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Designing an Integrated Delivery Routing Optimizer for a Logistics Service Provider: Key Requirements, Techniques and Lessons Learned.

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In this paper we present a real-life case study which investigates how to solve a rich vehicle routing problem in practice. The study was carried out within a logistics service provider, operating in Morocco; an emergent country. We provide a detailed description of the methodological approach that we have developed in practice. This entails several steps including the problem assessment, the data preparedness and the modelling of cost functions. Based on an exact primal algorithm, our solution approach was able to provide executable and cost-effective transportation plans. Meanwhile, the flexible formulation and the algorithm framework made it possible to accommodate technical and business-rule constraints. This study also reveals the complexity of the LSP environment, and highlights its specific needs in terms of resilient and generic solution models.

Key words: Rich VRP; OR practice; integer primal algorithm; transport and logistics; decision-support systems ...

Introduction

With its 180 worldwide connections and proximity to the Strait of Gibraltar, Tangier Med Port has become the 35th largest container port in the world (*Source: Med Port Authority*). Surrounded by a multi-sector industrial hub including automotive, aeronautics, logistics, textiles, food processing and trade, this world-world port has elevated Morocco to a truly global scale of logistics. Since 2010, an ambitious national logistics strategy has been launched to consolidate this dynamic and to upgrade the logistics sector in Morocco. Indeed, the success of this transformation requires the emergence of integrated and efficient

logistics service actors offering adapted and sophisticated services. Several 3PL operators on the market offer an integrated range of logistics services including transport, warehousing, order preparation and other value-added operations. The courier activity is growing by 15% annually with more than 6 million parcels shipped annually, however, 40% of the market is held by the informal sector. On another level, the market for IT equipment for logistics has grown by 30 to 40% over the last 5 years. Nevertheless, the adoption rate of IT remains low in the logistics sector in Morocco (*Source: MLD Agency, National Strategy report, June 2016*). Overall, the multiplication of operators on the market and the diversification of the offer of logistics services had a beneficial impact on logistics costs. Despite these efforts, logistics activities are severely penalized by: (i) unfair competition from the informal sector, (ii) competition from new international actors, (iii) lack of transparency, and (iv) scarcity of standardized regulations. This said, the implementation of the related action plan must be the subject of close collaboration between the ministerial departments, local authorities and stakeholders.

The present paper is a part of a project aiming at developing a new vehicle routing optimizer for a 3PL provider which operates in an extremely complex landscape. This case study summarizes the pre-implementation phase of our system. It is aimed at (i) testing the performance of our solution on several real business configurations at a 3PL company, and (ii) verifying that the developed system's functionality meets specification and business requirements.

The company that participated in this case study is SNTL Group, a leading Moroccan logistics provider since 1937, offering a range of value-added services involving four business activities: supply chain; infrastructure and urban logistic; fleet management; finance and insurance. With the aim of contributing to the foundation of African resilient supply chain solutions, the company has established a research centre, focusing on research, consulting, certification and training activities.

The main **contribution** of this paper is an integrated approach able to provide practical and efficient vehicle routing solutions that integrate both the sourcing level (carrier selection and outsourcing decision) and the control of operations, for long-haul and last-mile deliveries. The proposed models and algorithms are based on a novel primal-based algorithm that produces better solutions in smaller times compared to state-of-the-art metaheuristics. In contrast with classical branch-and-price methods, the proposed approach

can display numerous alternatives to the planner, who can then select the most suitable solution and it guarantees feasible solutions wherever we stop the process.

This paper is organized as follows: first, we give an insight into the VRP systems. Next, we describe the problem and the scope of our study. Then, we describe the overall process of data preparedness, and the adoption of new technical and managerial patterns. Given the unavailability of relevant data, managerial accounting techniques were used to construct reliable cost models. After that, we describe our system's capabilities. Finally, we report the results achieved and the lessons learned.

Relevant Work

Logistics services providers (LSP), commonly known as the third party logistics provider (3PL), are the backbone of logistics operations, and act as a link between the shipper and its operational solutions by handling logistics and transportation operations and developing both standardized and customized services.

In the operations research (OR) literature, planning transportation activities is defined as a vehicle routing problem (VRP), often claimed to be easy to understand but hard to solve. VRP has been extensively covered in the operations research literature in the sense that it props up the logistics and transportation industry as well as the decision-making process. In fact, in the years between 2009 and 2015, 277 papers have been published, they are analyzed and classified in the VRP taxonomy of Braekers et al. (2015). More recent study (Konstantakopoulos et al. 2020) revealed that 263 papers on the subject of freight transportation have been published; from 2010 to 2020. We summarized some of their results in Figure 1, which represents the classification of algorithms for the VRP. For each class, the related number of published papers during the last decade is indicated between parentheses.

The VRP literature shows a predominant trend of heuristics and metaheuristics, which do not guarantee optimality, but they do find improving solutions for large-sized problem instances within a reasonable amount of time. On the other hand, exact methods are rarely applied to solve rich VRPs as they are computationally demanding.

3PLs handle logistics operations of different customers; hence, constraints atomize into hundreds of complex ones, making route planning even more challenging and making it impossible to solve the problem manually. Hence, using VRP software (VRPS) systems

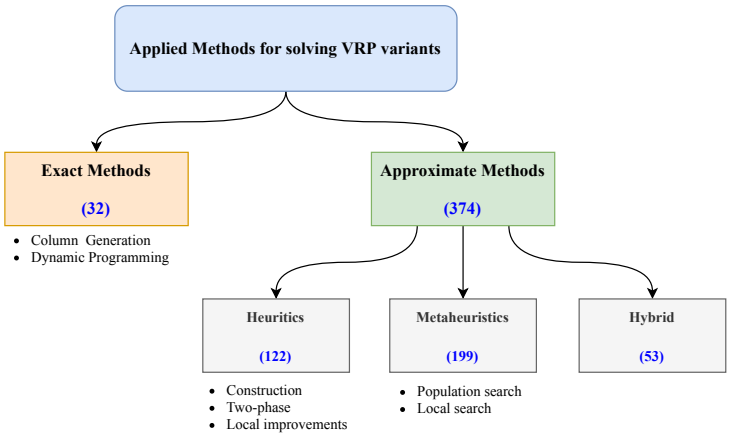

Figure 1 **Classification of algorithms for solving VRP variants, adopted from Lin et al. (2014) and Konstantakopoulos et al. (2020)**

helps them control costs and maintain customer service levels. The main capabilities of commercial VRPS are presented in Figure 2; adopted from the studies of Rincon-Garcia et al. (2018), Bräysy and Hasle (2014), Crainic et al. (2009), Drexl (2012).

