

Contents

Figures	1
0 Executive Summary.....	2
1 Introduction.....	2
2 Initial Optimization	2
2.1 Generating Potential Routes	2
2.2 Optimizing Routes	3
3 Simulation.....	3
3.1 Simulation of Demands.....	4
3.2 Adjusting Routes	4
3.3 Simulation of Time Taken.....	4
3.4 Cost Simulation	4
4. Results	5
4.1 Optimization.....	5
4.2 Simulation	5
5 Conclusions.....	7
5.1 Implementation and Practical Issues.....	7
5.2 Recommendations for Future Work.....	8
6 Appendix.....	8
6.1 Stores and their region	8
6.2 Weekday Solution.....	8
6.3 Saturday Solution.....	9
6.4 Saturday Visualisation	10
6.5 Weekday Cost Simulation.....	11
7 References	11

Figures

Figure 1: Visualisation of the Optimal Routes on Weekdays.

Figure 2: Histogram of simulated costs on Saturdays.

Figure 3: Visualisation of the Optimal Routes on Weekdays.

Figure 4: Histogram of simulated costs on weekdays.

0 Executive Summary

Foodstuffs is seeking to minimize the costs of transporting food to their 46 Auckland supermarkets. They have a fleet of trucks and access to wetleased Mainfreight trucks. Information was provided on past daily demands at each of the supermarkets, travel times and the costs and constraints faced by Foodstuffs.

The problem was simplified by assuming that food would be delivered in whole pallets, and that each store received its daily demand from a single truck. Heuristics were used to generate several thousand potential routes, and a linear program was used to solve for the routes that would minimize the cost of the daily operation. This was done separately for Weekdays and Saturdays. There was no activity on Sundays. The weekly optimized cost was \$56,107.

Simulation was performed to see how the optimal routes would perform in reality given that demand changes daily and traffic is quite variable. A Beta-PERT distribution was used to generate a multiplier for each route in each simulation that increased the driving times for each route. The demand data was used to simulate demands at each store, which meant that sometimes routes previously suitable were unable to handle above average demands. When this occurred, extra Mainfreight trucks dealt with some stores.

The expected weekly cost was found to be \$75,294 through our simulations. Daily costs will vary by up to several thousands per day due to changing traffic and demands. Foodstuffs should implement the optimal routes if they wish to minimize the cost of their operation, but they should also consider further work using better assumptions, data and more computing power to produce more realistic simulations and find more efficient ways of transporting the food to decrease costs even further.

1 Introduction

Foodstuffs, who operate the Four Square, Pak 'n Save and New World brands of supermarkets, need to transport food daily to their 46 supermarkets in Auckland. They have 10 trucks which operate a morning shift at 8am each day and an afternoon shift at 2pm. They can also 'wetlease' additional trucks from Mainfreight. They are seeking to minimize the cost of transporting food to their supermarkets, with the operation of the trucks costing \$150 per hour for the first 4 hours, \$200 thereafter in a shift, and wetleases costing \$1200 per four hour block. The food is transported in pallets, and each store requires a whole number of pallets.

We were provided with the daily demands at each supermarket over a four week period and the location of each supermarket. The travel times between supermarkets, calculated with OpenStreetMaps (OSM), were also provided.

2 Initial Optimization

2.1 Generating Potential Routes

A brief inspection of the demand data showed that weekdays had fairly similar demands with no obvious pattern, while Saturdays had significantly less, and Sundays none. Therefore, we optimized and simulated Saturdays separately from weekdays.

The complete set of all possible routes would number 2^{46} (around 7×10^{13}), which is far too many to work with. Even considering that each truck only carries 12 pallets and is required to be expected to take under 4 hours, there are still too many routes to make a complete enumeration. Therefore we used heuristic algorithms to generate routes that are potentially optimal.

In our formulation of the problem we assume that each supermarket is visited once per day and cannot receive pallets from multiple trucks. One instance of a daily demand of 13 in the demand data was adjusted to 12 to prevent our assumption from causing problems. For our route generation algorithm, we found the mean demand at each store over the four weeks and rounded this up to the nearest integer.

