The Patrol Officer Relocation Problem for the City of Surrey

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Abstract

The goal of this paper is to maximize the demand patrol officers can cover over various points within the City of Surrey. These demand points have an associated value based on a combination of population density and crime occurrences. For a fixed number of officers, the model will place them accordingly to cover the most demand at that point in time.

When an event occurs that requires an officer's assistance, the number of available officers will change. The model will then relocate them in a practical manner to re-maximize the covered points. A Pareto analysis is conducted that produces multiple patrol plans using an integer linear program which was written in Python 3.8 and solved using Gurobi. The solutions highlight the trade off between population versus crime coverage. With a selected patrol plan, a simulation is performed to show its effectiveness.

1 Introduction

The city of Surrey is preparing to replace the RCMP with a new municipal police department. Most police departments have patrol divisions that assign officers to monitor specific areas of the city. A patrol officer must be patrolling a nearby location in order to provide adequate coverage. The model aims to solve the problem of choosing where to best place patrol officers using population and crime data of the City of Surrey.

When a patrol officer on duty leaves to respond to a call or disturbance, it may leave a significant portion of the city uncovered. Therefore, it is important for the patrol division to apply a relocation policy to maintain optimal coverage. To avoid unrealistically relocating officers, there is a restriction placed that limits the number of officer allowed to relocate.

Most studies on such problems address the prediction and forecasting of where to place patrol officers [CHQ10], however very few include a relocation policy. Gendreau et al. [GLS06] addresses a relocation strategy with a focus on emergency medical vehicles. Their study only uses population data which would not be an accurate indicator alone for patrol officer placement. Their techniques can be applied to our problem by introducing crime data in addition to population data.

This paper formulates and solves a dynamic problem in patrol officer relocation. Random events require a patrol officer to become unavailable at discrete times during the day. When such an event occurs, the patrol officer leaves to handle the incident and a fleet relocation may take place; subject to an upper bound on the maximum number of relocations allowed. The solution is pre-calculated for a various number of patrol officers available while maximizing the expected coverage based off population density and crime frequency. By pre-computing the solutions, the model can quickly provide a new patrol scheme for various patrol sizes.

A Pareto analysis is conducted that produces multiple patrol plans highlighting the trade-off between population versus crime coverage. Using one of these solutions, multiple relocation policies are applied to analyze how relocating officers affects the overall coverage. Then, a simulation is performed to show the effectiveness of that patrol plan. The results show that having a relocation policy versus no relocation policy provided better overall coverage and response times. We call this problem *The Patrol Officer Relocation Problem* where data from the City of Surrey is used to verify our approach. This problem is based on *The Maximal Expected Area Relocation Problem for Emergency Medical Vehicles* [GLS06].

1.1 Background

Within the next few years, Surrey's new municipal police department will be implemented; it will be crucial where they allocate their resources. One of the key divisions within a police department is the patrol/operations division. If officers in this division are patrolling optimal areas, the police department is able to efficiently use all their officers. Our model aims to allocate limited resources while trying to guarantee an appropriate response time for all covered demand points.

Recently, the budget of the new municipal police has grown from $45 million – as initially estimated in June 2019 – to a $63.7 million projected budget in 2022 [Woo]. According to a poll commissioned by the National Police Federation, "a staggering 90 percent of residents feel Mayor and Council should take a step back to evaluate spending plans to focus on residents' most urgent priorities" [She20]. It is important that they allocate their budget efficiently and this paper highlights the coverage plans obtained for a different number of officers. This allows the user of the model to decide their desirable number of officers based on their budget.

2 Data

The goal is to optimally place patrol officers across Surrey. To achieve this, geographic data is important as this will help partition Surrey into district blocks. To decide which district blocks to prioritize, population density and crime data will be required. Since patrol officers are responding to crime incidents, the distance between them is significant in determining the response time. Additionally, where the patrol officers are initially located is important. Therefore, having a set of potential locations for patrol will allow the model to select the best locations.

Our data can be divided into four main entities that are the inputs to our model. They consist of demand points, waiting points, crime points, and the distance matrix that defines the driving distance between every waiting point and demand point. In this section, the data

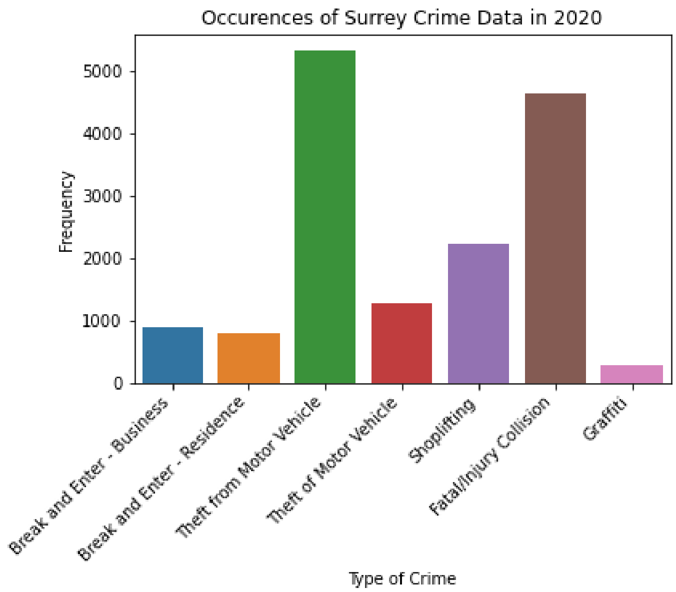

Figure 1: Types of crimes and their occurrences from the Surrey Data Catalogue

acquisition and a description of each entity will be presented. In subsequent sections, it will be explained how these points will be used in our mathematical model.

2.1 Description

An SQLlite database was used with the following tables:

Waiting Points	Demand Points	Distances	Crime Points
Longitude	Longitude	Demand Point	Location
Latitude	Latitude	Waiting Point	Month
	Population	Distance (m)	Year
			Type
			Longitude
			Latitude

The headings define the name of each type of entity and the sub-items define the fields/attributes. Waiting points are high traffic areas where police patrols are located. Demand points are dissemination areas across Surrey. Dissemination areas are the smallest unit of area that Census Canada acquires data for [Sur]. In figure 2, all of the 631 demand points and 88 waiting points are illustrated. Likewise, figure 3 displays a single waiting point and all the demand points within its radius. Crime points are points which represent an occurrence of crime. A plot of the catalogued crimes of 2020 are plotted in figure 1.

