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A Mixed-Integer Linear Programming Model for the Pickup Problem with a Heterogeneous Fleet

The Hoan Phung[1,2], Thi Diem Chau Le[1,2*]

[1]Department of Logistics and Supply Chain Management, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, Dien Hong Ward, Ho Chi Minh City, Vietnam
[2]Vietnam National University Ho Chi Minh City, Linh Xuan Ward, Ho Chi Minh City, Vietnam

Abstract

Modern logistics networks typically include pickup points for handling shipments before they are transferred. In networks with multiple hubs, it is necessary to strategically distribute pickup points to these hubs to optimize distance, cost, and other factors while ensuring the hubs' capacity constraints. This is an important decision that needs to be optimized. Additionally, the increasing use of a heterogeneous fleet makes vehicle selection also a significant decision in the pickup problem. This study proposes a Mixed-Integer Linear Programming model for both of these decisions. The model allocates pickup points to the hubs while considering hub capacity constraints. Then, it selects the type and number of vehicles needed to collect shipments at the pickup points and transport them to the hub. The main objective is to minimize total costs; the constraints that need to be met are the capacity constraints of the hubs and the vehicle capacity constraints. The model is solved using an exact method. The model has been tested using different scenarios and a large-scale real dataset comprising 3 hubs, 127 pickup points, and 52 vehicle types in a heterogeneous fleet from an express company in Ho Chi Minh City, Vietnam. The model provides optimal solutions for the tested instances and achieves a fleet utilization of over 80% for the real-world data. Scenario analysis shows how the model responds to changes in demand, fleet composition, and hub capacity. The model's solution time is also quite short, at 46.52 seconds, making it suitable for daily planning.

Keywords: Logistics optimization, pickup point – hub assignment, heterogeneous fleet, mixed-integer linear programming

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1. Introduction

The increasing demand for transportation today has led to increasingly complex distribution networks for shipping companies. From direct networks from manufacturers or warehouses to customers, intermediate points known as hubs have gradually emerged. Then, between hubs and warehouses, or between hubs and customers, further, smaller intermediate points appear to handle shipments. This creates numerous problems that need to be addressed, requiring transportation companies to develop optimal solutions to operate their networks effectively and compete with other businesses. To facilitate shipment transportation, modern shipping companies often establish pickup points within their hub-based operational networks. These points receive shipments from customers, process them beforehand, and then transport them to hubs for sorting and distribution to other areas. These points can also serve as delivery points, receiving shipments from hubs and delivering them to customers. These routes are called feeder routes, and their purpose is to reduce the need for vehicles to travel long distances and to avoid overloading hubs with excessive workloads. Therefore, the problem of allocating and

*Corresponding author. Email: lechau@hcmut.edu.vn

assigning points to specific hubs for shipment delivery is studied, known as the pickup problem. Furthermore, due to the quantity and diversity of shipments, companies use various types of vehicles to suit their transportation needs. This fleet is called a heterogeneous fleet, with vehicles having different capacities and costs. Suboptimal vehicle selection will lead to waste. Small vehicles increase the number of trips and fixed costs. Large vehicles waste cargo space. The problem of deciding which type of vehicle to use within this heterogeneous fleet is also a crucial problem in the field of logistics operations optimization.

Previous studies have mainly focused on vehicle routing, fleet selection, or assignment decisions separately. Few studies jointly consider pickup point assignment and heterogeneous fleet selection with hub capacity constraints. Therefore, this study proposes a Mixed-Integer Linear Programming (MILP) model that combines these decisions. The model assigns pickup points to hubs and determines the type and number of vehicles required for collection. The objective is to minimize total operating costs while satisfying hub and vehicle capacity constraints. The model is tested using different instances, operational scenarios, and real-world data from a courier company.

The subsequent sections of the study will include: Section 2 presents a summary of related work in the same field from recent years. The model for the problem will be presented in Section 3, and Section 4 presents the computational test results of this model using real-world data and various scenarios. Section 5 is the final section, providing conclusions on the study and recommendations for future development.

