GREEN CITIES
GREEN LOGISTICS FOR GREENER CITIES

7th International Conference Green Cities 2026 –
Green Logistics for Greener Cities,
15-17 April 2026, Szczecin, Poland

Sustainable Logistics through Consolidation: The Two-Phase Load Planning Model (2Ph-LPM) for a Cross-Docking Facility in the Philippines

Rovie Manansala[a], Francis Adrian Viernes[a], Varsolo Sunio[b]

[a]*School of Management, University of Asia and the Pacific, Pasig City, 1605, Metro Manila, Philippines*
[b]*School of Sciences, Engineering and Technology, University of Asia and the Pacific, Pasig City, 1605, Metro Manila, Philippines*

Abstract

This study examines how shipment consolidation can improve truck utilization in a cross-docking facility operated by a logistics service provider (LSP) in the Philippines. Using actual order and dispatch data from December 2024 to February 2025, the study identified inefficiencies such as underutilized truck dispatches and limited multi-order consolidation. To address this, a hybrid optimization model (2Ph-LPM) was developed in Python under Google Colab Environment with 2 Phases: (1) Phase 1, using Mixed Integer Linear Programming (MILP) to achieve majority of shipment assignment adhering to set constraints having the goal of maximizing feasible assignment and utilization quality; (2) Phase 2, using a Greedy Heuristic Fallback as a post-optimization recovery phase for remaining unassigned shipments. The produced model showed significant improvement and success in attaining a high utilization profile, resource efficiency, increased multi-order consolidation and computational performance. The resulting utilization profile is predominated by highly utilized truck dispatches (40.95%) and a lower percentage of underutilized (18.67%). While the actual dispatch is not directly comparable with model results because of unassigned shipments, the significant reduction in truck dispatches from 6,448 to 2,110 is notable, signaling potential efficiency benefits in labor and vehicle maintenance. Finally, using cloud computation, its computational efficiency is demonstrated with only 15-20 minutes of execution time for a 3-month worth of planning horizon. These findings validate the potential of applying algorithmic formulation in solving a utilization, assignment and operational rules adherence case in a cross-dock environment. The study concludes with recommendations on the model's cost implications, practical implementation, future enhancement, and ethical considerations for achieving a sustainable and ethical logistics practice.

Keywords: logistics service provider; consolidation; multiple shipments; sustainable logistics; Philippines

---

1 Introduction

In the Philippines, the geographical context of this study, the logistics sector has entered a period of rapid expansion. In 2023, logistics activities generated approximately ₱768 billion (13 M USD) in gross value added, accounting for 3.6% of national GDP, and the sector is projected to grow at an annual rate of 8.2%, reaching ₱1.16 trillion (20 B USD) by 2027 (Moral, 2023). While this growth reflects rising shipment volumes and economic activity, it also intensifies pressure on limited transport resources, raising concerns related to cost efficiency, congestion, emissions, and operational sustainability.

One promising strategy for addressing these challenges is shipment consolidation through horizontal logistics collaboration. Prior studies have demonstrated that consolidating shipments across orders or shippers can significantly improve truck utilization, reduce empty or underutilized trips, and lower logistics costs (e.g., Ferrell et al., 2019).

Despite this potential, much of the literature relies on stylized models or synthetic data, with limited application to real-world operations. To address this gap, the present study leverages a research partnership with a large Philippine logistics service provider (hereafter referred to as LSP Firm), which operates a nationwide, end-to-end logistics network. The analysis focuses on one of its business-to-business (B2B) cross-docking facilities, a context where shipment consolidation decisions are both operationally critical and particularly challenging due to tight delivery schedules and high daily throughput.

Cross-docking operations involve the rapid transfer of goods from inbound to outbound trucks with minimal storage time. Shipments originating from multiple suppliers are sorted and reassembled based on customer requirements, delivery clusters, and requested delivery dates before dispatch. LSP Firm employs a transport management system that records detailed order-level and dispatch-level data, providing a rich empirical basis for analyzing consolidation performance and identifying inefficiencies across the planning horizon.