2.2 Data Acquisition

The data for the 631 demand points in our model was acquired using the *Statistics Canada Dissemination Areas*. A dissemination area is defined as a ”small area composed of one or

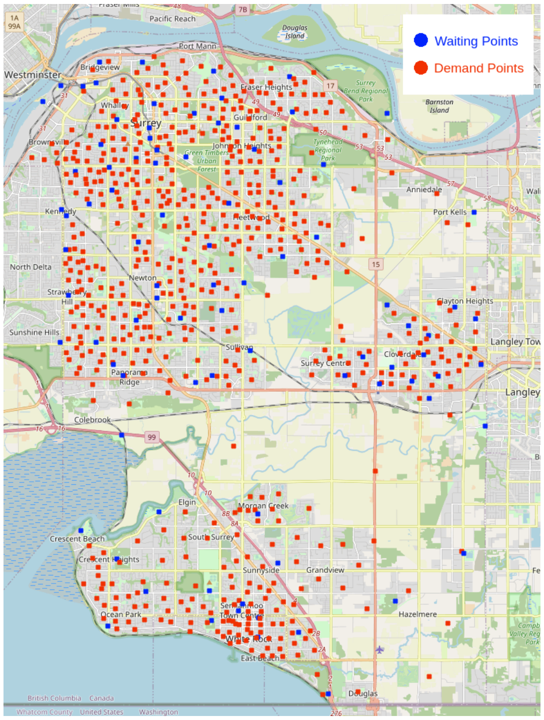

Figure 2: Demand and waiting points

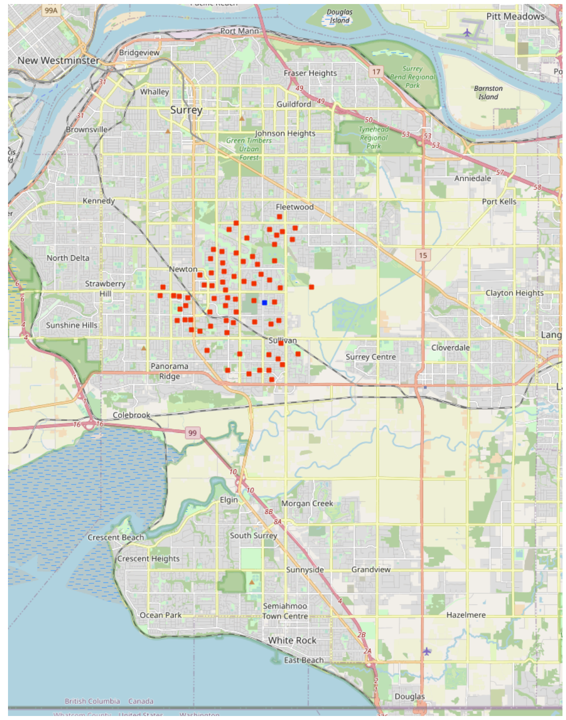

Figure 3: A single waiting point

more neighbouring dissemination blocks, with a population of 400 to 700 persons" [Sur]. Each dissemination area is composed of roughly three to four neighbourhood blocks; *Statistics Canada* provided a (latitude, longitude) pair to represent the approximate centroid of each. An example of a dissemination area is shown in figure 4. A population value is provided with each dissemination area which contributes to the demand point value.

The 88 waiting points were selected using the author's familiarity of Surrey. They were strategically chosen in high traffic areas that would make great spots for a patrol officer such as parks, RCMP detachments, and shopping centers. The complete list of waiting points is shown in section 6 (Appendix). In order to get the distances between each waiting point to each demand point, the *Google Maps API* was used. A demand point is in range of a waiting point if it is within the radius of the waiting point. Further discussion on how this radius is selected is provided in section 4.1. By using the acquired driving distance, one can determine if a demand point is in range of a waiting point.

The crime data was obtained from the *Surrey Data Catalogue* [RCM21] and was also used to give a demand value for each demand point. The weight of each crime was calculated using the maximum sentence of each crime from *The Criminal Law Notebook* [Dos]. For example, an area that has a certain number of graffiti incidents is weighed less than an area with the same number of break and enter incidents. The priority of the waiting points goes to the area with a higher demand value. The location of each crime point is given in street addresses and our model required longitude and latitude; the *Google maps API* was used to convert them. This allowed the model to connect the locations of crime points to the closest demand point using the Euclidean distance. Other measurements such as travel time can be used to assign crime incidents to each demand point, however this would require more *Google Maps API* calls and the Euclidean distance is a sufficient approximation for time in

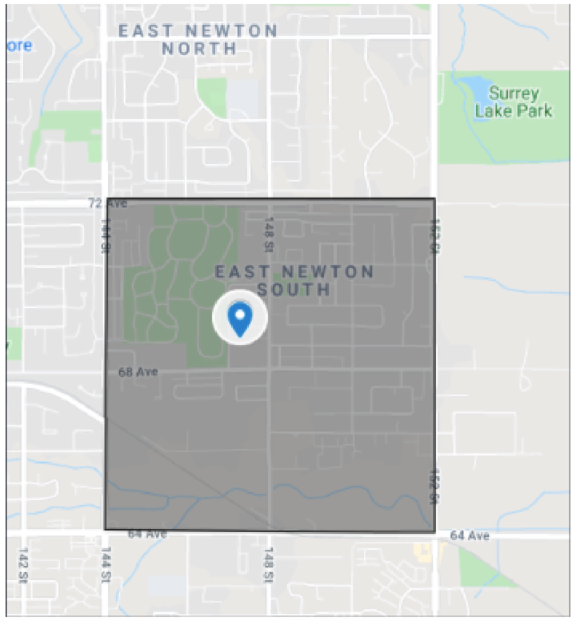

Figure 4: A dissemination area with the corresponding demand point representing the dissemination area

Surrey. The crime data obtained from the *Surrey Data Catalogue* excluded the uncommon crimes such as homicide or arson. The data instead had incidents of the more commonly occurring crimes such as shoplifting, fatal auto collisions, and graffiti. All seven types of crime and their frequency are shown in figure 1. We believe these crimes are a good proxy for crime overall since the location of the crimes not included would roughly be in the same area. The model is receptive to additional crime data and can be rerun to produce new patrol plans with the new data added. Due to the frequency of the uncommon crimes, their impact is minimal when selecting waiting points for officers.

