

## ODL LIVE WHITE PAPER SERIES

# *Predictive route optimisation for next-day deliveries with same-day collections*

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### Abstract

In this whitepaper we examine the performance of predictive route optimisation for a particular use case - *next-day deliveries with same-day collections*. This case arises for both parcel couriers and palletised freight networks. We examine how the introduction of predictions changes the structure of the optimised routes and we demonstrate efficiency savings. This work is part of the on-going development of the prediction engine for ODL Live – our realtime route optimisation system.

## 1 Introduction

Route optimisation is the process of designing a set of efficient vehicle routes to serve a set of stops. In realtime route optimisation problems, one or more stops must be assigned to drivers while some upcoming stops for the same shift are still unknown. In other words, some jobs are assigned to drivers before other jobs have even been created and entered onto the system. The assignment of currently-known stops affects the ability of drivers to efficiently serve future currently-unknown stops.

Realtime route optimisation problems feature in a number of different industries and exhibit different levels of 'realtime' depending on the job booking patterns. A realtime problem implies that part of the problem – i.e. future stops – is currently unknown, so incorporating predictions of those stops within the optimisation algorithm is an obvious way to increase the quality of the resulting routes. In the published academic research, realtime problems are known as *dynamic vehicle routing problems* and realtime problems using predictions are known as *dynamic and stochastic vehicle routing problems*, however we favour using the words 'realtime' and 'predictions' over 'dynamic' and 'stochastic' as we feel their meaning is more easily understood.

In this whitepaper we look at one particular realtime case - *next-day collections with same-day deliveries* - and present preliminary testing of our integrated prediction and route optimisation engine. Next-day deliveries occur when a set of items need to be delivered on a specific day but these deliveries are known (i.e. booked onto the system) on the preceding day. Same-day collections occur when a set of items need to be collected on a specific day, but these collections are not known about until that day (usually after drivers have already started working). Typically, next-day deliveries would be delivered from a central depot to many locations and same-day collections would be collected at multiple locations (warehouses, factories, company offices or homes) for delivery back to a central depot.

Pallet networks, parcel couriers and other types of logistics provider run last-mile routes containing next-day deliveries with same-day collections. For example, in pallet networks palletised freight is shipped from a central hub to a local depot the night before, to be delivered in the morning. The local depot would also accept new same-day collections from its customers, to be added to vehicles when they're already out making the deliveries. Parcel couriers would make deliveries from a central depot of items they picked up the preceding day, whilst picking up new collections from businesses on the same routes.

The most efficient way to serve next-day/same-day is to combine the next-day deliveries and same-day collections together on the same vehicle routes. For example, a driver might have a route which does three next-day deliveries, followed by two same-day collections and finishing with another next-day delivery. The key difficulty with planning is that once a vehicle has left the central depot, its deliveries are physically on-board and cannot be reassigned to different vehicles, however the same-day collections it needs to do may not even be known about yet. As a result, **the depot has to plan delivery routes to include collections, without knowing what or where the collections are.**

This is where a prediction engine is useful. The prediction engine should optimise the next-day-delivery routes taking into account demand patterns for the future collections. This next-day-deliveries-only plan is then used to load the next-day deliveries onto the delivery trucks at the depot, in the morning. This 'pre-truck-loading' plan can also include any collections which are already known about at the time, though to keep things simple in this article we assume all collections are booked after the trucks are loaded. The trucks then leave the depot, with their deliveries on-board. The optimiser engine then locks these deliveries to the trucks, but continues to optimise in realtime to (a)

assign new collections to trucks as they are booked and (b) change the order of pending deliveries on a truck as needed.

Strictly speaking, from a logistics modelling perspective, the next-day/same-day problem doesn't actually need to have bookings on separate days – **what matters most is when the jobs become known relative to the start of the drivers' shift**. Imagine running two separate drivers shifts – say 8am–2pm and 3pm–8pm with all drivers returning to the depot between shifts. Deliveries booked during the 1<sup>st</sup> shift for delivery in the 2<sup>nd</sup> shift, combined with collections ordered and made within the 2<sup>nd</sup> shift would still follow the next-day/same-day logistics model, even though they're technically all same-day.

## 2 Delivery scenario and tests

In the next sections we test whether our combined prediction engine and route optimiser correctly takes account of likely upcoming collections, when constructing the next-day-deliveries-only plan, used to load vehicles at the depot. We present two tests: (a) a qualitative test which sense-checks the impact of predictions on route design and (b) a quantitative test which measures the efficiency gains when run on a large number of scenarios. These tests form a part of our ODL Live test suite, which we run prior to releasing each new build of the system.

