MERGING LANES: WHERE E-LEARNING DIVERSITY MEETS FUTURE TRENDS

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HEURISTIC APPROACHES FOR LAST-MILE DELIVERY OPTIMIZATION

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ABSTRACT

Last-mile delivery represents the final and most costly segment of the supply chain, accounting for a significant portion of total logistics expenditure. As e-commerce continues to expand globally, the pressure to optimize last-mile operations has intensified. Exact optimization methods, while ensuring optimal solutions, are computationally intractable for large-scale real-world instances. Heuristic approaches offer a practical alternative by producing good quality solutions within acceptable timeframes. This article reviews the principal heuristic methodologies applied to last-mile delivery problems, covering classical construction heuristics, metaheuristics, and hybrid approaches. The review highlights significant algorithmic contributions, discusses their strengths and limitations, and outlines new direction including the integration of machine learning with heuristic. Findings suggest that heuristics remain essential tools for practitioners and researchers seeking efficient, scalable delivery route planning.

Keywords: last-mile delivery, heuristics, vehicle routing problem, metaheuristics, logistics optimization

1. Introduction

The last mile of the supply chain, referring to the movement of goods from a distribution hub to the final customer, is widely recognized as the most complex and expensive phase of the delivery process. Studies consistently estimate that last-mile logistics accounts for between 41% and 53% of total supply chain costs (Savelsbergh & Van Woensel, 2016). The explosive growth of e-commerce, accelerated by the COVID-19 pandemic, has amplified demand for fast, reliable, and cost-effective home delivery, making the optimization of last-mile operations a critical competitive priority for logistics companies worldwide.

At the heart of last-mile optimization lies the Vehicle Routing Problem (VRP) and its many variants. The VRP seeks to determine optimal routes for a fleet of vehicles to service a set of geographically dispersed customers subject to various constraints, such as vehicle capacity, time windows, and driver working hours. The VRP is NP-hard in the classical sense (Lenstra & Rinnooy Kan, 1981), meaning that exact algorithms such as branch-and-bound or dynamic programming quickly become computationally prohibitive as problem size grows. In real-world urban delivery scenarios involving hundreds or thousands of stops, exact methods are generally impractical.

Heuristic algorithms have therefore emerged as the dominant solution methodology for large-scale last-mile routing. Unlike exact methods, heuristics do not guarantee optimality but are designed to find high-quality solutions quickly. This makes them well-suited to the time-sensitive, large-scale nature of operational logistics planning. This article provides a comprehensive review of heuristic approaches applied to last-mile delivery, covering classical construction and improvement heuristics, population-based metaheuristics, and hybrid strategies. The article is organized as follows: Section 2 provides background on the problem landscape; Section 3 reviews classical heuristics; Section 4 discusses metaheuristics; Section 5 studies hybrid and adaptive approaches; Section 6 discusses emerging directions; and Section 7 conclusion.

2. The Last-Mile Delivery Problem

The generic VRP, first formulated by Dantzig and Ramser (1959), has since produced several extensions to reflect real-world constraints. The Capacitated VRP (CVRP) considers vehicle load limits, while the VRP with Time Windows (VRPTW) requires customers to be served within specified time intervals. The Split Delivery VRP (SDVRP) allows a customer to be served by more than one vehicle, and the Multi-Depot VRP (MDVRP) considers fleets operating from multiple warehouses. More recently, variants addressing stochastic demand, dynamic customer requests, and electric vehicles have gained prominence (Braekers et al., 2016). A comprehensive review by Asghari and Mirzapour Al-E-Hashem (2021) further documents the rapid expansion of the Green VRP literature, highlighting the growing importance of sustainability objectives.

Last-mile delivery introduces additional real-world complexities beyond the classical VRP framework. Urban traffic congestion creates dynamic and uncertain travel times, customer availability constraints result in failed delivery attempts, and the increasing prevalence of same-day and on-demand delivery compresses planning horizons. Sustainability pressures require minimizing carbon emissions alongside distance and cost, while the rise of crowd-sourced delivery platforms introduces new workforce management considerations (Perboli et al., 2018). A wide-ranging review by Giuffrida et al. (2022) confirms that these complexities collectively demand solution methods that are not only computationally efficient but also flexible and robust.

3. Classical Heuristics

3.1 Construction Heuristics

Construction heuristics build a solution from scratch by iteratively adding customers to routes according to simple, greedy criteria. The Nearest Neighbor heuristic, one of the earliest and most intuitive methods, starts from the depot and repeatedly visits the closest unrouted customer until all customers are served (Rosenkrantz et al., 1977). While computationally fast, running in $O(n^2)$ time, it often produces solutions 20 to 25% above optimal due to its myopic nature.