3 Model

The Maximal Covering Location Problem (MCLP) was a problem first formulated in 1974 [CR74] which is described as finding the best set of locations to place facilities such that these facilities maximize the coverage within a certain radius. The MCLP has a range of applications such as cell tower placements, deciding where to open retail stores, and calculating optimal locations for ambulances and fire halls. The goal of the model is to optimize the coverage of both population and crime incidents by selecting the waiting points (officer patrol areas) that maximize said coverage.

As previously mentioned, Surrey is divided into 631 different areas with a (latitude, longitude) pair approximately near the center of the demand area it represents. As noted previously in section 2.2, the center of the dissemination area is given from *Statistics Canada*. An assumption is made that it will take only a single officer to handle a demand point. The model will not take into account if extra officers are required but instead focuses on getting a patrol officer to the location. This is because an event will be handled by an initial responder and potential back-up.

The model described is generic and can be easily reconfigured to receive new data on crime incidents or population changes. The parameters can also be changed to accept a range of radii to vary response times for covered demand points. Additionally, the user can change the size of patrol officers to fit their needs and considerations.

When relocating an officer, the model allows the user decide how many officers can relocate when an event occurs. This ensures that the relocation is done in a practical manner. Overall, there are many ways in how the user wishes to use the model so that it can be applied to any police department.

3.1 Static Case

The static case of our model produces the optimal placement of n patrol officers at a given moment in time. This is analogous to the classic MCLP and helps us build towards incorporating key features of the model such as relocating officers and a probabilistic approach to the availability of officers.

3.1.1 Variables, Sets, and Parameters

The following inputs are given to the model to produce n locations of where the officers should be placed. A brief overview of each input is given in table 1.

Type	Name	Description
Sets		
	V	Set of demand points
	W	Set of potential waiting points for officers to patrol
	W_i	Set of waiting points that can cover demand point $i \in V$
	A	Set of edges on $(V \cup W)$ such that $A_{i,j}$ is the distance between $i \in V, j \in W$
Parameters		
	n	Total number of patrol officers
	d_i	Demand at vertex $i \in V$
	r	The radius for determining the coverage of a waiting point
Variables		
	x_j	Binary variable indicating whether an officer is placed at location $j \in W$
	y_i	Binary variable indicating whether a demand point $i \in V$ is covered

Table 1: Inputs to the model

We note two key details about the inputs. First, we analyze the model using two different metrics for d_i: The population and the crime incidents at/near $i \in V$. The user of the static model can decide on which metric to use or a combination of the two. Next, the parameter r determines whether a demand point $i \in V$ is covered. More specifically, $y_i = 1$ if and only if there exists $j \in W$ such that $A_{i,j} \leq r$. This would also mean $|W_i| \geq 1$.

3.1.2 Static Model

For the static case, we consider the two main constraints needed for the model in addition to the binary variables. The maximum number of allowed officers that can be placed has to be equal to n. Additionally, we add the constraint that vertex $i \in V$ is covered if there is at least one patrol officer placed at a waiting point in W_i. The objective is to maximize the coverage of demand points that gets the user the greatest sum of demand values. These components result in the following linear program:

$$\text{Maximize} \quad \sum_{i \in V} d_i y_i \tag{1}$$

Subject to:

$$\sum_{j \in W} x_j \leq n \tag{2}$$

$$\sum_{j \in W_i} x_j \geq y_i \quad (i \in V) \tag{3}$$

$$x_j \in \{0,1\} \tag{4}$$

$$y_i \in \{0,1\} \tag{5}$$

Constraint (2) ensures we never deploy more than n officers. Constraint (3) makes it so that the model will only include demand points such that there is at least one patrol officer at a waiting point covering that demand point.

3.2 Relocating Officers

During the course of a patrol, events will occur that makes an officer unavailable. This could be for reasons like receiving a call that requires an officer's attention or an incident occurring near an officer while on patrol. When an event occurs, we say that the state k changes where k is the number of available officers from $1,\ldots,n$. When an officer becomes unavailable, it is usually the case that the $k-1$ officers currently available are not located at the optimal waiting points. A relocation of a number of officers may help to obtain better coverage. As well, it is unrealistic to assume that all k officers will be available at once at a given point in time. We can get a probability of what fraction of time an officer is busy, called the busy fraction which is used in the Maximum Expected Covering Problem [Das83]. We use the busy fraction to produce a probability that k of n officers are available.

3.2.1 New Variables and Model

There are a few key differences one must consider to model a realistic scenario of relocating an officer. Instead of using y_i and x_j in the static case, we will now use y_{ik} and x_{jk} to represent whether the demand point $i \in V$ is covered in state k and whether an officer is placed at location $i \in W$ in state k respectively. It is impractical to be relocating the entire fleet when an event occurs. We introduce a constraint, α_k, that enforces k number of officers that are allowed to relocate. α_k could be a constant or a function of k such as $\lceil k/2 \rceil$. When we move from state k to $k \pm 1$ (for $0 < k < n$), we want to avoid double-counting of waiting points. Consequently, we define a binary variable u_{jk} such that $u_{jk} = 1$ if our waiting point loses an officer when relocating from state k to state $k+1$.

