A DYNAMIC POLICING SIMULATION FRAMEWORK

by

KHAN MD ARIFUL HAQUE

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

December 2018

ACKNOWLEDGEMENTS

First of all, I would like to give all credits to the Creator, the most benevolent and the Almighty, for His boundless grace in our life and to give me patience to complete all the requirements of my doctoral degree.

I would like to express my whole-hearted respect and gratitude to Dr. Victoria Chen, my dissertation advisor, for her thoughtful suggestions, continuous guidance, and encouragement throughout the progress of the degree. Her suggestions and kindness for my family life are also deeply appreciated.

I am also thankful to other committee members, Dr. Brian Huff, Dr. Yuan Zhou, and Dr. Kent Kerley, and the academic advisor, Dr. Sheik Imrhan for their advice and attachment to this dissertation. Specially, I would like to acknowledge Dr. Brian Huff for his time and help develop simulation model in WITNESS.

I want to thank Jorge Salazar worked on fitting probability distribution to call data, Dishita Mehtalia and Li Zhang fit the predictive model with Arlington, TX data, and also Joana Gonzalez to extract information from data and summarizing them, which are the parts of this dissertation.

Special thanks to National Institute of Justice for providing three years of funding for this research and Arlington Police Department, TX for providing data and information to understand the policing system.

Profound thanks and gratitude to Dr. A. F. M. Anwarul Haque, my undergraduate professor for his continuous inspiration to obtain doctoral degree from USA.

Finally, I would like to extend my sincere thanks to my parents for their unparalleled love, sacrifice, and support encourage me to complete my study. To my wife, who is always with me in hard time, I love you and thank you. To my little son, Abraq, who always makes me happy with his smiling face and is my hope, I love you very much.

November 27, 2018

ABSTRACT

A DYNAMIC POLICING SIMULATION FRAMEWORK

Khan Md Ariful Haque, PhD

The University of Texas at Arlington, 2018

Supervising Professor: Victoria C. P. Chen

Crime is a serious problem to a society, and its costs are an economic burden. With the help of technology and developed tools, law enforcement agencies are making significant efforts to combat crime, so as to create a safer environment for society, both mentally and physically. The dynamic nature of crime and limited police resources often make their efforts challenging. Although there are numerous crime prediction models found in the policing literature, guidelines for policing strategies based on those models are still lacking. Towards addressing this gap, this dissertation constructs a dynamic policing simulation framework based on the concept of prediction-led policing that combines decision strategy, predictive policing, and simulation modules to enable the study of strategies for dynamic deployment of police resources to reduce crime. The decision strategy dynamically adjusts a policing strategy to try to minimize crime, the predictive policing model is used as a state transition function to predict future crime and the simulation evaluates the policing strategy and produces performance metrics. The main focus of this research is developing the simulation module and integrating it within a framework with the dynamic decision strategy and predictive policing modules. Data provided by Arlington, Texas Police Department (APD) are used to estimate probability distributions for the simulation module and to build a preliminary predictive policing model

appropriate for a dynamic policing framework. The developed framework has the flexibility to apply for any city over any time scale, provided an appropriate predictive policing model can be estimated.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

INTRODUCTION

Crime is a major problem in urban societies. Its costs and effects are widely varied. Some costs are short-term while others are long-term. Some losses are tangible while some are intangible [1]. In the United States, 7,993,631 property crimes were estimated in 2015, resulting in estimated losses of $14.3 billion to the victims of property crimes, excluding arson (due to the variations in the level of participation by the reporting agencies) [2]. The aggregate incarceration cost (includes costs of corrections, costs borne by incarcerated persons, their families, children, and communities) exceeded $1 trillion in USA in 2015, which is 6% of GDP [3]. Law enforcement agencies are continuously struggling to reduce crime, but the typical nature of the law enforcement is reactive. Within the last decade, law enforcement has sought to be more proactive [4]. This proactive revolution is due to the availability of more data, leading to data-driven models called predictive policing [5].

According to John Morgan, “Predictive Policing refers to any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention” [6]. The practice of predictive policing involves analyzing data on the time, location and nature of past crimes, along with factors, such as geography and the weather, to gain insight into where and when future crime is most likely to occur [4, 5, 7]. Forewarned with predictive policing, the hope is to be better able to prevent crime. In practice, it does not replace traditional policing, but can enhances existing approaches.

Prediction-led policing is another term often used in the broader sense where predictive policing is used in part. Prediction-led policing refers to a comprehensive business process, which is summarized in Figure 1-1. The first two steps collect and analyze crime, incident, and offender data to make predictions. Data from different sources in the community require some form of data fusion. The last two steps focus on the response to the predictions. Police personnel use the predictions for their responses and then respond using evidence-based approaches. Criminals also react to the changed environment. Some will be removed from the environment; those who are still operating may change their practices or move to a different area. This adaptation makes predictive policing dynamic. As the environment has been altered, the initial data will be outdated, and new data will be required for analysis [8].

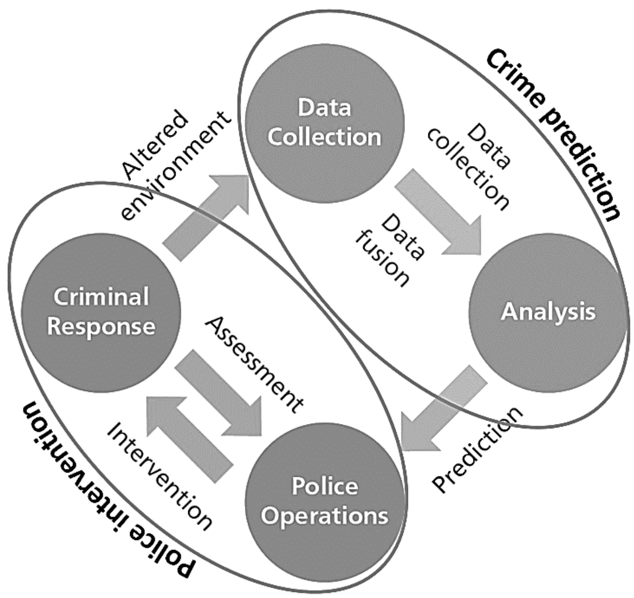


Figure 1-1 The prediction-led policing process. The original figure in RAND 2013 report [8] has been modified.

1.1 Motivation

In Arlington, Texas there is a high incidence of vehicle burglary relative to the size of the city population. Part of that can be attributed to the presence of high-profile entertainment venues in the city, including the Six Flags Over Texas theme park, AT&T Stadium (home of the Dallas Cowboys football team), and Globe Life Park in Arlington (home of the Texas Rangers baseball team). The research in this dissertation evolved out of work initiated as a collaboration with the Arlington, TX Police Department (APD) to reduce vehicle burglary. Later, the scope was extended to all types of crimes.

According to the prediction-led policing concept, there should be a relationship between police interventions and crime prediction. In the policing literature, this relationship is not well-defined. Some research [9-11] studied the relationship between crime and the size of the police force. It is a constant struggle to effectively balance limited resources and crime prevention. As evidenced by the RAND report [8] on predictive policing, significant research has been conducted to predict the occurrence of crime, with the intention of preventing future crime and enabling more effective deployment of resources. However, too many of these studies focus solely on the accuracy of predictive models, often creating very sophisticated modeling [12-22]. While accuracy is important, the utility of a predictive model, regardless of model sophistication, depends on the factors upon which the model is built. If the factors are not controllable, such as weather or location of buildings, then the model cannot be directly used to take action towards reducing crime. Although it may be inferred from a model that crime increases when the weather is nice, one cannot control the weather directly to reduce crime. Indirectly, this relationship with weather combined with a weather forecast can be used to predict how much crime will increase in specific regions on a future day, but it does not directly answer the question of how many police units need to be deployed to these regions.

As the criminal environment is altered due to policing operations, effective deployment of police resources is not a one-time decision. Prediction of future crimes are affected by this new environment data as shown in Figure 1-1 and the police force needs to continually adjust their use of resources for this dynamic system. Although there are some research efforts found for patrol allocation to meet some performance measures such as response time [23, 24], guidance on dynamic strategies for policing, such as dynamic deployment of police units to reduce crime, is a research need.

1.2 Research Contributions

In this dissertation, a dynamic policing simulation framework is developed to aid in effective dynamic allocation decisions under limited police resources to cover probable crime incidents. Three major contributions of this work are:

- Identifying key structural components of dynamic policing strategies,
- Identifying constraints of dynamic policing strategies, and
- Building a dynamic policing simulation framework for staff allocation.

For the first item, examples of structural components that can enable dynamic strategies include regular police units that patrol on a regular basis, but allow adjustments in the patrol schedule. More specialized structure is represented by Dynamic Policing Units (DPUs), such as disruption units, task forces, or foot patrols. DPUs provide the ability to more quickly alter the police presence at a local level. Disruption units, for example, move around hot spots so that police presence can be higher in hot spots, and can move around as hot spots move around. A disruption unit consists of officers as a unit for hot spot policing, whereas a task force is a unit that combines officers borrowed from neighboring municipalities to deter a special situation of crime. Foot patrols walk around areas for increased vigilance and to interact with citizens. As DPUs come from existing officers, it should not require additional hiring of officers.

For the second item, the primary constraints for policing are resource constraints, such as staffing and economic resources. While increasing police presence can decrease criminal activities, there number of officers is limited. By dynamically adjusting the allocation of officers over space and time, it will be possible to make more efficient use of the available resources. However, it will be important to respect the constraints that define stable and fair workloads for officers.

Finally, for the third item, this research develops a dynamic policing simulation framework based on the prediction-led policing concept to study hypothetical dynamic policing strategies. This framework is important because law enforcement currently does not have well-defined dynamic policing strategies, and it will not be practical to study new potential strategies in the real world environment. A simulation permits the study of hypothetical strategies and scenarios without human risk. The framework integrates three modules, a decision strategy module, a predictive policing module and a simulation module. The decision strategy module defines the specific policy for taking action, such as how a disruption unit patrols hot spots. The ultimate goal is for the decision strategy module to optimize strategies, and that will be a topic for future work. The predictive policing module takes the history of crime and policing actions to predict crime in a future time period at specific locations. Prediction policing models have been a popular topic in the last decade and will be discussed more in Chapter 2. Finally, the simulation module serves to create possible realizations of the dynamic policing system, including the occurrence of crimes at specific locations and times and the ability of the available policing force to respond. The simulation can study how hypothetical dynamic policing strategies might perform and can potentially simulate the criminal response to police interventions. In this dissertation, the general framework is developed and a discrete-event simulation is developed to demonstrate the framework for a case study of the city of Arlington, TX.

1.3 Problem Statement

The goal of this research is to build a framework to bridge the gap between predictive policing and dynamic policing strategies. Together, these create the concept of dynamic policing. In order for predictive policing to have an impact on policing actions, the structure of policing strategies must become more temporally and spatially dynamic. The purpose of this dissertation is to create a framework to facilitate the assessment of dynamic policing strategies to reduce crime. The framework is based around a discrete-event simulation model [25] to simulate how a dynamic policing strategy performs. The advantage of a simulation tool is the ability to inexpensively explore “what-if” scenarios. The framework would enable exploration of a variety of dynamic strategies, including those that are currently employed by police departments, such as task forces and disruption units. Discrete-event simulation can be used to observe how a dynamic decision strategy performs over a simulated time period, and dynamic optimization can be used to derive an optimized strategy as the simulation evolves.

The rest of the report is organized as follows. Chapter 2 provides a literature review on predictive policing, policing strategy, simulation, and dynamic policing. Chapter 3 describes the framework based on prediction-led policing concept. Chapter 4 discusses a preliminary simulation model built in WITNESS. The framework is then demonstrated with an APD case study in Chapter 5, and finally, conclusions and possible future work are discussed in Chapter 6.

Chapter 2

LITERATURE REVIEW

2.1 Concepts of Crime

Crime is defined by the law. In the USA, it can vary by states [26, 27]. In general, crime can be defined as any act or omission that violates a law and results in a punishment that ranges from the payment of a fine to incarceration in jail depends on the levels of severity of the crime [27]. Along with the economic burden, the negative effects of crime on a society can include feelings of fear that disrupt a population's sense of unity, the breakdown of social associations, hinder free movement, especially at night, and defame the image of the community [28, 29].

Dramatic variations of crime across time and space (countries, states, cities, even neighborhoods) are attributed as "the most puzzling aspect of crime" [30, 31]. The shifting distribution of crime in space and time is also recognized as a research challenge [24]. Ludwig and Kling [32] studied if crime is contagious in nature and did not find enough evidence to support their hypothesis which can be a consideration for the allocation of police resources.

2.1.1 Types of Crimes

There are hundred kinds of crimes committed by criminals [33]. Based on the level of seriousness, crimes are classified into two broad categories: felonies and misdemeanors. Felonies are serious crimes punishable by death or by imprisonment for at least one year. On the other hand, misdemeanors are crimes punishable by a fine or confinement for less than a year [34].

Crimes can also be categorized in five general forms: violent crimes, property crimes, white collar crimes, organized crimes, and Cyber-crimes [35]. A violent crime is a crime in which the offender uses or threatens to use force upon a victim [36]. A common form of crime is property crime that involves theft of money or property without bodily harm [37]. White collar crimes are non-violent crimes committed by an individual or business entity. Organized crime is committed by structured groups typically involving the distribution and sale of illegal goods and services [38]. Cyber-crime is a crime involving the use of computers in cyberspace to injure a person or property [39].

In this research, crime has been categorized by priorities following the research paper by Srinivasan et al. [40]. In their paper, calls have been classified into seven priority levels depending on the type of emergency. Priority levels starts with 0 being the highest level of priority and priority 6 has the lowest priority.

2.1.2 Crime Measures

Employing and mapping different measurements of crime improves crime analysis by allowing a comparison to be made. Crime counts and crime rates are easy to calculate and widely used to measure crime [41]. Crime count is simply the frequency of crimes and is a measure of the volume of criminal activity. Crime rates are commonly used for assessing the risk of crime based on the size of the population. Brantingham et al. [42] introduced crime location quotients (LQCs) as another measure of crime derived from economics. Crime rates is of interest for the model building in this research.

Crime hot spots can be considered as another measure to determine a crime location. A crime hot spot is formed if crime events are highly concentrated in small geographic areas on a map. There are different crime hot spot prediction models in the literature [18, 21, 43-45], and there is still a debate in defining a crime spot as a hot spot [46]. In general, an area with a significantly high concentration of crime, relative to the average level of crime, can be treated as a hot spot.

2.1.3 Criminology Theories

Researchers in criminology proposed different theories to explain why crimes occur in some places, not everywhere. James Q. Wilson and George Kelling [47] proposed the well-known “Broken Windows” theory that states that acts of public disorder in a neighborhood, such as graffiti, litter, abandoned homes, loitering, panhandlers, etc., can encourage future crime. “Opportunity Theory” states that crime occurs when community relationships or interactions with local institutions fail or are totally absent [48]. “Routine Activity Theory” is a sub-field of “Opportunity Theory” and was developed by Marcus Felson and Lawrence E. Cohen. This theory states that a motivated offender, a suitable target, and the lack of capable guardian in the same place at the same time leads to crime [49, 50]. “Situational Crime Prevention Theory” states that crime can be prevented by reducing opportunities or altering situation factors (including increasing difficulties or risks of offending, making crime less rewarding) in the environment [51, 52]. “Crime Pattern Theory” tells why crime is committed in certain areas. It states that crimes do not occur randomly or uniformly in time or space. Crimes, decisions to commit crime, and the way of committing crime are patterned and predictable [53]. These theories can be linked to our research scope that considers the spatial and temporal aspect of crime, so as to create an unfavorable environment to offenders by using dynamic policing strategies.

2.1.4 Police Interventions

Three broad types of police interventions have been mentioned in the RAND report [8], although they may vary with the situation. They are described below from simplest to most complex. Generic interventions allocate more resources at high risk areas. For hot spots, it could mean allocating more officers and for hot people (i.e., perpetrators and suspects), it could mean allocating more parole or probation officer contacts [54]. In crime-specific interventions, resources are assigned that are customized for combating expected types of crime and more focused on a given hot spot or a particular person who is at risk of offending [1, 55]. Problem-specific interventions analyze the nature of the crime problem and tailor interventions addressing the causes of the problems. It focuses on places- or people-specific problems generating crime risks and fix them [56, 57]. Regardless of the type, all levels of officers who are involved will need information for successful intervention. This research can fit to the generic type and to some extent it can fit to the crime-specific interventions.

2.2 Predictive Policing

In 2008, police chief (ret.) William J. Bratton at the Los Angeles Police Department started working with the acting directors of the Bureau of Justice Assistance (BJA) and the National Institute of Justice (NIJ) and brought the idea of predictive policing to the forefront [8, 58]. It is a paradigm shift of the policing system that makes it more proactive than reactive. Predictive policing does not replace current policing techniques. Rather, it builds on the essential elements of all policing strategies [59].

Some descriptions about predictive policing make it sound like it is the winner of all approaches in crime reduction. Sometimes people expect unrealistic results from it. People can be misguided to use predictive policing with four common myths or hypes that have been mentioned in the RAND report [8]: “the computer actually knows the future,” “the computer will do everything for you,” “you need a high-powered model,” “accurate predictions automatically lead to major crime reduction.” In reality, predictive policing uses computer speed to take computational advantage and the accuracy of the prediction depends on the quality of input data. Humans still must identify the relevant data, preprocess it based on the crime situation, choose the appropriate data analysis method, then review and interpret the findings to take appropriate actions. Without actions, prediction does not automatically eliminate crime regardless of its accuracy. Some models may be so simple that police departments do not need expensive and super-fast machine to run the model [54, 60].

Although predictive policing opened a new dimension of the policing system, models must still be interpreted and utilized with care. Focusing on prediction accuracy without considering tactical utility can create an essentially unhelpful model. Prediction that is constructed based on poor quality data or a misunderstanding of the factors could yield misleading results [61].

2.2.1 Crime Prediction

Methods for predicting crimes are predictive policing methods used to predict locations and times with an increased risk of crime. Sometimes it also identifies factors driving crime risk.

2.2.1.1 Spatial prediction of crime

Using historical data, crime mapping and risk terrain analysis are used to identify areas with increased crime risk. Crime mapping is a graphical representation of crimes on a map using a Geographic Information System (GIS) to help see the locations of crime concentration and understand where they need more interventions [62, 63]. Dot maps, line maps, ellipse, choropleth, and isoline maps are used to detect different levels of hot spots [64, 65]. The predictive power of risk terrain analysis over crime mapping has been shown by Caplan et al. [17]. They viewed risk terrain modelling as a function of a dynamic interaction between social, physical and behavioral factors [66]. Risk terrain analysis is also applied to identify geographic factors (e.g. locations of bars, liquor stores, major roads, dwellings of known gang members etc.) that influence crime risks [67].

With a range of additional data, statistical regression, classification, and clustering can be used to predict crimes. Regression analysis is frequently used to investigate the relationships between explanatory variables and an outcome (e.g. crime rate) [68] and to estimate the mean crime rate from the predictors [69, 70]. It is also used to study the effects of social interactions [71], impact of public policy [72], and climate change [73, 74] on the crime rate for social network analysis. Regression models [19, 20], such as logistic regression [75], Poisson-based regression [68], geographically weighted regression [76] are commonly used in crime prediction and can be used as state transition models of crime. Classification and clustering are data mining techniques. Classification classifies an outcome based on a set of explanatory factors. Decision-tree algorithms [75], neural networks [77], etc. can be used to classify crimes. Clustering separates crime or crime hot spots into groups sharing similar attributes. Clustering is used on a crime data set to find those exhibiting similar tactics [8], to find, for example, crime hot spots [78-80] and crime matching [81].