The Clarke and Wright Savings Algorithm (1964) is arguably the most influential classical heuristic for the VRP. It begins with a solution in which each customer is served by a dedicated vehicle and iteratively merges routes based on the 'savings' achieved by combining two routes into one. The savings value for combining routes visiting customers *i* and *j* is computed as $S_{ij} = c_{0i} + c_{0j} - c_{ij}$, where *c* denotes travel cost and *0* denotes the depot. Routes with the highest savings are merged first, subject to capacity constraints. The savings algorithm is both simple to implement and produces solutions of reasonable quality, making it a popular choice for practitioners.

Insertion heuristics offer another family of construction methods. The cheapest insertion approach identifies the customer and position whose addition to an existing route incurs the smallest cost increase. Regret-based insertion variants, such as those used in the Large Neighborhood Search framework, prioritize customers whose exclusion from their best insertion position would be most costly, leading to improved solution quality (Ropke & Pisinger, 2006). A data-informed insertion heuristic specifically adapted for real-world last-mile sequencing was proposed by Özarık et al. (2024), representing that learning from historical route data can meaningfully improve construction quality.

3.2 Improvement Heuristics

Once an initial solution is constructed, improvement heuristics apply local search moves to reduce total cost. The 2-opt algorithm removes two edges from a route and reconnects the resulting segments in a different order, eliminating route crossings (Lin, 1965). The 3-opt extension considers removing three edges simultaneously, exploring a larger neighborhood. Or-opt moves relocate one, two, or three consecutive customers to a different position within the same or a different route, offering a complementary search strategy. These local search procedures are typically iterated until no improving move is found, yielding a local optimum.

The Lin-Kernighan heuristic (Lin & Kernighan, 1973) generalized k-opt exchanges into a variable-depth search strategy and became the foundation for some of the most powerful TSP solvers. Its VRP adaptation, combined with perturbation mechanisms, remains competitive with state-of-the-art metaheuristics on standard benchmarks.

4. Metaheuristics

4.1 Simulated Annealing

Simulated Annealing (SA) is a probabilistic local search method inspired by the annealing process in metallurgy (Kirkpatrick et al., 1983). Unlike pure local search, SA accepts worsening solutions with a probability that decreases over time according to a 'temperature' schedule, allowing the algorithm to escape local optima. SA has been successfully applied to various VRP variants, with studies reporting solutions within 1 to 3% of optimal on standard benchmarks (Osman, 1993). Its main limitation is sensitivity to the cooling schedule, which requires careful parameter tuning.

4.2 Tabu Search

Tabu Search (TS), introduced by Glover (1986), is a local search metaheuristic that maintains a memory structure, known as the tabu list, to prevent revisiting recently explored solutions. By forbidding certain moves for a fixed number of iterations, TS encourages diversification and escape from local optima. Tabu Search has produced some of the best-known results on VRP benchmarks. The TABUROUTE algorithm by Gendreau et al. (1994) and the unified Tabu Search by Cordeau et al. (2001) are landmark contributions that demonstrated TS could consistently find near-optimal solutions across multiple VRP variants, including the VRPTW and the Periodic VRP. More recently, Sze et al. (2024) proposed an adaptive variable neighborhood search incorporating Tabu Search mechanisms to handle dynamic VRP settings in urban environments.

4.3 Genetic Algorithms and Evolutionary Computation

Genetic Algorithms (GAs) are population-based metaheuristics inspired by biological evolution. A population of candidate solutions (chromosomes) is evolved through selection, crossover, and mutation operators. For routing problems, specialized crossover operators that preserve route feasibility, such as the Order Crossover (OX) and the Partially Mapped Crossover (PMX), are critical to performance (Potvin & Bengio, 1996). GAs are naturally suited to parallel implementation and can effectively explore diverse regions of the solution space, though they typically converge more slowly than trajectory-based methods like Tabu Search.

Hybrid Genetic Algorithms that embed local search within the evolutionary process, known as memetic algorithms, have achieved outstanding results. The algorithm by Vidal et al. (2012) combines a population-based genetic search with a powerful local search component and has set benchmark records on hundreds of VRP instances. This work emphasizes the importance of tight integration between global exploration and local exploitation in effective metaheuristic design.

4.4 Ant Colony Optimization

Ant Colony Optimization (ACO) simulates the foraging behaviour of ants, which release pheromone trails on paths leading to food sources (Dorigo & Gambardella, 2002). In the context of routing, pheromone intensities reflect the desirability of including particular edges in a route. Ants probabilistically construct solutions guided by pheromone levels and heuristic information (typically inverse distance), and pheromone levels are updated based on solution quality. ACO has proven effective for the VRP, particularly in dynamic environments where customer requests arrive in real time and frequent re-optimization is required.