Note that an officer will not be available during their entire shift as they will be handling events and doing routine work. Following Gendreau et al. [GLS06], we use the busy fraction $\lambda/(n\mu)$ where λ is the average calls per hour and μ is the average service time. While λ

can be calculated using the available crime data, it is difficult to calculate μ as each incident is unique. For this reason, the model will make an assumption that the average service time is one hour. Therefore, the amount of time an officer is available is $p = 1 - \lambda/n\mu$. The probability of having k available vehicles, defined as q_k, is $q_k = \binom{n}{k} p^k (1-p)^{n-k}$. This is obtained through a binomial distribution. We can now construct the Patrol Officer Relocation Problem as:

$$\text{Maximize} \quad \sum_{k=1}^{n} \sum_{i \in V} q_k d_i y_{ik} \tag{6}$$

$$\text{Subject to:} \quad \sum_{j \in W} x_{jk} = k \quad (k = 0, \ldots, n) \tag{7}$$

$$\sum_{j \in W_i} x_{jk} \geq y_{ik} \quad (i \in V, k = 0, \ldots, n) \tag{8}$$

$$\sum_{j \in W} u_{jk} \leq \alpha_k \quad (k = 0, \ldots, n) \tag{9}$$

$$x_{jk} - x_{j,k+1} \leq u_{jk} \quad (j \in W, k = 0, \ldots, n) \tag{10}$$

$$x_{jk} \in \{0,1\} \tag{11}$$

$$y_{ik} \in \{0,1\} \tag{12}$$

$$u_{jk} \in \{0,1\} \tag{13}$$

This model follows the approach used in *The maximal expected coverage relocation problem for emergency vehicles* proposed by Gendreau et al. [GLS06]. Constraint (7) ensures that only k amount of officers are allowed to patrol at once in state k. In constraint (8), the model only includes covered demand points. Constraints (9) and (10) control how many officers can relocate when moving between states. Lastly, probability q_k is added to the objective function to simulate situations in which officers are busy for various states. The user can apply the model in a dynamic manner by simply looking at all outputs of x_{jk} for each state k.

There are a few similarities when compared to the static scenario. Constraint (7) acts like constraint (2) to enforce our bounds in the amount of officers. Additionally, constraint (8) acts like constraint (3) where only covered demand points are included.

3.3 Trade-off of Crime and Population Coverage

Recall that the demand at a demand point, d_i, can be measured in two ways: occurrences of crime and population. Rather than making an assumption about which metric is more valuable, we make a multi-objective problem (i.e. maximizing population coverage and maximizing crime coverage) to optimize. The solution to the multi-objective function can be obtained through a Pareto analysis [CHQ10]. Given a patrol plan (the waiting points selected to place officers), the plan is assessed through the fraction of crime and the fraction of population the patrol covers. The user determines which metric to prioritize and can make a decision about which patrol plan to use based on the Pareto frontier. We create a two-dimensional plot of both metrics and the Pareto frontier is the points that

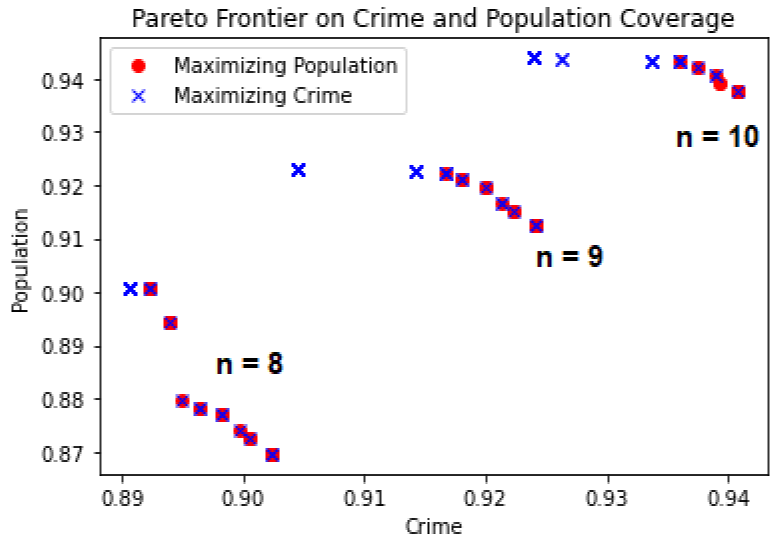

Figure 5: Parteo frontier for fleet size of 8, 9 and 10

are non-dominated points (i.e. no other patrol is better than them in at least one of the performance metrics).

To achieve an accurate Pareto frontier, the model is given two different scenarios: maximizing population coverage with respect to meeting a specific crime coverage and vice versa. This results in requiring one extra constraint to the model and a slight modification to the objective function. Let d_{ip} and d_{ic} be the demand value of population coverage and crime coverage (both on a [0,1] scale) at demand point $i \in V$ respectively. Suppose we wish to maximize population while fulfilling a constraint that the crime coverage must meet a certain percentage. Call this percentage constraint β. Then, (6) becomes:

$$\text{Maximize} \quad \sum_{k=1}^{n} \sum_{i \in V} q_k d_{ip} y_{ik} \tag{14}$$

We also add the constraint of requiring that at least β percent of the total crime is covered:

$$\sum_{i \in V} d_{ic} y_{in} \geq \beta \tag{15}$$

Note that in (15), we only look at the maximal fleet size n as it makes the most sense to achieve the best coverage with the entire fleet. In the Pareto analysis, the model then becomes (1)-(5) and (15) with the change that (1) is switched out for (14). To obtain most of the patrol plans on the Pareto frontier, the model varies the size of β in the range [0,1] with a step size of 0.01. This will produce a sufficient number of patrol plans because even if the step size β were smaller, the difference in coverage is very small. The Pareto analysis additionally looks at the same model but with d_{ip} and d_{ic} swapped (i.e. maximizing on crime with the constraint on population). This is to discover additional patrol plans on the Pareto frontier not found by the first configuration of the model. The user can choose the patrol plan based on their needs and considerations. We display the Pareto frontier for several values of n in figure 5.

The plot shows that trade-off between crime and population can occur differently for several values of n. For example at $n = 8$, each point on the Pareto frontier varies more in population whereas when $n = 9$, the crime varies more. Overall, the Pareto plot only displays small gains when prioritizing one metric over the other which is seen at the extreme points of the Pareto frontier for each n. At $n = 8$, the maximum value for population is roughly 90% and the minimum value is roughly at 87% which is a small difference overall. The same trend can be seen in crime. Lastly, we note that the Pareto optimal patrol plans are all closely related to each other. The patrol plans for $n = 8$ on the Pareto frontier all differ by at most two waiting points but usually only by one; there are always six base waiting points that are selected in every patrol plan. This trend can also be seen at different values of n.

