fully aligned with the classical modeling tradition in RSCs,[31–35] where explicit network and allocation decisions under operational and financial constraints are central. In parallel, contemporary sustainability optimization research continues to advance reverse/closed-loop logistics modeling—often in manufacturing-anchored or cross-sectoral contexts—by incorporating coordination structures (e.g., fourth-party logistics), cleaner production, and remanufacturing,[36] or by designing customer-centric closed-loop configurations that explicitly pursue reverse-chain financial self-reliance.[37] Although not retail-specific, these studies are methodologically relevant as they expand the modeling toolkit (e.g., uncertainty representations, coordination and remanufacturing logic, self-reliance constraints) that can be selectively adapted to RRSC formulations.

Importantly, while the above works collectively establish a robust foundation for reverse logistics and RSC research, our study did not reveal a clear introduction of the profit–loss budget concept as it is used in real-world retail practice, nor did we find studies that define the concept and examine its operational implications in depth. Because the problem addressed in this paper is a real-world application with one of the largest retailers in Canada—focused on how to optimally utilize an available profit–loss budget to improve inventory health—this fiscal mechanism may not be widely visible to the academic community, even though it materially shapes tactical decisions in large retail operations. Moreover, our findings reinforce that the dominant modeling tradition in the RSC literature has remained oriented toward manufacturing contexts (e.g., product/material recycling, end-of-life recovery, waste collection and disposal), whereas retail settings involve distinct operational levers and fiscal constraints.

Accordingly, our study contributes to the emerging modeling stream on RRSCs by formalizing the retailer's tactical problem as a joint product selection and product allocation decision for unsold store inventory within a retailer-operated network, under a budgetary limitation that represents margin reversals. Based on our understanding of retail practice, the profit–loss budget functions as a necessary mechanism to handle product returns and their downstream effects on financial statements, accounting, and ultimately tax deductions/adjustments. Large retailers—such as Walmart, Target, Costco, and Home Depot—typically do not manufacture the products they sell; rather, they source merchandise from various vendors and face business-to-business returns and margin reversals on quarterly and annual cycles. This institutional context suggests that profit–loss budget utilization may be retail-specific, although whether analogous mechanisms exist in other industries (e.g., manufacturers, vertically integrated brands that both produce and sell through their own channels) remains an open and promising direction for future research.

3. Motivation and contribution

Although reverse logistics and RSCs have been extensively studied, a substantial portion of the literature has predominantly emphasized network design questions—namely, strategic location–allocation decisions, such as whether to open collection centers and/or processing facilities, how many to establish, and where to site them so as to minimize system-wide costs. Accordingly, numerous dominant formulations in the field are facility–location and network-configuration models that aim to determine an optimal reverse network structure rather than to support day-to-day operational decisions within an existing system. This emphasis is understandable from a strategic planning perspective; however, it also means that the literature offers comparatively fewer decision models for organizations that already operate an established reverse network and require tactical and operational guidance to manage returns and reallocations efficiently.

Relatedly, many existing models assume that all returned items necessarily enter the reverse flow, which naturally pushes the analysis toward design questions, because the principal challenge becomes balancing uncertain inflows across candidate facilities and routes. In practice, however, firms frequently face situations in which only a subset of SKUs should be selected for reverse processing, while the remainder may be retained, deferred, or managed through alternative internal actions. Such selection decisions—particularly when embedded in an operating network with fixed facilities and routes—are inherently tactical: they determine which products should participate in reverse activities and how those selected products should be allocated across available channels. These decisions directly affect short-run costs, service levels, and fiscal outcomes, and therefore call for models that move beyond facility-opening choices to address operational reallocation within an already-deployed network.

A second limitation is that reverse logistics has largely been modeled from the manufacturer-centric viewpoint, even though manufacturers are not the only actors that manage reverse flows. Retail organizations purchase products from manufacturers, distributors, or vendors and operate their own forward and RSC environment, typically characterized by fewer echelons and more constrained operational options than the manufacturer's universal reverse network. Because retailers generally do not perform physical transformation of products (e.g., remanufacturing or disassembly), their RSC decisions concentrate on internal redistribution among stores and warehouses, and on vendor returns governed by contract terms. Yet, despite the practical importance of such RRSCs, they remain under-represented in the broader reverse logistics modeling literature, which continues to prioritize upstream recovery networks and strategic design.

Motivated by this gap, the present study advances an operationally grounded modeling framework for RRSC with a particular emphasis on the fiscal mechanism that drives decision-making in large retailers: the profit–loss budget. Unlike conventional budget constraints that act as caps on spending, the profit–loss budget in retail practice functions as a planned margin-reversal allowance tied to fiscal reporting and tax adjustments, and, importantly, must be utilized as closely as possible to its predetermined value within the fiscal cycle. Consequently, the retailer's tactical problem is not simply to minimize logistics and handling costs, but to jointly determine which unsold products should enter the reverse process and how they should be routed (e.g., internal reallocation versus vendor return) so that margin reversals are executed in a manner consistent with the profit–loss budget while avoiding unnecessary penalized returns.

Crucially, the RRSC decision is governed by an explicit fundamental trade-off between (i) minimizing realized margin losses associated with identifying and returning unsold products and (ii) satisfying the financial obligation of maximizing the utilization of the profit–loss budget. In our setting, the budget-consumption requirement arises because margin reversals for unsold products must be recognized, and the physical inventory must be repositioned within or outside the retailer's network. Thus, the managerial objective is not purely inventory-cost minimization; rather, it is to identify an optimal balance in which margin reversals are "consumed" against an available margin reversal budget (i.e., the profit–loss budget) as efficiently as possible. This trade-off also shapes SKU selection behavior: under a relatively high profit–loss budget, the retailer is incentivized to prioritize higher-margin items to consume the budget with fewer units, whereas under a relatively low profit–loss budget, lower-margin items may be preferable to achieve budget utilization more finely and avoid over-consuming the allowance. The resulting SKU–route choices define the core tactical decisions that must be optimized to allocate products within the RRSC while satisfying fiscal constraints.

In this context, the contributions of our research are as follows. First, we model RSC activities specifically for large retail organizations, explicitly reflecting the structure and controllable routes of retailer-operated networks. Second, we provide a real-world operational formulation of how retailers manage profit–loss budgets by modeling the margin-reversal process that arises when store transfers do not translate into end-customer sales and items are returned or reallocated within the network. Third, our model integrates two decisions that are typically treated separately—product selection (identifying which SKUs should enter the reverse process) and product allocation (routing the selected SKUs across internal redistribution or vendor-return channels)—under a binding requirement to utilize the necessary profit–loss budget as efficiently as possible. Fourth, we clarify that although labeled as a "budget," the profit–loss budget is best interpreted as a tax credit/deduction mechanism that enables retailers to account for expected returns and corresponding margin reversals; therefore, utilizing it near its pre-calculated level is essential to align fiscal adjustments with operational reality. Finally, the study is grounded in an applied setting: the problem definition, constraints, and parameterization reflect a consultation with a major Canadian retailer, for which the core challenge involves inventory reallocation under margin-reversal requirements, where the profit–loss budget constitutes the primary operational target and constraint in the allocation decision.