Townsley et al. in 2003 [82] first quantified the near-repeat pattern of crime. The near-repeat model is used to understand the spatial distribution of the risk of repeated crime within a short period of time. It assumes that a near repeat exists, if at least two crimes occur within a short period of time and within a limited area [83]. A near repeat area could be defined as a specific geographical space, where the amount of near repeats is significantly high [84-86]. Since a near repeat exists for a short period of time, the analytical capacity to identify a pattern and the operational flexibility to rapidly respond are the organizational challenges discussed by Haberman et al. [87]. Without overcoming these challenges, police departments will not be able to effectively utilize near repeat predictions.

Using agent-based simulation, Lanier and Carter [88] examined the contribution of several variables to homicide rates in USA. They found that the homicide rates increased when population density and the availability of handguns increased. Kohtz et al. [89] built an agent-based model to predict the crime spread and crime behavior in the city of Chicago.

2.2.1.2 Temporal prediction of crime

Prediction of crime over time alone is not common in the literature. Some existing methods of location prediction with time information are using to predict the time of crimes. Time series regression models [9, 90, 91] and time series clustering [92, 93] that predict crime trends and crime maps by time and date information are used to predict time of crime occurrence for a short period of time. Chen et al. [94] applied randomized experimental design to study levels of robbery and burglary by season (Spring, Summer, Autumn, and Winter). Crime hot spot maps are a well-established tool for visualization of space-time crime patterns and can be used as a method for prediction of near-repeat crimes [18]. Hot spot analysis is used to find static spatial patterns of crime events. Spatial hot spots with temporal information are used for temporal hot spot analysis [95].

2.2.2 Predicting Offenders

Methods for predicting offenders identify individuals who may become future offenders and also identify criminal groups, especially gangs that are likely to carry out violent assaults on each other in the near future. Considering possible risk factors, regression and classification models are used to identify future offenders. Probationers and parolees that are more prone to reoffending could be an important factor consideration in the data analysis [8]. Mandracchia et al. [96] used hierarchical linear regression models to find future offenders. Classification models classify individuals as a subgroup of either an offender or non-offender. Classification trees were employed to identify violent offenders by Stalans et al. and Chaiken et al. [97, 98]. Another application of near-repeat analysis is to predict violence between criminal groups [99].

2.2.3 Predicting Perpetrators' Identities

Methods for predicting perpetrators' identities are used to identify suspects using a victim's criminal history, determine serial crimes, identify a perpetrator's most likely anchor point [100], and find suspects using sensor information (GPS tracking, license plate reader) around a crime scene. The most probable residential locations of serial offenders based on the relative locations of their crime sites can be found by geographic profiling [101-103]. Besides this, computer-assisted queries and analysis of intelligence and sensor database support crime analyst to find suspects [8].

2.2.4 Predicting Victims of Crimes

Methods for predicting victims of crimes mainly focus on offenders, crime locations, and times of heightened risk. These methods are used to identify groups or, in some cases, individuals who are likely to become victims of crime, e.g., groups associated with various types of crime, individuals in proximity to at-risk locations, individuals at risk of victimization, and individuals at risk of domestic violence [104]. There is no dedicated model found in this type of prediction. Existing methods discussed above are used to predict people at high risk. Computer-assisted database queries play a major role in this case. Sometimes risk terrain analysis is employed to detect a vulnerable population of an area [8]. Some simulation efforts have been seen to predict victims. Malleson et al. [105] applied agent-based simulation for the identification of the characteristics of individual victims and to predict the effects of urban regeneration on individual burglary risk [106].

2.3 Policing Strategy Studies

2.3.1 Randomized Experimental Design

Randomized experimental design provides a tool for developing criminal justice policy by establishing a relationship between interventions and outcome. It provides the greatest reliability and validity to explore a particular process or system [107]. This statistical method is applied to evaluate the effects of different policing strategies. Deterrent effects of police patrol on crime have been tested by Sherman et al. [108]. Foot patrol experiments in Philadelphia have been conducted by Ratcliffe [109, 110]. Different cities have run a pilot project of body-worn cameras (BWCs) with patrol officers to see if any improvement can be achieved by adopting new technologies. As a part of this, an experiment was conducted by Headley et al. [111] to study the impact of BWCs on patrol officer behavior, and the effect of BWCs on citizens' complaints against the police was investigated by Ariel et al. [112]. Telep et al. [113] studied the effectiveness of hot spots policing in Sacramento, California.

Although this is the most reliable method to study a relationship, the major limitation of this method is that it needs to conduct real experiments with of the actual implementation of a new system. Conducting experiments costs time and money without guaranteed benefits. In many cases, it is not practical to alter the existing system [114].

2.3.2 Optimization

Some research efforts on optimization in policing have been attempted. Saladin [115] introduced goal programming for patrol allocation to meet some performance measures. A queueing model was implemented by Linda Green [116] for multiple dispatching of police cars. The number of police patrols per period per day of a week per precinct achieved from his model remained unchanged throughout the year. Curtin et al. [117] applied a maximal covering location model for patrol allocation to maximize the number of weighted incidents covered within the acceptable response time. Oghovese et al. [118] attempted to apply dynamic programming to determine optimal allocation of available police patrol officers without considering performance measures. They treated location as stage and state variable in each stage is the number of available patrol units for allocation. Since the model is not time dependent (such as per shift per month allocation), it cannot be considered as dynamic allocation. Linear programming with Bender's decomposition was applied for patrol allocation to optimize response time [24]. Most of the aforementioned research is valid for static allocation and a lack of research in optimization to minimize crime still exists.

2.3.3 Simulation

mathematical programming seeks an optimal or near-optimal solution of a problem considering some limitations from application perspective. The model typically simplifies the real problem without including all aspects of the problem [119, 120]. Simulation can overcome these limitations. Simulation is an excellent decision support tool that seeks to mimic a real system via a computer model and facilitates 'What-if' scenario analysis by changing the values of model parameters without any physical change of a current system. Simulation fills the gap between the reality and hypothetical [121]. Bogard [122] states that it "produces a reality effect, while at the same time concealing the absence of the real." De Lint et al. [123] viewed simulation as a shift in policing to control crime.

Agent-based simulation has wide applications in the policing literature. Quijada et. al. [124] built an agent-based simulation model to evaluate different social policies (Education index, environmental index, unemployment rate, etc.) on crime reduction. Malleson et. al. [125] presented an agent-based model to predict burglary rate in Leeds, UK, and evaluate the effectiveness of the crime reduction strategy of target hardening

[126]. Devia and Weber [127] investigated the influences of police distribution (uniform, random, hot-spot, mixed strategy) and police types on street crime reduction. Weisburd et al. [128] concluded that hot-spot policing has a significant impact on street robberies in a large area by agent-based simulation. Michael Yonas et al. [129] studied effectiveness of community-wide and spatially focused interventions in reducing offences.

Discrete-event simulation (DES) is another simulation tool that can be used in crime analysis. Although the applications of DES on criminology are not many, it is becoming more popular. Ortiz et al. [130] used DES to model regional level interactions of the illegal drug supply chain. Using DES, police staffing decisions based on some performance measures are evaluated by Srinivasan et al. [40].

2.3.4 Dynamic Policing

Hot spot policing has been proven its effectiveness of preventing crime and disorder in crime hot spots [128]. More police resources need to be deployed to high crime areas [131, 132]. Some research efforts [115, 117] have been found that were trying to optimize police staff allocation, but these studies could not address dynamic nature of crime. The dynamic nature of crime detected by Ratcliffe [133] and de Melo [134] and spatial displacement of crime studied by Weisburd et al. [135, 136], Bowers et al. [137, 138], Guerette et al. [139]. Since crime is highly dynamic over space and time [140], dynamic allocation of police resources might be more effective than the current static approach. Yang’s [141] ozone pollution paper demonstrated that dynamic optimization is more cost-effective for a complex system that is clearly dynamic, and this dissertation work is exploring this fact through the dynamic allocation of police patrols and DPUs.

Effects of a disruption unit (DU) have been studied by Jang et al. [142]. They explored which policing action is the most significant for reducing crime when DU deployment is on rotational basis to crime hot spots. Although DU deployment seems dynamic, it does not address regular police units. The dynamic allocation of regular patrols and other dynamic police units will be studied in this research.

2.3.5 Hot Spot Policing

Hot spot policing has drawn significant attention to the policing community. Directed patrol and Problem-Oriented Policing (POP) are the most common strategies applied to control crime in hot spots [143]. Directed patrol "involves assigning officers to intensively patrol particular areas at particular times (while often freeing them from answering calls-for-service)" [143]. POP analyzes crime data, identifies underlying causes of specific crime problems, and design strategies based on the analysis. It also involves community representatives for better performance [56, 144, 145]. Randomized experimentation is frequently used to evaluate the effectiveness of hot spot policing strategies.

Some experiments, e.g., the Minneapolis Hot Spots experiment [108], the Sacramento, California Hot Spots experiment [113], the Jacksonville, Florida randomized control trial [143], the Philadelphia foot patrol experiment [110], the London hot bus stops experiment [146], etc., proved the effectiveness of directed patrol. How much time police officers should spend at hot spots is a general debate of directed patrol. In this context, Koper [147] recommended that random rotation of police officers between hot spots and about 15 min patrolling at each of them would be ideal for significant impact of crime reduction. In a separate experiment, this recommendation is reinforced by Telep et al. [113].

To control street-level prostitution and drug crime in Jersey City, NJ [136], POP was applied and found to be very effective. Some examples of POP interventions are the Boston Safe Street Team hot spots policing program [148], the Lowell, MA policing crime and disorder hot spots project [149], reducing illegal drug dealing at nuisance bars in Pittsburgh, PA [150], civil remedy program [151] in Oakland, CA, etc.

In addition to the effectiveness at reducing crime at a hot spot, researchers studied the impact of hot spot strategies on crime displacement and diffusion of crime control benefits. “Displacement refers to the shift of crime either in terms of space, time, or type of offending from the original targets of crime prevention interventions [152],” and diffusion of crime control benefits refers to “the spread of the beneficial influence of an intervention beyond the places which are directly targeted [153].” Diffusion of crime control benefits to the adjacent areas of hot spots have been evidenced by some studies [128, 136, 146, 154], but no significant crime displacement has been concluded [136, 155].

2.4 Discrete-Event Simulation

2.4.1 Basic Concepts

Schmidt and Taylor [156] defined a system as a collection of entities, e.g., people or machines, that act and interact together toward the accomplishment of some logical end. Systems can be categorized into two types: discrete and continuous. In a *discrete* system, state variables change instantaneously at separate points in time whereas state variables change continuously with time in a *continuous* system [157].

Discrete-Event Simulation (DES) models the operation of a system as it evolves over time, in which the state variables change instantaneously at discrete points in time. These points in time are the ones at which an event occurs, where an event is an instantaneous occurrence that may change the system’s state. Most DES models have some common components programmed in a general-purpose language. These are:

<u>System state:</u> The collection of state variables necessary to describe the system at a particular time.

Simulation clock: A variable giving the current value of simulated time in whatever measurement units are suitable for the system.

Event list: A list that contains the next time when each type of event will occur. Sometimes it is called “Pending event set” [158].

Statistical counters: Variables used for storing statistical information about system performance.

Initialization routine: A subprogram to initialize the simulation model at time 0.

Timing routine: A subprogram that determines the next event from the event list and then advances the simulation clock to the time when that event is to occur.

Event routine: A subprogram that updates the system state when a particular type of event occurs. There is one event routine for each event type.

Library routines: A set of subprograms used to generate random observations from probability distributions that were determined as part of the simulation model.

Report generator: A subprogram that computes estimates from the statistical counters of the desired measures of performance and produces a report when the simulation ends.

Main program: A subgroup that invokes the timing routine to determine the next event type and advances the simulation clock, then transfers control to the corresponding event routine to update the system state. The main program may also check for termination and invoke the report generator when the simulation ends [157, 158].

2.4.2 Simulation Time-Advance Mechanisms

Time advance mechanism ensures that events occur in correct order. There are two principal approaches have been followed for advancing the simulation clock:

Next-event time advance: In this mechanism, the simulation clock is initialized at 0. The first time of occurrence for each event type is determined and stored in the event list. From the event list, the most imminent future event is determined and the simulation clock is advanced to that time, at which point the state of the system is updated accordingly. A new event (if any) of this type will be scheduled, and the event list is updated. Advancing the clock will be continued until the termination condition is satisfied [159].

Fixed-increment time advance: In this approach, the simulation clock is advanced in increments of exactly Δt time units, where Δt is chosen appropriately. After each advance of the clock, a check is made to find if any events should have occurred during the previous interval of length Δt. If one or more events were scheduled during this interval, then these events are considered to occur at the end of this interval, and the system state and the statistical counter are updated accordingly [157, 160].

The next-event time advance mechanism is typically used in DES. Next-event time advance has a computational advantage over the fixed-increment time advance mechanism as next-event time advance ignores inactive time periods by jumping the clock from event time to event time [160].

2.5 Simulation Optimization

Simulation optimization can be defined as a process of finding the optimal values of some decision variables (simulation inputs) given an objective function (in terms of simulation output) with a set of constraints [161, 162]. A simulation experiment evaluates the effects of different settings of input variables of a system. Researchers are often interested in finding the optimal values of those inputs. One way to achieve optimal values is to run a simulation for each possible scenario. Often this is not realistic because there are too many possible values of input variables, and the simulation model might be too complicated and expensive to run for many inputs. To find the optimal values of input variables rather than trying all possible scenarios, an optimization model is integrated with a simulation model, leading to what is called simulation-optimization [163, 164]. A simulation optimization model is shown in Figure 2-1. The figure describes a loop that sends input from an optimization strategy to the simulation model, and then sends the simulation output to provide feedback on the search for the optimal solution [165]. One substantial limitation of simulation-optimization is that it does not guarantee an optimal solution. In addition, it can be difficult to create a model of a dynamic system and to define the objective function [166, 167].

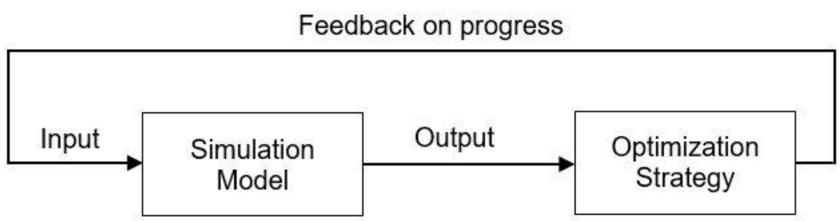


Figure 2-1 A simulation optimization model [165].

Chapter 3

DYNAMIC POLICING SIMULATION FRAMEWORK

In this research, a dynamic policing simulation framework based on prediction-led policing is developed to study dynamic strategies for policing. Through an iterative process, the framework provides an analytical structure to study hypothetical approaches for dynamic policing without requiring the significant cost and inconvenience of real implementation. The framework has three modules, as mentioned in Section 1.2. In this chapter, Section 3.1 discusses each module from the prediction-led policing perspective. The three modules of the framework and how they share information to each other are discussed in Section 3.2.

3.1 Framework from the Prediction-led Policing Perspective

One of the motivations of this dissertation is the prediction-led policing process discussed in Section 1.1. The decision strategy module, predictive policing module, and simulation module are the components of the developed framework and these modules can be described in terms of the prediction-led policing concept.

For the decision strategy module, a static decision-making structure will not work. Policies for police operations must be dynamically dependent on the criminal response and the crime prediction, as shown in Figure 3-1. The highlighted loop iterates from the criminal response, through new data to crime prediction, to yield an updated action for police operations that is implemented as an intervention, and produces a potentially different criminal response. Hence, there is a need to define new dynamic policing strategies that can be updated via this iterative loop

Figure 3-1 Decision strategy module from the prediction-led policing perspective.

Figure 3-2 Predictive policing module from the prediction-led policing perspective.

The predictive policing module in the framework can be diagrammed via prediction-led policing shown in Figure 3-2. This loop iterates from police operations, observes the criminal response to intervention, obtains new data, and then updates the predictive policing analysis to yield a new crime prediction that informs actions for police operations. The current paradigm for predictive policing does not execute the complete loop in Figure 3-2. Rather, it starts with data collection, conducts and analysis of that data, and ends with a crime prediction. What is missing the current predictive policing approach is the connection with police operations and criminal response. In prediction-led policing, the paradigm of predictive policing must be shifted to consider how police operations and the subsequent criminal response affect the prediction of future crime. In effect, current predictive policing methods are only accurate under the assumption that police operations do not change and criminal behavior does not change. Hence, this renders the current predictive policing paradigm ineffective for prediction-led policing.

Figure 3-3 Simulation module from the prediction-led policing perspective.

Finally, the appropriate simulation module, which is the focus of this dissertation, must work with the predictive policing module, to dynamically update crime distributions, and with the decision strategy module, to dynamically alter police operations. As shown in Figure 3-3, the loop from the simulation module perspective iterates from the data collection to generate the crime prediction that informs police operations and results in a potentially new criminal response. The crime prediction, police intervention, and the altered environment of crime are then incorporated into new data collection that is used to update the predictive policing analysis.

3.2 Dynamic Policing Simulation Framework

The purpose of this chapter is to create a general dynamic policing simulation framework that has the potential to study and, ideally, optimize dynamic policing strategies via the prediction-led policing structure. In dynamic policing, the decision strategy in each decision stage might be different in response to the crime environment. Here, the decision stage can be defined as the time scale or frequency of updating dynamic policing decisions. The general structure of the dynamic policing simulation framework is discussed in this section. The framework comprises three modules: decision strategy, predictive policing, and simulation, which are shown with three solid circles in Figure 3-5. The arrows indicate, what information is passed back and forth to each module. Three modules are discussed separately in the following subsections.

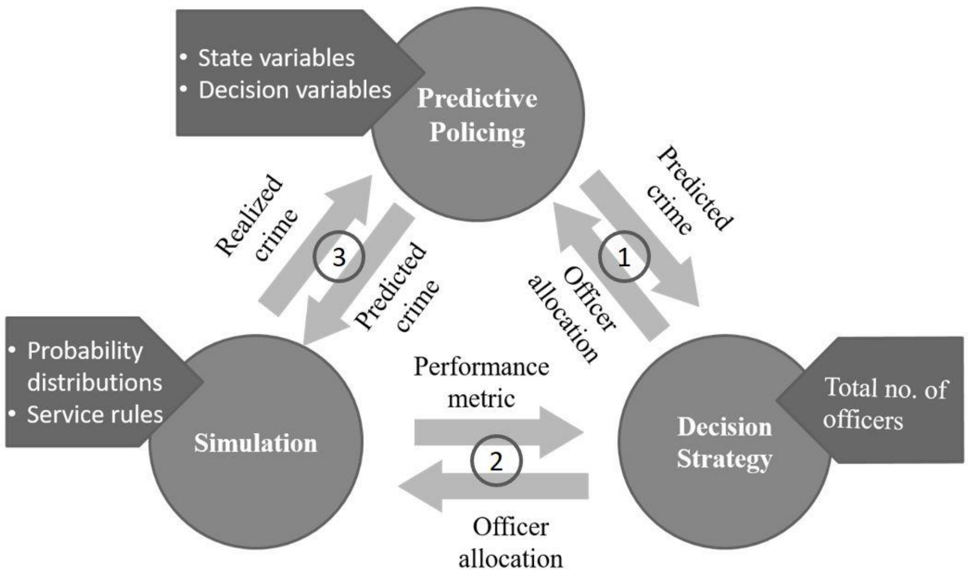


Figure 3-4 Dynamic policing simulation framework.

3.2.1 Decision Strategy Module

The decision strategy module makes decisions on police operations, such as intervention strategies and patrol allocation strategies, using available resources. The decisions are dynamically dependent on the past information on police decisions and the criminal environment, and the current state of the policing system. Example decisions include the dynamic allocation of patrol officers across beats, hot spot policing, CCTV surveillance, body worn cameras, community watch, special signage, home security campaigns, etc. As discussed in Section 1.2, constraints of the system must be considered when conducting decision-making. The decision strategy module needs to incorporate these and makes decision within the available resources.