According to Drexl (2012), Bräysy and Hasle (2014), Rincon-Garcia et al. (2018), Crainic et al. (2009), commercial VRPS systems commonly use a large set of heuristics, derived from published research, internally customized methods, and in-house algorithms (Holland et al. 2017). Certainly, heuristic methods are fast and generally provide a good compromise between efficiency and quality of the solution. However, some heuristic implementations are tailored to work well in specific test instances, by carefully tuning parameters, these might be a barrier to their practical take-up. Particularly, 3PLs market segment is known for its dynamic constraints (new clients requirements, regulations amendments, etc). Therefore, only agile and resilient VRP systems (Aka., algorithms) can keep these businesses profitable.

Problem Statement

Through this section, we will present the general framework of our case study. We will first introduce the scope of our mission, and then we will bring the reader closer to the operational context of the company.

Scope and Mission

SNTL Supply Chain is a 3PL operating a very large central mixed flows logistics platform, located in the vibrant economic centre of the country and benefiting from a multimodal

Capabilities

Daily routing; weekly routing; turn-by-turn route instructions; re-optimization (orders, stops, rest periods, etc); manual adjustments; historical travel times; statistical reports.

Supported constraints

Time-windows; heterogeneous fleet; pickup-and-delivery; FTL/LTL shipment; geographical restrictions; multi-criterion compatibility; service times; driver rules and skills; overnight parking and resting; cost functions and tariffs.

Applied methods

Heuristics:

1) **Constructive procedures:**
   Parallel saving; Insertion; Cluster first, route second; Nearest Neighbour; Proprietary
2) **Improvement procedures:**
   Relocate; k-opt; Swap/exchange; String-relocate; Cross/string-exchange; Proprietary

Metaheuristics:

Tabu search; genetic algorithms; threshold accepting; simulated annealing; adaptive large neighbourhood search; ant colony

Exact:

Branch-and-cut; branch-and-price; column generation; constraints programming

Performance:

Problem size:

Unrestricted (stops and vehicles)

Running time:

Seconds-20 minutes

Benchmarks:

Solomon VRPTW instances Solomon (1987);
Gehring/Homberger VRPTW instances Gehring and Homberger (1999);
Li/Lim PDPTW instances Li and Lim (2003)

Solvers

Cplex; Boost; COIN; Express; Gurobi; LEDA

Figure 2 **VRPS in a nutshell**

logistic connectivity. The company is the exclusive logistics subcontractor for a wide range of customers from different industries: household appliances (eg.,*Samsung*, *Whirlpool*, ...), home furniture (eg.,*Ikea*), automotive (*Renault*), textile (Government) and food products.

Transport operations fall into three categories: urban last-mile delivery, regional delivery and national delivery.

As part of its 2025 strategic vision, the company wants to strengthen and develop its transport offer both for inbound (long haul) and outbound (last mile) activities. On a further level, the company is expanding rapidly in West Africa, hence the need for automated, generic and resilient transport planning solutions that are effective in practice, scalable with the dynamic environment of the 3PL, and that come as close as possible to the real business process.

The study we are presenting in this paper is the result of a research project carried out jointly with the company's research centre over a period of 3 years. The elicitation phase was the subject of a one-year observation internship within the company. Prior implementation was carried out at the Samsung warehouse. The next step is to deploy to production.

Template of an Operational Day

LSP manages the logistics activities of its contractors, by ensuring all operations from the receiving of goods, through the storage, to the delivery of products as required by the final customers. As illustrated in Figure 3, on a daily basis, contractors (retails or manufacturer) receive purchase orders (POs) from their customers, spread throughout the country, and transfer them from SAP to the 3PL's WMS system. He also forwards the arrival plannings (AP) in preparation for the receiving of goods at the warehouse. After the cut-off time, POs are extracted to excel files, to proceed to a manual planning according to the cluster first, customer second strategy. Then, the assignment of vehicles is carried out by a dedicated department. Once the orders are prepared for the dispatch, the loading operators proceed to place the parcels inside the vehicles following the delivery orders (DOs). Manual loading operation is often efficient, as it is carried out according to field experience, whereas the sequence of visits is the driver's decision.

Delivery time agreements vary according to the transport type. Urban destinations must be served within one day, while the lead time for regional and national deliveries is up to two days. Plus, the company outsources some deliveries to an external courier service in three cases: (i) the destination is poorly connected; (ii) the parcels are light but have high value; and (iii) for facing urgent events. The in-house fleet consists of 300 vehicles of various types and capacities (see Table 1), in addition to the external fleet, chartered as required.

