# Optimizing Police Resources Deployment

By

**Mozhdeh Hashemian**

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# Abstract

The Ottawa Police Service (OPS) deploys its resources based on the needs of predefined zones. However, the current zoning approach has been acknowledged as inefficient due to negative impacts on costs, proficiency, quality of services and time management. The zoning approach has also been acknowledged as inefficient due to its static nature, its inflexibility and its inability to adjust systematically according to the number of currently available police vehicles. It also cannot assist in addressing demand changes throughout the day in order to reduce call responses in neighbouring zones. Therefore, the demand variation could lead to a significant decrease in police efficiency, since those officers who have been allocated to other zones are not able to participate in events outside their zones without permission. It may cause a high volume of waiting calls and increased response time depending on the time of day, shifts, seasons, etc. Hence, the OPS needs to find a new model for resource deployment that can provide the same coverage but with better service quality.

Resource allocation has always been a challenge for emergency services like police, fire emergency, and ambulance services since it has a direct impact on the efficiency and effectiveness of the service activities. The ambulance and fire emergency services have received research attention while the optimization of police resources remains largely ignored. While there are many similarities between ambulance and police deployment there are also significant differences that mean the direct transfer of ambulance models to police deployment is not feasible.

This research addresses the lack of an effective tool for the deployment of police resources. We develop a simulation model that analyzes potential deployment plans in order to determine their effect on response times. The model has been developed in partnership with the

Ottawa Police Service (OPS) and will address the obstacles, disadvantages, and geographical constraints of the existing allocation model. The OPS needs to align deployment with the service demand and their operational goals (response times, visibility, workload, compliance, etc.). Repositioning police vehicles in real time helps in responding to future calls more effectively without adding more officers.

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# 1. Chapter 1: Introduction

## 1.1 Background and Motivations

Resource allocation has always been a challenge for social emergency services like police, fire, and ambulance (Naoum-Sawaya 2013) as they attempt to balance the need to respond quickly to current demand while also maintaining sufficient resources for potential future demand. By definition, the when and where of demand is unknown in advance and thus the positioning of resources is crucial to the ability of the emergency service to respond in an appropriate amount of time. Therefore, it is critical to allocate emergency services resources efficiently and effectively (Green and Kolesar 2004). The ambulance and fire emergency services have received research attention while the optimization of police resources remains almost ignored by operations researchers. However, it is highly acknowledged that police service is one of the critical social service agencies that require effective and efficient resource management in order to provide better safety and protection for a community.

Given that the police force has a finite set of vehicles dispatched throughout the city and that demand originates in a stochastic fashion, the department must determine which vehicles to send to the scene of a crime and then whether or not to re-deploy the remaining vehicles to optimally cover the city with fewer vehicles while that particular unit is servicing a call.

Ottawa Police Service (OPS) has deployed its officers based on the needs of different zones. However, zones are acknowledged to be an inefficient means of resource allocation with negative impacts on costs, proficiency, quality of service, and time management. Due to these important problems, the OPS decided to redeploy its forces based on what is called point policing. In this method, units are not assigned to zones but to points in the city and can respond to any call as required. The goal of this method is to benefit from the same coverage with better service quality, and to reduce the amount of time needed for dispatching the officers to each event. There remains the issue of determining a) where to initially place units b) which unit to send to the scene (may not be optimal to send closest one) and c) whether to redeploy the other units due to some being unavailable due to servicing a call.

This research study addresses the lack of effective tools for police resource deployment. It aims to develop a model that allows the department to explore options for deployment and determine the potential performance of each in terms of minimizing call response time. The model has been developed in partnership with the Ottawa Police Service (OPS). The OPS is looking to align deployment with demand for service and with its operational goals (response times, visibility, workload, compliance, etc...). Repositioning police vehicles in real time helps the OPS respond to future calls more effectively without necessarily adding more capacity.

The aim of this study is to find a resource allocation policy that the OPS can use to determine the number of available officers for each event efficiently with a focus on reduction of response time and cost savings. Zoning has been a common practice for allocating police officers in many cities as well as in Ottawa and it lets the OPS distribute officers across different zones based on each zone's expected demand. The officers allocated to a specific zone are responsible for calls associated just within their zone. The OPS currently has eight rural zones which are costly as officers stationed there are often under-utilized.

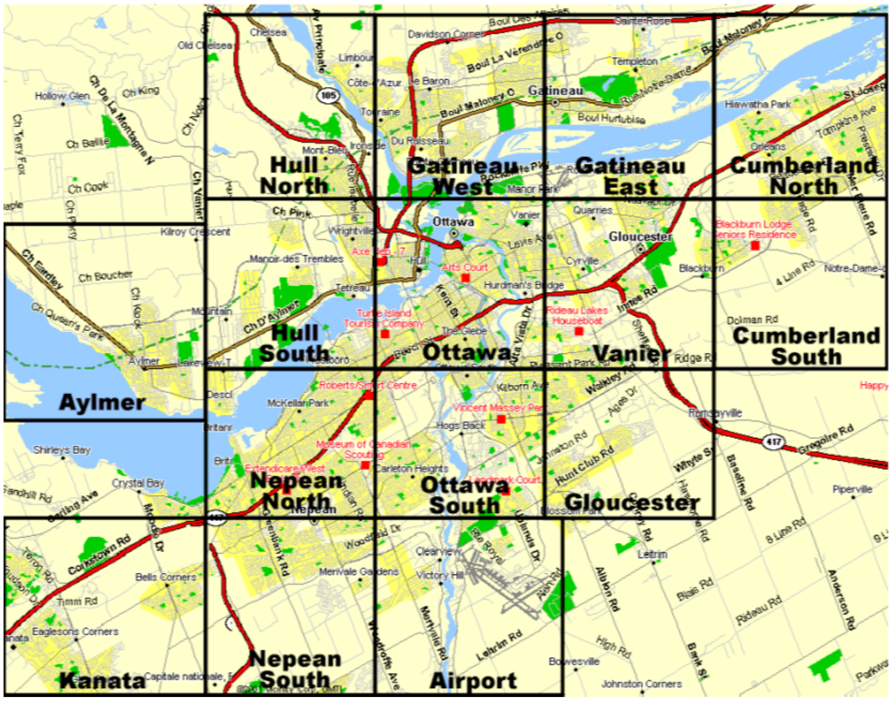


Figure 1.1: Neighborhood Maps, Ottawa, 2011

The zoning approach has been acknowledged as inefficient due to its static nature and lack of flexibility and its inability to be adjusted systematically according to the number of currently available police vehicles. The OPS currently deploys their resources to different zones based on the population in each area. However, zoning does not take into consideration varying crime rates, travel times, and seasonality. As a result, on those days with high demand, the effectiveness of the zoning allocation can be quite poor. Those officers who have been allocated to other zones are not able to participate in events outside their zone without permission. Thus, zoning is perceived to cause a high volume of waiting calls and likely increase response time based on the time of day, shifts, seasons, etc.

In order to improve the existing zone-based approach of police resource deployment this research aims to develop a new demand-based model that seeks to reduce the call response time subject to constraints on the number of police cruisers and officers.

Hence the main objective of the study is to develop and validate a model that allocates police resources based on a predictive demand model while maximizing coverage and minimizing response time.

## 1.2 Research Questions and Objectives

In order to meet this objective this study also answers the following sub-research questions:

1. How best can crime types be classified based on the resources required and response time threshold?
2. What is the demand profile based on location and type of crime?
3. What are the other critical factors that impact on the waiting time of each crime?

This document consists of five sections. The current section provides the introduction and defines the research objectives. The second section reviews the existing literature on the models of resource deployment in emergency services. It is followed by the methodology utilized for this research. Section four presents a preliminary research model development with the following results and the last section illustrates the summary of this study, some recommendations for the OPS, and some guidelines for future studies.

# 2. Chapter 2: Literature review

## 2.1 Recent studies in similar fields

Due to the lack of research on police deployment, we reviewed ambulance models as they have many similarities to this research. For instance, both have multiple demand nodes, limited resources, and they must meet demand within a specified target window. They also have similar issues with variability in demand based on time and location as well as calls with varying levels of urgency.

One way to manage the deployment of police services is called Data-Driven Approaches to Crime and Traffic Safety (DDACTS). This was applied to help police departments allocate resources in a more efficient way in the city of College Station, TX, USA. An analysis of police dispatch times was done to compare police patrol routes with and without organized hotspots. The hotspots are those nodes with the maximum crimes. After analysing different types of crime using ArcGIS between January 2005 and September 2010 based on the data obtained from the College Station Police Department (Kuo, Lord et al. 2013), they found that the total dispatch time for two routes could be reduced by 36% and 44% respectively under favorable conditions (i.e., the largest effectiveness, and the widest effect area). Also, it could be reduced by 6% and 7% respectively for the same two routes under less favorable conditions (i.e., the lowest effectiveness and narrowest effect area).

According to Budge et al (Budge, Ingolfsson et al. 2009), calculating the dispatch probability (i.e., the probability of dispatching ambulances to the scene), is done using four items: location of station, number of vehicles per station, average workload, and average service time (call time and service time). Using data from the city of Edmonton, they compared the results of their procedure to the results of a discrete-event simulation model for 12 ambulance allocations to evaluate the accuracy of the estimation procedure and found that the overall coverage of the system is slightly overestimated (a difference of 6%). Moreover, some performance measures, such as average response times and frequency of inter-district responses, are easily calculated using the estimated dispatch probabilities. They also mentioned that, cost, probability of the served call station location, vehicle allocation, time (speed of response), and shift scheduling, can be considered as performance measurement tools.

In another paper written by Rajagopalan, et al, a multi-period set covering location model for dynamic redeployment of ambulances has been represented. As the demand for services fluctuates based on the week, the day and even the time of the day (Rajagopalan, Saydam et al. 2008), the demand pattern can be improved by dynamic relocation. Not only is responding to changes in the demand pattern a goal, but also meeting the coverage. But, the primary goal was meeting coverage by responding to changes in the demand pattern. They created a dynamic redeployment model to minimize response time by adjusting for predicted demand fluctuations. They used a tabu search heuristic to maximize the backup coverage and minimize the relocation costs in fuel and gas. They also designed a simulation model using busy probabilities with a server independency assumption. They assumed that units are independent and the probability of officers being busy is uncertain.

Revelle and Hogan (1989) formulated the Probabilistic Location Set Covering Problem (PLSCP) to minimize the number of required resources with a predetermined minimum coverage requirement. In reality, demand is not static and is based on the week, time of the day, and hour, but here they assumed that it is static and created two models with the first maximizing the coverage and the second minimizing the response time.

The probability that a particular vehicle might be busy at a given time was not considered in the early linear integer models that were static models. The Set Covering Location Problem (SCLP) provides the least number of officers needed to cover all demand points within a given response time when a call is received and until the officer arrives. SCLP considers all demand points equally, therefore as a solution, more servers may be required for those locations with high demand (Saydam and Aytuğ 2003).

To avoid such results, the Maximal Covering Location Problem (MCLP) was originally proposed by Church and ReVelle (1974). They developed this model to use demand and the number of available vehicles for relocation problems (Straub, Keil et al. 1997). The goal of their model was to maximize the population covered with limited resources. They extended the model to a multi objective model that seeks to minimize the number of facilities and maximize demand coverage by at least two vehicles. This is known as the Double Standard Model (DSM) that ensures that there is always a reserve vehicle in cases where multiple calls occur at once.

MCLP or the maximal covering location problem model that was formulated by Church and ReVelle in 1974 for the first time is one of the first covering models that evolved from the location set covering problem (LSCP). The difference here is that, the LSCP covered those demand nodes within a maximum distance of a minimal number of facilities, while the MCLP model deals with financial constraints that could limit the number of placed facilities. Many aspects of the original MCLP model have been changed through its development (Overholts Ii, Bell et al. 2009).

Drezner and Goldstein (2010) proposed a stochastic gradual coverage model by implementation of the Tabu Search (Gendreau, Laporte et al. 2001) to obtain near optimal solutions to establish its convergence properties. In their model the short and long distance standards are random variables. They also formulated the Cooperative Location Set Covering Problem (CLSCP) and the Cooperative Maximum Covering Location Problem (CMCLP) to replace the individual coverage assumption with a mechanism where all facilities contribute to the coverage of each demand point. These models were all deterministic static models.

One of the models that maximized backup coverage and minimized relocation costs was deployed by Gendreau et al (Gendreau, Laporte et al. 2001) and called the Dynamic Double Standard Model (DDSM) for redeployment. The objective was the formulation of a multi-period model for dynamic demand environments which minimizes the number of ambulances required while meeting predetermined ambulance availability requirements. They developed a tabu search heuristic to solve the model. Validation of the solutions was done by a comprehensive simulation model that provides computational statistics. They utilized "Jarvis' hypercube approximation algorithm" to compare the performance of several meta-heuristic implementations. They approached the problem from a multi-objective perspective and used the concept of Pareto domination to analyze the compromise among these conflicting objectives. They also developed trade-off curves and used an incremental search algorithm to solve the problem.

Approximate dynamic programming (ADP) has been applied successfully to resource allocation problems and is a very powerful approach for modeling and solving large-scale stochastic and dynamic optimization problems. Schmid (Schmid 2012) used ADP to solve the classic re-deployment optimization problem. Travel time, arrival time and response time were all considered and a stochastic dynamic model for the relocation and dispatching problems was solved by means of ADP. Having a more accurate model of reality needs time-dependent information variations with respect to changing request volumes and travel times, varying throughout the course of the day. Timeliness (response and waiting time) is considered as the primary objective to improve dispatching and relocation strategies. In order to achieve minimum average response time, it is not necessarily a good choice to always dispatch the closest vehicle available. Number of locations, call arrival rates, and the priority also should be included in dispatching strategies. The Double Standard Model (DSM) helps in having maximum expected multiple coverage locations by dispatching more than one vehicle. However, at the same time the cost and the probability of unavailability or being busy should be considered.

Bammi considered assigning geographical areas of the city of Chicago, Illinois to patrol units aiming to minimize the response time to calls for service (CFS). An optimization model was used to find the best locations for police cars using a predictive model of the police response time function to determine the expected response time (including waiting time and travel time) for each location. He considered all possibilities of moving cars to each node using a computer program to improve initial beat assignments and finally re-evaluated the new assignment to reach its optima. Since the number of calls vary between each shift, day, and week, a variable number of cars is needed for different shifts (Bammi 1975).

Othmar (Othmar 2003) in The Austrian Red Cross rescue organization considered a simulation model to analyze transport logistics with an emphasis on modeling the scheduling of ambulance service using ARENA simulation software. They compared the current structure of the organization with a potential alternative scenario to improve the ambulance service's efficacy. Having stations, intersections, 30 nodes and 1400 links provided a distance module of a network with different types of transporters. The authors also considered reducing waiting time for patients and decreasing required mileage between transports. After trying three different scenarios, they concluded that the previous routes were in a good position and their resource allocation was quite effective and natural.

Another version of the maximal covering location problem (MCLP) is called Dynamic MCLP (DMCLP) that has been used by F.Zarandi (Zarandi, Davari et al. 2013). They extended the traditional version of MCLP to the dynamic one and considered up to 2500 demand nodes and 200 potential facilities with errors less than 1% in their solution. The objective function was to maximize the covered demand. A set of demand nodes and a set of facility sites were defined as parameters of the model (Zarandi, Davari et al. 2013). They used a simulated annealing (SA) approach to solve the problem. In another study, they also presented another way to solve the same problem using a customized Genetic Algorithm (GA). (Fazel Zarandi, Davari et al. 2011),

Tables 1.1 and 1.2 summarize some related models in redeployment (Luce Brotcorne 2003):

Table 1. 1: Summary of deterministic static and dynamic models

| Reference | Model | Objective | Coverage constraints | Constraints on location sites | Ambulances |
|---|---|---|---|---|---|
| **ReVelle and coworkers (1971)** | LSCM | Minimize the number of ambulances | Cover each demand point at least once | At most one ambulance per site | One type. Number unlimited |
| **Church and ReVelle (1974)** | MCLP | Maximize the demand Covered | None | At most one ambulance per site | One type. Number given |
| **Schilling et al. (1979)** | TEAM | Maximize the demand covered | None | At most on ambulance of each type per site. Type A can only be located if B is located | Two types. Numbers given |
| **Schilling et al. (1979)** | FLEET | Maximize the demand covered | None | At most one ambulance per site. Only p sites can be used | Two type. Number given |
| **Daskin and Stern (1981)** | Modified MCLP | Maximize the demand covered, then the number of demand points covered more than once | Cover each demand point at least once | At most one ambulance per site | One type. Number given |
| **Hogan and ReVelle (1986)** | Modified MCLP (BACOP1 and BACOP2) | Maximize the demand covered twice, or a combination of the demand covered once or twice | Cover each demand point at least once | At most one ambulance per site | One type. Number given |
| **Gendreau et al. (1997)** | DSM | Maximize the demand covered at least twice within r1 | All demand covered within r2. Proportion a of all demand covered within r1 | Upper bound on the number of ambulances per site | One type. Number given |
| **Gendreau et al. (2001)** | DDSMt | Dynamically maximize the demand covered at least twice within r1, minus a redeployment penalty term | All demand covered within r2. Proportion a of all demand covered within r1 | Upper bound on the number of ambulances per site | One type. Number given |

L. Brotcorne et al. / European Journal of Operational Research 147 (2003) 451–463

Table 1. 2.Summary of probabilistic models

| Reference | Model | Objective | Coverage constraints | Constraints on location sites | Ambulances | Busy period |
|---|---|---|---|---|---|---|
| **Daskin (1983) MEXCLP** | Daskin (1983) MEXCLP | Maximize the expected demand covered | None None | None None | One type. Upper bound given (always reached). | Same for each ambulance. Given value |
| **ReVelle and** | Hogan (1989) | Maximize the total demand covered with a probability a | None | None | One type. Number given | Same for all potential location site |
| **ReVelle and Hogan (1989)** | MALP II | Maximize the total demand covered with a probability at least a | None | None | One type. Number given | Varies according to each demand point |
| **Batta et al. (1989)** | Adjusted MEXCLP (AMEXCLP) | Maximize the expected demand covered | None | None | One type. Number given | Varies according to each demand point. Ambulances not independent |
| **Goldberg et al. (1990b)** | Adjusted MEXCLP | Maximize the expected demand covered within 8 minutes | None | At most one ambulance per site | One type. Number given. Two types of calls | Same for each ambulance. Given value |
| **Ball and Lin (1993)** | Modified LSCM (Rel-P) | Minimize the sum of ambulance fixed costs | Proportion a of all demand covered within $r_1$ | At most $p_j$ ambulances at site j | One type. Number unlimited | Upper bound computed on busy period |
| **Repede and Bernardo (1994)** | Time dependent MEXCLP (TIMEXCLP) | Maximize the expected demand covered | None | None | One type. Number given. Varying speeds | Same for each ambulance. Given value |
| **Marianov and ReVelle (1994)** | QPLSCP | Maximize the total demand covered with a probability at least a | None | None | One type. Lower bound computed for each demand point | Varies according to demand points |
| **Mandell (1998)** | TTM | Maximize the expected total demand | None | Bounds on each type per site | Two types. Inclusive system. Numbers given | Computed using a queueing model |

In another study by Bammi, an optimization model to minimize average call response time, determination of the best assignment of beats to units was considered with two critical constraints including the available resources and priority of calls (Bammi 1975). The number of beats was fixed for each specific shift. The fixed number of shifts made the optimization model simpler to solve. Also, arrival rates followed a Poisson distribution, but the service time distribution was arbitrary.

