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Location-Routing Optimization for Pickup Operation in Reverse Logistics Systems †

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Abstract: This paper presents a Location-Routing Problem (LRP) model for optimizing pickup operations in reverse logistics while incorporating drivers' well-being constraints. The LRP is formulated as a Mixed-Integer Linear Programming (MILP) model, integrating collection center selection and vehicle routing to minimize total costs, including facility operation, vehicle fixed costs, travel expenses, and driver salary rates. A key contribution of this study is the inclusion of maximum driving time and mandatory break constraints to enhance drivers' well-being, ensuring compliance with regulations and mitigating fatigue-related risks. We solve the problem using the MILP model in Gurobi and validate it with data from the literature. We test multiple instances to check the model's performance and solution quality. The results show that the model effectively optimizes collection point allocation and routing while considering cost efficiency and drivers' well-being. The inclusion of breaks leads to a trade-off between cost minimization and operational sustainability, highlighting the importance of incorporating social factors in logistics planning.

Keywords: location-routing problem; pickup; reverse logistics; drivers' well-being; Gurobi

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1. Introduction

Circular economic trends are transforming resource management with a growing focus on sustainability. Reverse logistics is a key element of the circular economy, through which it facilitates backflow, recovery, and reuse of the product and material. Through the formation of closed-loop supply chains, the strategy reduces wastage, extends product life, and optimizes resource use. Reverse logistics can be utilized in the circular economy to manage products at the end of life, recover resources, and sustain development. LRP is one of the most prominent features of these models, which combines the facility location problem and the vehicle routing problem into a unified model. The problem aims to determine how to allocate collection points to the selected collection center and optimize the distance between the established collection center and assigned collection points [1]. Over sixty years ago, it was thought of as uniting these two types of optimization problems, but computers were incapable of dealing with complex mathematical models [2]. In the late 1980s, ref. [3] first quantitatively solved the facility siting problem and route optimization. Their work confirms that separating the vehicle routing problem from the location problem of the depots (collection centers) has the tendency to give suboptimal solutions. The optimization goals of LRPs are centered on three primary aspects. First, they

aim to minimize the overall cost of facility setup by selecting the optimal facilities to open among a set of candidate locations. Second, they determine the assignment of customers (collection points) to these available facilities to manage the effective distribution of service. Third, they are interested in reducing vehicle travel expenses as they serve customers, driving optimally to keep transport low. Combining these objectives guides effective facility location and vehicle route planning in the network [4]. The three sub-objectives interplay and constrain one other; therefore, the problem needs to be viewed and tackled from a logistics network perspective [1]. LRPs are variants depending on their assumptions and constraints. Capacitated LRP (CLRP), for instance, takes collection centers and vehicles to be adequately fitted [5]. LRP and CLRP, however, do not consider the reverse movement of the supply chain, i.e., reverse logistics, which is an opportunity to earn profit a second time [6]. The CLRP considers the choice of the collection center and the routing of vehicles within logistics. There are numerous applications of the LRP, including food and beverage delivery, newspaper delivery, trash collection, bill deposit, military logistics, used oil disposal, disaster relief planning, battery exchange centers, package delivery, consumer product distribution, and emergency supplies. It is a highly versatile tool that can be used to improve supply chain optimization in numerous industries due to its adaptability [7–9]. Pickup points in LRP are only viewed to have delivery requirements, not considering the role of reverse logistics, where returned products create pickup requirements. In most cases, there is a need for companies to pick up returns, defective goods, or recyclables, and this creates pickup requirements within the system. Our research directly deals with this problem by focusing on pickup requirements in the context of a reverse logistics system.

The goal of LRP is to minimize overall costs, including facility operating costs, fixed costs of vehicles, travel costs, and labor costs. Our model addresses drivers' well-being factors by considering maximum driving time limits, compliance with regulations, and driver fatigue prevention. Contrary to traditional LRP models that place more importance on cost and efficiency, our approach integrates drivers' well-being as a fundamental component, promoting sustainable and moral transportation planning for reverse logistics. This study offers computational output from Gurobi through a number of test instances in measuring the performance and efficiency of the model towards solving the optimization problem.

