

Operational Plan for the Amazonoff Company

52086

A report submitted The Amazonoff Company

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Chapter 1

Executive Summary

Objective: This report's objective is to document the modelling and simulation completed on behalf of the Amazonoff Company. This report also outlines changes that we feel could improve operating efficiency, whilst minimising costs.

Findings: Section 2.1 describes the cost-minimising assignment of customers to facilities so that we satisfy each customer's demand. We find the optimal operating cost to be 238.56, even after we account for the capacity of each facility. We also suggest methods which allow the company to balance loads between facilities. In Section 2.2 we construct optimal routes for the delivery vehicles to follow. We show that the two processes discussed above can be modelled separately, and therefore are easily actionable. Our routing implementation offers an additional cost of just 100.37, using just one delivery vehicle. We believe it is important to consider uncertainty in our research and in Section 2.3, we offer insights into how we can factor this into the internal running of the depot. Finally, in Section 2.4, we simulate the next 12 months for your insurance subsidiary. It should be noted that we estimate the probability of legal issues for the company to be just over half. To help remedy this, we further estimate the value of your capital holdings to a high degree of certainty and find it to be in the region of 27375.34. We, therefore, suggest a small increase in the monthly rate you charge customers, or sourcing a capital injection before the next year begins.

Conclusion: Following our research, if our suggestions are implemented, we find a short-term operations cost of 338.93. In the longer term, we suggest following the advice laid out in the rest of the report so as to avoid legal issues.

Chapter 2

Management Report

In this chapter, we lay out a more detailed analysis of your operations, and offer distinct guidelines on how to fulfil your warehousing, routing and e-commerce requirements.

2.1 Warehousing

The Amazonoff Company operates in the space of a 21×21 grid, in which exist the entire customer base and potential facilities. We suggest only opening a subset of these facilities, as we give a satisfactory assignment of all 60 of your customers with just 12 facilities, allowing the firm to save expenditure on unnecessary rent. We recommend leaving out facilities 1, 2, and 12. Outlined in Table 2.1 are the assignment and respective facilities we consider to be optimal, and we refer the reader to xxx for a technical discussion of our modelling process.

We find that even upon factoring in the demands of each client, the facilities are easily able to hold the required stock, and as such our allocation remains optimal. It may seem odd to the reader we suggest opening so many facilities, but upon consideration of the costs for opening facilities, the motivation becomes clear. As the index of the facility increases, the cost to open it decreases exponentially, and as such it incurs a minimal cost to open an extra facility. With this in hand, it makes sense to open many facilities, so we can truly minimise the distance between them and the clients.

In Table 2.2, we observe the demand faced by each facility. It is clear that the distribution is extremely unbalanced, with facility 3 facing 219 units, and facility 5 facing just 8. As such, we refer the reader to xxx for a modelling approach that allows the firm to control this difference.

We calculate the cost of this approach 238.56 if implemented correctly.

Facility	3	4	5	6	7	8	9	10	11	13	14	15
Customers Assigned	1	4	10	25	34	28	27	47	44	43	45	49
	2	7	22	33	38	29	30	51	52	48	53	50
	3	11		35	42	39	31			60	54	55
	5	12		36			37				56	57
	6	17		40			41					58
	8	18					46					59
	9	23										
	13	24										
	14	32										
	15											
	16											
	19											
	20											
	21											
	26											

Table 2.1: Assignment of customers to facilities

Facility	3	4	5	6	7	8	9	10	11	13	14	15
Demand Faced	219	137	8	69	25	51	84	13	36	43	35	77
Capacity	300	400	500	600	700	800	900	1000	1100	1300	1400	1500