The dynamic ambulance relocation model (DYNACO) was originally presented by Andersson and Värbrand (Andersson 2007) and was extended by Liu, in 2013. It was then deployed in Shanghai, China. The model considered the demand, travel time, and vehicle availability in order to present an optimal redeployment of emergency vehicles. A genetic algorithm and a Monte-Carlo simulation were developed to solve the stochastic version (Liu, Yuan et al. 2013).

The main goal of this study is to provide the OPS with a means of analysing the performance of any proposed allocation policy in order to improve the performance of the police services in Ottawa. The simulation has been done using ARENA and the model has been validated using historical data from the last five years. This simulation process helps us to find the potential limitations of any allocation policy and to determine how to overcome them before implementation. After the validation process, we look to determine alternate allocation patterns that improve the quality of police services in terms of the response time to crime throughout the region.

In order to improve the existing zone-based approach of police resource deployment this research aims to develop a new demand-based simulation model that predicts the call response time for a given allocation policy subject to constraints on the number of police cruisers and officers. Hence the main objective of the study is to develop and validate a model that allocates police resources based on predicted demand and that provides statistically valid performance measures for coverage and response time. In order to meet this objective this study also aims to achieve the following sub-research goals:

1) Classifying crime types based on the resources required and the response time threshold;
2) Defining demand based on the crime type.

# 3. Chapter 3: Research Methodology & Model Description

This chapter provides an introduction to the concept of discrete-event simulation modelling and also describes the development process for the model generated in this thesis. The model is based on the characteristics of the current system at the Ottawa Police Services (OPS). The simulation software used in this research is ARENA version 14.5 with professional license.

## 3.2 Introduction to ARENA

ARENA is a user-friendly and Windows-based interface simulation and automation software developed by Rockwell Automation Company that provides an environment to translate the actions of users into SIMAN code. The output of the simulation is an estimation of the true system behavior that takes into account the stochastic nature of the system through random-number generators. Determination of a sample of system performance metrics requires multiple runs and a confidence interval is used to describe the output results. A 95% confidence interval is calculated automatically but users may change it to any confidence level. Arena calculates the confidence interval using the following variables and equations: (Devore 1999):

$n$ = the number of samples
$\bar{X}(n)$ = the sample mean
$S^2(n)$ = the variance of the sample
$t_{n-1,1-\frac{\alpha}{2}}$ = the critical value from a t distribution with n-1 degrees of freedom

$$\bar{X}(n) = \frac{1}{n}\sum_{i=1}^{n} X_i$$

$$S^2(n) = \frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \bar{X}(n)\right)^2$$

Then the 100(1-α)% confidence interval is:

$$\bar{X}(n) \pm t_{n-1,1-\frac{\alpha}{2}}\sqrt{\frac{S^2(n)}{n}}$$

Arena, using the SIMAN processor and its simulation language, is widely used to simulate a manufacturing or service process in order to analyse current performance as well as the performance of possible alternative configurations. By simulating a process model, we can adjust the resource allocation and then observe system behaviour.

Simulation is a useful tool for analysing and modeling a complex system. In reality, for some systems it would be very difficult or even impossible to provide sufficient detail using analytical models due to the size and/or complexity of the system. Conversely, simulation can manage such situations by running a model that generates system histories based on statistical information. The reason that simulation works for these kinds of situations while analytical models do not is that simulation provides practical computable solutions. The role of simulation is thus to help users to determine how well a system may work under various scenarios. Simulation can also be used in combination with optimization to discover the optimal value of the controllable parameters. In other words, it has a critical role as a decision-support tool in many industries. All in all, the reason we used simulation over analytical models, was its ability to provide results while incorporating significantly higher levels of realism.

## 3.3 Discrete Event Simulation Modeling

This section provides a description of discrete-event modelling as applied to the OPS department.

### 3.3.1 System Components

A system in a discrete-event simulation model is shown as a sequence of events where each of them occurs at an instant in time and changes the state of the rest of the system (Robinson 2004). The basic terminology related to this kind of modelling are summarized below:

1. An entity is an object of interest in the system. The entities in this thesis include crimes and police cars.
2. An activity represents a time period of a specified length during which an entity acts or is acted upon. The activity in this simulation model includes the time to service a crime.
3. The state of a system is the collection of variables used in the system description at any time in terms of the objectives. In this study, examples include the number of crimes waiting in queue or being served and the police utilization.
4. An event is a potentially random occurrence that can change the state of the system. Endogenous events are those that happen within the system and describe activities; whereas, exogenous events are activities and events in the surroundings that affect the system. In this simulation model, the arrival of a call is an exogenous event, the arrival time of the next call, and the completion of a service to a crime is an endogenous event.
5. An attribute is a property of an entity. These data values determine the route the crime takes through the system. Refer to Table 3.1 for a list of attributes used in this simulation model.

This study has a process-oriented approach to simulation modeling with involved individual entities and describes the experience of a typical entity as it flows through the system.

Table 3. 1: List of attributes used in the simulation model

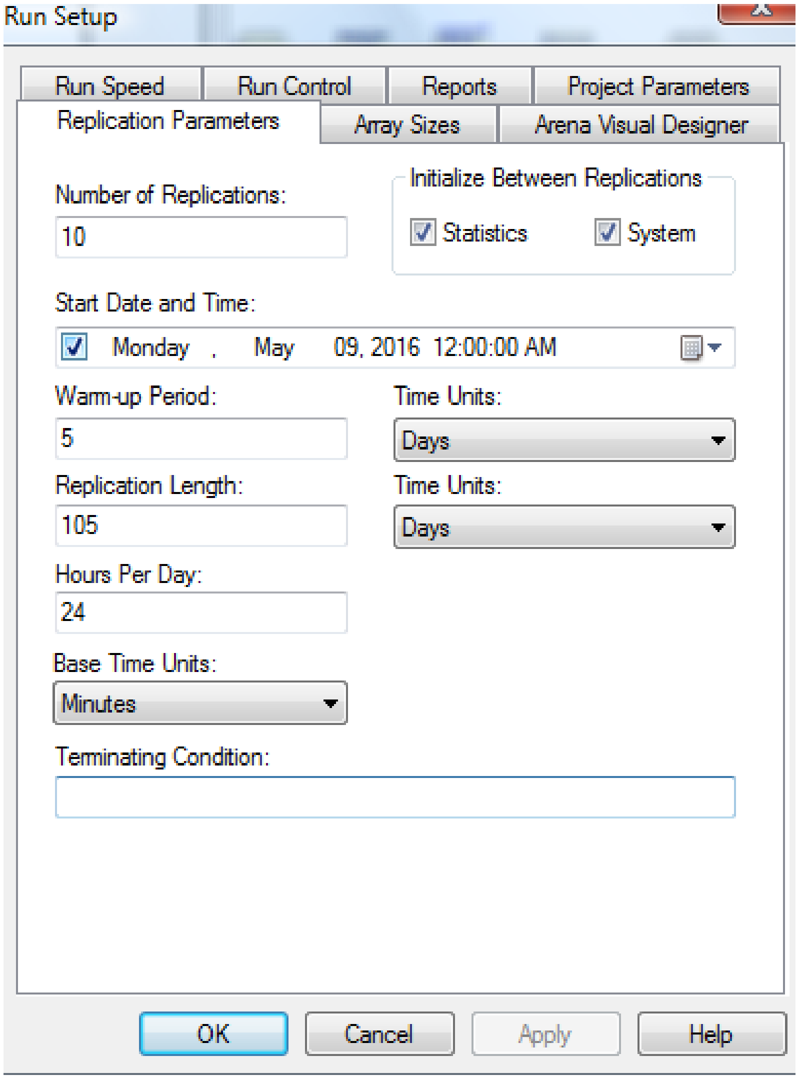
| **Attributes** | **Description** |
|---|---|
| Location | The location of each crime |
| Call Priority | The priority of each crime from 1 to 7 based on the classification of the OPS system |
| Service Time | The time for each crime to received service from a police unit |
| Crime Number | Assigned to each crime to count it and also to match the police units to each crime in the service logic. |
| Received to Dispatch Time | The time required to dispatch officers to the scene after a call is received |
| Police Location | The location of each police unit |
| Police Travel Time | The time between when an officer is dispatched to when the officer is on scene |
| Call Type | Categorized based on the average service time required and they grouped from A to E (A for those with average of service time less than 50 min, B for 51-100, C for 101-150, D for 151-200, and E for those with greater than 200 minutes service time) |
| Dispatch Group | Grouped number of dispatches from 1 to 6 (1 for those crime that need only 1 officer unit, 2 for 2, etc. Only the 6th one is for all number of dispatches that are more than 6) |
| Dispatch Quantity | The number of officer units to send to each crime |
| Crime Occurrence Time | The time that each crime happens |

## 3.4 Baseline parameters

The baseline parameters can be determined as the input parameters of the simulation model and also as a guideline for future studies and researchers by providing the standard needed for reproducing the model.

### 3.4.1 Replication Parameters

A replication of the simulation is a simulated run of the system for a specified length of time. Replication parameters control a number of aspects about the run(s) including the number of replications, replication length, replication start day, time units and warm up period and can be changed under the Run Setup in the ARENA toolbar. With longer replication lengths, more performance will be found to measure within a desirable confidence interval. In this study, the number of replications is set to 10 to make sure that the percentage of error is kept reasonably low and the model runs for 6 months (180 days) each time. Figure 3.1 shows the replication parameters in ARENA.



Number of Replications: 10

Initialize Between Replications: ☑ Statistics ☑ System

Start Date and Time: ☑ Monday , May 09, 2016 12:00:00 AM

Warm-up Period: 5

Time Units: Days

Replication Length: 105

Time Units: Days

Hours Per Day: 24

Base Time Units: Minutes

Terminating Condition:

Figure 3. 1: Run setup box in ARENA showing the replication parameters

## 3.5 Uncontrollable Parameters (UP)

Uncontrollable parameters are those values in the model that are fixed and uncontrollable in the OPS current state. The uncontrollable parameters, in most cases, are based on the historical data so as to match reality, such as types of calls responded, service time needed for each crime, and the arrival rate of calls.

## 3.6 Controllable Parameters (CP)

Controllable parameters are those values that are controllable by the OPS. These include the number of officer units, the number of police cars, and the shift schedules.

## 3.7 Modified Parameters

The effects of changing parameters from the baseline values and their impacts on the model, while keeping all other baseline parameters consistent, is a critical way of understanding any relationship between the key parameters and waiting time.

A general flow of calls within the model can be seen in the figure below.

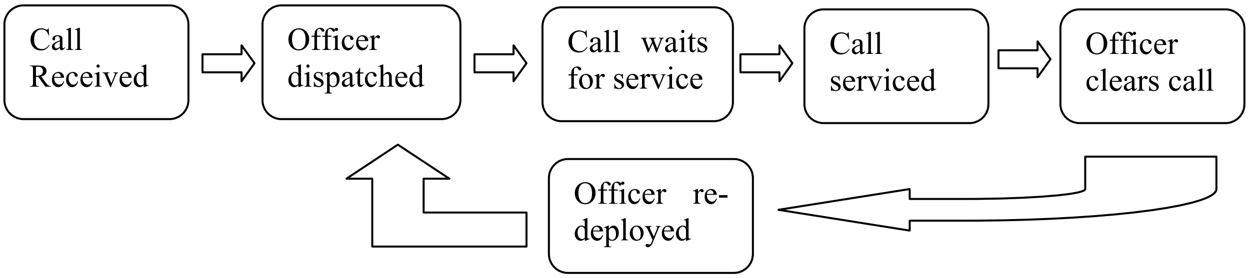


Figure 3. 2: Basic flow of call arrival in the model

## 3.8 Data

The methodology presented in this research has been developed in conjunction with the Ottawa Police Services, Ontario, Canada. This study used data obtained from the OPS that was collected between January 2010 and December 2014. It includes crime reports with the date they occurred, the type of call, the priority, the number of officer units dispatched, and the recorded times after a call was received up until an officer clears the scene. The information provided to us that we used includes the following:

- Call number: This Call Occurrence number uniquely identifies a call. The format is YY+Call Number (for example 13000000012, 12 is the call number).
- Initial call type number: Numeric Code associated to Initial case type description.
- Initial call type description: Plain text description of how a call is initially entered in CAD.
- Final call type description: Plain text description of how a call is closed on CAD (Final Call Type)
- Priority: Numeric ranking of call priority from 1 to 7 (1 being highest priority) Priority is determined based on information provided by the caller and is associated to the Initial Call Type.
- Call location: X, Y coordinates of where an event takes place and the address of the crime.
- Place name: name of the place where the event occurs: (typically corporate entities or public places such as hospital, school , parks, parking lot etc)
- Occurrence date: Date when event occurred.
- Occurrence time: Time the event occurred.
- Reported date: Date an event is reported.
- Reported time: Time at which an offence or event is reported (In the case of calls Occurred date and Reported Date are mostly the same)
- Occurrence creation: Time at which the call is logged in the CAD system.
- Unit ID: unit assigned to the call.
- Unit Type (PT – Patrol): Unit type that is assigned to the call. This data includes only unit type classified as PT.

- Officer dispatched: The time at which a unit is dispatched to a call.
- Officer en-route: The time at which unit is en route to a call.
- Officer on-scene: The time at which unit arrives on offence scene.
- Occurrence closure date for officer/Officer clear time: Time at which an officer dispatched to a call clears the scene.
- Occurrence closure time: The time at which a call is closed.
- Ottawa Police Service Geography Districts: There are 6 districts in the city including: Rural West (11), West (12), Central West (23), Central East (24), East (35), and Rural East (36).

## 3.9 Arena Simulation Model

The simulation model in this study creates demand according to distributions calculated from the historical data. By a location, we mean a node of the city with a specific latitude and longitude from which a call may originate. We selected locations based on the historical data and grouped them using their latitudes and longitudes. Since latitudes and longitudes varied from 45.2 to 45.52, and from -75.96 to -75.44 respectively, we created 17 groups for latitudes and 27 groups for longitudes with interval widths of 0.02. In binning these data, we looked at the frequency of these latitudes and longitudes and determined that 0.02 provided a reasonable level of granularity. The main reason that we did this classification was that it was impossible and unnecessary to consider millions of nodes together. Thus we chose this size of grid to best balance accuracy with complexity. After determining the cumulative demand at each location, we eliminated those nodes with no crimes as they were located in the river based on the map. Finally 313 locations have been selected and the frequency of crimes at each location and for each hour of the day and day of the week was tabulated via a pivot table in excel. When a call is received and enters the system, and before the dispatching of police cars, some parameters of the call are first generated including the priority of the call, the type of call, the required police dispatch quantity, and the travel time between each available car and the generated demand. Each of these parameters is dependent on the hour of the day and day of the week. All these steps have been explained in detail with numeric data in the following chapter. Police are then dispatched based on shortest travel time.

When a police car reaches a location along the network, ARENA assigns a service time (based on the historical distribution) for that type of crime. Some of the data used to drive the simulation, such as call type and priority, are generated from a distribution embedded in ARENA while others are read in from arrays contained in an excel file. If no service is requested, the queue of police cars waiting for deployment is held for a potential crime to occur.

For those calls with higher priority, an admissible police car is assigned first. A police car is considered admissible for servicing a crime if it is not assigned to another crime.

Variation in demand based on time of day and day of week is determined based on data provided by the OPS. Calculating the probability of demand occurring based on the historical data, we can predict the number of potential calls for each shift, each location, and each type of event knowing that both service times and calls-for-service rates are influenced by the time of day and day of week. This model represents the allocation of police officers to specific crimes at different times of the day/week. The actions are constrained by the number of available officer police units in each shift. In the following chapter, all parts of this model have been clarified separately.

# 4. Chapter 4: Analysis, Results and Comparison

This chapter contains the explanation of the model step by step with the corresponding numbers, results, verification and validation procedures used to authenticate the model which are further described in the following sections.

## 4.1 Call Arrival

The number of call types in the OPS system is significant (364 initial call types). Modeling that many is time consuming and unnecessary as the only relevant features for our objective are priority and service time. Thus, we grouped all call types into five groups based on expected service times (each group is then further divided by priority). Group “A” refers to those call types with an average service time less than 50 minutes while groups B, C, D, and E refer to those with expected service times between 50 to 99, 100 to 149, 150 to 199, and more than 200 minutes respectively. All types of calls were created with separate create modules with an arrival rate based on a schedule which is specified for each call type and each hour of the day/week as determined from the historical data.