Firstly, we created all the possible routes consisting of just 1 or 2 stores, to help speed up the route generation algorithms. The first algorithm was based on visiting the nearest store that stays within the 12 pallet limit, and the second based on visiting the store with the greatest demand possible. In each algorithm, we divided the stores into 5 geographic regions (see Appendix), and routes generated stay within a single region. The algorithm starts at a particular store and generates a route. To avoid creating overlapping routes, the next route generated will only visit remaining stores. Multiple second routes within a region were created, each one starting at a different store. Third routes also started at each of the remaining stores, but a fully recursive approach took too long and generated too many routes, so for the fourth route onwards, if it was needed, the starting store was arbitrary.

Our route generation algorithms generated 9,389 routes for weekdays, and 3,289 for Saturdays and expected times for each. It should be noted that the data from OSM is not entirely accurate, for example we noticed that for one route in Papakura an unneeded detour was made that probably added about a minute to that route. However, overall the data is of acceptable quality and there is no alternative data that can be obtained cheaply and quickly.

2.2 Optimizing Routes

A linear program was constructed in order to find the optimal routes. The objective function, to be minimized, was \$150 per hour multiplied by the sum of the times of the optimal routes using Foodstuffs trucks, plus \$1200 per route using Mainfreight trucks. The first constraint was that each store must be visited exactly once, and the second was that no more than 20 routes could use Foodstuffs trucks.

3 Simulation

The optimization of routes we had performed assumed fixed demands at each store and ideal traffic. In practice, both demand and traffic varies from day to day. If the stores along a route

have a higher than average demand, there is a possibility that the truck cannot fit all the pallets required by those stores, necessitating an adjustment to that route.

3.1 Simulation of Demands

The demand at each store was simulated through sampling with replacement ('bootstrapping') from the provided data. The demand at each store was independent of the demands of the other stores.

3.2 Adjusting Routes

If during a simulation a route is unable to handle the demand, stores are removed from the route to get the demands less than or equal to 12 pallets. In the simulation, it is assumed that these stores will be visited by additional Mainfreight trucks. This assumption is not ideal on Saturdays when there are additional Foodstuffs trucks available. These extra trucks may visit multiple stores that were unable to be visited, if that is possible. We additionally assumed that these extra routes will be under 4 hours and thus incur only a single \$1200 charge.

3.3 Simulation of Time Taken

Simulation of traffic times was done using the Beta-PERT distribution. The Beta-PERT distribution generated a number that was multiplied with the expected driving times from OSM. Traffic obviously varies between mornings, afternoons and Saturdays, so different parameters were used for these times. The minimum multiplier was always 1, since OSM uses the speed limits of roads to calculate travel times and makes no allowance for traffic.

For weekday mornings, we used a modal value of 2 and a maximum of 2.5, for afternoons 1.25 and 2, and for Saturdays 1.2 and 1.5. These figures were obtained by looking at average traffic times recorded on Google Maps for different times of the day.

There is also an unloading time for each pallet that averages 5 minutes. Given that each route has multiple pallets, it is assumed that the time spent unloading along a route will end up being exactly 5 minutes per pallet.

3.4 Cost Simulation

The simulation of demands and traffic was put together to produce 1,000 simulations of the daily cost. In each simulation for weekdays, the longer routes were assigned to the afternoon shift when traffic was less. An assumption was made that morning routes taking more than 6 hours (past 2pm) would not disrupt the afternoon shift- it would simply start later. In practice when this occurs wages will still need to be paid to the next diver while they wait to be able to start. Traffic on each route was independent of the other routes- Auckland is a large enough city for traffic to differ greatly between suburbs, and furthermore traffic is often caused by local incidents. This assumption is unlikely to be completely true.

4. Results

4.1 Optimization

For Weekdays, the optimal solution requires all 10 of Foodstuff's truck to operate in both shifts and the use of 4 wetleases. The cost of the solution is \$10,441 per day. Because the sum of the average demands was 262, more than the total capacity of Foodstuff's trucks, it was not possible to avoid using wetleases. On Saturdays 12 shifts were required for a total cost of \$3,902. Therefore, the optimal weekly cost of transporting food is \$56,107.

Using Python's folium package and OSM, a visualisation was made of the optimal solution. The weekday visualisation is provided below in Figure 1. A visualisation for Saturday and a list of the stores in each route can be found in the Appendix.

