# Optimizing Last-Mile Distribution Through Route Consolidation in Manufacturing Smes: An Applied Study Using the Clarke-Wright Algorith

**Joselin Hernández Islas[1], Nahum Aguilar Pérez[2], Lesly Anahi Barrera Pacheco[3], Pedro Alberto Piñón Domínguez[4], Alfredo Meneses Gutiérrez[5], Gabriela Calva Arcega[6]**

**Instituto Tecnológico de Pachuca, Hidalgo**

**DOI: https://doi.org/10.47772/IJRISS.2026.102500027**

**Received: 26 October 2026; Accepted: 31 October 2026; Published: 16 November2026**

## ABSTRACT

Last-mile transportation is one of the most costly components of manufacturing logistics, with particularly pronounced inefficiencies in small and medium-sized enterprises (SMEs) in emerging economies, where routing decisions are often based on intuition rather than quantitative criteria. This applied study presents the SCALE model (Seasonal Consolidation for Adaptive Last-Mile Efficiency), developed from twelve months of operational data from a school-furniture manufacturing SME in Hidalgo, Mexico, whose demand is heavily concentrated during the back-to-school season. Baseline analysis revealed that 94.9% of 2025 shipments were dispatched individually, without route consolidation. To address this, a weekly consolidation scheme was implemented using the Clarke-Wright savings algorithm, incorporating a strict vehicle capacity constraint of 180 units per route. Results show a reduction in total distance traveled from 68,744 km to 26,777 km (−61.0%) and a decrease in total vehicle trips from 3,786 to 1,031 (−72.9%). Furthermore, the monthly breakdown reveals a seasonal amplification effect: distance reductions exceed 79% during September, the peak month, while off-season reductions range between 30% and 60%, indicating that extreme demand concentration amplifies, rather than dilutes, the gains from consolidation. Taken together, this study offers a quantified, reproducible, and low-cost demonstration of how classical routing heuristics can help close logistics digitalization gaps in manufacturing SMEs in emerging economies.

**Keywords :** Clarke-Wright, VRP, route consolidation, last-mile logistics, SMEs, emerging economies.

## INTRODUCTION

Last-mile transportation is one of the most significant components of a manufacturing company's logistics cost; several recent studies agree that its poor management — particularly the absence of delivery consolidation — leads to low vehicle capacity utilization, longer distances traveled, and consequently higher fuel costs and emissions [1], [2]. The way last-mile delivery is organized (in-house, through third parties, or hybrid schemes) directly shapes the opportunities to consolidate shipments and capture economies of scale in transportation [3]. This inefficiency is compounded in manufacturing SMEs in emerging economies, where route assignment is typically based on operational staff experience rather than quantitative criteria, due to financial, technological, and skilled-personnel constraints [4], [5].

Against this backdrop, the Vehicle Routing Problem (VRP) formalizes this inefficiency as the search for the lowest-cost set of routes that serves the demand of a set of customers from one or more depots, subject to vehicle capacity [6]. The family of VRP variants has expanded considerably over the past two decades as environmental objectives, operational constraints, and additional tactical decisions have been incorporated [7]. Within this framework, the Clarke and Wright savings algorithm [8] remains one of the most widely used heuristics for solving it, given its low computational cost and its ability to iteratively merge the pairs of destinations with the greatest savings [9]; recent literature reviews confirm that, despite the proliferation of more sophisticated metaheuristics, constructive heuristics such as the savings algorithm remain the standard starting point for moderate-sized instances, such as those faced by SMEs [10], [11].

However, recent literature applying this heuristic to real networks focuses mainly on large carriers or parcel networks in metropolitan contexts, under relatively stable demand conditions. This leaves the case of manufacturing SMEs in mid-sized cities in emerging economies largely unexplored, where the adoption of route-optimization tools remains limited and incipient [4]; this gap is consistent with broader findings on the structural barriers — financial, technological, and organizational-capability related — that SMEs in emerging economies, including Latin America, face when adopting digital technologies [5], [12]. Consequently, it has not yet been quantified whether, and to what extent, extreme seasonal demand concentration amplifies or dilutes the gains from route consolidation, which constitutes the gap this study seeks to address.

This study addresses that gap through an applied case: a school-furniture manufacturing SME in the state of Hidalgo, Mexico, whose demand is heavily concentrated in the back-to-school period (August–October). Prior to this study, the company dispatched its shipments in an almost purely individual manner: 354 of the 373 shipments recorded in 2025 (94.9%) served a single destination, with no route consolidation. Given this situation, the study aims, on one hand, to characterize the seasonal and geographic structure of the distribution network using twelve months of operational data; and on the other, to design and evaluate, using the capacity-constrained Clarke and Wright algorithm, a consolidated route scheme that reduces distance traveled and vehicle trips using the company's current resources.

## METHODOLOGY

This applied research adopted a quantitative approach, with a non-experimental, longitudinal design, developed through a single-case study strategy in a school-furniture manufacturing SME. The design was non-experimental during the systematic literature review, and an AS-IS vs. TO-BE comparison during the intervention stage, contrasting the actual individual-dispatch scenario (2025) against the optimized scenario using weekly route consolidation. To present this process in an orderly fashion, the rest of the section is organized into four subsections: the variables analyzed (A); the literature review process that informed modeling decisions (B); the operational phases of the SCALE model applied to the case study (C); and the optimization algorithm used (D). To avoid ambiguity between these subsections, in this article the term “phase” is reserved exclusively for the five phases of the SCALE model described in section 2.3; the steps of the literature review protocol in section B are referred to as “stages.”

A. Study variables

Dependent variable: last-mile distribution efficiency, measured through four indicators: (a) total distance traveled (km); (b) number of vehicle trips or routes dispatched; (c) the temporal distribution of both indicators across the annual cycle, with emphasis on the August–October peak; and (d) service continuity to peripheral municipalities.