An initial diagnostic analysis of actual dispatch data from December 2024 to February 2025 (Figure 1) reveals substantial underutilization of truck capacity. Truck utilization was categorized into four bins: Underutilized (≤50%), Moderately Utilized (51–75%), Utilized (76–90%), and Severely Utilized (91–100%). Nearly half of all dispatches fell into the underutilized category, and a large proportion of trips carried only a single order, severely limiting consolidation benefits. Even among higher-capacity trips, latent inefficiencies were observed, indicating unrealized consolidation potential despite apparent high utilization. These patterns highlight structural limitations in current manual or rule-based planning practices.

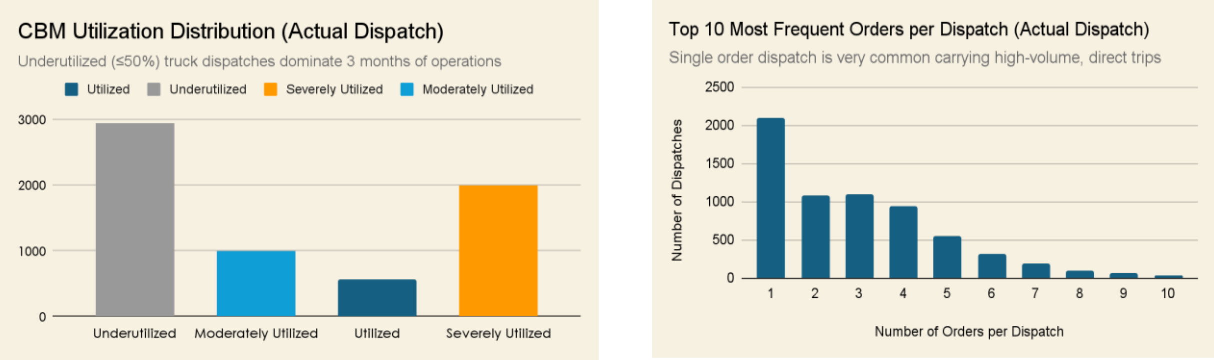

Figure 1. (a) Utilization Categories Distribution; (b) Most Frequent Orders per Dispatch

These findings underscore the need for a systematic solution framework that can improve truck utilization while respecting operational constraints such as delivery dates, cluster schedules, and vehicle capacity limits. Accordingly, this study proposes a Two-Phase Load Planning Model (2Ph-LPM) designed to (1) reduce the number of underutilized truck dispatches and (2) increase the frequency of multi-order consolidation in a cross-dock environment. The model combines a Mixed Integer Linear Programming (MILP) formulation to achieve high-quality initial assignments with a greedy heuristic fallback to recover unassigned shipments efficiently. By applying the proposed model to real-world logistics operational data, this study contributes empirically grounded evidence on how hybrid optimization approaches can enhance consolidation, improve resource efficiency, and support more sustainable logistics operations in rapidly growing urban contexts.

2 Related Works

Prior literature consistently demonstrates the potential of shipment consolidation to improve logistics efficiency by reducing empty capacity, lowering operating costs, and mitigating environmental impacts. Consolidation problems are typically modeled as decision-making challenges involving trade-offs among shipment quantity, delivery timing, vehicle capacity, and operational constraints. Two dominant methodological streams emerge from the literature: (1) exact optimization approaches, particularly Mixed Integer Linear Programming (MILP), and (2) heuristic and simulation-based approaches designed to enhance computational efficiency and realism.

2.1 Optimization Modelling for Shipment Consolidation

Mixed Integer Linear Programming (MILP) remains the most widely used approach for modeling shipment consolidation problems, particularly in intermodal transport, less-than-truckload (LTL) operations, and collaborative logistics networks. Numerous studies have shown that MILP-based formulations can achieve substantial cost reductions and improved utilization by explicitly optimizing shipment-to-vehicle assignments under capacity and service constraints. For instance, recent work combining MILP with stochastic optimization has demonstrated measurable gains in both economic efficiency and system resilience (Goodarzi et al., 2024; Mercurio et al., 2024).

However, the literature also highlights inherent limitations of purely exact optimization approaches when applied to operationally complex and large-scale settings. Strict consolidation targets may lead to excessive shipment holding times, increased delivery delays, or terminal congestion, particularly when demand is volatile or delivery windows are tight (Wei et al., 2023). Similarly, large consolidation batches can create downstream inefficiencies in cross-docking and terminal handling, offsetting some of the anticipated benefits (Kumar and Anoop, 2025). These findings suggest that while MILP can deliver high-quality solutions, its direct application in fast-paced, rule-intensive environments may be constrained by computational burden and operational rigidity.