2. Related Works

Studies on heterogeneous fleets have been extensively investigated in recent years, particularly in research on the Vehicle Routing Problem (VRP). For example, the study by Han and Yaman [1] on routing problems for mixed fleets that have time constraints. Their study developed an MILP model and used the Branch-and-Cut method. This study only considers the fleet and time constraints, without addressing multi-depot networks with intermediate points. Similarly, the study by Liu et al. [2] used a fleet of different electric vehicles, each with several compartments to solve the problem of collecting sorted waste. The study created a Mixed-Integer Programming (MIP) model and combined the Ant Colony Optimization (ACO) and Variable Neighbourhood Search (VNS) algorithms to solve, and the results showed the advantages of using vehicles with multiple compartments. However, this problem is a collection problem and does not involve a hub-and-spoke structure.

Table 1. Summary of related works

Study	Problem	Problem Features			Model	Method
		Hub/ Depot	Heterogeneous Fleet	Assignment Decisions		
Han and Yaman (2024) [1]	VRP, Last-mile delivery		✓		MILP	Branch-and-cut
Liu et al. (2023) [2]	Electric-VRP		✓		MIP	ACO + VNS
Mishra and Mitra (2024) [3]	Fleet optimization		✓		MINLP	CPLEX + GA
Arsyilviasari and Husein (2025) [4]	VRP	✓	✓		MILP	Exact solver
Alsaadi et al. (2025) [5]	Fleet scheduling		✓		MILP	Exact solver
Sawik (2024) [6]	Last-mile logistics	✓		✓	Multi-objective MILP	Exact solver
Mo et al. (2024) [7]	VRP	✓	✓	✓	Bi-level programming	BL-PSO-ALNS
This study (2026)	Pickup, Fleet optimization	✓	✓	✓	MILP	Exact solver

The study by Mishra and Mitra [3] addresses the heterogeneous truck fleet optimization problem using a Mixed-Integer Non-Linear Programming (MINLP) model. The study compares the exact solver CPLEX and the Genetic Algorithm (GA) to evaluate solution quality. This is a vehicle-route assignment problem that does not incorporate depot allocation decisions. Arsyilviasari and Husein [4] apply an MILP model to solve the Capacitated VRP for a small business. The results show that MILP can be effectively applied to real-world data. However, the study considers only one depot and does not include decisions regarding collection point assignment. A study on the heterogeneous fleet scheduling problem in a multimodal transportation network by Alsaadi et al. [5] developed an MILP model. Experimental results show that the model reduces costs by 23% and improves fleet performance by 25% compared to the baseline. However, this problem focuses on trip scheduling and does not include decisions regarding the assignment of collection points.

Sawik [6] proposed a multi-criteria optimization model for last-mile delivery using smart lockers, which includes the decision of assigning customers to lockers. The model minimizes both the assignment cost and the transportation cost. However, the study did not consider a heterogeneous vehicle fleet and did not include hub capacity constraints. A study by Mo et al. [7] developed a bi-level programming model for a multi-stage VRP problem with a heterogeneous fleet and pickup point selection in last-mile delivery. The study proposes the Bi-Level Particle Swarm-Adaptive Large Neighbourhood Search (BL-PSO-ALNS) algorithm to solve the problem and applies it in both urban and rural contexts. This study fully integrates both pickup point selection and routing. However, this model does not address the problem of assigning pickup points to fixed hubs on a one-to-one basis.

Existing studies have extensively addressed heterogeneous-fleet routing, fleet optimization, and assignment decisions; however, the simultaneous integration of pickup-point-to-hub assignment, heterogeneous fleet selection, and explicit hub-capacity constraints remains comparatively underexplored. This study addresses this gap through an MILP formulation that jointly determines pickup-point assignments and the type and number of vehicles required for collection while explicitly enforcing hub and vehicle capacity constraints. Unlike detailed routing models, the proposed formulation focuses on tactical/operational assignment and fleet-selection decisions, enabling exact solution within computation times suitable for daily planning in the tested instances.