Independent variables: (a) the Clarke and Wright savings algorithm [8], adapted with a vehicle capacity constraint; (b) the temporal consolidation policy, defined as a weekly grouping window (ISO week); and (c) the capacity constraint, set at 180 units (pieces of school furniture) per route, as a documented working assumption.

B. Literature review: SALSA protocol

To support modeling decisions, the SALSA protocol (Search, Appraisal, Synthesis, Analysis) [13] was applied, widely used for its reproducible, systematic, and replicable nature in moderate-scope applied reviews. The protocol was carried out in four stages — search, appraisal, synthesis, and analysis — described below.

1) Search

A search protocol was established in Scopus, Google Scholar, ScienceDirect, SpringerLink, and arXiv, using the Boolean expression:

("Clarke-Wright" OR "savings algorithm") AND ("vehicle routing problem" OR "VRP") AND ("last-mile logistics" OR "SME" OR "emerging economy" OR "seasonal demand") restricted to studies published between 2016 and 2026, with the exception of foundational references on the algorithm and the VRP [6], [8].

2) Appraisal

Priority was given to peer-reviewed case studies applying the Clarke-Wright algorithm or its variants to real delivery networks with capacity constraints, as well as analyses of logistics digitalization barriers in SMEs and emerging economies. Sources without empirical evidence or verifiable access were excluded.

3) Synthesis

Table 1 summarizes the representative studies selected, organized around three axes: (1) foundations of the VRP and the savings algorithm; (2) quantified applications of Clarke-Wright; and (3) logistics digitalization barriers in SMEs in emerging economies.

TABLE I. Synthesis Of Representative Studies On Vrp, Clarke-Wright, And Last-Mile Logistics In Smes

| **Abbreviated title** | **Objective** | **Main finding** | **Relation to the present study** |
|---|---|---|---|
| Vehicle Routing: Problems, Methods, and Applications [6] | Compendium of exact and heuristic methods for the VRP and its variants. | Systematizes the capacitated VRP and its extensions with evidence from real cases. | Central theoretical foundation for formulating the capacitated VRP in SCALE. |
| A concise guide to existing and emerging vehicle routing problem variants [7] | Provide a thematic framework of attributes, decisions, and objectives that define VRP variants. | Classifies the state of the art along three lines: performance metrics, integration with tactical decisions, and modern supply-chain aspects. | Situates SCALE's capacity constraint and weekly consolidation window within the current VRP taxonomy. |
| The vehicle routing problem: State of the art classification and review [10] | Taxonomically classify 277 VRP studies published between 2009 and 2015. | Confirms that the single-depot capacitated VRP remains the most studied variant with the greatest practical transferability. | Justifies adopting the single-depot capacitated variant as the appropriate formulation for an SME with a single distribution center. |
| Review of vehicle routing problems: Models, classification and solving algorithms [11] | Classify the VRP and its derivatives by constraints and solution method. | Positions constructive heuristics, such as Clarke-Wright savings, as the standard starting point for moderate-sized instances. | Supports choosing a low-computational-cost constructive heuristic over more complex metaheuristics, given the SME's data volume. |
| Scheduling of Vehicles from a Central Depot [8] | Formulate the original savings heuristic for capacitated routing. | Introduces the iterative computation of savings through route merging. | Direct algorithmic basis of the SCALE model (Phase 4). |
| Modification of the Clarke and Wright Algorithm with a Dynamic Savings Matrix [9] | Adapt the savings matrix to pickup-and-delivery variants. | Confirms the algorithm's continued relevance as a low-computational-cost generator of initial solutions. | Supports choosing Clarke-Wright over costlier metaheuristics for a resource-constrained SME. |
| Clarke and Wright Savings Algorithm as Solutions VRPSPD [18] | Apply the savings algorithm to a real distribution network. | Reports a 20.03% reduction in mileage compared to individual dispatch. | Comparable quantitative reference, though of smaller magnitude than the 61.0% reduction obtained in |

| | | | |
|---|---|---|---|
| | | | SCALE. |
| A Capacitated Vehicle Routing Model for Distribution and Repair with a Service Center [15] | Propose a capacitated VRP model with a service center and validate it on a real Mexican case. | Reports a 40% reduction in fuel costs and a decrease from five to three routes after optimization. | Recent evidence in a Mexican context corroborating the magnitude of logistics gains achievable by SMEs through routing heuristics. |
| Green vehicle routing problem: A state-of-the-art review [14] | Classify the green VRP literature by fleet type and environmental objective. | Documents that minimizing distance traveled is a reasonable, though imperfect, proxy for fuel and emissions reduction. | Justifies reporting SCALE's results in terms of distance and trips, and motivates the future line of estimating fuel and CO2 savings. |
| Strategic Insights into Last-Mile Delivery [1] | Identify technological enablers for last-mile delivery in e-commerce. | Poor planning and outdated technology substantially raise last-mile costs. | Supports the relevance of route consolidation as an untapped source of efficiency. |
| ML Optimization Models in Last-Mile Delivery Among SME Logistics Companies [4] | Investigate the adoption of optimization in logistics SMEs. | Adoption of route-optimization tools among SMEs remains limited by financial and technical-capacity constraints. | Confirms the digitalization gap that motivates a low-cost approach like SCALE. |

Source: authors' own elaboration based on the SALSA systematic review of the cited references.