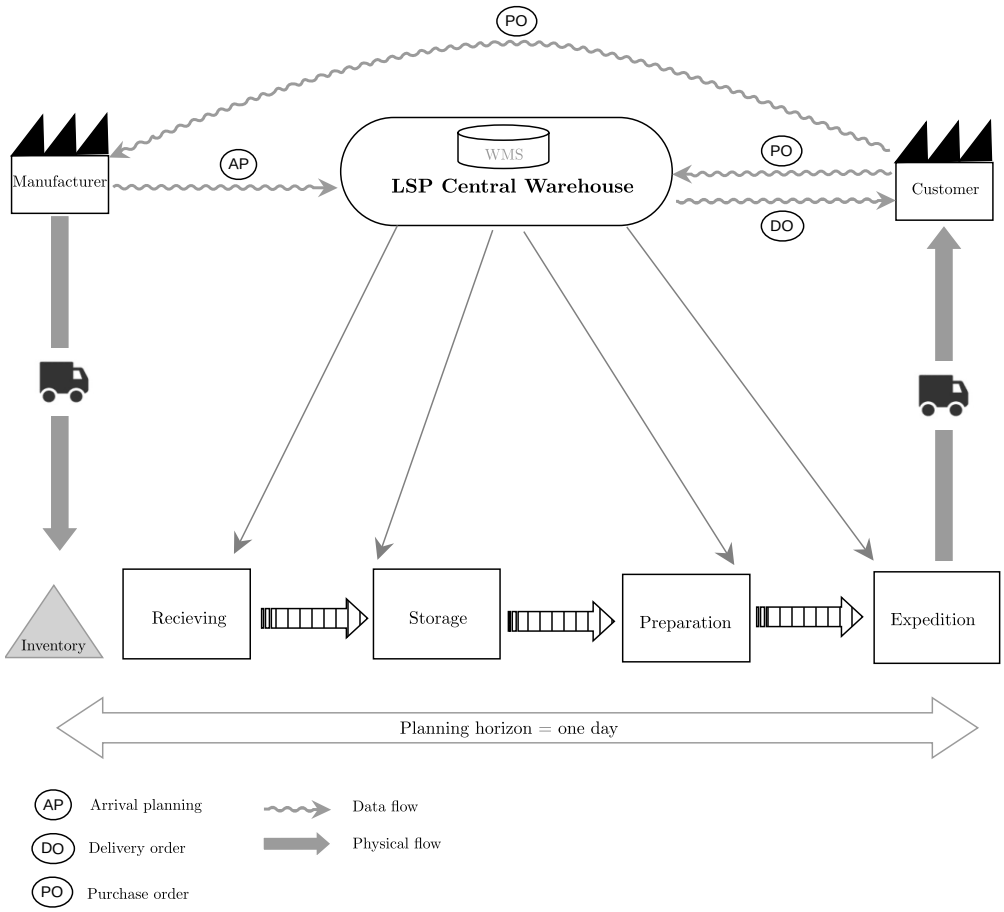

Figure 3 **Value Stream Mapping of the 3PL**

Acronym	GCW*(ton)	Road Network
T_1	3.5	Street class 1
T_2	7	Urban area
T_3	14	Road class 2
T_4	19	Road class 3
T_5	25	Road class 3

*Gross Combination Weight.

Table 1 **Vehicles types and network classes**

The 3PL orchestrates very heterogeneous flows in terms of customer segmentation, product types and sectors. This amplifies the complexity of delivery planning, each one subject to a different set of constraints as shown in Table 2.

Once we have introduced the global context of this study, we can observe that planning transport activity for a 3PL is a major challenge, regulated by a set of endogenous and exogenous constraints. In the following sections, we will describe the fundamental steps and tools undertaken to solve this difficult problem.

Attribute	Related context
Time windows	Customers
Heterogeneous fleet	Customers, profession
Min/Max fill rate	Business-rules, regulation
Compatibility (site/vehicle)	Business-rules
Compatibility (product/vehicle)	Business-rules
Restricted urban accessibility	Regulation
Driving hours	Work-Unions

Table 2 The relevant attributes related to the 3PL context

Data Preparedness

In this section, we will outline a key stage for solving a VRP, namely the modelling and the data preparedness. In what follows, we will present how to successfully conduct this process.

Requirements Elicitation

In practice, things are not as neat and linear as they appear in theory. To gather, evaluate and process accurate requirements, we have followed the following steps:

1) Requirements Gathering. Modelling a real-world problem involves hierarchical sources of information, multi-echelon levels of flows, field-related practices, etc. We used the following techniques:

- Observation: a one-year observation internship was carried out within the company. The direct follow-up of the operations allowed us to identify the main delivery incidents which involve order reject, order return and delivery failure. These incidents are mainly triggered by wrong addresses, wrong orders, unavailable customers, reported requested delivery dates, truck delays, technical problems, expired POs, and lost DOs.
- Interviews: involving executive managers, stakeholders, users, operators, drivers, customers, and authorities.
- Analysis of internal documents: including customer database, carrier database, POs history, DOs history, contracts agreements, financial reports, and legal documents.

Note that diversifying the sources of information contributes to building a mathematical model that is close to reality and prevents obtaining solutions that are not feasible in practice.

2) Evaluation. A good analysis of activities and flows allowed us to determine which factors drive margins at the end-user node, which can be used as guidelines to best improve

future profits. Also, this step provided opportunities to examine new supply chain and distribution approaches. Indeed, the profit margin losses and the rise in operating costs are not only the result of the distribution plans, but also the result of the global transport master plan. That said, the mathematical program had to meet operational and strategic objectives. At the end of this step, we have identified the weakest legs affecting both the operational level (transport planning) and the strategic level (contract negotiation and bidding). These are summarized in Table 3.

Operational level	**Strategic level**
Faulty design of the transportation network and schedules.	Low customer service level and responsiveness.
Poor data accuracy.	Complex business scenarios.
Manual data entry.	Cannot assign the best rate.
Non-optimized planning capabilities across different modes of deliveries.	No constraints are checked before the proposal.
Non-compliance with regulation.	

Table 3 The main inherent weaknesses in the process.

3) Prioritization. Since the context is extremely complex and entangled, incidents and problems are recorded every hour and every day. Their global management is impossible, however, the Pareto principle comes in handy in this context since that 80% of incidents come from 20% of factors, the importance of prioritizing becomes therefore obvious. We have identified the sources of the most penalizing problems which we will expand in the following section; covering data correction.

4) Consolidation. Once the problem is understood, analyzed and separated, it was then possible to consolidate the gathered requirements to set the mathematical formulation of the rich VRP and the definition of its specific attributes. A careful study of the literature investigating close VRP variants provided the guideline for the solution methods that might be successful. Then, the next step is to analyze and prepare the key data.

Data Correction

The company suffers from a major challenge: many of the essential data components were either incorrect, incomplete or unstructured. In what follows, we will describe how this issue has been addressed. We will also provide the statistical analysis techniques that we have used to model the cost functions. This crucial step, entailing correcting and building data, required over 6 months of work.

Customer address. Over a quarter of the customer addresses were incorrect. Physical addresses have been corrected and then transformed into geocodes (i.e. latitudes and longitudes). For a dynamic adjustment, we utilized the internal tracking service to discard long, problematic and risky roads. We will show latter how we were able to make accurate delivery locations by introducing the new service address concept.

Service Time. Delivery stop times are heavily dependent on the processes that occur at each delivery. These processes are often dictated by the customer receiving the delivery and the sidewalk distance from the park point to the actual delivery point. The service time was established with regard to the customer segment. It took into account the loading time per unit of volume, the confirmation orders time, the average wait. These elements have been developed based on the experience of the drivers, business rules, the geographical area of the customers and the delivery reports which indicate the delay factors.