Table 4. 1: Call type groups based on the average of service time

| Call Type | Rule | For Formula |
|---|---|---|
| A | Avg. Service Time <= 50 | 0 |
| B | 50 < Avg. Service Time <= 100 | 50 |
| C | 100 < Avg. Service Time <= 150 | 100 |
| D | 150 < Avg. Service Time <= 200 | 150 |
| E | Avg. Service Time > 200 | 200 |

For each generated demand, historical distributions are also used to determine the priority of the call and the dispatch quantity (number of police units required for service).

## 4.2 Crime Creation Logic

The random arrival of calls is generated through applying a specific distribution from the table below that varies depending on the day of the week and the hour of the day. This table has 24 hours representing hours of a day, and 7 columns showing days of the week. At first, we looked at each day of the week separately, but as there was not much difference between the weekdays and similarly for the weekends, we lumped these together in two groups that represented weekdays and weekends. In our ARENA model, days 1 & 7 are weekends and days 2 through 6 represent weekdays. These distributions came from analysing the arrival time of each call in the historical data from 2014, for all days of week and all hours of day. As an example, figure 4.1 shows how demand changes over the hours of a typical weekday. Table 4.2 provides the distributions that were used to govern inter-arrival times between calls for each hour of the day and for weekdays versus weekends.

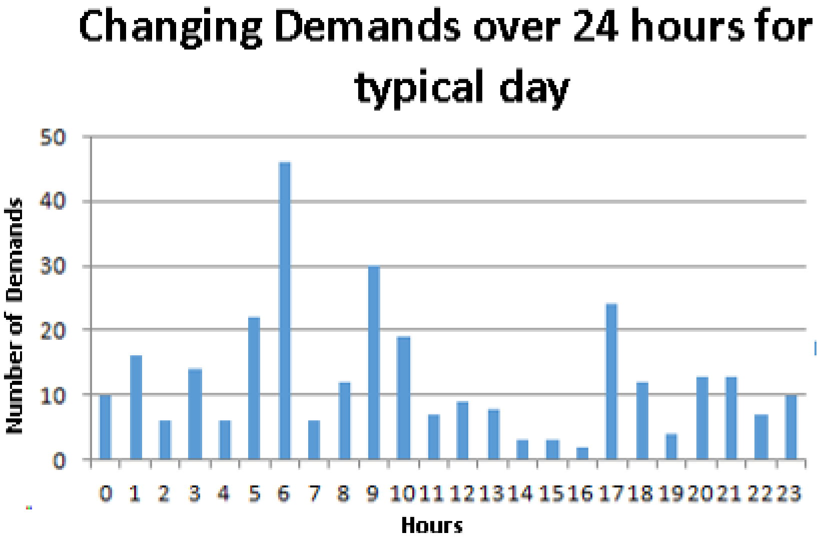


Figure 4. 1: Changing demand over 24 hours of a typical day

Table 4. 2: Distributions of Inter Arrival Times (IAT) for 24 hours in weekdays and weekends

| Day Hour | Weekdays | Weekends |
|---|---|---|
| 0 | -0.5 + LOGN(6.61, 8.81) | -0.5 + LOGN(4.06, 4.48) |
| 1 | -0.5 + LOGN(7.43, 10.3) | -0.5 + GAMM(2.8, 1.5) |
| 2 | -0.5 + LOGN(8.17, 11.1) | -0.5 + LOGN(4.32, 5.05) |
| 3 | -0.5 + LOGN(9.64, 13.9) | -0.5 + LOGN(5.24, 6.4) |
| 4 | -0.5 + GAMM(9.7, 1.25) | -0.5 + LOGN(6.76, 8.15) |
| 5 | -0.5 + GAMM(11.9, 1.18) | -0.5 + GAMM(7.8, 1.25) |
| 6 | -0.5 + LOGN(13.3, 19.4) | -0.5 + GAMM(10.3, 1.13) |
| 7 | -0.5 + LOGN(8.31, 11.7) | -0.5 + LOGN(11.3, 17.7) |
| 8 | -0.5 + LOGN(5.92, 7.43) | -0.5 + GAMM(6.72, 1.19) |
| 9 | -0.5 + LOGN(4.98, 5.96) | -0.5 + LOGN(6.86, 9.24) |
| 10 | -0.5 + LOGN(4.84, 5.68) | -0.5 + GAMM(3.57, 1.43) |
| 11 | -0.5 + LOGN(4.5, 5.34) | -0.5 + LOGN(5.1, 6.29) |
| 12 | -0.5 + LOGN(4.33, 5.01) | -0.5 + LOGN(4.77, 5.86) |
| 13 | -0.5 + LOGN(4.39, 5.01) | -0.5 + LOGN(4.52, 5.34) |
| 14 | -0.5 + LOGN(3.93, 4.54) | -0.5 + GAMM(2.77, 1.47) |
| 15 | -0.5 + LOGN(3.72, 4.15) | -0.5 + GAMM(2.99, 1.41) |
| 16 | -0.5 + LOGN(3.67, 4.11) | -0.5 + LOGN(4.29, 5.02) |
| 17 | -0.5 + LOGN(3.72, 4.07) | -0.5 + LOGN(4.29, 4.98) |
| 18 | -0.5 + LOGN(3.87, 4.35) | -0.5 + LOGN(4.2, 4.83) |
| 19 | -0.5 + LOGN(4.11, 4.66) | -0.5 + LOGN(4.36, 5.11) |
| 20 | -0.5 + LOGN(4.2, 4.83) | -0.5 + LOGN(4.56, 5.58) |
| 21 | -0.5 + LOGN(4.23, 5) | -0.5 + LOGN(4.1, 4.57) |
| 22 | -0.5 + LOGN(4.41, 5.13) | -0.5 + LOGN(4.38, 5.23) |
| 23 | -0.5 + LOGN(4.91, 5.95) | -0.5 + LOGN(4.56, 5.36) |

The next step in the crime creation logic is to consider the location of each crime. Given the historical origin of crime in Ottawa, and as explained above, we categorized those potential crime locations into 17 latitudes and 27 longitudes and created two matrices (one for weekends and one for weekdays) to determine the probability of a crime's location based on hours of the day for each of the 313 locations mentioned earlier. Then, using the frequency, we found the probability of each crime occurrence in each of these locations separately for weekdays and weekends. The crime arrival process is shown in figure 4.2.

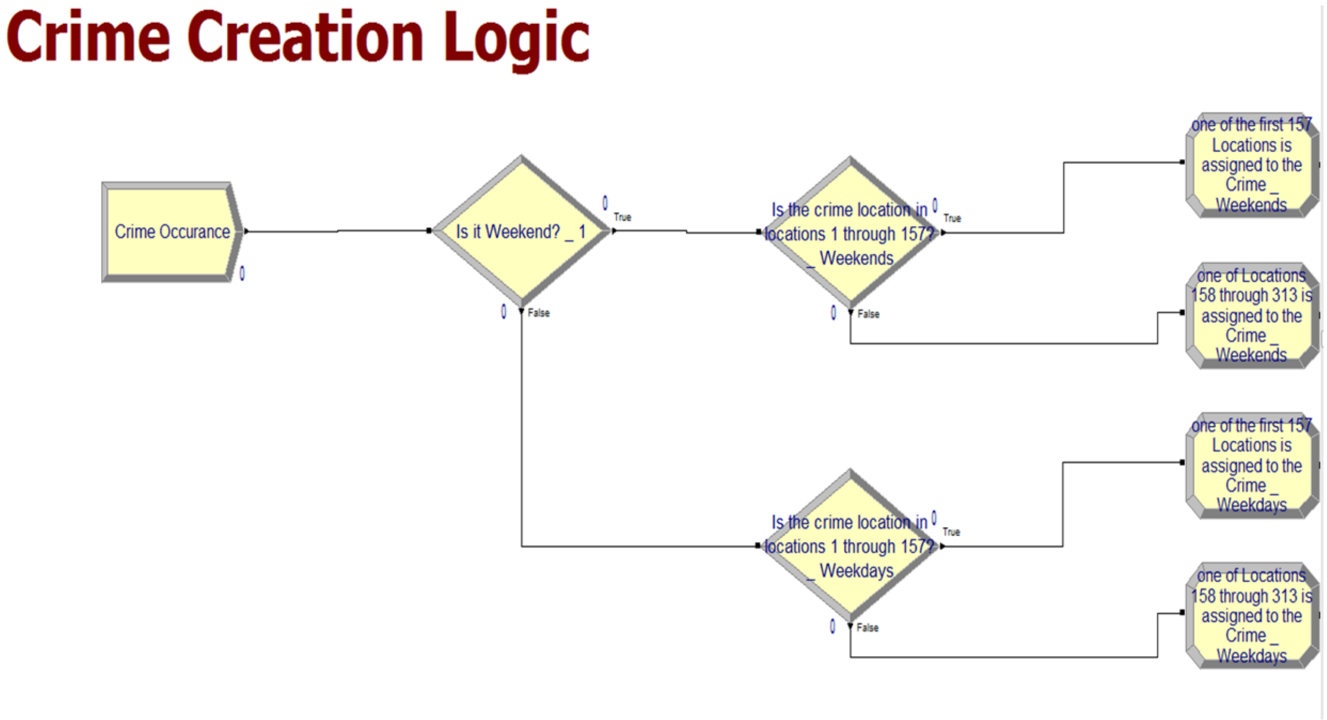


Figure 4. 2: Arrival process of Crime in ARENA

## 4.3 Crime Assignment Logic

Every crime entering the system is assigned a number of attributes to help identify characteristics of that crime. The assign modules are used to assign the attribute values immediately following the crime creation logic. The attributes assigned consist of Call Type, Dispatch group, and Priority.

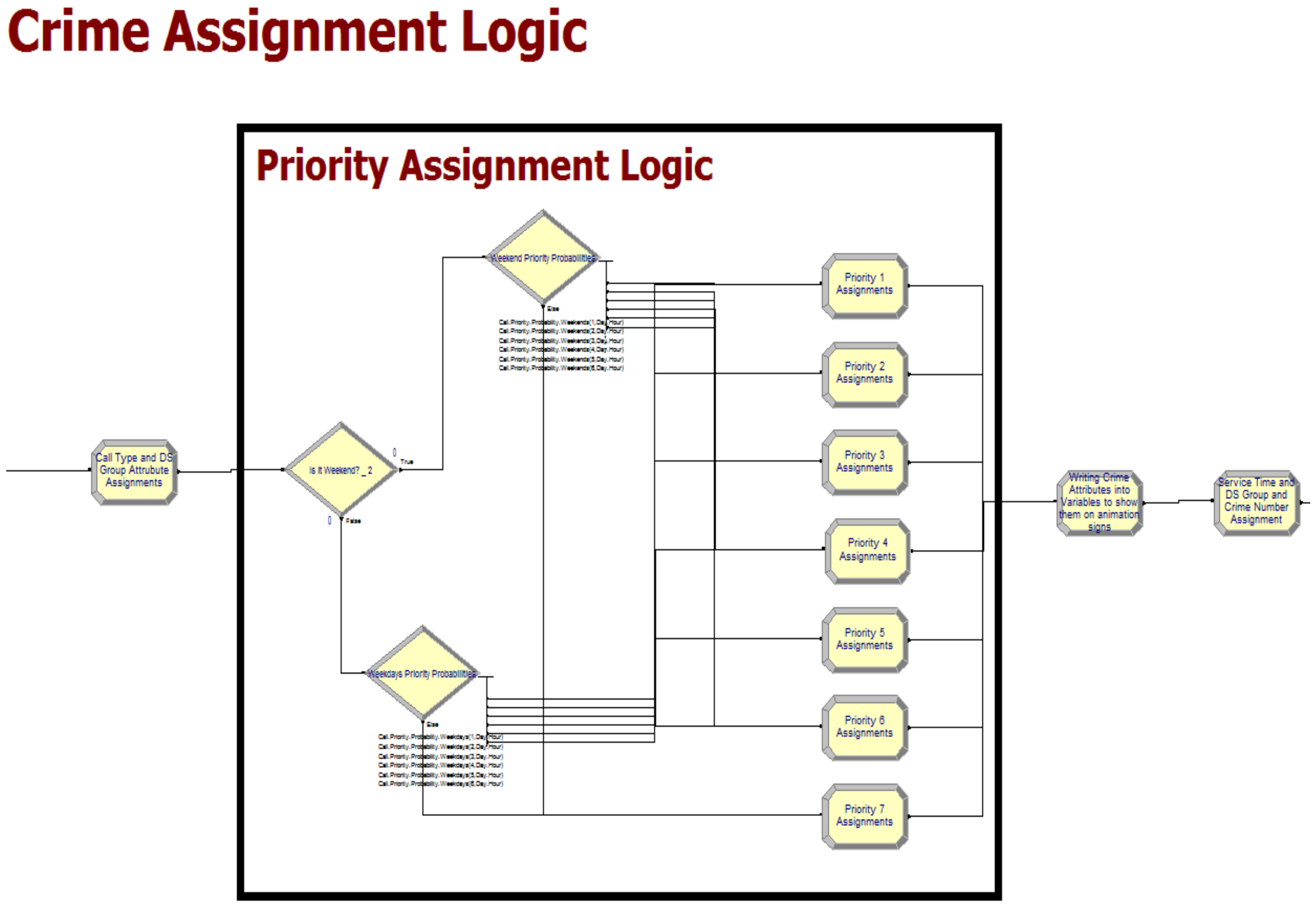
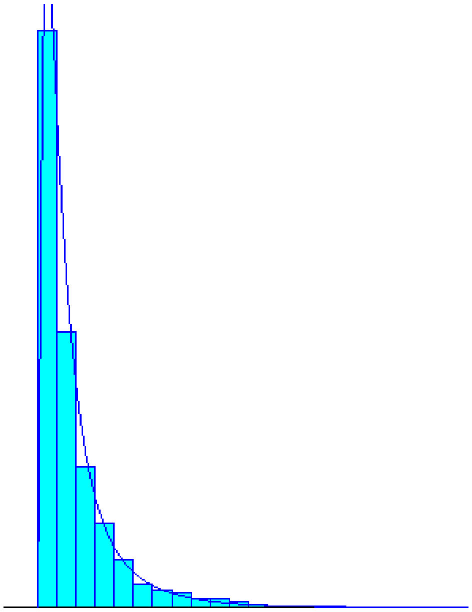


Figure 4. 3: Crime assignment logic in ARENA

Dispatch quantities are categorized in 6 groups. Those crimes with only 1 officer unit dispatched are in the first group, 2 officer unites dispatched are in the second and so on up to group 5 with officer unites dispatched. Crimes with 6 or more officer units dispatched are combined in the 6th group. The dispatches of group 6 follow a Lognormal distribution 5.5 + LOGN(1.97, 2.48) with mean of 7.47, and standard deviation of 2.48 for weekdays, and a Weibull distribution 5.5 + WEIB(2.1, 0.823) with mean of 7.6 and standard deviation of 0.823 for weekends.



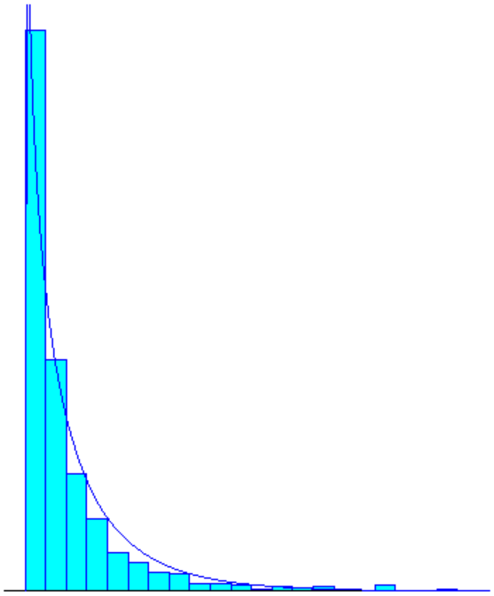


Figure 4. 4: Distribution of Dispatched for Group 6 in Weekdays-LogNormal

Figure 4. 5: Distribution of Dispatches forGroup 6 in Weekends- Weibull

By counting the number of calls for each dispatch group and finding their frequencies, cumulative probabilities have been calculated for both weekdays and weekends as figure 4.6 shows below:

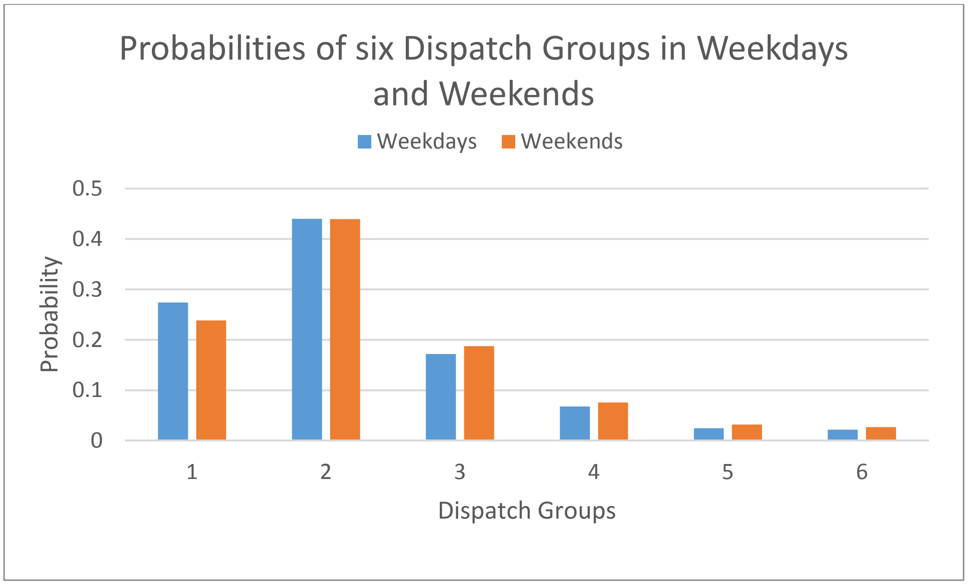


Figure 4. 6: Probabilities of six Dispatch Groups in Weekdays and Weekends

Call Type probability is summarized in Figure 4.7. As mentioned earlier, we categorized all types of calls into 5 groups labelled A to E based on average service times and then calculated the frequency of each for both weekdays and weekends.