2.2 Heuristic Approaches and Simulation-Based Methods

To address scalability and real-world variability, many studies have turned to heuristic and simulation-based methods. Heuristics—such as greedy algorithms, metaheuristics, and rule-based consolidation logic—are particularly effective in producing near-optimal solutions within acceptable computation times for large problem instances. These approaches have been widely applied to variants of the Vehicle Routing Problem with Shipment Consolidation (VRPSC) and the Multiple Constraint Knapsack Problem (MCKP), where exact methods become computationally prohibitive (Aringhieri et al., 2018; Zuhanda et al., 2024; Carlomana et al., 2024).

Greedy heuristics, in particular, have shown strong practical relevance due to their interpretability and alignment with operational rules. By prioritizing feasible insertions and incremental utilization gains, such methods can increase consolidation rates while preserving service-level requirements (Memon et al., 2021). In parallel, Monte Carlo Simulation (MCS) has been used extensively to evaluate the robustness of consolidation strategies under demand uncertainty, stochastic arrivals, and fluctuating network conditions. Simulation-based studies have provided valuable insights into the economic and environmental impacts of consolidation across diverse urban logistics scenarios (Venkatadri et al., 2016; Elbert et al., 2020). Despite their flexibility, heuristic and simulation approaches often lack guarantees on solution quality and may struggle to systematically balance competing objectives such as assignment completeness, utilization efficiency, and rule compliance.

2.3 Positioning of the Current Study

While prior studies provide strong evidence on the effectiveness of shipment consolidation, much of the literature has examined the problem using stylized settings, synthetic datasets, or simplified operational assumptions (Carlomana et al., 2024). Existing analyses typically focus on cost minimization, routing efficiency, or theoretical utilization gains, with limited attention to real-world cross-docking environments characterized by strict delivery schedules, cluster-based dispatching, and high-volume transactional flows. Empirical studies that incorporate actual operational data remain relatively scarce, particularly in developing country contexts. As a result, there is a gap in understanding how consolidation strategies perform under realistic constraints and day-to-day planning conditions.

Building on these insights, this study adopts a hybrid optimization approach that integrates the strengths of both methodological streams. The proposed Two-Phase Load Planning Model (2Ph-LPM) combines a MILP-based core optimization phase—designed to maximize assignment and utilization quality—with a greedy heuristic fallback phase that efficiently recovers unassigned shipments while respecting delivery feasibility rules. This design explicitly addresses the dual requirements of solution quality and computational efficiency, making it suitable for large-scale, multi-month planning horizons in real-world cross-docking operations.

3 Data and Methodology

This section describes the operational data provided by the logistics service provider (LSP Firm), the associated delivery and capacity constraints, and the formulation of the proposed Two-Phase Load Planning Model (2Ph-LPM). The hybrid modeling framework is designed to maximize shipment consolidation quality while maintaining computational tractability in a real-world cross-docking environment.

3.1 Data and Operational Context

The empirical analysis is based on three months of real operational data from LSP Firm, covering the period from December 2024 to February 2025. The data were extracted from the firm's Transport Management System (TMS) and anonymized in accordance with confidentiality agreements. Two datasets were utilized:

- **Order-Level Data:** Contains 19,576 incoming shipment orders prior to consolidation. After filtering incoming orders, including only 'Planned' and removing orders with RDDs not within December 2024-February 2025, 18,468 records were used. Key variables include a unique 'Order No.',' Requested Delivery Date' (RDD), Volume (cubic meters m^3) and Weight (kg). From the raw data, columns 'RDD_Day' and 'FDS_Cluster' were generated to set cluster zone delivery schedule.
- **Dispatch-Level Data**: Includes 6,453 records reflecting actual consolidated shipments, serving as the baseline performance evaluation. Key variables are 'Shipment No.', 'TruckType', shipment's 'Volume' and 'Weight' and 'Proof of Delivery' date.

In addition to shipment data, the modeling framework incorporates operational rules that govern daily dispatch planning. These include truck capacity limitations by vehicle type, strict adherence to requested delivery dates RDD (with allowance for one-day-early delivery or RDD-1), and delivery cluster availability (or 'open') schedules. These constraints reflect the firm's actual operating policies and are explicitly enforced in the optimization model.