4 Simulations

With our model, we would like to apply it to the City of Surrey as the patrol plans the model produces will be a proof of concept for the upcoming new municipal police force. To verify our model's effectiveness, we create a real-time simulation. This will highlight the benefits of the selected patrol plan by gathering statistics such as response times for events.

4.1 Set Up

The relocation integer program (6)-(13) is solved using a 10th gen i7 Intel processor with 16GB RAM. Once the input values to the model were chosen, Gurboi was able to solve the problem on average 0.6753 seconds over 10 executions. As noted in section 2.2, the model had $|W| = 88$ waiting points and $|V| = 631$ demand points around Surrey. A value of $\lambda = 1.756$ calls per hour is derived from the 15382 reported incidents over the year of 2020. As noted in section 3.2.1, the average service time μ, is difficult to calculate as each incident is unique. For this reason, the model will make an assumption that $\mu = 1$ hour. This allows us to calculate the probability when an officer is not busy $p = 1 - \lambda/n\mu$ which is used in the probability distribution q_k.

The Surrey-Leader newspaper reported that the average response time for emergency vehicles was 8.5 minutes [Rei14]. A fast response time is important as this is a desirable quality in evaluating police patrols [SWS80]. Therefore, we aimed for an achievable response time given a realistic number of officers which led us to choose a response time of 7 minutes. The desired response time is related to the radius r, as any demand point within the radius of an officer is said to be covered by the officer and is reachable within the given response time. To observe the relationship between distance and time, we create a linear regression plot shown in figure 6. The data points are obtained by randomly sampling 40 pairs of points in Surrey and recording the distance and travel time between each pair using the *Google Maps API*. The plot shows that a radius of $r = 4.2$km predicts a response time of just under 7 minutes for all demand points covered by an officer.

We tried various patrol sizes n to see when the model approaches the maximum objective of 100% coverage of a demand criterion. Objective values of crime and population coverage for various n are plotted in figure 7. One can see the diminished gains as n increases. We observe that near $n = 9$, the objective values of both population and crime are greater than

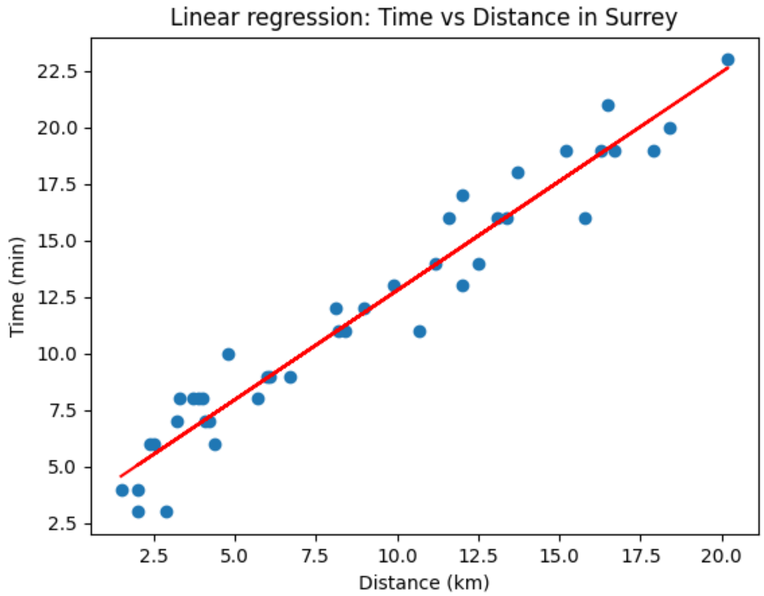

Figure 6: The relationship between time and distance

90%. Thus, this is the value of n used for a few points in the analysis. Although there are larger n that can achieve close to 100% accuracy, the cost of having extra officers on patrol would not be worth the marginal gains. However, the user of the model is free to choose the n that best satisfies their needs.

Distance between a waiting point and all of it's demand points were computed using the *Google Maps API*. Note that google has a threshold of 25,000 API calls before applying a fee. Since we required $|W||V| = 55528$ API calls, this was not feasible. To overcome this, we first calculate the Euclidean distance between a waiting point and all its demand points. For all $(i \in V,\ j \in W)$ pairs where their Euclidean distance was greater than 10km, we opted to keep the Euclidean distance rather than query the distance in *Google Maps API*. This makes sense as demand points far from a waiting point would not be covered given a reasonable r so it is redundant to make an API call for such a pair. Introducing this requirement before making an API call resulted in only 21,347 queries.

4.2 Implementation

We implement our integer linear program as defined in section 3.2.1 by first plotting the Pareto frontier for $n = 9$ and choosing a point on the frontier that gave the most even split on both metrics. Observing figure 8 opts for the choice of $\beta = 0.9185$ in constraint (15) meaning about 92% coverage on both metrics. For relocating, we follow the approach of Gendreau et al. [GLS06] and try the following four values of α_k: $\alpha_k = 0, 1, \lceil k/2 \rceil, k$. Note that the last two values correspond to permitting relocation of half the available fleet and the entire fleet respectively. Table 2 shows for each α_k, the chosen waiting points for each $k = 1, \ldots, 9$. As expected, the case for $\alpha_k = 0$ shows that all selected waiting points in state k (for $k < n$) will also be selected in state $k+1$. When $\alpha_k = 1$, we see that different waiting points are selected from $\alpha_k = 0$. An interesting point is that for any value of $\alpha_k > 1$, the

