Distributional transport optimization: theory versus practice

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Abstract— **The Vehicle Routing Problem (VRP) has been extensively studied in the literature, leading to various extensions that incorporate real-world constraints. However, many practical considerations remain underrepresented, particularly in the FMCG (Fast-Moving Consumer Goods) industry. In this study, we analyze a real-world VRP formulation based on logistics operations from an FMCG distribution network and identify critical gaps between theory and practice. Based on our experience, we identify typical requirements in real-world applications that are relatively underrepresented in the existing literature. To demonstrate that the problem remains solvable, we propose a genetic algorithm (GA)-based approach, implemented within an open-source, object-oriented model, specifically designed to optimize route planning while incorporating real-world operational constraints. The algorithm was tested on a dataset covering 60 days of real-world logistics data, demonstrating significant improvements over historical benchmarks in terms of cost reduction, route efficiency, vehicle utilization, and operational feasibility. Our findings highlight the importance of bridging the gap between theoretical VRP formulations and industry-specific challenges, opening new avenues for further research and optimization in complex logistics networks.**

Index Terms— **Rich Vehicle Routing Problem; Logistic Optimization; Genetic Algorithms; Real-world constraints**

I. Introduction

The problem of distributional transport optimization has been studied in the scientific literature since the 1950s, leading to hundreds of variants tailored to specific cases. At its core, this field is driven by models for idealized theoretical problems, beginning with the seminal work of Dantzig and Ramser (1959) [1], which introduced the Vehicle Routing Problem (VRP) as an extension of the previously studied Traveling Salesman Problem (TSP). Over time, the VRP has evolved into a fundamental problem in supply chain management, with applications spanning transportation, distribution, and urban logistics. At the same time, a broad spectrum of real-world adaptations of VRP has emerged, addressing the practical challenges encountered in business operations.

In this paper, we define a real-world problem that arises from analyzing actual customer requirements. Our study is based on experiences gained during the implementation of a research and development project conducted at Betacom company in collaboration with business clients operating in the FMCG (Fast-Moving Consumer Goods) sector in the East-Central Europe. Fast-Moving Consumer Goods are nondurable products sold quickly and at relatively low costs, including everyday products such as food and beverages, cleaning supplies, and household goods. Despite decades of advancements in VRP research, we find that practical requirements often extend far beyond the problem formulations commonly considered in the literature—even those that claim to be application-oriented. This raises a key question: can the modeling and algorithmic advancements discussed in the literature accommodate real-world requirements and scale effectively for practical applications?

The Vehicle Routing Problem (VRP) is a fundamental combinatorial optimization problem in logistics, aimed at determining optimal routes for a fleet of vehicles to service a set of customers. The objective is typically to ensure that each customer is visited exactly once while minimizing total cost, time, or distance. Over time, numerous VRP extensions have been introduced to capture real-world complexities. Some of the most recognized variants include:

- Capacitated VRP (CVRP) — Vehicles have a maximum carrying capacity [2].
- VRP with Time Windows (VRPTW) — Service at each customer must start within a given time window [3].
- VRP with Pickup and Delivery (VRPPD) -– Involves transporting items from multiple pickup locations to designated delivery points [4], [5].
- VRP with Backhauling (VRPB) – Extends VRP by allowing vehicles to pick up return loads after deliveries [6].
- Multi-Depot VRP (MDVRP) — Considers multiple depots instead of a single depot [7].
- Stochastic VRP (SVRP) — Incorporates uncertainty in demand, travel time, or service time [3].

While classical VRP formulations provide a theoretical framework, most studies focus on idealized models. However, real-world applications require incorporating multiple constraints to develop feasible and efficient routing solutions. Some works classify problems that combine multiple real-world constraints under the term Rich VRP (RVRP) [8]. Although numerous VRP surveys have been published, to the best of our knowledge, the most recent comprehensive review on Rich VRP dates back to 2015 [9]. Drexl compares the state of the art in academic research against real-world VRPs, highlighting the complexity of practical applications and the adaptations required in commercial software systems [10]. Both [9] and [10] provide a taxonomy of RVRP, which we reference when defining our problem in this paper.