3.2 2Ph-LPM Modelling Framework

The optimization process follows a two-phase structure combining two algorithms: MILP and greedy heuristics. Figure 2 provides a snapshot of the entire analysis process, from data input and the hybrid optimization procedure to the execution output and a future-oriented "what-if" analysis. The inputs consist of the necessary pre-processed order-level data, containing order attributes over a three-month period, along with operational rule constraints. Core optimization is achieved using a Mixed Integer Linear Programming (MILP) formulation in Phase 1 (Table 1 provides the detailed MILP formulation), followed by a post-optimization greedy heuristic fallback phase. This design maximizes shipment assignment and truck utilization while adhering to delivery feasibility rules. Unlike actual operations, where trucks may be used more than once in a day, the model encourages single usage to support better labor conditions and vehicle maintenance.

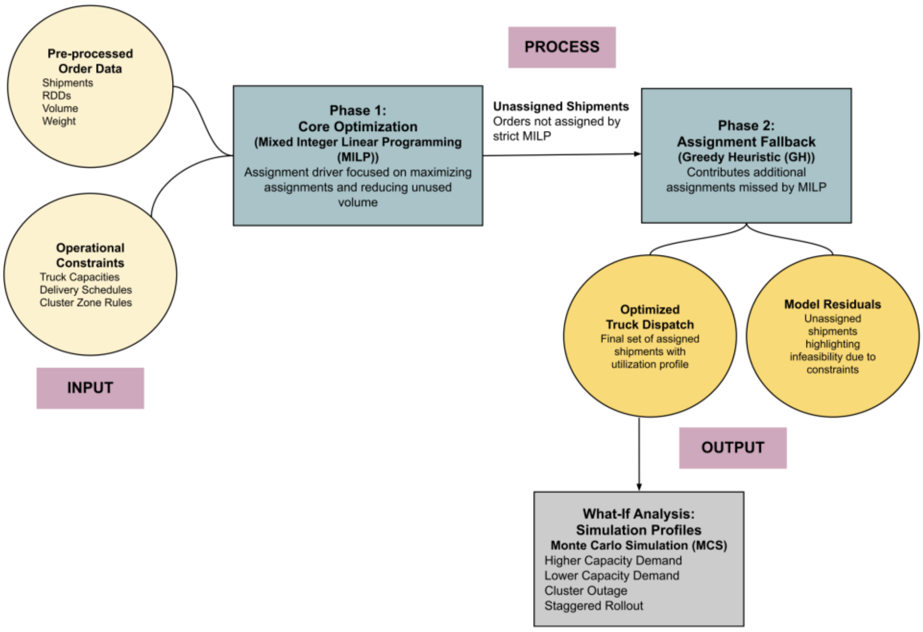

Figure 2. 2Ph LPM Conceptual Methodology

Phase 1: MILP Formulation

Table 1. 2Ph-LPM MILP Formulation

Sets and Indices	Notation	Remarks	
Set of shipments *s*	S		
Set of available trucks on a day *t*	T		
Set of planning days *d*	D		
Set of clusters *c*	C		
Set of feasible shipment-truck arcs	A	Arcs are generated based on feasibility in volume, truck compatibility, cluster availability and delivery date eligibility	
Parameters	Notation		Notation
Shipment		***Cluster Calendar***	
Volume in cubic meters (m^3) of shipment *s*	v_s	1 if cluster *c* is open on a day *d*, 0 if otherwise	$open_{c,d} \in \{0,1\}$
Weight in kilograms (kg) of shipment *s*	w_s	1 if day *d* is allowed by the RDD rule for a shipment, 0 if otherwise	$elig_{s,d} \in \{0,1\}$
Requested delivery date of shipment *s*	$RDD_s \in D$		
Delivery cluster for shipment *s*	$c(s) \in C$		
Truck Logs		***Availability and Compatibility***	
Volume capacity of truck-type slot *t*	$capCBM_t > 0$	1 if truck-type slot *t* is available on day *d,* 0 if otherwise	$avail_{t,d} \in \{0,1\}$