3. Mathematical Formulation

3.1. Problem Statements

Large urban transportation companies typically have pickup points to receive shipments from customers for processing and packaging before being consolidated at hubs for sorting and distribution to hubs in other regions. The problem aims to address the allocation issue in pickup operations as described above. Previous studies have often failed to consider the allocation of pickup points to hubs beforehand. Or, if they did, they often combined allocation and routing decisions because they didn't consider the hub capacity. Therefore, the proposed model jointly considers both pickup-point assignment and heterogeneous fleet-selection decisions. The first decision is to assign pickup points to specific hubs to minimize costs and avoid exceeding hub capacity. Each vehicle travels from the hub to one pickup point and then returns to the same hub. The distance from the hub to the pickup point is assumed to be equal to the distance from the pickup point to the hub. Therefore, the total travel distance is twice the distance between the hub and the pickup point. The second decision is to determine the number and type of vehicles from a heterogeneous fleet that will pick up shipments for each pickup point, ensuring each vehicle picks up the maximum amount of shipments without exceeding its capacity, allowing for demand splitting. Hubs have fixed capacity and cannot be changed. Furthermore, the fleet is heterogeneous with varying capacities and costs, and the number of vehicles of each type is unlimited to ensure flexibility in accommodating any assignment scenario. Each vehicle can make only one pickup trip per day. Therefore, the number of vehicle trips is equal to the number of vehicles used. Each pickup point is assigned to only one hub. However, the demand at a pickup point can be collected by more than one vehicle if one vehicle does not have enough capacity. Therefore, the demand can be split between vehicles but cannot be split between hubs. The notations of the mathematical model are presented in Table 2 below.

Table 2. Notations of mathematical models

Notation	Description
Sets	
P	Set of pickup points, indexed by $i \in P$
H	Set of hubs, indexed by $j \in H$
V	Set of vehicle types, indexed by $k \in V$
Parameters	
Cap_j	Capacity of hub j
C_k	Capacity of vehicle type k
d_{ij}	Distance from pickup point i to hub j
Q_i	Demand at pickup point i
f_k	Variable cost (VND/km) of vehicle type k
g	Fixed cost per trip (VND/trip)
Decision variables	
x_{ij}	Binary variable; equals 1 if pickup point i is assigned to hub j, 0 otherwise
y_{ijk}	Non-negative integer variable; number of vehicles of type k dispatched from hub j to serve pickup point i

3.2. MILP Formulation

The following is the mathematical model developed for the problem.

$$min \sum_{i\in P}\sum_{j\in H}\sum_{k\in V}(g + 2f_k d_{ij})y_{ijk} \quad (1)$$

subject to:

$$\sum_{j\in H} x_{ij} = 1 \qquad \forall i \in P \quad (2)$$

$$\sum_{i\in P} Q_i x_{ij} \leq Cap_j \qquad \forall j \in H \quad (3)$$

$$\sum_{k\in V} C_k y_{ijk} \geq Q_i x_{ij} \qquad \forall i \in P; \forall j \in H \quad (4)$$

$$y_{ijk} \leq M.x_{ij} \qquad \forall i \in P; \forall j \in H; \forall k \in V \quad (5)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in P;\ \forall j \in H \quad (6)$$

$$y_{ijk} \in \mathbb{Z}^+ \qquad \forall i \in P; \forall j \in H; \forall k \in V \quad (7)$$

Equation (1) is the objective function that minimizes total cost. The total cost includes the fixed cost per trip and the variable fuel cost. The term $2d_{ij}$ represents the round-trip distance between hub j and pickup point i. Equation (2) ensures that each pickup point is assigned to exactly one hub. Equation (3) ensures that the total volume of shipments collected from the assigned points does not exceed the hub's maximum processing capacity. Equation (4) ensures that the total capacity of the dispatched vehicles is sufficient to collect all shipments at the assigned pickup point. More than one vehicle can be used if one vehicle does not have enough capacity. Equation (5) ensures that a vehicle is only allowed to be dispatched from a hub to a pickup point if that point has already been assigned to that hub. Equations (6) and (7) define the binary nature of the assignment variable the non-negative integer vehicle variable.

4. A Case Study

4.1. Experiments Setup

To run the model's calculations, the study will use real-world data from the network of a courier company operating in Ho Chi Minh City, Vietnam. The model is based on daily planning, so the test day is chosen as a high-demand day for better evaluation. This network currently has 3 hubs and 127 pickup points. The locations of the hubs and pickup points are fixed. The distance between each hub and pickup point is calculated using the Euclidean distance. The coordinates of the hubs and pickup points are obtained from Google Maps.