4. Retail reverse supply chain network structure and profit–loss budget

A profit–loss budget is a budget prepared annually by a company's accountants to reverse the margins that are lost due to non-selling of the purchased products by the retailer. During a fiscal year, numerous products are purchased from vendors hoping that they will be sold to the customers; however, a portion of these purchases end up not selling as well, or not selling at all, for various reasons, such as customer desires, product unpopularity, competitive products in the market, price, and/or quality of the product. Over time, these products accumulate in store inventories and fill up scarce shelf/warehouse spaces. To relieve this limited and highly productive space to products with a higher chance of sale, the retailer needs to salvage some or all of this ineffective inventory optimally via a reverse logistics process from time to time. Every year, the retailer forecasts a budget (using expected effective and ineffective inventory levels, historical sales and non-sales of the purchased products, and historical inventory removal amounts) that accounts for this situation, and some portion of the ineffective inventory has to be removed from store shelves/inventory, where the total expenditure of the RSC process has to fit within this pre-calculated budget. The basic idea of the profit–loss budget is to account for and forecast the margin reversal cost of upcoming product returns that will be disposed of in the current year. Once it is calculated, the profit–loss budget can then be used to remove the profits of the "could-have-been sold" products from company books (these are the products that are already purchased within the year and presumed to be sold but not actually sold due to reasons as mentioned above, therefore presumed profit margins on the books should be reversed due to tax implications). Therefore, this budget is calculated by the company's financial team for financial planning and, most importantly, taxation purposes. We note that the retailer must file taxes before customer sales are realized. The profit–loss budget is therefore based on customer sales predictions.

During a fiscal year, many products are sold to stores by the retailer, and their possible profit gains are incorporated and accounted for as gains to the corporation's financial books. When some of these products are not sold to the end customer by the stores, and some portion of this inventory is removed from store inventories (when the retailer wants to make some inventory clearance via returns and relocations), the margins of the disposed inventory that are entered in the books has to be reversed, meaning that retailer's profit–loss (margin recovery costs, unrecoverable costs, vendor return penal-ties, and similar costs of doing business) should be calculated and then the books have to be readjusted for tax implications. Since identifying the products that are not sold, disposing some of them, reversing the margins of the returned ones, fixing those entries on books by reversing their margins (with additional return related costs), and then adjusting the taxation side can be a highly complex and time consuming act, the retailer uses forecasts to estimate the dollar amount of the potential returns using historical data and expects the RSC activity to fulfill this obligation of consuming the forecasted budget instead of reversing the margins of the products that would most ideally be disposed.

In an ideal world, the retailer should reverse the margins of the "sold-and-then-returned" products for its tax implications; however, this process is almost impossible for even a regular-sized retailer, since a large number of products are sold and returned within a fiscal year. To simplify the tax implications of this issue, the retailer uses a pre-calculated profit–loss budget as a workaround for handling returns. As a result, when it is time to clear a portion of the inventory via a reverse supply process, the retailer must use this predetermined/forecasted budget, and the goal is to limit the total profit losses due to actual product returns.

In a real retail environment, if some products in stores are not selling, the retailer identifies them as ineffective inventory and chooses a portion to relocate within the network to other stores where demand exists, or sent back to their vendor. These products (at stores deemed ineffective) move up in the supply chain network until they reach their last destination, which might be the products' original vendors or the warehouse (and then a store with demand for those products).

If an ineffective store product is returned or relocated, there are two options for routing the products. A store product can be routed to:

- Warehouse: If the product has warehouse demand. Warehouse demand is referred to as aggregate store demand when a store or a set of stores has a demand for that particular product. If any product has a purchase order/replenishment entry (most probably from the vendor) in the regular forward supply chain system, the RSC process will consider these purchase orders as warehouse demand because it is preferable to supply the item to the stores from an internal source—in this case a store which has that product in their current inventory and deemed as ineffective—as opposed to ordering them from its original source. The main benefit and savings for the warehouse supply of the returned products come from the fact that: (i) Products are already purchased from the vendor and internally available to sell. (ii) The company pays for placing an order, the shipment, the cost of the good and other related costs which, most probably, will end up higher than internally sourcing the products in the end (no reason to double pay), and (iii) using the ineffective inventory to cover potential demand is the most efficient way to get rid of the unwanted inventory, get returns on investment, and open shelf and inventory space for new products that has potential to sell.
- Vendor: If the product is chosen to go back to its vendor. We can send products back to their vendor to exhaust the "vendor funds" if the product is under the warranty of returnable products and the retailer has related vendor funds to recover a portion of the product's cost (cost of goods, COG). In general, a retailer has vendor funds from a vendor that they regularly purchase products from. The amount of vendor funds is negotiated through a purchasing agreement between the retailer and the vendor and calculated as a certain percentage of sales over a specified period of time. For example, if the retailer purchases USD 500,000 worth of products from a vendor in a year, the return agreement might be negotiated so that the retailer can return 10% of the yearly sales with a 25% penalty next year, i.e., the retailer can return up to USD 50,000 worth of products and would pay up to USD 12,500 in penalties.

To address the challenges of a profit–loss-based RSC, we propose a model to aid the retailer in deciding on which store products should be returned and whether they should be returned to a warehouse or to a vendor. Thus, our model involves both selection and allocation tasks. In this respect, our RRSC network is the only model in the literature that addresses an RRSC environment by considering product selection as a decision variable. We consider product selection as a decision variable and do not pull all predetermined ineffective inventory from stores, as only a portion needs to be disposed of.

The retailer's goal is to efficiently use scarce shelf space for products that are likely to sell. Since continuously pulling all predetermined ineffective inventory is not a practical option, retail companies clear their ineffective inventory periodically. They may fix the amount of cleared ineffective inventory, say one million worth of products annually, or keep a fixed percentage of effective inventory at the start of each year. Based on such inventory-cleaning policies, our model efficiently finds optimal selection and allocation decisions that minimize the RRSC costs within a given profit–loss budget.

5. Problem definition

In this chapter, we consider RRSC budget planning for an independent retailer with a supply chain network comprising multiple vendors, a warehouse, and multiple stores. Some portion of the retailer's inventory does not sell as expected, and the retailer needs to salvage it optimally to refill the space with better products and hold a more effective inventory with a higher sell-through rate to increase sales and hence profit. The goal of the retailer is to decide which products should be selected from stores for relocation within the network to achieve a healthier inventory level within a given profit–loss budget that should be fully utilized.

The retailer makes such decisions to clear a certain amount of inventory at specific time points, such as at the end of each fiscal year or at the beginning of each quarter. This policy defines the basis of our problem since it requires the retailer to clear and dispose of a certain amount of its ineffective inventory. The retailer is obliged to dispose of some of its ineffective inventory and has to reverse the margins of the unsold products, which were reported in their previous year's financial and tax statements as profits. An important input to our model is the profit–loss budget, which is predetermined by the retailer's finance department. The retailer's goal is to use this budget as efficiently as possible by returning ineffective products to inventory. The profit–loss budget is a budget that has to be spent as much as possible, against the profit margins that will be lost due to the relocation of products previously entered in the retailer's budget as profit-generating sales.

In summary, our goal is to select a set of products worth returning from a predefined amount (in terms of store value) of the ineffective store products. The chosen ineffective store products need to be routed to a warehouse or a vendor based on factors such as warehouse demand, warehouse capacity, available vendor funds, and products' profit margins. We model this problem as a mixed integer linear program (MILP) where the objective is to minimize all the related margin losses due to relocations and returns of the ineffective inventory that is chosen to be returned, subject to using the available profit–loss budget as much as possible.