2. Literature Review

2.1. Foundational Concepts in Location and Routing Problems

The problem of logistics location is normally the location of logistics facilities and is otherwise referred to as the Location Allocation Problem (LAP) [10]. In 1909, an American logistics expert studied how warehouse location affects delivery distances and logistics costs. This made many researchers focus interest on logistics center locations [10]. Therefore, the first single-center location problem, known as the Single Weber Problem, attempted to find a location that has the shortest total distance to multiple collection sites. If more than one location must be determined, the problem is known as a Multi-Weber Problem or alternatively known as the P-Median Problem [10]. The Vehicle Routing Problem (VRP), first proposed by Dantzig and Ramser, is the problem of finding the best routes for driving [11]. In a logistics firm, variables like receiving locations, delivery locations, vehicle numbers, capacity limits, and average daily volume of distribution are usually constant or altered slowly based on a scheduled plan. The Location-Routing Problem (LRP) has been highly researched, particularly during the last few decades. Maranzana, Ref. [2] the founder of LRP Research, was the first to study supply point locations and their total distance to service points at the same time.

2.2. Social Sustainability and Drivers' Well-Being in Logistics

Social supply chain sustainability means optimizing the social impact of logistics activities on stakeholders (e.g., employees and communities) relative to economic and environmental interests. True sustainability means concern for drivers' well-being [12]. Recent research indicates that social sustainability in supply chain management has not been prioritized as much as environmental sustainability [13,14]. Social sustainability is needed for the fulfillment of stakeholder expectations and increasing economic development objectives [15]. Social sustainability of supply chain management encompasses the socio-economic dimensions—such as equitable pay, rights for the working community, access to education, workplace safety, health and sanitary conditions, and good housing—of all the concerned individuals in the supply chain [16]. Drivers' well-being and human factors are major components in logistics activities that affect safety, service quality, and the retention of employees. Sodhi and Tang [17] identify eight social sustainability themes and propose a "4P" model linking external pressures and partnerships with practice, such as supplier development, that translates into measurable performance gains. Hutchins and Sutherland pioneered social sustainability metrics for supply chains, such as worker safety and community impacts, and demonstrated their decision-making value, closing a gap following environmental metrics. Zorzini et al. [18] present a comprehensive review of 157 socially responsible sourcing reviews, categorizing the social problems addressed (e.g., human rights and working conditions) and the theoretical frameworks applied. They cite that most of the previous research has addressed upstream supplier-related issues—more specific labor conditions in developing nations—and call for more examination of social sustainability at various stages of the supply chain.

While drivers' responsibilities are paramount to safety, service quality, and driver retention, location-routing studies—especially reverse logistics—have focused little attention on their well-being. Important human-factor indicators (e.g., drivers' fatigue, hours-of-service adherence, job satisfaction, safety record, and work–life balance) are most often excluded because models have traditionally prioritized cost and efficiency above drivers' well-being.

2.3. The Research Most Directly Relevant to This Study

Several recent papers have proposed reverse logistics network optimization models, predominantly focusing on economic and environmental aspects. For instance, recent reverse logistics models, such as the bi-objective MILP and MOGA method in [19] for infectious medical waste, highlight cost minimization and exposure risk minimization through integrated location and routing. However, they fall short of presenting fully feasible, sustainable solutions by omitting social sustainability considerations (e.g., workers' health, community health, and equity in service access). Another study by [20] combines an SEIR-based demand forecasting model with a multi-objective location-routing model and a self-adaptive modified NSGA-II algorithm to minimize costs and logistics risks in reverse logistics for medical waste disposal under uncertainty. Furthermore, a study by [21] proposes a bi-objective MILP model to coordinate medical waste management, which reduces costs and operational risk by the use of location-routing, queuing theory, and scenario-based modeling. While the model is well-organized, the reliance on AUGMECON2 restricts scalability, and the model ignores social drivers of sustainability like worker welfare and community health. The study by [22] proposes a multi-cycle, multi-echelon reverse logistics location-routing problem to minimize cost and social harm with panel-data-based social impact estimations and a PSO-MOIGA algorithm, but its panel data dependency may reduce accuracy in dynamic settings, and its scalability has not been tested.

Few studies have so far tackled the social aspect of the LRP, such as drivers' well-being, in reverse logistics. This study fills this research gap by adding a Maximum Driving Time Constraint and a Break Constraint to enhance drivers' well-being by designing routes in such a manner that they do not lead to excessive working hours and have adequate rest periods. By performing this, this approach attempts to strike a balance between operational efficiency and social sustainability, making reverse logistics more realistic and worker-friendly.