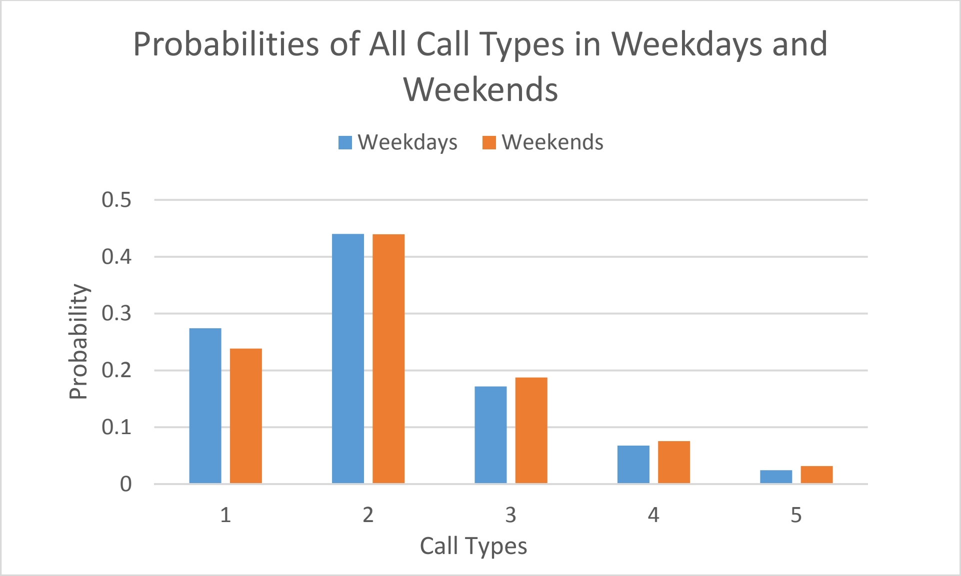


Figure 4. 7: Probabilities of All Call Types in Weekdays and Weekends

## 4.4 Priority Assignment Logic

The OPS uses a scale of 1 through 7 to assess the priority of a call with 1 being the most urgent. The probability of each priority in each hour of a day is shown in the following figures for weekdays and weekends separately. It can be seen that hour of the day has a significant impact and that the vast majority of calls fall in the 2 through 4 range.

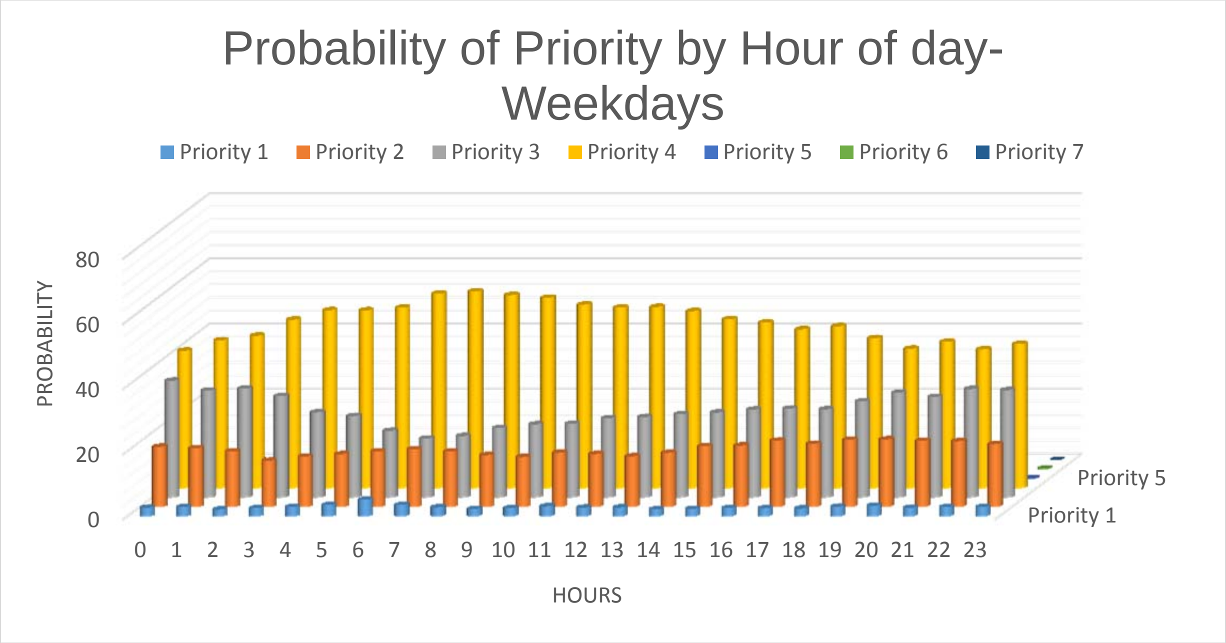


Figure 4. 8: Probability of Priority by Hour of day- Weekdays

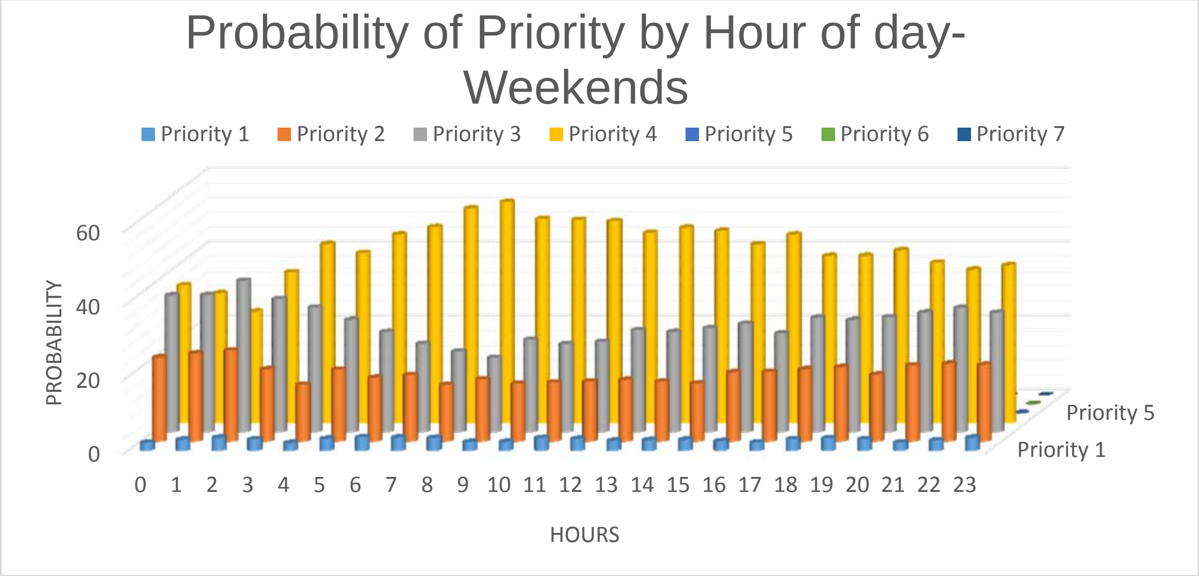


Figure 4. 9: Probability of Priority by Hour of day- Weekends

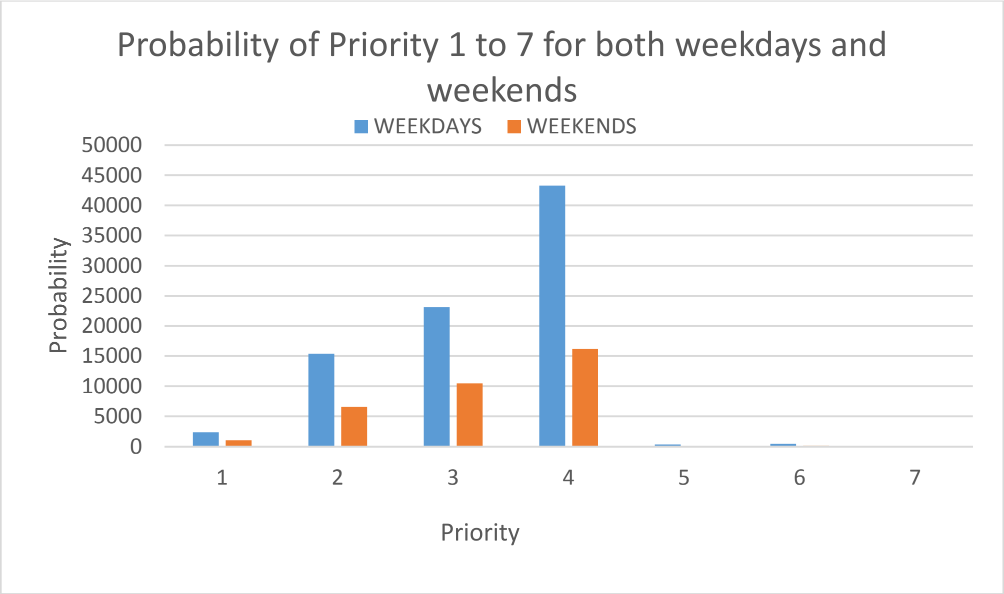


Figure 4. 10: Probability of Priority 1 to 7 for both weekdays and weekends

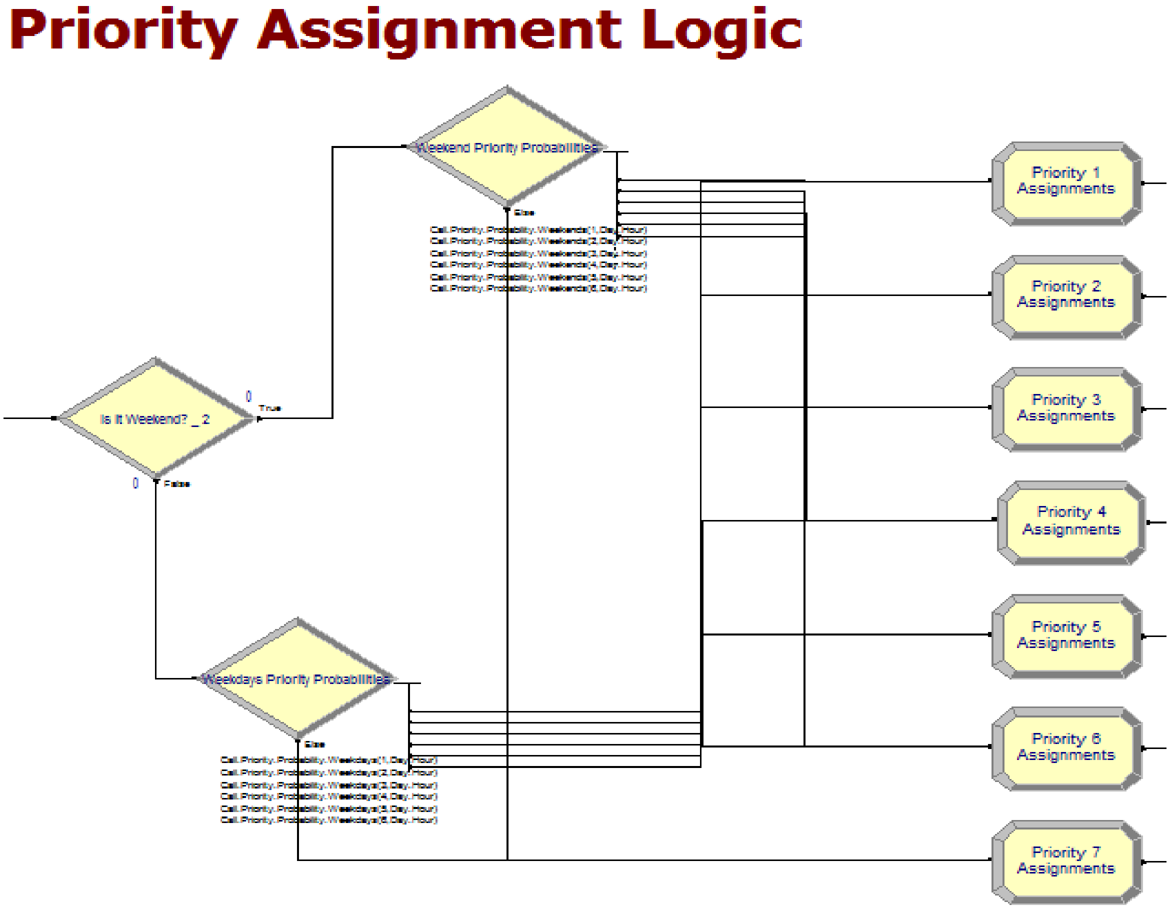


Figure 4. 11: Priority Assignment Logic

After assigning all of these attributes to each crime, service time needs to be assigned. In order to do this process, we calculated the distributions of service time for each type of call based on the historical data. Table 4.3 shows a summary of all the distributions of service time for each call type group from A to E. Each call is now fully described so we move on to the crime processing logic.

Table 4. 3: Distributions of Service Times for each Types of Call

| Call Type | Distributions |
|---|---|
| A | -0.001 + LOGN(38.1, 91.5) |
| B | -0.001 + LOGN(93.2, 240) |
| C | -0.001 + GAMM(113, 1.09) |
| D | -0.001 + WEIB(191, 1.34) |
| E | 2 + GAMM(277, 0.86) |

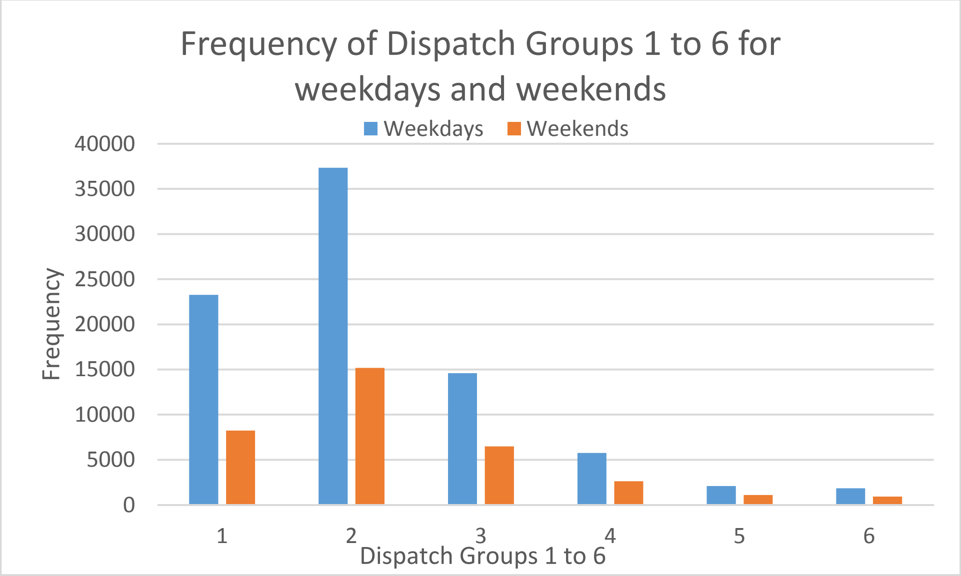


Figure 4. 12: Frequency of Dispatch Groups 1 to 6 for weekdays and weekends

## 4.5 Crime Processing Logic

The first module in the crime processing logic section is a decision module that considers if there is an in-process crime in the model. Once the crime occurrence time is determined and if the number of available officer units is sufficient, the model sends a signal to the closest police entities to dispatch. Another important logic here is the calculation of the travel time (described in detail later) to the crime to see which of those available police cars are closer to the crime in progress. In sum, the model sends a signal to dispatch officer units to each crime after determining which are closest.

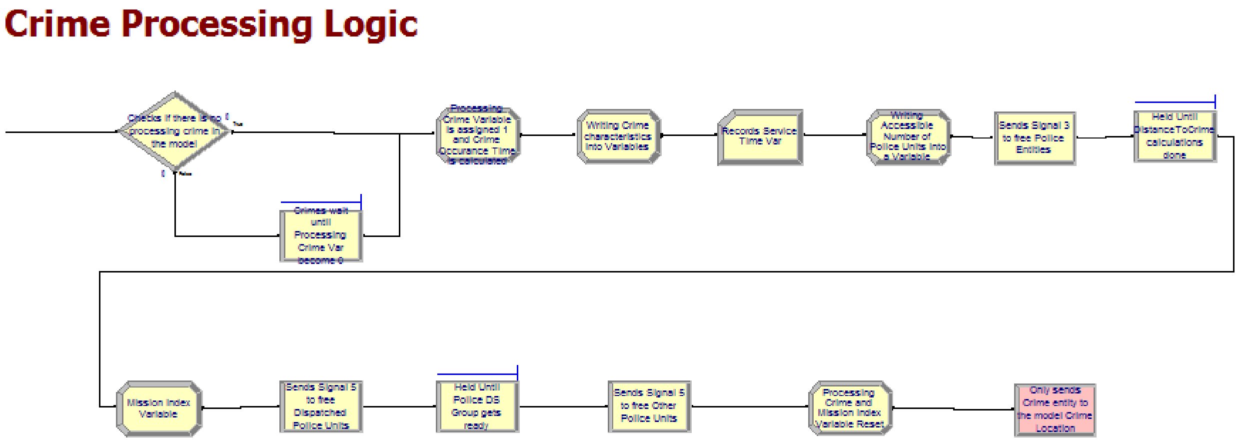


Figure 4. 13: Crime Processing Logic

## 4.6 Police Quantity and timeslot Controller Logic

This logic contains two parts namely “Initialization” and a controller loop for time slot and police quantity. Police quantity in each hour of the day and each day of the week are different. The OPS has the following staffing shifts as below::

Days from 06:45 to 17:30hrs

Afternoons from 11:00 to 21:45hrs, or 16:45 to 03:30hrs,

Nights from 20:45 to 07:30hrs (Meal Break of a duration of 45 minutes)

Fixed Days: 06:45 to 17:30hrs (Meal Break of a duration of 45 minutes)

Fixed Afternoons: 11:00 to 21:45hrs (Meal Break of a duration of 45 minutes)

Based on this schedule, we created 7 time slots to avoid any overlap between the hours of these shifts and to remove any duplication in the number of available officers in each shift. Table 4.4 shows these categorized time slots.