6. Notation and abbreviations

To design our optimization problem, we start by defining the basic definitions of sets, variables, parameters, abbreviation, and notations as follows:

(i) Set notations:

I	The set of all products that are NOT effectively selling in the stores (Ineffective Inventory)
S	The set of all stores
V	The set of all Vendors

(ii) Index notations:

i	Product index of the products in the stores (i = 1, 2, ..., I)
s	Store index of the stores (s = 1, 2, ..., S)
v	Vendor index of the vendors (v = 1, 2, ..., V)

(iii) Parameters and abbreviations:

P_i	Store purchase price of the product from the retail company ($P_i > C_i$)
L_i	Landed cost of the product (COGs + transportation COGs + freight + exchange rates + customs + all related costs)
C_i	COGs (purchase cost of the product from the vendor, $L_i > C_i$)
$Q_{s,i}$	Number of items (quantity) of the product in each store
W	Maximum return allowance (in terms of money, USD) to the warehouse
D_i	Warehouse demand capacity of a product (in terms of the number of items of a certain product)
E_v	Vendor penalty fee for returning any of its products
F_v	Vendor fund available for the vendor B profit–loss budget for the retail company
R	Total reverse supply chain (store removal) amount
M	A relatively small number (USD) that is predetermined by the retail management in order to adjust the B range

(iv) Decision and dummy variables:

$r_{s,i}$	The binary variable decides whether a product in a store should be returned or not (0 for NOT return, 1 for return)
n_i	The number of items goes back to a vendor for a product
w_i	The number of items goes back to the warehouse for a product
f_v	Total vendor funds used

7. Optimization model

To solve the problem defined in **Section 4**, we propose an MILP to find optimal usage of the profit–loss budget via allocating returned products as follows (**Equation 1**):

$$\min z = \int_{i=1}^{I} \left[(n_i - w_i) P_i - 2 n_i C_i + (n_i + w_i) L_{\mathrm{I}} \right] + \sum_{v=1}^{V} E_v f_v \tag{1}$$

Vendor penalty fee E_v is modeled as an ad valorem (percentage) rate applied to the vendor-specific return funds f_v. In practice, each vendor v offers a contractual pool of return allowances (vendor funds) and specifies a penalty rate that is triggered when products are returned under the agreed terms; hence, the penalty component in **Equation 1** is represented via $\sum_{v=1}^{V} E_v f_v$, capturing the marginal fiscal burden associated with routing returns to vendors. For example, if a retailer returns USD 100,000 (at cost) to vendor v and the applicable contractual penalty rate is 20%, the penalty charge incurred is USD 20,000 on that returned value. In addition to this direct penalty, vendor returns also induce a margin reversal for the affected SKUs: the previously recognized gross margin embedded in the internal store transfer (store purchase price P_i relative to COGs C_i) must be reversed upon return, thereby drawing down the profit–loss budget. Consequently, vendor returns contribute to the objective through both (i) explicit penalty charges (the $E_v f_v$ term) and (ii) the implicit loss of recognized margin reflected in the price–cost differentials within the first summation of **Equation 1**.

$$s.t. \sum_{s=1}^{S} (r_{s,i}) Q_{s,i=} = n_i + v_i \qquad \forall\, i \in I \tag{2}$$

The objective in **Equation 1** decomposes the retailer's fiscal impact into channel-specific cost components and minimizes the total expected loss. The first three terms correspond to the vendor-return option: (i) the gross-margin reversal associated with returning unsold units, captured by the gap between the internal store transfer price P_i and the landed cost C_i; (ii) the non-recoverable cost component reflected by the difference between C_i and the cost-of-good metric L_i, which aggregates logistics-related burdens, such as transportation, freight, customs, and exchange-rate effects; and (iii) the contractual vendor penalty incurred when routing products back to their original suppliers, modeled as an ad valorem charge $\sum_{v=1}^{V} E_v f_v$ applied to vendor-specific return funds. The final term captures the internal reallocation (warehouse/store) alternative, where products are redirected to demand locations within the retailer's network to preserve value relative to vendor returns. Because the profit–loss budget must be utilized within the fiscal cycle, the model must balance value preservation with budget utilization, which in turn makes the selection of higher- versus lower-margin SKUs a central tactical lever across different budget levels.

$$\sum_{i=1}^{I} w_i C_i \leq W \tag{3}$$

Constraint in **Equation 3** enforces the warehouse (or distribution center) intake limitation in monetary terms by bounding the aggregate value of items routed to the warehouse. Specifically, $\sum_{i=1}^{I} w_i C_i \leq W$ ensures that the total inbound return value—measured using a unit cost metric C_i (e.g., COGS or landed cost) and the decision variable w_i denoting the number of units of product i assigned to the warehouse—does not exceed the warehouse's admissible capacity W. This representation is consistent with retail practice, where reverse inflows are frequently capped not only by physical space (volume/pallet positions) but also by a managerial or accounting limit expressed in value at cost. The variable w_i is endogenously linked to store-level availability and selection decisions through $Q_{s,i}$ (available units at store s) and $r_{s,i} \in \{0, 1\}$ (whether SKU i at store s is selected for reverse processing), such that only selected quantities contribute to the inbound warehouse total; consequently, **Equation 2** restricts the combined returns from all participating stores to remain within the warehouse intake cap.

$$w_i \leq D_{\mathrm{I}} \quad \forall\, i \in I \tag{4}$$

$$\sum_{i=1}^{I} n_{i(v)} C_i = f_v \quad \forall_v \in V \tag{5}$$

$$f_v \le F_v \quad \forall_v \in V \tag{6}$$

$$\sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i} P_i Q_{s,i} \ge R \tag{7}$$

$$\left(\sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i}\left(P_i - L_i\right) Q_{s,i}\right) + \left(\sum_{i=1}^{I} n_i\left(L_i - C_i\right)\right) + \left(\sum_{v=1}^{V} E_v f_v\right) \le B \tag{8}$$

$$\left(\sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i}\left(P_i - L_i\right) Q_{s,i}\right) + \left(\sum_{i=1}^{I} n_i\left(L_i - C_i\right)\right) + \left(\sum_{v=1}^{V} E_v f_v\right) \ge B - M \tag{9}$$

$$r_{s,i} \in \{0,\ 1\} \quad \forall s \in S,\ i \in I \tag{10}$$

$$n_p,\ w_i \in \mathbb{N} \quad \forall i \in I \tag{11}$$

$$f_v \in \mathbb{R} \quad \forall_v \in V \tag{12}$$

The objective function in **Equation 1** represents the total costs of losses, penalties, and the cost of gains redeemed when a product is returned to another store or warehouse. The constraint in **Equation 2** ensures that, for each product, the total number of items pulled from stores equals the number distributed to warehouses and vendors. Constraint in **Equation 3** ensures that the maximum return amount (in terms of value) to the warehouse should be less than the capacity of that warehouse. Constraint in **Equation 4** ensures that for each product, the total number of items that are returned to the warehouse cannot exceed the warehouse capacity (in terms of quantity) for that product. The constraint in **Equation 5** ensures that the value of the products sent to the vendor equals the total vendor funds that should be used. Constraint in **Equation 6** ensures that the total vendor funds that should be used to return products cannot exceed the vendor's available vendor funds. Constraint in **Equation 7** ensures that a certain amount of ineffective store products is removed from all stores' inventories. Constraints in **Equations 8 and 9** enforce the profit–loss budget. The constraints in **Equations 10– 12** define the set of binary, integer, and continuous variables, respectively.