Regardless of the specific VRP variant, the problem is typically NP-hard, meaning that exact solutions be-

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come computationally infeasible for large instances. Two fundamental approaches exist for solving VRPs: mathematical programming-based (exact) methods and heuristic/metaheuristic algorithms.

Exact approaches are generally based on Mixed Integer Linear Programming (MILP) models, often employing branch-and-cut methods [11], sometimes in combination with column generation techniques [12]. However, due to their high computational complexity, exact methods are typically limited to small-scale instances and are impractical for large, real-world problems.

As a result, heuristic and metaheuristic approaches are widely used to obtain near-optimal solutions within a reasonable timeframe. Heuristic methods can be categorized into: constructive heuristics, such as nearest neighbor or insertion methods, which build an initial feasible solution, and improvement heuristics, such as inter-route exchanges [13], which iteratively refine solutions. Common metaheuristic approaches include population-based methods, such as genetic algorithms [14] and ant colony optimization [15], and local search methods, such as tabu search [16] and simulated annealing [17].

Over the past decades, there has been a clear trend toward defining increasingly "richer" VRP variants [18], alongside efforts to develop more generic and unified modeling frameworks [19]. While Rich VRP models were originally intended as a bridge between theoretical research and practical implementations, their increasing complexity may, paradoxically, pose a barrier to real-world adoption. On one hand, we have simplified theoretical VRP variants that often fail to capture real-world constraints. On the other hand, the expansion of RVRP formulations has led to a vast number of problem variants, making their direct implementation in practical settings increasingly challenging.

In this paper, we analyze a formulation of RVRP with real-world practices in the FMCG industry. Drawing from our experience, we identify key areas and critical gaps in RVRP that must be addressed to enhance practical applicability. Our intention is to reduce the gap between formulations found in the scientific literature and practical problems by indicating which known requirements are encountered in practice and which practical requirements are not found in the literature. In particular, this opens the door to further work considering variants of VRP not considered in the literature so far. Our contribution is as follows:

- We define a VRP variant based on real-world FMCG industry cases. We identify which elements of RVRP are relevant to such problems and introduce new practical requirements, including: semi-trailer and truck combinations, and dynamic warehouse throughput constraints.
- We demonstrate that this problem can be effectively tackled using a dedicated genetic algorithm. The implementation is based on our open-source library that provides an object-oriented model of the problem. The library has been made openly available, allowing for further development and algorithmic enhancements by the research community.

The rest of paper is organized as follows. Section II introduces the problem formulation, discusses specific practical requirements making the problem "rich", and outlines our solution approach. Section III presents results obtained for a real large-scale network of FMCG stores. Section IV provides conclusions and final remarks.

II. Methods

A. Problem formulation

Let $G=(V,E)$ denotes an undirect graph, where V represents set of nodes, and E set of edges. The basic formulation of VRP assumes a single depot represented by $v_0 \in V$, and the fleet of m homogeneous vehicles. The remaining nodes $v_i \in V \setminus v_0$ represent customers (Points of Interest, PoIs), and customer i is characteized by demand d_i. Traveling along edge $(i,j) \in E$ induces cost c_{ij}. The problem is to find cycling routes of m vehicles that minimizes the total cost while each customer is visited exactly once and their demand is satisfied, the total demand on each route does not exceed vehicle's capacity, and each route starts and ends in the depot.

The above formulation of the generic VRP problem is typically a starting point for introducing practical constraints and requirements. In the following subsections we indicate which of the known requirements, in particular those recognized in the taxonomies [9], [10], occur in practice, and above all we indicate which elements have been rather omitted in the literature so far.

1) Vehicles: In the operation of large distribution networks, the fleet of vehicles is typically highly heterogeneous, although the vehicles exhibit a certain degree of standardization. The typical parameters used to describe a vehicle align with those commonly found in the literature and include capacity, length, width, height, and curb weight. It is standard practice to define capacity in terms of the number of standard Euro pallets. Vehicle standardization is particularly evident in the list of capacity values, which typically includes vehicles with capacities of 6, 8, 10, 13, 14, 18, 19, 20, 21, 22, 27, and 33 Euro pallets.