4.2 Simulation

On Weekdays, the mean simulated cost was \$14,201, with a 95% Confidence Interval of [11383, 17019]. On Saturdays, the mean simulated cost was \$4,289, with a confidence interval of [3188, 5389]. Histograms were generated for both, and the Saturday histogram is presented below as Figure 2 while the weekday histogram can be found in the Appendix. The mean weekly cost is therefore \$75,294, about a third higher than when optimal conditions are assumed.

Given that traffic in the simulation is always worse than the travel times used in the optimizing, a natural question is why for Saturdays we obtained some simulations with costs below the \$3,902 obtained previously. Our use of averages rounded up in the optimization means that simulated demand is often less than the demand assumed previously, which leads to less time unloading pallets. This effect is not observed on weekdays at least in part due to the much heavier traffic.

The histograms are notably multimodal. This is due to the extra Mainfreight trucks; the gap between peaks is about \$1200.

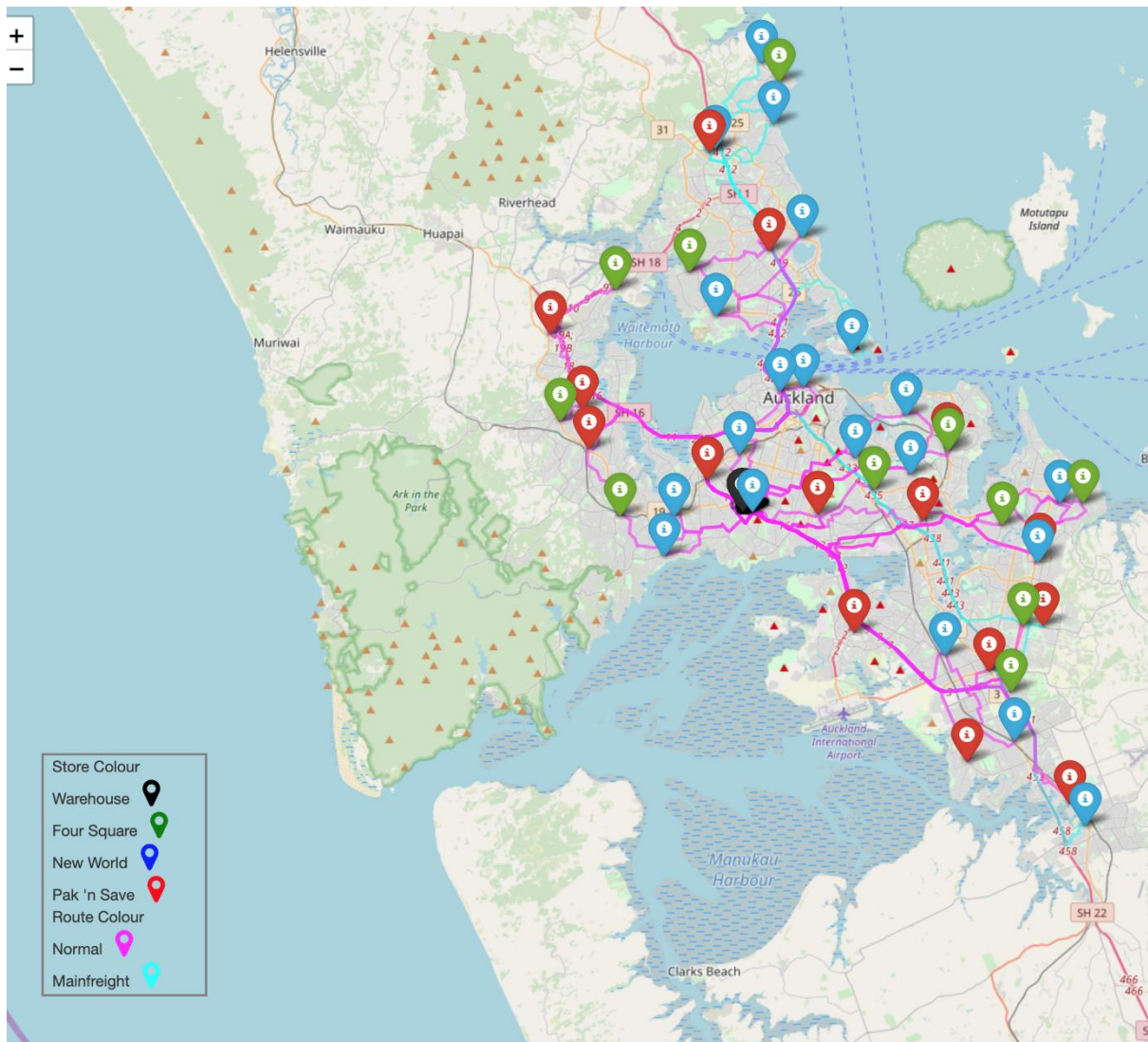


Figure 1: Visualisation of the Optimal Routes on Weekdays.

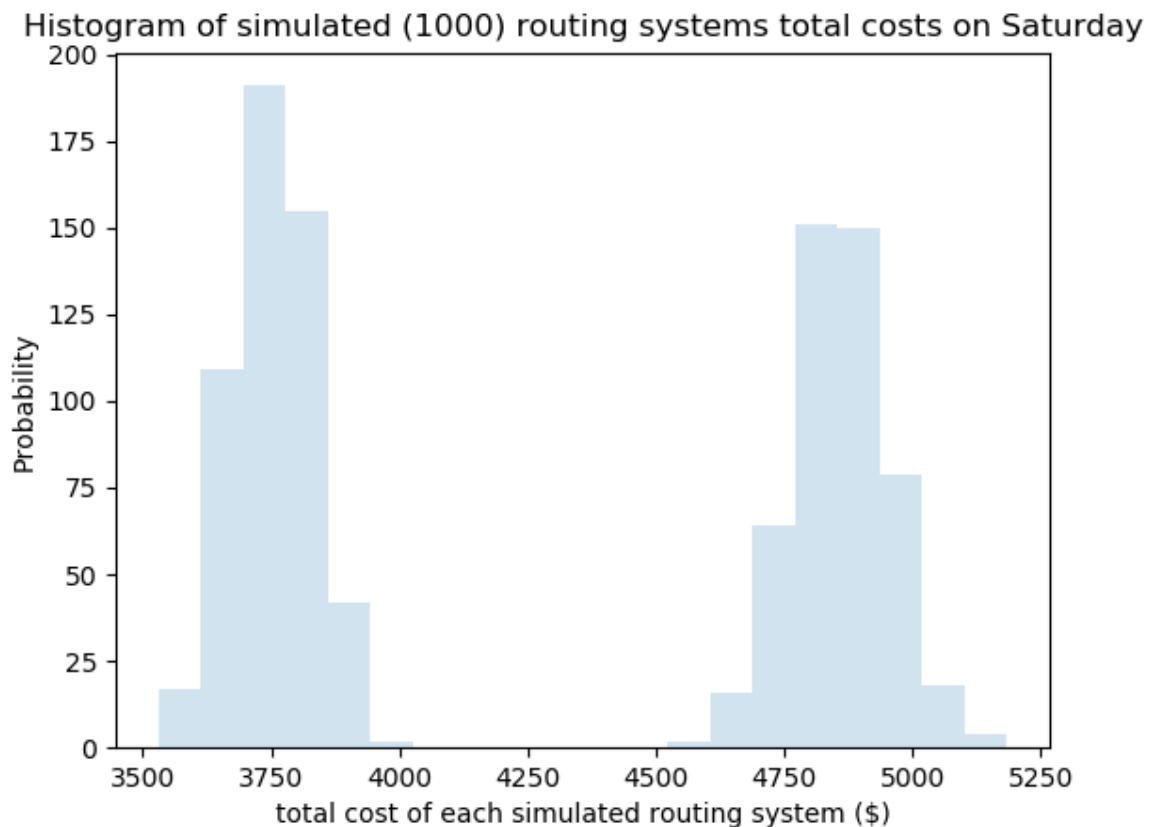


Figure 2: Histogram of simulated costs on Saturdays.

5 Conclusions

5.1 Implementation and Practical Issues

It is recommended that Foodstuffs adopts the routes laid out in the visualisation and appendix if they wish to minimize costs.