8. Heuristic algorithm for budget optimization in retail reverse supply chain

Our test has shown that commercial solvers run out of memory and storage space when solving problems in **Equations 1–11**. From our experience with the industrial partner, we have also learned that a commercial solver license can add remarkable operating costs. This has convinced us of the need to develop a heuristic algorithm. The heuristic pseudo code is shown in **Subroutine 1**, where an initial allocation is determined, and **Subroutine 2**, where the budget allocation is determined. We also illustrate the two subroutines graphically in **Figures 1** and 2.

9. Heuristic algorithm steps for budget optimization in the retail reverse supply chain

In this section, we define the heuristic algorithm steps in detail. The algorithm is described as the pseudo code in **Section 7** and also visually shown in **Figures 1** and 2 to gain deeper insights into the inner workings of the heuristic. For a more detailed version of the algorithm, the steps are as follows:

(i) Calculate the total amount of ineffective store product returns—in terms of value—that need to be pulled from all stores using Constraint (7), (total inventory return = R).

(ii) Create a list of ineffective store products, list 1, where there is any amount of demand for a product at the warehouse.

(iii) Rank list 1 by "cost of returning to warehouse ratio" ($(P_i - L_i)\ /\ P_{\ i}$) in descending order.

(vi) Select the set of store products from the ranked list 1, top-to-bottom, until either the total inventory return is satisfied or the warehouse capacity is full. If the total inventory return is full, then STOP; else go to the next step.

(v) Calculate the inventory amount that is returned to the warehouse ($WarehouseReturn = \sum_{i=1}^{I} w_i P_i$).

(vi) Calculate the remaining inventory return amount from the total inventory return amount and warehouse return amount ($RemainingInventoryReturn = Total\ InventoryReturn - WarehouseReturn$).

(vii) Remove the chosen store products (that are identified in list 1) from the overall store product list, and create a new list, list 2.

(viii) Rank list 2 by "total cost of returning (profit margin loss from COGs + return penalty) to vendor ratio" ($\frac{((P_i\ -\ C_i) +\ C\ _i E_v)}{\mathrm{Pi}} P_i$) in an ascending or-

Subroutine 1. Heuristic solution for budget optimization

Result

$L1 = \{(s,i) \text{ for } s \in S, i \in I \text{ s.t. } Q_{s,i} > 0 \text{ and } D_i > 0\} \text{ sorted by } \frac{L_i}{P_i}$;

$U = \text{newSet}()$;

$w_i = 0, \forall_I \in I$;

while $|L1| > 0$ and $\sum_{I \in I} w_I \times C_I < W$ do

  $(s,i) =$ pop top element from L1;

  add (s,i) to U;

  If $\sum_{I' \in I} w_{I'}\ 0 \times C_{I'}\ 0 \leq W - Q_{s,I} \times C_I$ and $Q_{s,I} + w_I \leq D_I$ then

    $w_i += Q_{s,i}$;

  end

end

$\text{WarehouseReturn} = \sum_{i \in I} w_i \times P_i$;

$\text{VendorReturn} = R - \text{WarehouseReturn}$;

$L2 = \{(s,i,V_i) \text{ for } s \in S, i \in I \text{ s.t. } Q_{s,i} > 0 \text{ and } (s,i) \notin U\} \text{ sorted by } -C_i \frac{E_i}{P_i}$;

$n_i = 0, \forall i \in I$;

$f_v = 0, \forall v \in V$;

while $|L2| > 0$ and $\sum_{I \in I} n_I \times Pi < \text{VendorReturn}$ do

  $(s,i,v) =$ pop top element from L2;

  If $\sum_{I' \in I} n_{I'} \times P_{I'}\ 0 \leq \text{VendorReturn} - Q_{s,I} \times P_I$ and $(Q_{s,I} + n_I) \times C_I \leq F_v$ then

    $n_i += Q_{s,i}$;

    $f_v += Q_{s,i} \times C_i$;

  end

end

$\text{Budget} = \sum_{i \in I} n_i (P_i - C_i) + \sum_{i \in I} n_i (L_i - C_i) + \sum_{v \in V} E_v f_v + \sum_{i \in I} w_i (P_i - L_i)$;

$\text{VendorBudget} \leftarrow \text{Budget} - \text{WarehouseReturn}$

der.

(ix) Select the set of store products from the ranked list 2 until the remaining inventory return is satisfied.

(x) Observe whether the model is under-budget. If the model solution is under-budget $((\sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i}(P_i - L_i)Q_{s,i}) + (\sum_{i=1}^{I} n_i(L_i - C_i)) + (\sum_{v=1}^{V} E_v f_v) \leq B)$, it means that we can minimize all the costs while using all the available budget. We can proceed directly to Step 11 to use all available budget, if applicable. If the model solution uses more than the given budget $((\sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i}(P_i - L_i)Q_{s,i}) + (\sum_{i=1}^{I} n_i(L_i - C_i)) + (\sum_{v=1}^{V} E_v f_v) > B)$ in the optimal solution, then we are over-budget and therefore the costs can NOT be minimized with the given budget. In this case, skip the next steps and directly proceed to Step 16.

(xi) When the model is under-budget, it means that the minimized cost structure uses/spends less than the given budget, and products that need to be sent to the vendors should have a higher "total cost of returning (profit margin loss from COGs + return penalty) to vendor ratio" so that the model can use more of the available profit–loss budget by sending more profitable products, instead of the less profitable products, back to vendors.

(xii) Calculate the total amount of inventory (in terms of store price) that needs to be pulled from store inventories and

Subroutine 2. Heuristic solution for budget optimization

```
Result
If Budget < B then
    TotInv = ∑_{i∈I} n_i × P_i + ∑_{i∈I} w_i × P_i;
    ReturnCostRatio = VendorBudget/P ∑_{s∈S} ∑_{i∈I} n_i × P_i × Q_{s,i};
    ExpectedReturnCostRatio = (B − VendorReturnCost)/(R − P ∑_{i∈I} w_i × P_i);
    ∀i ∈ I : n_i = 0;
    Picked = newSet();
    i_s = i ∈ I s.t. C_i/P_i ≤ ExpectedReturnCostRatio and
    ∀i_2 ∈ I, C_{i_2}/P_{i_2} ≤ ExpectedReturnCostRatio ⇒ C_{i_2}/P_{i_2} < C_i/P_i;
    StartCost = C_{i_s}/P_{i_s};
    while ∑_{i∈I} n_i × P_i < R − WarehouseReturn do
        (s_u, i_u) = any s_u ∈ S, i_u ∈ I s.t. (s_u, i_u) ∉ Picked and C_{i_u}/P_{i_u} ≥ StartCost and
        ∀i_2 ∈ I, C_{i_2}/P_{i_2} ≥ StartCost ⇒ C_{i_2}/P_{i_2} ≥ C_{i_u}/P_{i_u};
        Add (s_u, i_u) to Picked;
        (s_d, i_d) = any s_d ∈ S, i_d ∈ I s.t. (s_d, i_d) ∉ Picked and C_{i_d}/P_{i_d} ≤ StartCost and
        ∀i_2 ∈ I, C_{i_2}/P_{i_2} ≤ StartCost ⇒ C_{i_2}/P_{i_2} ≤ C_{i_d}/P_{i_d};
        n_{i_u} = r_{s_u, i_u};
        Add (s_d, i_d) to Picked;
        n_{i_d} = r_{s_d, i_d};
    end
else
        I′ = {(s, i) for s ∈ S, i ∈ I s.t. n_i = 0} sorted by Q_{s,i} × P_i − C_i;
        I″ = {(s, i) for s ∈ S, i ∈ I s.t. D_i > 0} sorted by Q_{s,i} × P_i − L_i;
        WhFix = ∅;
    while ∑_{i∈I} n_i × (P_i − C_i) + E_v × f_v + w_i × (P_i − L_i) ≤ B and |I″| > 0 do
        (s, i) = pop top item in I″;
        w_i = 0;
        Q_{s,i} × C_i;
        (s′, i′) = pop minimum item in I″ s.t. Q_{s,i} × C_i ≤ Q_{s′i′} × C_{i′};
        w_{i′} = 1;
        Add i′ to WhFix;
        diff = Q_{s,i} × P_i − Q_{s′i′} × P_{i′};
        pick = 0;
        while pick < diff do
            (s″, i″) = pop minimum item from I′ s.t. Q_{s″i″} × P_{i″} ≥ diff;
            pick += Q_{s″i″} × P_{i″};
            n_i = Q_{s″i″};
        end
    If |I″| = 0 then
        w_i = 0 for all i ∈ I except in WhFix;
        while ∑_{i∈I} n_i × (S_i − C_i) + E_v × f_v + w_i × (P_i − L_i) ≤ B and |I′| > 0 do
            (s′, i′) = pop minimum item from I′;
            n_{i′} = Q_{s′,i′};
        end
        If |I′| = 0 then
            Return infeasible;
        end
    end
    Return current assignment;
end
```