Each vehicle has a designated starting and ending location, which is typically one of the depots. In operational practice, route planning is usually performed on a daily cycle. However, the start of a new cycle does not necessarily mean that all vehicles used in the previous cycle will have returned to their original locations.

This means that vehicle availability must be taken into account. A vehicle may be unavailable at the beginning of the planning horizon due to its engagement in fulfilling orders from the previous cycle, as well as due to breakdowns or scheduled maintenance work.

The following elements represent requirements that are not commonly addressed in the literature:

a) Two general types of vehicles are used for transporting goods: straight trucks and semi-trailer trucks. A straight truck is a medium-sized vehicle with all its axles connected to a single frame and typically has a capacity of 21 Euro pallets or less. A semi-trailer truck consists of a tractor unit and a semi-trailer, requiring proper pairing of tractors and trailers. Although there are usually no technical constraints on these pairings (any tractor can attach to any trailer), there are cost and logistical considerations, discussed further below.

b) Semi-trailers can be placed at warehouse loading docks before the arrival of a tractor. In logistics depot, usually there is a set of local tractors that are used solely for local trailer movement. Therefore, a tractor designated for transportation must be available after the loading process is completed, but in some cases, it may even be required later. In distribution centers where temporary storage of assembled pallets is difficult, goods are often loaded onto semi-trailers immediately after pallet completion and stays there until a tractor can be attached. This trailer-based storage is time-limited and requires power supply to maintain the proper temperature. Therefore, a VRP algorithm must consider the availability of both tractors and semi-trailers separately, as semi-trailers must be available earlier for loading, while tractors are needed only after loading is completed. Additionally, the problem should account for storing pallets on semi-trailers parked in designated areas, which is related to warehouse throughput constraints, discussed later.

c) Vehicles may be owned by third-party carrier companies which introduces semi-trailer-tractor pairing constraints. In some cases, tractors and semi-trailers may only be paired within the same carrier company. Another common scenario involves logistics centers owning a pool of semi-trailers, where carrier-owned tractors may either be restricted to using only their own semi-trailers or be allowed to haul both carrier-owned and logistics center-owned semi-trailers.

d) Vehicle attributes may restrict access to specific Points of Interests. For example, vehicle dimensions may prevent access to a store's loading dock, while some stores require vehicles equipped with liftgates. Additionally, such restrictions may be time-dependent—a large vehicle may be prohibited from accessing a store during peak hours, but allowed to make deliveries at night.

e) Service intervals between consecutive routes of single vehicle must be considered. While the literature sometimes mentions vehicle washing, practical operations require scheduling mandatory service breaks for vehicles between routes. These intervals may be necessary due to regulatory formalities that drivers must complete before starting a new trip.

2) Drivers: The requirement to account for drivers applies in some real-world cases, as the burden of scheduling and optimization is often shifted to transportation companies.

As recognized in the literature [10], the greatest challenge in modeling driver availability lies in complying with legislative requirements related to working hours, driving time, and mandatory rest breaks. These regulations are often complex and, in many cases, ambiguous in interpretation.

To account for the legal complexities, driver availability must be managed over a longer planning horizon. However, since VRP problems are typically solved in a daily cycle, this management is often reduced to a set of constraints applied within a single planning cycle. These constraints include maximum expected driving and working hours, which should ideally not be exceeded, and hard limits on maximum permissible working and driving times. which must never be violated.

Exceeding the expected limits may be technically possible but is undesirable, as it leads to reduced driver availability in subsequent planning cycles.

Similar to vehicle availability, it is essential to consider driver availability, taking into account ongoing trips from the previous cycle, which may delay a driver's readiness for new assignments, and planned or unplanned absences, such as scheduled leaves, regulatory rest periods, or unexpected unavailability.

