REPORT

Route optimization: when theory meets reality

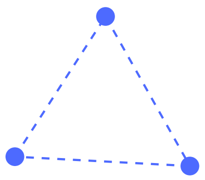
THE STARTING POINT

Delivery route planning is a hyper-complex mathematical problem

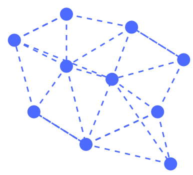
The number of possible tours for a given set of points explodes at a dizzying rate as points are added. If a driver makes 25 deliveries in a day, there are as many different possible routes as there are grains of sand on Earth.

On top of that come numerous operational constraints. Each one narrows the space of valid solutions, yet makes finding the best of the remaining ones even harder to compute.

3
points to visit
=
6
possible tours



10
points to visit
=
3,628,800
possible tours



THE CONSTRAINTS ADDED TO THE CALCULATION

- Vehicle capacity
- Weight and size of packages
- Delivery time slots
- Traffic and congestion

Figuring out the best tour, even in relatively simple contexts, is almost impossible for a human brain.

This takes nothing away from an experienced planner: they do not compare every combination, they draw on their field experience to reach a reasonable solution quickly, with no guarantee that it is the optimal one.

THE PROMISE

Fortunately, solutions exist: algorithmic route optimization

Faced with this complexity, optimization algorithms converge towards tours that are close to optimal, within a reasonable computation time.

The benefits of these solutions are potentially enormous, on costs as much as on service quality.

-30%

reduction on operating costs.

-30%

reduction on CO_2 emissions.

100%

of delivery time slots observed.

Hundreds

of hours saved per year on planning.

Yet in practice, very few companies make full use of these solutions.

The reason is not that the algorithms lack maturity, but that there is a gap between the mathematical theory of the problem and the operational reality of the field.

So what's wrong with route optimization solutions?

The data is poor quality or incomplete

Some of the information the calculation needs simply does not exist in the database, and is only known by the operational team: the preferences of certain customers, the specifics of access to a site, or informal constraints that were never written down.

WHAT IT MEANS IN PRACTICE

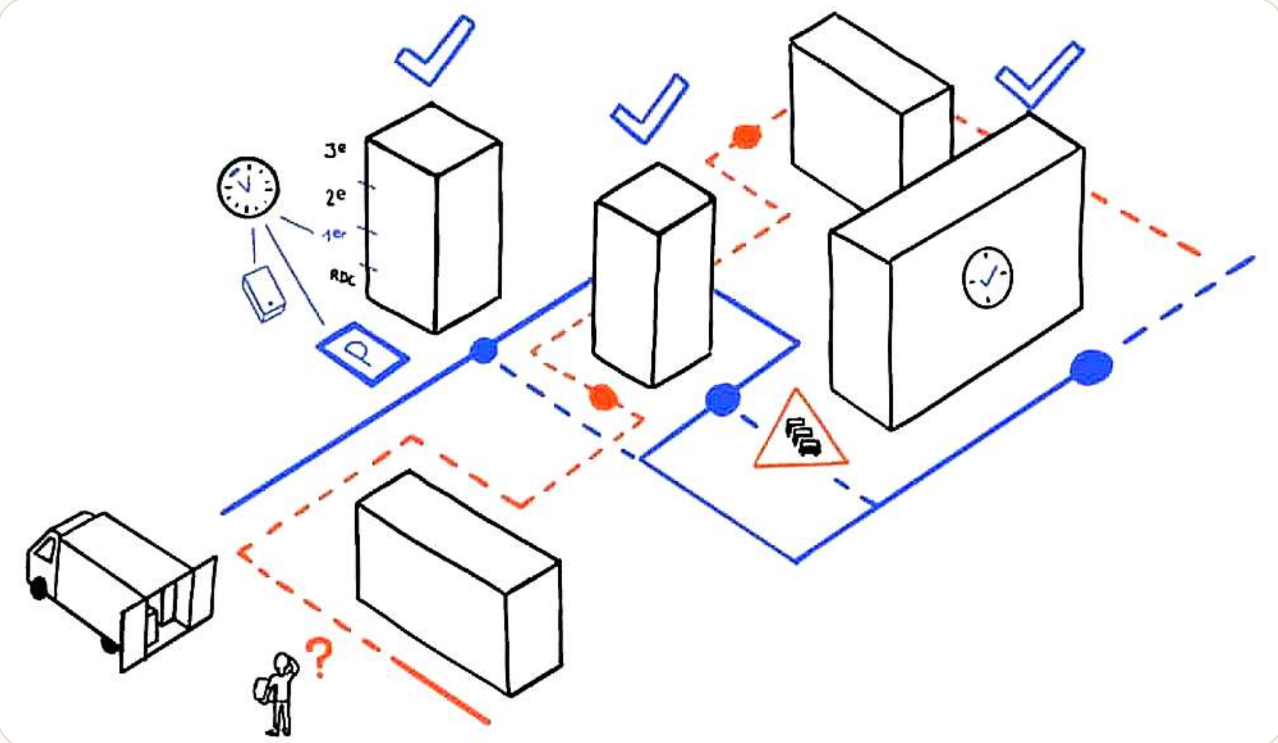
An algorithm computes an “optimal” tour from incomplete data: a tour that ignores real constraints and turns out to be unworkable in the field.