Customer segmentation. Customer analysis is a crucial step and must be done in a loop to maintain control and be sure to integrate all constraints and relevant details. The 3PL manages a wide range of subcontractors from different industries. As a result, downstream customers are very heterogeneous in terms of geographical locations (urban, rural areas), order characteristics (volume, declared value, type), and constraints (multiple time windows, vehicle compatibility, service time). Thus, the customers and related constraints had to be split into subsets.

Fleet of vehicles. The fleet K contains 300 owned vehicles, and when required, these are chartered from external carriers. Each vehicle $k \in K$ is characterized by the type (rear opening, side opening, swap body, semi-trailer); the volume capacity in cubic meters (CBM); the Vehicle Fill Rate (VFR); the ownership (owned or chartered vehicle); the fixed cost F^k, and the variable cost V^k. Note that the VFR is the ratio of the actual capacity used in a vehicle to the total capacity available in terms of weight and volume. To secure loads against movements, and to maximise efficiency, each vehicle must satisfy $\text{VFR}_{min} = 60\%$ and $\text{VFR}_{max} = 90\%$.

Business rules. It is extremely difficult to accommodate exogenous constraints for the 3PL as customers and flows come from different sectors. Business rules file was created, where all rules and constraints from the profession, transport agreements, national transport agency, the ministry, and work union were translated into appropriate readable rules.

The Need for New Paradigms

Following the elicitation phase, we came up with the conclusion that financial inefficiency comes both from operations and business models, highlighting the need not only to optimize operations, but above all to implement new solutions paradigms based on best practices.

Service address vs. physical address. The thorough analysis of the data let us state that the addresses of the customers appearing in the official files, represent physical addresses and do not correspond to the accurate location where the deliveryman will park to make the deliveries (delivery door or the loading dock). This results in errors of several kilometers and hours. Indeed, in urban areas, stops and U-turns might cause security incidents, tickets and delays. We have therefore come to an agreement that a new customer must communicate his exact delivery address. For existing customers, the information was provided by their agents and also by the drivers.

Courier service delivery option. We have already mentioned that, in predefined cases, some deliveries are outsourced; they are operated by an external courier operator. By analyzing transport costs, as well as the operational flows, we have noticed that parcel delivery is a useful transport solution offering a good compromise between cost, efficiency and safety. That said, we have integrated the courier option as a new vehicle type, and the solver decides when to outsource a delivery according to the profitability of the route. Note that additional assignment constraints have been considered, including the maximum number of daily requests, or the order CBM range. The impact of this strategy will be outlined in Table 6.

Inter-regional delivery. In order to facilitate planning, the internal business processes banned inter-regional deliveries. As explained earlier, the operator consolidates orders so that each vehicle visits one city. This decision was the result of a weak information system and a lack of planning resources. Based on data analytic techniques, the distribution network was clustered into five zones, connected by non-overlapping delivery axis. Also, infeasible arcs regarding the real road network and traffic regulations were discarded. Finally, nodes located at the same shopping malls and supermarkets were aggregated. The distribution network was modelled on an *expert-guided* graph $G(A_{SD_d}, V_{SD_d})$ where A_{SD_d} represents the connecting arcs towards the five shipping direction $\widehat{SD_d}$, and V_{SD_d} represents the cluster of customers where cycles are permitted. This modelling, efficiently solved by the dynamic programming algorithm, made it possible to tackle both inter and intra-regional deliveries, which proved to be very practical.

Order planning. Loading and unloading operations benefit from the human know-how and the field- experience, thus arrangement of the goods in the vehicles is often optimized. Our concern was rather the automation of loading orders. This process must comply with several constraints, mostly practical: (i) a stock keeping unit (SKU) cannot be split; (ii) prioritize least-cost vehicles assignment; (iii) respect the permitted VFR intervals; (iv) respect the customer contractual terms (full truckload and less than truckload modes); and (v) minimize empty space.

After going through the crucial stages of modelling and preparedness, in the following section, we will present the implemented solution, its components and advantages.

Managerial Accounting Techniques

In practice, the cost function is not always structured and yet further analytical processing is required. Our objective function aims at maximizing the profit generated from operating deliveries. It is calculated as revenue (transport rate less transport cost). In the following, we will describe the statistical analysis tools we employed to model the transport rate and the transport cost functions.

Transport Rate Model

The transport rate is the price paid by the customer n to receive the order ξ^n. For a better comprehension, Figure 4 displays a sample of the pricing grid used by the 3PL. The columns framed in red indicate thirty CBM volume intervals of the demand ξ^n, ranging from 0.1 CBM to 40 CBM. The rate is quoted in accordance with the destination and the volume interval. Here for example, a customer n, located in *Boujdour*, with demand $\xi^n = 0.26$ CBM, will pay the rate circled in green. Note that for higher volumes, pricing is switched to FTL; a flat rate depending on the destination and the shipment type (20"FN, 40"FH, 40"FN). The transport rate is a piecewise linear function, given by:

$$\mathcal{P}(\xi^n) \quad = \quad R_v^n \times \xi^n \qquad a_v \leq \xi^n \leq b_v \quad \forall v = 1, 2, \ldots, 30 \tag{1}$$

where R_v^n stands for rate associated with the vth volume interval $[a_v,\ b_v]$.

Transport Cost Model

In what follows, we describe the steps that allowed us to model the transport cost function.

Departure site	Destination City	CBM Range								
		0	0.1	0.2	.....	35	40	20FN	40FH	40FN
		0.1	0.2	0.3	.....	40	FTL			
Casa Warehouse	Agadir	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Al Hoceima	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Azilal	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Ben Slimane	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Béni mellal	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Boujdour	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Boulemane	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Casablanca	x	x	x	.....	x	x	x	x	x
Casa Warehouse	Chefchaouen	x	x	x	.....	x	x	x	x	x

Figure 4 **Example of the transport rate (tariffs) data file**

Destination	Total transport cost				
	T1 (3.5t)	T2 (7t)	T3 (14t)	T4 (19t)	T5 (25t)
	Carriers offer	Carriers offer	Carriers offer	Carriers offer	Carriers offer
City 1	carrier 1	_	carrier 1	carrier 1	carrier 1
	:	_	:	:	:
	carrier m	_	carrier m	carrier m	carrier m

Figure 5 **Example of the transport cost data file**

Linear Interpolation. To analyze the total transport cost, we examined first the relative database, an extract of which is presented in Figure 5.