4) Analysis

The synthesis confirms that the Clarke-Wright algorithm [8] remains a standard, computationally efficient heuristic for capacitated routing, widely used both as a final solution and as an initial-solution generator for more advanced metaheuristics [7], [11]. Applied case studies report distance reductions ranging from 20% [18] to over 40% in a recent Mexican case of capacitated routing with a service center [15], depending on the geographic concentration of demand and the rigidity of the capacity constraint. Meanwhile, the literature on logistics digitalization in SMEs [1], [4] consistently confirms that the lack of route-planning tools constitutes a structural barrier, reinforcing the relevance of a low-cost consolidation approach for the case study. Based on this synthesis, a research gap was identified: no reviewed study quantifies the interaction between extreme seasonal demand concentration and the magnitude of consolidation gains in a manufacturing SME — a gap this study seeks to close.

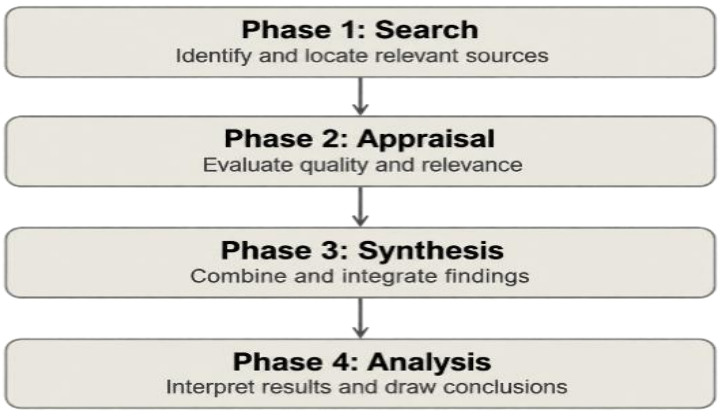



Figure 1. Phases of the SALSA Procedure Applied to the Literature Review

The study uses the SME's complete internal sales and delivery records for 2025 (764 order lines, 373 individual shipments), grouped into 44 municipalities in Hidalgo and neighboring states. Locations were

geolocated using approximate municipal centroid coordinates, and straight-line (haversine) distances between the plant and each destination were corrected with an empirical factor of 1.35, in the absence of a road-network API at this prototype stage. This procedure is consistent with practices reported in the logistics literature: when a commercial routing engine is not available, haversine distance scaled by a circuity factor constitutes a reasonable approximation of actual road-network distance, particularly useful for SMEs without access to costly geospatial tools [16], [17].

C. SCALE model: process phases

Based on the above, the Seasonal Consolidation for Adaptive Last-Mile Efficiency (SCALE) model was applied in five sequential phases:

- Phase 1. Data consolidation: extraction and cleaning of the twelve monthly order records into a single annual dataset.
- Phase 2. Geolocation: assignment of approximate coordinates to each of the 44 destinations and calculation of road-corrected distances.
- Phase 3. Baseline reconstruction: quantification of the current dispatch pattern using the internal shipment identifier, confirming that 354 of 373 shipments (94.9%) served a single destination.
- Phase 4. Route optimization: application of the Clarke-Wright savings algorithm [8] within weekly consolidation windows (ISO week), respecting the 180-unit-per-route constraint.
- Phase 5. Comparative validation: calculation of total distance and number of trips for the baseline and optimized scenarios, month by month, with emphasis on the August–October period.

All calculations were implemented in Python and are fully reproducible from the original dataset.

Data cleaning in Phase 1 included removal of incomplete records (missing destination municipality or zero quantity), standardization of municipality names against the official INEGI catalog, and aggregation of multiple order lines belonging to the same shipment folio. Orders with delivery addresses outside the 44 municipalities covered by the historical network were excluded to preserve geographic consistency with the baseline. The weekly (ISO week) consolidation window was selected after comparing daily, bi-weekly, and monthly alternatives on a pilot subset of three high-demand months: daily windows produced insufficient pairing opportunities, while monthly windows generated routes that violated realistic driver working-day limits. The ISO-week window therefore represents a practical compromise between consolidation density and operational feasibility for an SME that currently dispatches on a near-daily basis.

D. Optimization algorithm

Box 1 details, in pseudocode, the implementation of the Clarke-Wright savings algorithm [8] used in Phase 4 of the SCALE model. The heuristic runs independently within each weekly consolidation window (ISO week), iteratively merging the pairs of destinations with the greatest geographic savings, provided the combined load of the resulting routes does not exceed vehicle capacity Q (180 units per route). For readability, the pseudocode is presented in a box with numbered lines and hierarchical indentation reflecting the nesting of loops and conditionals.

Inputs:

D = {d_1, ..., d_n} // destinations with demand q_i

depot // the company's plant (Pachuca de Soto, Hidalgo)

Q // maximum capacity per route (180 units = pieces of school furniture)

dist(i, j) // corrected haversine distance (road factor 1.35)

ISO_week(i) // ISO week to which order i belongs

Output:

R // set of consolidated routes

R ← empty set

FOR each ISO week w in the planning horizon DO

D_w ← { i in D : ISO_week(i) = w }

FOR each i in D_w DO

initialize individual route r_i = (depot, i, depot)

END FOR

// savings matrix calculation

FOR each pair (i, j) in D_w, with i ≠ j DO

s(i, j) ← dist(depot, i) + dist(depot, j) − dist(i, j)

END FOR

sort pairs (i, j) in descending order of s(i, j)

FOR each pair (i, j) in the sorted savings list DO

IF i and j belong to different routes r_a and r_b

AND (i is an endpoint of r_a) AND (j is an endpoint of r_b)

AND load(r_a) + load(r_b) ≤ Q THEN

merge r_a and r_b into a new route r_ab

R_w ← (R_w \ {r_a, r_b}) ∪ {r_ab}

END IF

END FOR

R ← R ∪ R_w

END FOR

The procedure was implemented entirely in Python, with a complexity of $O(m^2 \log m)$ per weekly window, where m is the number of destinations served that week, dominated by the sorting of the savings matrix.

