A Hybrid Data-Driven Approach for Optimizing Last-Mile Logistics in an Electrical Products Company Using K-Means Clustering and the Clarke-Wright Savings Algorithm

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ABSTRACT

Managing last-mile delivery presents significant challenges when customer locations are widely dispersed, route demand fluctuates across dispatch days, and planning relies on historical route groupings. This study introduces a hybrid, data-driven decision-support framework designed to enhance last-mile delivery planning for an electrical products company. The baseline system was evaluated using 2025 delivery records and operational indicators, including distance per trip, cost per drop, backload rate, loaded volume, drops per trip, trip duration, and truck utilization. Pareto analysis identified recurring backload categories that impeded delivery completion. The proposed framework integrates K-Means clustering with the Clarke-Wright Savings Algorithm. K-Means assigned 1,573 customer delivery points to five geographically coherent service clusters based on coordinate proximity. Within each cluster, the Clarke-Wright algorithm established preliminary route groups by prioritizing customer pairings with greater distance savings. Route outputs were validated against operational constraints, such as a 4-CBM capacity threshold, route continuity, loop prevention, a practical stop-count range of 17 to 22 drops, and flexible merging rules for low-density groups. The framework produced 79 preliminary route groups, all of which satisfied the 4-CBM capacity constraint, while 69 groups (87.34%) met the practical stop-count range. Simulation-based comparisons demonstrated distance reductions ranging from 37.77% to 77.59% across comparable clusters. A controlled-cost simulation for 4W deliveries indicated that the optimized route structure could reduce estimated distance-related fuel costs and decrease the cost per drop from PHP 132.45 to PHP 114.03 under constant-cost assumptions. These findings support the framework as a practical reference for route planning, pending pilot validation using road-network distance, traffic conditions, unloading time, customer receiving conditions, and actual dispatch records.

Keywords: Last-mile logistics, route optimization, K-Means clustering, Clarke-Wright Savings Algorithm, delivery cost per drop

INTRODUCTION

Last-mile delivery represents a highly operationally sensitive segment of distribution, as it directly links the company to the final customer and requires significant resources in vehicle time, fuel, labor, and route coordination. For distributors of electrical products, this challenge is heightened by diverse customer locations, fluctuating order volumes, customer receiving constraints, backloads, and the necessity to balance truck capacity with daily delivery density. When route planning depends primarily on historical route groupings or dispatcher experience, delivery areas may become fragmented, resulting in trucks traveling extended distances with few deliveries or underutilized loads.

This study examined a single-depot last-mile delivery system serving Metro Manila, Rizal, and adjacent urban areas. Historical delivery data revealed quantifiable issues in cost per drop, variability in route distances, number of drops per trip, frequency of backloads, and overall fleet utilization. These findings indicate that route planning may benefit from a more systematic analytical approach. In operations research, vehicle routing methods facilitate customer sequencing and delivery consolidation, while clustering techniques reduce complexity by grouping geographically related demand points prior to route construction [3], [4], [7], [12].

The objective of this study was to develop and assess a hybrid data-driven framework that integrates K-Means clustering with the Clarke-Wright Savings Algorithm for last-mile route planning. This framework is designed to serve as a planning reference rather than to replace dispatcher expertise. It aims to support route consolidation, capacity assessment, feasibility validation, and ongoing improvement in dispatch decision-making.

Research questions

This study addresses three primary research questions: (1) Which operational and logistical factors most significantly contribute to high cost per drop, frequent backloads, and low fleet utilization in last-mile delivery operations, as identified through Pareto analysis and baseline performance evaluation? (2) In what ways can the integration of K-Means clustering and the Clarke-Wright Savings Algorithm within a data-driven framework optimize delivery route planning and improve last-mile performance? (3) What strategic guidelines can be formulated to assist organizations in achieving delivery efficiency and continuous improvement in last-mile logistics operations, based on the results of clustering and routing optimization?

LITERATURE REVIEW

The vehicle routing problem (VRP) serves as a foundational model for designing efficient delivery routes from a depot to multiple customers [4]. Its capacitated variant, the capacitated vehicle routing problem (CVRP), incorporates vehicle load limits and is particularly relevant to practical delivery planning, as a short route may be infeasible if the assigned volume exceeds truck capacity [7], [12]. The Clarke-Wright Savings Algorithm is a classical constructive heuristic for VRP that estimates the distance saved when two individual depot-customer-depot routes are merged into a single route [3]. Due to its transparency and computational simplicity, this algorithm is valuable in decision-support contexts where planners require clear rationale for customer groupings.