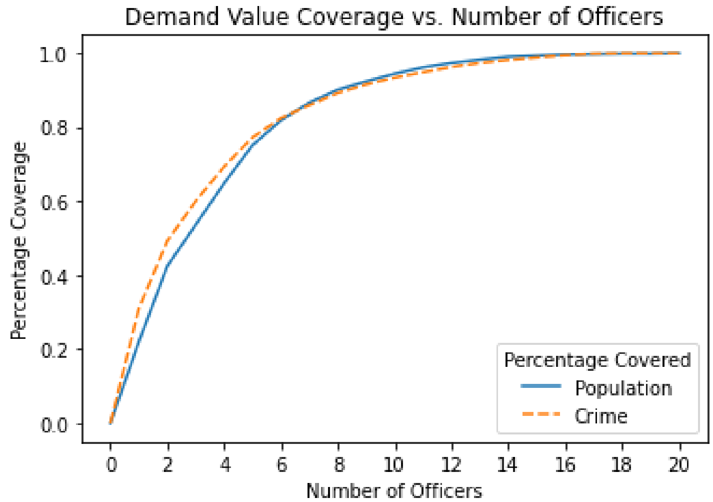

Figure 7: Comparing population coverage to crime coverage as n increases

waiting points selected are the same ones selected in $\alpha_k = 1$. This suggests that for $n = 9$, only one officer relocation needs to take place when an event occurs to maintain maximum coverage. Note that this may not be true for different values of n.

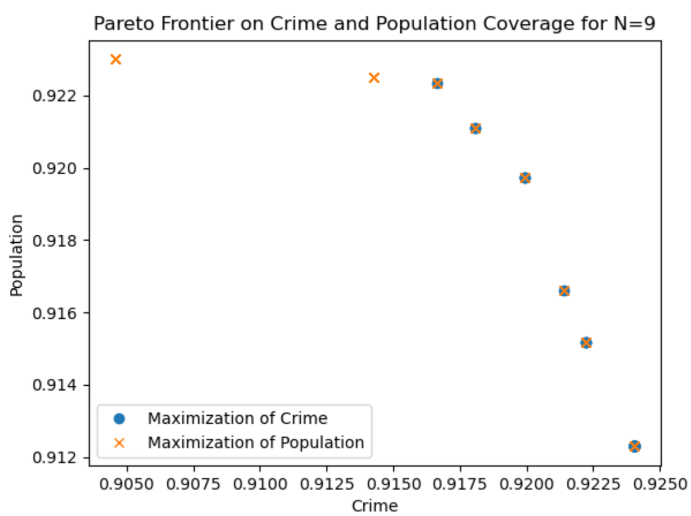

Figure 8: We chose a point on the Pareto frontier that equally weighs crime and population

Using these set of waiting points, a simulation is performed to show the effectiveness of the patrols so some performance measurements could be extracted. We chose the scope of the simulation to be one week. In our data, we had occurrences of crime in Surrey along with the month that they occurred in. However, to simulate a realistic one week period, time stamps associated with each occurrence are needed. For Surrey, no crime data with time stamps was publicly available. Hence, *The Vancouver Data Catalogue* provided data related to crime incidents and the time that they occurred [Osa17]. As these are both cities in the Lower Mainland of British Columbia, the time distribution of crimes should follow a similar trend. With this new data, probability distributions were created for a day in a

k	$\alpha_k = 0$	$\alpha_k = 1$	$\alpha_k = k/2$	$\alpha_k = k$
1	29	16	16	16
2	29,44	16,35	16,35	16,35
3	12,29,44	19,35,42	19,35,42	19,35,42
4	12,29,44,88	19,35,42,88	19,35,42,88	19,35,42,88
5	12,29,44,68,88	19,35,42,68,88	19,35,42,68,88	19,35,42,68,88
6	12,29,44,48,68,88	19,27,29,42,68,88	19,27,29,42,68,88	19,27,29,42,68,88
7	12,27,29,44,48,68,88	12,27,29,44,54,68,88	12,27,29,44,54,68,88	12,27,29,44,54,68,88
8	12,27,29,44,48,68,73,88	12,27,29,44,54,68,82,86	12,27,29,44,54,68,82,86	12,27,29,44,54,68,82,86
9	12,27,29,44,48,68,73,86,88	3,16,27,29,41,48,68,82,86	3,16,27,29,41,48,68,82,86	3,16,27,29,41,48,68,82,86

Table 2: Waiting points selected for each α_k for $n = 9$

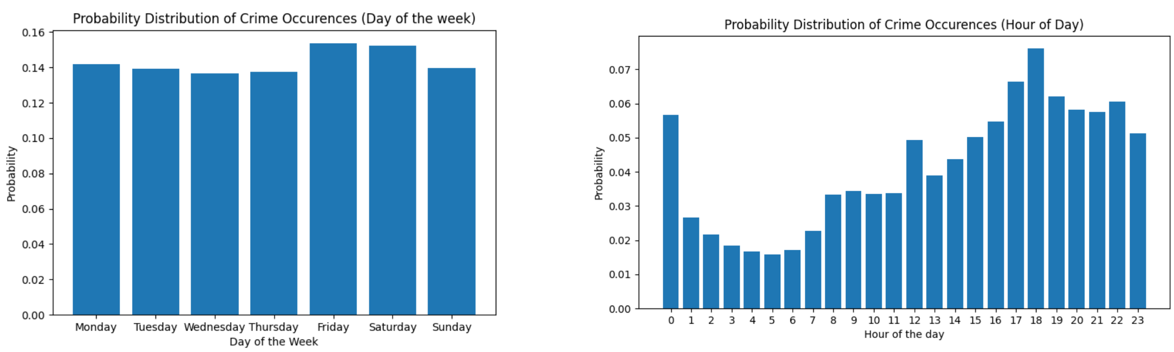

Figure 9: Crime Incidents Probability Distributions

given week and for each hour of a given day. Figure 9 shows these distributions for the Vancouver data set that stems from 2003 to 2017. Since our data included crime incidents for an entire year, we were able to obtain a rough estimate on the total number of crimes per week on average. This ended up being 264 crimes for a one week period. With this information, the crime incidents and their location were selected at random from our crime data set. Then, each of those crime incidents were given a day and hour value pulled from the constructed probability distributions in figure 9. Finally, they were assigned a random minute value within that hour for simplicity.