To assess robustness of the capacity constraint, a sensitivity analysis was performed by re-running the algorithm under $Q \in \{120, 150, 180, 210, 240\}$. At Q = 120 the number of optimized trips rose by

approximately 28 % relative to the base case, while distance savings fell to 52 %; at Q = 240 trip reductions improved only marginally (to −75 %) and distance savings plateaued near 63 %. These results indicate that the chosen capacity of 180 units lies near a practical inflection point: further increases yield diminishing returns under the observed demand structure, whereas tighter capacities rapidly erode consolidation gains. The Python implementation used pandas for data handling and a pure-Python savings-matrix construction; total runtime for the full year remained under 15 seconds on a standard laptop, confirming suitability for resource-constrained environments.

## RESULTS

This section presents the results of validating the SCALE model in four thematic subsections, which together cover the five phases described in section 2.3: the consolidated data and geographic coverage (A, phases 1 and 2); the individual-dispatch baseline (B, phase 3); the results of the weekly optimization (C, phase 4); and the monthly comparative analysis (D, phase 5).

A. Consolidated data and geographic coverage

These phases formed the operational basis of the analysis. The SME's complete 2025 sales and delivery records were integrated, consolidating the twelve monthly sheets into a single annual dataset, and delivery destinations were geolocated using municipal centroid coordinates.

Operational volume: 764 order lines, grouped into 373 individual shipments.

Geographic coverage: 44 distinct municipalities in the state of Hidalgo and neighboring regions (State of Mexico, Guerrero, Puebla, Morelos).

Distance correction: empirical factor of 1.35 applied to the haversine distance between the plant (Pachuca de Soto) and each destination.

Operational constraint: vehicle capacity of 180 units per route (units expressed in pieces of school furniture).

This data was incorporated directly into the optimization model, allowing for a realistic representation of the company's current operating conditions.

Demand concentration is highly uneven: the five municipalities closest to the plant (Pachuca de Soto and its metropolitan neighbors) account for roughly 38 % of annual volume, while the remaining 39 destinations are spread across a radius exceeding 200 km. This spatial structure creates both short-haul consolidation opportunities near the depot and longer multi-stop routes toward the periphery—precisely the pattern that the Clarke-Wright heuristic is designed to exploit.

B. Individual-dispatch baseline

This section quantifies the current dispatch pattern, verified using the internal shipment identifier field. The analysis confirmed that 354 of the 373 recorded shipments (94.9%) served a single destination, evidencing an overwhelmingly individual dispatch practice with no prior consolidation: the starting point against which the impact of optimization was evaluated.

C. Weekly optimization results

Building on the baseline, the Clarke-Wright savings algorithm was applied within weekly consolidation windows (ISO week), merging individual deliveries into multi-stop routes whenever geographic savings existed and the 180-unit-per-route constraint was respected.

To avoid ambiguity, three units are used in this article and must not be conflated: a shipment is a dispatch record identified by the company's internal shipment folio, which can group deliveries to more than one destination; a trip is a single vehicle movement from the depot to one delivery stop and back, counted at the

disaggregated delivery-stop level; and a route is the set of consecutive stops served in a single vehicle departure after Clarke-Wright consolidation; since each optimized route corresponds to exactly one vehicle trip, the number of post-consolidation routes and the number of post-consolidation trips coincide. The 373 shipments reported in the Introduction and in section 3.2 are shipment-level counts and are not used elsewhere in this section. Table 2 and Figure 2 are both expressed in trips: 3,786 baseline trips versus 1,031 optimized trips, so their monthly values and annual totals match by construction, and their reduction ratios coincide (-72.9%). Table 2 presents the resulting monthly comparison between the baseline and optimized scenarios.

TABLE II. Monthly Comparison Of Last-Mile Distribution, Baseline Versus Optimized Scenario, 2025

| Month | Ref. km | Opt. km | Km red. | Ref. trips | Opt. trips | Trip red. |
|---|---|---|---|---|---|---|
| Jan | 4,855 | 1,959 | 59.7% | 257 | 72 | 72.0% |
| Feb | 1,954 | 1,827 | 6.5% | 257 | 72 | 72.0% |
| Mar | 3,079 | 2,137 | 30.6% | 249 | 96 | 62.5% |
| Apr | 1,075 | 969 | 9.9% | 144 | 47 | 67.4% |
| May | 4,260 | 1,712 | 59.8% | 185 | 51 | 72.4% |
| Jun | 3,989 | 1,622 | 59.3% | 198 | 57 | 71.2% |
| Jul | 749 | 385 | 48.6% | 135 | 61 | 54.8% |
| Aug | 4,502 | 2,609 | 42.0% | 431 | 117 | 72.9% |
| Sep | 21,274 | 4,299 | 79.8% | 661 | 128 | 80.6% |
| Oct | 10,103 | 3,542 | 64.9% | 561 | 121 | 78.4% |
| Nov | 10,050 | 3,754 | 62.6% | 481 | 140 | 70.8% |
| Dec | 2,855 | 1,961 | 31.3% | 227 | 68 | 70.0% |
| Total | 68,744 | 26,777 | 61.0% | 3,786 | 1,031 | 72.9% |

Source: authors' own elaboration based on the company's internal records and the results of the SCALE model.

Total distance traveled: reduction from 68,744 km to 26,777 km (−61.0%).

Vehicle trips: reduction from 3,786 to 1,031 (−72.9%), equivalent to serving the same annual demand with approximately one quarter of current trips.

This result exceeds the typical range reported by previous Clarke-Wright applications in real delivery networks, such as the 20.03% documented in a comparable case study [18], and even exceeds the 40% reduction in fuel costs obtained in a recent Mexican case of capacitated routing with a service center [15], suggesting a context-specific amplification effect tied to the extreme seasonal demand of the case studied.