Weight capacity of truck-type slot *t*	$capWT_t \geq 0$	1 if truck-type slot *t* is compatible with shipment *s*, 0 if otherwise	$compat_{s,t} \in \{0,1\}$
Decision Variables	Notation		Notation
Binary variable equal to 1 if shipment *s* is assigned to a truck-type slot *t* on day *d*	$x_{s,t,d} \in \{0,1\}$	Accounting variable to quantify unused volume	$u_{t,d} \geq 0$
Binary variable equal to 1 if truck-type slot *t* is used on day *d*	$y_{t,d} \in \{0,1\}$	Slack variable to quantify weight violation	$overWT_{t,d} \geq 0$
Objective Function	Notation		
Balances maximum assignment and utilization quality *(This formulation internalizes utilization efficiency inside the optimization process instead of a post-solution evaluation metric)*	$\max Z = \alpha \sum_{(s,t,d)\in A} x_{s,t,d} - \gamma \sum_{t\in T}\sum_{d\in D} u_{t,d} - \delta^{WT}\,\lambda \sum_{t\in T}\sum_{d\in D} overWT_{t,d}$		(1)
Objective Weights			
Reward for successful assignment	$\alpha = 1000$	$\delta^{WT} = \begin{cases} 1, \text{if weight capacity violations are penalized} \\ 0, \text{otherwise} \end{cases}$	(2)
Penalty per unused volume units	$\gamma = 0.01$		
Penalty per overused weight units	$\lambda = 0.01$		
Constraints			
Each shipment can only be assigned once in the entire planning days	$\sum_{(t,d):\,(s,t,d)\in A} x_{s,t,d} \leq 1$		
For each truck-type slot and day, the total truck volume cannot exceed truck capacity	$\sum_{s:(s,t,d)\in A} v_s x_{s,t,d} \leq capCBM_t\, y_{t,d}$		
Unused capacity is defined and bounded	$\forall t \in T, \forall d \in D: u_{t,d} \geq capCBM_t \cdot y_{t,d} - \sum_{s:(s,t,d)\in A} v_s x_{s,t,d}$ $\forall t \in T, \forall d \in D: u_{t,d} \leq capCBM_t \cdot y_{t,d}$		
Weight limit as a soft constraint	$\sum_{s:(s,t,d)\in A} w_s x_{s,t,d} \leq capWT_t y_{t,d} + overWT_{t,d}$		
Shipments can only be assigned on RDD of one day early (RDD-1) and when delivery cluster is open	$x_{s,t,d} = 0 \; if \; d \notin \{RDD_s, RDD_s - 1\}$ $x_{s,t,d} = 0 \; if \; open_{c(s),d} = 0$		

Phase 2: Post-Optimization Greedy Fallback

Remaining unassigned shipments after the MILP undergo Phase 2 in an attempt to insert shipments into partially utilized trucks per day, while preserving RDD, cluster feasibility, and volume capacity. It serves as a recovery mechanism for the remaining residuals.

The proposed Two-Phase Load Planning Model (LPM) follows a simple and scalable truck-day assignment structure that targets two major objectives: balancing optimal utilization and delivery adherence. The hybrid design aims to achieve computational efficiency, making it suitable for large datasets or a multi-month planning horizon. While the model attempts to assign all shipments after Phase 2, residuals remain due to the prioritization of solution quality. Finally, the model is further evaluated under scenario profiles using Monte Carlo Simulation (MCS) with varying demand and operating conditions to effectively observe model performance across different scenarios.

4 Results and Evaluation

Overall Performance

The aggregated results from 3-month planning demonstrated an improvement in resource efficiency and consolidation quality. Truck-day dispatches were reduced by nearly two-thirds from actual dispatch (6,448 to 2,110). This substantial reduction showcased potential for cost savings in labour, fuel, and vehicle maintenance. The model also shifted the utilization profile to a more dominant high-capacity usage. 'Severely Utilized' (at 91–100% capacity) accounts for 40.99% of all dispatches, and a significantly lower proportion of 'Underutilized' (at ≤50% capacity) trucks occupy 18.67% of dispatches. There are also fewer single-order dispatches, accounting for 15.35% (324 out of 2,110), and a frequent consolidation of 3 orders per truck-day dispatch. This overall performance confirms the model's ability to achieve the primary objective of utilization quality (Figure 3a).