Clustering techniques are frequently employed to simplify routing problems by grouping customers with similar spatial characteristics prior to route sequencing. K-Means clustering partitions observations into groups by minimizing the distance between points and their assigned cluster centroids [6], [8], [9]. In delivery applications, clustering facilitates the creation of service zones that are more interpretable and manageable. Although Euclidean distance is commonly used as a proximity measure in coordinate-based clustering, its results should be validated against road-network distances and operational expertise before implementation.

Research in last-mile logistics emphasizes that operational improvement should not be evaluated solely based on distance. Factors such as delivery cost, customer receiving conditions, unloading time, route accessibility, service reliability, and dispatch feasibility significantly influence actual performance [1], [5], [10]. Accordingly, the present study integrates route compactness with operational validation, considering vehicle capacity, practical stop counts, route continuity, and flexible route merging. This approach enhances the framework's utility as a planning tool rather than limiting it to a mathematical routing solution. Time-window considerations are also relevant in practical routing because delivery feasibility may be affected by customer availability, receiving schedules, and service-time restrictions [2], [11].

METHODOLOGY

Research design and data sources

A quantitative, simulation-based case study design was employed. Historical delivery data from January to December 2025 provided the foundation for baseline performance measurement and route optimization. The dataset comprised delivery points, customer locations, delivery volume, delivery frequency, distance measures, route codes, trip records, cost components, truck type, and backload records. The analytical process involved spreadsheet-based data preparation, coordinate processing, cluster assignment, distance computation, and route-feasibility validation.

The delivery system was modeled as a single-depot operation originating from Lingunan, Valenzuela. Baseline analysis included both 4W and 6W delivery performance for diagnostic comparison. Optimized route validation and simulated cost comparison were focused on the 4W planning benchmark, as route construction was based on a 4-CBM capacity threshold.

Table 1: Research questions, evidence, and assessment approach

Research question	Evidence used	Assessment approach
RQ1	Baseline descriptive statistics, backload rate, cost per drop, truck utilization, and Pareto analysis.	The baseline showed route distance variability, uneven cost performance, low delivery density, utilization gaps, and recurring backload categories. Pareto results showed that the top four backload categories accounted for 87.03% of the recorded issues.
RQ2	K-Means cluster output, Clarke-Wright route groups, feasibility validation, and simulated distance comparison.	The hybrid framework grouped 1,573 points into five service clusters and produced 79 preliminary route groups, all capacity-feasible and mostly within the preferred stop-count range.
RQ3	Route feasibility rules, flexible merging logic, cost simulation, and managerial validation.	The results were translated into planning guidelines covering cluster review, capacity checks, stop-count validation, flexible merging, pilot testing, and regular route-performance monitoring.

Hybrid framework

The framework comprised six steps: data extraction and cleaning, baseline performance measurement, K-Means clustering, Clarke-Wright route construction, feasibility validation, and comparison with baseline performance. K-Means clustering grouped customer points into service zones. Euclidean distance was used to measure coordinate-based proximity using the formula: $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. This approach facilitated both cluster assignment and interpretation of customer proximity.

Following clustering, the Clarke-Wright Savings Algorithm was applied within each cluster. For customer points i and j and depot point 0, the savings value was computed as $S_{ij} = d_{0i} + d_{0j} - d_{ij}$. Customer pairs with higher savings were prioritized for route construction, provided that the merge did not violate capacity constraints, route-end continuity, or loop-prevention rules. The resulting outputs were interpreted as preliminary route groups rather than fixed daily trips, due to daily variability in customer orders.

Table 2: Operational constraints considered in route validation

Constraint	Treatment in the study	Status
Vehicle capacity	Total delivery volume should not exceed 4 CBM for route validation.	Directly considered
Customer location and proximity	Coordinates were used to group nearby customers and calculate route distances.	Directly considered
Savings value	Customer pairings with higher distance savings were prioritized in route construction.	Directly considered
Route continuity	Route-end merging and sequence continuity were checked to avoid disconnected groupings.	Directly considered

Constraint	Treatment in the study	Status
Loop prevention	Customer points were prevented from being assigned in impractical repeated loops.	Directly considered
Practical stop count	Route groups were assessed against the preferred 17-to-22-drop range.	Directly considered
Flexible merging	Low-density route groups were not treated as failed; they were tagged for possible merging.	Directly considered
Traffic, road access, and unloading time	Recognized as implementation factors but not fully modeled in the simulation.	Recognized limitation
Customer receiving conditions	Recognized as an important cause of backload and as a future data requirement.	Recognized limitation

RESULTS

Baseline delivery performance

The baseline analysis identified quantifiable delivery inefficiencies within the existing system. The estimated cost per drop was PHP 139.23, with an average route distance of 82.63 km per trip and a backload rate of 7.36%. The average delivery density was 15.49 drops per trip, which is below the practical range of 17 to 22 drops per trip applied in subsequent route feasibility assessments. A summary of the baseline results is presented in Table 3.