On the one hand, we can notice that for each destination and for each vehicle type, there are several price quotations offered by third-party carriers. For the sake of simplicity, and since these offers are generally similar, we have considered an average transportation cost per destination and for each vehicle type. On the other hand, as it is shown in Figure 5, entries for truck type T_2 are not available. Therefore, we used the linear interpolation technique to predict the missing transport cost from data of trucks T_1 and T_3, according to the following interpolation equation:

$$y_2 = y_1 + (y_3 - y_1)\frac{(x_2 - x_1)}{(x_3 - x_1)}$$

where x_i (resp., y_i) is the volume capacity (resp., the transport cost) of vehicle T_i, $i = 1, 2, 3$.

Linear Regression Analysis. In this section, we explain how regression analysis was used to estimate fixed and variable costs of each vehicle type. First, in the input data file (see

Figure 5), we added a column that displays the distance travelled between the destination (city) and the central warehouse. Then, linear regression was calculated to predict variable cost V^k of vehicle k (dependent variable) based on the travelled distance η^k by vehicle k (independent variable). In fact, linear regression uses a series of mathematical equations to find the best possible fitting line to the data points (see example in Figure 6).

Regression analysis calculates: $\mathcal{C}_T^k$ the total cost; F^k the fixed cost; V^k the variable cost per travelled distance units η^k, where distance is measured in kilometers and costs are measured in Moroccan currency (MAD). The total transport cost is given by:

$$\mathcal{C}_T^k = V^k \times \eta^k + F \qquad \forall k \in K \tag{2}$$

Regression analysis in *Excel ToolPak* add-in provided the summarized output presented in Table 4. In the column marked "Coeff", the number labeled F^k is a statistical estimate of the fixed cost, and the number labeled V^k is a statistical estimate of the variable cost per distance unit. The column labeled "$p-value$" expresses the level of statistical significance. Finally, columns 4 and 5 display the confidence interval values.

Costs	*Coeff*	*p-value*	*Lower 95%*	*Upper 95%*
F^k	510.74	1.4e-11	396.15	625.33
V^k	5.45	3.2e-41	5.23	5.67

(a) Vehicle type $K_1 = 3.5t$

Costs	*Coeff*	*p-value*	*Lower 95%*	*Upper 95%*
F^k	528.27	4.1e-09	381.79	674.75
V^k	6.73	1.4e-40	6.45	7.01

(b) Vehicle type $K_2 = 7t$

Costs	*Coeff*	*p-value*	*Lower 95%*	*Upper 95%*
F^k	545.82	1.1e-06	349.91	741.73
V^k	8.01	2.3e-38	7.64	8.38

(c) Vehicle type $K_3 = 14t$

Costs	*Coeff*	*p-value*	*Lower 95%*	*Upper 95%*
F^k	458.96	6e-08	316.15	601.78
V^k	9.59	7e-48	9.32	9.86

(d) Vehicle type $K_4 = 19t$

Costs	*Coeff*	*p-value*	*Lower 95%*	*Upper 95%*
F^k	499.97	1e-05	292.50	707.44
V^k	12.21	2e-45	11.81	12.60

(e) Vehicle type $K_5 = 25t$

Table 4 Regression analysis calculations summary for each vehicle type

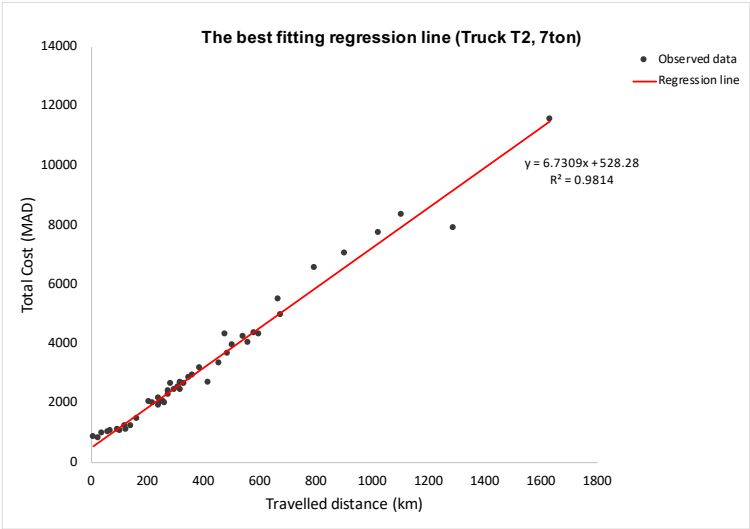

Figure 6 **Regression line, vehicle type** T_2

From Project to Reality

After a period of testing on several configurations, we were able to successfully implement the solution. Notations, mathematical formulations and algorithms are provided in the Appendix. For extensive details on the primal-based solution approach, we refer the reader to the following papers Tahir et al. (2019), Messaoudi et al. (2020), Zaghrouti et al. (2014), Bouarab et al. (2017).

Applied Methods

The main objective aimed at solving a complex vehicle routing problem, with time windows, a heterogeneous fleet, site compatibility, delivery options and a set of business constraints. The master problem (MP) was modelled as a set partitioning problem (SPP). The subproblem (SP) was modelled as the shortest path with resource constraints (SPPRC), defined on a customized cyclic urban network, and solved using a dynamic programming (DP) algorithm (Feillet et al. 2004). To provide feasible and efficient solutions, we utilized a primal integer programming algorithm, called integral column generation (ICG) (Tahir et al. 2019). ICG is a sequential algorithm, embedding an integral primal algorithm in a column generation scheme. As shown in Figure 7, the column generation (CG) process splits the problem into two problems: SP and restricted MP (RMP). The latter is solved using the integral simplex using decomposition (ISUD) algorithm (Zaghrouti et al. 2014) and decomposed into two subproblems: (i) the reduced problem (RP) contains a very small number

of variables and constraints. (ii) The complementary problem (CP) finds a direction which improves the actual solution by updating the set of variables and constraints.