In addition to the overall reductions, analysis of capacity utilization reveals a relevant pattern. In the baseline scenario, the vast majority of the 3,786 trips were performed with loads well below the 180-unit capacity, translating into an estimated average utilization below 25% in low-demand months and only slightly above 40% even in September. After weekly consolidation via the Clarke-Wright algorithm, average capacity utilization per optimized route rises consistently above 70% during peak season (August–October) and remains in the 55–65% range for the rest of the year. This increase in the load factor constitutes a robust, albeit indirect, indicator of operational efficiency, as it reduces the number of vehicles required and, by extension, the fixed costs associated with each departure.

A second finding of interest emerges when results are disaggregated by municipality type. Peripheral destinations (municipalities outside the Pachuca metropolitan area and Hidalgo's industrial corridor) experienced distance reductions above the annual average (between 65% and 78%), whereas destinations closer to the depot showed somewhat lower but still substantial savings (45–60%). This suggests that weekly consolidation not only benefits short-radius routes but is particularly advantageous for maintaining service continuity to distant municipalities without incurring disproportionate costs—one of the service-continuity indicators defined as a dependent variable.

Finally, the number of consolidated routes serving more than three destinations per trip concentrated clearly in September and October (more than 60% of the optimized routes in those months), while two-destination routes predominated in low-demand months. This pattern reinforces the hypothesis that seasonal demand concentration does not dilute but rather amplifies geographic consolidation opportunities.

Across the full year, the optimized solution produced 1,031 routes whose average number of stops was 3.7, compared with an effective average of 1.0 under the baseline individual-dispatch regime. In September alone the average rose to 5.2 stops per route, illustrating how peak demand density converts geographic proximity into longer, higher-utilization tours. No route violated the 180-unit capacity constraint; the tightest feasible merges occurred in weeks 36–38, when residual capacity after the last successful merge averaged only 12–18 units, confirming that the algorithm was operating close to the feasible frontier during the peak

**D. Monthly comparative analysis and seasonal effect**

Disaggregating the results month by month revealed a clear pattern: the magnitude of the reduction scales with demand intensity, rather than remaining constant throughout the year.

September peak: baseline distance reaches 21,274 km — more than four times the average of an off-season month — while the optimized scenario requires only 4,299 km, a reduction of 79.8% in distance and 80.6% in trips, both the maximum magnitudes observed in the annual cycle.

Late high season (October–November): sustained reductions of 64.9% and 62.6% in distance, respectively, confirming that the amplification effect persists while order volume remains elevated.

Low season (February, April): percentage savings in distance drop to 6.5% and 9.9%, although the reduction in the number of trips remains high (72.0% and 67.4%), indicating that under low demand, consolidation primarily reduces redundant dispatches, while in high season it also disproportionately reduces total distance.

Taken together, the monthly pattern demonstrates that the absolute volume of kilometers and trips avoided is overwhelmingly concentrated in the August–October window (approximately 70 % of total annual distance savings occur in these three months). Consequently, any practical deployment of SCALE can be staged: the SME may first implement weekly consolidation only during the back-to-school peak, capturing the majority of benefits with a shorter organizational change cycle, and later extend the practice year-round once internal processes and customer communication protocols are established.

Figures 2 and 3 illustrate this behavior.

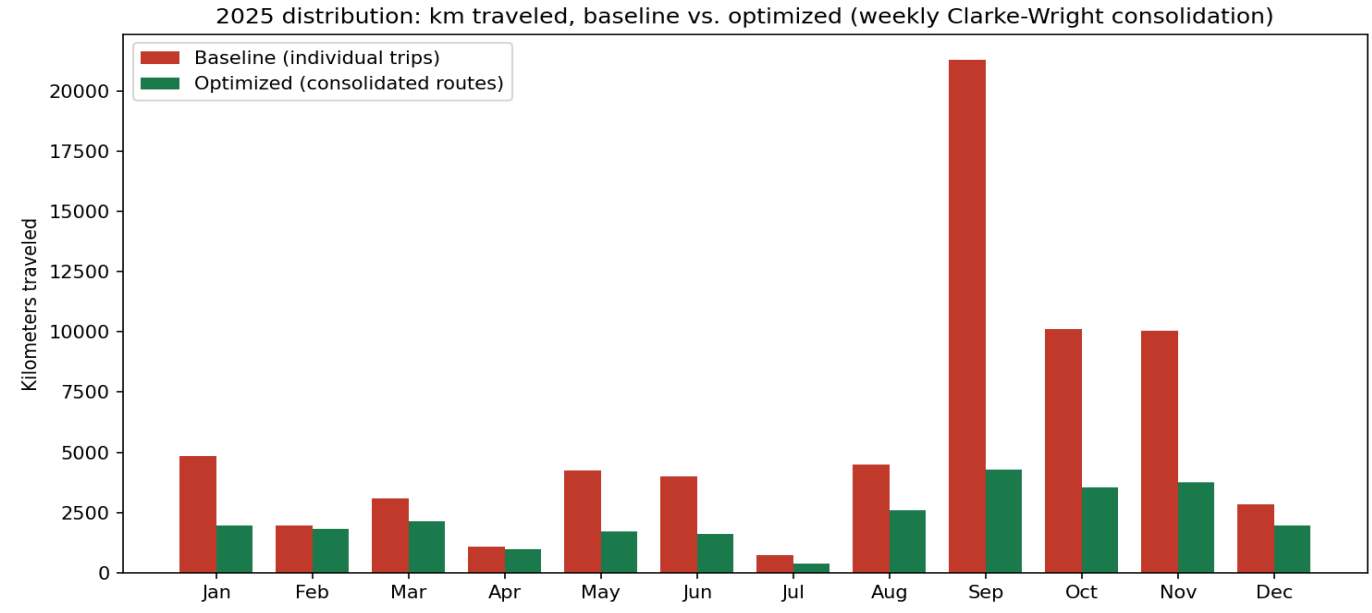


Figure 2. Distance traveled, baseline versus optimized scenario, by month (2025-2026).