3. Problem Definition

The Location-Routing Problem (LRP) involves optimizing reverse logistics operations by determining where to locate a collection center, assigning the collection points (customers) to collection centers, and developing ideal vehicle routes for making pickups. The goal of LRP with Max Driving Time is to find the minimum total cost of the distribution system, including truck travel cost, opening cost of collection centers, fixed cost of trucks, and salary rates, subject to meeting each collection point's demand and truck capacity requirement. A set of potential collection centers with predetermined coordinates is provided, and each of them has an opening cost. A homogeneous fleet of identical-capacity trucks is used to best serve collection points. There are also other constraints that have to be satisfied by an LRP solution. A truck's capacity must not be utilized more than its capacity. Each collection point must be visited once by one truck, and their demand must be fully satisfied. The sum demand allocated to a collection center is constrained by the maximum capacity of the collection center. In addition, each truck route starts and terminates at a collection center and covers the allocated collection points along the way. Moreover, to ensure drivers' welfare, the model involves maximum driving time and obligatory rest periods for compliance with regulatory regulations and sound fleet management.

Model Formulation

Sets

$N = CC \cup CP$: Set of all nodes, where
CC: Set of collection centers.
CP: Set of collection points.
$E = \{(i, j): i, j \in N, i \neq j\}$: Set of edges (possible travel paths).
T: Set of available trucks.

Parameters

d_{ijt}: Travel cost (distance) between nodes i and j for truck t.
v_{ijt}: Speed of truck t between nodes i and j.
$C_k{}^c$: Capacity of collection center k.
$F_k{}^c$: Fixed cost of opening collection center k.
$F_t{}^V$: Fixed truck operating cost for truck t.
C_t: Truck capacity for truck t.
P_i: Pickup demand of collection point i.
WT_{max}: Maximum allowed driving time per truck.
CDT_{max}: Maximum continuous driving time before a mandatory break
BD: Break Duration (time required for one break, in hours).
SR_t: Driver salary rate for truck t.

Decision Variables

$x_{ijt} \in \{0,1\}$: 1 if truck t travels from node i to node j, 0 otherwise.
$y_k \in \{0,1\}$: 1 if collection center k is opened, 0 otherwise.
$z_{ik} \in \{0,1\}$: 1 if collection point i is assigned to collection center k, 0 otherwise.

$L_{ijt} \geq 0$: Transported Load in arc (i, j) by truck t.
$NB_t \in Z_+$ Numbers of breaks for truck t.

$$\min \sum_{t \in T} \sum_{i \in N} \sum_{j \in N} d_{ijt} * x_{ijt} + \sum_{k \in C_C} F_k^C * y_k + \sum_{t \in T} \sum_{k \in C_C} \sum_{i \in C_P} F_t^V * x_{ikt} + \sum_{t \in T} \left(\sum_{i,j \in E} \frac{d_{ijt}}{v_{ijt}} \cdot x_{\{ijt\}} + NB_t \cdot BD \right) \cdot SR_t \quad (1)$$

Subject to

$$\sum_{t \in T} \sum_{j \in N} x_{ijt} = 1, \ \forall i \in CP \quad (2)$$

$$\sum_{t \in T} \sum_{j \in N} x_{ji_t} = \sum_{t \in T} \sum_{j \in N} x_{ij_t}, \ \forall i \in N \quad (3)$$

$$\sum_{t \in T} \sum_{j \in N} L_{ij_t} - \sum_{t \in T} \sum_{j \in N} L_{ji_t} = p_i, \ \forall i \in CP \quad (4)$$

$$L_{ij_t} \leq C_t * x_{ij_t}, \ \forall i, j \in N, i \neq j, \forall t \in T \quad (5)$$

$$\sum_{t \in T} \sum_{j \in CP} L_{jk_t} = \sum_{j \in C_P} z_{jk} * p_j, \forall k \in CC \quad (6)$$

$$\sum_{t \in T} \sum_{j \in CP} L_{kj_t} = 0, \ \forall k \in CC \quad (7)$$

$$\sum_{k \in CC} z_{ik} = 1, \ \forall i \in CP \quad (8)$$

$$\sum_{i \in C_P} p_i z_{ik} \leq C_k^C y_k, \ \forall k \in CC \quad (9)$$

$$x_{ik_t} \leq z_{ik}, \ \forall i \in CP, \forall k \in CC, \forall t \in T \quad (10)$$

$$x_{ki_t} \leq z_{ik}, \ \forall i \in CP, \forall k \in CC, \forall t \in T \quad (11)$$

$$x_{ij_t} + z_{ik} + \sum_{m \in CC, m \neq k} z_{jm} \leq 2, \ \forall i, j \in CP \, i \neq j, \forall k \in CC, \forall t \in T \quad (12)$$