We identified the following requirements that are not commonly considered in existing research:

a) Drivers can be pre-assigned to vehicles. In many cases, a fixed group of two or three drivers is assigned to a specific vehicle and operates in shifts. The algorithm should prioritize assigning drivers already associated with a given vehicle and avoid assigning external drivers unless necessary. However, in some cases, there exists a pool of unassigned drivers who are not linked to any specific vehicle but can operate any available vehicle if primary drivers are unavailable due to time constraints or other scheduling limitations.

b) Drivers may change along the route. While vehicles always start and finish at a depot, it may happen that drivers are replaced mid-route when passing by their homes, eliminating the need for them to travel to and from the depot. This arrangement may require a small deviation from the shortest path to a Point of Interest and must be reflected in travel time calculations.

3) Routes: A typical practical assumption in vehicle routing is that routes are closed, meaning that they start and end at the same depot.

In terms of the road network, distances and travel times may differ depending on the direction. In some cases, these differences can be significant, making a symmetric distance matrix an oversimplification.

Additionally, distances and travel times also depend on vehicle size. However, in most cases, it is possible to classify vehicles into a few distinct categories, eliminating the need to compute separate distance and travel time matrices for every individual vehicle specification.

We did not identify any specific practical requirements related to routes not already covered in the VRP literature.

4) Requests: The most critical requirement in transport request scheduling is considering time windows. A typical requirement involves distinguishing between hard and soft time windows. Hard time windows are strict constraints that cannot be violated, such as store operating hours or nighttime noise restrictions. Soft time windows are preferred delivery periods, where deviations result in penalties for late or early deliveries.

We identified several practical requirements that are only partially addressed in the existing literature:

a) Discontinuous time windows. In real-world cases, deliveries may be allowed within a specified time range but prohibited during certain intervals within that period. This often occurs due to nighttime restrictions or peak-hour congestion, during which deliveries to stores may be temporarily forbidden.
b) Prioritized time windows. Some time windows have a defined priority order, meaning that deliveries can only be scheduled within a lower-priority window if all higher-priority windows have already been used. For example, a store must receive a morning delivery, and only if this is insufficient can a second delivery be scheduled in the afternoon. However, a sole afternoon delivery without a morning one is not allowed.
c) Time windows with dynamic capacity. Many Points of Interest (PoIs) can accommodate vehicles of specific sizes, often expressed in terms of Euro pallet capacity. However, this capacity may vary over time. For instance, large vehicles may be restricted during peak hours, allowing only small trucks to make deliveries, while during nighttime hours, larger trucks may be permitted.
d) Multiple deliveries within a single time window. Some time windows allow for more than one delivery or specify a maximum number of accepted pallets. However, it is typically required that multiple deliveries within the same time window do not occur simultaneously.
e) Handling of returns. When visiting a PoI, a vehicle may need to collect return items, such as empty containers, plastic wrap, or cardboard packaging. However, specific rules must be followed, that is, returns cannot be picked up if the vehicle still has deliveries scheduled for other PoIs, and as it is undesirable to schedule the exact same route on consecutive days, as this would prevent some locations from returning their items. Instead, routes should vary to allow for balanced return collection across all visited locations.
f) Backhauls from suppliers. In practical scenarios, transport schedules may include pickups from suppliers to the depot. This is particularly relevant for return trips, where the vehicle would otherwise travel empty, allowing it to bring back inventory and reduce transportation costs. However, these pickups are often optional, making their scheduling more complex.

5) Pallet picking: Although the need for balancing of pallet loading is occasionally mentioned in the literature, practical applications emphasize this aspect much more strongly. We have identified the need to account for dynamic pallet assembly capacity, which is typically expressed as the number of pallets loaded per unit of time, such as per hour.

Fluctuations in pallet production capacity arise due to warehouse shift schedules, where efficiency tends to drop at shift transitions. Other factors, such as lunch breaks, can also temporarily reduce pallet assembly capacity.

Route plans should be designed to reflect these temporary variations, ensuring that the number of pallets scheduled for loading does not exceed the warehouse's capacity at any given time. Typically, an expected pallet volume per unit of time is defined, and the actual number of pallets loaded should remain close to this target value.

Moreover, it is essential to maintain a cumulative balance. Slightly exceeding the preferred production capacity for a single hour may be acceptable, but sustaining this over several consecutive hours is not. If a temporary overload occurs in one hour, it should be expected that pallet production in the following hour will decrease accordingly. Ultimately, cumulative pallet production should align with cumulative warehouse capacity over time.