Table 3: Baseline delivery performance indicators for 2025

Baseline indicator	Result	Interpretation
Total trips	2,481 trips	Total dispatched delivery trips during the study period
Total customer drops	38,023 drops	Total completed customer delivery stops
Total delivery receipts	76,914 DRs	Total delivery documents processed
Backloaded delivery receipts	5,659 DRs	Delivery receipts not completed as originally planned
Backload rate	7.36%	Indicates delivery completion issue
Average route distance	82.63 km/trip	Shows route exposure and travel-distance requirement
Average loaded volume	4.59 CBM	Shows average load assigned per trip
Average drops per trip	15.49 drops	Below the practical target range of 17 to 22 drops
Average trip duration	9 hours, 24 minutes	Shows delivery execution time exposure
Estimated cost per drop	PHP 139.23/drop	Baseline estimated delivery cost per customer drop

Pareto analysis was employed to prioritize recurring backload categories. The top four categories represented 87.03% of all recorded backload issues. Customer receiving issues and order cancellations constituted the largest categories. These categories were not automatically classified as routing problems, as they may involve factors such as customer availability, order modifications, schedule constraints, or business decisions unrelated to route design. The delivery and transport category was most directly associated with delivery execution and route planning. This distinction is significant because the optimization framework focuses on route structure and dispatch feasibility, whereas other backload categories necessitate additional reason coding and process controls.

Table 4: Pareto summary of major backload issues

Backload category	Frequency	Share	Cumulative share	Interpretation
Customer receiving issue	1,618	28.59%	28.59%	Highest recurring backload category; requires more detailed reason coding.
Order cancellation	1,612	28.49%	57.08%	Major source of failed delivery completion; not automatically attributable to routing.
Booking and encoding error	850	15.02%	72.10%	Indicates coordination or system-documentation issue.
Delivery and transport issue	845	14.93%	87.03%	The category most directly connected to delivery execution and route planning.
Documentation and payment issue	506	8.94%	95.97%	Requires document and collection process controls.
Warehouse and inventory issue	228	4.03%	100.00%	Requires warehouse and stock-readiness controls.

K-Means clustering output

K-Means clustering was applied to 1,573 customer delivery points, resulting in five service clusters. The interpretation of the five-cluster solution prioritized geographic compactness and practical dispatch review, rather than relying solely on mathematical fit. This methodology facilitated alignment of the clustering output with established delivery areas and managerial route familiarity. Table 5 presents the resulting service clusters and the number of preliminary route groups constructed within each cluster.

Table 5: Optimized service cluster mapping

Cluster	Mapped route area	Service interpretation	Preliminary route groups
Cluster 1	RL	Rizal Lower service area	13
Cluster 2	CAMANAVA and QCU	North Metro Manila and Quezon City Upper	17
Cluster 3	RU	Rizal Upper service area	14
Cluster 4	LPM	Las Pinas, Paranaque, and Muntinlupa	9
Cluster 5	PMS, PMT, QCL, SAM, STC, and TON	Dense Metro Manila and nearby routes	26
Total	All service areas	Optimized preliminary route groups	79

Clarke-Wright route grouping and feasibility validation

The Clarke-Wright Savings Algorithm produced 79 preliminary route groups across five service clusters. All route groups met the 4-CBM capacity threshold, demonstrating effective control of delivery volume allocation. Regarding delivery density, 69 route groups, representing 87.34%, fell within the practical range of 17 to 22 drops. The remaining 10 route groups were designated as flexible merging candidates, rather than failed outputs, due to potential variations in dispatch demand, truck availability, route compatibility, and customer receiving conditions.

Table 6: Capacity, stop-count, and flexible merging summary

Cluster	Route groups	Within 4-CBM capacity	Within 17-22 drops	Flexible merging candidates	Interpretation
Cluster 1	13	13	13	0	All route groups satisfied capacity and stop-count requirements.
Cluster 2	17	17	14	3	Three short route groups may require merging.
Cluster 3	14	14	12	2	Two short route groups may require consolidation.
Cluster 4	9	9	7	2	Two route groups may serve as supplementary segments.
Cluster 5	26	26	23	3	Three route groups may require merging to avoid underutilization.
Total	79	79	69	10	100.00% capacity-feasible; 87.34% within the practical stop-count range.