The costs modelled in this study may be difficult to achieve in practice. The cost of time is calculated exactly, whereas in practice charges and wages will be incurred in larger blocks or rounded. Truck drivers will need to always use the most optimal route when driving between stores, and at any one time it is likely that roadworks somewhere in Auckland will make this impossible even if drivers are informed of their routes and diligently follow it. This and other general inefficiencies in working mean the true costs will probably be slightly higher than calculated in this report.

5.2 Recommendations for Future Work

This study was limited and made many simplifying assumptions. Future work on this issue should be done to obtain improved and more realistic solutions. More time and computing power would be required to achieve this. Not allowing stores to receive multiple truck visits in one day is a major assumption whose relaxation could lead to cheaper ways of formulating the problem.

Ideally, in each simulation or on each day that Foodstuff's uses this formulation, the route generation and linear program should be solved afresh. If this was not possible, the way routes are adjusted when they become unusable due to higher than average demand should be revamped. Other trucks with spare room should be able to deliver to some of the stores on busier routes if possible.

Improved input data would also be beneficial. Only four weeks of data was provided, which is especially limited for Saturdays given there are only 4 data points per store. Having data from a longer period of time will clarify whether some weekdays have different demand patterns, and whether there are any other seasonal effects. Improved travel time data should also be obtained, perhaps from Google Maps which has large quantities of data about past traffic.

6 Appendix

6.1 Stores and their region

	North Shore	West Auckland	Central Auckland	East Auckland	South Auckland
Four Square	BKs Torbay Lancaster	Fair Price Henderson Glen Eden Hobsonville	Ellerslie Great Eastern Fresh Collective Alberton	Botany Junction Cockle Bay Pakuranga Heights	Everglade
New World	Albany Birkenhead Browns Bay Devonport Long Bay Milford	Green Bay Mt Roskill New Lynn	Eastridge Metro Queen St Remuera Stonefields Victoria Park	Botany Howick	Papakura Papatoetoe Southmall
Pak 'n Save	Albany Wairau Road	Henderson Lincoln Road Mt Albert Westgate	Glen Innes Royal Oak	Botany Ormiston	Clendon Mangere Manukau Papakura Sylvia Park

6.2 Weekday Solution

As outputted in the text file OptimalWeekdays.txt:

Wetleased_Route1181, warehouse, New World Devonport, New World Papakura, warehouse

Wetleased_Route131, warehouse, New World Browns Bay, Pak 'n Save Ormiston, warehouse

Wetleased_Route1522, warehouse, New World Albany, New World Long Bay, warehouse

Wetleased_Route5647, warehouse, Pak 'n Save Albany, Four Square BKs Torbay, warehouse
_Route1284, warehouse, Four Square Botany Junction, Pak 'n Save Manukau, warehouse
_Route1310, warehouse, Four Square Pakuranga Heights, Pak 'n Save Sylvia Park, warehouse
_Route1382, warehouse, New World Birkenhead, New World Milford, warehouse
_Route2697, warehouse, Four Square Hobsonville, Pak 'n Save Westgate, warehouse
_Route3112, warehouse, Four Square Fair Price Henderson, Pak 'n Save Lincoln Road, warehouse
_Route3354, warehouse, New World Metro Queen St, New World Victoria Park, warehouse
_Route3622, warehouse, Pak 'n Save Royal Oak, warehouse
_Route3867, warehouse, Four Square Cockle Bay, Pak 'n Save Botany, warehouse
_Route3874, warehouse, New World Botany, New World Howick, warehouse
_Route4641, warehouse, New World Papatoetoe, New World Southmall, warehouse
_Route4718, warehouse, Pak 'n Save Clendon, warehouse
_Route4942, warehouse, Four Square Everglade, Pak 'n Save Papakura, warehouse
_Route522, warehouse, New World Mt Roskill, New World Remuera, warehouse
_Route5920, warehouse, Pak 'n Save Wairau Road, Four Square Lancaster, warehouse
_Route6347, warehouse, New World Green Bay, New World New Lynn, warehouse
_Route6571, warehouse, Four Square Glen Eden, Pak 'n Save Henderson, warehouse
_Route718, warehouse, Pak 'n Save Mt Albert, Fresh Collective Alberton, warehouse
_Route7677, warehouse, Four Square Ellerslie, Four Square Great Eastern, Pak 'n Save Glen Innes, warehouse
_Route8072, warehouse, New World Eastridge, New World Stonefields, warehouse
_Route8299, warehouse, Pak 'n Save Mangere, warehouse