B. Objectives

Surprisingly, the typology of Rich VRP tends to provide only a brief treatment of potential objective functions [9], [10]. In practice, nearly all routing problems involve multiple objectives. The primary goal is typically to minimize costs. The cost model includes fixed costs associated with vehicle usage, variable costs based on distance traveled, and variable costs based on travel time. Driver-related costs may either be calculated separately or incorporated into vehicle costs.

A cost factor often overlooked in the literature is the departure cost, i.e., the cost incurred for processing vehicles at the warehouse gate. Experience shows that this is one of the leading cost drivers in total transportation expenses. This cost is often charged per planned route, which encourages the consolidation of routes into fewer combined trips rather than planning many short routes.

The following is a list of key performance indicators (KPIs) that logistics managers typically monitor and evaluate:

- Total cost
- Total route distance and number of routes
- Average, min./max. vehicle load utilization
- Number of used vehicle type and assigned drivers
- Average and maximum delivery delay/early; number of delayed/early deliveries
- Number of undelivered pallets
- Deviation from the expected pallet assembly curve, e.g., mean squared deviation from the desired pallet picking schedule
- Measures of carrier load balancing

The last two KPIs are particularly noteworthy, as they are not commonly recognized in the literature. The carrier load balancing metric reflects the expectation that no carrier should be underutilized ("starved"), and that the solution should fairly distribute transportation demand across all carriers. Typically, the list of KPIs is long, and decision-makers struggle to reduce the number of indicators to a single metric.

C. Algorithm overview

The practical requirements identified in the previous sections have been incorporated into a general data model, which has been made publicly available in the repository: `https://bitbucket.org/control-system/vrptw-model/`. Based on this model, we developed a genetic algorithm that accounts for the formulated requirements and serves as an example of a real-world approach to solving the Rich Vehicle Routing Problem.

A key element of the algorithm is the chromosome encoding method, illustrated in Figure 1. The encoding vector consists of four sub-vectors:

- The first sub-vector maps transport tasks to routes. As shown in Figure 1, the first three transport tasks are assigned to route 0, while route 1 consists of only one transport task.
- The second sub-vector represents a permutation of transport tasks. In the example, route 0 consists of transport tasks 5, 10, and 8, whereas route 1 includes task 33.
- The third sub-vector encodes the assignment of vehicles to routes.
- The fourth sub-vector encodes the assignment of drivers to routes.

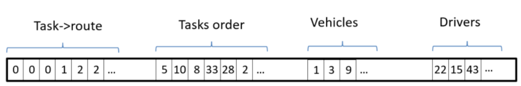


Fig. 1: Coding the solution

For this chromosome representation, we developed a comprehensive set of mutation operators, categorized as follows:

- Tasks order
  - Modification of task order within a route/subroute
  - Delay or advance the start of a route
- Tasks switching between routes
  - Move request to another route
  - Swap request between routes
  - Merge routes
  - Merge/split requests
- Route resource modifications
  - Change a driver/vehicle assigned to a route
  - Change a resource for unscheduled task
  - Swap resources between routes

As a recombination operator, we use importing a route from another solution.

The complete solution is constructed based on the chromosome-encoded representation using a greedy approach, taking into account all constraints, particularly: vehicle and driver availability, driver working and driving time regulations, and limited pallet assembly capacity. The algorithm detects stagnation in the population and triggers a restart when necessary.

III. Numerical results

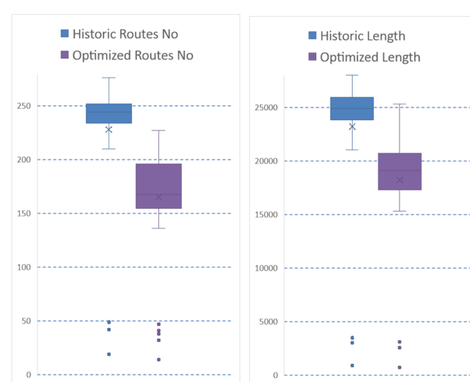
The algorithm outlined in the previous section was applied to a dataset covering 60 days of real-world data from a sample distribution network. This network consists of approximately 220 stores, 160 vehicles, and nearly 6,000 pallets to be delivered. All data has been extracted from existing IT systems, including all elements described in section II-A. These include vehicles, drivers, and requests with a rich set of attributes for each object type. The distance matrix was prepared based on the service of a map provider.