The data poorly reflects the reality of the field

A typical example: a delivery time averaged at 5 minutes per point, when in practice it varies from 3 to 20 minutes depending on access, floor level, or the nature of the parcel.

WHAT IT MEANS IN PRACTICE

Tours built on smoothed averages systematically under- or over-estimate certain travel times, which cascades into delays across the rest of the route.



THE 4 PRACTICAL OBSTACLES

The business environment is dynamic and changing

Traffic jams, missing customers, wrong phone numbers, parking difficulties: the last mile concentrates most of the hazards that cannot be foreseen at the time of the calculation.

WHAT IT MEANS IN PRACTICE

A tour that is theoretically optimal at the start of the day quickly becomes sub-optimal, or even unworkable, as soon as the first surprises appear.

The business constraints are very specific

For example: “the delivery of some furniture requires 2 deliverymen”, a precise business rule, rarely anticipated by generic solvers that were not configured for this case.

WHAT IT MEANS IN PRACTICE

If the algorithm cannot model that constraint, it produces a tour that, once in the field, requires manual intervention or fails outright.

WHAT THESE FOUR OBSTACLES HAVE IN COMMON

A tour calculated without taking them into account is not simply less good: it is often plainly not achievable in the field.

It is precisely this gap that explains why many companies, after a first disappointing attempt, abandon or under-use these tools.

At Kardinal, every problem has its solution

As with any software solution, how well these mechanisms work depends on the implementation context (quality of the integrations, volume of historical data available, change management): they significantly reduce these obstacles without making them disappear entirely.

Poor quality or incomplete data

Kardinal's optimization engine never stops optimizing, rather than running one frozen calculation: when a data error or gap is detected or corrected along the way, the algorithm adjusts the affected tour incrementally, without restarting the optimization from scratch.

Data that poorly reflects the field

Kardinal's algorithms learn from field data through Machine Learning, trained on the history of times actually observed rather than on declared averages, so as to progressively refine travel and service time predictions by type of stop, time of day, or geographic area.

Dynamic and changing environment

Kardinal supports the operational team even after the drivers have left: hazards reported from the field (delays, traffic jams, missing customers) trigger a re-adjustment of the tours during the day, rather than a mere alert requiring systematic manual action.

Very specific constraints

After several years of R&D, Kardinal built its own proprietary solver, designed to model specific business constraints: required skills, number of people per intervention, compatibility between parcel types and vehicles.

Ten years of logistics optimization, within reach.

Kardinal supports logistics players in the digitization and optimization of their transport operations.

Thanks to artificial intelligence, Kardinal provides solutions dedicated to performance optimization and decision support, for more efficient, more agile and more sustainable logistics.

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