Table 2.2: Demands faced by each facility

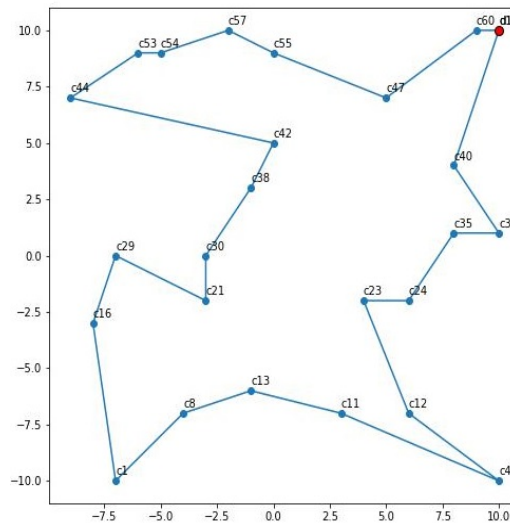


Figure 2.1: Suggested delivery route

2.2 Vehicle Routing

We next tackle the routing operation. The company has 25 *composite* clients whose deliveries are to be prioritised. There is a single depot and the delivery vehicles have no capacity limit. In our modelling, we considered using one delivery vehicle or three and found that the cost of using either is the same, that being 100.37. This is to be expected since all routes must return to the depot, and if we used more vehicles, we would pay unnecessary costs on the return leg. In Figure 2.1 we outline the optimal route, where the depot is highlighted in red and labelled **d1**. Each composite client is then labelled by their index and prefixed with a **c**.

2.3 Internal Depot Transportation with Uncertainty

Given the nature of the company, it is important to factor in uncertainty when modelling, specifically in the internal depot operations. In this section, we propose two models that allow the firm varying degrees of control. The first is a *robust* model, meaning regardless of the dimensions of each item, there will always be some way to pack the electric vehicle. The second allows the firm some control over the likelihood that the vehicle cannot be packed. We, therefore, label this model as the *non-robust* formulation. We briefly discuss both models in the following subsections, but for a more detailed description, we refer the reader to xxx.

2.3.1 Robust Formulation

A key assumption of the robust model is that we can, prior to production, garner some information about the maximum volume and weight of each item. With this

data in hand, we simply consider the problem using only these maximum weights. In doing this, we have essentially removed the uncertainty from the problem. Despite this, we can imagine a situation where the volume and weight of a given item can vary drastically, so if we pack an item using only its maximum weight, then there is a good chance there is a lot of empty space on the vehicle. As such, we are not effectively maximising the profit garnered on each vehicle. To account for this loss, we recommend implementing the second model, which we now turn our attention to.

2.3.2 Non-Robust Formulation

Our next model allows the firm to retain some control over the uncertainty. More specifically, we add a notion of risk control. Once again we assume we can garner some information about the volume and weight of each item. In this case, we want to consider the average volume and weight, along with the variation of these estimates. We suggest performing some data analysis on the items to acquire these values. Then, we model the problem using the expected volumes and weights. For this situation, however, we require a further parameter to be set, that being some tolerated level of risk, which refers to the probability that we cannot fit the items on the vehicle. Using this approach, we better utilise the space on each vehicle. Of course, there is a small chance that the allocation of goods will not fit on the vehicle, but this can be remedied with the appropriate setting of the risk level. Running simulations on this situation will inform this decision, and with this, we hypothesise that the overall profit would be higher in this model.

The choice between these two approaches will depend largely on the needs of the company. If the consequences of allocating too many items to one vehicle are large, then we recommend the robust approach. Otherwise, we suggest the second model since the profit per vehicle would certainly be higher. It is our opinion that the firm would be better off implementing the second.

2.4 Product Specific Insurance

We now bring our attention to the insurance subsidiary of the company. In particular, we wish to simulate the next 12 months of your operations and deduce meaningful estimates of key values, so as to inform your decision-making in the next year. The key values we considered are the likelihood of legal issues for your firm, and the expected capital stock at the end of the term.

Based on your data, we run the simulation with a starting capital stock of 50,000 and a fixed monthly incoming fee of 300. By then considering the entry and leaving rates of your service, and the rate at which customers lodge claims, we can generate estimates of these values in the long run.