The logic of the simulation was also relatively simple. To start, each tick of the simulation represented one minute. Then at each tick, the following was done:

```
if (Officers become free):
     Add x officers back to pool of waiting points (k := k + x)
if (Crimes are waiting for an officer to become free):
    dispatch x officers to x crimes from queue (k := k - x)
if (Crime occurred at this tick):
    if(Officers available):
        Send to crime location (k := k - 1)
    if(No Officers Available):
        Add crime to waiting pool
```

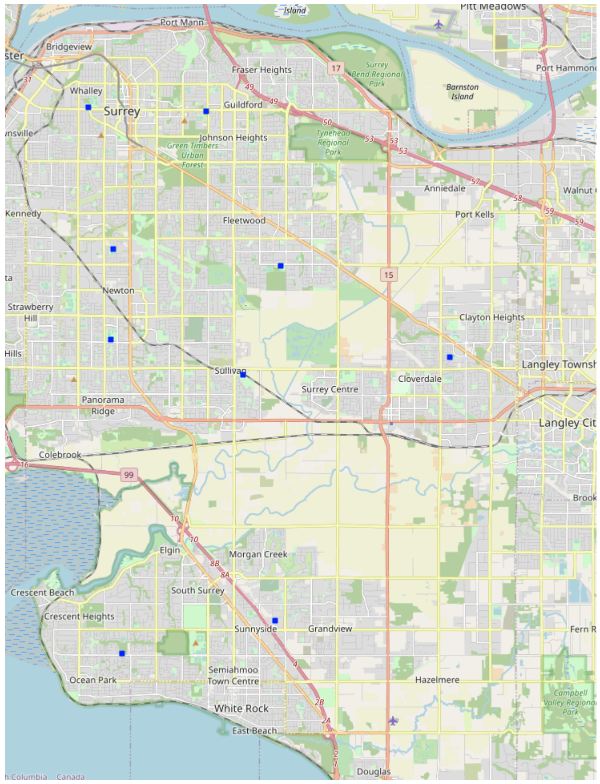

Figure 10: Plot of optimal patrol points for $n = 9$ officers

4.3 Results

With nine officers available, we can optimally place them to ensure that we get 92.1% coverage of population and 91.9% of crime coverage. This essentially means that when an incident occurs, the patrol plan will likely be able to respond to an incident within at most seven minutes. As shown in figure 10, the officers are spread out over Surrey evenly.

We collect data from our simulation for relocation policies of $\alpha_k = 0, 1$. It takes the simulation 76 - 78 seconds to complete. Note that as mentioned in section 4.2, any value of $\alpha_k > 1$ produced the same patrol plan as $\alpha_k = 1$ so we only needed to analyze these two cases. The results of the simulation is shown in table 3.

α_k	Average Response Time	Minimum Response Time	Maximum Response Time	Average Demand Coverage	Average Population Coverage	Average Crime Coverage
0	5.511014	3.023909	17.195811	0.817715	0.795694	0.857143
1	5.346244	2.807536	17.195811	0.840058	0.817748	0.891156

Table 3: Simulation results over a one week period

With $\alpha_k = 0$, the results indicate an average population coverage of roughly 80% and an average crime coverage of roughly 86%. $\alpha_k = 1$ gains a small percentage over $\alpha_k = 0$ in population coverage but a much larger gain in crime coverage by almost 5%. In terms of the actual demand points covered, both patrol plans cover about 80% on average with $\alpha_k = 1$ having a 2% improvement. The average response times for $\alpha_k = 0$ and $\alpha_k = 1$ are 5.51 minutes and 5.35 minutes respectively; differing only by a few seconds. This matches up with the linear regression plot shown in figure 6. From this, we can conclude that relocating an officer does not make a significant difference in the average response time. The minimum response time for $\alpha_k = 1$ is slightly faster than $\alpha_k = 0$ whereas both values of α_k have the same maximum response time.

To conclude, results drawn from this data show that on average, the patrol plans are effective at covering a minimum of roughly 80% in all coverage criteria. This indicates that the patrol plans will give an efficient response time to about 80% of the population. Even though the gains from $\alpha_k = 1$ are marginally better, the results conclude that the relocation policy versus no relocation policy obtains betters results in all of the given criteria.

5 Conclusion

With the new Surrey police force coming soon, our goal is to provide an efficient patrol plan for them. The Patrol Officer Relocation Problem for the City of Surrey has modeled and solved a dynamic relocation problem occurring in police patrol by pre-computing patrol plans. The model maximizes coverage based on population and historical crime data. In addition, the model is able to apply a relocation policy that re-maximizes coverage when a crime incident occurs. We explore the model solution for a value of $n = 9$ officers. One of the Pareto optimal solutions is balancing 92.1% of population and 91.9% of crimes covered (shown in figure 8) and attempts to achieve a response time of at most 7 minutes. Real life population data and crime data of the City of Surrey is used in our simulations to verify our approach. The results reveal the benefits of using a relocation strategy in terms of population and crime coverage. Overall, the model is able to successfully select a patrol plan that patrols the city of Surrey effectively and is validated through our simulations.

5.1 Future Considerations

The following things to work on are important aspects that should be incorporated in future work of the model. This may include the incorporation of the travel distance saved between waiting points and covered demand points. The approach to this would be to compare the current RMCP's patrol plan to the proposed patrol plan from our model. The distance can be calculated from each officer to each demand point in a simulation. We hypothesize that the distance travelled through our patrol plan will be less than the distance travelled using the Surrey Police Department's patrol plan. This will produce quantifiable evidence and support why the model is able to obtain the given response time. This also helps justify the use of our model as the distance saved can translate to fuel cost savings.

Currently, the RCMP's patrol plans are not available to the public. This confidential information is important to ensure that criminals do not know the patrolling patterns of the police force. However, the general public would like this level of transparency to ease the concern of bias displayed in these patrol plans.

There are policing algorithms in place that help predict crime, some of which are location-based or person-based algorithms. The criticism that these algorithms receive is that the data the model uses is biased toward specific neighbourhoods or individuals [Hea20]. Moving forward, our model would like to utilize more crime-specific data. This data may include arrest data or conviction data, so our model will produce more accurate results. However, the introduction of this data will have bias. To mitigate some of the bias, our model uses population data and can weigh population more than the other data used (through the Pareto analysis). It is important that the model uses different types of data because despite the bias, it is still significant in improving the results of the model.