6.3 Saturday Solution

_Route2017, warehouse, Pak 'n Save Ormiston, Pak 'n Save Manukau, warehouse
_Route2074, warehouse, New World Devonport, Pak 'n Save Sylvia Park, warehouse
_Route2117, warehouse, New World Birkenhead, New World Milford, Pak 'n Save Wairau Road, Four Square Lancaster, warehouse
_Route2160, warehouse, New World Albany, New World Browns Bay, New World Long Bay, Pak 'n Save Albany, Four Square BKs Torbay, warehouse

_Route2249, warehouse, New World Green Bay, New World Mt Roskill, New World New Lynn, warehouse

_Route2359, warehouse, Four Square Hobsonville, Pak 'n Save Mt Albert, Pak 'n Save Westgate, warehouse

_Route2367, warehouse, Four Square Fair Price Henderson, Four Square Glen Eden, Pak 'n Save Henderson, Pak 'n Save Lincoln Road, warehouse

_Route2401, warehouse, Four Square Ellerslie, Four Square Great Eastern, New World Eastridge, New World Stonefields, Pak 'n Save Glen Innes, warehouse

_Route2425, warehouse, Fresh Collective Alberton, New World Metro Queen St, New World Remuera, New World Victoria Park, Pak 'n Save Royal Oak, warehouse

_Route2466, warehouse, Four Square Botany Junction, Four Square Cockle Bay, Four Square Pakuranga Heights, New World Botany, New World Howick, Pak 'n Save Botany, warehouse

_Route2492, warehouse, Four Square Everglade, New World Papakura, New World Papatoetoe, New World Southmall, Pak 'n Save Papakura, warehouse