Consider the case of patrol officer allocation strategies. The primary constraint in this case is the number of available patrol officers. This can be further constrained by the preferences of the officers for specific beats, days and/or shifts. Since the policing system is dynamic, the decision strategy module evolves dynamic policing decisions with time. For dynamic allocation, the number of patrol officers allocated to different beats, days, and shifts could vary depending on the state of the criminal environment. This allocation could vary at whatever time scale is deemed appropriate, e.g., weekly, monthly, or seasonally. Consider the case of hot spot policing. Since hot spots can vary in magnitude, time, and location, it could be appropriate for the police to implement a DPU to move around the region, specifically patrolling hot spots. One decision pertains to how many officers are needed for form a DPU, and the other decision controls how the DPU conducts patrolling of hot spots. Constraints on DPUs would need to balance resources with other police activities, including both staffing and budgetary limitations. These two cases of dynamic policing decisions are executed for the APD case study in Chapter 5. However, these are only two examples, and the framework is intended to encompass any form of dynamic policing strategies.

Hot spot policing has been studied in the literature, as discussed in Section 2.3.5. Deployment of DPUs to crime hot spots for hot spot policing following hot spot policing strategies is made by the decision strategy module. In this case, only hot spots are targeted for special intervention to control crime levels. To do this, number of hot spots are identified based on crime threshold. Intervention strategy for identified hot spots will be determined with the available DPUs. DPUs can monitor hot spots following a directed patrol or POP strategy, and crime will be probabilistically reduced by the estimated crime reduction factor *r,* as shown in Figure 3-5.

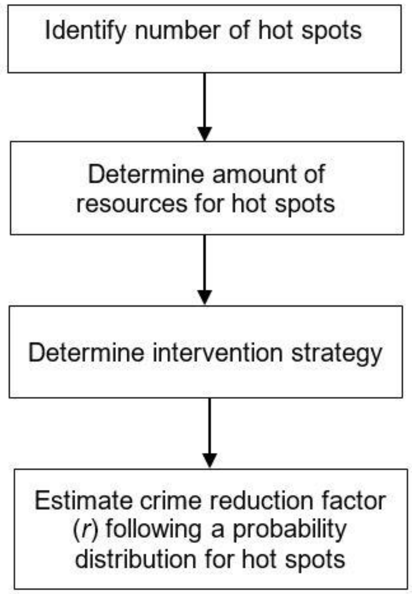


Figure 3-5 Hot spot policing parameterization.

An Example of Directed Patrol:

In this example, shown in Figure 3-6, six hot spots (H1, H2, H3, H4, H5, H6) have been identified, and a DU is randomly rotated across those hot spots. The length of stay at each hot spot is varied from 10 to 20 minutes following a uniform distribution. After a complete rotation over the six hot spots, represented by shaded boxes, the DU begins a new rotation.

In the figure, the DU starts patrolling at H2 and spends 15 minutes there, then it moves to H3, H6, H4, H1, H5 and spends 15, 20, 15, 20, 15 minutes at each these, respectively. The travel time from one hot spot to another hot spot is assumed to be 5 minutes. When the first rotation is completed, the next rotation randomly starts with H3. At the end of each decision stage, the total DU stay time in each hot spot is calculated and based on this, crime levels will be reduced by the probabilistically-specified crime reduction factor, *r*.

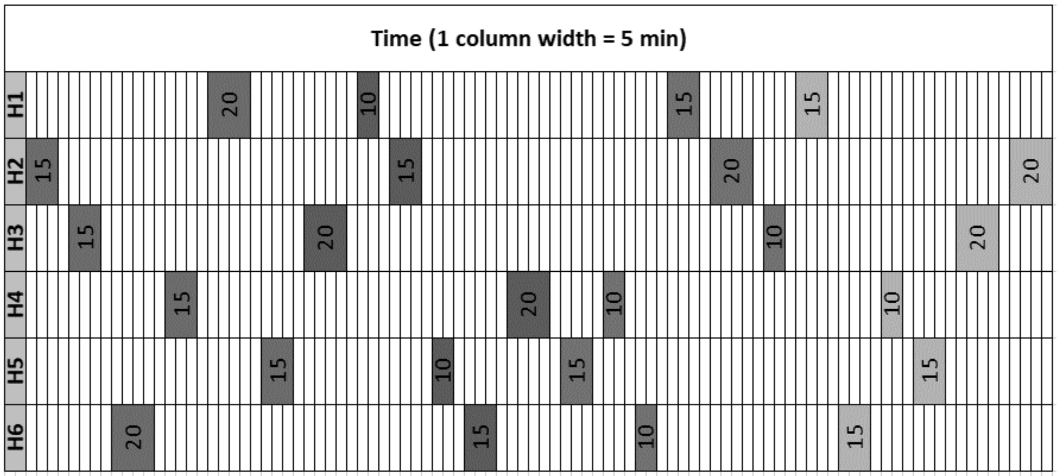


Figure 3-6 Example of hot spot policing intervention following directed patrol strategy.

The decision strategy module could also seek to optimize decisions, for example, minimize predicted crime, or minimize waiting time for calls, or to balance officers' utilization, etc. Currently, there are no optimization tools available to conduct such optimization for dynamic policing. One vision for the framework is to enable the development of such optimization tools. The optimization could be constructed using methods from dynamic programming [168-170], multi-objective optimization [171, 172], etc. to dynamically evolve optimized decision over time. However, much research is still needed to understand how these methods can be used to formulate appropriate and practical optimization algorithms for policing.

3.2.2 Predictive Policing Module

The predictive policing module must work appropriate within a dynamic system. Hence, it is proposed that this module predicts crime using a state transition model [173-176]. State transition models are used to evolve dynamic systems over time. For the dynamic policing framework, it is important for the predictive policing module to take into account the decision strategy, such as police patrol allocation. The decision strategy module depends on the predictive policing module to predict crime. If the crime prediction is constructed independently of the decision, then there the link between police operations and crime prevention is lost (refer to Section 3.1). Hence, the predictive policing module must utilize the past history of the system and possible decisions to predict future crime.

The challenge here is creating a structure that enables an appropriate predictive policing model for dynamic policing. All predictive policing models that do not involve a decision strategy would be inappropriate, and that encompasses most of the predictive policing literature. However, the literature does offer a few appropriate models. One example is the predictive model by Deadman and Pyle [9] that incorporates the size of the patrol force. This predictive policing model is employed in Chapter 5 to demonstrate the dynamic policing simulation framework for the APD case study. Another example of an appropriate prediction model was presented by Jang et al. [142]. For a Dallas case study, they incorporated actions of DUs, such as, the number of days DUs were dispatched, the number of stops by DUs, etc. However, more research is needed on incorporating actual actions, allocations, interventions, or other decisions into predictive policing, so as to build the link between police operations and crime.

3.2.3 Simulation Module

The purpose of the simulation module is to study the performance of dynamic strategies within the dynamic policing system by actually integrating specific processes of the real system. The simulation module needs predicted crime and the dynamic decision strategy to evolve the system over time. The structural components and the constraints discussed in Section 1.2 can also be addressed in the simulation module. The simulation module can incorporate a variety of decision strategies separately or in combination. For example, the simulation could study both regular patrol officer allocation and DPUs separately or together to evaluate their performance. The simulation module has the capability to study "what-if" scenarios. As part of these studies, the constraints should be the inputs of the simulation module, so that modifications to police resources can be explored.

One primary structure for police operations is the 911 call structure, for which a call comes in, an operator takes information from the caller, the case is placed in a queue based on priority, a police unit is dispatched, the unit arrives on the scene, additional units could be dispatched, and finally, the call is cleared. DES (discrete-event simulation) is appropriate for this structure because it can represent the specific events that occur. With regard to police operations, DES can modify the number of patrol officers allocated to beats, days, and shifts, can allocate some officers to DPUS, and can modify rules for dispatching and monitoring hot spots. Another type of simulation model is an agent-based simulation. This could allow the study of interactions between different entities (agents) in the policing system, such as how criminals at hot spots will react to higher police presence. This type of simulation will be studied in future work.

To build the DES model to simulate the policing system, the components discussed in Section 2.4 must be constructed. The simulation is initialized with the decision made by the decision strategy module and predicted crime from the predictive policing module. The system states for the policing system can be officers' state: busy or idle, call queue status: empty or not-empty, etc. The unit of the simulation time can be varied depending on how the model has been constructed, e.g., the system can be monitored every second or every minute or every hour, etc. The events of the policing system include call-arrival events, service completion events, etc., that change the system state upon occurrence. For example, if a call comes in, it may change the queue status or an officer's status. The statistical counters that store statistical information could be number of calls cleared, the total delay of calls in queues, etc. The event list contains the list of the next event times when each event will occur. This event list is used by the timing routine to determine what would be the next event. Each of the next event times involve uncertainties following probability distributions. For example, the time when the next call arrives is determined by generating random numbers following a probability distribution (commonly an exponential distribution). The policing system can also be simulated the dispatching rule that determines how officers will be dispatched. As long as events can be modeled with discrete triggers, DES can incorporate them.

3.2.4 Interactions among Three Modules

First, appropriate data are needed to build predictive policing models that link decisions with crime. The process starts with an initial decision on a police action/intervention from the decision strategy module. The police action/intervention is sent to the predictive policing module, along with the past history and current state of the system, and the predictive policing sends predicted crime back to the decision strategy. The decisions and predicted crime can iterate back and forth to potentially optimize decisions, as indicated by "1" in Figure 3-4. The decision strategy is then sent to the simulation module to evaluate through loop 2. After evaluation, the simulation module sends performance metrics back to the decision strategy. The decision strategy will ultimately combine what information from loop 1 and loop 2 in order to identify an improved decision strategy.

Chapter 4

CASE STUDY

This chapter discusses a preliminary DES model with a case study of the city of Arlington, Texas. This preliminary model is built in WITNESS simulation software to represent the basic structure of the APD 911 call system, and it also provides a graphical animation of the simulation of the system. Section 4.1 introduces the Arlington, Texas police area, the policing system, and the available APD data. Section 4.2 discusses the three modules of the framework from the perspective of this particular case study, and the preliminary WITNESS simulation model is presented in Section 4.2.3 with a scenario analysis.

4.1 System Set-up and APD Data

4.4.1 Arlington Police Service Area

The Arlington, Texas police service area is shown in Figure A-1. It is divided into four districts: North, South, East, and West. Each district is also subdivided into eight beats. The four districts each have their own characteristics. North contains the entertainment district: Six Flags over Texas, which is a roller coaster park; Hurricane Harbor, which is a big water park.; the baseball stadium for the Texas Rangers; and a brand new stadium for the Dallas Cowboys football team. Hence, a distinct characteristic of North is the population of visitors to these attractions. South is the commercial district with many large shopping areas, such as the Parks Mall and the Arlington Highlands Lifestyle Center. The East district has industrial zones, such as the General Motors assembly plant. Finally, the West district is mostly residential area and generally quiet. Hot spots are most prevalent in North because of the tourism area, and can occur in South because of the shopping areas. By contrast, the West district generally has the lowest crime.

4.4.2 Shift Schedule

APD follows two different working shift schedules: 8-hr shift and 10-hr shift. There are six different shifts (Day_1, Day_2, Eve_1, Eve_2, Mid_1, Mid_2) in the 8-hr shift schedule. On the other hand, four different shifts (A, B, C, D) in the 10-hr shift schedule. In Figure 4-1, Start time and End time of each shift is shown. The active shift in the current simulation is determined from these START and END times. Each day is also divided into three patrol periods as Mid (12am – 8am), Day (8am – 4pm), and Eve (4pm – 12am) to predict crime per patrol period using the predictive policing model discussed in Chapter 5.

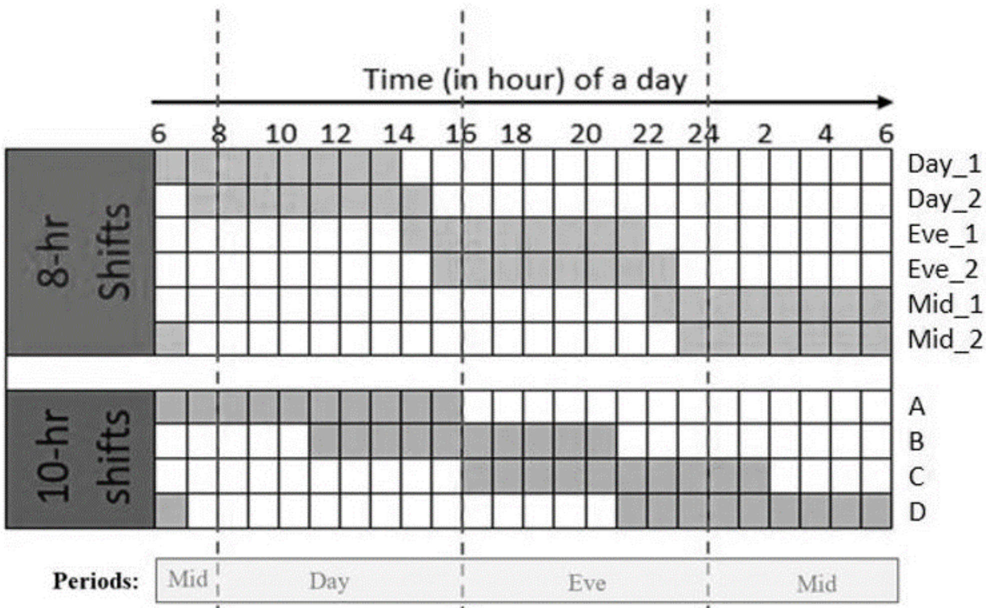


Figure 4-1 Shift schedules followed by APD.

4.4.3 Call Receiving and Dispatching System

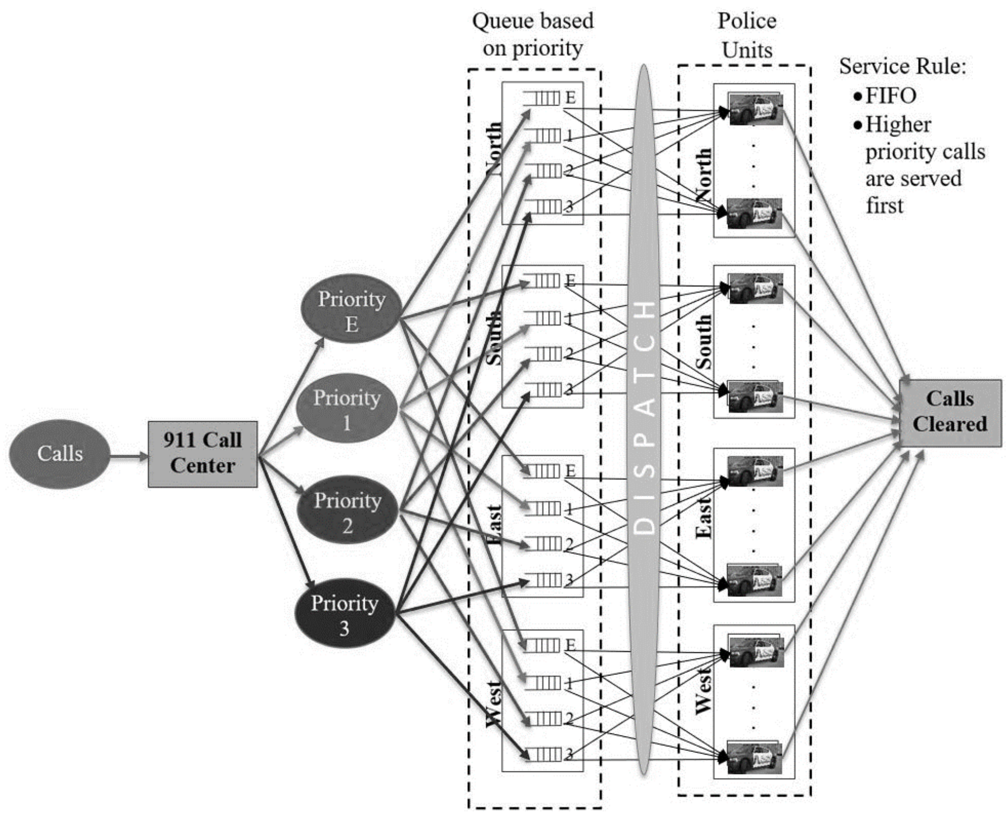


Figure 4-2 911 call receiving and dispatching system at district level.

Figure 4-2 shows how the 911 call receiving and dispatching system works, based on the information provided by APD. When a citizen makes a call, it enters into a 911 call center. The 911 operator collects relevant information to provide the proper services needed. Based on the collected information, the call is assigned one of four priority levels: E, 1, 2 and 3, where “E” represents emergency, which is the highest priority level and priority 3 has the lowest priority level. Then the call is sent to the corresponding queue to get service. The dispatcher of the district where the incident occurred assigns the closest available Police Unit (PU) using the geographic information system. Here, a PU represents one on-duty patrol officer in a car. The four districts work independently, i.e., officers can be dispatched to the calls of their corresponding districts only. This is how PUs in the current active shifts take care of the calls in the queues in their district, using the priority level and First-In-First-Out (FIFO) basis. Higher priority calls always require a faster response.

At the beat level, PUs are usually dispatched to their corresponding beat calls. For an emergency call, if the corresponding beat officer is not available, then the closest available beat officer is dispatched to that call and considered as a cross-beat call. In the WITNESS simulation cross-district calls are not allowed. Since the call center activities do not affect police deployment, the call centers are not considered as elements in the simulation model.

4.4.4 APD Data

Calls for Service (CFS) data from the years 2011 and 2012 have been provided by APD. Included in the 2011 data are 349,923 CFS events and included in the 2012 data are 360,824 CFS events. Each CFS is categorized into one of four priority levels (E, 1, 2, and 3), based on the type of crime. Each CFS has corresponding beat, district, date/time, response time, priority, GIS coordinate, etc., information in the dataset.

4.2 Implementation of the Framework

4.2.1 Decision Strategy Module

At this point, as there is no decision strategy module that is able to handle the complexity of the system; a fixed decision strategy with regular patrol officers at the district level has been used. This allocation decision is used as input to the WITNESS model to evaluate. There is no hot spot policing or any other policing component considered. Table 4-1 presents how many officers were allocated to each district in each shift schedule for the 8-hr shift. For example, 9 officers were working in North in the Day_1 shift. Here, a total of

61 officers were working in each district in different shifts each day, so the total officer-hours was 488 (= 61*8) per day per district, and the total officer-hours per week per district was 3416 (= 488*7). If each officer works for 40 hours per week, then the average number of officers per week is 85.4 (3416/40). It was assumed that the same officers were working for the month, so, the average number of officers per district per month was 85.4 ≈ 86.

Table 4-1 Daily patrol officer-shift allocation for 8-hr shift at district level.

	Shift					
District	**Day_1**	**Day_2**	**Eve_1**	**Eve_2**	**Mid_1**	**Mid_2**
North	9	10	12	11	9	10
South	9	10	12	11	9	10
East	9	10	12	11	9	10
West	9	10	12	11	9	10

4.2.2 Predictive Policing Module

There was no predictive policing model fitted while the WITNESS model was being developed. Hence, the number of calls from the actual 2011 APD data was used by the simulation instead of predicted calls from a predictive policing model. Table 4-2 shows the number of actual calls per district per priority per period for January and July 2011.

Table 4-2 Number of calls per district per priority per patrol period.