Table 4. 4: Seven Time Slots (Shift Schedule)

| Time Slot No | Time Slots | hour | Duration |
|---|---|---|---|
| 1 | 3:30 -6:45 | 3.5 - 6.75 | 3.25 |
| 2 | 6:45 - 7:30 | 6.75 - 7.5 | 0.75 |
| 3 | 7:30 - 11:00 | 7.5 - 11 | 3.5 |
| 4 | 11:00 - 16:45 | 11 - 16.75 | 5.75 |
| 5 | 16:45 - 17:30 | 16.75 - 17.30 | 0.55 |
| 6 | 17:30 - 20:45 | 17.5 - 20.75 | 3.25 |
| 7 | 20:45 - 3:30 | 20.75 - 3.5 | 6.75 |

To create police units in the model, we need to know how many police officers are available in each shift. Using the historical data, we found how many police officers are available in each time slot of each single day of a year and created the table below showing the summary of results including minimum, maximum, and average number of available officers in each time slot for weekdays and weekends separately. The number of available officers was determined by counting the number of different police unit IDs that serviced a call in a given hour.

Given that the only way to estimate the available officer units in each time slot was using the historical data, in order to reduce the risk of errors in the results, the average number of police officers in each timeslot for weekdays and weekends has been used to determine the number of available officer units. This assumptions ensures that we do not utilize more officers over the course of a year than were present in the data set.

Table 4.5 shows the minimum, maximum, and average of number of officer units in each time slot for weekdays and weekends.

Table 4. 5: Number of officer units in each time slot for weekdays and weekends (Max-Min-Average)

| Summary | Index | Time Slot 1 | Time Slot 2 | Time Slot 3 | Time Slot 4 | Time Slot 5 | Time Slot 6 | Time Slot 7 |
|---|---|---|---|---|---|---|---|---|
| Total | Max | 67 | 64 | 88 | 105 | 48 | 79 | 96 |
| | Min | 11 | 0 | 24 | 54 | 5 | 34 | 50 |
| | **Average** | **31** | **11** | **41** | **78** | **22** | **55** | **71** |
| Weekdays | Max | 67 | 64 | 88 | 105 | 48 | 79 | 94 |
| | Min | 11 | 0 | 28 | 54 | 6 | 35 | 50 |
| | **Average** | **28** | **11** | **42** | **79** | **23** | **56** | **70** |
| Weekends | Max | 64 | 31 | 49 | 94 | 40 | 69 | 96 |
| | Min | 18 | 0 | 24 | 56 | 5 | 34 | 52 |
| | **Average** | **38** | **10** | **38** | **74** | **21** | **52** | **74** |

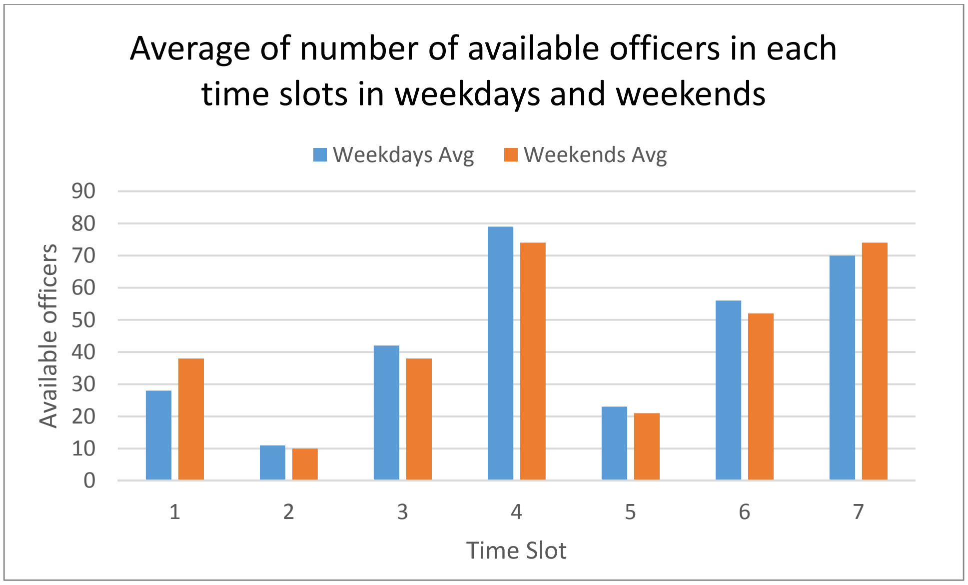


Figure 4. 14: Average of number of available officers in each time slots in weekdays and weekends

Obviously, the available officers for time slots 4 and 7 are more than in others as they have longer duration. ARENA reads the average of police quantity from table 4.5 and then generates the appropriate number of officers for that time slot.

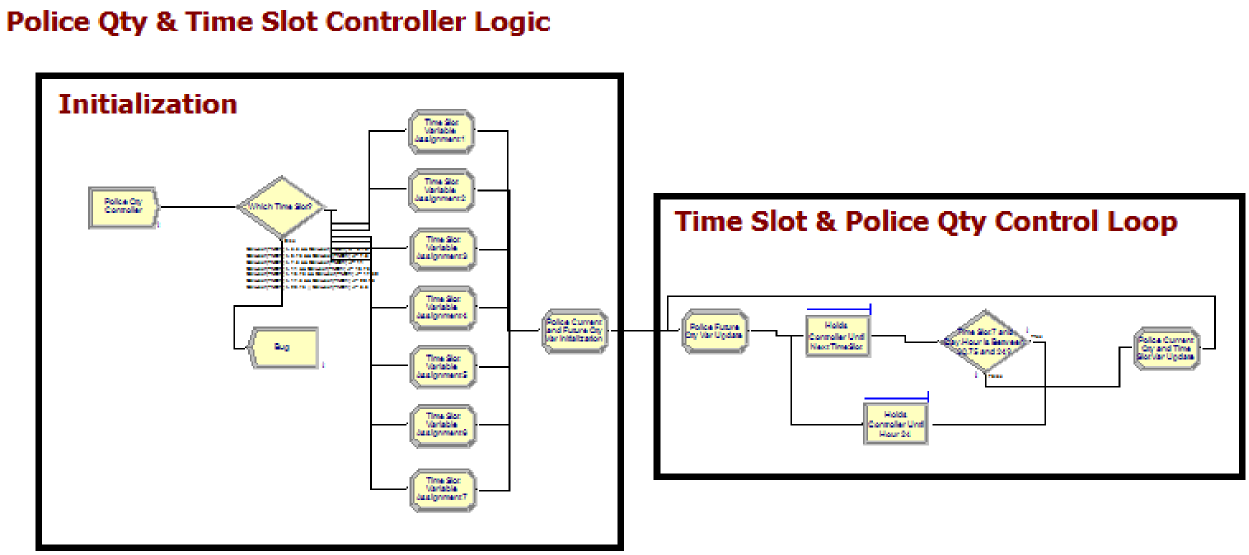


Figure 4. 15: Police Quantity and Time Slot Controller Logic

## 4.7 Police Creation and Distance Calculation Logic

After a crime takes place and the required number of police is determined, the model needs to consider travel time between a crime and the available police units. The method used to calculate that is explained below.

### 4.7.1 Calculation of Distance and Travel times between nodes using ARCGIS

For this purpose, we used ARCGIS and Network Analysis software to find the real geographical travel time based on roads maps of Ottawa and made a matrix with 313 rows and columns, with those categorized latitudes and longitudes mentioned in the crime creation logic section. Figure 4.16 shows the location of each point on a map of Ottawa. The ARCGIS then calculates the real travel times between all 313 points and we used this matrix as an input in the model to let ARENA select the minimum travel time from this table and send the available police officers from the closest location.

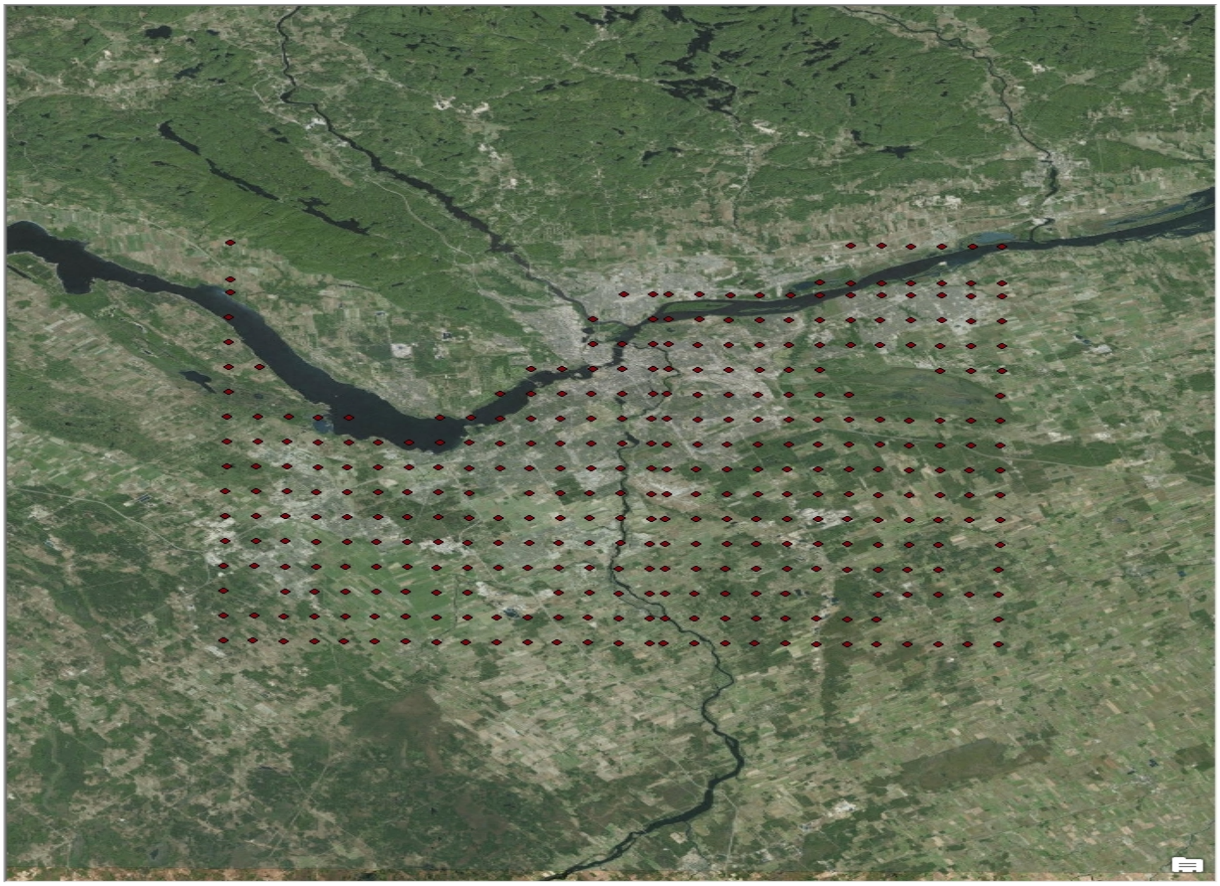


Figure 4. 16: 313 selected locations on the map of Ottawa

In the police creation logic, a decision module is used to determine if the number of available police is sufficient to respond to the current crime. It then sends a signal to the call that has been waiting in the crime processing logic to send a police car to that location. A hold module is needed to arrange police units in order of the travel times from lowest to largest in order to send them based on shortest travel time.

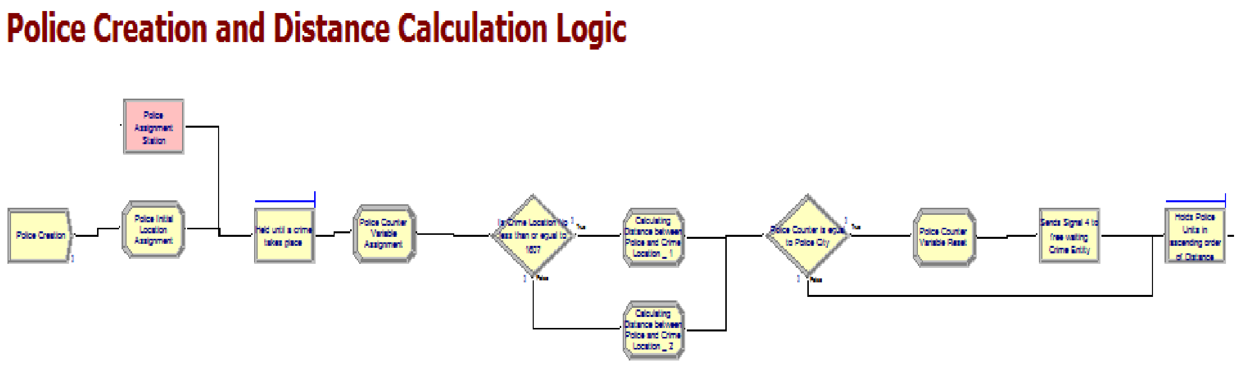


Figure 4. 17: Police Creation and Distance Calculation Logic

## 4.8 Service Logic

There is one additional time interval before travel time and service time that shall be considered in the model and that is the time from when a call is received to when the police station dispatches the police officers for that call. Based on the historical data from the OPS, we analysed this time and created a hold module in the model to account for this time lag. Table 4.6 shows the distribution of this time for each call type.

Table 4. 6: The Distribution of Received to Dispatch time by each Call Type

| Call Type | Receive To Dispatch Time Distribution |
|---|---|
| A | -0.001 + LOGN(33.6, 95.4) |
| B | -0.001 + LOGN(47.2, 197) |
| C | -0.001 + LOGN(126, 730) |
| D | -0.001 + LOGN(148, 1330) |
| E | -0.001 + 1390 * BETA(0.171, 1.89) |

Next each crime needs to be matched to its dispatch group and the number of available police on each shift needs to be updated. Thus, there is a set of modules to update this quantity by increasing or decreasing the number of available police based on each shift schedule. The last step in this logic is the assignment of each police unit to a (possibly new) location after service of a call has been completed.

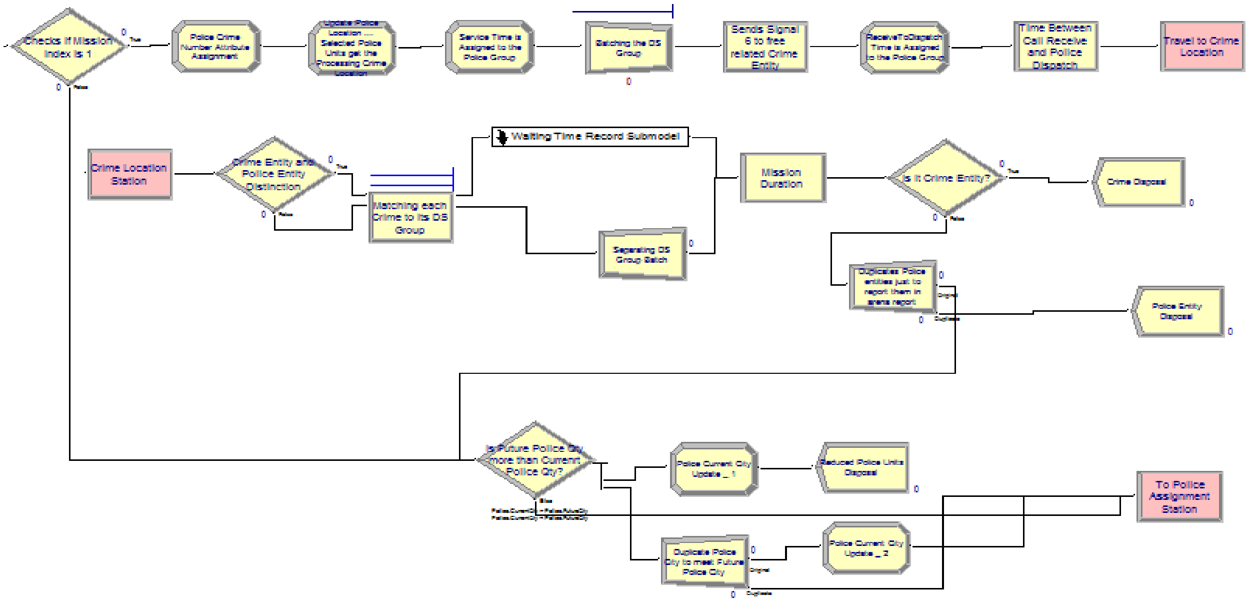


Figure 4. 18: Service Logic

## 4.9 Day Hour Controller Logic

As was mentioned above, the number of available police officers can vary in each hour of the day. Also, the rate at which crime occurs varies throughout the day and week as well. To keep track of the hour of day, the simulation models need to have the hour controller logic as figure 4.19 shows below:

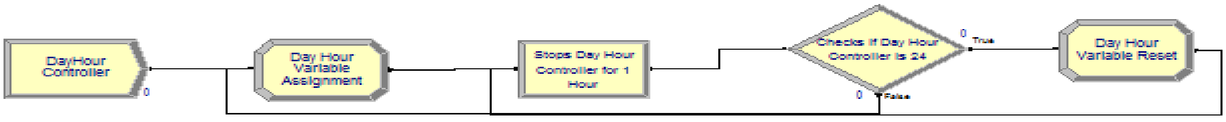


Figure 4. 19: Day Hour Controller Logic

## 4.10 Model Outputs

One of the important outputs of the model is the average waiting time. Figure 4.20 shows the histogram of average waiting time for calls arriving in each time slot. Waiting time is defined as the time between when a call is received to when the first officer arrives at the scene. As can be seen, time slot number five has the largest average waiting time. This could be due to fewer available police units at that time or an increase in the frequency of crime. This is one of the important things to be considered in order to improve the services and decrease the waiting time.