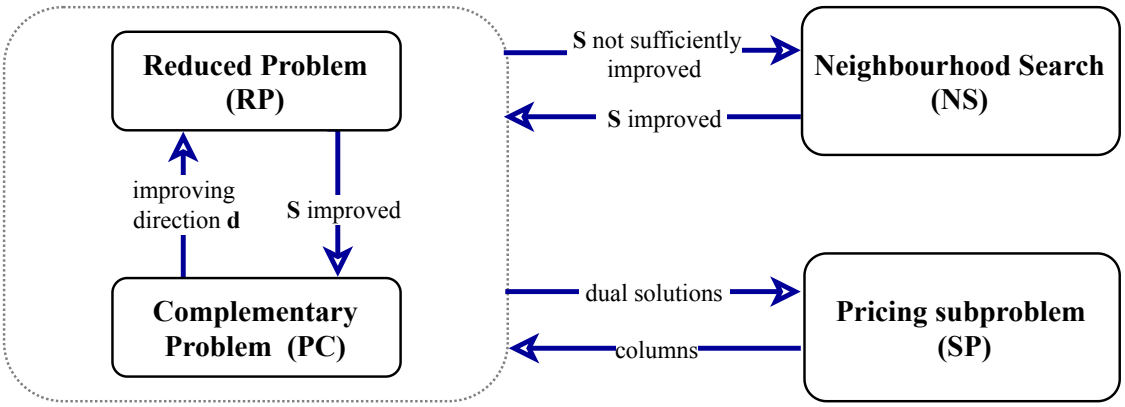

Figure 7 **ICG algorithm process**

ICG takes advantage of the performance of CG and the dynamic decomposition of the RMP allowing its fast re-optimization. Also, the primal programming framework guarantees that the feasible solutions can be obtained at any moment of the solution process; no necessity to wait until the final iteration. The four ICG modules collaborate in a coordinated approach to find fast and feasible solutions, without time-consuming tuning procedures, as only three easy parameters are used. Mainly, the latter define, according to the situation, the improvement rate of the output solutions as well as the stopping conditions of the process.

Key Features

The main features of our systems are summarized in Figure 8. The integrated delivery routing optimizer (IDRO) provides many advantages:

Algorithm. The solution approach is a fair compromise between the efficiency of heuristic methods and the reliability of exact methods, which results in a neat and generic scientific code; thus, the system does not become obsolete if it is confronted with new constraints or new customers. Indeed, SPPRC makes it possible to accommodate complex and non-linear constraints, while the neat decomposition of RMP provides fast re-optimization, required in case of a vehicle breakdown, insertion or cancellation of orders, road closures, etc.

Capabilities

Daily routing; inbound and outbound routing; re-optimization (orders, stops, rest periods, etc); manual adjustments; historical travel times; statistical reports, transport scenario simulation.

Applied methods

1) **ICG algorithm**
   CG; ISUD; SPPRC; B&P; DP
2) **Improvement procedures**
   NS; ZOOM (Zaghrouti et al. 2020) ;

Client Access

Dekstop-Web; Dekstop-exe;

Architecture

On-prem, dedicated-cloud instances, multi-tenant cloud;

Supported constraints

Time-windows; heterogeneous fleet; delivery options; FTL/LTL shipment; geographical accessibility; multi-criterion compatibility; driver rules.

Performance:

Accuracy:
0%- 2.37% (Messaoudi et al. (2020))

Problem size:
Unlimited fleet size; 700 B2C and B2B customers; 199 requests; unlimited parcels.

Running time:
0.8 sec- 500 sec.

Benchmarks:
Real extracted instances (home appliance segment).

Solvers

Cplex; Boost; COIN; user solver.

Figure 8 **IDRO key capabilities**

Architecture. In business-based applications, business rules and data processing logic vary according to the market landscape. It is crucial that the system can be customized by adding plugin modules to extend the functionality of the core system providing extensibility, flexibility, and isolation of application features. The overall architecture of our solution is illustrated in Figure 9.

Decision-support. There are two different interfaces for two personas users: managers and dispatchers. Via the first interface, the user has access to the production modules which enables the optimization of transport operations. The second interface gives access to the decision support modules, which ensures operations control, strategic bid and award process.