			Number of Calls	
District	**Priority**	**Period**	**January**	**July**
North	E	Mid	16	16
		Day	10	12
		Eve	21	16
	1	Mid	563	772
		Day	673	818
		Eve	1020	1385

	2	Mid	124	143
		Day	345	365
		Eve	360	398
	3	Mid	572	691
		Day	1668	1957
		Eve	1875	1794
South	E	Mid	10	9
		Day	16	8
		Eve	20	19
	1	Mid	418	526
		Day	587	645
		Eve	923	1077
	2	Mid	131	180
		Day	406	349
		Eve	444	426
	3	Mid	503	581
		Day	1524	2044
		Eve	1126	1310
East	E	Mid	15	36
		Day	10	19
		Eve	30	38
	1	Mid	910	876
		Day	641	553
		Eve	1025	1203
	2	Mid	97	142
		Day	261	229
		Eve	287	305
	3	Mid	460	566
		Day	1307	1180
		Eve	1472	1463
West	E	Mid	12	11
		Day	16	14

		Eve	22	20
	1	Mid	545	694
		Day	561	674
		Eve	887	1124
	2	Mid	119	133
		Day	318	354
		Eve	340	376
	3	Mid	782	748
		Day	1800	1756
		Eve	1650	1981

4.2.3 Simulation Module

WITNESS (http://www.lanner.com/) is a discrete-event simulation tool that has been used to model manufacturing and business processes in 2D and also in 3D visualization. As preliminary work for this dissertation research, a simple WITNESS model was constructed to build an understanding of the policing system's dynamic behavior. WITNESS simulation models have been developed at the district level with 8-hr shift and 10-hr shift. This WITNESS model is not integrated with the other two modules. Hence, inputs from other two modules are fed into the simulation model manually. In 8-hr shift model, six eight-hour shifts in Figure 4-1 are named as Day_1 (6am – 2pm), Day_2 (7am – 3pm), Eve_1 (2pm – 10pm), Eve_2 (3pm – 11pm), Mid_1 (10pm – 6am), and Mid_2 (11pm – 7am) and in 10-hr shift model, four ten-hour shifts are named as A (6am – 3pm), B (11am – 9pm), C (4pm – 2am), and D (9pm – 7am).

4.2.3.1 Simulation Assumptions

The WITNESS simulation models have been evolved under the following assumptions:

1) Calls arrivals assume a Poisson process. Hence, call interarrival times are assumed to follow an exponential distribution. Preliminary analysis has conducted to verify the exponential distribution assumption for call interarrival data per priority per period for different months. See analysis n Appendix B. In this analysis, different distributions could be better fit for different priority-period combination. However, overall, the assumption of the exponential distribution was reasonable.
2) Service time is the sum of travel time and response time. Response time is defined as the length of time (in minutes) that the primary unit took to respond to the call, from arrival on the scene until the primary unit was released back into service. Since all police units in active shifts are responsible for clearing calls within their district, travel times are very low and not significant. Only response times are considered as service times.
3) All police units are assumed identical, with the same skill and same service time distributions. Only one officer is dispatched to a call.

4.2.3.2 WITNESS Model for 8-hr Shift

The model is built based on the dispatch rule described in Section 4.4.3. In the available data, it is observed that call interarrival times vary by month and by three different patrol periods of a day. Mean interarrival times in minutes per district per priority per period are used as input parameters of the exponential distributions that generate call arrival times. Table 4-4 shows the mean interarrival times per district per priority per period for January and July 2011, which are derived from the call data shown in Table 4-2. It can be seen from these two tables that average crime rates (number of CFS per minute) are higher in the evening and in July, as summer has higher crime incidents than any other season. On the other hand, CFS service times are not significantly varied by districts and patrol periods, but do vary by priority level. Hence, service times for different priority levels are the model inputs to determine PUs' service times. Table 4-3 shows fixed response times per priority call obtained from the 2011 data that are used as service times in the model.

Table 4-3 Fixed response times per priority call.

Priority	Response Time (min)
E	6.87
1	9.2
2	25
3	43.5

In Appendix B, a screenshot of the full WITNESS model with the 8-hr shift is shown in Figure B-9, and a North district model is shown in Figure B-10. Here, CFS_N_E represents CFS of North with priority E, CFS_Q_N represents call center queue for all types of CFS in North, CR_N represents the call center in North, Q_N_E represents the queue of CFS_N_E before getting service, and PUs_N_Day_1 represents police units of North working in shift Day_1. Figure B-10 shows that 9 police units are working in shift Day_1 in North. All the notations in the model can be described in similar fashion. Since call centers do not take much time, they do not have impact on officers' allocation. Hence, the statistics of the call centers queues and call centers have been ignored in results analysis. Model input parameters are not interdependent. CFS data from 2011 is used to calculate mean interarrival times and service times to demonstrate the simulation model.

Table 4-4 Mean interarrival times of calls in January and July, 2011.

			Mean interarrival time (in minute)	
District	Priority	Period	January	July
North	E	Mid	930	930
		Day	1488	1240
		Eve	708.5714	930
	1	Mid	26.42984	19.27461
		Day	22.10996	18.19071
		Eve	14.58824	10.74368
	2	Mid	120	104.0559
		Day	43.13043	40.76712
		Eve	41.33333	37.38693
	3	Mid	26.01399	21.53401
		Day	8.920863	7.603475
		Eve	7.936	8.294314
South	E	Mid	1488	1653.333
		Day	930	1860
		Eve	744	783.1579
	1	Mid	35.4067	28.28897
		Day	25.21295	23.06977
		Eve	16.03467	13.81616
	2	Mid	113.5878	82.66667
		Day	36.65025	42.6361
		Eve	33.51351	34.92958
	3	Mid	29.5825	25.61102
		Day	9.76378	7.279843
		Eve	13.21492	11.35878
East	E	Mid	992	413.3333
		Day	1488	783.1579
		Eve	496	391.5789
	1	Mid	16.35165	16.9863

		Day	23.21373	26.90778
		Eve	14.51707	12.36908
	2	Mid	153.4021	104.7887
		Day	57.01149	64.97817
		Eve	51.84669	48.78689
	3	Mid	32.34783	26.28975
		Day	11.38485	12.61017
		Eve	10.1087	10.17088
West	E	Mid	1240	1352.727
		Day	930	1062.857
		Eve	676.3636	744
	1	Mid	27.30275	21.44092
		Day	26.52406	22.07715
		Eve	16.77565	13.23843
	2	Mid	125.042	111.8797
		Day	46.79245	42.0339
		Eve	43.76471	39.57447
	3	Mid	19.02813	19.89305
		Day	8.266667	8.473804
		Eve	9.018182	7.511358

The simulation is based on a M/D/S queuing model. Consider North in Figure B-10 as an example. CFS of different priorities are arriving into the model according to a Poisson process with corresponding mean interarrival times as shown in Table 4-4. They will wait in queue CFS_Q_N, if CR_N is busy, otherwise the CFS will go through CR_N and will be sent to the queues (Q_N_E, Q_N_1, Q_N_2, or Q_N_3) according to the priority levels to obtain service from PUs of the active shift, determined from Start times and End times of the shifts. If the simulation time is within 6am to 2pm of a day, shift Day_1 will be activated, and the PUs in shift Day_1 will take care of the CFS with corresponding service times from the queues based on FIFO. CFS_N_E will get service first, then CFS_N_1, CFS_N_2, and CFS_N_3 subject to the availability of PUs. Overtime is considered if any PU needs additional time for clearing the call after its corresponding shift has ended. Only the district PUs can be dispatched to corresponding district calls. Cross-district calls are not allowed in this model. Description of the WITNESS model with the 10-hr shift can be found in the paper [177].

4.2.3.3 Scenario Analysis

To understand the impact of the patrol officers' allocation, the model was run for the simulation time of one month with multiple replications using the available CFS data of 2011. In this scenario analysis, call rates of January and July were considered to see the impact on the 8-hour shift allocation. January and July represent winter and summer seasons, respectively, and January has lower crime rates compared to July crime rates. The performance of the system is monitored every minute in the WITNESS model.

From the simulation run with crime rates of January and July for the 8-hour shift, the average number of calls in queues (Avg size) and average amount of time that calls spent in queues (Avg Time) were compared in Table 4-5 for all priorities and districts. In the table, it is observed that in almost all cases Avg Size and Avg Time for July are greater than those for January, as crime rates in July are higher than crime rates in January.

Table 4-5 Average Size and Average Time of the queues in January and July, 2011.

	Avg Size		**Avg Time (minute)**	
Name	**January**	**July**	**January**	**July**
Q_N_E	0.01	0.01	14.95	14.36
Q_N_1	0.14	0.21	2.81	3.09
Q_N_2	0.01	0.02	0.71	0.83
Q_N_3	0.03	0.04	0.34	0.41

Q_S_E	0.02	0.01	16.63	17.51
Q_S_1	0.11	0.12	2.47	2.5
Q_S_2	0.02	0.02	0.81	0.82
Q_S_3	0.01	0.02	0.21	0.22
Q_E_E	0	0.01	3.85	3.24
Q_E_1	0.1	0.12	1.7	2.05
Q_E_2	0.01	0.01	0.72	0.73
Q_E_3	0.02	0.02	0.3	0.32
Q_W_E	0.02	0.02	19.58	16.49
Q_W_1	0.09	0.11	1.93	2.07
Q_W_2	0.01	0.01	0.53	0.5
Q_W_3	0.01	0.02	0.15	0.19

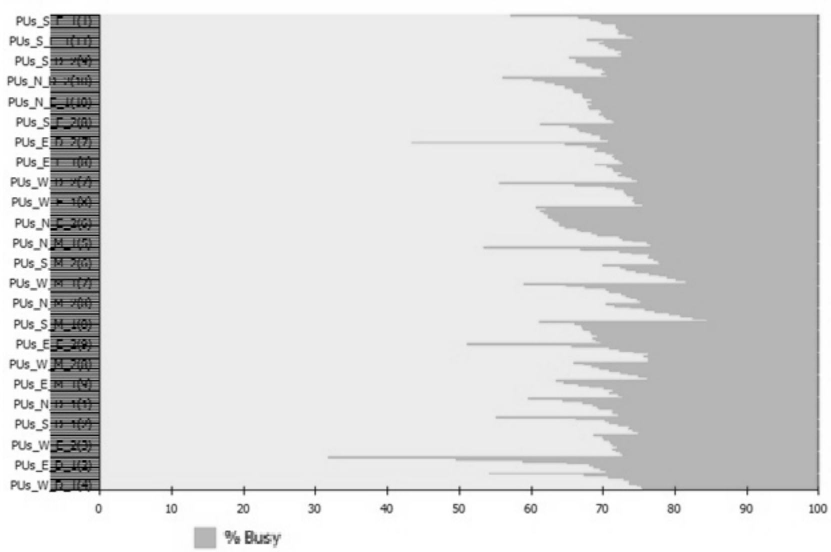


Figure 4-3 Average utilization of PUs by on shift time for January 2011.

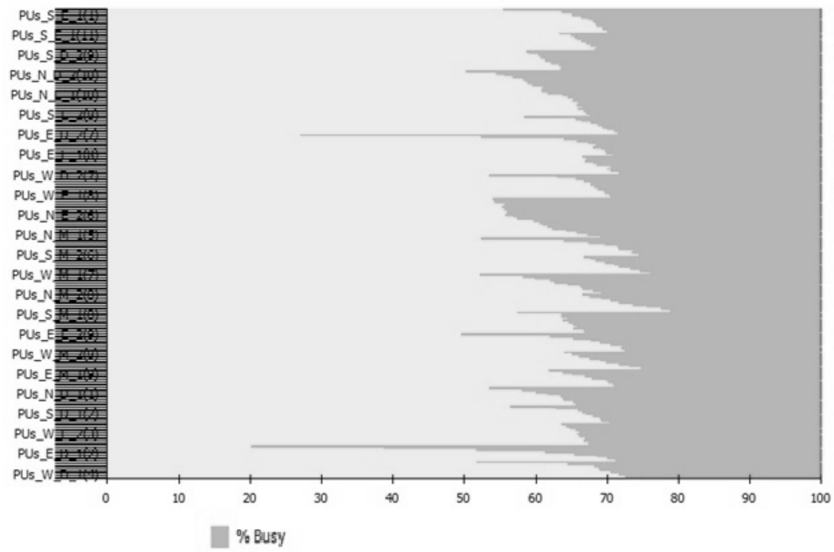


Figure 4-4 Average utilization of PUs by on shift time for July 2011.

The shaded region in Figure 4-3 and 4-4 represents the average utilization of on-shift officers. The area of the shaded region in Figure 4-4 is higher than the area of the shaded region in Figure 4-3. Since call rates are higher in July compared to January, percentage of busy time (% Busy) of police units is higher in July than in January.

Chapter 5

IMPLEMENTATION OF THE FRAMEWORK AND COMPUTATIONAL STUDIES

Computational studies of different scenarios are conducted through the implementation of the developed framework. Since the main focus of this dissertation is to build the simulation module and demonstrate an integration with the other two modules, a DES model has been built and coded in MATLAB for this purpose. This chapter illustrates how the simulation module works with other two modules in the framework with some real and hypothetical data. The framework is demonstrated based on APD data from 2011 and 2012 and on the system set-up discussed in Section 4.1. Both district level and beat level allocation decisions are studied and effects on the crime levels are investigated. Crime count is considered as the measure of crime level. Also DPUs are employed for hot spot policing.

The framework can provide analytical support to a police department for dynamic decision-making instead of the current annual static decisions. However, if the decision strategy is too dynamic, then it will disrupt the semblance of workload stability. In the framework, the time scale for the dynamic nature of decisions is flexible. It could be weekly, monthly, or seasonally. Weekly could be hard to manage for the police department, so, monthly and seasonal could be more reasonable time scales. All the scenarios presented in this chapter are based on monthly allocations and crime trajectories for different priorities and different locations for the year of 2012. “What-if” analyses for different scenarios is discussed in different sections. In the baseline scenario, a sample allocation provided by APD with no DPU is employed for the 8-hr shift. Alteration of the baseline by moving some officers from one location to another location, from one shift to another shift, hot spot policing with DPU deployment and by changing the shift schedules to 10-hr shift are applied for other “what-if” scenario analyses.

The MATLAB code was executed for each scenario on a desktop computer with an Intel(R) Xenon(R) CPU E3-1285 v6 processor at 4.10 GHz and 32 GB memory. On average, it takes about 65 hours (≈ 2.7 days) to complete each scenario with 300 replications and a 28-week warm-up simulation initialization period.

5.1 Framework Modules

5.1.1 Decision Strategy Module

The decision strategy module makes decision on how many available patrol officers will be deployed per beat per shift for a month. The total number of available officers is a main constraint along with a budget constraint. For hot spots, the intervention strategy and allocation of DUs to hot spots is another decision for this module. Since a decision strategy module is not currently available to conduct optimal decisions, hypothetical allocation data for the decision strategy module is used for the APD case study and passed on to the simulation module. A sample daily patrol-shift allocation for North has been provided by APD. The same allocation is used for other districts and corresponding beats for all months of a year. District and beat patrol-shift allocations are shown in Tables 5-1 and 5-2, respectively, as a base allocation. As discussed in Section 4.2.1, about 86 available patrol officers are working per district per month in this allocation strategy. According to Table 5-1; 19 officers are working in Day, 23 officers are working in Eve, and 19 officers are working in Mid. A total of 61 (= 19+23+19) patrol-shifts are working per district in same manner. Hence, 61 officer-shifts are distributed by about 31%, 38%, 31% to Day, Eve, and Mid, respectively. Based on this distribution, the total set of 86 officers per month is distributed to each patrol period, which corresponds to approximately 26, 32, and 26 officers per month to Day, Eve, and Mid, respectively. This allocation of officers is sent to the predictive policing module to predict crime count per district per priority per patrol period. This connection can be seen in Figure 3-4 as the outward arrow of the decision strategy module in loop 1.

Table 5-1 Daily patrol-shift allocation per district per patrol period for the 8-hr shift.

	Period		
	Day	**Eve**	**Mid**
North	19	23	19
West	19	23	19
East	19	23	19
South	19	23	19

Table 5-2 Daily patrol-shift allocation per beat per shift for the 8-hr shift.

		Shift					
District	**Beat**	**Day_1**	**Day_2**	**Eve_1**	**Eve_2**	**Mid_1**	**Mid_2**
North	210	1	1	1	1	1	1
	220	1	1	2	1	1	1
	230	1	1	1	1	1	1
	240	1	2	2	2	1	2
	250	1	1	2	2	1	1
	260	1	1	1	1	1	1
	270	2	2	2	2	2	2
	280	1	1	1	1	1	1
West	310	1	1	1	1	1	1
	320	1	1	2	1	1	1
	330	1	1	1	1	1	1
	340	1	2	2	2	1	2
	350	1	1	2	2	1	1
	360	1	1	1	1	1	1
	370	2	2	2	2	2	2
	380	1	1	1	1	1	1
East	410	1	1	1	1	1	1
	420	1	1	2	1	1	1
	430	1	1	1	1	1	1
	440	1	2	2	2	1	2
	450	1	1	2	2	1	1
	460	1	1	1	1	1	1

	470	2	2	2	2	2	2
	480	1	1	1	1	1	1
South	510	1	1	1	1	1	1
	520	1	1	2	1	1	1
	530	1	1	1	1	1	1
	540	1	2	2	2	1	2
	550	1	1	2	2	1	1
	560	1	1	1	1	1	1
	570	2	2	2	2	2	2
	580	1	1	1	1	1	1

For hot spot policing, a beat is considered as a hot beat if the total crime count for a given month is equal or more than the crime threshold. Here, the crime threshold used is 150. A DU is deployed to hot beats based on the availability. It is assumed that crimes are affected only in hot beats for DU intervention, and crime in other beats is not affected. The directed patrol intervention strategy discussed in Section 3.2.1 is followed, with the exception that a DU can stay at the current hot beat for next move. For the next move of a DU, the next hot beat is selected at random using a discrete uniform distribution. In this case study, the DU stay time at each hot beat is chosen by a continuous uniform distribution with minimum and maximum stay times of 14 and 16 minutes, respectively. Decisions on regular patrol officer and DU intervention for hot beats are sent to the simulation module. This connection can be seen in Figure 3-4 through the outgoing arrow of loop 2.

5.1.2 Predictive Policing Module

The predictive policing module predicts crime counts per district per priority per period for a month using a state transition model. For this purpose, a state transition model that relates crime with the number of officers is needed, as discussed in Section 3.2.2. To build a proper state transition model for the dynamic policing framework, Deadman and Pyle's equation [9] shown in equation 5.1, was used as a state transition model.

$$Crime_t = \beta_1 Crime_{t-1} + \beta_2 Crime_{t-2} + \beta_3 E_t + \beta_4 E_{t-1}$$
$$+ \beta_5 Con_t + \beta_6 Con_{t-1} + \beta_7 Pol_t + \beta_8 Pol_{t-1} + \gamma \qquad (5.1)$$

where,

Crime_t = Predicted crime rate at month *t,*

Crime_{t-1} = Crime rate at month *t*-1,

Crime_{t-2} = Crime rate at month *t*-2,

E_t = Predicted unemployment count at month *t*,

E_{t-1} = Unemployment count at month *t*-1,

Con_t = Predicted conviction rate at month *t*,

Con_{t-1} = Conviction rate at month *t*-1,

Pol_t = Number of police officers at month *t*,

Pol_{t-1} = Number of police officers at month *t*-1,

β = Coefficients to be estimated,

γ = Intercept.

The above state transition model is estimated for each district-priority-period combination using 2011 APD crime data, unemployment data (https://fred.stlouisfed.org/search?st=unemployment+of+Dallas+fort+worth), conviction rate data (www.txcourts.gov/media/885306/Annual-Statistical-Report-FY-2011.pdf), and artificial police allocations due to the unavailability of actual APD allocation data. A total of 48 models were constructed for 48 district-priority-period combinations. These are given in Table C-1. Unemployment count, conviction rate, and the artificial police allocations are given in Table 5-3, Table 5-4, and Table 5-5, respectively.

Table 5-3 Unemployment count per month.