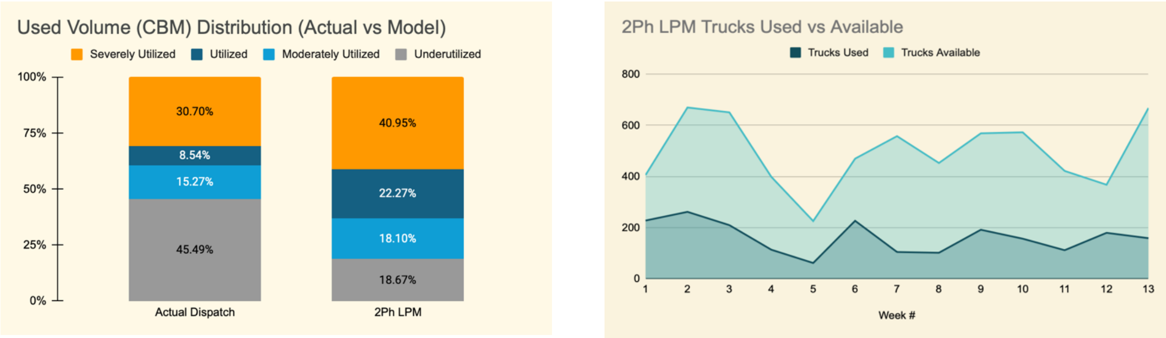

Figure 3. (a) Performance of 2Ph LPM compared to actual dispatch; (b) Weekly performance.

4.1 Weekly Performance

The model's consistent performance on a weekly basis is illustrated by its ability to adapt to non-uniform demands (Figure 3b). Weekly distribution showed consistent and dominant high-capacity assignments (median rate of 37.74% 'Severely Utilized') and maintained a week-by-week median rate level of low-capacity ones (median rate of 18.32% 'Underutilized'). Consolidation also centered on a frequent size of 2 orders per dispatch, establishing a recommended baseline of consolidation on a weekly basis. Higher underutilization performance (peaks at 40.32% in week 5) and a greater presence of single-order dispatches are seen around the holiday season. This revealed the difficulty that the model experiences in assigning isolated, high-volume, single-order deliveries due to RDD or cluster constraints. Weekly demand performance demonstrated the model's flexibility and quality-driven assignment logic while revealing challenges in peak seasons.

4.2 Assignment and Efficiency

The model's assignment rate is at 70.23% (12,970 out of 18,468 planned orders) as a direct outcome of a stricter model design that prioritizes adherence to feasibility rules (volume, weight, RDD, and cluster zone schedule) over a 100% assignment rate. In actual dispatch, these rules were more flexible given the manual loading and planning that are very much present in the LSP firm's daily operations. Nevertheless, beyond solution quality, the computational efficiency of a 15–20-minute execution is also a key achievement. By using cloud computation (Google Colab Environment) to process a three-month planning horizon of 18,468 orders, the model demonstrated potential in complementing a fast-paced, cross-docking environment. The combination of solution quality and efficiency has been 2Ph-LPM's strength.

5 "What-If" Analysis

The baseline performance of the 2Ph-LPM model served as a controlled reference point of evaluation. To introduce non-baseline conditions and test its consistency and adherence, scenario profiles were created using Monte Carlo Simulation (MCS). This extends a single-point estimate by generating distributions of future states. For this analysis, only December 2024 shipments were selected to balance computational efficiency and depth. The truck fleet used during this month was held constant, isolating demand as the primary source of variation.

Profile specifications and results are summarized in Table 2. The '*Description*' column defines the operational adjustment made to baseline dataset. The *'Random Factor Range'* contains the multiplicative interval of random factors applied to each order's volume/unit, as illustrated in the *'Example'* column. The *"# of Orders"* showing the number of orders subject to assignment under the modified condition. The resulting '*Assignment Rate Range*' and '*Trucks Used*' report the outcomes. Each iteration was applied independently per scenario, passing it through the same optimization pipeline of the combined MILP and Greedy Fallback algorithm. Each profile generated five (5) scenarios each, yielding a total of twenty (20) independent runs.