_Route2584, warehouse, Pak 'n Save Clendon, Pak 'n Save Mangere, warehouse

6.4 Saturday Visualisation

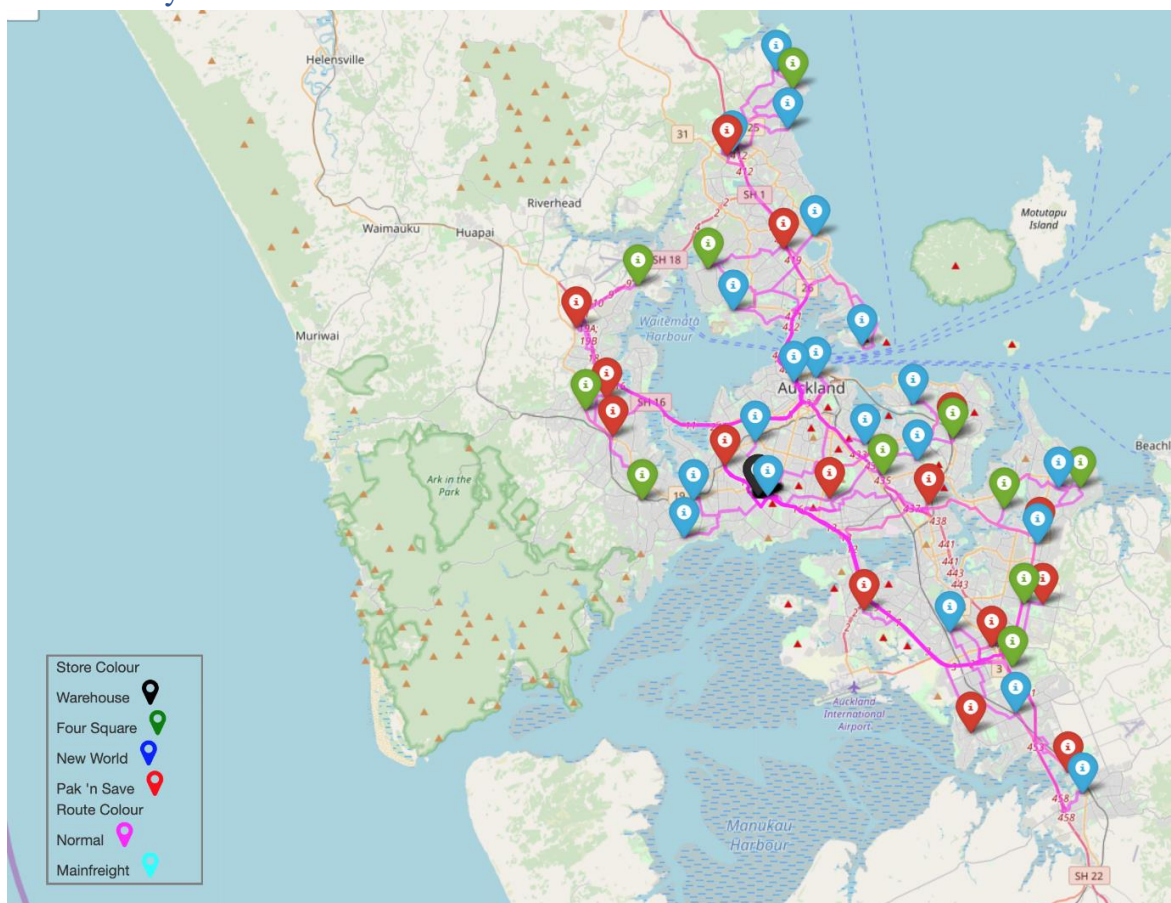


Figure 3: Visualisation of the Optimal Routes on Weekdays.

6.5 Weekday Cost Simulation.

Histogram of simulated (1000) routing systems total costs on weekdays

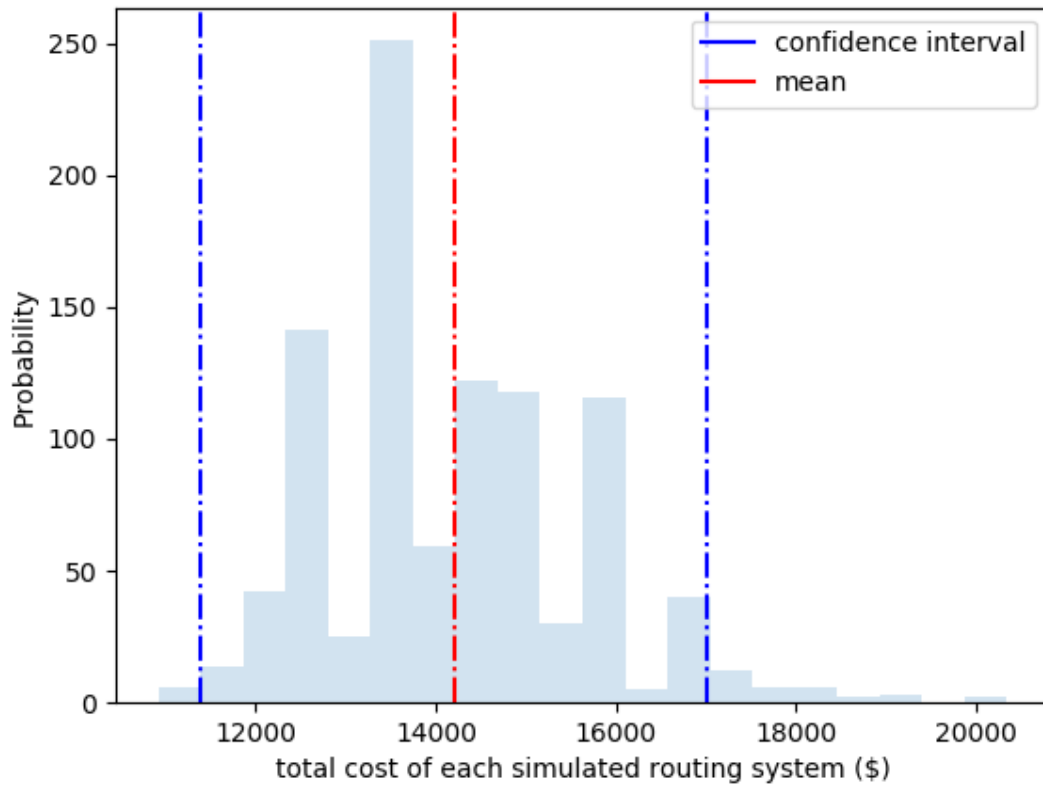


Figure 4: Histogram of simulated costs on weekdays.

7 References

Open Street Maps

Google Maps