The heterogeneous fleet consists of 52 vehicle types, with no limit on the number of vehicles available for each type. This heterogeneous fleet varies in capacity and operating fuel costs. The fixed costs remain the same for each trip. Each trip is considered to be one trip per day. Detailed parameters used for the problem are presented in Table 3.

Table 3. Real-world data (Source: Current study)

Parameters	Value
Pickup points	127
Distribution hubs	3
Hub 1/ 2/3 capacity (shipments/day)	900,000 / 500,000 / 200,000
Vehicle types	52
Vehicle capacity range (shipments)	2500 – 9800
Vehicle trip limit (trips/day)	1
Fixed cost per trip (VND)	300,000
Fuel variable cost range (VND/km)	1700 – 3960

To evaluate the validity of the proposed MILP model, this study will run the model using the exact method for multiple instances. The five test instances were generated from the real-world dataset. Pickup points and vehicle types were selected from the full dataset for each instance. The number of pickup points increases from 20 to 100. The number of vehicle types increases from 5 to 25. The number of hubs increases from 1 to 3. The demand, vehicle capacity, vehicle cost, and location data were taken from the corresponding records in the real-world dataset. The instances are presented in Table 4 below. After running the instances, the study will run on a real dataset to evaluate practical performance. This calculation was performed on an Intel Core i5-10300H CPU @2.30GHz and 8GB of RAM. The solution program was Python version 3.11, using IDLE. The MILP model was solved using SCIP solver, Google OR-Tools.

Table 4. Instances (Source: Current study)

Instance	1	2	3	4	5
No of Hub	1	1	2	2	3
No of Pickup points	20	40	60	80	100
No of Fleet types	5	10	15	20	25

4.2 Computational Results

Table 5 presents the cost, vehicle utilization, and CPU time results for the instances.

Table 5. Instance results (Source: Current study)

Instance	Cost (VND)	Vehicle Utilization (%)	CPU Time (s)
1	9,137,946.3	52.94	0.0142
2	16,975,224.9	55.03	0.0652
3	26,684,022.1	56.38	0.4317
4	34,863,058.5	69.26	0.7738
5	42,150,068.6	80.24	14.8485

The model obtains an optimal solution for each tested instance, confirming that the formulation can solve the assignment and fleet-selection decisions at the evaluated problem scales. As the number of pickup points and fleet types increases across the test instances, total operating cost also increases. The model obtains an optimal solution for each tested instance, confirming that the formulation can solve assignment and fleet-selection decisions at the evaluated problem scales. Vehicle utilization also increases as the instance size increases. In smaller instances, vehicle utilization is about 50% to 60%. It reaches 80.24% in Instance 5. However, vehicle utilization alone cannot show the benefit of heterogeneous fleet selection. This benefit is further evaluated through the fleet composition scenarios in Section 4.3. In smaller instances, the utilization rate is only about 50% to 60% due to low demand. However, as demand increases, the utilization rate increases significantly, showing that the model selects suitable vehicles to collect all shipments rather than dispatching many trips with unsuitable vehicle types, thus avoiding waste. The running time for all instances is quite short. Instances 1 and 2 are small-scale instances, while 3 and 4 are medium-scale instances. For small-scale and medium-scale data, the model provides solutions in less than one second. For large-scale data with over 100 pickup points, the model takes longer to solve, but the time taken is still relatively small and reasonable. These results indicate that the solution times remain computationally manageable for the tested instances.

Table 6. Optimal results (Source: Current study)

Performance Metric	Value
Total pickup routes	145
Total distance traversed(km)	1,962.13
Average distance per route (km)	13.53
Vehicles employed	145
Vehicle average utilization (%)	81.36
Total operating cost (VND)	53,145,878
Fixed costs (145 routes) (VND)	43,500,000
Variable fuel costs (VND)	9,645,878
Average cost per route (VND)	366,523
Hub average utilization (%)	33.89
CPU Time (s)	46.5243