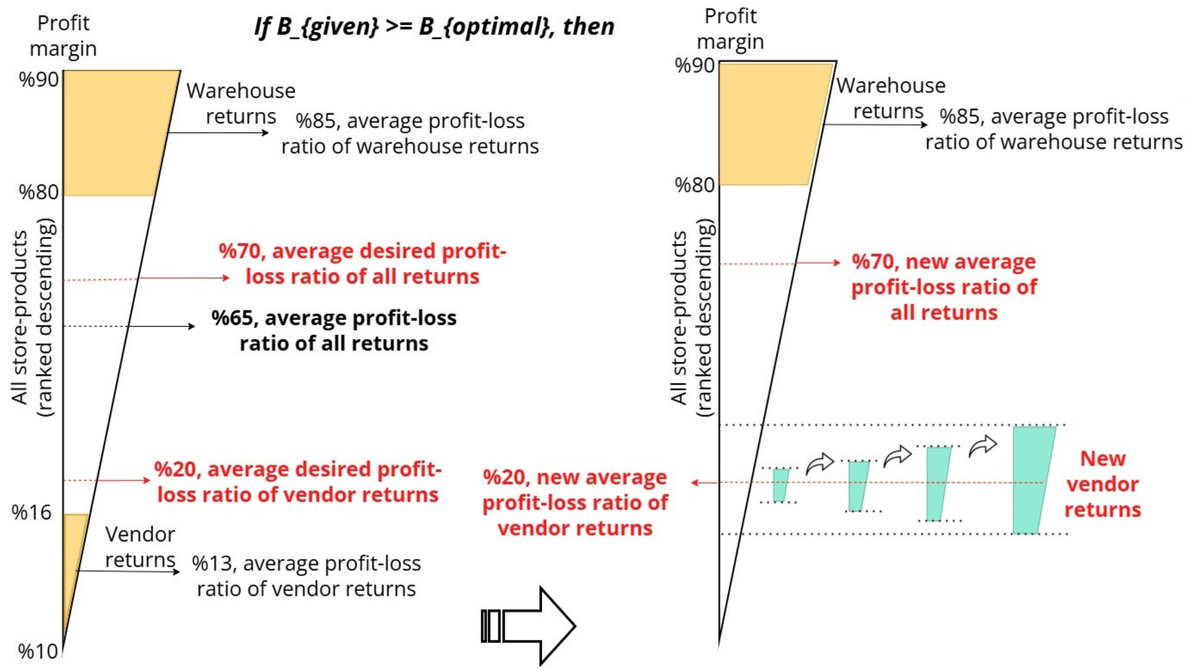

Figure 1. Heuristic algorithm, part 1

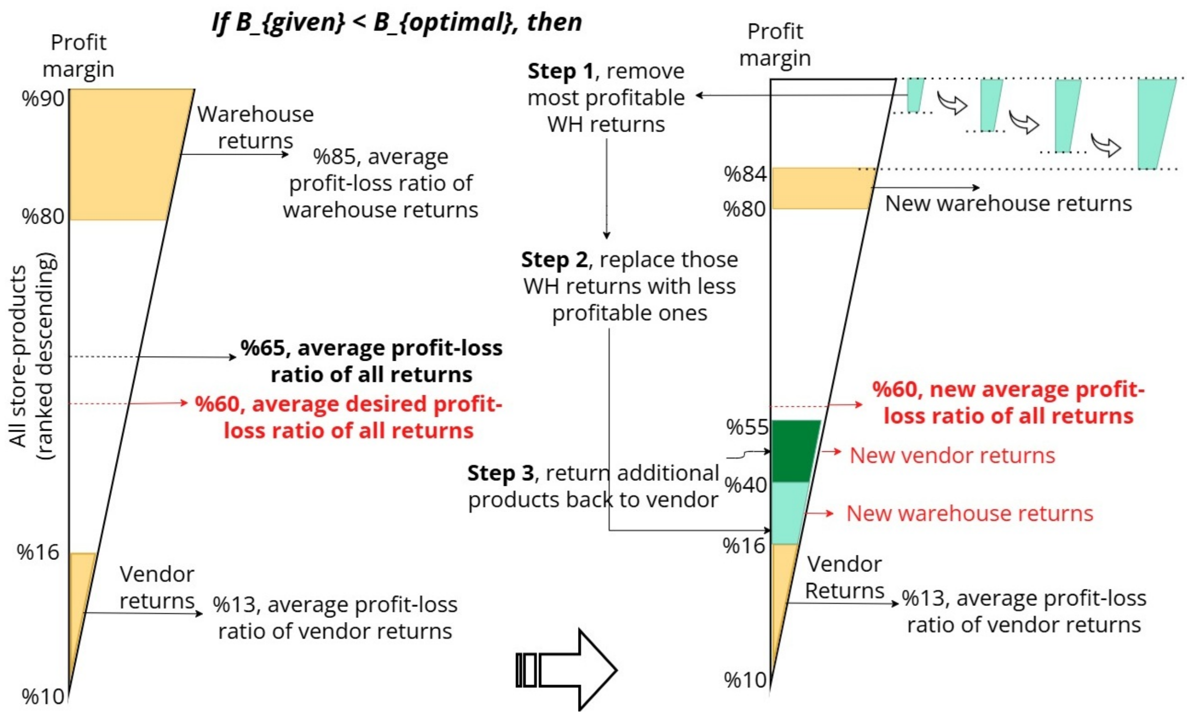

Figure 2. Heuristic algorithm, part 2

identify how much of the returns are vendor returns versus warehouse returns. ($WarehouseReturn = \sum_{i=1}^{I} w_i P_i$, $VendorReturn = \sum_{i=1}^{I} n_i P_i$), in this case, vendor return equals the remaining total inventory return.