Baseline versus optimized distance comparison

Baseline and optimized route structures were compared at the cluster level. Because the optimized outputs were generated through simulation, the comparison reflects planning potential rather than actual post-implementation savings. Among comparable clusters, the optimized route structure achieved distance reductions between 37.77% and 77.59%. These findings suggest that clustering, followed by savings-based route construction, produces more compact preliminary route groups than the existing baseline mapping.

Table 7: Baseline versus optimized average distance comparison by cluster

Comparable cluster	Baseline average distance (km)	Optimized average distance (km)	Distance reduction
Cluster 1 - RL	110.79	36.70	66.87%
Cluster 2 - CAMANAVA/QCU	69.92	15.67	77.59%
Cluster 3 - RU	149.35	66.07	55.76%
Cluster 4 - LPM	116.63	72.58	37.77%
Cluster 5 - PMS/PMT/QCL/SAM/STC/TON	72.26	30.28	58.09%

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Simulated cost implication for 4W deliveries

To address the requirement for a before-and-after key performance indicator (KPI) comparison, the study estimated simulated cost implications for four-wheeler (4W) deliveries. The analysis maintained consistent assumptions for fuel price, fuel yield, driver allowance, helper allowance, toll assignment, and customer drop count. Only the distance-related fuel cost was recalculated based on the optimized distance structure. This conservative methodology prevented the overstatement of savings, as labor and toll costs were not reduced unless actual implementation demonstrated lower trip requirements or altered dispatch assignments.

Table 8: Estimated optimized cost computation basis

Cost component	Baseline cost basis	Optimized cost basis	Treatment
Fuel cost	Based on baseline distance, fuel yield, and fuel price.	Recomputed using optimized distance.	Changed
Fuel price	PHP 58.00 per liter.	PHP 58.00 per liter.	Held constant
Fuel yield	Baseline 4W fuel-yield assumption.	Same 4W fuel-yield assumption.	Held constant
Driver allowance	Baseline driver allowance per trip.	Same trip allowance assumption for comparable dispatch planning.	Held constant
Helper allowance	Baseline helper allowance per trip.	Same helper allowance assumption for comparable dispatch planning.	Held constant
Toll cost	Based on baseline route toll assignment.	Same applicable toll assumption for comparable route/cluster.	Held constant
Distance	Historical route distance.	Optimized coordinate-based route distance.	Changed
Cost per drop	Total estimated cost divided by total drops.	Simulated optimized cost divided by drops served.	Compared

Applying the cluster-level distance reduction rates to the 2025 4W baseline distance, the simulated optimized total 4W distance is estimated at 48,728.86 km, compared to the baseline value of 125,344.00 km. Based on the constant-cost assumptions presented in Table 8, the estimated cost per drop decreased from PHP 132.45 to PHP 114.03. These findings represent simulated planning estimates rather than actual realized savings.

Table 9: Baseline and simulated optimized 4W cost implication

KPI or cost component	Baseline 4W	Simulated optimized 4W	Estimated improvement	Percentage effect
4W total distance	125,344.00 km	48,728.86 km	76,615.14 km lower	61.12% lower
Estimated fuel cost	PHP 694,928.74	PHP 286,060.11	PHP 408,868.63 lower	58.84% lower
Driver allowance	PHP 1,229,400.00	PHP 1,229,400.00	No change	Held constant
Helper allowance	PHP 994,448.00	PHP 994,448.00	No change	Held constant
Toll cost	PHP 21,924.00	PHP 21,924.00	No change	Held constant

KPI or cost component	Baseline 4W	Simulated optimized 4W	Estimated improvement	Percentage effect
Total estimated 4W cost	PHP 2,940,700.74	PHP 2,531,832.11	PHP 408,868.63 lower	13.90% lower
Estimated cost per drop	PHP 132.45/drop	PHP 114.03/drop	PHP 18.42/drop lower	13.91% lower

DISCUSSION

The findings address the first research question by demonstrating that last-mile delivery inefficiency resulted from multiple contributing factors. High cost per drop was associated with distance variability, uneven route density, and differences in truck utilization. Frequent backloads were identified through Pareto analysis; however, the analysis also indicated that several high-frequency backload categories were not exclusively related to routing. Consequently, the study does not attribute customer receiving issues or cancellations solely to routing. Instead, these are considered significant delivery-completion challenges that necessitate more detailed operational reason coding and enhanced coordination controls.