Barocas and Selbst define online proxies as "factors used in the scoring process of an algorithm which are mere stand-ins for protected groups, such as zip code as proxies for race, or height and weight as proxies for gender" [BS14]. For the Patrol Officer Relocation Problem, it could be the case that the demand points act as proxies for certain demographics. Lee, Resnick, and Barton go into further detail by talking about bias impact statements:

> Once the idea for an algorithm has been vetted against nondiscrimination laws, we suggest that operators of algorithms develop a bias impact statement, which we offer as a template of questions that can be flexibly applied to guide them through the design, implementation, and monitoring phases.
>
> As a self-regulatory practice, the bias impact statement can help probe and avert any potential biases that are baked into or are resultant from the algorithmic decision. As a best practice, operators of algorithms should brainstorm a core set of initial assumptions about the algorithm's purpose prior to its development and execution. We propose that operators apply the bias impact statement to assess the algorithm's purpose, process and production, where appropriate. [TRB19]

Taking this into account, it should be the case that the user discusses with the Surrey Police Force a bias impact statement and how best to use the model so that it achieves its purpose.

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6 Appendix

Index	Waiting Point Name	Latitude	Longitude
1	Bear Creek Park	49.161	-122.840
2	Walmart Supercenter	49.164	-122.877
3	Plaza at 88 and scott road	49.163	-122.891
4	LA Matheson Secondary School/Moffat Park	49.175	-122.884
5	Tannery Park	49.198	-122.900
6	Brownville Pub	49.203	-122.891
7	Aria Banquet Convention Center	49.202	-122.880
8	Bridgeview Park	49.210	-122.872
9	Bolivar Park	49.210	-122.850
10	Scott Road Skytrain	49.204	-122.873
11	Surrey memorial parking	49.178	-122.844
12	William Beagle Park	49.169	-122.865
13	Cedar Hills Shopping Center	49.176	-122.867
14	Central City Shopping mall	49.186	-122.846
15	Kwantlen Park	49.192	-122.863
16	King George Skytrain	49.182	-122.843
17	Surrey Central	49.189	-122.847
18	Surrey RCMP City Centre	49.197	-122.844
19	APH Matthew Park	49.179	-122.853
20	Nordel Crossing Shopping Mall	49.161	-122.888
21	Scott Road Centre Shopping Mall	49.149	-122.888
22	Srawberry Hill Shopping Centre Shopping Mall	49.135	-122.887
23	Sunshine Hills Center Shopping Mall	49.120	-122.891
24	Mud Bay Park	49.089	-122.861
25	Sullivan Park	49.117	-122.797
26	TE Scott Park	49.130	-122.811
27	Chimney Heights Park	49.138	-122.815
28	Hazelnut Meadows Community Park	49.127	-122.831
29	Unwin Park	49.127	-122.853
30	Panorama Park	49.112	-122.865
31	Tamanawis Park	49.120	-122.873
32	Goldstone Park	49.109	-122.816
33	Royal Canadian Mounted Police Newton	49.107	-122.824
34	West Newton Community Park	49.109	-122.860
35	Surrey RCMP District #3 Newton	49.134	-122.843
36	Robson Park	49.184	-122.871
37	Fominion Park	49.152	-122.852
38	King's Cross Shopping Centre	49.138	-122.843
39	Hawthorne Park	49.194	-122.825
40	Guildford Town Centre Shopping Mall	49.189	-122.803
41	Fraser Heights Park	49.194	-122.776
42	Lionel Park	49.182	-122.795
43	Enver Creek Park	49.151	-122.817
44	Royal Canadian Mounted Police Guildford	49.191	-122.813
45	Riverside Heights Shopping Centre Shopping Mall	49.199	-122.811
46	Surrey Bend Regional Park	49.194	-122.729
47	Hemlock Park	49.171	-122.782
48	Fleetwood Park	49.147	-122.781
49	Surrey Lake Park	49.139	-122.800
50	Maple Green Park	49.165	-122.807
51	RCMP E-Division Headquarters	49.180	-122.829
52	Invergarry Bike Park	49.207	-122.815
53	Fraser View Park	49.206	-122.777
54	Bonnie Schrenk Park	49.154	-122.764
55	Tynehead Regional Park	49.178	-122.761
56	Port Kells Park	49.162	-122.686

57	North Creek Park	49.132	-122.729
58	Hazelgrove Park	49.131	-122.696
59	Brooks Crescent Park	49.113	-122.683
60	Sunrise Ridge Park	49.109	-122.704
61	Don Christian Park	49.116	-122.711
62	Cloverdale Ball Park	49.115	-122.741
63	Katzei Park	49.128	-122.685
64	Hi-Knoll Park	49.093	-122.680
65	Claude Harvie Park	49.107	-122.717
66	Cloverdale Heights Park	49.109	-122.750
67	Royal Canadian Mounted Police Cloverdale	49.106	-122.733
68	Hillcrest Park	49.122	-122.709
69	North Cloverdale West Park	49.125	-122.719
70	Hunter Park	49.102	-122.708
71	Greenaway Park	49.112	-122.727
72	Crescent Beach	49.058	-122.881
73	Crescent Park	49.050	-122.863
74	South Meridian Park	49.026	-122.773
75	Kwomais Point Park	49.027	-122.868
76	South Surrey Athletic Park	49.039	-122.818
77	Peace Arch Hospital	49.030	-122.793
78	Peace Arch Provincial Park	49.006	-122.758
79	Redwood Park	49.036	-122.725
80	Latimer Park	49.051	-122.691
81	Dr. RJ Allan Hogg Rotary Park	49.024	-122.793
82	Dogwood Park	49.039	-122.849
83	Semiahmoo Shopping Centre	49.032	-122.803
84	Centennial Park	49.030	-122.817
85	Blumsen Park	49.064	-122.794
86	The Shops at Morgan Crossing Outlet	49.048	-122.783
87	Elgin Heritage Park	49.065	-122.842
88	South Surrey RCMP	49.035	-122.801

Table 4: All potential waiting points