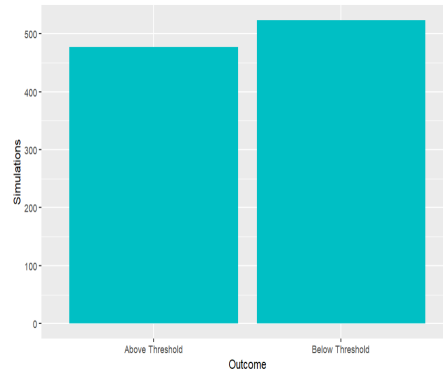
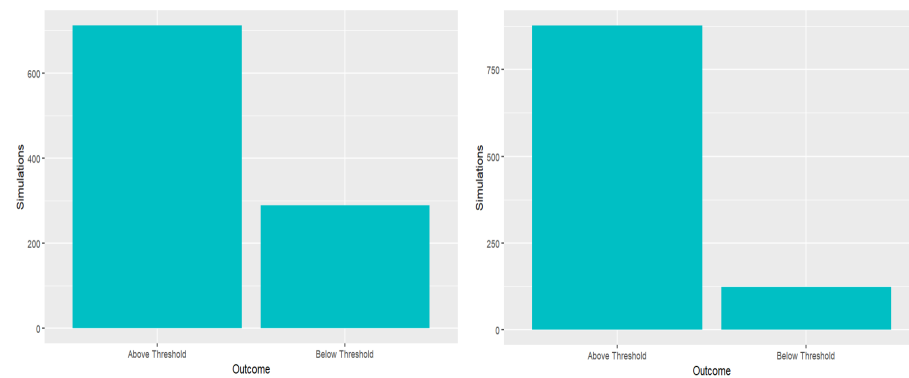


Figure 2.2: Distribution of outcomes (1000 simulations)

2.4.1 Likelihood of Legal Issues

We first wish to estimate the probability that your firm encounters legal issues. After running the simulation 1000 times, we return with the distribution laid out in 2.4. We immediately see how even the distribution is, and precisely we found the probability of legal issues to be 0.523. We deem this figure to be far too high, and to counteract this we suggest raising the monthly fee. In Figure 2.3 we depict the results of further two simulations in which we raise the monthly fee for the service to $M = 350$ and $M = 400$. We see that with an increase of 350, the failure decreases by almost half, and in the case of 400 it halves again. Specifically these probabilities are 0.283, and 0.124 respectively.

There is also the option of sourcing a capital injection, and we ran further experiments with this idea. However, we found that an increase of around 20,000 in initial capital gave us comparable results to the monthly fee increases, and as such, we suggest an increase in only the monthly fee to decrease the chances of legal issues.

Figure 2.3: Distribution of outcomes with $M = 350, 400$ (1000 Simulations)

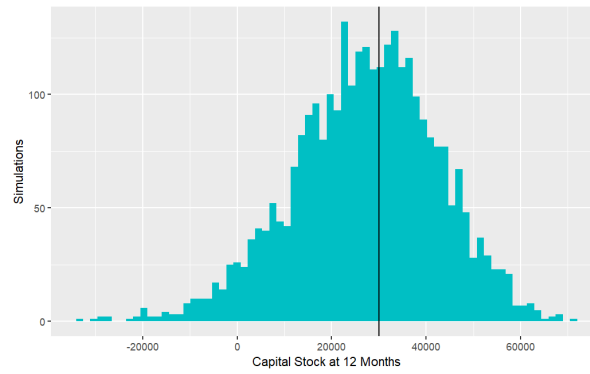


Figure 2.4: Distribution of capital stock after 12 months (3000 Simulations)

2.4.2 Estimation of Capital Stock

The next section is dedicated to the estimation of your capital stock after a 12-month period, which is only more justified given the analysis in the previous section. If we can gain a good estimate, we can provide a more accurate value for a suggested monthly fee.

We aim to find an estimate for the capital stock after 12, which we denote C_{12} , that we can be 90% sure is within 500 of the true value. To build a better picture, we ran the simulation many more times than in the previous section, and at iteration 2538, we find 27375.34 as our estimator of capital stock. We also have the standard deviation of this estimate to be 303.95, and with this estimate, we can give an interval to which we are 95% the true value lies within, and we calculate this to be $C_{12} \pm 595.06$. A detailed description of the simulation process, and how we arrived at our estimates, can be found in xxx. In xxx, we also describe measures to reduce variance in our estimate, since as shown in Figure 2.4, estimates between simulations take on wildly different values.

We have now presented a clear image of the 12 months for your insurance subsidiary, and with this, we would like to recommend a specific monthly service charge, with the intent of reducing the likelihood you encounter legal issues. Using our analysis laid out in this section, we suggest $M = 445$, which will allow the firm to avoid legal issues 95% of the time.

Appendix A

Warehousing Methodology

Contained in this appendix is detailed, technical report of the methodology applied in the warehousing scenario.