(xiii) Calculate the profit–loss budget used by the vendor returns ($BudgetUsedByVendorReturn = \sum_{i=1}^{I} n_i(Pi - Ci) + \sum_{i=1}^{I} \sum_{v=1}^{V} n_i C_i E_v$), warehouse returns ($BudgetUsedByWarehouseReturn = \sum_{i=1}^{I} w_i(P_i. - L_i)$), and remaining budget ($RemainingBudgetNewVendorReturn = B - \sum_{i=1}^{I} w_i(P_i - L_i)$) that needs to be used by the new vendor return in order to use all the available budget.

(xiv) Calculate the "total cost of returning (profit margin loss from COGs + return penalty) to vendor ratio" for the vendor returns and then calculate the "expected total cost of returning to vendor ratio" ($DesiredProfitLossRatio = RemainingBudgetNewVendorReturn/ (\sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i}P_i\ Q_{s,i} - \sum_{i=1}^{I} w_iP_i)$), that should satisfy the remaining budget after we remove the profit–loss budget that is used by warehouse returns.

(xv) After determining the "expected total cost of returning to vendor ratio" or the remaining budget, rank remaining ineffective store products that could be returned to vendors by "cost of returning to vendor ratio" ($\frac{((P_i\ -\ C_i)+\ C_i\ E_v)}{\mathrm{Pi}}P_i$) in a descending order and identify a lower and upper bound (by iteration) of "cost of returning to vendor ratio," which will include a set of store products that will be returned to vendors and would satisfy both the remaining returns (*VendorReturn = RemainingTotalInventoryReturn*) and profit–loss budget (remaining budget new vendor return), if applicable. If not, choose the set store products from the top of this list, which could only satisfy the remaining return amount. In the case of picking the highest "cost of returning to vendor ratio," then store products that do not satisfy the profit–loss budget will occur, which means we cannot use the given budget, even if we choose the best possible store products to return to the warehouse and vendor. Even though this solution is not a feasible solution to the original problem, the solution is letting us know that the result is the best result that can use the maximum amount of profit–loss budget that is available within the given product parameters, and it is still an acceptable solution to the general problem since we are using the given budget as much as possible.

(xvi) When the model is over-budget, then it means that the minimized cost structure uses all of the available profit–loss budget, and products that need to be sent to the warehouse should have a lower profit margin (from the landed price) so that the model can use less of the available profit–loss budget by sending less profitable products to the warehouse. As a result, this would most likely end up in a lower value of warehouse return and higher value of vendor returns, in terms of store price/refund, since we are returning the same amount of value, in terms of COGs, with lower profit margins (from the landed price) to the warehouse because of the warehouse's capacity issue, in terms of COGs.

(xvii) Calculate the total amount of inventory ($TotalInventoryReturn = \sum_{s=1}^{S}\sum_{i=1}^{I} r_{s,i}P_i\ Q_{s,i}$) that needs to be pulled from store inventories and identify how much of it is a vendor return versus a warehouse return. ($WarehouseReturn = \sum_{i=1}^{I} w_iP_i$, $VendorReturn = \sum_{i=1}^{I} n_iP_i$).

(xviii) Calculate the profit–loss budget used by the vendor returns ($BudgetUsedByVendorReturn = \sum_{i=1}^{I} n_i(Pi - Ci) + \sum_{i=1}^{I}\sum_{v=1}^{V} n_iC_i\ E_v$) and warehouse return (*BudgetUsedByWarehouseReturn* $= \sum_{i=1}^{I} w_i(P_i - L_i)$).

(xix) Remove existing vendor returned store products from the list since they use the minimal profit–loss budget as possible.

(xx) Rank remaining store products by "cost of returning to vendor ratio" ($((P_i\ -\ C_i)\ +\ C_i\ E_v)\ /\ P_i$) in an ascending order, this is list 3.

(xxi) Create a separate list, list 4, of store products that are potentially warehouse returnable and rank these store products by "cost of returning to warehouse ratio" ($(P_i - L_i)\ /\ P\ _i$) in descending order. Choose a set of store products from the TOP of the list, which were potentially going back to the warehouse, and now some of them will stay in store inventories.

(xxii) Calculate the old warehouse return amount $\left(\sum_{i=1}^{I} w_i{}^{(original)}\ P_i\right)$ and the old warehouse return COGs amount $\left(\sum_{i=1}^{I} w_iC_i\right)$ of the chosen list, which may be returned to the warehouse.

(xxiii) Now, identify a set of store products (by iteration) from the BOTTOM of the list 4, that corresponds to the same total COGs value of the above list (which, in turn, should have a lower "total warehouse return amount" than the above "old warehouse return amount").

(xxiv) Assign the new set of store products to be returned to the warehouse and change the tag of "old warehouse returns" to "stay-in-store."

(xxv) Calculate the inventory amount of the new warehouse returns

$\left(\sum_{i=1}^{I} w_i{}^{(new)}\ P_i\right)$ and the 2nd vendor return $\left(\sum_{i=1}^{I} w_i{}^{(original)}\ P_i - \sum_{i=1}^{I} w_i{}^{(new)}\ P_i\right)$.

(xxvi) Choose a set of store products from the top of the ranked list 3 where the 2nd vendor return amount is satisfied.

(xxvii) Calculate profit–loss budget used by the new warehouse ($\sum_{i=1}^{I} w_i{}^{(new)}\ (P_i - L_i)$) and existing and new vendor returns $\left(\sum_{i=1}^{I} n_i{}^{(original)} (P_i - C_i) + \sum_{i=1}^{I}\sum_{v=1}^{V} n_i{}^{(original)} C_i\ E_v + \sum_{i=1}^{I} n_i{}^{(new)}\ (P_i - C_i) + \sum_{i=1}^{I}\sum_{v=1}^{V} n_i{}^{(new)} C_i\ E_v\right)$.

(xxviii) If the new profit–loss budget is less than the given profit–loss budget, then STOP; if it is greater than the given profit–loss budget, then return to Step 23.

10. Test problems, computations, and numerical analysis

10.1. Test cases and data generation

Our data generation was motivated by real industrial data. For each test problem, we consider 1,000 unique products, 500 unique stores, and 20 unique vendors in an RRSC network with only one warehouse. Each product is assigned to a random vendor. Each parameter of a product is generated with random data following a uniform distribution within specified bounds (lower and upper limits) consistent with the related parameters: COG, landed cost, and store purchase price. Warehouse demand for every unique product is also randomly generated with a uniform distribution. The overall warehouse and vendor parameters, such as capacity and available vendor funds, are chosen to limit returns of ineffective inventory and hence allow returns to both parties. A range of penalty fees/rates is generated for the 20 vendors, allowing and limiting returns to a specific vendor.

All the problems are generated with a relatively large size, 250 ineffective store products. In total, 20 problems are generated, 10 unique test problems are created with two distinct scenarios: one with a high profit–loss budget and one with a low profit–loss budget. As can be observed in **Table 1**, the odd-numbered test cases represent the high-profit–loss budget scenario, and the even-numbered test cases represent the low-profit–loss budget scenario.

Since these 250 store product combinations are randomly generated where each product is assigned to a random vendor and all the parameters of the products; COG, landed cost, store purchase price values are randomly generated between a certain range, every test case's ineffective store product, their quantity in each location, products' unrecoverable percentage, and profit margin differ from the other test cases and we have wide range of problems in terms of profitability, potential return amounts to the warehouse and vendors.

The RRSC budget optimization model is an MILP and is developed and coded with an exact solver software, CPLEX Optimization Studio (12.8, IBM ILOG, USA) on a PC with an Intel Core i7-8550U CPU @ 1.8 GHz, 4 Cores, 8 Logical Processors, and 20 GB of RAM.