The MILP model was applied to a real-world dataset comprising 127 pickup points, 3 hubs, and 52 vehicle types. The results are presented in Table 6 above. The total operating cost was VND 53,145,878. 145 vehicles were used. The total distance travelled was 1,962.13 km. The average vehicle utilization rate was quite high at 81.36%, indicating that the model successfully selected the appropriate vehicle type from the heterogeneous fleet to meet the needs of the pickup points. Fixed costs significantly outweigh travel costs. Therefore, the number of trips dispatched, rather than the distance travelled, largely determines the cost. Consequently, deploying vehicles that can collect all the shipments at the pickup point without needing to dispatch many other vehicles would be more efficient. The average hub utilization rate was 33.89% across the three hubs. This indicates that the hubs still have available processing capacity under the current demand. Therefore, hub capacity is not a limiting factor in the current case. Furthermore, the 46.52-second run time is suitable for daily planning.

4.3. Scenario Analysis

The study conducts a scenario analysis. The purpose of this analysis is to examine how the model responds to changes in key input parameters. The scenario analysis includes three groups: demand variation, fleet composition, and hub capacity. The demand variation scenarios will keep the heterogeneous fleet and change demand. The fleet composition scenarios will consider using only one type of vehicle, large or small, to compare with using a heterogeneous fleet. Demand is kept constant in fleet composition scenarios. Finally, the hub capacity scenario group will increase or decrease hub capacity while keeping demand constant and using a heterogeneous fleet. Table 7 below details the scenarios.

Table 7. Scenario descriptions (Source: Current study)

Scenario Group	ID	Parameter Changed	Level
Demand Variation	S1	Demand Q_i	-30%
	S2	Demand Q_i	Base
	S3	Demand Q_i	+30%
Fleet Composition	F1	Vehicle types	Small only
	F2	Vehicle types	Large only
	F3	Vehicle types	Base

Hub Capacity	H1	Hub capacity Cap_j	-20%
	H2	Hub capacity Cap_j	Base
	H3	Hub capacity Cap_j	+20%

Table 8 below shows the results for the demand variation scenarios and is visually illustrated in Figure 1.

Table 8. Demand variation scenario results (Source: Current study)

Scenario	S1	S2	S3
Cost (VND)	49,154,795	53,145,878	58,420,768
Vehicles Used	136	145	156
Vehicle Utilization (%)	73.89%	81.36%	81.46%
Hub Utilization (%)	23.72%	33.89%	44.06%
CPU Time (s)	37.023	46.5243	261.3557

Scenario S1 shows a 30% decrease in demand, while scenario S3 shows a 30% increase in demand. From S1 to S3, demand increases by 60%, while total operating cost increases by approximately 19%. The results show that the model adjusts pickup-point assignments and vehicle selections as demand changes. The model also makes good use of a heterogeneous fleet to reduce costs. Even when demand decreases, one vehicle still has to be driven to each pickup point. Therefore, the vehicle utilization rate decreases because there is less cargo, and the vehicles are not fully occupied. However, when demand increases, the model finds vehicles with higher capacity, resulting in a higher utilization rate. The computational time for S3 is much longer than for S1 and S2 due to the increased demand, requiring the model to consider more vehicle allocation options. Therefore, when demand is high, it is necessary to consider the computational time, and further optimization may be required.

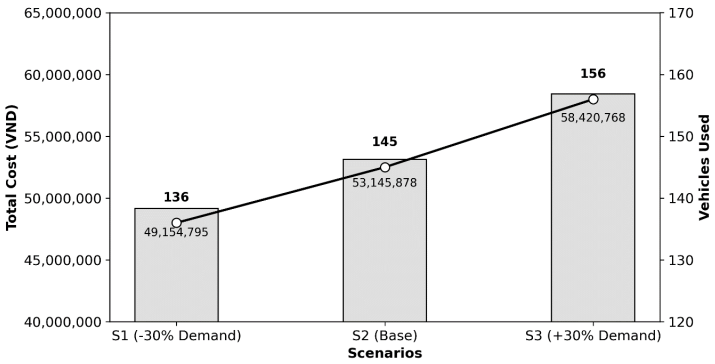


Figure 1. Demand variation scenarios results (Source: Current study)

Table 9 below shows the results for the fleet composition scenarios and is visually illustrated in Figure 2.