Table 2. MCS Scenario Profile Generation

Profile	Description	Random Factor Range	Example	# of Orders	Assignment Rate Range	Trucks Used
Higher Demand Capacity	Increase in demand capacity by +10 to +20%	1.11-1.2	$4.93\ m^3 * 1.11 = 5.47\ m^3$	6094	67.97-68.23%	830-871
Lower Demand Capacity	Decrease in demand capacity by 10-20%	0.84-0.9	$4.93\ m^3 * 0.84 = 4.14\ m^3$	6094	69.59-69.92%	784-811
Cluster Outage Demand Capacity	Localized disruption in one cluster where 80-90% drop is observed	0.1-0.2	$4.93\ m^3 * 0.11 = 0.54\ m^3$	6094	72.09-72.38%	513-566
Staggered Rollout	Product launch simulating a surge in order demand by duplicating 10-20% of existing orders	N/A	N/A	7,058-7,286	71.78-72.36%	983-1032

Across all scenario profiles, the model demonstrates stable performance under varying demand conditions. Higher demand scenarios result in slightly lower assignment rates due to capacity constraints, while reduced demand improves assignment feasibility. Disruptions such as cluster outages reallocate capacity more efficiently, leading to higher assignment rates, whereas demand surges increase resource utilization without significantly degrading performance. Overall, the results indicate that the model maintains consistent assignment quality and utilization efficiency across different operational conditions, highlighting its robustness under demand variability.

6 Cost Impact Implications

Confidentiality agreements with the LSP firm withheld the inclusion of costing data. Regardless of this, operational improvements can still be estimated. By achieving a major shift to a higher utilization profile of truck fleets, the model showcased potential in addressing key drivers of logistics costs: underutilized truck capacity and excessive resource deployment. Table 3 provides a summary of potential gains:

Table 3. Cost Impact Summary

Operational Metric	Baseline	Optimized	Implications
Underutilized Trips (≤50% Truck Capacity)	45 – 50%	18.67% of dispatches (394 in total)	**Reduced Waste**: Efficient usage of truck space, significantly lowering cost-per-unit delivered
Severely Utilized Trips (>90% Truck Capacity)	30 – 35%	40.99% of dispatches (865 in total)	**Increased Asset Utilization**: Maximized load density, improving asset profitability
Single-order truck dispatches	2091	324	**84.5% reduction:** Increased consolidation directly lowers handling costs and increases operational efficiency per order
Total Truck dispatches	6,448	2,110	**67.3% Reduction**: Can translate to substantial savings on fuel, labor cost, and vehicle maintenance
Resource Usage (Truck Used/Available)	N/A	Median Weekly Usage Rate of 28.57%	**Capital Efficiency:** Reduced truck usage frees up capital or reducing the need for acquiring new vehicles

The model achieved lower underutilized dispatches, increased severely utilized trips, and a sharp drop in single-order dispatches, demonstrating a better and more cost-effective utilization profile where most dispatches carry optimal load density. It highlights potential consolidation gains, targeting a lower cost per delivery since the cost of an individual truck is spread across a greater volume of orders. The model's ability to consolidate shipments also led to a 67.3% reduction in truck dispatches over the three months. This significant cost implication yields direct savings in fuel consumption, labor, and vehicle costs. These enhancements provide a good basis for the LSP firm in implementing sustainable transport solutions in load planning to achieve its strategic objective of cost efficiency internally and for customers.

7 Practical implications

The findings demonstrate that adopting a hybrid optimization approach such as the 2Ph-LPM can significantly enhance operational efficiency in real-world cross-docking environments. By reducing total truck dispatches and increasing load utilization, logistics service providers can achieve meaningful cost savings in fuel, labor, and vehicle maintenance while maintaining service feasibility. The model's scalability and relatively short computation time also suggest its suitability for integration into existing transport management systems as a decision-support tool. Moreover, the results highlight important operational trade-offs—particularly between strict adherence to delivery constraints and full shipment assignment—indicating that modest flexibility in delivery policies could further improve consolidation outcomes.

8 Summary and Conclusion

This study examined shipment consolidation in a cross-docking environment using a hybrid optimization approach (2Ph-LPM) applied to real operational data from a Philippine logistics service provider. The results demonstrate that the model can substantially improve truck utilization and reduce the number of required dispatches while maintaining adherence to operational constraints. These findings highlight the potential of combining exact optimization and heuristic methods to achieve both solution quality and computational efficiency in large-scale, real-world logistics planning. The study contributes empirical evidence on the effectiveness of consolidation under realistic conditions and offers a practical decision-support approach for improving operational performance. Future research may extend the model to incorporate more dynamic and real-time logistics planning settings.

References

Aringhieri, R., Duma, D., Grosso, A., Hosteins, P., 2018. Simple but effective heuristics for the 2-constraint bin packing problem. Journal of Heuristics. https://doi.org/10.1007/s10732-017-9326-0.