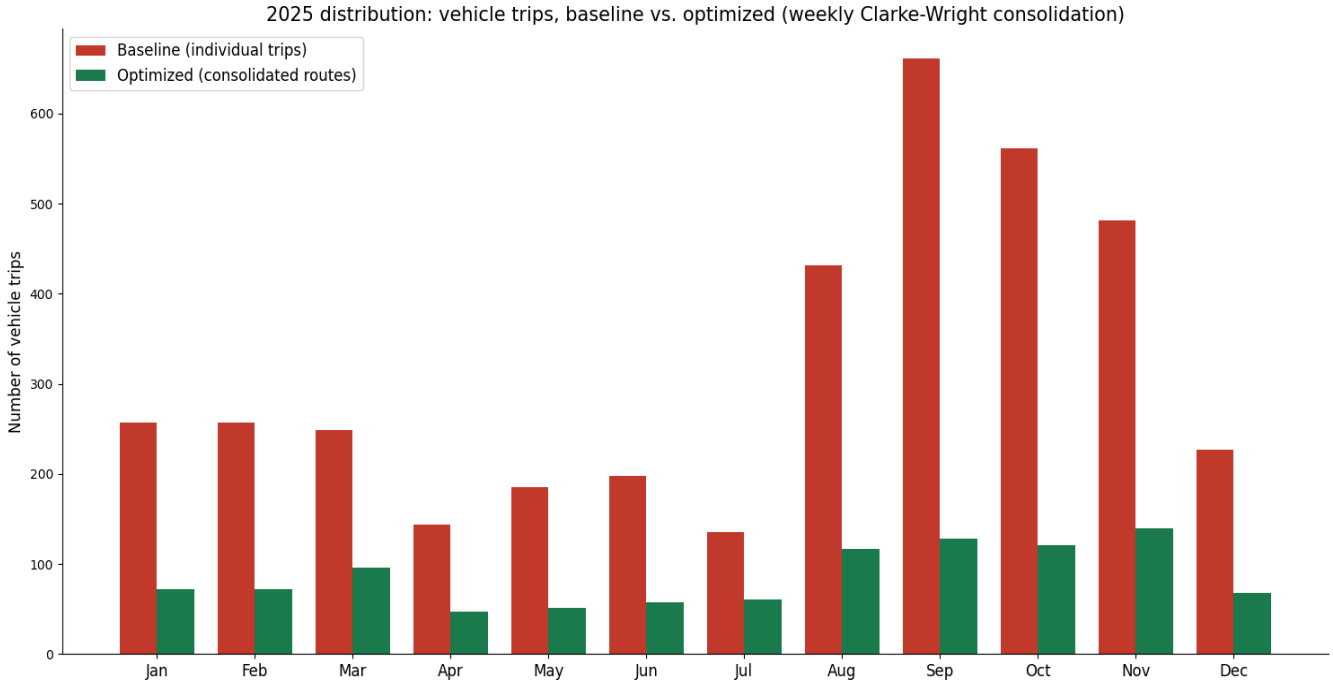



Figure 3. Vehicle trips, baseline versus optimized scenario, by month (2025-2026).

Both figures show a widening gap between the two scenarios as the high season approaches, and its gradual closing toward the end of the year: a pattern that quantitatively reinforces the relationship between seasonal demand concentration and the magnitude of logistics savings, discussed in greater depth below.

## DISCUSSION

The results indicate that the SME's current dispatch pattern — an almost purely individual, order-by-order delivery model — leaves substantial, quantifiable efficiency on the table, particularly during the seasonal demand peak that defines the company's commercial calendar. The magnitude of the September reduction (approximately 80%) exceeds the general 20–40% range reported in previously reviewed Clarke-Wright applications [15], [18], suggesting that extreme seasonal demand concentration, rather than diluting routing gains, can disproportionately amplify them when many deliveries occur to nearby or overlapping destinations within a short time window. This is a nuance that has received little attention in prior literature, which more often evaluates the Clarke-Wright algorithm and related heuristics under stable or moderately variable demand conditions [10], [11].

These findings are consistent with, and extend, the broader observation in the last-mile logistics literature that SMEs in emerging economies face disproportionate exposure to demand peaks, precisely because they lack the route-planning technology commonly used by large carriers [4], [19]. They are also consistent with evidence that the way a company organizes its last-mile logistics — not just the algorithm employed — largely determines the real opportunities for consolidation [3]. The SCALE workflow demonstrates that a substantial share of the theoretical efficiency gain is achievable using only the company's own historical order data, open-source computational tools, and a well-established, computationally inexpensive heuristic, without requiring investment in commercial transportation-management software or real-time telematics.

The seasonal amplification effect documented here (79.8% distance reduction in September versus single-digit reductions in February and April) carries both theoretical and practical implications. From a theoretical standpoint, it suggests that capacitated VRP models assuming relatively stable demand may systematically underestimate the potential benefits of constructive heuristics in contexts characterized by marked seasonality, typical of sectors such as school furniture, stationery, or certain agro-industrial branches. From a practical standpoint, the result indicates that manufacturing SMEs in emerging economies can obtain disproportionately

high returns from consolidation precisely in the periods when they need them most: when order volume threatens to saturate their logistics capacity.