$$\sum_{i,j \in N} \frac{d_{ij_t}}{V_{ij_t}} * x_{ij_t} + NB_t * BD \leq WT_{max}, \ \forall t \in T \quad (13)$$

$$\sum_{i,j \in N} \frac{d_{ijt}}{v_{ijt}} * x_{ijt} \leq CDT_{max} * (NB_t + 1), \ \forall t \in T \quad (14)$$

$$\sum_{i \in CC} \sum_{j \in CP} x_{ijt} \leq 1, \forall t \in T \quad (15)$$

The objective function (1) minimizes the total cost by optimizing travel expenses, collection center opening costs, vehicle usage costs, and salary costs. Constraint (2) guarantees that each collection point must be visited exactly once. Constraint (3) ensures that the number of entering and leaving arcs at each node is equal. Constraint (4) ensures that the pickup demand at each collection point node is met by the vehicles, balancing the flow of the pickup demand into and out of the node. This constraint eliminates subtours. Constraint (5) ensures that the total load on any arc does not exceed the vehicle's capacity. Constraint (6) ensures that the total pickup demand assigned to a collection center is fulfilled by the vehicles coming from that collection center. Constraint (7) ensures that collection centers do not store any pickup demand. Constraint (8) ensures that each collection point is assigned to exactly one collection center for servicing. Constraint (9) ensures that the total pickup demand assigned to a collection center does not exceed the collection center's capacity. Constraints (10)–(11) ensure that vehicles only travel to and from collection points assigned

to the collection center they are servicing. Constraint (12) ensures that a vehicle's route is consistent with its collection center assignment and does not conflict with other vehicles or collection points. Constraint (13) ensures that the total working time for each truck, t, does not exceed the maximum allowed working time. Constraint (14) ensures that a truck t cannot continuously drive for more than the allowed continuous driving time, $CDT_{max,}$ without taking a break. Constraint (15) ensures that each truck can depart from at most one collection center.

4. Numerical Experiment

The optimization problem was solved using Gurobi Optimizer 12.0.0 on a computer with Intel Xeon CPU @ 2.20 GHz, employing one physical core and two AVX, AVX2-supported logical processors for efficient computations.

4.1. Test Instances

The Location-Routing Problem (LRP) model was tested against different test instances with 21–40 collection points, five collection centers, and 18 trucks, differentiated based on different demand levels (40–4000 units) and truck capacities (250–11,000 units). Computational tests were executed on four CLRP instances available in the literature [23].

Key instance characteristics:

- Collection center capacities: 15,000 to 35,000 units.
- Distance metric: Euclidean distances, ranging from compact clusters to widely dispersed urban and semi-urban networks.
- Instance categorization:
- Small-scale (21–30 points): Feasibility and efficiency testing.
- Medium-scale (31–40 points): Scalability and computational stress testing.

Operational constraints:

- Truck speed: 40 distance units per time unit.
- Max working time per truck: 8 h (including driving and breaks).
- Max continuous driving time: 2 h before a mandatory 30 min break.
- The salary rate (SR) for drivers is set at 10 per unit time for all trucks.

The model was evaluated for optimality of solutions, computational efficiency, route quality, and sensitivity to reverse logistics constraints (pickup demands, collection center selection, and routing).

4.2. Results

We validated our LRP model using benchmark instances (21–36 collection points, five centers), demonstrating its ability to replicate known optimal solutions in terms of optimality and computational efficiency (Table 1).

Table 1. Comparison of our model with benchmark solutions.

Instance	Best Known Results	Our Solution (Without Well-Being Constraints)	CPU Running Time (min)
Gaskell67-21x5.	424.9	424.9	30
Gaskell67-36x5	460.4	460.4	40
Gaskell67-32x5	504.3	504.3	35
Gaskell67-29x5	512.1	512.1	30

The results indicate that our model efficiently captures the most popular solutions in the literature on all test cases, being both precise and consistent in solving the LRP without imposing additional well-being constraints. The CPU running time remains within a reasonable range (30–40 min), justifying the computational efficiency of the model. These are the baseline results prior to introducing drivers' well-being constraints such as mandatory breaks and working time restrictions. Through the comparison of outcomes before and after integrating these constraints, we aim to establish their impact on solution feasibility, cost, and routing optimality in order to possess a realistic and well-balanced reverse logistics operation.