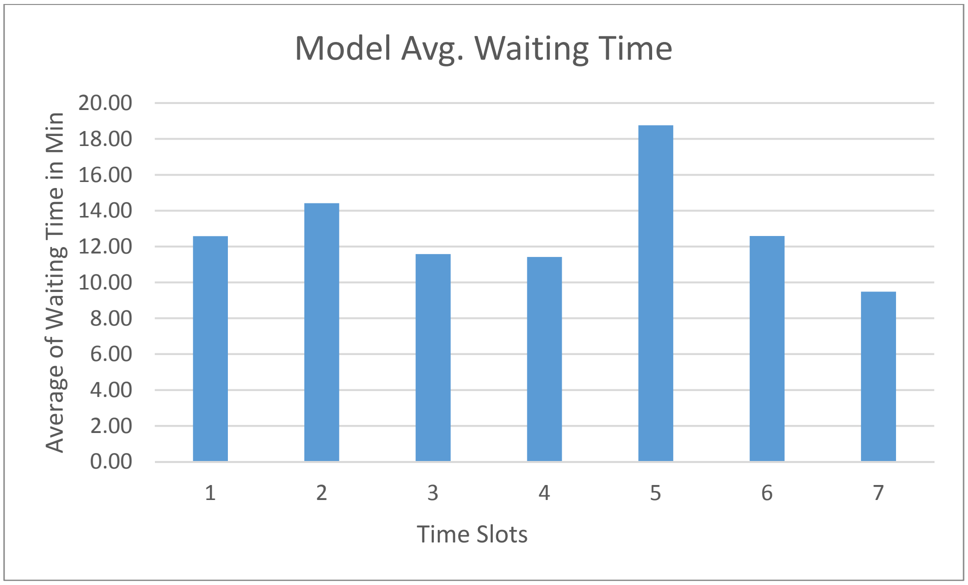


Figure 4. 20: Average of waiting time for each time slot

Furthermore, the average waiting time for each call type is shown in figure 4.21. They all are pretty similar with around 11.5 minutes for the different types of call. Also, for call priority, the average of waiting time has been shown in figure 4.22.

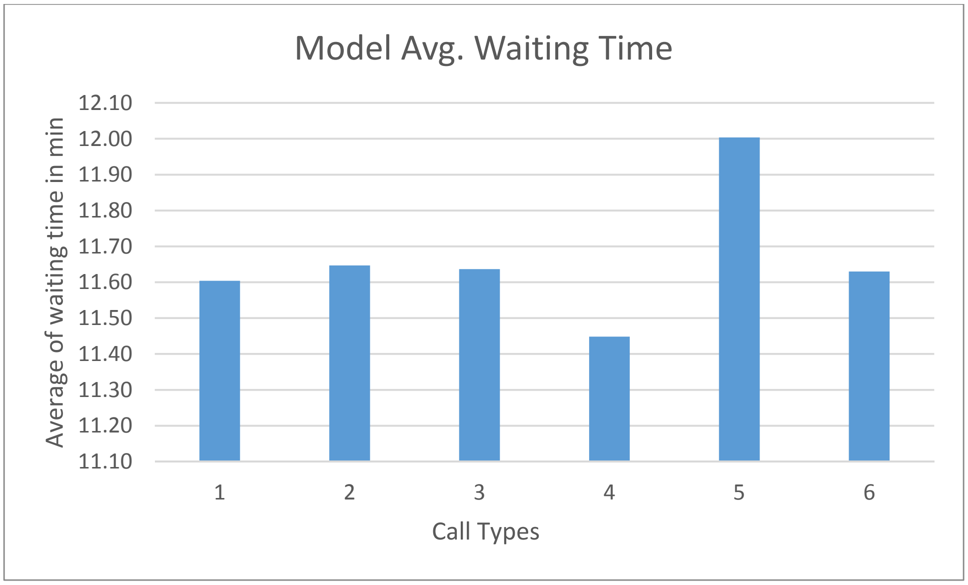


Figure 4. 21: Average of waiting time for each Call Type

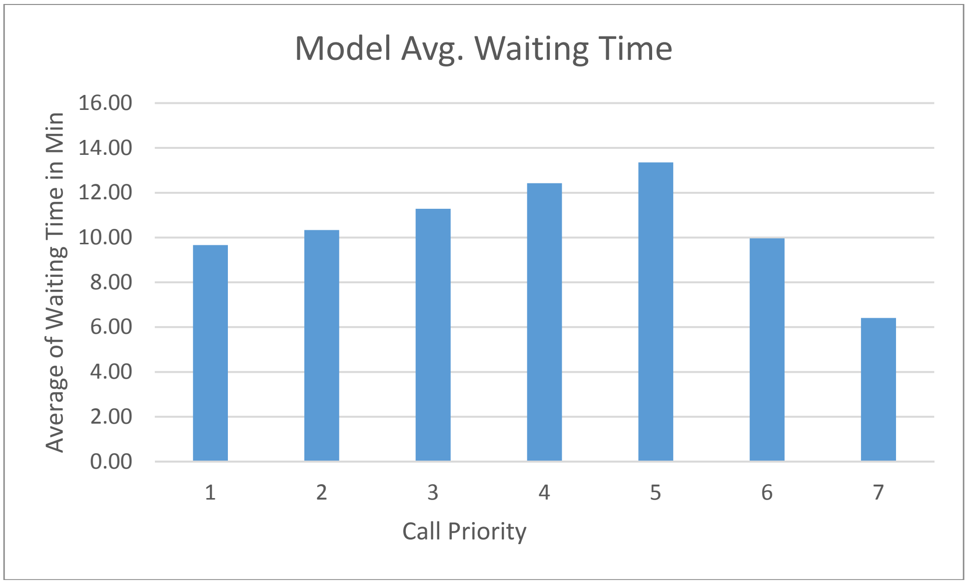


Figure 4. 22: Average of waiting time for each Call Priority

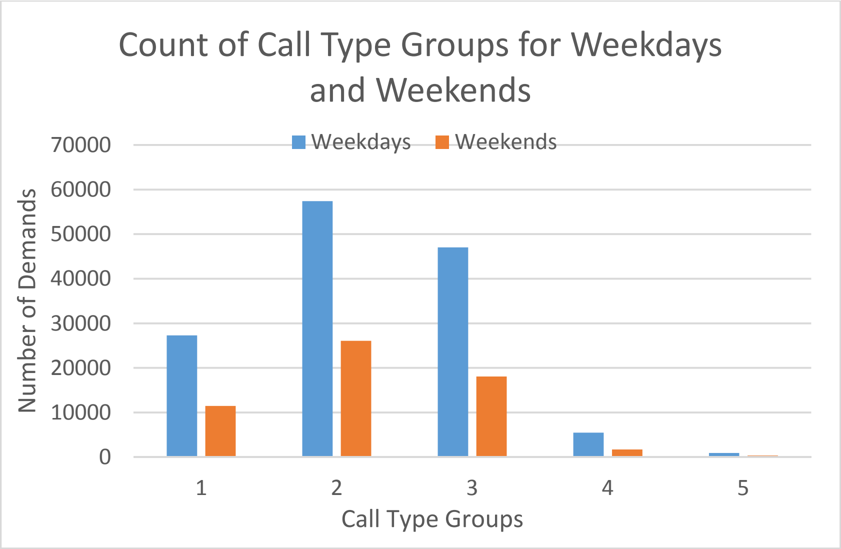


Figure 4. 23: Count of Call Type Groups for Weekdays and Weekends

The frequency of each of the six dispatch groups has been calculated for weekdays and weekends separately, as well as overall. Figure 4.23 shows the histogram of the number of received calls (demand) for each call type group. And figure 4.24 depicts the count of DS groups for both weekdays and weekends.

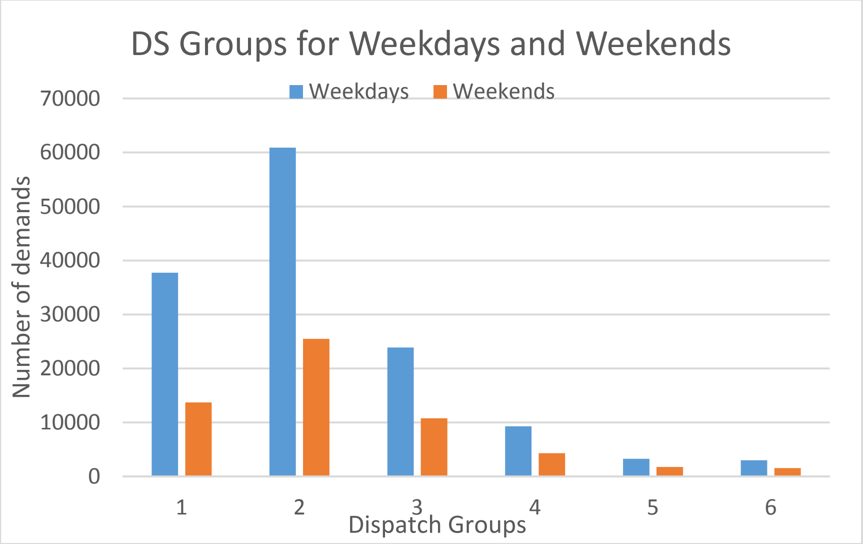


Figure 4. 24: Count of DS Groups for Weekdays and Weekends

The number of available police cruisers per shift for weekdays and weekends based on the simulation model for each time slot has been shown in Table 4.7. In case of a change in the pattern of crime in each time slot, the simulation can be adapted to different resource configurations.

Table 4. 7: Police quantity for each time slot during weekdays and weekends

| Time Slots | Current Model Police Qty | |
|---|---|---|
| | Weekdays | Weekends |
| 1 | 28 | 38 |
| 2 | 11 | 10 |
| 3 | 42 | 38 |
| 4 | 79 | 74 |
| 5 | 23 | 21 |
| 6 | 56 | 52 |
| 7 | 70 | 74 |

The frequency of call priority has been calculated for both weekdays and weekends as shown in figure 4.25. The reason for tracking priority is to ensure that higher priority calls are served first and that the wait time targets for each priority class are respected.

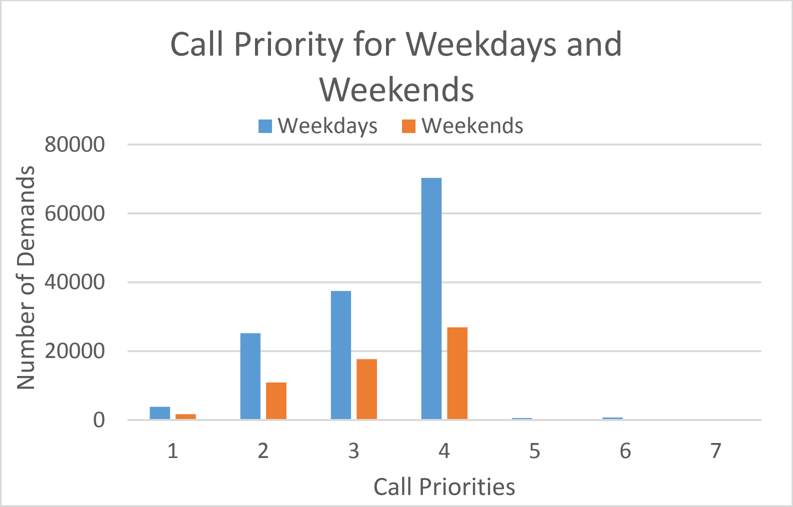


Figure 4. 25: Count of Call Priority for Weekdays and Weekends

## 4.11 Comparison and Validation

In order to systematically analyze the difference between the historical data and the Arena simulation models, we ran the model under a variety of settings for the input parameters in order to examine the reasonableness of the model output. To make sure that the values of the model generated from the correct distributions based on the historical data, the sample mean and sample variance of the average waiting time in the simulation was compared with the historical mean and variance of the real waiting time. Table 4.8 shows the comparison of mean and standard deviation for all priority classes between real data and the model.

Table 4.8: Comparison of mean and standard deviation of waiting time between Real data and Model for all priorities

| | Real | | Model | |
|---|---|---|---|---|
| Priority | Mean | SD | Mean | SD |
| 1 | 7.76 | 4.23 | 7.98 | 4.61 |
| 2 | 9.81 | 5.22 | 8.77 | 4.71 |
| 3 | 10.8 | 5.26 | 9.73 | 4.92 |
| 4 | 13.2 | 6.35 | 10.7 | 5.42 |
| 5&6&7 | 11.4 | 7.9 | 9.25 | 4.93 |

Also, the distributions of waiting time for real data and for the model have been shown in Figure 4.26. As the pattern of allocation of police officers to areas that the OPS used, was not exactly the same as what was used in our model, there is a little bit of a difference between these two distributions, but they both follow a similar trend.

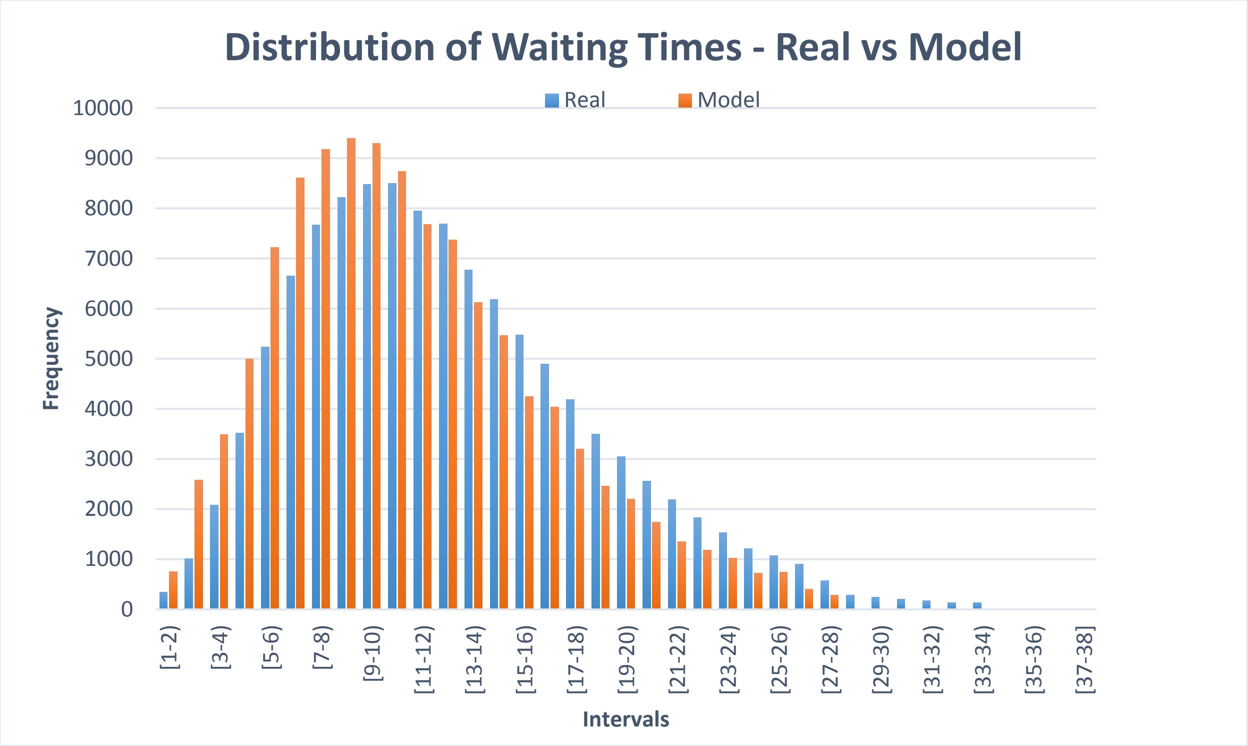


Figure 4. 26: Distribution of waiting time for real data vs Model

After running the simulation model, we did an in-depth comparison between the inputs from the real data and the outputs of the model. For example, Table 4.9 shows this comparison for simulation model output compared to historical data for each call priority in both weekdays and weekends.

Table 4. 9: Comparison of Simulation Model Output to Historical Data for Call Priority

| Call Priority | Model | | | Real | | | Difference | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Weekdays** | **Weekends** | **Grand Total** | **Weekdays** | **Weekends** | **Grand Total** | **Weekdays** | **Weekends** | **Grand Total** |
| 1 | 2.77% | 2.94% | 2.82% | 2.76% | 3.00% | 2.83% | 0.36% | -2.00% | -0.35% |
| 2 | 18.26% | 18.86% | 18.43% | 18.13% | 18.98% | 18.38% | 0.72% | -0.63% | 0.27% |
| 3 | 27.12% | 30.66% | 28.16% | 27.20% | 30.29% | 28.10% | -0.29% | 1.22% | 0.21% |
| 4 | 50.92% | 46.70% | 49.68% | 50.99% | 46.92% | 49.81% | -0.14% | -0.47% | -0.26% |
| 5 | 0.41% | 0.39% | 0.40% | 0.38% | 0.38% | 0.38% | 7.89% | 2.63% | 5.26% |
| 6 | 0.51% | 0.42% | 0.49% | 0.51% | 0.42% | 0.49% | 0.00% | 0.00% | 0.00% |
| 7 | 0.02% | 0.01% | 0.02% | 0.01% | 0.01% | 0.01% | 100.00% | 0.00% | 100.00% |

As the table depicts, the differences of call priority (excepting priority 7 calls) between real data and the model outputs are between -0.47% and 7.89% in total. The difference is significantly higher for priority 7 calls primarily because the sample size is very small due to the small frequency of priority 7 calls.