Table 9. Fleet composition scenario results (Source: Current study)

Scenario	F1	F2	F3
Cost (VND)	73,361,671	55,925,293	53,145,878
Vehicles Used	209	145	145
Vehicle Utilization (%)	87.67%	45.23%	81.36%
Hub Utilization (%)	33.89%	33.89%	33.89%
CPU Time (s)	5.3249	14.6929	46.5243

Scenario F1 has substantially higher costs than the base scenario while achieving a moderately higher vehicle utilization rate (87.67% versus 81.36%). Because F1 restricts the fleet to smaller vehicles, 209 vehicles are required compared with 145 in the heterogeneous-fleet base case. The resulting increase in trip-related fixed costs outweighs the improvement in capacity utilization. Because this scenario only uses smaller vehicles, more vehicles are needed to collect all the cargo. Since fixed costs account for a large portion of total costs, deploying more vehicles significantly increases expenses. However, the vehicles are still fully loaded, so the vehicle utilization rate remains quite high. Scenario F2 has a total operating cost approximately 5.2% higher than the base scenario, while its vehicle utilization is substantially lower. Demand at different pickup points varies; some pickup points have low demand. Therefore, deploying larger vehicles to these pickup points leaves a significant amount of empty space. These larger vehicles also consume more fuel than smaller ones, leading to increased costs. Therefore, scenario F3, using a heterogeneous fleet, is better than the two scenarios above. This confirms that in today's modern networks, where the demand for transporting goods is increasingly diverse, the use of heterogeneous fleets will bring more cost and operational efficiency benefits. Tanash and As'ad [8] also confirmed in their study the benefits of heterogeneous fleets. That study showed that using these fleets would result in greater cost savings and greater operational flexibility. However, in terms of computation time, F3 is considerably longer than F1 and F2. This is because using more types of vehicles requires the model to process more data. Nevertheless, this computational time is still reasonable for daily planning.

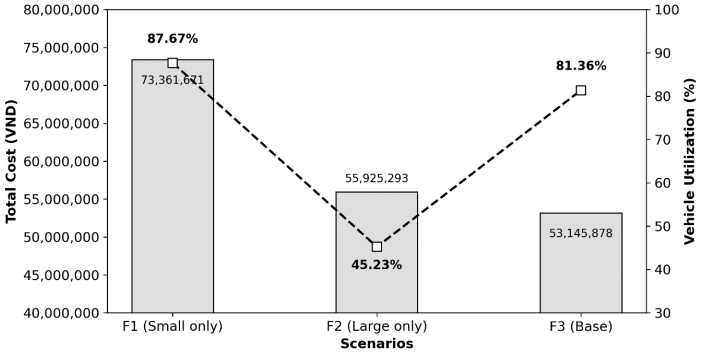


Figure 2. Fleet composition scenarios results (Source: Current study)

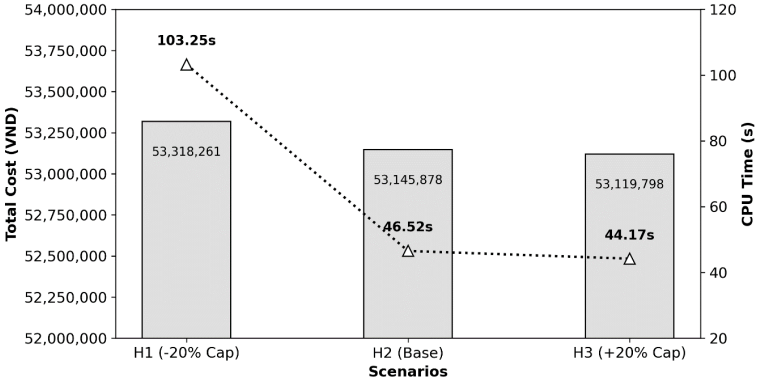


Figure 3. Hub capacity scenario results (Source: Current study)

Table 10 below shows the model results for the hub capacity scenarios and is visually illustrated in Figure 3.