Month	**Year 2011**	**Year 2012**
January	15921	14047
February	15261	13986
March	15113	13058
April	14437	12397
May	14662	13050
June	16251	14179
July	15999	14196
August	15701	13908
September	15580	12355
October	14892	12232
November	13886	11726
December	13458	11997

Table 5-4 Conviction rate per month.

Month	**Year 2011**	**Year 2012**
January	63%	66%
February	64%	69%
March	68%	68%
April	67%	70%
May	70%	71%
June	69%	69%
July	68%	70%
August	65%	68%
September	68%	68%
October	69%	69%
November	69%	69%
December	68%	72%

Table 5-5 Artificial police allocation data.

Month	**Mid**	**Day**	**Eve**
January	25	20	16
February	16	18	12
March	14	13	18

April	14	17	10
May	12	11	14
June	10	19	15
July	8	13	20
August	10	10	23
September	9	16	17
October	14	21	21
November	15	15	9
December	25	20	16

The state transition model in equation 5.1 predicts crime rate. The crime rate is the reported crime count per thousand population. The predicted crime rates are converted to crime counts by multiplying with population in thousands of the corresponding district given in Table 5-6. To predict crime rate for a simulated month, crime rates for November and December 2011 are used as initial points.

Table 5-6 Population of each district in thousand.

District	**Population**
North	40.569
West	81.309
East	93.633
South	159.794

Although predicted crime counts per district per priority per patrol period can be obtained from the above discussed approach, predicted crime counts per beat per priority per patrol period are needed for the simulation input to produce simulated crime counts at beat levels. To distribute district crime counts over corresponding beats, the percentage of respective district total crime counts for each beat from the previous month is used. For example, to distribute the predicted crime count of each district over the corresponding district beats for the next month, the percentage of respective district total crime counts for each beat was used from December 2011, as an initialization. Once the simulated crime count for each beat in a simulated month is obtained based on the calculated beat crime, the district total crime is calculated and the percentage of district total crime counts for each beat is updated. Then this updated percentage of district total crime counts is used to determine the distributed crime count for each beat in the next month. This approach is followed by each priority and by each patrol period.

As an example, from the December 2011 crime data, crime count for each beat was obtained from the data set. Total district crime count can be calculated from beat crime counts for each district, and the percentage of respective district total crime counts for each beat is calculated by beat crime counts. Table 5-7 shows the calculated percentage of respective district total crime counts for each beat, which is used to distribute predicted district crime counts to each corresponding beat in the next month. In Table 5-4, the total crime count for North is calculated by summing up all the beat crime in North, which is 912. The percentage of North crime for beat 210 can be calculated as (79*100/912), which is 8.66. The percentage of West crime for beat 370 can be calculated as (108*100/914), which is 11.82. Similarly, the percentage of district total crime for each beat can be calculated.

Table 5-7 Initialize using December 2011.

District										
North	Beat	**210**	**220**	**230**	**240**	**250**	**260**	**270**	**280**	**Total**
	# Crime	79	104	87	126	93	132	168	123	912
	% Total	8.66	11.40	9.54	13.82	10.20	14.47	18.42	13.49	
South	Beat	**510**	**520**	**530**	**540**	**550**	**560**	**570**	**580**	
	# Crime	87	86	90	292	114	102	73	108	952
	% Total	9.14	9.03	9.45	30.67	11.97	10.71	7.67	11.34	
East	Beat	**410**	**420**	**430**	**440**	**450**	**460**	**470**	**480**	
	# Crime	117	103	97	127	133	80	75	87	819
	% Total	14.29	12.58	11.84	15.51	16.24	9.77	9.16	10.62	
West	Beat	**310**	**320**	**330**	**340**	**350**	**360**	**370**	**380**	
	# Crime	96	132	103	106	117	126	108	126	914
	% Total	10.50	14.44	11.27	11.60	12.80	13.79	11.82	13.79	

In Table 5-8, the crime counts for North, South, East, and West are predicted as 850, 901, 758, and 998, respectively, for the next month. These district level crime counts are distributed into beats by the percentage of respective district total crime counts obtained from Table 5-7. For example, the crime count for beat 550 can be calculated as (901*11.97/100) = 107.85. All the calculated values are rounded down for implementation in the simulation. That means the predicted crime counts for beat 550 in the simulation is 107. Since the numbers are rounded down, there is a crime count discrepancy. This crime count discrepancy is added to the beat that has the maximum percentage of district total crime. After predicting crime counts, they are sent to the simulation module to simulate crime following Poisson process. This connection can be seen in Figure 3-4 through the outgoing arrow in loop 3.

Table 5-8 Predicted crime count of each district is distributed to corresponding beats using percentage of district total crime counts from December 2011 for the next month.

District										
North	Beat	**210**	**220**	**230**	**240**	**250**	**260**	**270**	**280**	**Total**
	# Crime	73	96	81	117	86	123	160	114	850
	% Total	8.66	11.40	9.54	13.82	10.20	14.47	18.42	13.49	
South	Beat	**510**	**520**	**530**	**540**	**550**	**560**	**570**	**580**	
	# Crime	82	81	85	279	107	96	69	102	901
	% Total	9.14	9.03	9.45	30.67	11.97	10.71	7.67	11.34	
East	Beat	**410**	**420**	**430**	**440**	**450**	**460**	**470**	**480**	
	# Crime	108	95	89	117	126	74	69	80	758
	% Total	14.29	12.58	11.84	15.51	16.24	9.77	9.16	10.62	
West	Beat	**310**	**320**	**330**	**340**	**350**	**360**	**370**	**380**	
	# Crime	104	144	112	115	127	142	117	137	998
	% Total	10.50	14.44	11.27	11.60	12.80	13.79	11.82	13.79	

5.1.3 Simulation Module

The simulation module, which is the main focus, simulates crime for the next month based on the predicted crime from the predictive policing module. Simulated beat crime counts are shown in "# Crime" rows in Table 5-9. From these simulated beat crimes, the total district crimes are recalculated and the percentage of district total crime for each beat is updated and used in the following month. The "% Total" rows in Table 5-9 are the updated percentages of district total crime count. The simulation module sends these simulated (or realized) crimes back to the predictive policing module to predict crimes for the following month. This connection can be seen in Figure 3-4 through loop 3.

Table 5-9 Simulate next month's crime and update percentage of district total crime counts for each beat.

District										
North	Beat	**210**	**220**	**230**	**240**	**250**	**260**	**270**	**280**	**Total**
	# Crime	72	93	75	115	82	120	192	110	859
	% Total	8.38	10.83	8.73	13.39	9.55	13.97	22.35	12.81	
South	Beat	**510**	**520**	**530**	**540**	**550**	**560**	**570**	**580**	
	# Crime	80	75	80	310	104	90	70	99	908
	% Total	8.81	8.26	8.81	34.14	11.45	9.91	7.71	10.90	
East	Beat	**410**	**420**	**430**	**440**	**450**	**460**	**470**	**480**	
	# Crime	103	89	83	110	165	70	65	75	760
	% Total	13.55	11.71	10.92	14.47	21.71	9.21	8.55	9.87	
West	Beat	**310**	**320**	**330**	**340**	**350**	**360**	**370**	**380**	
	# Crime	99	178	107	111	123	133	114	133	998
	% Total	9.92	17.84	10.72	11.12	12.32	13.33	11.42	13.33	

For the hot spot policing decision made by the decision strategy module, the simulation module simulates the DUs rotation over hot beats. Crime count is adjusted by the crime reduction factor following a uniform distribution with a minimum reduction of 0.06 per hour and maximum reduction of 0.13 per hour. The predicted crime counts for hot beats are adjusted, and the total percentage of reduction are calculated. The original predicted crime counts are also reduced by these percentages for the following months.

The simulation also evaluates the allocation of officers from the decision strategy module based on some service rules and probability distributions that capture the uncertainty of the system. Service rules are:

a) All four districts work independently,

b) Officers are dispatched based on call priorities,

c) For the same priority, calls are handled by First-In-First-Out (FIFO) basis,

d) Beat calls are served by corresponding beat officers,

e) If beat officers are busy, the highest priority calls can be served by the closest available beat officers in the corresponding district.

f) If any call is being served and requires longer time than the remaining time of the current shift, then the additional time is treated as overtime.

The following probability distributions are embedded in the simulation to evolve the system stochastically:

a) Exponential distributions are fitted to call interarrival times.

b) Service time per priority is assumed to be exponential.

c) Travel time is estimated following a normal distribution truncated at 0.

d) Additional calls are added for each crime calls following a Poisson process with mean 6. Note: This is based on the number of calls in the 2011 APD data for the same crime.

The simulation is assumed to start at midnight. The system is monitored every minute. The simulation clock advances following the next-event time advance mechanism. Crime calls are assumed to follow a Poisson arrival process, as discussed in Section 4.2.3.1. The mean interarrival time per beat per priority per period per month is obtained from corresponding predicted crime count. This mean interarrival time is used as the parameter of the exponential distribution used to generate each crime call arrival. The service time (equivalent to the response time as in Section 4.2.2) per priority call is fitted to the exponential distribution, and the response times in Table 4-3 are used as mean service times for the parameter input of the exponential distributions. Travel time is estimated using a truncated normal distribution and is only considered for cross-beat calls. Mean travel times in minutes per priority from the centroid of one beat to the centroid of other beats were obtained using Google Maps, shown in Table C-2, and the standard deviation is assumed to be 2 minutes in all cases. From the data, it is observed that total 911 calls are 7 times the number of crimes. For this reason, only crime calls are considered for crime prediction and additional calls are added using a Poisson distribution with mean of six (6) for each crime arrival in the simulation.

The following important components have been built in the simulation model:

Simulation State Variables:

State variables are created that represent the system state at a particular time. The number of officers in current active shifts, officer status, number of calls in queues, number of cross-beat calls, total realized calls, current active shifts, DU current hot beat, total DU stay time per hot beat, etc., are system state variables. These state variables are updated whenever an event occurs.

Simulation Clock:

A simulation clock has been created to keep track of the simulation run time. At any point, this clock tells how much time the system has been executing. The measurement unit of the clock is considered in minutes.

Simulation Event List:

An event list is created that contains when the next event will occur for each type of event. There are six events have been created in the simulation model: arrival event, service completion event, shift change event, DU state change event, warm-up event, and end simulation event. This event list is updated whenever an event occurs.

In an arrival event, calls of different priorities of different periods for each beat arrive following an exponential distribution. At the beginning, call arrival times are initialized for all priorities, for all periods, for all beats with the mean time of the first arrival for each type of call. Whenever a call arrival is occurred, the next arrival time of a call is generated. Then it will check the availability of officers according to service rules. If no officer is available, then the call will be added to the corresponding queue; otherwise, the service completion time of this call is scheduled and the corresponding officer is switched to busy. In this event, variables affected by the arrival are updated.

In the service completion event, a scheduled completed call is cleared, and the corresponding queues are checked. If the queues are empty, an officer will become idle; otherwise, subtract 1 from the number in the respective call queue, and a service completion is then scheduled for this call. If there is no call in the system, then there is no service scheduled, and the service completion event is eliminated from consideration. To do this, initialize all service completion times to infinity. Variables of the system affected by this event are also updated.

A shift change event determines the active shifts at current simulation time and the time of next shift change. The number of officers (obtained from the decision strategy module) are updated for shift change. For new officers, the queue is checked to schedule the service completion time. If the queues are empty, then the officers will remain idle. This event also updates related variables of the system.

A DU state change event determines the next DU state change time, what the next hot beat will be, and the total stay time per hot beat. The total stay time per hot beat impacts crime via the crime reduction factor. Necessary variable updates also occur with this event.

Every simulation requires an initialization period (or warm-up) to reach a stable simulation status. The actual recorded simulation run begins once the initialization period is completed. Simulation results can be viewed to determine the appropriate length of the initialization period. In this case study, warm-up initialization period is 28 weeks.

End simulation event stores the simulation end time. Whenever the system reaches this event, the simulation will be terminated, and the necessary output will be generated and passed to the decision strategy module. For each month, the simulation run time is the total time in minutes for a given month. For January, the simulation run time was 31*24*60 = 44640 minutes. The simulation end time is the summation of warm-up period and simulation run time, which for January was 326880 (= 28*7*24*60 + 44640) minutes.

Statistical Counters:

There are several statistical counters have been created that are used to calculate system performance at the end of the simulation. For example, simulation clock, number of simulated calls, total delay time for each queue, total busy time of officers, total overtime, number of cross-beat calls, etc. These statistical counters are updated as the system evolves.

Initialization Routine:

An initialization routine has been created to initialize the simulation at the start. At the beginning, the simulation is initialized with predicted crime counts from the predictive policing module, and the daily allocation decision from the decision strategy module. Other variables, such as state variables and statistical counters, are also initialized by this routine.

Timing Routine:

The timing routine in this case study reads the event list and determines which of the six events will occur next. Then it advances the simulation clock to that next time and updates following the next-event time advance mechanism, discussed in Section 2.4.2. This routine is essential to guide the simulation.

Event Routine:

This is the component that updates the system state variables when an event occurs. Since there are six events in the model, six event routines were created. Whenever an event occurs following the timing routine, the corresponding event routine updates the relevant system variables. For example, if an arrival event occurs, then the arrival routine updates queues status, PU status, etc.

Library Routine:

The library routine generates random numbers following probability distributions. In this model, predefined functions are called. For example, the *exprnd* MATLAB function is called to generate the next arrival time of a crime call.

Report Generator:

A subprogram has been created that generates the output of the simulation at the end of the simulation time. It computes performance measures from the statistical counters and exports them to external files. Here, all the results are exported to MS Excel files for each month.

Main Program:

The main simulation program has been created to control and coordinate all the subprograms. It also checks the stopping criteria and stops the simulation. Since the simulation evaluates monthly allocation, one stopping criterion is the total minutes in a month. After each month, it invokes a report generator to generate simulation output for that month. In this case study, the system is simulated for a year.

After the simulation run for each month, the performance output of allocation and simulated crime counts are generated and stored in external files. For each month, the following output is generated:

- average simulated or realized crime counts per beat per priority per period,
- average number of calls in queue per beat per priority per period,
- average waiting time of a call in queue per beat per priority per period,
- average utilization of officers within working shifts per beat,
- average total overtime in minute per beat per shift,
- average number of cross-beat calls.

At the end of each month, average realized crime counts are passed to the predictive policing module and the performance of the allocation is passed to the decision strategy module.

5.2 Baseline Simulation

Baseline is defined by the simulation scenario with regular patrol officer allocation using the 8-hr shift as in Table 5-1 and Table 5-2 to produce crime trajectories for a simulated year. No hot spot policing or any other intervention is applied to the baseline simulation.

5.2.1 Warm-up Period Determination

To determine the length of time as a warm-up period of the simulation, the average simulated utilization of officers per district over weeks using July 2011 crime data were examined. Figure 5-1 shows the average simulated utilization of officers per district up to

60 weeks. From this figure, it can be seen that after the 28th week, utilization stabilizes for each district. Hence, 28 weeks could be a reasonable choice for the warm-up period.

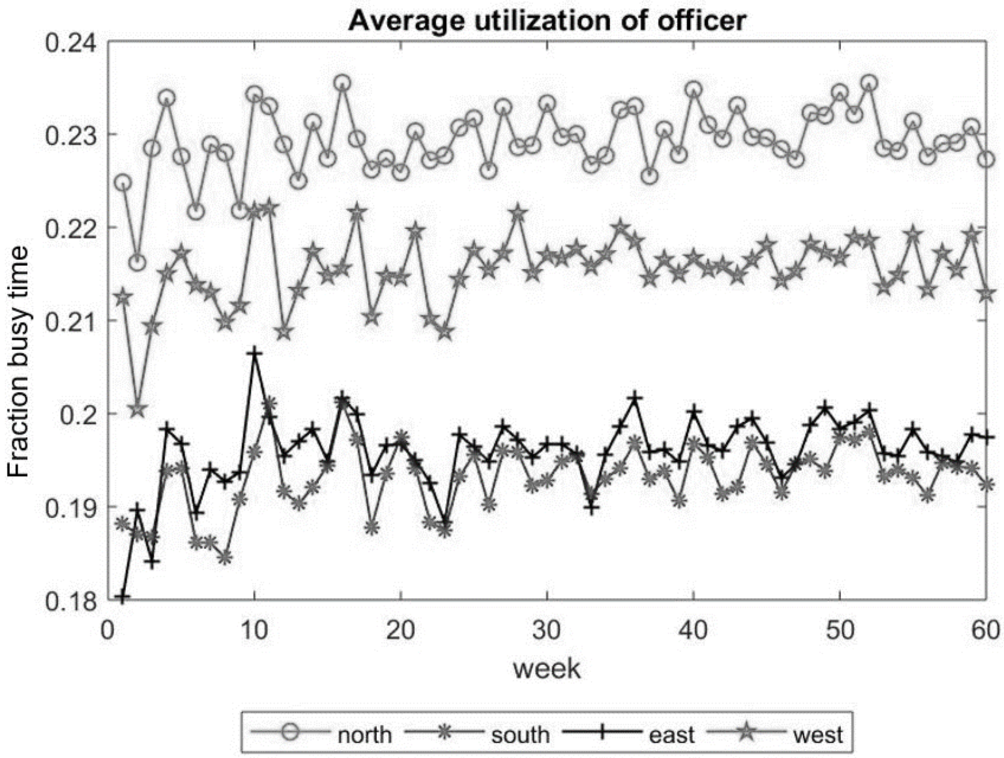


Figure 5-1 Average utilization of officer per district over weeks.

5.2.2 Convergence Test

To determine the number of replications, convergence of the average realized crime count per district, per priority and per period, to the predicted crime count, per district per priority and per period, is tested. Figure 5-2 plots deviations of average simulated crime count from the predicted crime count, for each district, for each priority, and for each period, for January 2012. This figure shows that the deviations converge to zero, as the number of replications increases, and the deviations are quite low after 300 replications with a maximum deviation of 2. All the plots of convergence are in Appendix D.

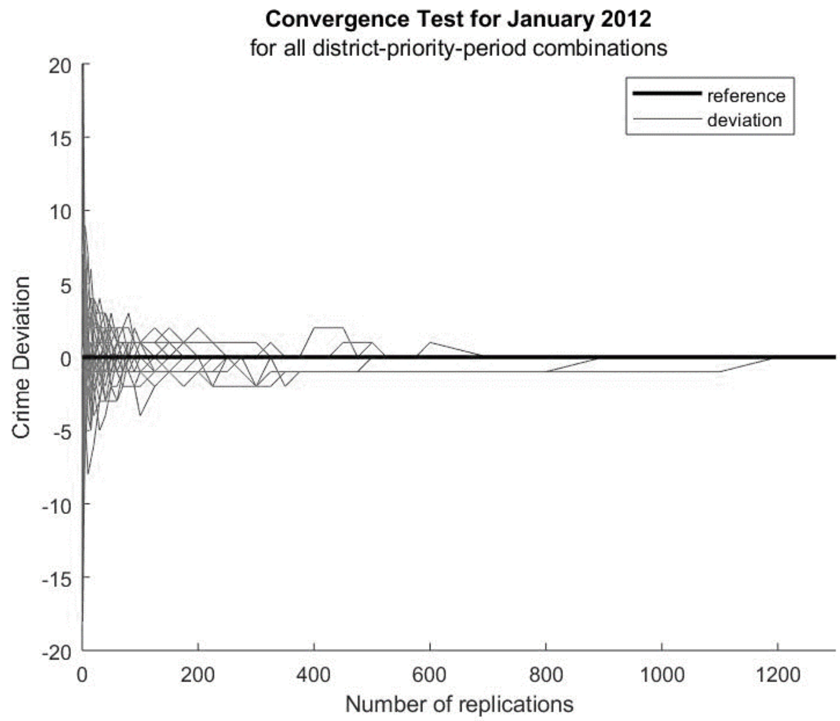


Figure 5-2 Deviation of average realized crime count from the predicted crime count for number of replications.