In Table 4.10 the average waiting time for each priority has been shown for the model and the real data. The last two columns also show the proportion of calls responded within the target for each priority in percentage.

Table 4.10: Comparison of average of waiting time between model and real data for each call priority

| Call Priority | Model Avg. Waiting Time | Real Avg. Waiting Time | Model Proportions of calls responded within the target | Real Proportions of calls responded within the target |
|---|---|---|---|---|
| 1 | 9.66 | 9.94 | 64.05% | 65.97% |
| 2 | 10.33 | 11.89 | 71.55% | 63.82% |
| 3 | 11.29 | 12.61 | 70.10% | 63.20% |
| 4 | 12.43 | 14.62 | 73.99% | 59.85% |
| 5 | 13.36 | 12.98 | 62.40% | 55.30% |
| 6 | 9.96 | 16.18 | 85.12% | 70.25% |
| 7 | 6.41 | 3.22 | 17.65% | 88.89% |
| Total | 11.63 | 12.84 | 72.16% | 62.60% |

As can be seen in Table 4.11, the comparison for DS groups (Dispatch groups) between simulation model outputs and historical data in both weekdays and weekends has been shown. The differences vary from -3.77% to 0.92%.

Table 4. 11: Comparison of Simulation Model Output to Historical Data for Dispatch Group

| DS Group | **Model** | | | **Real** | | | **Difference** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Weekdays** | **Weekends** | **Grand Total** | **Weekdays** | **Weekends** | **Grand Total** | **Weekdays** | **Weekends** | **Grand Total** |
| 1 | 27.32% | 23.81% | 26.29% | 27.41% | 23.85% | 26.38% | -0.33% | -0.17% | -0.34% |
| 2 | 44.09% | 44.22% | 44.13% | 44.00% | 43.95% | 43.99% | 0.20% | 0.61% | 0.32% |
| 3 | 17.29% | 18.72% | 17.71% | 17.19% | 18.75% | 17.64% | 0.58% | -0.16% | 0.40% |
| 4 | 6.74% | 7.50% | 6.96% | 6.78% | 7.57% | 7.01% | -0.59% | -0.92% | -0.71% |
| 5 | 2.38% | 3.06% | 2.58% | 2.46% | 3.18% | 2.67% | -3.25% | -3.77% | -3.37% |
| 6 | 2.19% | 2.68% | 2.33% | 2.17% | 2.69% | 2.32% | 0.92% | -0.37% | 0.43% |

Similarly, Table 4.12 shows this comparison of the model inputs and outputs for dispatch quantity for both weekdays and weekends, as well as in total. As the table clearly shows, the differences in average dispatch quantity between the real data and the model outputs are 0.21% and 0.07% for weekdays and weekends respectively.

Table 4. 12: Comparison of Simulation Model Output to Historical Data for Dispatch Quantity

| | Average Dispatch Quantity | | |
|---|---|---|---|
| | Weekdays | Weekends | Grand Total |
| Model | 2.226735096 | 2.351417917 | 2.263448466 |
| Real | 2.231320248 | 2.353056971 | 2.266533804 |
| Difference | **0.21%** | **0.07%** | **0.14%** |

Moreover, a comparison between the average waiting time in each time slot between the real data and the model outputs has been shown in Table 4.13. This comparison also, has been done between all five call type groups in Table 4.14. The total waiting time for both time slots and call types is the same with 11.63 minutes for the model and 12.84 minutes for the real data respectively, that means

Table 4. 13: Comparison of the average waiting time between the model output and the historical data for each time slot

| Time Slot | Model Avg. Waiting Time | Real Avg. Waiting Time |
|---|---|---|
| 1 | 12.58 | 11.65 |
| 2 | 14.42 | 13.87 |
| 3 | 11.58 | 14.00 |
| 4 | 11.42 | 13.84 |
| 5 | 18.76 | 14.54 |
| 6 | 12.59 | 13.06 |
| 7 | 9.49 | 11.50 |
| Total Average | 11.63 | 12.84 |

Table 4. 14: Comparison of the average waiting time between the model output and the historical data for each call type

| Call Type | Model Avg. Waiting Time | Real Avg. Waiting Time |
|---|---|---|
| 1 | 11.60 | 12.38 |
| 2 | 11.65 | 12.18 |
| 3 | 11.64 | 14.04 |
| 4 | 11.45 | 13.68 |
| 5 | 12.00 | 11.85 |
| Total Average | 11.63 | 12.84 |

In sum, these results provide sufficient reason to trust the model, as the inputs are all reasonably accurate and the key output measure (waiting times) is only slightly different from reality. This slight difference is likely due to the fact that we are not able to utilize the OPS allocation policy both in terms of where they place the police cars as well as how they assign officers to calls. Also we used the average available police officers which may not exactly reflect reality.

## 4.12 Discussion and Scenarios

After reviewing model outputs carefully and comparing them to the real data, some scenarios could be considered for the OPS in order to improve service and decrease the average waiting time for each crime. We offer some scenarios such as changing the police quantity, reducing the time between call received to unit dispatch time by 5%, 10%, 15%, and 20%, and, most promisingly, a reallocation scenario that describes a method for reallocating police officers once they are finished servicing a crime.

### 4.12.1 Changing the police quantity

Increasing and decreasing the quantity of available police units while keeping other components fixed has an understandable impact on the average waiting time for each crime. We started with increasing the police quantity by 20% and compare it to the current model and then continued these changes while reducing the number of police units from 10% to 50% and extracted the diagram below (Figure 4.27) to show the trend of these changes.

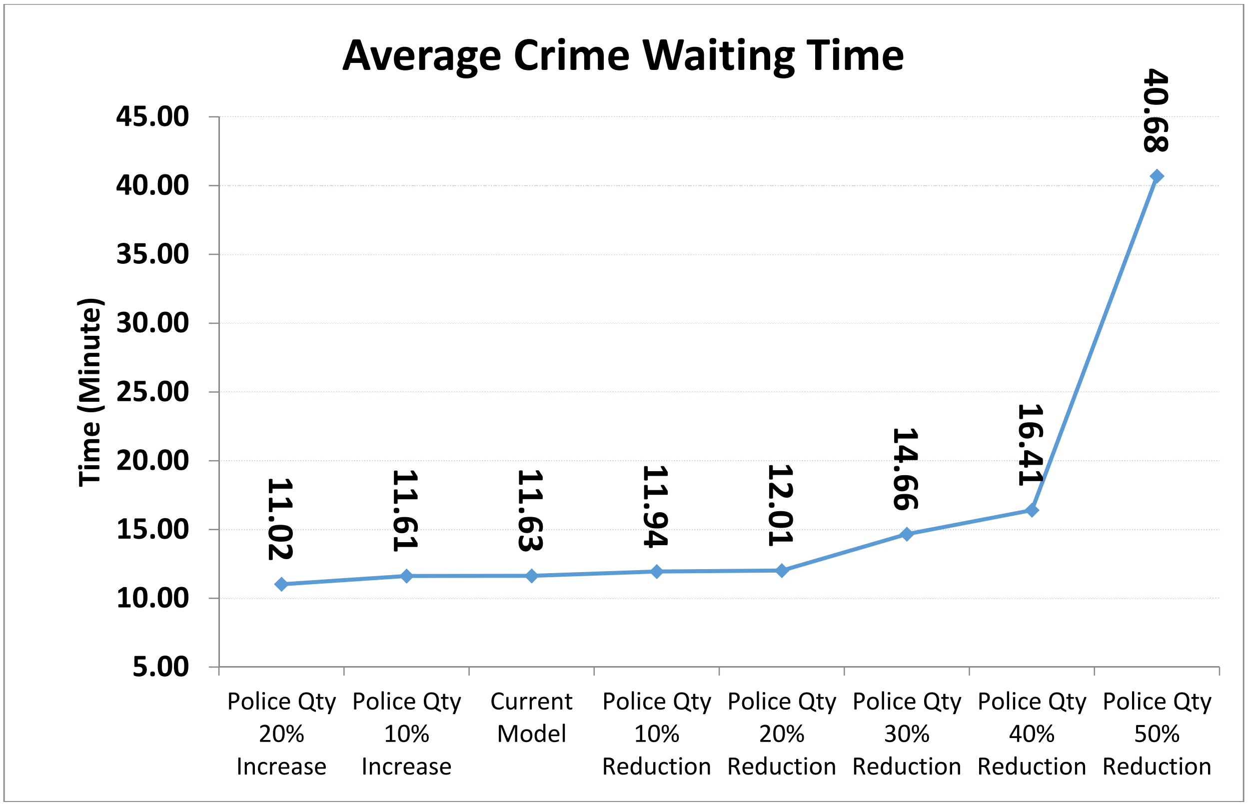


Figure 4. 27: Changing Trend for the Average of Waiting Time by changing Police Quantity from -20% to +50%

Moreover, the average police travel time and the average police idle time are two more critical measurements that change with different police quantities. Figures 4.28 and 4.29 depict the impact on these performance metrics for the same scenarios. It is worth noting that high idle times are not necessarily an issue as police have other duties to attend to other than responding to calls.

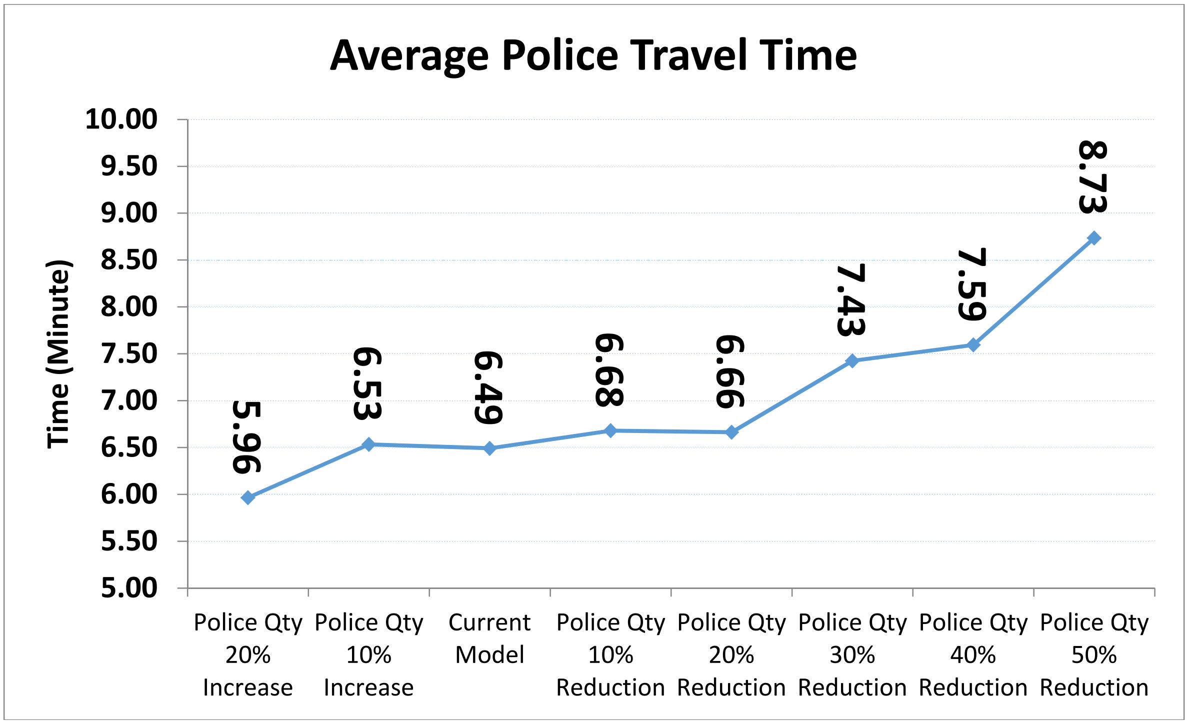


Figure 4. 28: Changing Trend for the Average of Police Travel Time by changing Police Quantity from -20% to +50%

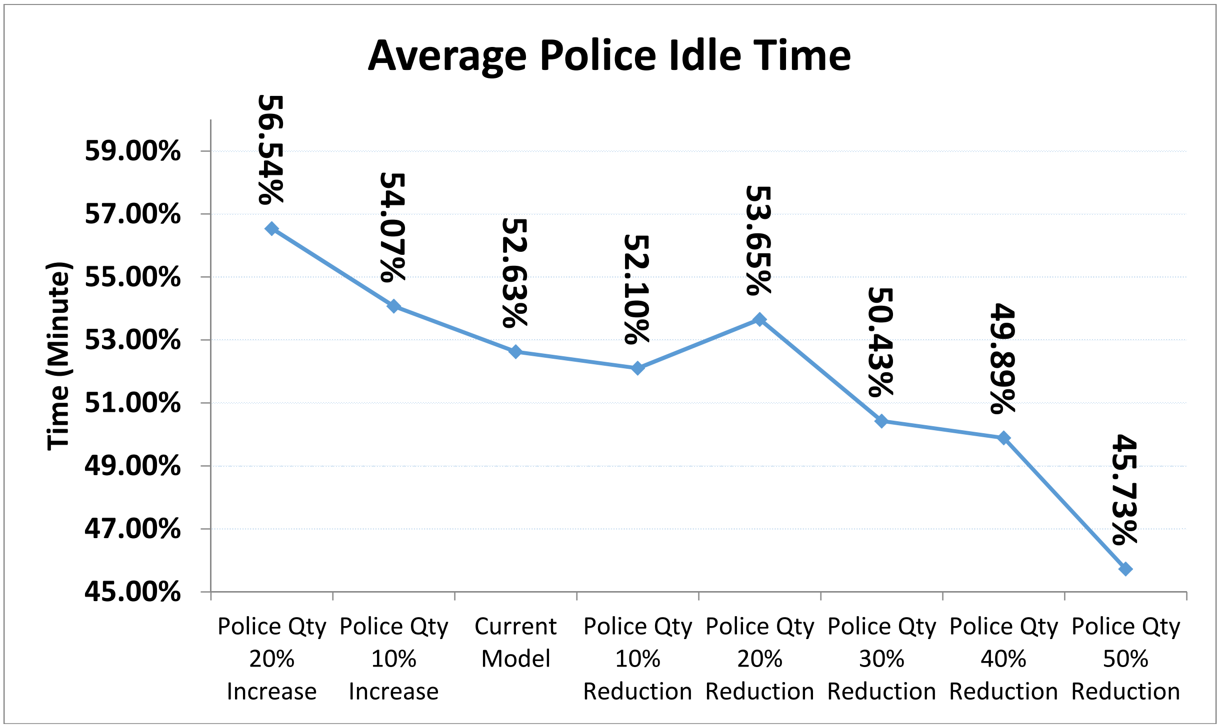


Figure 4. 29: Changing Trend for the Average of Police Idle Time by changing Police Quantity from -20% to +50%

The proportion of calls responded to within the target is shown in Figure 4.30. According to this diagram, an increase of 20% in the police quantity causes the proportion of calls responded to within the target to increase to 75.16%. In contrast, this proportion is reduced to 59.44% by decreasing the police quantity by 50%.  We have omitted category 7 due to the low number of calls in that priority class.

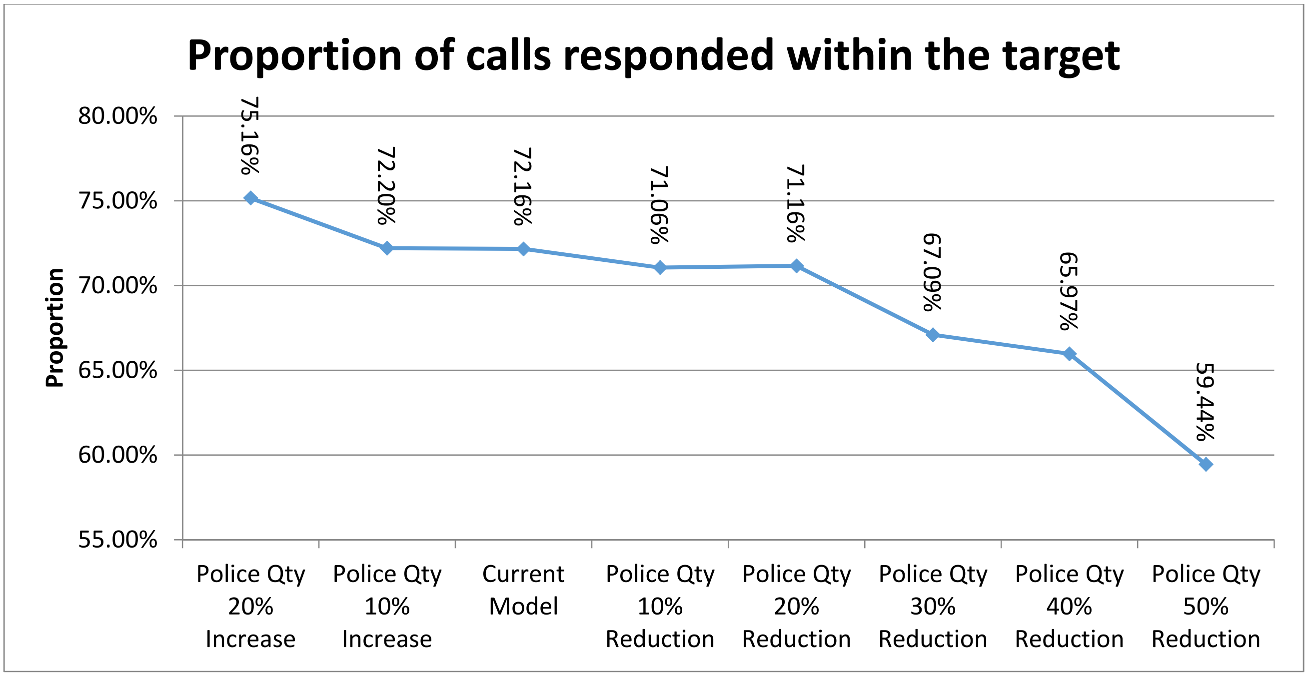


Figure 4. 30: Proportion of calls responded within the target

A diagram for the proportion of calls responded to within the target for each priority class is shown in Figure 4.31 over the same scenarios.  For example, for priority 6 calls the proportion of calls responded to within the target goes from a high of 87% for the scenario with a 20% increase in police quantity and down to a low of 75% for the scenario with a 50% reduction in police quantity.