Table 10. Hub capacity scenario results (Source: Current study)

Scenario	H1	H2	H3
Cost (VND)	53,318,261	53,145,878	53,119,798
Vehicles Used	145	145	145
Vehicle Utilization (%)	81.44%	81.36%	81.52%
Hub Utilization (%)	42.36%	33.89%	28.24%
CPU Time (s)	103.25	46.5243	44.1728

Costs, number of vehicles, and vehicle utilization rates are almost the same in all three scenarios. This is because, at the current demand level, the hub capacity is still very much in excess; the current system still has a lot of capacity before reaching its limit, which will not significantly affect costs. The results indicate that hub capacity is non-binding under the tested demand levels, including the −20% capacity scenario. Therefore, the current network appears to have substantial capacity slack within the tested range. However, decisions regarding physical capacity reduction would require additional analysis of peak-demand variability, service-level requirements, and long-term demand growth. Alternatively, the business can consider expanding its operations because, as seen in the demand variation scenarios above, hub utilization remains quite low even when demand increases by 30%. However, Figure 3 shows that when hub capacity is reduced, computation time increases. It can be concluded that if the business tightens hub capacity, the solution will become less efficient in terms of time. This is because reducing capacity narrows the space for finding feasible solutions, so the model has to spend more time on computation. In summary, within the tested ±20% range, changes in hub capacity have only a limited effect on operating cost, fleet size, and vehicle utilization.

Overall, the scenario analysis indicates that the model remains feasible and produces optimal solutions under the tested variations in demand, fleet composition, and hub capacity. When demand changes from −30% to +30% relative to the base case, total operating cost increases from VND 49.15 million to VND 58.42 million, while the number of vehicles increases from 136 to 156. These results demonstrate the model's ability to adapt to the tested parameter changes, although they should not be interpreted as a formal proof of robustness. Computation time increases when the problem becomes more complex. This increase is significant in the high-demand scenario. However, the solution time is still suitable for daily planning in the tested scenarios. If the complexity of the problem increases, this time issue can still be addressed by applying modern algorithms to find the optimal solution within a shorter computation timeframe. In summary, the model successfully solved the pickup problem by allocating pickup points across the network and deploying a heterogeneous fleet, laying the foundation for more complex problems such as vehicle routing or network optimization.

5. Conclusion

This study proposes a MILP model for the pickup problem with two decisions: the decision to allocate pickup points to a hub and the decision on the vehicle types and quantities from a heterogeneous fleet to collect shipments. The goal of the model is to reduce total costs and ensure that hub capacity constraints and vehicle capacity are maintained. The model was run with multiple scenarios and real-world datasets. This real-world dataset is from a transportation company operating in Ho Chi Minh City with 127 pickup points, 3 sorting hubs, and 52 different vehicle types. The results of solving the real-world dataset showed a high vehicle utilization rate of over 80%. The solving time of 46.52 seconds can be considered suitable for daily planning. Scenario analysis showed the effects of changes in demand, fleet composition, and hub capacity on the model results. The fleet composition analysis further shows that the heterogeneous-fleet configuration achieves lower operating cost than the tested homogeneous-

fleet alternatives while maintaining relatively high vehicle utilization.

This study presents a simplified model to serve as a foundation for more complex problems in logistics optimization research. The model obtained an optimal solution for the tested real-world data. However, the study still has limitations. The current model does not consider vehicle routing. Each vehicle travels directly from a hub to one pickup point and returns to the same hub. A vehicle routing model could allow one vehicle to collect shipments from several pickup points in one route. This may reduce the number of trips and total operating cost. However, it will also increase the complexity and solution time of the model. Future research can extend the current model by including vehicle routing decisions through a set of pickup points. Distances are approximated using Euclidean distances derived from geographic coordinates. Consequently, the current model does not capture actual road-network distances, traffic conditions, or directional travel-time asymmetry. Future implementations could replace Euclidean distances with road-network distances or travel times obtained from a routing engine. The solution time for the precise solution is relatively high when running on large datasets. Therefore, using more modern algorithms could help shorten the solution time. Future research could continue to expand the problem in these directions to provide improved solutions for optimizing logistics operations. The current model also assumes that the number of vehicles of each type is unlimited. In practice, the number of available vehicles can be limited. This limitation may change the selected vehicle types and increase the total cost. Future research can add vehicle availability constraints to represent this condition.

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