Both the qualitative and quantitative tests use the same relatively simple setup. We assume next-day deliveries are located in a square area, where a delivery has an equal probability of being placed anywhere in the square. To make the test more demanding, we choose a separate distribution for same-day collections, and restrict them to the North-West quadrant of the area covered by the next-day deliveries. This could correspond to a city where deliveries are made everywhere but collections are restricted to a single manufacturing or warehouse district.

A second reason for this two-distribution setup is that **different spatial distributions for next-day/same-day collections can only be modelled correctly by a combined route optimiser and prediction engine**. You cannot model the next-day-deliveries-only routes by simply balancing workload across your fleet and ensuring each route is only at say 50% capacity, as the **spare capacity must be available in the right places**. This is further compounded once you consider temporal patterns – i.e. what if same-day collections are more likely to require serving at particular times of the day?

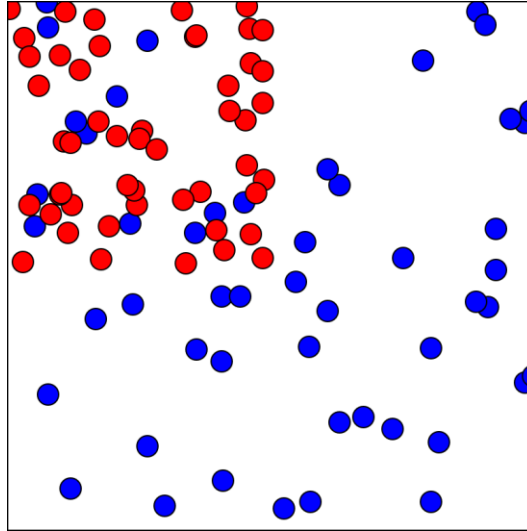
### 2.1 Predictive route optimiser

Roughly speaking, our combined route-optimisation and prediction engine thinks about multiple possible scenarios at once – one scenario is optimising only those stops which are known at the current time, another scenario might be optimising the known stops and a set of predicted stops, a third scenario another set of predicted stops. The engine places constraints on how well the assignments of stops must agree across scenarios, so it can relate different scenarios to each other and let one scenario influence another. How closely these assignments must agree is actually dependent on the use-case; full realtime route optimisation requires the most agreement.

Generating the next-day-deliveries-only route plans requires that the assignment of deliveries to routes is in-agreement across predicted scenarios but does not require the stop order to be in-agreement too. Currently we only implement the maximum level of agreement across scenarios, where the assignment and stop order must agree. This works well for 100% realtime problems but is a little too restrictive for the next-day/same-day problem. The upshot of this is **we expect the tests to underestimate the performance of a prediction engine on next-day/same-day**, as our next-day-deliveries-only route plans are designed for a related, but different problem.

### 3 Qualitative test

The following image shows the single day's jobs for our qualitative test, with next-day deliveries shown in blue and same-day collections shown in red. We create 50 jobs for each category, so 50 deliveries are booked the day before and 50 collections are booked during the same day:



We assume a limited number of vehicles, with limits on the driver shift length and truck volume for each vehicle. We also assume the objective is to firstly minimise the number of vehicles used and secondly minimise the total travel time.

We analyse the structure of routes generated with and without predictions. The grid of four images in the appendix shows our qualitative test results using the distribution of stops shown in the previous image.

#### 3.1 Route structure without using predictions

Firstly, look at the top left image in the appendix image grid - called *next-day-deliveries-only, no prediction model*. In this image we generated a set of routes without using the prediction model, to serve the next-day-deliveries-only. This set of routes would then be used for the loading plan at the depot.

In the top right image - *next-day deliveries and same day collections, no prediction model* - we lock down the next-day deliveries to the routes chosen in the previous image, to simulate the vehicles leaving the depot with their assigned deliveries on-board. We then add the same-day collections and allow the optimiser to freely assign them to any route. This gives an approximation of the next-day/same-day problem – as we have assigned next-day deliveries to vehicles before we know about the same-day collections. In the image, next-day deliveries are shown with a large circle and same-day collections are shown with a small circle.

When we compare the top left and top right images, we see that the routes outside of the NW quadrant (where the same-day collections are situated) are unchanged. Same-day collections have been added to the brown route in the NW and a new same-day-collections-only route has also been added (shown in pink). The two routes containing same-day-collections overlap each other in a disorganised fashion. Subject to certain caveats, overlapping routes can be a sign of poor efficiency and are usually regarded negatively by human transport planners and by drivers.