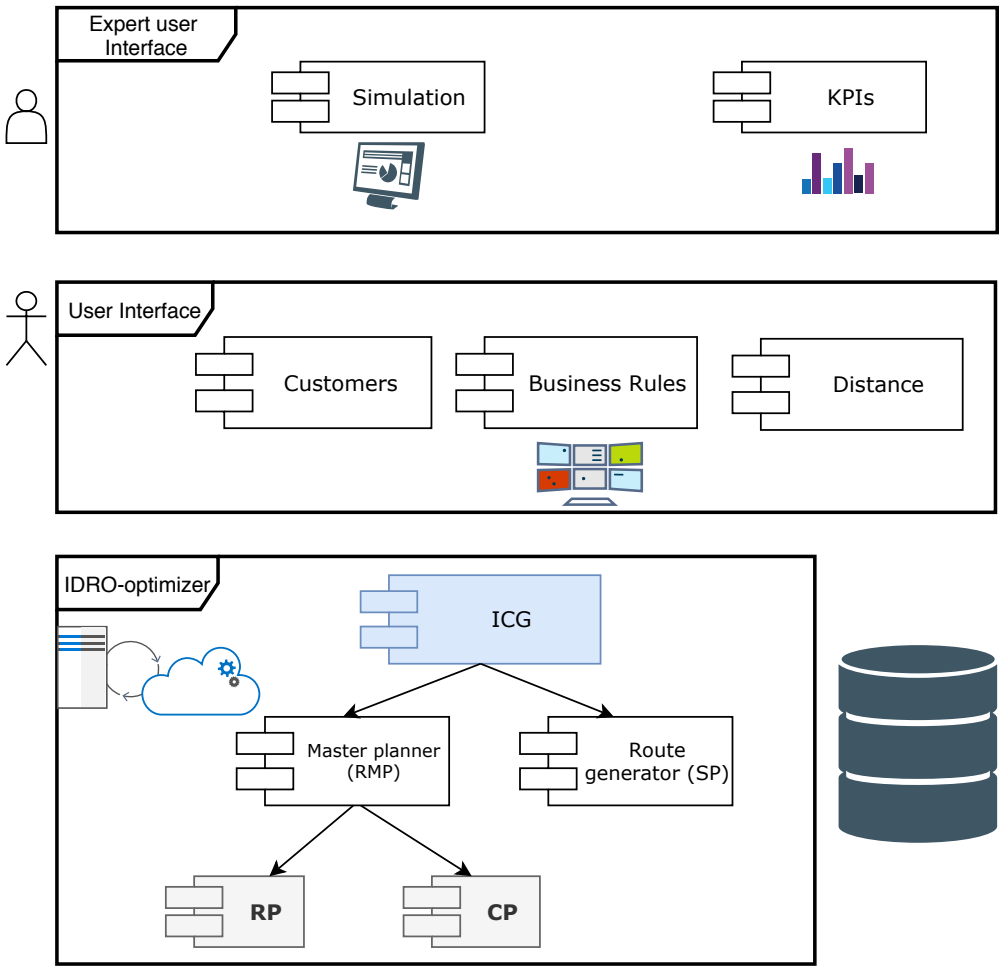

Figure 9 **IDRO architecture overview**

System parameters. We use five parameters that are easy to configure and understand, without requiring that the user should have technical or theoretical knowledge. In addition, it is possible to set up default settings by type of business or contractors.

Human knowledge. The system accommodates manual interventions for example set up priorities, discard some constraints, activate and deactivate vehicles, etc. Besides, a feasible solution is always available, means that the dispatcher could stop the process whenever he deems it beneficial. This is a particularly required asset in breakdown situations.

Available information. It is crucial for a primal algorithm to start from a good initial point to enhance its performance. Thus, we take advantage of available information such as delivery history to build feasible visit patterns. The algorithm is primal insofar as it optimizes the problem itself and uses the currently available information to build the improving

solutions. In such a competitive environment, governed by bidding and contracting, it is essential to capitalize on the information at hand.

Results and Impact

Through this section, we will present the impact that the solution has achieved. The realized benefit is roughly divided into financial and nonfinancial components.

Financial Results

The finance department has estimated a 5% increase in overall profit, and is projecting 15% growth within 5 years, with roll-out to all other seven warehouses. Table 5 reports a small insight on the performance of the integrated delivery route optimizer (IDRO); compared to the in-house solution of the 3PL. For a meaningful, unbiased results, the instances correspond to nine operational days from different periods. Column 1 is for the name of the instance (Name). Column 2 is for the number of customers ($|N|$). Column 3 displays the percentage of customers served through a last-mile network (% L.Mile). Columns 4 and 7 display the financial profit generated by the route in Moroccan currency (Profit); columns 5 and 8 display the number of trucks (Nb.Trucks). Finally, column 6 displays the total computing real time in seconds (Time). IDRO successfully solved all the instances in just a few seconds. This applies even to large instances. The gain is calculated as the difference between the profit made by our solution and the profit made by the in-house solution. The *partial* profit achieved by IDRO showed a substantial improvement compared to the in-house solution (50%). The *total* projected gain was estimated considering: (i) roll-out to the other seven warehouses, (ii) coverage of all customers, and (iii) the average number of daily requests. Finally, we note that no profit could be achieved for the instance S-03. Indeed, this is the result of poorly negotiated selling rates.

Nonfinancial Results

Service Address. The new geocoding paradigm we have introduced made it possible to locate the exact address of the unloading, avoiding delays, U-turns and stops. This has resulted in considerable savings in terms of delivery times. A minimum of 15 minutes per route visiting 3 customers can be saved. For an average of 45 vehicles per day, this results in monthly savings of 20,250 minutes.

Instance			**IDRO**			**In-house.Sol**	
Name	$\|N\|$	% L.Mile	Profit(MAD)	Nb.Trucks	Time(sec)	Profit(MAD)	Nb.Trucks
S-01	27	78	3768	21	1.15	2505	8
S-03	34	76	-1207	26	0.62	-6027	6
S-04	40	90	2100	36	2.2	510	4
S-05	45	38	5780	17	2.29	3700	13
M-02	63	65	4005	41	7.48	1711	9
M-03	66	52	3708	34	6.61	2600	18
M-04	66	89	2080	59	7.36	594	18
M-05	83	64	6200	53	24.46	5500	10
M-08	98	41	7048	40	67.61	5390	23
Total 9-day profit			33,482			16,483	
9-day gain (MAD)			16,999				
Annual *partial* gain (US)			49,485.98				
Annual *total* gain (US)			519,277,5				

Table 5 Numerical results comparing IDRO and the in-house solution on 9 real instances

Courier Service delivery option. Let us now look at the impact of the courier service integration. Table 6 compares the performance of the algorithm implemented with and without the courier delivery option: IDRO and DRO, respectively. The improved version yielded a daily substantial cost decrease, reaching 1,600 US on average.

Instances		**IDRO**			**DRO**		
Name	$\|N\|$	Time(sec)	Cost(MAD)	No.Veh	Time(sec)	Cost(MAD)	No.Veh
S-03	34	0.9	6854	26	1.1	27891	10
S-04	40	4.4	5294	36	5.6	23209	10
S-07	49	1.1	27099	21	2.2	30676	14
M-01	62	4.4	9366	50	709	35752	14
M-03	66	6.6	18775	34	19.8	31979.8	14
M-04	123	12.9	116130	59	12.87	129783	52
Avg	62	4.6	30586	38	125	46548.9	19

Table 6 Quantitative impact of the Courier Service delivery options on six real-world instances

Customer service. An analysis of the results obtained over a period of 30 days showed that delivery incidents were reduced by 70%, particularly those caused by address errors, delays, order errors and lost documents. Incidents intrinsic to the customers and to the fleet's management are still persistent, and are the result of the holistic environment.

From operational, tactical and strategic angles, the indirect repercussions of the solution are summarized in Figure 10.

Figure 10 **Operational, tactical and strategic impact.**

Lessons Learned

the sharing of success and failure experiences is of great benefit to both researchers, students and the business community. Based on our experience, lessons learned worth sharing and capitalizing on are as follows:

- contrast to theory, the correlation between the performance of the algorithm and the quality of the solution is not obvious in practice. Several factors from operational, organizational or technical backgrounds can limit performance and efficiency, those include data accuracy, the business process, the transport master plan, and the geographical representation of the network.
- The elicitation phase is a key step, which contributes to outlining the problem and to develop a good model supporting the entire distribution network. It is necessary to succeed in federating all the stakeholders, of all hierarchical levels. Nevertheless, external actors must not be neglected.
- Data processing is the most fastidious stage, whereby it is necessary to correct and build the needed data.