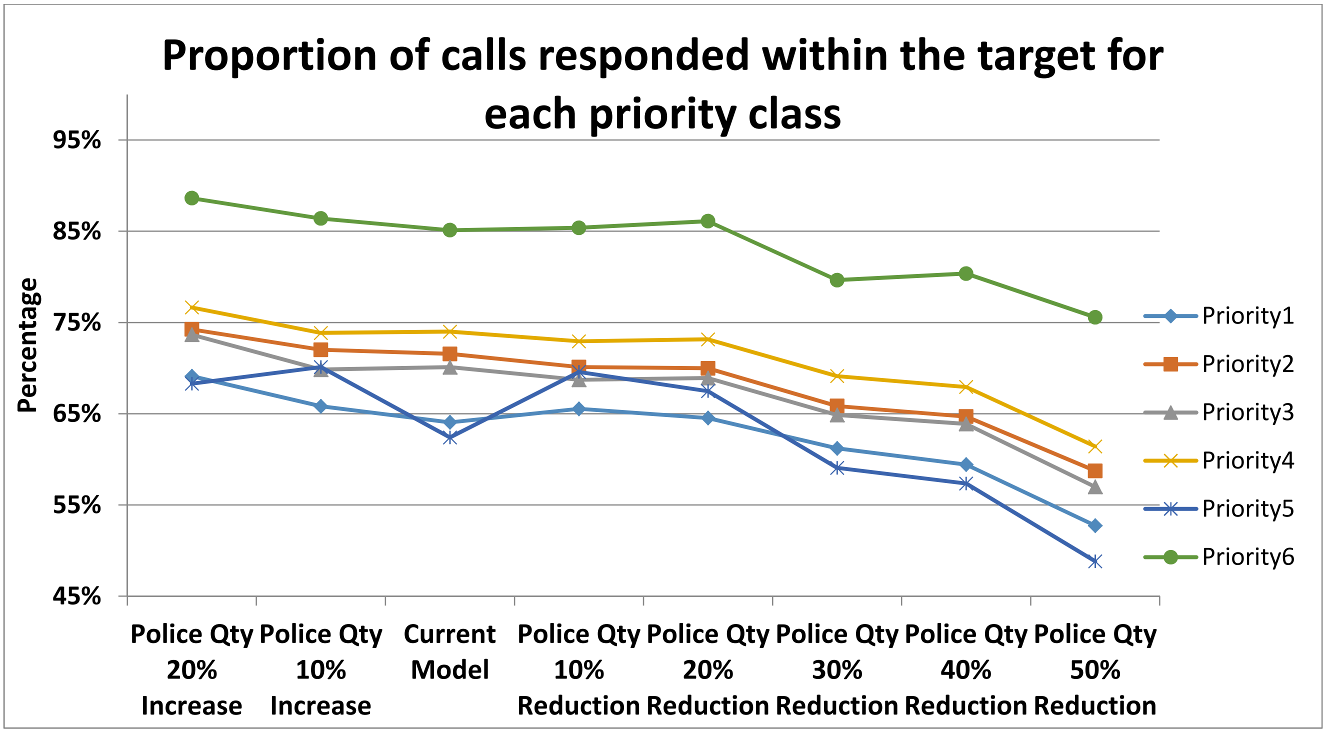


Figure 4. 31: Proportion of calls responded within the target for each priority class

## 4.13 Reallocation

Under the base scenario, after servicing a call, police cars stayed at the same location where the crime occurred. In contrast, in this section, we present an alternative reallocation policy that reacts more appropriately. The logic of this reallocation is determined using two parameters: the desired police quantity (DPQ) and the minimum police quantity (MPQ) for each location.

For each location, we consider a neighborhood for that location representing the 20 nearest (in time travelled) locations. Using data from 2014, these 20 neighboring locations are ranked in ascending order based on the frequency of crimes. The reallocation logic attempts to take into account the potential for crime at points in the neighbourhood and to adjust based on perceived areas of weakness. As an example, if the index of the location of a police unit that recently closed a call is “i”, and the index of destination location is “j”, the model sends a car from i to j if the following conditions have been met:

1) The number of police officers in the current location is at least equal to the number MPQ. This means that the current location must have at least MPQ+1 police units to be able to send the extra police car to a neighboring location.
2) The second condition is that the destination location must be the location in the neighbourhood of the current location with the highest frequency of crime that has less than DPQ police units. In other words, the destination location must have DPQ-1 police units to be able to be a destination location and no location in the neighbourhood of the current location of the police unit that has a higher crime rate is under-serviced.

In sum, the model first checks if the location where the recently released police car is currently has sufficient police units already. If this condition is met, then it will check the first location in its neighborhood based on the highest number of crimes to see if it is appropriate to send a police unit there based on condition 2. If it is not appropriate then it checks the second, third, and forth locations down to the twentieth one until it finds one for which the second condition is met. If none of these conditions are met for all of these 20 neighborhoods, then the police car stays at its current location.

Thus, these two parameters are checked in this way: MPQ for the current location and DPQ for the destination. The logic ensures that the location with the most need of a police officer that does not require too much travel time of the unit is the one that receives the newly released officer. It also prevents a build up of units at the locations with a higher frequency of crime.

### 4.13.1 MPQ and DPQ Calculations

MPQ and DPQ are calculated based on the probability of occurrence of crime at each location. DPQ is calculated based on the probability of multiple crimes occurring at the same time in the same location. For each location, we check the probability of x crimes occurring simultaneously and set the DPQ equal to the lowest x for which the probability of simultaneous occurrence is less than 5%. Thus, if for a specific location, the probability of 4 crimes in the same hour is equal to 5.5% and the probability of 5 crimes in the same hour is 4.9% then the DPQ for that location is set to 5. We set a maximum value for DPQ of 10. This is assigned based on the limited number of police officers in the system. Without a maximum value, those locations which have a high probability of crime occurrence can have such a high DPQ that too many police units end up being amassed in one location.

To calculate the MPQ, all locations are grouped based on the frequency of crime in 2014 (see Table 4.15 for weekdays and Table 4.16 for weekends). For weekdays, the first group includes those locations with 0 to 40 crimes per year, the second for those with 40 to 120 crimes per year, the third with 120 to 580 crimes per year and the rest are placed in the fourth group.

Table 4. 15: Location Grouping for Weekdays

| Location Grouping for Weekdays | |
|---|---|
| Location Group | Yearly Frq of Crime |
| 1 | 0 - 40 |
| 2 | 40 - 120 |
| 3 | 120 - 580 |
| 4 | > 580 |

This result has been also done for weekends in Table 4.16 below:

Table 4. 16: Location Grouping for Weekends

| Location Grouping for Weekends |
|---|

| Location Group | Yearly Frq of Crime |
|---|---|
| 1 | 0 - 20 |
| 2 | 20 - 60 |
| 3 | 60 - 200 |
| 4 | > 200 |

Then for each group we arbitrarily determine a proportion of the DPQ that can be "shared" with other locations (see Table 4.17) with that proportion decreasing the more crime a location is anticipated to generate. We call this proportion the Shareable Portion of Police Quantity (SPPQ).

Table 4. 17: Shareable Portion of Police Quantity (SPPQ)

| Location Group | SPPQ |
|---|---|
| 1 | 80% |
| 2 | 60% |
| 3 | 40% |
| 4 | 20% |

The MPQ is then calculated using the function:

$$MPQ = ROUND (DPQ * (1 - SPPQ))$$

Obviously both the thresholds that demarcate the groupings as well as the SPPQ values are arbitrarily determined. Other values for these parameters may lead to different results. The intent here is simply to show the potential improvement possible through a re-allocation policy that is sensitive to the amount of crime at each location. The intuition behind the method is that locations with lower crime rates need fewer cars present (lower DPQ) and can more readily "share" cars due to the small likelihood of multiple crimes occurring in the same hour (lower MPQ). The method re-allocates in order to more readily serve high crime areas without leaving low crime areas completely devoid of officers. As a result of all these calculations, the following procedure is used to calculate DPQ and MPQ:

1. Calculate the probability of occurrence of crime in any location and determine the DPQ.
2. Determine the neighbourhood for each Location.
3. Determine the SPPQ based on the Location Group.
4. Calculate the MPQ Using this formula MPQ = ROUND (DPQ * (1 - SPPQ))

As an example:

If DPQ = 7 for a location, and it is in Group 4 (SPPQ = 20%), it can share 20% of its DPQ to another location. In other words,

MPQ = ROUND (7 * (1-0.2)) = ROUND (7 * 0.8) = ROUND (5.6) = 6

This means that if there are 7 police units available at a location where a crime was just serviced then the recently released police unit can be sent elsewhere. Where it is sent is determined by looking at the neighbouring locations starting from the one with the highest crime frequency and working down. The first location that has less than its DPQ will receive the available officer. Obviously, if the number of police in current location is not 7 or more, then it is not able to send any police units to other locations.

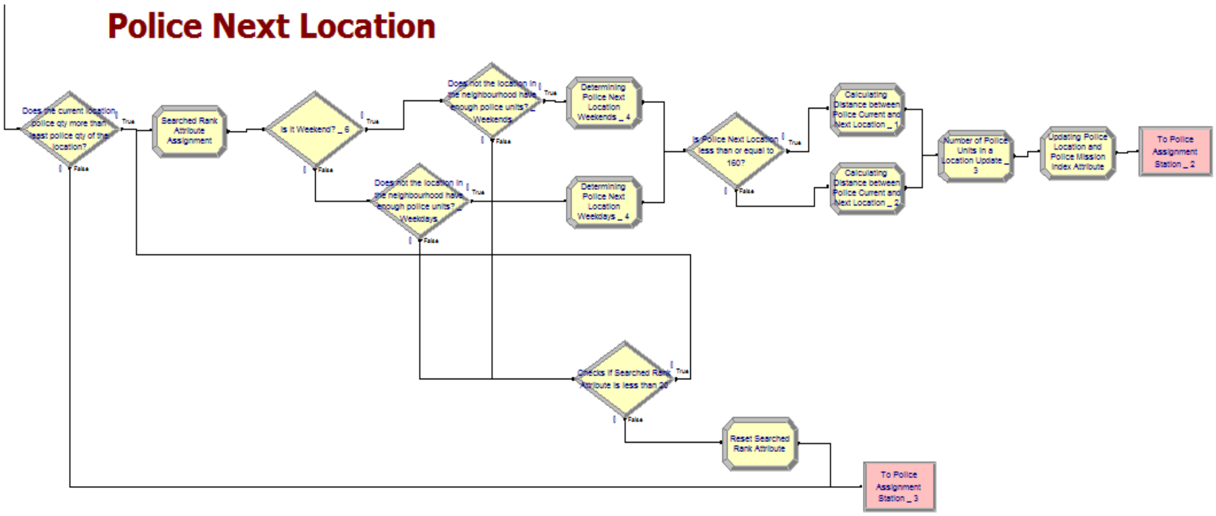


Figure 4. 32: Police Next Location Logic

### 4.13.2 Reallocation Scenario

As mentioned earlier in Section 4.13 a reallocation scenario could work as a means of improving the average waiting time. Since the whole explanation of this scenario has been presented above, only the comparison between the results of the current simulation model that we created and the results of the new model with the reallocation logic has been shown in this section. Table 4.18 represents a comparison between the average waiting time for each time slot between the current model and the new model with the reallocation logic. The last column also shows the difference between the average waiting time in each time slot for the current model and the new model with this reallocation logic. It is worth noting that this reduction is achieved without adding any new capacity.

Table 4. 18: Comparison of the average of waiting time between the current model and the new model for each time slot

| Time Slot | Current Model Avg. Waiting Time | Reallocation Model Avg. Waiting Time | Difference |
|---|---|---|---|
| 1 | 12.58 | 10.36 | -2.22 |
| 2 | 14.42 | 11.30 | -3.12 |
| 3 | 11.58 | 9.24 | -2.33 |
| 4 | 11.42 | 8.94 | -2.48 |
| 5 | 18.76 | 13.79 | -4.97 |
| 6 | 12.59 | 10.11 | -2.48 |
| 7 | 9.49 | 8.06 | -1.42 |
| Total | 11.63 | 9.34 | -2.29 |

We also did this comparison for each call priority, as well as for the call type groups, and again a reduction in waiting time occurred. It is clear that the new reallocation policy allows for a greater ability to respond to priority calls more appropriately as the higher priority classes have a much more marked decrease in waiting time.

The most important result after running the model with the reallocation logic was the analysis of proportion of calls that are responded to within the target for each priority class.

Table 4.19 shows the comparison of average waiting time for each call priority class showing the proportion of calls responded within the target for both the base model and the reallocation model. The reallocation scenario does a better job of increasing the proportion of calls met within the target than a 20% increase in the police force.

Table 4. 19: Comparison of the average of waiting time between the current model and the new model for each Call Priority

| Call Priority | Current Model Avg. Waiting Time | Reallocation Model Avg. Waiting Time | Current Model Proportions of calls responded within the target | Reallocation Model Proportions of calls responded within the target |
|---|---|---|---|---|
| 1 | 9.66 | 7.33 | 64.05% | 78.74% |
| 2 | 10.33 | 8.17 | 71.55% | 82.56% |
| 3 | 11.29 | 8.98 | 70.10% | 81.87% |
| 4 | 12.43 | 10.06 | 73.99% | 85.22% |
| 5 | 13.36 | 10.90 | 62.40% | 80.43% |
| 6 | 9.96 | 10.12 | 85.12% | 90.57% |
| 7 | 6.41 | 10.55 | 17.65% | 14.29% |
| Total | 11.63 | 9.34 | 72.16% | 83.61% |

# 5. Chapter 5: Conclusions and Recommendations

This chapter provides a short summary of the limitations of the model while also outlining some recommendations to the OPS department to help them improve their current system.

The techniques discussed in this research will be presented to the Ottawa Police Services (OPS) to provide them with a better allocation of their resources through the city of Ottawa in order to minimize the response time to each crime and maximize the coverage of police services in the city.

## 5.1 Limitations

A deeper understanding of simulation modeling and prediction of the OPS process needs a discussion of the limitations of the methodology. The intention is not to highlight how the software falls short of reality but to help the reader properly interpret the results, provide a foundation and motivation for improvement, as well as give some guidelines for future research. Below, a short summary of limitations of both the software and the system are discussed.

### 5.1.1 Modeling Limitations

In this model, officer units represent the resources, but in ARENA there is no way to determine an attribute or a location for resources. Therefore, we had to use entities to model the officer units, and this caused a complicated logic including many hold and signal modules that forced us to take more time to test and validate the logic. It should be emphasised that, using these complex logics was required for the validation and verification of the results of the model.

### 5.1.2 System Limitations

This study is also limited by a number of assumptions that were made during the creation of the model.

The first limitation is the overlapping between the shifts and schedules of officer units. In order to fix this problem we had to create seven new timeslots without any overlap to remove any impact of duplication in officer unit usage. Indeed, the only way to estimate the number of available officer units based on the historical data was to analyse the dispatch pattern in these seven time slots.

Second, there were too many locations and call types to model all of them and thus we group them based on the average service time for the call types and based on latitudes and longitudes for locations. These groupings were necessary due to the large number of both locations and call types but results in some loss of granularity in the model.

Third, the travel time between all regions represented by one of our “locations” has been assumed as zero but in reality there is always a distance between two locations even if they are close and the real travel time between them, though not large, will nonetheless be non-zero.

The exact capacity of available officer units in each shift is the fourth limitation as we used an estimation of available officers based on the historical data in each shift.

Last but not least, to find the real travel time based on GPS we were forced to rely on the ARCGIS and the Network Analysis software. It would have been much better to be able to use the actual travel time of police cars. Unfortunately, in the dataset we were given, though we had travel times we only had access to the location of crime and not the location of police car at the time when the call was received and thus we could not make use of the travel times as given.

## 5.2 Summary

In conclusion, in this research we tried to analyse all of the critical factors that have an indirect or direct impact as well as a positive or negative impact on the process of deployment of police resources in the city of Ottawa using a simulation model in ARENA. After careful consideration of the results, we found that with a new method for reallocating released police units a higher proportion of calls can be responded to within the target window. The model provides an excellent what-if analysis tool that could allow the OPS to determine the impact on the waiting times of any change to deployment.

## 5.3 Direction of future study and recommendations

The major future work is the introduction of an optimization model to optimize the current model and find the best method for the redeployment of police resources in the city. Allocating resources in an evidence based manner that reflects the changing demand patterns by hour of day would also undoubtedly improve performance.

Furthermore, since shift schedule has an indirect impact on dispatching, optimizing the shift schedule for on call officers can be another helpful method to improve services. For this purpose, they can provide different shifts for weekdays and weekends and also consider more flexibility in timing and availability of police officers.

The OPS could also benefit from a more complex analysis with a multi-objective optimization function that seeks to redeploy services with the aim of both minimizing service time while remaining conscious of cost. For these cases, similar objectives exist for improvement of deployment and resource management approaches in the literature.

Last but not least, to improve the reallocation results, in the process of finding the best receiving location among the 20 neighbourhoods, one could look for the most "under-serviced" rather than simply scrolling through from the one with the highest crime rate through to the lowest.

All in all, there remain many open issues that deserve in-depth investigations for future studies.

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## Appendices

# FULL ARENA MODEL