5.2.3 Crime Trajectories

After running the baseline simulation with a warm-up period of 28 weeks and 300 replications, the baseline simulation output is obtained. Figures 5-3 to 5-6 show some examples of crime trajectories over months in a simulated year. In these figures, line with star represents predicted crime trajectory from past prediction using the state transition model in equation 5-1. The dashed line with circles represents the predicted crime trajectory from average realized crime counts. For example, to get the predicted crime count for July on the dashed line, the average of 300 realized crime counts of May and June were entered into equation 5-1 after converting into crime rates. Gray lines represent the realized trajectories plotted from simulated crime counts per month, generated based on dashed line. There are 300 grey lines of realized trajectories for 300 replications.

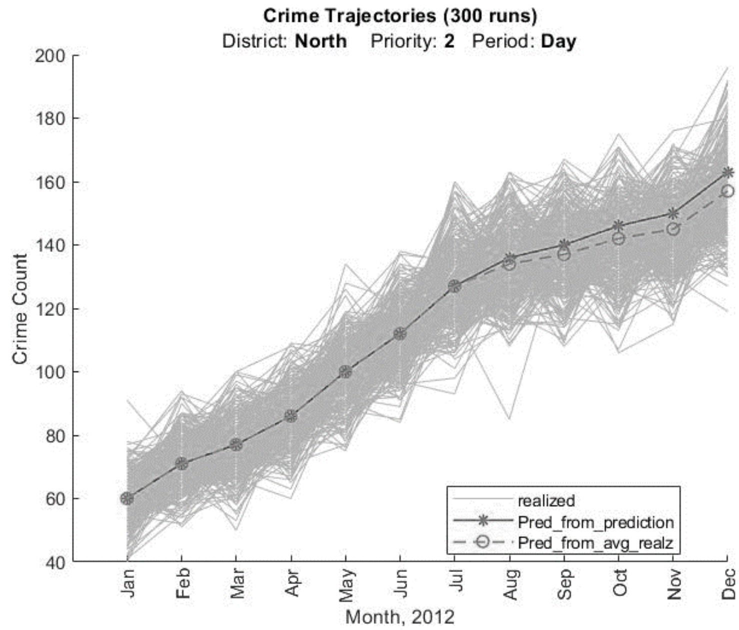


Figure 5-3 Crime trajectories for North, Priority 2, Day.

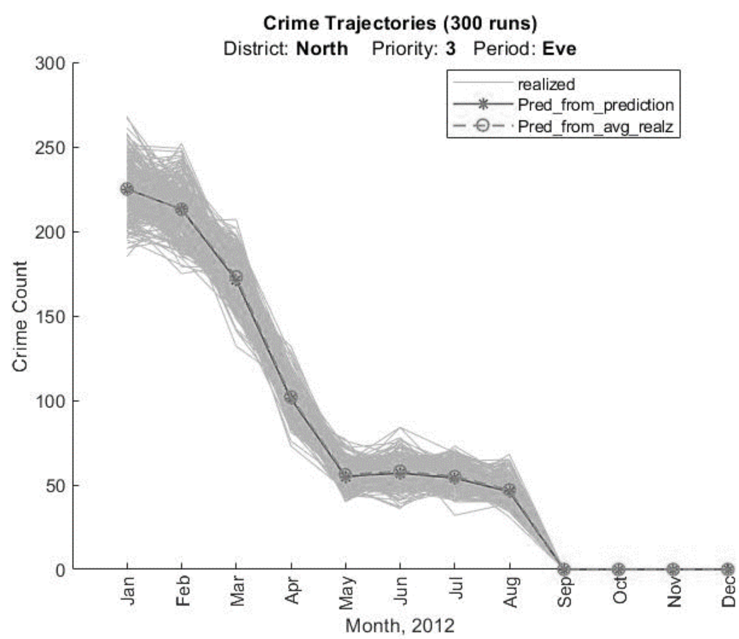


Figure 5-4 Crime trajectories for North, Priority 3, Eve.

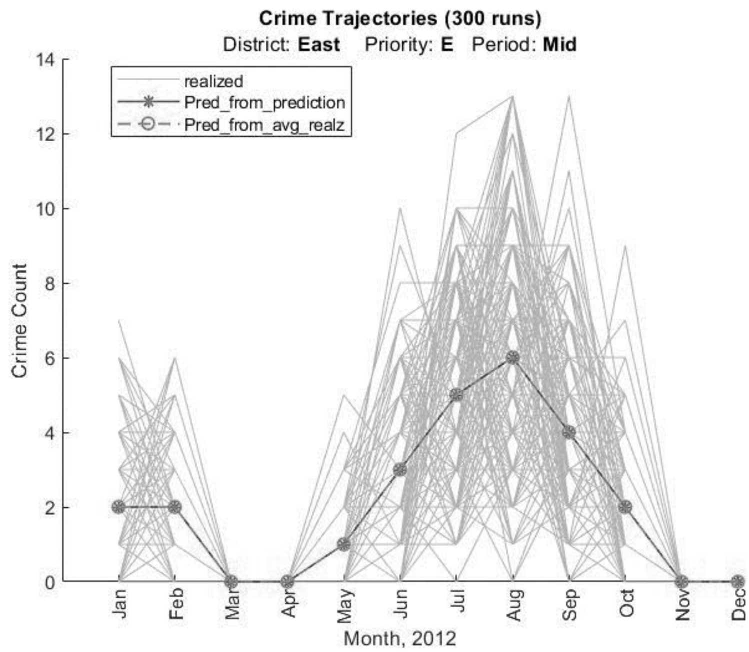


Figure 5-5 Crime trajectories for East, Priority E, Mid.

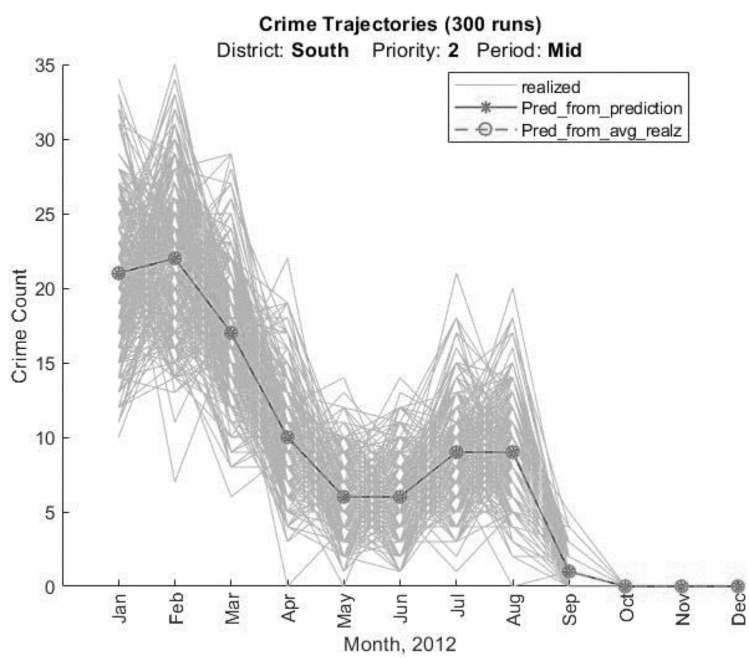


Figure 5-6 Crime trajectories for South, Priority 2, Mid.

The above figures are a few examples of different crime patterns of different district-priority-day combinations, which means the criminal environment is dependent on location, time, and also on crime types. That means different allocations might be effective based on different times, locations and crime types. Detailed output of the baseline simulation run is attached in Appendix E. For the scenario analyses, priority E calls are not considered since priority E calls are very few.

5.3 Simulation Scenario Analysis

5.3.1 Comparison Between 8-hr Shift and 10-hr Shift

To study the impact of two different shift schedules, the simulation has been run with the 8-hr shift and the 10-hr shift for a simulated year. To compare between shifts, the total number of officers per month should be equal. For this reason, 84 officers per month per district was chosen for this comparison. Tables 5-10 and 5-11 show the daily district and beat level allocation for the 8-hr shift schedule; Tables 5-12 and 5-13 show the daily district and beat level allocation for the 10-hr shift schedule.

Table 5-10 Daily patrol-shift allocation per district per patrol period for the 8-hr shift.

	Period		
	Day	**Eve**	**Mid**
North	18	23	19
West	18	23	19
East	18	23	19
South	18	23	19

Table 5-11 Daily patrol-shift allocation per beat per shift for the 8-hr shift.

		Shift					
District	**Beat**	**Day_1**	**Day_2**	**Eve_1**	**Eve_2**	**Mid_1**	**Mid_2**
North	210	1	1	1	1	1	1
	220	1	1	2	1	1	1
	230	1	1	1	1	1	1
	240	1	2	2	2	1	2
	250	1	1	2	2	1	1
	260	1	1	1	1	1	1
	270	1	2	2	2	2	2
	280	1	1	1	1	1	1
West	310	1	1	1	1	1	1
	320	1	1	2	1	1	1
	330	1	1	1	1	1	1
	340	1	2	2	2	1	2
	350	1	1	2	2	1	1
	360	1	1	1	1	1	1
	370	1	2	2	2	2	2
	380	1	1	1	1	1	1
East	410	1	1	1	1	1	1
	420	1	1	2	1	1	1
	430	1	1	1	1	1	1
	440	1	2	2	2	1	2
	450	1	1	2	2	1	1
	460	1	1	1	1	1	1
	470	1	2	2	2	2	2
	480	1	1	1	1	1	1
South	510	1	1	1	1	1	1
	520	1	1	2	1	1	1
	530	1	1	1	1	1	1
	540	1	2	2	2	1	2
	550	1	1	2	2	1	1
	560	1	1	1	1	1	1
	570	1	2	2	2	2	2
	580	1	1	1	1	1	1

Table 5-12 Daily patrol-shift allocation per district per patrol period for the 10-hr shift.

	Period		
	Day	Eve	Mid
North	15	18	15
West	15	18	15
East	15	18	15
South	15	18	15

Table 5-13 Daily patrol-shift allocation per beat per shift for the 10-hr shift.

		Shift			
District	Beat	A	B	C	D
North	210	1	1	2	1
	220	1	2	1	1
	230	1	1	2	1
	240	2	2	2	2
	250	1	2	1	2
	260	1	1	1	2
	270	2	2	3	2
	280	1	1	2	1
West	310	1	1	2	1
	320	1	2	1	1
	330	1	1	2	1
	340	2	2	2	2
	350	1	2	1	2
	360	1	1	1	2
	370	2	2	3	2
	380	1	1	2	1
East	410	1	1	2	1
	420	1	2	1	1
	430	1	1	2	1
	440	2	2	2	2
	450	1	2	1	2
	460	1	1	1	2
	470	2	2	3	2
	480	1	1	2	1

South	510	1	1	2	1
	520	1	2	1	1
	530	1	1	2	1
	540	2	2	2	2
	550	1	2	1	2
	560	1	1	1	2
	570	2	2	3	2
	580	1	1	2	1

After running the simulation, the average simulated utilization of officers and the average simulated total overtime of the 10-hr shift and there 8-hr shift were compared. The simulated utilization was calculated for officers within working shifts, it did not include overtime. Simulation results for both the 8-hr and 10-hr shift are in Appendix F. Figures 5-7 and 5-8 show two examples of the comparison in terms of average officers' utilization. In January, the utilization in the 8-hr shift is shown to be low compared to the 10-hr shift. In February, in some beats, the utilization in the 10-hr shift is lower compared to the 8-hr shift. Overall officers in the 8-hr shift have lower utilization. Table 5-14 presents the gain of average free time of officers in the 10-hr shift for a simulated year. The negative numbers indicate an average loss of days in the 10-hr shift compared to 8-hr shift. On an average, the total gain for the entire city is -141.15 days in a simulated year, i.e. officers in the 10-hr shift will lose 141.15 days of free time, which is the gain in 8-hr shift. With respect to utilization, in the 8-hr shift officers have more free time, which is desirable by the police department to get officers involved in other tasks in their free time, such as in building community relationships. Since 336 (= 84*4) officers are working per month for the entire city, the average time gained per officer in the 8-hr shift is (141.15/336 ≈) 0.42 days or 10.1 hours in a simulated year, which seems not to be a significant difference.

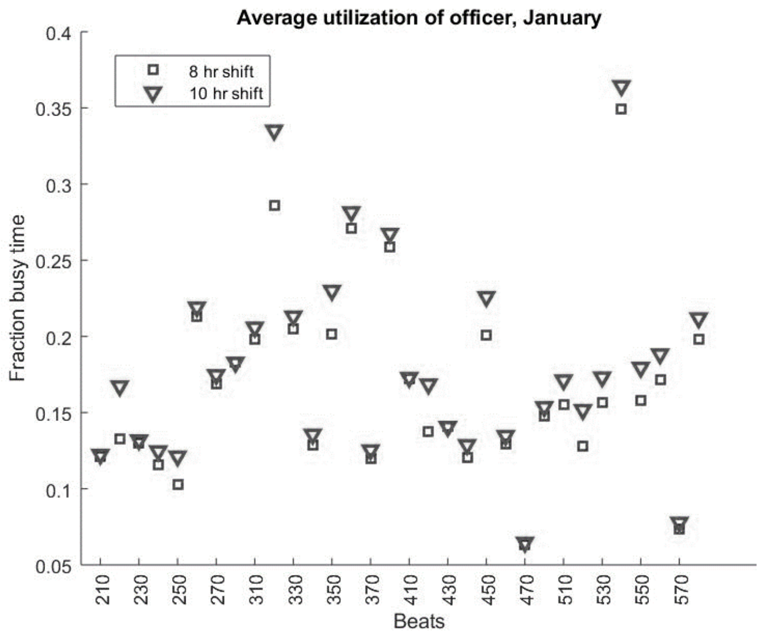


Figure 5-7 Average simulated utilization per beat in January.

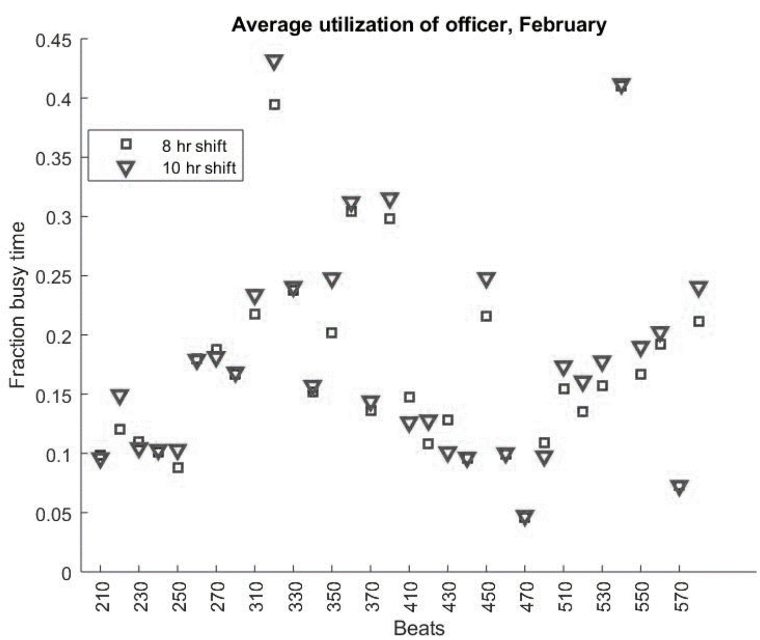


Figure 5-8 Average simulated utilization per beat in February.

Table 5-14 Average total free time (in days) gain in the 10-hr shift in a simulated year.

Beat	**Day**
210	0.31
220	-12.21
230	0.85
240	-1.92
250	-5.99
260	2.00
270	-1.21
280	1.01
310	-6.83
320	-12.28
330	-9.68
340	-5.50
350	-7.02
360	-3.78
370	-4.80
380	-8.72
410	2.50
420	-12.80
430	2.10
440	-0.93
450	-7.28
460	1.23
470	-1.26
480	2.35
510	-6.48
520	-10.31
530	-5.26
540	-4.22
550	-11.94
560	-6.45
570	-3.65
580	-2.98
Total =	-141.15

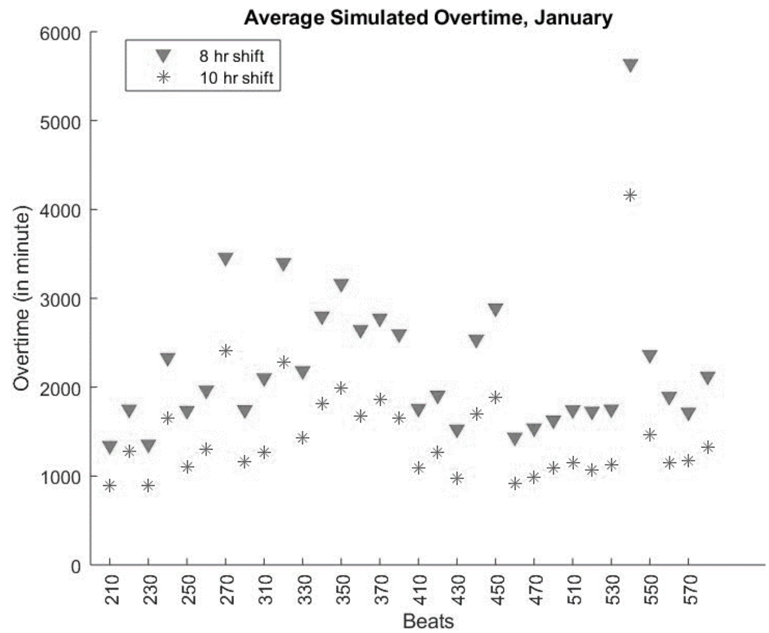


Figure 5-9 Average simulated total overtime (in minutes) per beat in January.

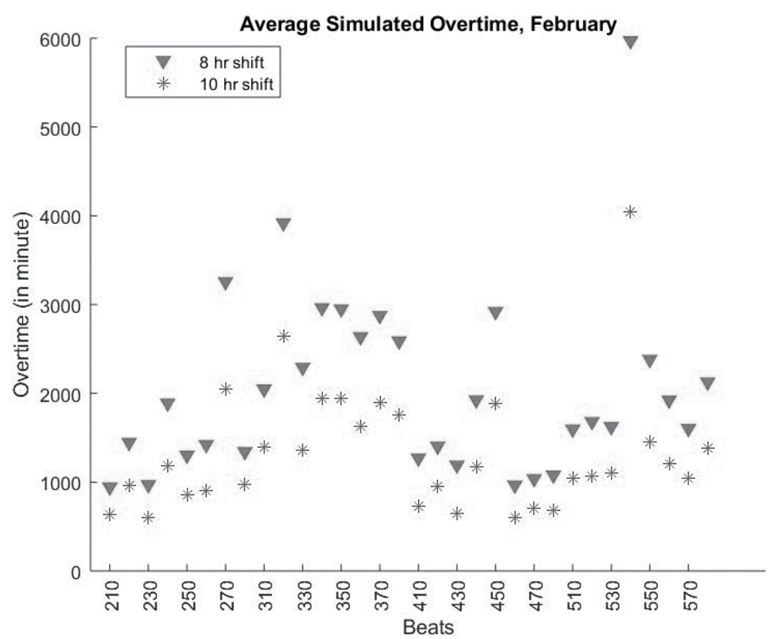


Figure 5-10 Average simulated total overtime (in minutes) per beat in January.

Figures 5-9 and 5-10 show examples of the comparison between the 8-hr shift and the 10-hr shift in terms of average total overtime per beat. Figures show that overtime is higher in the 8-hr shift compared to the 10-hr shift. Table 5-15 presents how much additional average total overtime was incurred in the 8-hr shift compared to the 10-hr shift for a simulated year. From this table, it can be seen that additional overtime of 7473.84 hours is incurred in the 8-hr shift compared to the 10-hr shift in a simulated year. The average total overtime per officer for a simulated year was (7473.84/336 ≈) 22.24 hours incurred in the 8-hr shift, which might be significant.