### 3.2 Route structure with predictions

The prediction engine is enabled for the bottom left image in the image grid – *next-day-deliveries-only with prediction model*. Here we again plan routes for the next-day deliveries on their own, but we use the prediction engine to incorporate the probability distribution of same-day collections, so the next-day jobs are planned with consideration for likely collections. Crucially we don't assume any knowledge of the actual same-day collections, only their probability distribution (which in real-life could be estimated by crunching historic data).

The bottom left and top left images are the next-day-deliveries-only with and without prediction model respectively. When comparing them, we see crucial differences. When we turn predictions on (bottom left) we get four routes instead of the three routes generated without predictions. With predictions on, we see two small routes (blue and green), containing far fewer stops than the other routes, situated in the North-West quadrant. It is obvious what is happening - the blue and green routes in the NW quadrant have been designed by the predictive optimiser with a lot of spare capacity so they can serve the upcoming future collections. In other words, **when we turn predictions on the optimiser appears to leave space in the right places for future collections.**

In the bottom right image, we lock deliveries to the vehicles chosen in the bottom-left 'with-predictions' image, to simulate vehicles leaving the depot with their assigned deliveries on-board. We then add in same-day collections and allow the optimiser to choose their vehicle, following exactly the same methodology as per the top images in the grid, but instead informed by the prediction model.

The top right and bottom right images both serve exactly the same combination of next-day deliveries and same-day collections, but in the top right image the deliveries were locked down to vehicles without the prediction model and in the bottom right image they were locked down with the prediction model. In the bottom right image, the same-day collections were added to the blue and green routes in the NW quadrant, which were initially created in the next-day-deliveries-only plan (bottom left image) with lots of empty space, to serve the predicted collections. So, **the optimiser left space in its routes for the predicted same-day-collections, which was then used when the collections became known.**

Examining the overall structure of the routes in the bottom-right 'with-predictions' image, the next-day deliveries (large circles) and same-day collections (small circles) are integrated together on the same set of clean non-overlapping routes. These routes form the classic 'petal' shaped pattern radiating out from the central depot, which human planners take as a sign of good, efficient routes. In contrast, in the top-right 'no-predictions' image the routes containing same-day collections overlap and look disorganised. In other words, **the final routes look better when the prediction engine is used.**

These visual indicators of more efficient routes from using predictions are also borne out by the numbers. Although both next-day/same-day plans (bottom right and top right images) use four routes, the **total travel time is 5.4% less for the with-predictions plan** (bottom right).

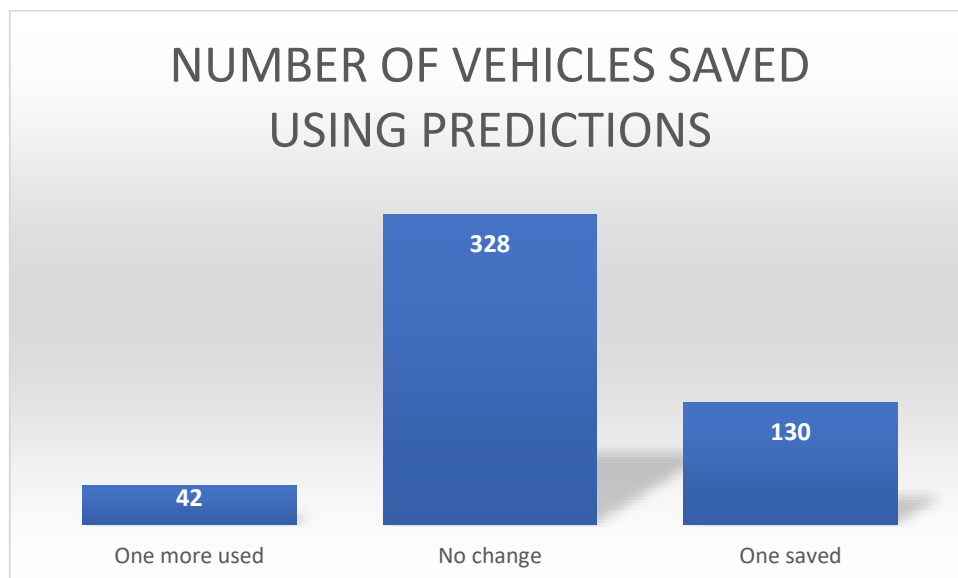
## 4 Quantitative test

For our quantitative tests we kept the same probability distributions for next-day and same-day jobs and the same number of jobs (50 of each). We generated 500 different versions of the problem by sampling differently from the probability distributions each time. Again, we optimised to primarily reduce the number of vehicles used and then the travel time.