Büyükdeveci, Ö., Özpeynirci, S., Özpeynirci, Ö., 2024. Multi-objective shipment consolidation and dispatching problem. Computers & Operations Research 169, 106728.

Campos, M., Montreuil, B., McGinnis, L., Kaboudvand, S., Kwon, S., Bahrami Bidoni, Z., Faugere, L., Buckley, S., 2021. Enabling scientific assessment of large scale hyperconnected urban parcel logistics: System configuration and assessment. Proceedings of the 2021 IISE Annual Conference. https://www.researchgate.net/publication/354401337.

Carlomana, A.N., Bermudo, U.V.W., Estilloso, E.M., Llantosa, O.E., 2024. Bundle AI: An application of multiple constraint knapsack problem (MCKP) through genetic algorithm (GA). Procedia Computer Science 231, 24–31. https://doi.org/10.1016/j.procs.2023.12.153.

Chen, L., Li, W., Sun, H., 2019. Incentivizing vehicular crowdsensing system for large-scale smart city applications. ResearchGate. Retrieved March 24, 2025, from https://www.researchgate.net/publication/332055588_Incentivizing_vehicular_crowdsensing_system_for_large_scale_smart_city_applications.

Elbert, R., Schöder, S., Friedrich, C., Kourounioti, I., 2020. Urban consolidation and cargo bikes: A simulation study. Transportation Research Procedia 48, 439–451. https://doi.org/10.1016/j.trpro.2020.08.051.

Ferrell, W., Ellis, K., Kaminsky, P., Rainwater, C., 2019. Horizontal collaboration: Opportunities for improved logistics planning. International Journal of Production Research. https://doi.org/10.1080/00207543.2019.1651457.

Goodarzi, A., Jabbarzadeh, A., Fahimnia, B., Paquet, M., 2024. Evaluating the sustainability and resilience of an intermodal transport network leveraging consolidation strategies. Transportation Research Part E: Logistics and Transportation Review 188, 103616.

GoFreight, n.d. What is cross-docking? GoFreight. Retrieved March 24, 2025, from http://go-freight.io/what-is-cross-dock/.

Kumar, M., Anoop, K.P., 2025. An innovative modelling framework for freight consolidation in transportation planning. IIMB Management Review 37(100550), 1–12. https://doi.org/10.1016/j.iimb.2025.100550.

Memon, M.A., Shaikh, A., Sulaiman, A., Alghamdi, A., Alrizq, M., Archimède, B., 2021. Time and quantity based hybrid consolidation algorithms for reduced cost products delivery. Computers, Materials & Continua 69(1), 409–432. https://doi.org/10.32604/cmc.2021.017653.

Mercurio, F., Schlicher, L., Rohmer, S.U.K., Van Woensel, T., 2024. Freight consolidation through carrier collaboration—A cooperative game. Operations Research Letters 56, 107142.

Moral, M.A., 2023. Overcoming challenges in the Philippine logistics and transport sector. BusinessWorld Online. https://www.bworldonline.com/special-features/2023/09/22/547245/overcoming-challenges-in-the-philippine-logistics-and-transport-sector/.

Venkatadri, U., Kasinadhuni, S.K., Ülkü, M.A., 2016. On Physical Internet logistics: Modeling the impact of consolidation on transportation and inventory costs. IEEE Transactions on Automation Science and Engineering 13(4), 1517–1527. https://doi.org/10.1109/TASE.2016.2590823.

Wei, B., Çetinkaya, S., Cline, D.B.H., 2023. Inbound replenishment and outbound dispatch decisions under hybrid shipment consolidation policies: An analytical model and comparison. Transportation Research Part E 175, 103135. https://doi.org/10.1016/j.tre.2023.103135.

Zhang, W., Wu, Y., 2022. Two-dimensional irregular packing problems: A review. ResearchGate. Retrieved March 26, 2025, from https://www.researchgate.net/publication/362605146_Two-dimensional_irregular_packing_problems_A_review.

Zuhanda, M.K., Hartono, S.A.R.S., Hasibuan, S.A.R., Napitupulu, Y.Y., 2024. An exact and metaheuristic optimization framework for solving vehicle routing problems with shipment consolidation using population-based and swarm intelligence. Decision Analytics Journal 13, 100517. https://doi.org/10.1016/j.dajour.2024.100517.