Table 5-15 Additional average total overtime in 8-hr shift compared to the 10-hr shift.

Beat	Minute	Hour
210	9838.56	163.9759
220	11275.71	187.9284
230	10181.83	169.6972
240	13777.49	229.6248
250	12113.54	201.8923
260	11515.61	191.9268
270	17469.43	291.1571
280	11219.71	186.9951
310	13386.93	223.1155
320	17853.42	297.557
330	13237.07	220.6178
340	20423.66	340.3943
350	23634.85	393.9142
360	15031.05	250.5174
370	20858.76	347.646
380	14096.22	234.9369
410	11190.37	186.5061
420	11892.44	198.2073
430	10260.28	171.0047
440	15311.30	255.1883
450	21689.20	361.4867
460	9134.03	152.2338
470	9997.61	166.6268

480	9997.05	166.6174
510	10278.32	171.3053
520	9889.00	164.8167
530	10323.38	172.0563
540	32473.99	541.2332
550	15977.17	266.2862
560	12653.37	210.8895
570	7737.33	128.9555
580	13711.55	228.5258
	Total =	7473.84

From the above discussion and results, it can be said that the 10-hr shift is efficient in terms saving overtime, but the 8-hr shift is slightly better in terms of utilization. Usually, police officers prefer the 10-hr shift, so that they have three days off in a week. Ultimately, police management will make the decision of shift schedule. The simulated results might help them in decision-making.

5.3.2 Move 10 officers from East-Mid to North-Mid

To study how a different allocation decision could impact the criminal environment and the performance of the decision strategy, 10 officers were moved from East-Mid to North-Mid in September through the rest of the year. Before September, the allocation remained the same as the baseline. The month September and the period Mid were selected because, in most cases, changes of crime counts are very high in September and the Mid time period. The new allocation that is effective from September is shown in Tables 5-16 and 5-17, and the highlighted cells indicate changes in the allocation.

Table 5-16 New daily patrol-shift allocation per district per patrol period for the 8-hr shift from September.

	Period		
	Day	**Eve**	**Mid**
North	19	23	29
West	19	23	19

East	19	23	9
South	19	23	19

Table 5-17 New daily patrol-shift allocation per beat per shift for the 8-hr shift from September.

		Shift					
District	**Beat**	**Day_1**	**Day_2**	**Eve_1**	**Eve_2**	**Mid_1**	**Mid_2**
North	210	1	1	1	1	2	1
	220	1	1	2	1	2	1
	230	1	1	1	1	2	1
	240	1	2	2	2	2	3
	250	1	1	2	2	1	1
	260	1	1	1	1	2	1
	270	2	2	2	2	4	3
	280	1	1	1	1	1	1
West	310	1	1	1	1	1	1
	320	1	1	2	1	1	1
	330	1	1	1	1	1	1
	340	1	2	2	2	1	2
	350	1	1	2	2	1	1
	360	1	1	1	1	1	1
	370	2	2	2	2	2	2
	380	1	1	1	1	1	1
East	410	1	1	1	1	0	1
	420	1	1	2	1	0	1
	430	1	1	1	1	0	1
	440	1	2	2	2	0	1
	450	1	1	2	2	1	1
	460	1	1	1	1	0	1
	470	2	2	2	2	0	1
	480	1	1	1	1	0	1
South	510	1	1	1	1	1	1
	520	1	1	2	1	1	1
	530	1	1	1	1	1	1
	540	1	2	2	2	1	2
	550	1	1	2	2	1	1
	560	1	1	1	1	1	1

	570	2	2	2	2	2	2
	580	1	1	1	1	1	1

5.3.2.1 Impacts on the Criminal Environment

Figures 5-11 to 5-16 show changes in crime counts from the baseline allocation for different priorities and for North and East. From the figure, it is seen that the criminal environment starts changing from September due to the new allocation decision that is effective from September. Although there is a slight increase in crime shown in Figure 5-12 for priority 1 in east in September, it is decreasing in North by a significant amount in Figure 5-11. Overall, priority 1 crime decreases using the new strategy. The opposite scenario can be seen in Figures 5-13 and 5-14. Priority 2 crime is decreasing in North by some amount, while in East, it is increasing by a significant amount. For priority 3 in Figures 5-15 and 5-16, crime goes down in North in September and October, but in November and December it goes up from the original predicted crime counts, while in East, priority 3 crime is consistently increasing. Overall the new strategy makes higher priority crimes low and lower priority crimes high.

The trend of the crime change looks different in Figure 5-15. This shape is dependent on the allocation decision and the predictive policing model. Some trends like this may not quite make sense because the prediction model was not trained on the correct data. To fit the model, an artificial size of the police force varied from 8 to 25. However, in this scenario of the APD case study, the number of officers is more than 25. This means this decision strategy is extrapolating from the original data range, causing the prediction model to be less reliable. This is why, the predictive model will potentially need to be updated with new data.

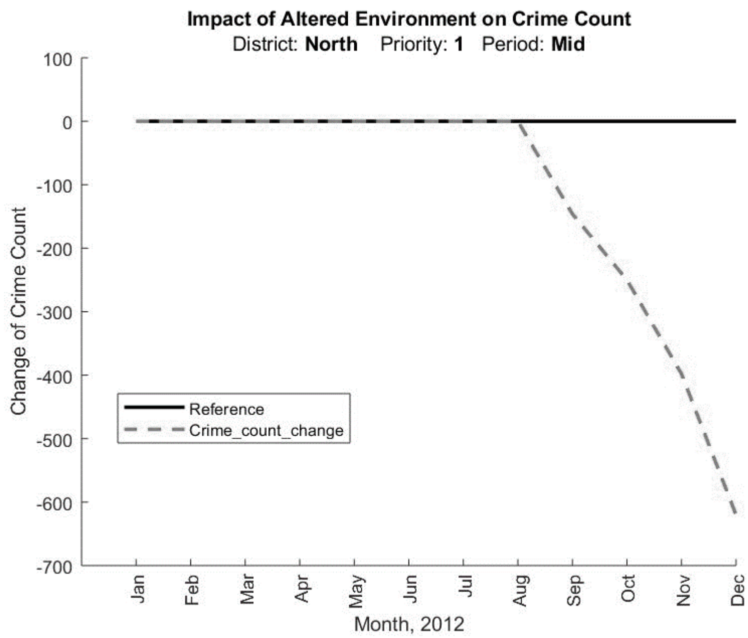


Figure 5-11 Crime count change in the new allocation for North for Priority 1.

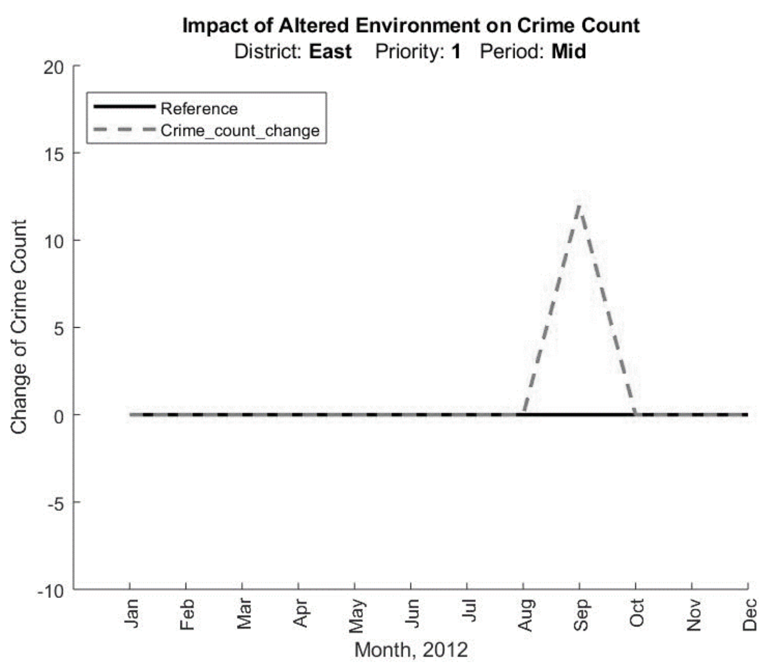


Figure 5-12 Crime count change in the new allocation for East for Priority 1.

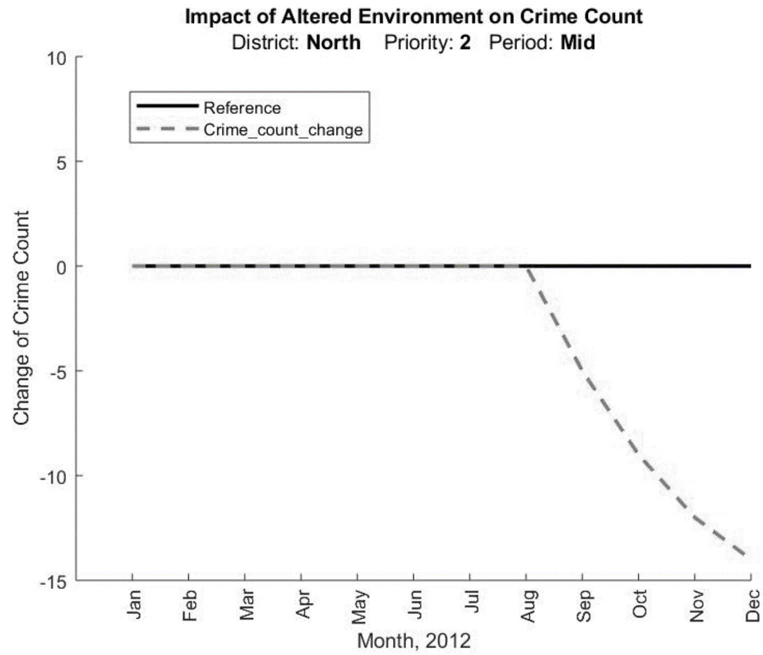


Figure 5-13 Crime count change in the new allocation for North for Priority 2.

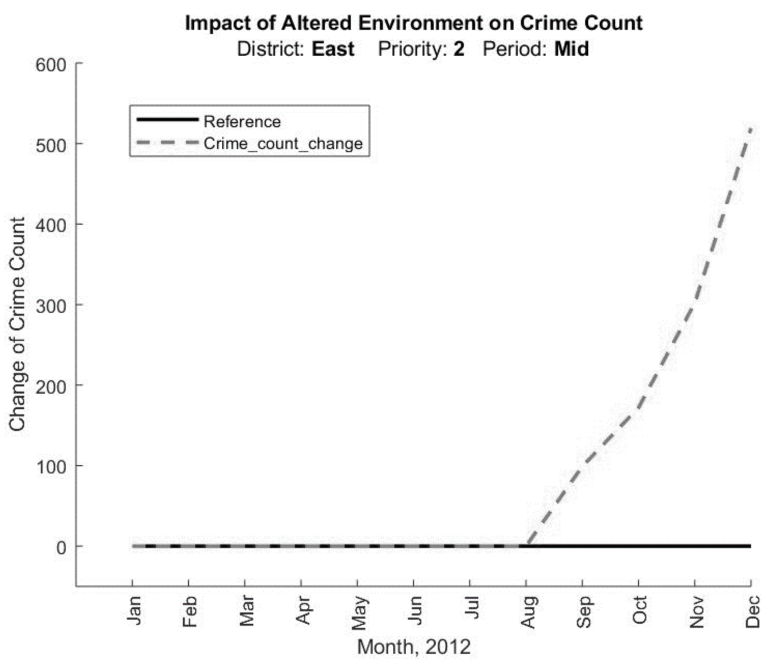


Figure 5-14 Crime count change in the new allocation for East for Priority 2.

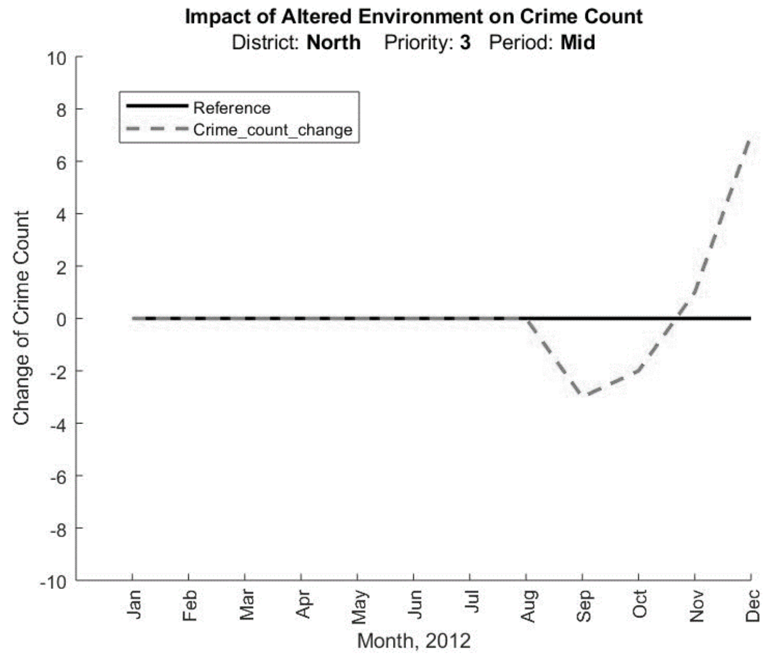


Figure 5-15 Crime count change in the new allocation for North for Priority 3.

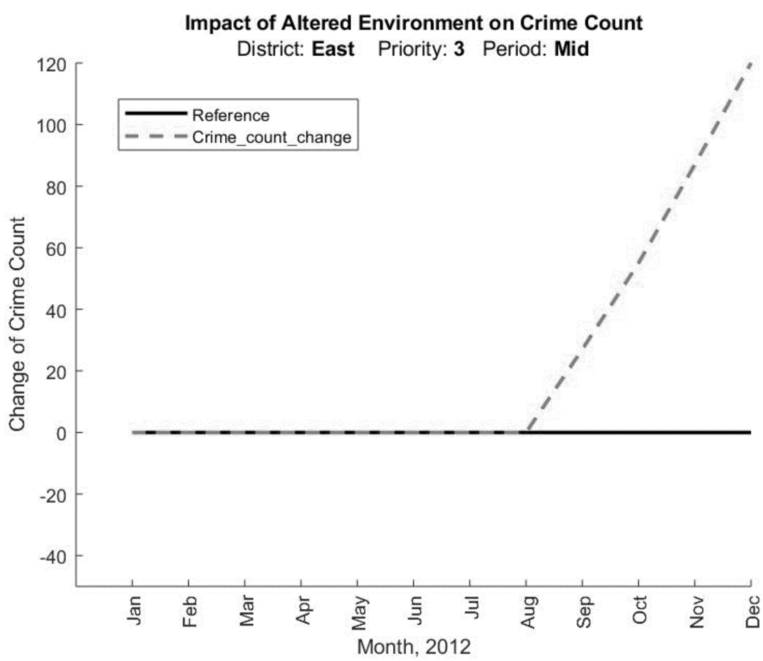


Figure 5-16 Crime count change in the new allocation for East for Priority 3.

5.3.2.2 Impacts on Performance

Figures 5-17 to 5-20 shows the overall officers' utilization change per beat in North and East from September to December. Since the crime level goes down and the number of officer is increased in North, the utilization goes down in all beats of North. On the other hand, higher crimes and lower numbers of officer cause higher utilization in East.

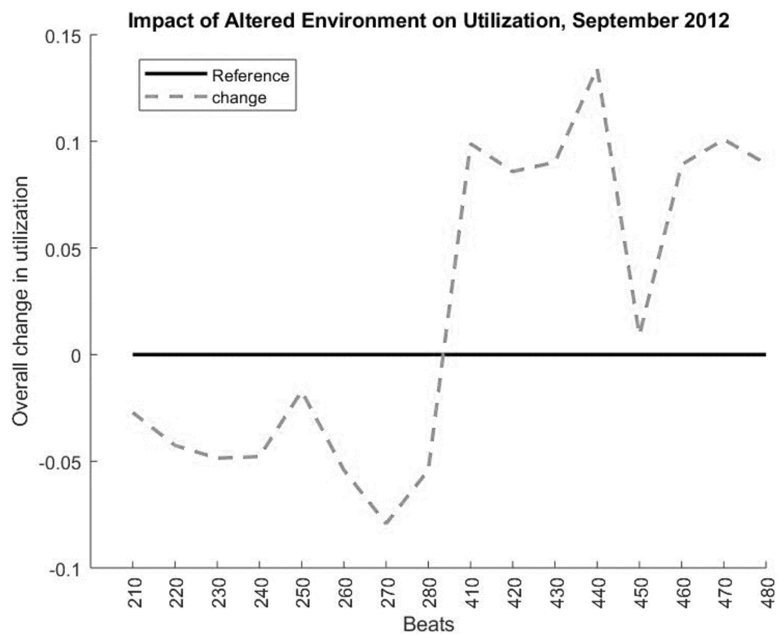


Figure 5-17 Overall utilization change per beat in North and East in September.

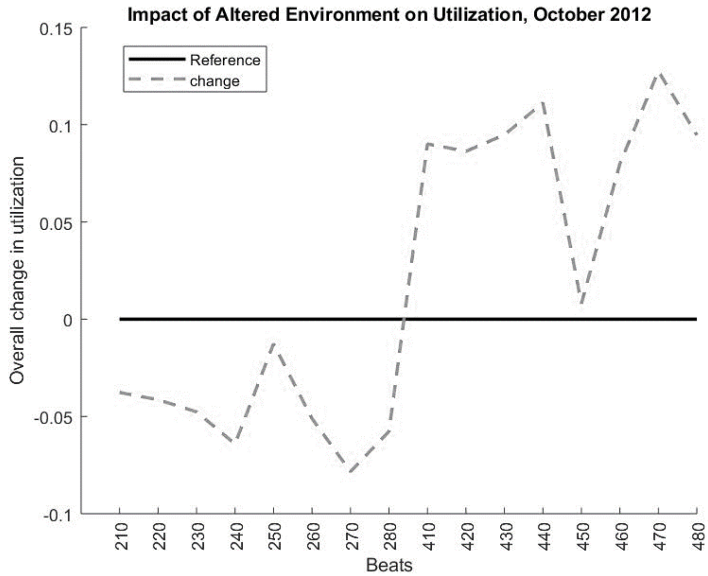


Figure 5-18 Overall utilization change per beat in North and East in October.

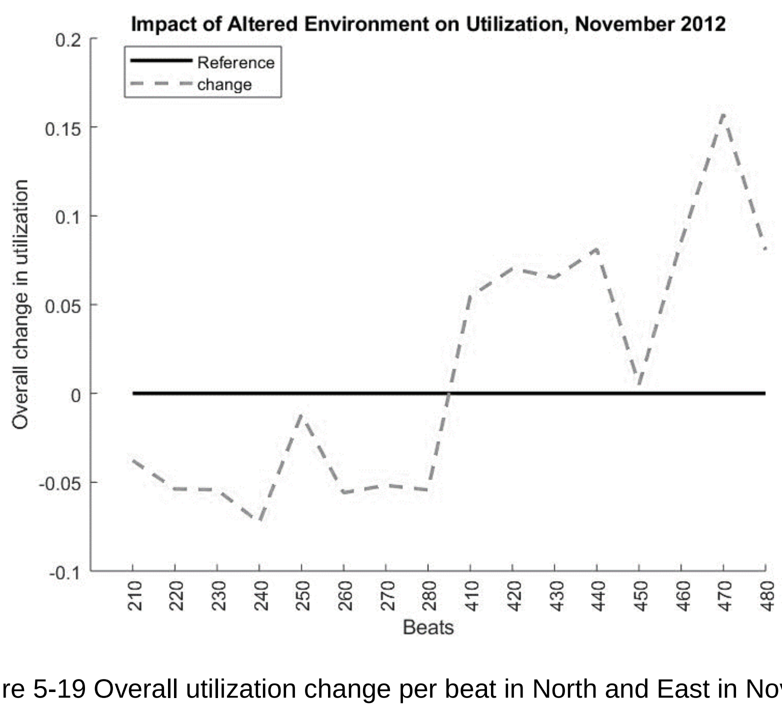


Figure 5-19 Overall utilization change per beat in North and East in November.