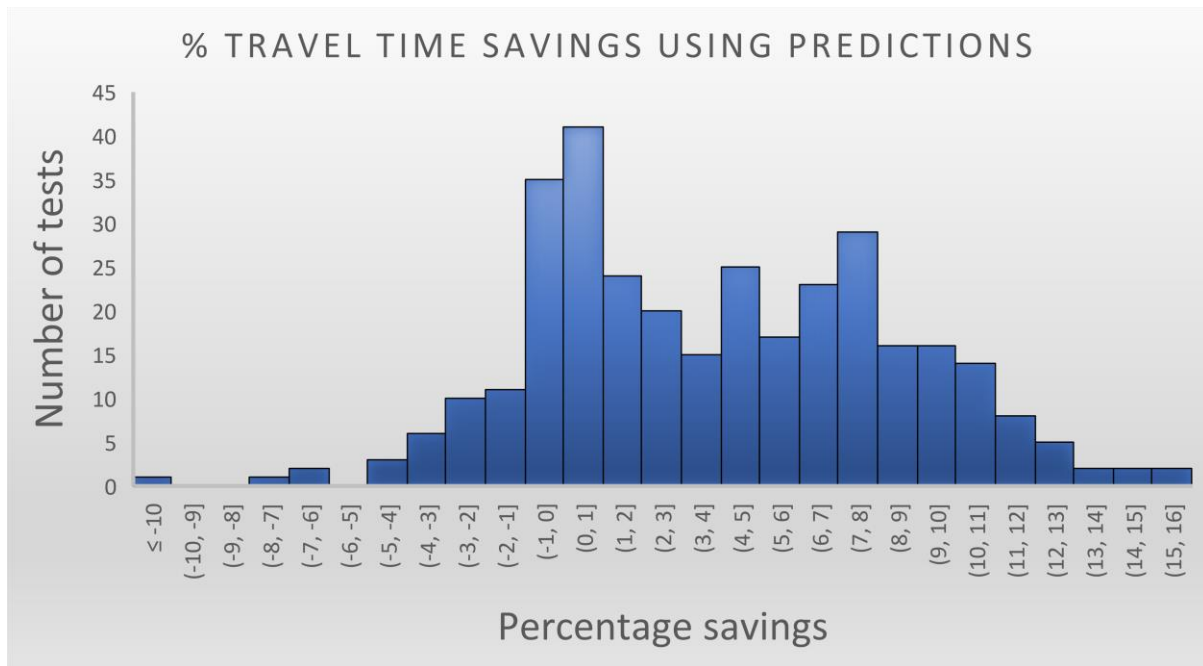
We compare the performance of planning next-day deliveries and same-day collections together, with and without the prediction model being used to determine the next-day-delivery-only routes used to load trucks at the depot. For the 500 tests, **77.4% of the time the prediction engine had found a better set of routes, after we add in the same-day collections.** For these improved routes we had either reduced the number of vehicles used, or the number of vehicles stayed the same but the total travel time was less. About 2.2% of the time we found the same results with and without using the prediction engine and for the remaining 20.4% the results with the prediction engine were marginally worse than without.

Given that the problem size is relatively small – 100 stops in total – small random deviations in the distribution of same-day collections compared to the average distribution can have a much larger effect than would be expected for more realistically-sized problems (i.e. planning problems with hundreds or even thousands of stops). We therefore suspect that the 20.4% of cases where we generated slightly worse routes using the prediction model are essentially ‘bad luck’, due to the same-day collections distributions in those tests deviating more than normal from the average. In preliminary runs with larger problems the degradation appeared less common, so we hypothesize that the prediction model will be more accurate for larger problems, as things will ‘average out’ more with larger numbers.

As shown in the following bar chart, the number of times we saved a vehicle by using predictions (130) is far greater than the number of times we used an extra vehicle (42). As most tests used only four or five vehicles, saving one vehicle is a significant gain. From this we conclude that if you’re doing next-day deliveries with same-day collections, **integrating a prediction model into your route optimisation will save you vehicles on-average.**



Next, we compare total travel times. Total travel times between the combined next-day/same-day planned routes with and without predictions can only be compared when the number of vehicles used is the same, and so we have 328/500 relevant tests. The following graph shows the percentage savings using predictions:



Again, we see a similar pattern as per the used routes. We see a small number of tests where the savings were negative – indicating the prediction model had slightly worse travel time – however **in the vast majority of tests the prediction model reduced total travel time**. The average reduction in travel time using the prediction model – which would translate approximately to fuel costs - was 3.9%.