The second research question was addressed by integrating K-Means clustering with Clarke-Wright route grouping. K-Means clustering organized geographically dispersed customers into five distinct service zones, and the Clarke-Wright Savings Algorithm generated preliminary route groups within these zones. This two-stage approach reduced route-planning complexity and resulted in routes that were more compact, capacity-feasible, and operationally manageable.

The third research question was addressed by converting the results into actionable planning guidelines. The findings support a structured process where planners begin with cluster-based zones, construct or select compatible route groups, verify CBM capacity, assess stop-count density, consolidate low-density route groups when appropriate, and monitor backload reasons during implementation. These guidelines are summarized in Table 10.

Table 10: Strategic delivery planning guidelines developed from the study

Guideline	Recommended action	Expected planning value
Cluster-based dispatch planning	Use the five service clusters as planning zones before final daily dispatch.	Reduces route fragmentation and improves route ownership.
Capacity validation before dispatch	Check each proposed route against CBM capacity before assigning a truck.	Prevents infeasible route loading.
Stop-count review	Review whether route groups fall within the 17-to-22-drop practical range.	Improves delivery density and cost per drop.
Flexible route merging	Merge nearby low-density route groups when volume and route continuity permit.	Helps avoid underloaded dispatches.
Backload reason coding	Improve the detail of backload records, especially customer receiving issues and cancellations.	Supports root-cause action beyond routing.
Pilot implementation	Test optimized route groups against actual road-network distance, traffic, unloading time, and receiving conditions.	Validates actual operational savings before full rollout.

Managerial and industry validation

Managerial and industry validation was conducted to assess the practical relevance of the proposed framework. The validation did not assert realized cost savings but evaluated whether the clustering output, route grouping logic, capacity thresholds, stop-count practicality, flexible merging, and dispatch planning utility were comprehensible and applicable to logistics decision-making. This process reinforced the interpretation of the framework as a decision-support tool for route planning, rather than as a fully implemented routing software.

Limitations And Future Research

Several limitations must be acknowledged when interpreting these results. First, the optimized distances were derived from simulations based on coordinates, without fully incorporating actual road-network distances, traffic conditions, road restrictions, or travel times. Second, customer receiving issues, cancellations, documentation delays, and warehouse readiness were categorized using Pareto analysis but were not further decomposed into specific sub-reasons. Third, the cost optimization comparison was limited to four-wheeler (4W) deliveries due to the use of a 4-cubic meter (CBM) planning threshold in route validation. Fourth, the route groups served as preliminary planning references and have not yet been implemented as actual dispatch routes across multiple delivery cycles.

Future research should validate the optimized route groups through pilot implementation, incorporating actual road-network distances, time-window constraints, unloading durations, customer receiving schedules, and daily active order patterns. Additionally, further studies could compare the hybrid K-Means and Clarke-Wright framework with alternative routing methodologies, such as geographic information system (GIS)-based routing, metaheuristic algorithms, and dashboard-supported dynamic dispatch systems.

CONCLUSION

A hybrid data-driven framework was developed to enhance last-mile delivery route planning for an electrical products company. Baseline analysis identified inefficiencies in cost per drop, distance variability, backload occurrence, delivery density, and truck utilization. K-Means clustering was used to group 1,573 delivery points into five service clusters, while the Clarke-Wright Savings Algorithm produced 79 preliminary route groups. All route groups met the 4-CBM capacity constraint, and 87.34% fell within the preferred range of 17 to 22 drops. Simulation-based comparisons demonstrated improved route compactness, with distance reductions observed across all comparable clusters. The simulated four-wheeler (4W) cost analysis indicated that distance-related fuel savings could reduce cost per drop under controlled assumptions. The primary contribution of this study is a practical decision-support framework that integrates data cleaning, baseline key performance indicator (KPI) review, geographic clustering, savings-based route construction, and operational feasibility validation. Verification of actual savings through pilot implementation is recommended prior to full operational adoption.

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Ethical Considerations

This study used historical operational delivery records and framework validation information for academic and publication purposes. No human-subject experimentation, clinical intervention, animal research, or collection of personally identifiable customer information was conducted. Formal ethical approval was not required based on the nature of the study and the thesis requirements; nevertheless, company data were treated with confidentiality and reported only in aggregated form.

Conflict Of Interest

The authors declare no conflict of interest.

Data Availability

The data used in this study were obtained from company delivery records and are not publicly available due to confidentiality restrictions. Aggregated results are presented in the manuscript.

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