As we can observe in **Table 1**, CPLEX can solve the test problems to optimality in a remarkably short time, even for large problem sizes such as 250 store product combinations that generate 750 decision variables and 2044 constraints. The total data intake process of CPLEX can range between 3–4 minutes; however, when the data intake process is done, CPLEX can solve the problems between 1–30 seconds, depending on the complexity of the data/problem, available total store removal amount, warehouse capacity, total available vendor funds, and most importantly, profit–loss budget given to problem.

10.2. Comparison of CPLEX and heuristic

In our test case problems, these large problems are generated and solved using both CPLEX and our heuristic algorithm. However, processing this large amount of data using the tools took most of the solution time for the given problems. As can be seen in **Table 1**, the CPLEX required almost 3–4 minutes to process the data, and the problem's solution times ranged from 1 to 30 seconds. Therefore, we do not worry about solution times or algorithmic comparisons, since data processing took most of the solution time for the given problems. Even though the solution times of our heuristic might be slightly longer than CPLEX in some scenarios, we can find solutions close to optimality in remarkably short time. Our heuristic can solve problems on average within 4–5 seconds for the same problem sizes. Basically, our heuristic can calculate 250 rows of data points with profit/cost parameters within seconds, then rank them by condition, and extract the best possible store products from the dataset. This way, a near-optimal solution can be generated in a remarkably short time for even exceptionally large problems, such as problems with several million store products.

Even though the need of using a heuristic to solve this problem might seem unreasonable because of the short solution times acquired by the state-of-the-art solver, the intention to develop a heuristic results from the curiosity of understanding the inner structure of optimal solutions so as to develop more sophisticated heuristics to solve not only this problem, but also more complex problems in RRSC or in related/other fields (such as forward supply chains, logistics, finance, and portfolio management) that have similar budgetary limitation issues. The cost of using state-of-the-art solvers to solve this problem is also extremely high, especially for smaller companies. This might also be one of the main reasons why we need to develop similar heuristics to solve such problems.

As shown in **Table 1**, when a given problem is solved without budgetary constraints, CPLEX can find an optimal solution in most cases in 1–2 seconds. However, when budgetary constraints are applied, the solution times increase with the complexity of budgetary boundaries. When the test problems are solved under budget constraints, the solution times do not increase significantly; however, when they are solved under budget constraints, the solution times may increase significantly. We have investigated the underlying reasons, and the details are included in **Section 11**. Our heuristic was developed based on this investigation and the insights gained.

11. Results and insights

When over-budget constraints are applied to a given problem, compared to the case of optimized inventory, where the best profitable store products are allocated to their new location, the profit–loss budget is underspent. To resolve this issue, the optimal solution should identify a solution where more profit–loss budget can be allocated while compromising inventory optimality. Since more budget is given to the problem than when the inventory is optimized, the solution needs to identify less profitable products and spend more of the allocated potential profit–loss budget. Since most profitable products are already relocated to other stores in the optimal inventory problem, similarly, most profitable products will also be relocated to other stores in the case of the over-budget constraint problem. However, more profitable products need to be returned to their vendors, which is inconsistent with the optimal inventory problem. We therefore developed the first part of our heuristic based on this fact and identified "good" solutions close to optimality under over-budgetary boundaries.

When under-budget constraints are applied to a given problem, the optimal solution needs to spend the budget wisely since the profit–loss budget is tighter than the optimal inventory solution. When the problem is solved without any budgetary constraints, the least profitable products are returned to their vendor (with the use of minimal penalties). This phenomenon aligns with optimally spending the potential profit–loss budget. Therefore, the optimal solution relies (mostly) on the efficient use of warehouse returns, as they use more of the available budget because they identify the most profitable products and relocate them. This causes most of the available budget to be spent, and therefore, an optimal solution needs to be identified in which less profitable products should be relocated to a warehouse, which is also inconsistent with the optimal inventory problem. In certain scenarios where budgetary constraints are tighter, tightening the margins of warehouse returns might not be sufficient, and an optimal solution might exist in which more vendor returns (with less profitable products) are needed. We have also observed this phenomenon in our test problems, where more products (with either lower profit margins than warehouse-returned products or higher profit margins than vendor-returned products) are returned to their vendor. Since the least profitable products are already returned to their vendors, the additional vendor-returned products are more profitable than products already returned to vendors but less profitable than warehouse-returned products. We therefore also developed the second part of our heuristic based on these facts and identified "good" solutions close to optimality for under-budgetary boundaries.

12. Limitations and future research

Although our study provides an initial modeling framework that introduces RRSC decision-making into the optimization literature, it is intentionally scoped to a specific, finance-driven operational problem: the selection and allocation of unsold store inventory under a must-be-utilized profit–loss budget. Accordingly, the objective is not formulated as a classical inventory-cost minimization or service-level optimization problem; rather, it prioritizes efficient budget utilization while managing the margin-reversal consequences of returns. This framing reflects a niche but practically important setting faced by large retailers for financial planning, accounting recognition, and tax adjustment/deduction purposes. At the same

Table 1. Comparative performance of CPLEX and heuristic methods for RRSC optimization under profit–loss budget constraints

Test case	Number of decision variables	Number of binary variables	Number of integer variables	Number of constraints	Solution methodology used	Optimality range (%)	Total time (data processing + solution) (minutes: seconds)	Solution time (seconds)	Total cost of reverse supply chain activity (USD)
Test 01	750	250	500	2044	CPLEX	0.06%	4:28	0.98	5,124,307
	750	250	500	2044	Heuristic	0.15%		4.24	5,128,942
Test 02	750	250	500	2044	CPLEX	0.00%	5:32	2.21	4,696,156
	750	250	500	2044	Heuristic	0.67%		5.22	4,727,950
Test 03	750	250	500	2044	CPLEX	0.01%	4:26	0.97	3,650,263
	750	250	500	2044	Heuristic	0.14%		4.42	3,655,202
Test 04	750	250	500	2044	CPLEX	0.19%	6:00	33.7	3,921,456
	750	250	500	2044	Heuristic	0.71%		5.55	3,941,892
Test 05	750	250	500	2044	CPLEX	0.03%	4:39	5.01	6,036,595
	750	250	500	2044	Heuristic	0.05%		5.39	6,037,702
Test 06	750	250	500	2044	CPLEX	0.20%	5:20	30.81	5,860,545
	750	250	500	2044	Heuristic	0.20%		6.48	5,860,036
Test 07	750	250	500	2044	CPLEX	0.00%	4:46	1.45	5,144,050
	750	250	500	2044	Heuristic	0.07%		2.72	5,147,445
Test 08	750	250	500	2044	CPLEX	0.32%	4:55	21.64	5,437,146
	750	250	500	2044	Heuristic	1.30%		2.72	5,492,711
Test 09	750	250	500	2044	CPLEX	0.01%	4:43	1.34	6,406,204
	750	250	500	2044	Heuristic	0.04%		4.03	6,407,868
Test 10	750	250	500	2044	CPLEX	0.21%	5:11	24.02	5,806,250
	750	250	500	2044	Heuristic	0.64%		4.99	5,831,153
Test 11	750	250	500	2044	Heuristic	0.13%	4:35	15.91	6,257,732
	750	250	500	2044	CPLEX	0.23%		6.81	6,264,013
Test 12	750	250	500	2044	Heuristic	0.65%	4:45	22.84	6,296,726
	750	250	500	2044	CPLEX	1.17%		7.85	6,329,751
Test 13	750	250	500	2044	Heuristic	0.00%	4:25	2.48	6,112,795
	750	250	500	2044	Heuristic	0.10%		4.82	6,118,763
Test 14	750	250	500	2044	CPLEX	0.54%	5:02	30.26	5,925,310
	750	250	500	2044	Heuristic	0.64%		5.72	5,931,081
Test 15	750	250	500	2044	CPLEX	0.03%	4:24	0.98	3,467,624
	750	250	500	2044	Heuristic	0.18%		1.67	3,472,921
Test 16	750	250	500	2044	Heuristic	0.01%	4:56	1.45	3,574,916
	750	250	500	2044	CPLEX	0.38%		1.67	3,588,396
Test 17	750	250	500	2044	Heuristic	0.01%	4:23	0.98	7,398,248
	750	250	500	2044	CPLEX	0.06%		4.15	7,402,199
Test 18	750	250	500	2044	Heuristic	0.47%	4:59	25.27	7,681,737
	750	250	500	2044	Heuristic	0.71%		5.71	7,700,564
Test 19	750	250	500	2044	CPLEX	0.01%	4:26	2.65	5,277,186
	750	250	500	2044	Heuristic	0.10%		4.38	5,281,754
Test 20	750	250	500	2044	CPLEX	0.01%	4:34	2.76	5,966,628
	750	250	500	2044	Heuristic	0.45%		5.02	5,993,424