From these results we conclude that **a prediction engine doesn't guarantee you will get a better set of routes on a specific day but on-average your routes will be better.**

## 5 Conclusions

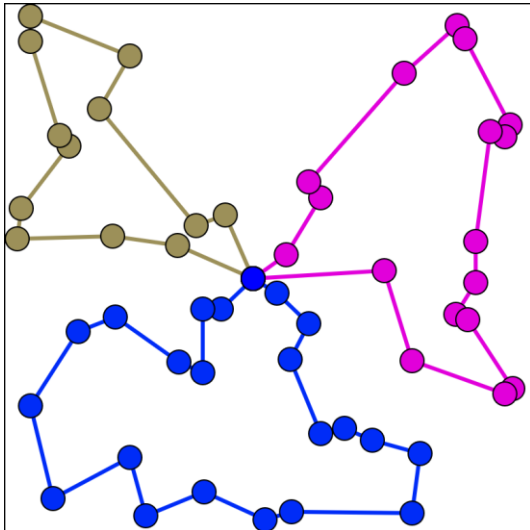
This simple test demonstrated both qualitatively and quantitatively that predictive route optimisation gives more efficient routes for serving next-day deliveries with same-day collections. By visually examining the planned routes, we showed that space is left on routes in the right places to incorporate likely future demand. By running 500 randomly generated scenarios, we demonstrated this translates into concrete savings for both vehicles used and travel time.

If you would like more information on our ODL Live system, please send us an email - see the contact details on our main website [www.opendoorlogistics.com](http://www.opendoorlogistics.com) or the product website [odllive.com](http://odllive.com).

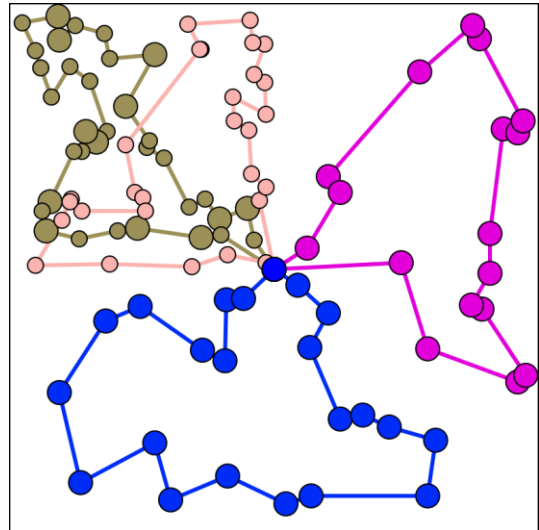


## 6 Appendix I – image comparison grid for qualitative test routes

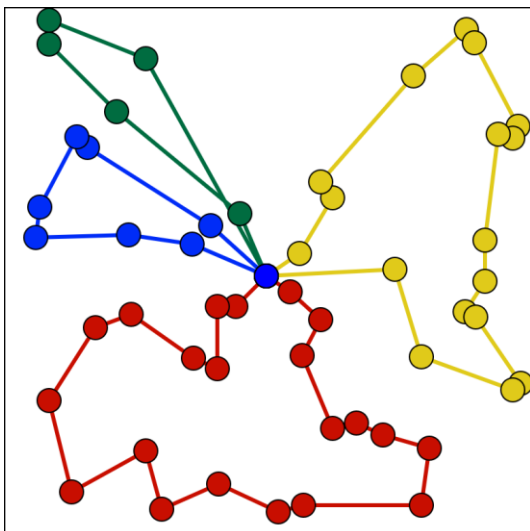
Next-day deliveries shown using larger circles, same-day collections shown using smaller circles.



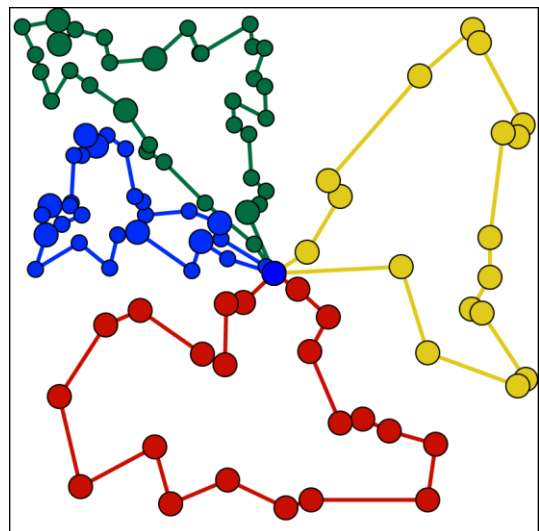
**Next-day-deliveries-only, no prediction model.**



**Next-day-deliveries and same-day-collections, no prediction model.**



**Next-day-deliveries-only, with prediction model.**



**Next-day-deliveries and same-day-collections, with prediction model.**