4.5 Large Neighborhood Search

Large Neighborhood Search (LNS), introduced by Shaw (1998) and extended by Ropke and Pisinger (2006) into the Adaptive LNS (ALNS) framework, operates by repeatedly destroying and repairing portions of a solution. A set of destroy operators (e.g., random removal, worst removal, route elimination) and repair operators (e.g., greedy insertion, regret insertion) are applied adaptively, with operators that have historically performed well receiving higher selection probabilities. ALNS has become one of the most widely adopted frameworks for VRP variants, consistently producing state-of-the-art results due to its flexibility and ease of customization. A recent study by Ammouriova et al. (2022) further extended ALNS-based simheuristics to address uncertainty and dynamic conditions in last-mile scenarios.

5. Hybrid and Adaptive Approaches

Modern heuristic research increasingly focuses on hybrid approaches that combine complementary strategies. Combining population-based methods with local search (memetic algorithms) utilizes global exploration for diversity and local search for intensification. Hybrid methods integrating exact solvers for subproblems within a heuristic framework, known as matheuristics, have demonstrated the ability to close optimality gaps that pure heuristics cannot (Boschetti et al., 2009). For instance, column generation can be used to re-optimize a subset of routes within a large neighborhood search framework, yielding solutions of exceptional quality on structured problem instances.

Machine learning is increasingly being integrated with heuristic solvers to improve performance. Reinforcement learning agents have been trained to make destroy and repair operator selection decisions in ALNS frameworks, replacing manually designed adaptive weight mechanisms with learned policies (da Costa et al., 2021). Graph neural networks have been applied to predict promising edges for local search moves, reducing the neighborhood search space and improving computational efficiency. In the context of real-world routing, Özarık et al. (2024) presented that a machine-learning framework combining classical TSP heuristics with a trained regression model could prescribe high-quality last-mile delivery sequences without an explicitly defined objective function. These developments suggest that the boundary between classical heuristics and artificial intelligence is becoming increasingly permeable.

Data-driven optimization frameworks have also emerged as a complementary paradigm. Chu et al. (2023) proposed a smart predict-then-optimize approach that integrates machine learning predictions directly into capacitated VRP solving, improving delivery time accuracy and route efficiency for online food delivery platforms. This line of research demonstrates that combining predictive analytics with heuristic optimization can produce tangible operational gains in dynamic, real-world last-mile settings.

6. New Directions and Challenges

Several emerging trends are reforming the landscape of last-mile delivery optimization. The proliferation of electric vehicles (EVs) introduces range constraints and charging requirements as additional optimization dimensions. Asghari and Mirzapour Al-E-Hashem (2021) provide a comprehensive classification of Green VRP variants, show that metaheuristics and hybrid methods dominate solution approaches for these problems. Dönmez et al. (2022) further studied the mixed fleet VRP with partial recharging by multiple charger types using an adaptive large neighborhood search, illustrating the growing complexity of sustainable routing problems. The Green VRP and its variants seek to minimize energy consumption and emissions alongside traditional objectives (Erdoğan & Miller-Hooks, 2012). Drone and autonomous vehicle delivery introduces new routing topologies and operational constraints that existing heuristics must be adapted to address.

The growth of real-time and dynamic delivery environments, driven by same-day and on-demand delivery services, requires algorithms capable of rapid re-optimization as new orders arrive and traffic conditions evolve. Online heuristics that maintain and update solutions incrementally are gaining attention as practical tools for dynamic dispatch systems. A recent study introducing the Tabu-guided Adaptive Large Neighborhood Search with Rollout-based Real-Time Dispatch (T-ALNS-RRD) framework demonstrates how integrating congestion-penalized cost functions and rollout-based dispatch mechanisms can substantially improve delivery performance under volatile urban traffic conditions (Liu and Wang, 2025). Additionally, multi-objective optimization approaches that explicitly balance economic, environmental, and social objectives are receiving increasing research interest, reflecting the growing importance of sustainable logistics practices (Perboli et al., 2018).

7. Conclusion

Heuristic approaches remain the cornerstone of practical last-mile delivery optimization. From simple construction methods to sophisticated metaheuristics and hybrid matheuristics, the field has produced a rich toolkit of algorithms capable of addressing the diverse and complex routing problems encountered in real-world logistics operations. Classical methods such as the Clarke-Wright savings algorithm and 2-opt local search continue to provide valuable benchmarks and practical starting points, while advanced metaheuristics including Tabu Search, Genetic Algorithms, Ant Colony Optimization, and Adaptive Large Neighborhood Search consistently deliver near-optimal solutions on large-scale instances. The integration of machine learning with heuristic represents a high potential domain that is likely to provide significant advances in both solution quality and computational efficiency in the coming years. As the demands of modern e-commerce continue to evolve, the development and refinement of heuristic approaches for last-mile delivery will remain a vibrant and practically important area of research.

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