These findings are consistent with recent evidence that the way last-mile logistics is organized (in-house, third-party, or hybrid) largely determines the real opportunities for consolidation [3]. In the case studied, the individual-dispatch scheme (94.9% single-destination shipments) represented an organizational decision rather than a technical constraint. The application of SCALE demonstrates that a substantial share of the inefficiency was "capturable" with low-computational-cost tools and without the need to invest in commercial transportation-management systems (TMS) or real-time telematics. This aspect is especially relevant for Latin American SMEs, where financial and technical-capacity barriers continue to limit the adoption of optimization technologies [4], [5], [12].

An important nuance is that weekly consolidation introduces a trade-off between efficiency and service level: customers who previously received their order on the same day or the following day could experience a delay of up to six days in the worst case (if the order is placed at the beginning of the weekly window). Although the study did not measure the impact on customer satisfaction or on-time delivery rates, the last-mile literature in e-commerce and B2B distribution suggests that, for non-perishable products with predictable demand (such as school furniture), customers often tolerate wider delivery windows in exchange for greater reliability and lower logistics costs passed on to them. Future implementations should monitor this trade-off explicitly.

From a managerial perspective, the results also highlight the value of treating the ISO week as a planning rather than a rigid dispatch window. Orders received early in the week can be held for consolidation, while late-week orders with high priority can still be released on dedicated or partially filled routes if customer service requirements demand it. This hybrid policy preserves most of the modeled savings while providing an operational safety valve. In addition, the marked improvement in capacity utilization (from <25 % to >70 % in peak months) implies that the same physical fleet can absorb a substantial increase in order volume without proportional growth in vehicle or driver resources—an especially relevant consideration for SMEs that face capital constraints when demand surges

# CONCLUSION

## A. Contributions

This study first contributes empirical evidence — based on a real, non-anonymized dataset from a manufacturing SME in a mid-sized city of an emerging economy — that savings-based route consolidation, with a capacity constraint, produces distance and trip reductions consistent with, and even exceeding under peak conditions, the ranges previously reported in the literature, which is mainly focused on e-commerce, food distribution, and large-carrier contexts [1], [15], [18]. Building on this finding, the study also offers a quantified demonstration that the returns to route consolidation scale disproportionately with seasonal demand concentration — a relationship documented here with numerical evidence, but not emphasized in the previously reviewed literature, which tends to treat demand as relatively stable [10], [11]. Consequently, this work proposes a replicable, low-cost, open-source decision-support workflow (SCALE), adapted to resource-constrained manufacturing SMEs, that directly addresses the digitalization and route-planning access gaps identified in the recent last-mile logistics literature for developing economies [4], [5], [12]. In this way, the study constitutes a real operational case that situates the freight distribution of Latin American, and particularly Mexican, manufacturing SMEs within the research agenda on AI-enabled multimodal transportation systems [2] — a geographic and firm-size segment that remains comparatively underrepresented in the reviewed literature.

Additionally, the study provides empirical evidence that the magnitude of consolidation savings scales non-linearly with seasonal demand concentration. This finding, documented numerically from real data of a Mexican manufacturing SME, helps close a gap identified in the literature review: most previous applications of the Clarke-Wright algorithm evaluate relatively stable or moderately variable demand scenarios and therefore do not capture the amplification effect observed here. Consequently, SCALE not only offers a

reproducible, low-cost workflow but also provides a concrete quantification of the seasonal amplification effect that can guide capacity-planning decisions in other seasonally driven manufacturing sectors.

### B. Limitations

Despite these contributions, the study has limitations that should be considered when interpreting its results. Delivery points were geolocated using approximate municipal centroid coordinates rather than exact addresses, introducing local-scale positional error; relatedly, distances were estimated as haversine (straight-line) distance corrected by an empirical road factor of 1.35, rather than calculated over an actual road network, so real routing engines or machine-learning-based alternatives would allow these estimates to be refined [16], [17]. Additionally, vehicle capacity (180 units per route) is a documented working assumption rather than a value validated against the company's actual fleet composition, load configurations, or driver working-hour constraints. Likewise, the company did not provide direct cost, fuel-consumption, or $CO_2$-emissions data, which is why all results are expressed in terms of distance and number of trips rather than monetary or environmental-impact terms, although the green VRP literature suggests that distance traveled is a reasonable, if imperfect, proxy for such impact [14]. Finally, it should be noted that the literature underpinning this study corresponds to a targeted, purpose-specific search rather than an exhaustive, multi-database systematic review with PRISMA-style screening counts [21].

Likewise, the study did not incorporate time-window constraints or load-compatibility restrictions (for example, stacking or fragility constraints typical of school furniture), which could partially reduce consolidation savings in a real implementation. Nor was the possibility of heterogeneous fleets or vehicles of different capacities modeled, constituting another simplification relative to the day-to-day operations of many SMEs.

A further practical consideration is that the baseline reconstruction assumes every historical delivery-stop corresponds to an independent vehicle trip returning to the depot. In reality, some multi-stop informal routing may already occur on an ad-hoc basis; if so, the reported savings would represent an upper bound. Field validation through driver logs or GPS traces would be required to quantify any pre-existing consolidation and adjust the net incremental benefit accordingly.

### C. Future research directions

Based on the limitations noted, several lines of future work are identified. First, it is proposed to replace the haversine-distance-plus-correction-factor indicator with actual road-network travel distances and times obtained from a routing engine, in order to revalidate the savings reported here [16]. In addition, it would be worthwhile to incorporate the company's actual fleet data (number of vehicles, capacities, fixed and variable costs, driver schedules) to reformulate the objective function in monetary terms and thereby estimate direct cost and $CO_2$-emission savings, drawing on the green VRP literature [14]. It is also recommended to extend the dataset to several years, with the aim of building a seasonal demand-forecasting model based on time series or machine learning, capable of proactively anticipating the back-to-school peak rather than optimizing it retrospectively, following approaches documented in the retail demand-forecasting literature [20]. Along the same lines, it would be valuable to conduct a full, multi-database systematic literature review under the PRISMA-SALSA approach [13], [21], enabling a broader mapping of the state of the art in vehicle routing adapted to SMEs and seasonality. Additionally, it is proposed to pilot the weekly consolidated-route program within the SME's actual operations over a full high season, and validate the savings obtained against the model's projections through a quasi-experimental pre-post design, consistent with the validation approaches used in comparable Green Vehicle Routing Problem studies [14]. Finally, it is suggested to explore generalizing the SCALE workflow by applying it to other manufacturing SMEs and sectors within Hidalgo and neighboring states [15], [19], in order to test whether the amplification effect observed during the high season holds for companies with different seasonal demand profiles.