The objective is a weighted sum of KPIs introduced in II-B. Constraints reflect requirements formulated in section II-A. However, while some constraints, such as the number of available vehicles and drivers, admissibility of the vehicle for the request, hard time windows, are hard, other constraints are soft, including soft time windows, maximum driving and working time, and vehicle capacity.

The population size and the number of threads in the genetic algorithm were set to 16 individuals. The computation time was limited to 60 minutes, and the algorithm was configured to restart after 30,000 stagnation iterations if no improvement was observed. Cost parameters were determined in collaboration with logistics experts.

As previously discussed, the problem formulation incorporates multiple aspects, making it an instance of Rich VRP. Due to the complexity of the problem, direct comparisons with other methods are not feasible, as existing approaches cannot be directly applied to this problem formulation. The main obstacle is that they do not consider all constraints that we identified in section II-A. Therefore, as a reference point, we used historical operational data, which represented the best available solutions achieved by logistics planners.

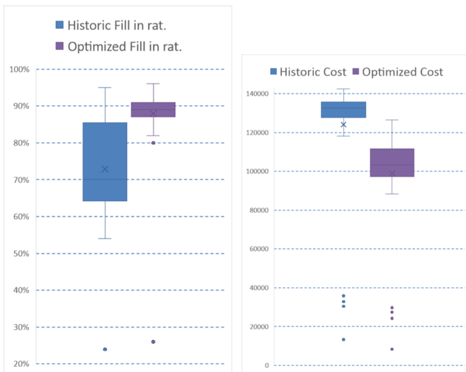
Figure 2a illustrates the number of routes. Although the number of routes in the optimized solution produced by the genetic algorithm exhibits greater variability, the values between the first quartile (Q1) and the third quartile (Q3) are significantly lower than those observed in historical solutions. Similarly, the total route length, presented in Figure 2b, is significantly improved compared to historical solutions.



(a) Number of routes (b) Total length

Fig. 2: Boxplot for historic and optimized number of routes (a) and total length (b)

The average vehicle load utilization, shown in Figure 3a, demonstrates a high degree of variability in the historical data. In contrast, the results produced by the proposed algorithm are considerably more stable, consistently oscillating just below 90%. The final quality metric is the total cost, illustrated in Figure 3b. Once again, the Q1 value of the historical solutions is higher than the Q3 value of the optimized solutions, highlighting the effectiveness of the proposed approach.



(a) Fill-in ratio (b) Total cost

Fig. 3: Boxplot for historic and optimized fill-in ratio (a) and total cost (b)

IV. Conclusions

In this paper, we examined the gap between theoretical formulations of the Vehicle Routing Problem and practical challenges encountered in real-world distribution networks. By analyzing a case study from the FMCG industry, we identified several practical requirements that are either underrepresented or entirely absent in the existing VRP literature. These include semi-trailer and truck combinations, dynamic warehouse throughput constraints, driver availability considerations, and time-dependent routing restrictions.

To address these challenges, we developed a genetic algorithm tailored to the problem's constraints and integrated it into a general data model, which has been made openly available for further research and development. Our approach successfully optimized route planning while incorporating real-world operational constraints, demonstrating its feasibility in large-scale logistics networks.

The numerical results confirmed that our approach outperforms historical benchmarks, leading to reduced costs, fewer routes, improved vehicle utilization, and better adherence to operational constraints. Notably, the stability of vehicle load utilization and the reduction in total route length indicate that optimization techniques can significantly enhance logistics efficiency when tailored to practical constraints.

By bridging the gap between theory and practice, this study contributes to the ongoing development of more applicable and efficient RVRP models, ultimately leading to more robust and scalable logistics solutions in dynamic and complex environments.

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