A.1 Data Generation

A.1.1 Grid Generation

Associated Files: `grid_generation.Rmd`

Before we carried out our modelling, it was necessary to generate certain data that we could feed into our models. First, we generated the coordinates of each client, and then the demands of each of these clients. Our method is outlined in Algorithm 1, and implemented in `grid_generation.Rmd`

Algorithm 1: Coordinate Generation
Data: $n_f = 15, n_c = 60$
Result: A 21×21 grid containing 15 facilities and 60 customers
1 $X \leftarrow 21^2 \times 1$ vector of random uniform(0,1) variables;
2 $Y \leftarrow 21^2 \times 1$ vector of zeroes;
3 Sort X in decreasing order, keeping the pre-sort indexes;
4 for $0 \leq f \leq n_f$ do
5 $i \leftarrow X[f]$;
6 $Y[i] \leftarrow "f"$
7 end
8 for $n_f + 1 \leq c \leq n_f + n_c + 1$ do
9 $i \leftarrow X[c]$;
10 $Y[i] \leftarrow "c"$;
11 end
12 Reshape Y to be 21×21 matrix;

We first let n_f be the number of facilities, and n_c be the number of customers. Lines 1 and 2 initialise vectors X and Y of random uniform(0,1) variables, and zeroes respectively. In line 3 we then sort the X , and we preserve the index of the original values. The loop on lines 4-6 then iterates through the integers between 0 and 15 and collects the index of the sorted value, and then overwrites that index in Y with the character "f", representing facilities. The second loop on lines 8-10, iterates through the next 60 indexes and does the same, except replacing with "c", representing customers. Finally, we then reshape our matrix to be a 21×21 grid.

Once we had our matrix, renamed the columns and rows with the coordinates they represented in the interval $[-10, 10]$, this then gave us our grid. From here we retrieved the indexes that had the "c" values and created a list of customers and their coordinates. Then we did the same for the facilities. This left us with our customer set C , and facility set F

A.1.2 Demand Generation

Associated Files: `demand_generation.Rmd`

Upon expansion of our model, it was also necessary to generate the demand of each of the 60 clients in C . We were given that each demand is between 1 and 25, and was uniformly distributed. The method for calculating these random variables is outlined in Algorithm 2 and implemented in `demand_generation.Rmd`

Algorithm 2: Demand Generation

Data: Set of customers C

Result: Set of demands for each customer c

```

1  $U \leftarrow 60 \times 1$  vector of random uniform(0,1) variables ;
2 for  $u \in U$  do
3    $u \leftarrow 25 \cdot u$  ;
4    $u \leftarrow \text{upper}(u)$  ;
5 end
6 Let each index of  $U$  represent the corresponding customer in  $C$  ;
```

In the first line, we initialise a 60×1 vector of random uniform(0,1) variables. Then the loop on lines 2-4 firstly multiplies those values by 25, to give us 25 random variables between 0 and 25, and then returns the upper integer of that value, which gives us 25 random integers between 1 and 25, as required.

A.2 Modelling

A.2.1 Base-Line Model

Associated Files: `model(1.1).mod`, `f_loc(1.1).dat`, `c_loc(1.1).dat`,
`data(1.1).dat`, `run(1.1).run`, `out(1.1).txt`

With our data in hand, we can now move to modelling our problems, the first of which can be modelled in the form of an integer program. The formal definition of our model is outlined below:

Sets

C set of Customers

F set of Facilities

Parameters

c_{ij} $(i, j) \in C \times F$ cost of assigning customer i to facility j

k_f $f \in F$ cost of opening facility f

Variables

$x_{ij} \in \{0, 1\}$ $(i, j) \in C \times F$ Assigning customer i to facility j

$b_f \in \{0, 1\}$ $f \in F$ Opening facility f

Objective

$$\min \sum_{(i,j) \in C \times F} c_{ij} x_{ij} + \sum_{f \in F} k_f b_f \quad (\text{A.1})$$

Constraints

$$\sum_{j \in F} x_{ij} = 1 \quad \forall i \in C \quad (\text{A.2})$$

$$x_{ij} \leq b_j \quad \forall (i, j) \in C \times F \quad (\text{A.3})$$

We first define sets C and F to denote customers and facilities respectively. For our model parameters, we define c_{ij} to denote the cost of assigning customer i to facility j , which is given by the l_1 norm between the two corresponding coordinates. Here we also define k_f as the cost of opening facility f , which is given explicitly by $100 \cdot 3^{-f}$. For decision variables we let x_{ij} be a binary variable that is equal to 1 if we assign customer i to j . Similarly, b_f is another binary variable that is equal to 1 if we open facility f .