- Allow two to three attempts to reach a first suitable solution. Each attempt should serve as a prototype, which will be used to gain shareholder support when validating decisions or new investments.
- The risk entailed by organizational changes, and business process reevaluation should be expected. Solutions must be smoothly implemented close to the drivers and operators to reduce and manage their resistance to change.
- Separating customers into sub-segments enables clustering customers with similar needs, which leads to a more effective analysis.
- Develop the skill to transform complex mathematical models and business processes into simple configuration such that the user does not see the complexity.

Conclusion

In this paper, we presented a summary of a real case study conducted within a 3PL. The objective was twofold: (i) to show what the implementation of VRP looks like in practice, and (ii) to highlight the needs of 3PLs in terms of planning and optimization tools to face the great challenges they face. In this study, we presented the various stages that led to the implementation of the solution. The direct follow-up of the operations on the field and the close collaboration with the actors gave us a good understanding of the flows, bottlenecks, sources of losses and also the potential areas for improvement. To summarize, the solution was able to achieve interesting results on the operational, tactical and strategic levels.

With the aim of creating solutions capable of solving more general VRPs, our system is currently undergoing improvement, by the integration of additional improving and accelerating approaches, from heuristics to Machine Learning techniques.

Appendix

Notation

In the remainder, we use the notation organized in Table 7.

Notation	Type	Description
Ω	–	Set of feasible routes
N	–	Set of customers to visit
K	–	Set of heterogeneous k-type vehicles
a_{ir}	binary	Is equal to 1 if and only if customer i is served by route r
ξ_i	real	Demand associated with customer $i \in N$
p_r	real	Profit collected by the route $r \in \Omega$
q_k	real	Capacity of vehicle $k \in K$
θ_r	binary	Is equal to 1 if and only if route r is selected

Table 7 Mathematical notation

Mathematical Models

The master problem and the subproblem are formulated as SPP and SPPRC, respectively.

$$(SPP): \quad \max_{\theta} \quad \sum_{r \in \Omega} p_r \theta_r \tag{3}$$

$$\text{s.t.} \quad \sum_{r \in \Omega} a_{ir} \theta_r = 1 \qquad \forall i \in N, \tag{4}$$

$$\theta_r \in \{0,1\} \qquad \forall r \in \Omega \tag{5}$$

Each variable θ_r is associated with a feasible route $r \in \Omega$ which specifies a sequence of customers $i \in N$ to be served. The objective function (3) aims to maximize the profit made by the feasible route r. The constraints (4) guarantee that each customer is delivered exactly once. The choice of binary variables is imposed by (5). The subproblem is modelled as a shortest path problem with resource constraints, and is solved using a dynamic algorithm as shown in Feillet et al. (2004). We have one supbroblem for each $k-$vehicle, put simply we omit the k-index. The reduced cost of feasible route r travelled by $k-$vehicle, starting and ending at the depot O and visiting a sequence of customers $i \in N$ is computed as :

$$\overline{p}_r = p_r - \sum_{i \in N} a_{ir} \pi_i > 0$$

where π is the dual variable associated to the partitioning constraints (4). If all columns have negative reduced cost, the algorithm stops and an optimal solution is obtained for the linear relaxation of (SPP) (3-4).

ISUD Algorithm

Columns in A are partitioned into three sets such that:

$$A = \begin{bmatrix} S & C & I \end{bmatrix}$$

Where S, C and I denote respectively the columns of the current integer solution, compatible columns subset and incompatible columns subset. ISUD algorithm (see Algorithm 1), splits the RMP into two small subproblems: the complementary problem (CP) handles the incompatible columns and finds a descent direction $\mathbf{d}$ leading to an improved solution, while the reduced problem (RP) handles the compatible columns and seeks to improve the current solution. Let $\bar{\theta}$ denote the current integer solution, and $\mathbf{d}$ denote the direction leading to the next improved solution.

Algorithm 1: $ISUD$ pseudocode

Find initial solution θ^0 and set $\bar{\theta} \leftarrow \theta^0$
$[S \quad C \quad I] \leftarrow$ Partition the binary matrix A into columns subsets
do
  Solve $RMP(\bar{\theta}, C)$ to improve the current solution
  $(Z^{CP}, d) \leftarrow$ Solve CP to find a descent direction
while $Z^{CP} > 0$ ***and d*** *is integer*
$\bar{\theta} = \bar{\theta} + d$
return $\bar{\theta}$

ICG Algorithm.

The integral column generation (ICG) algorithm is outlined in Algorithm 2.

1. The initialization step builds an artificial initial solution (θ^0, π^0).
2. The first step starts by solving the subproblems $SP(\pi^t)$. Using the duals π^t, positive-reduced cost routes are generated and included in RMP. If no such routes are generated, we stop the algorithm and the best solution found θ^* is returned.
3. In the second step, ISUD solves the RMP to improve the solution. The criterion $minImp$ decides whether the improvement is sufficient or not. If so, neighborhood search is explored around θ^t by solving a very small MIP using a commercial solver (*Cplex*). This improvement step is iterated until the number of consecutive improvement failures $consFail$ reaches $maxConsFail$.

Algorithm 2: ICG pseudo-code

Parameters: $maxConsFail$, $minImp$.

Initialize : $t \leftarrow 0$; $(\theta, \pi) \leftarrow (\theta^0, \pi^0)$; $consFail \leftarrow 0$

Output : (z^*, θ^*)

```
repeat
    Step 1: CG
    Ω' ← Solve the SP(π^t)
    if Ω' = ∅ then
        break
    end
    Ω ← Ω' ∪ Ω
    t ← t + 1
    Step 2: RMP
    (θ^t, z^t, π^t) ← Solve the RMP using ISUD
    if (z^{t-1} − z^t)/z^{t-1} ≤ minImp then
        consFail ← consFail + 1
        θ^t_NS ← search an improved solution around θ^t by solving a restricted MIP
        if z^t_NS > z^t then
            θ^t ← θ^t_NS
            (θ^t, z^t, π^t) ← Resolve RMP using ISUD
        end
    else
        consFail ← 0
    end
    (z*, θ*) ← (z^t, θ^t)
until consFail ≥ maxConsFail
return (z*, θ*)
```

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