Figure 1 illustrates the Location-Routing Optimization with pickup operations, with trucks (Truck 0, Truck 1, Truck 2, and Truck 3) routed to pick up merchandise from designated collection points (black circles) and drop it off at open collection centers (orange squares). The routes, represented by differently colored dashed lines, indicate how the optimization model saves costs on travel while being efficient in pickup operations under given constraints.

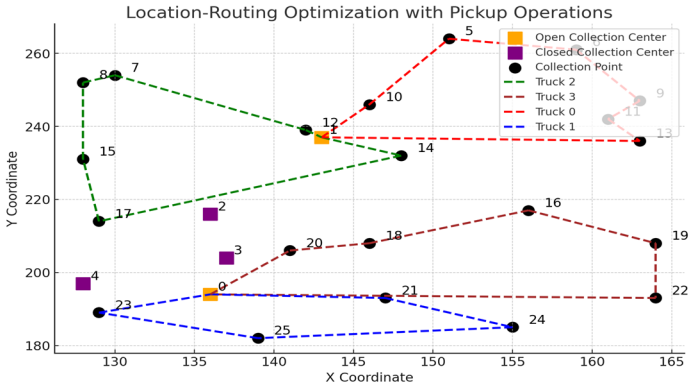


Figure 1. Optimized Location-Routing for pickup operations in reverse logistics (Gaskell 67-21x5).

The research presents the efficient integration of drivers' well-being constraints into the LRP to ensure effective operations (Table 2). The integration of mandatory breaks and regulated working hours ensures enhanced scheduling, better driver conditions, and green logistics practices. Although the total cost is greater than that of the solution ignoring drivers' well-being constraints, this is offsetting the practical benefit of disciplined break times in terms of safer and more stable transport operations. For the big Gaskell 67-36x5 instance, we increased the solver time limit to 3 h and achieved a solution with an 8% optimality gap—the best attainable within time limits. Combining these constraints with well-being raises overall costs through scheduling inflexibility due to mandatory breaks but is an investment in safety and robustness. The payoffs include fewer fatigue-related risks and accidents, aligning with sustainable logistics and long-term performance [24]. The following regulations add expenses but improve safety by reducing driver fatigue and crashes. These also result in lower insurance rates and less downtime over the long run. The model quantifies trade-offs between cost savings and social gains. While traditional models aim only to reduce expenses, including the health of drivers ensures that a modest cost premium can play an important role in driver satisfaction and network durability. For example, unlike the study by [25], which is solely focused on regulatory compliance by using a large neighborhood search to create legally viable vehicle tours without regard to broader trade-offs or social impacts, our LRP model situates these regulations in a MILP framework. In comparison to several real-world cases, we quantify not only cost and efficiency impacts but also the social benefits of improved driver welfare, demonstrating scalability, robustness, and the practical value of including human centricity in reverse

logistics network design. The model currently incorporates fixed break durations. With variable break durations, it would introduce further flexibility in scheduling. For example, shorter breaks may be utilized on shorter trips to save time, and extended breaks may be scheduled when fatigue would be a greater concern. This flexibility might lead to more efficient routing as well as better cost and driver safety trade-offs.

Table 2. Impact of drivers' well-being constraints on LRP solution metrics.

Instance	Num. Trucks	Num. Breaks	Working Time	Cost
Gaskell67-21x5.	4	3	8	521.12
Gaskell67-36x5	6	4	8	600.47
Gaskell67-32x5	4	4	8	637.91
Gaskell67-29x5	4	4	8	635.12

5. Conclusions

This study formulates the reverse logistics Location-Routing Problem by integrating collection center selection, vehicle routing, and drivers' well-being. The model aims to minimize overall costs with costs like facility, vehicle, travel, and salary costs in solving efficient logistics planning so as to meet driving time as well as break regulations.

Our validation proves that the inclusion of break constraints is costly but necessary for an ecologically sound, driver-friendly logistics system. It prevents fatigue at the expense of low cost and shows the trade-off between cost minimization and compliance with regulations, demanding social sustainability in reverse logistics.

By integrating real-world constraints like the work regulations of drivers, the model promotes Location-Routing Optimization for environmentally friendly logistics. While Gurobi found it hard to handle larger instances, the balance between cost efficiency and social sustainability that the model brings is especially advantageous to industries involved with product returns and recyclable collections.

In the future, the more significant problem instances may be approached using meta-heuristics, and environmental issues such as CO_2 emission reduction.

Overall, this study contributes to the enhancement of reverse logistics optimization by providing a cost-effective, operationally feasible, and socially responsible solution to pick up operation location-routing decision-making.

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