We then wish to minimise the cost of the operation. We model the objective function (A.1) as the cost of assigning customer i to j , multiplied by the decision variable. We then add this to the cost of opening the facilities, constructed similarly. The problem is constrained by (A.2), which ensures that every customer is assigned to at least one facility, and (A.3), which ensures that only facilities that are open can have customer assigned to them.

A.2.2 Capacitated Model

Associated Files: `model(1.2).mod`, `f_loc(1.2).dat`, `c_loc(1.2).dat`,
`data(1.2).dat`, `run(1.2).run`, `out(1.2).txt`

We then wish to expand the model, by factoring in the demands we generated earlier. We do this first by simply adding two variables. d_c defines the demand of customer c , and l_f defines the capacity limit of facility f . The parameter l_f is more specifically given as $100 \cdot 2^f$. We must then add one more constraint, namely:

$$\sum_{i \in C} d_i x_{ij} \leq l_j b_j \quad \forall j \in F \quad (\text{A.4})$$

This constraint (A.4) ensures that, summed over all customer assigned to facility f , the demand must not exceed the capacity of the facility. The binary variables here ensure this constraint holds only for open facilities. Other than this, our model remains unchanged from the previous section

A.2.3 Balanced Loads

We are now presented with the situation in which the firm wishes to retain some control over the demands faced by each facility. In Section 2.1, we learn that the optimal solution is indeed unbalanced, and there are numerous reasons why we may want to control this, one being to protect against shocks in demand.

For this, we let there be some L that defines the greatest allowable difference between the smallest demand faced, and the greatest. We define two new positive decision variables, u_{min} and u_{max} , to describe these values specifically. Finally, we add 3 more constraints to our current model, which are outlined below:

$$\sum_{i \in C} d_i x_{ij} \geq u_{min} \quad \forall j \in F \quad (\text{A.5})$$

$$\sum_{i \in C} d_i x_{ij} \leq u_{max} \quad \forall j \in F \quad (\text{A.6})$$

$$u_{max} - u_{min} \leq L \quad (\text{A.7})$$

Constraints (A.5) and (A.6) ensure the demands faced do not break the bounds of the limits described by u_{min} and u_{max} , and then constraint (A.7) ensures these two limits do not exceed our predefined limit L . This proposed model forces the largest and smallest demands to adhere the limit L in any solution, as required.

Appendix B

Vehicle Routing Methodology

Contained in this appendix is detailed, technical report of the methodology applied in the vehicle routing scenario.

B.1 Data Generation

B.1.1 Composite Client Generation

Associated Files: `client_generation.Rmd`

As in the previous problem, it was first necessary to generate data to be used in our modelling. In this case, it was necessary to generate 25 composite clients, who we prioritise the delivery service to. We outline the process used below in Algorithm 3, and the implementation can be found in `client_generation.Rmd`:

Algorithm 3: Composite Client Generation

Result: Set of composite clients C_{comp}

```
1 while all  $c \in C_{comp}$  are not unique do
2    $C_{comp} \leftarrow 25 \times 1$  vector of random uniform(0,1) variables ;
3   for  $c \in C_{comp}$  do
4      $c \leftarrow 60 \cdot c$  ;
5      $c \leftarrow \text{upper}(c)$  ;
6   end
7 end
```

Our process is very similar to that laid out in Algorithm 2, except we have added a loop enclosing the whole process that ensures the list we produce contains entirely unique numbers, otherwise, we would not have 25 composite customers. The other change is multiplying the random variables by 60, since there are 60 potential customers.

B.2 Modelling

B.2.1 Base-Line Model

Associated Files: `model(2.1).mod`, `data(2.1).dat`, `locations(2.1).dat`,
`run(2.1).run`, `out(2.1).txt`

B.2.2 Multiple Vehicles

Associated Files: `model(2.2).mod`, `data(2.2).dat`, `locations(2.2).dat`,
`run(2.2).run`, `out(2.2).txt`

Appendix C

Internal Depot Transportation with Uncertainty Methodology

Appendix D

Product Specific Insurance Methodology