time, the underlying decision logic—coordinating competing operational actions to meet a binding budget utilization target—suggests broader research opportunities if the model is extended to a more comprehensive inventory optimization context.

A primary limitation concerns the simplified RRSC network representation. The current model abstracts away from several structural features that commonly characterize real retail networks, such as multiple distribution centers, multiple warehouses, heterogeneity in store formats (e.g., flagship stores, small-box outlets, regional depots), and additional disposition channels, such as liquidators or secondary markets. Extending the network topology would enable the model to capture richer routing alternatives and to study the interaction between budget consumption and value recovery across multiple echelons. However, introducing such complexity would also require explicitly modeling additional operational cost drivers—transportation and consolidation costs, receiving and handling capacity, store rebates and internal transfer pricing, facility activation decisions, and potentially time-dependent constraints related to lead times and seasonal clearance cycles.

A second limitation is the treatment of contractual heterogeneity in the retail channel. Retailers often operate through mixed structures that include company-owned stores as well as dealers or franchisees, and return policies are rarely uniform across these entities. Contractual obligations may differ by partner in terms of return eligibility windows, cost-sharing rules, compensation mechanisms, and penalty structures. The present formulation does not incorporate such contract-level heterogeneity; a more general model could explicitly represent store-specific or partner-specific return constraints and incentives, thereby enabling a finer-grained analysis of how contractual design shapes the feasible set of RRSC actions and the efficiency with which the profit–loss budget can be consumed.

Beyond structural extensions, several methodological and behavioral dimensions remain open for future work. The current study can be extended to multi-period formulations in which profit–loss budget targets evolve over quarters and fiscal years, potentially with rollover rules, dynamic reforecasting, or penalties for systematic under- and over-consumption. Similarly, incorporating uncertainty—such as stochastic demand at destination stores, uncertain recovery rates, or variability in vendor acceptance—would enable the development of robust or stochastic optimization variants and better reflect operational risk in return decisions. Finally, richer calibration of vendor-specific terms (e.g., penalties, allowances, and negotiated thresholds) using empirical data could strengthen external validity and support data-driven parameter estimation or learning-based policy adaptation.

Importantly, while the profit–loss budget is motivated here by the retail context, analogous budget-consumption mechanisms exist in many organizational functions and industries, including manufacturing, information technology, human resources, marketing, and sales. Departments commonly face binding budgets that must be utilized near fully to avoid future reductions, while simultaneously managing competing objectives (e.g., hiring versus equipment procurement, training investments versus service quality, capital expenditures versus operational spending). We therefore view the trade-off formalized in this paper—between operational efficiency (here, inventory efficiency via RRSC actions) and mandatory budget utilization—as a transferable modeling concept. Future research could explore how similar multi-objective trade-offs can be systematically encoded and solved across different domains, and how policies should adapt under under-budget and over-budget regimes to achieve both fiscal compliance and operational effectiveness.

13. Conclusion

In this paper, we studied an RRSC setting for an independent retailer operating under a profit–loss budget limitation, where a predetermined profit–loss budget must be used through reverse logistics actions that operationalize margin reversals associated with unsold, and therefore returned, inventory. The RRSC considered in our study comprises multiple stores, a warehouse, and multiple vendors. Each store holds a portfolio of low-performing items that the retailer aims to remove from store inventories; operationally, the firm may (i) reallocate part of this inventory internally to demand locations within its network, or (ii) return part of it to vendors under contractual terms that may include penalties. The managerial requirement is to identify and extract an appropriate subset of this ineffective inventory while using the profit–loss budget to support fiscal planning and align margin-reversal recognition with taxation obligations.

We formulated the problem as an MILP in which the objective captures profit-related losses and contractual charges induced by alternative return routes, while explicitly imposing a budget-consumption requirement. A central implication of this structure is that the retailer's decision problem is governed by a fundamental trade-off between competing objectives: the model must balance the marginal impact of product returns on margin losses (which may differ depending on whether products are reallocated internally or returned to vendors) against the necessity of achieving near-complete utilization of the profit–loss budget. In this sense, the problem is not a standard "minimize inventory cost subject to a budget cap" formulation; rather, it is a budget-consumption problem in which the key tactical question is how the budget should be allocated to improve inventory efficiency while limiting avoidable margin erosion and penalized vendor returns.

To support practical implementation, we developed a heuristic algorithm and benchmarked its performance against a state-of-the-art commercial solver (CPLEX). Beyond numerical performance, we articulated the decision logic embedded in the heuristic and linked it to the economics of RRSC operations under a must-be-utilized budget. The rationale for proposing a heuristic is twofold. First, reliance on commercial optimization platforms can be prohibitively expensive or operationally impractical for numerous organizations; thus, a structured heuristic provides a viable alternative for deploying decision support without heavy solver dependencies. Second, and more importantly, the decision structure studied here—namely, a must-be-utilized budget competing with multiple operational objectives—is not unique to retail returns. Similar budget-consumption mechanisms routinely arise across organizational functions, such as procurement, marketing, finance, and operations, where managers must allocate a fixed budget close to 100% to avoid future budget reductions, while simultaneously trading off multiple objectives (e.g., hiring versus equipment acquisition, opening new locations versus investing in inventory, staff training versus service quality outcomes).

Accordingly, our modeling and heuristic framework provides an initial, generalizable basis for structuring and solving decision problems in which several competing objectives must be coordinated under a binding budget-consumption constraint. In particular, it provides guidance on how to reason about both under-budget and over-budget regimes—i.e., when feasible actions are insufficient to consume the budget without excessive loss, or when budget utilization pressures risk driving inefficient actions—and how to reconfigure decision rules to achieve fiscally consistent outcomes. These insights constitute a first step toward a broader class of operational decision models in which budget utilization is not incidental, but rather an explicit constraint shaping tactical choices and performance.

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Conflict of interest

The authors declare they have no competing interests.

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Availability of data

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

AI tools statement

All authors confirm that no AI tools were used in the preparation of this manuscript.

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