Finally, it is suggested to explore the integration of seasonal demand-forecasting techniques (time series or machine-learning models) with the Clarke-Wright algorithm, so that weekly consolidation can be anticipated

proactively rather than applied retrospectively. This combination would allow SMEs not only to react to the peak season but to prepare logistically weeks in advance, further maximizing the benefits of consolidation.

In parallel, open-source implementations of SCALE could be packaged as a lightweight decision-support tool (for example, a Jupyter notebook or a simple web form fed by the SME's existing spreadsheet exports), lowering the adoption barrier still further and enabling comparative multi-firm studies across the Hidalgo manufacturing corridor.

## REFERENCES

1. V. P. Sharma, S. Prakash, R. Singh, R. Ojha, and B. Ramtiyal, "Strategic insights into last-mile delivery: Modelling the industry 4.0 enabler for e-commerce industry," RAUSP Management Journal, vol. 60, no. 1, pp. 149–174, 2025.
2. S. Ieva, I. Bilenchi, F. Gramegna, A. Pinto, F. Scioscia, M. Ruta, and G. Loseto, "Enhancing last-mile logistics: AI-driven fleet optimization, mixed reality, and large language model assistants for warehouse operations," Sensors, vol. 25, no. 9, Art. 2696, 2025.
3. J. Hagberg and K. Hulthén, "Consolidation through resourcing in last-mile logistics," Research in Transportation Business & Management, vol. 45, Art. 100834, 2022.
4. N. Samsuddin, M. Mohd Nor, and M. Sulaiman, "A study on the application of machine learning optimization models in last-mile delivery among SME logistics companies in Malaysia," International Journal of Research and Innovation in Social Science, vol. 10, no. 4, pp. 7612–7621, 2026.
5. S. Philbin, R. Viswanathan, and A. Telukdarie, "Understanding how digital transformation can enable SMEs to achieve sustainable development: A systematic literature review," Small Business International Review, vol. 6, no. 1, Art. e473, 2022.
6. P. Toth and D. Vigo, Vehicle Routing: Problems, Methods, and Applications. Philadelphia, PA: SIAM, 2014.
7. T. Vidal, G. Laporte, and P. Matl, "A concise guide to existing and emerging vehicle routing problem variants," European Journal of Operational Research, vol. 286, no. 2, pp. 401–416, 2020.
8. G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," Operations Research, vol. 12, no. 4, pp. 568–581, 1964.
9. J. Fikejz, M. Brázdová, and Ľ. Jánošíková, "Modification of the Clarke and Wright algorithm with a dynamic savings matrix," Journal of Advanced Transportation, vol. 2024, Art. 8753106, 2024.
10. K. Braekers, K. Ramaekers, and I. Van Nieuwenhuyse, "The vehicle routing problem: State of the art classification and review," Computers & Industrial Engineering, vol. 99, pp. 300–313, 2016.
11. H. Zhang, H. Ge, J. Yang, and Y. Tong, "Review of vehicle routing problems: Models, classification and solving algorithms," Archives of Computational Methods in Engineering, vol. 29, pp. 195–221, 2022.
12. L. A. Joia, "Digital transformation in Latin America: Challenges and opportunities," Information Systems Journal, vol. 34, no. 4, pp. 985–992, 2024.
13. W. Mengist, T. Soromessa, and G. Legese, "Method for conducting systematic literature review and meta-analysis for environmental science research," MethodsX, vol. 7, Art. 100777, 2020.
14. M. Asghari and S. M. J. Mirzapour Al-e-hashem, "Green vehicle routing problem: A state-of-the-art review," International Journal of Production Economics, vol. 231, Art. 107899, 2021.
15. I.-D. Rojas-Cuevas, E. Olivares-Benitez, A. S. Ramos, and S. Nucamendi-Guillén, "A capacitated vehicle routing model for distribution and repair with a service center," Logistics, vol. 9, no. 1, Art. 28, 2025.
16. P. Veres, "ML and statistics-driven route planning: Effective solutions without maps," Logistics, vol. 9, no. 3, Art. 124, 2025.
17. R. H. Ballou, H. Rahardja, and N. Sakai, "Selected country circuity factors for road travel distance estimation," Transportation Research Part A: Policy and Practice, vol. 36, no. 9, pp. 843–848, 2002.
18. Tunnisaki, Fadlah, and Sutarman, "Clarke and Wright Savings Algorithm as Solutions Vehicle Routing Problem with Simultaneous Pickup Delivery (VRPSPD)," Journal of Physics: Conference Series, vol. 2421, Art. 012045, 2022.

19. V. P. Sharma, S. Prakash, and R. Singh, "What prevents sustainable last-mile delivery in Industry 4.0? An analysis and decision framework," Sustainability, vol. 14, no. 24, Art. 16423, 2022.
20. R. Fildes, S. Ma, and S. Kolassa, "Retail forecasting: Research and practice," International Journal of Forecasting, vol. 38, no. 4, pp. 1283–1318, 2022.
21. M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," BMJ, vol. 372, Art. n71, 2021.