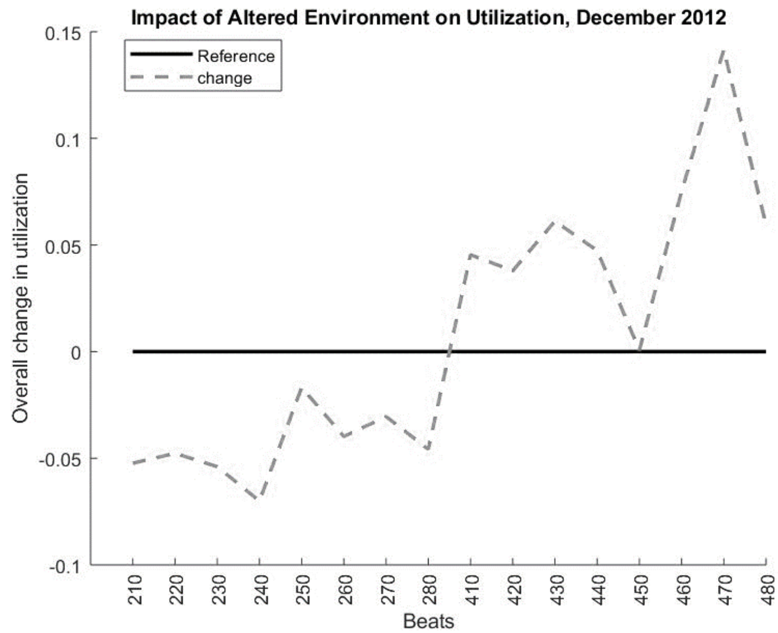


Figure 5-20 Overall utilization change per beat in North and East in December.

On an average, officers' utilization is reduced by about five percent (5%) per beat in North for each month from September to December. In East, utilization is increased by about 9% in September and October and about 7% and 6% in November and December, respectively.

The following figures compare the waiting times of a call between the baseline allocation and the altered allocation. Figures 5-21 to 5-32 present waiting times per priority, per beat (in North and East), and per month (from September to December) for patrol period Mid.

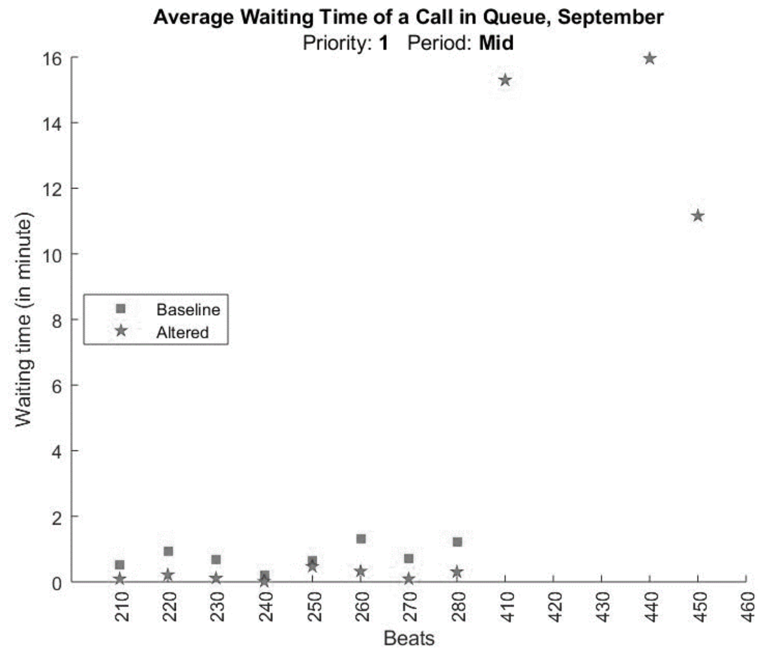


Figure 5-21 Waiting times of priority 1 call for two allocation strategies in September.

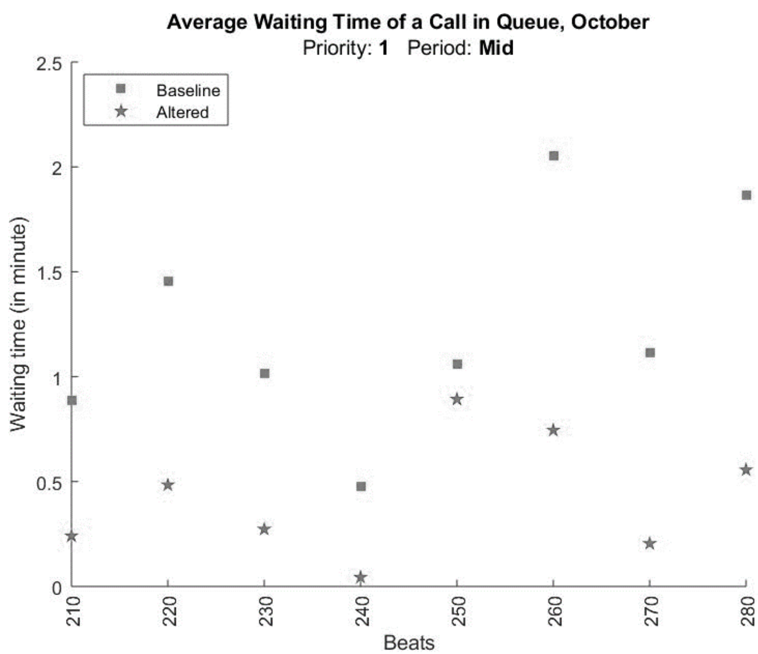


Figure 5-22 Waiting times of priority 1 call for two allocation strategies in October.

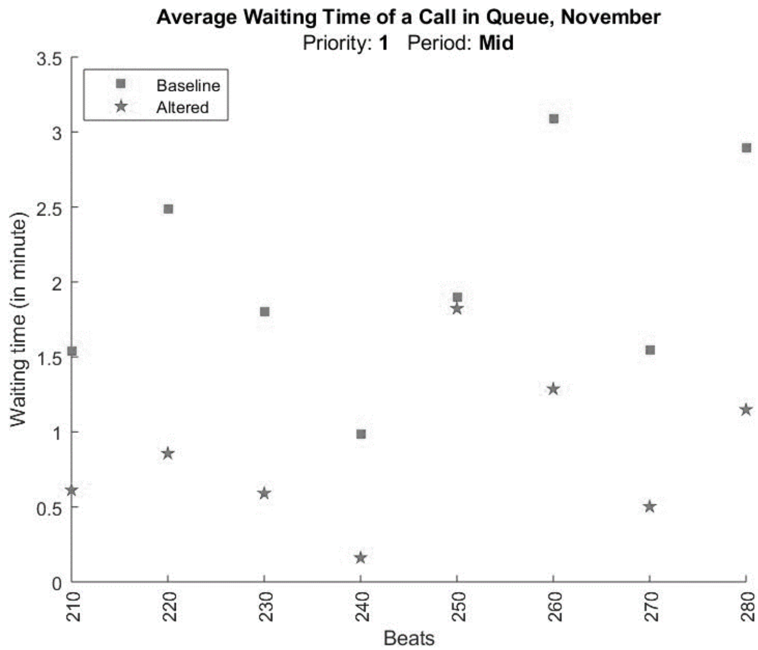


Figure 5-23 Waiting times of priority 1 call for two allocation strategies in November.

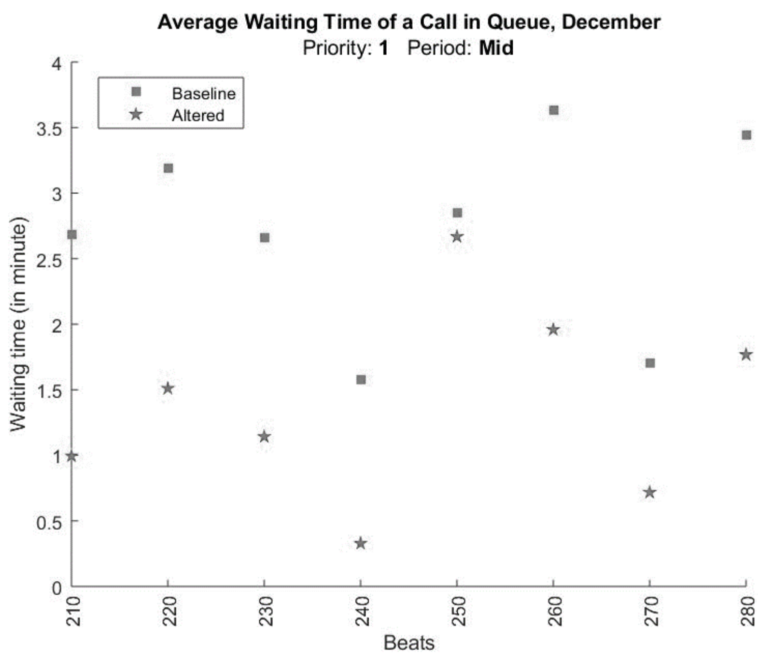


Figure 5-24 Waiting times of priority 1 call for two allocation strategies in December.

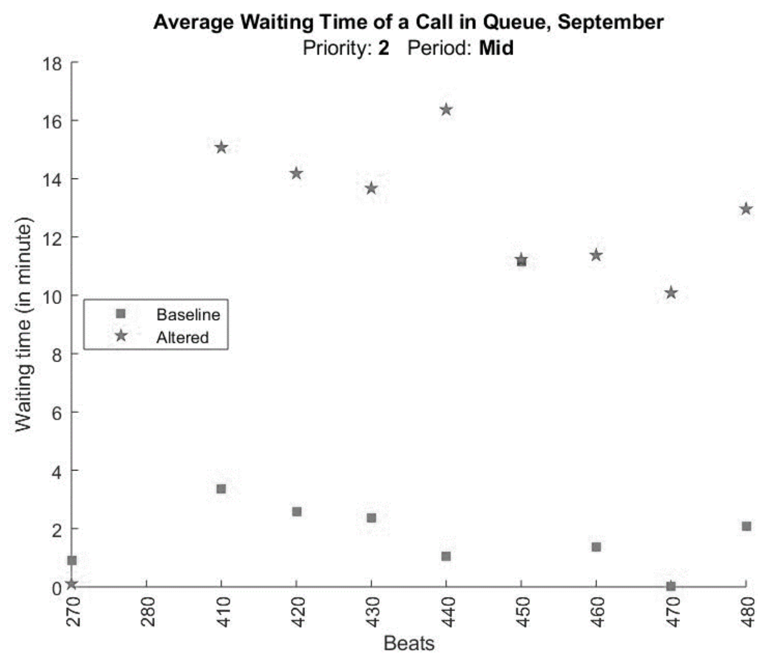


Figure 5-25 Waiting times of priority 2 call for two allocation strategies in September.

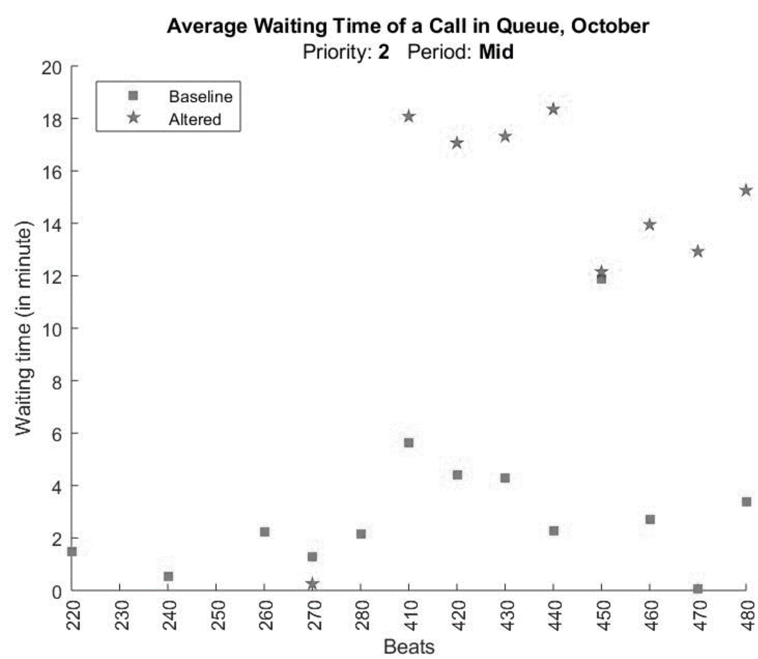


Figure 5-26 Waiting times of priority 2 call for two allocation strategies in October.

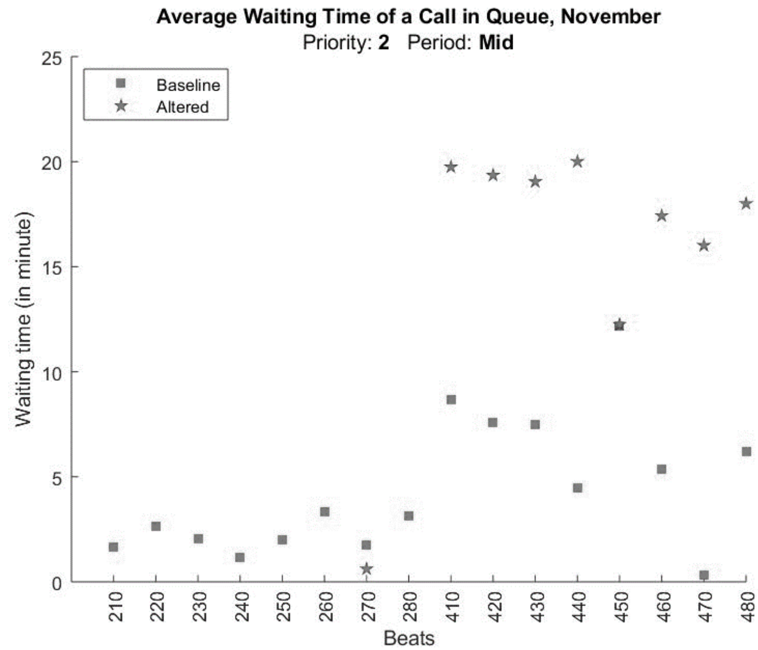


Figure 5-27 Waiting times of priority 2 call for two allocation strategies in November.

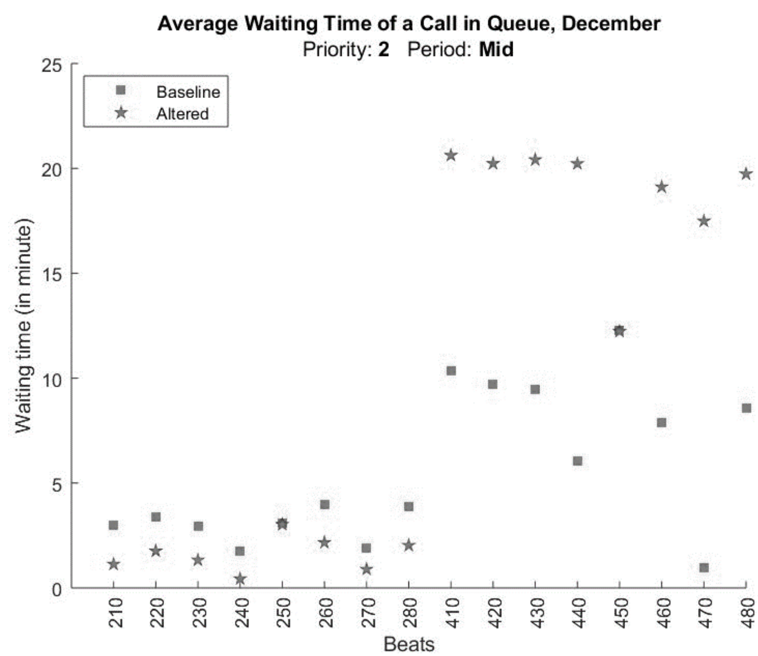


Figure 5-28 Waiting times of priority 2 call for two allocation strategies in December.

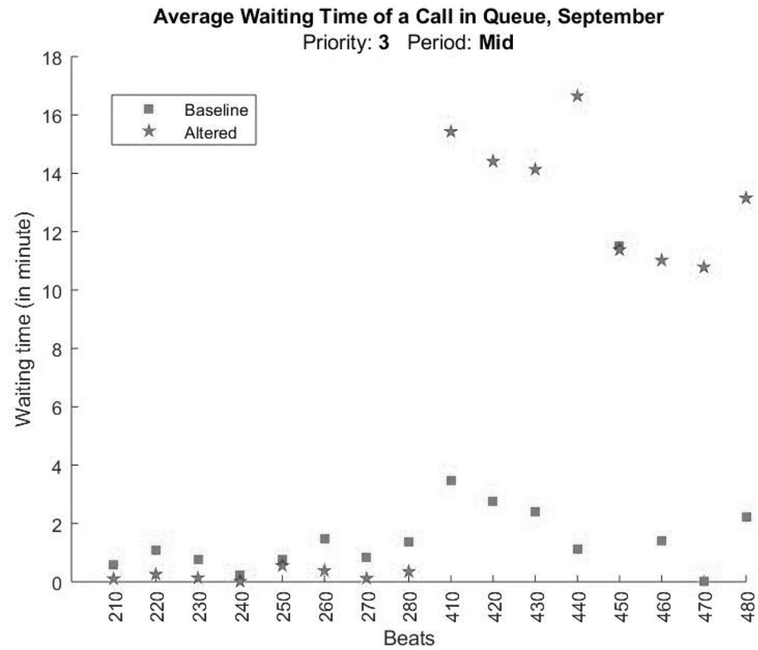


Figure 5-29 Waiting times of priority 3 call for two allocation strategies in September.

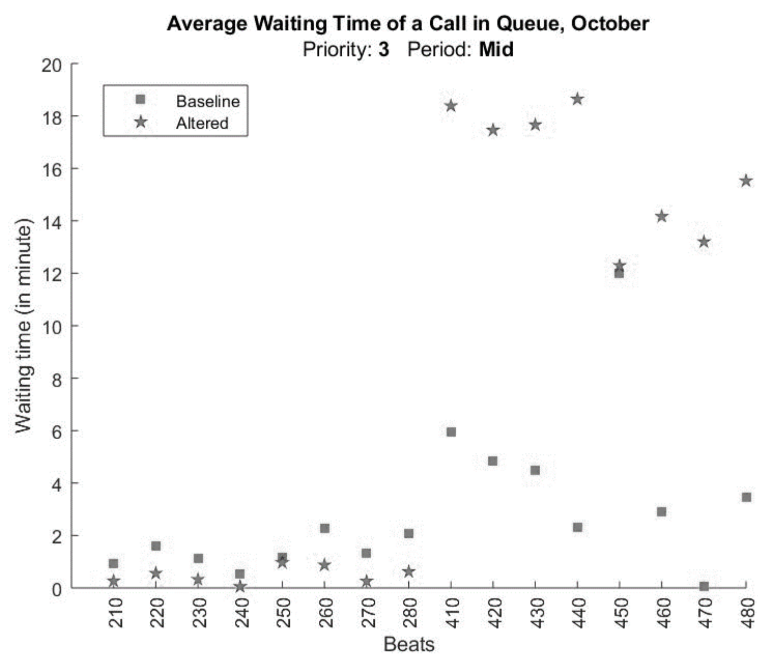


Figure 5-30 Waiting times of priority 3 call for two allocation strategies in October.

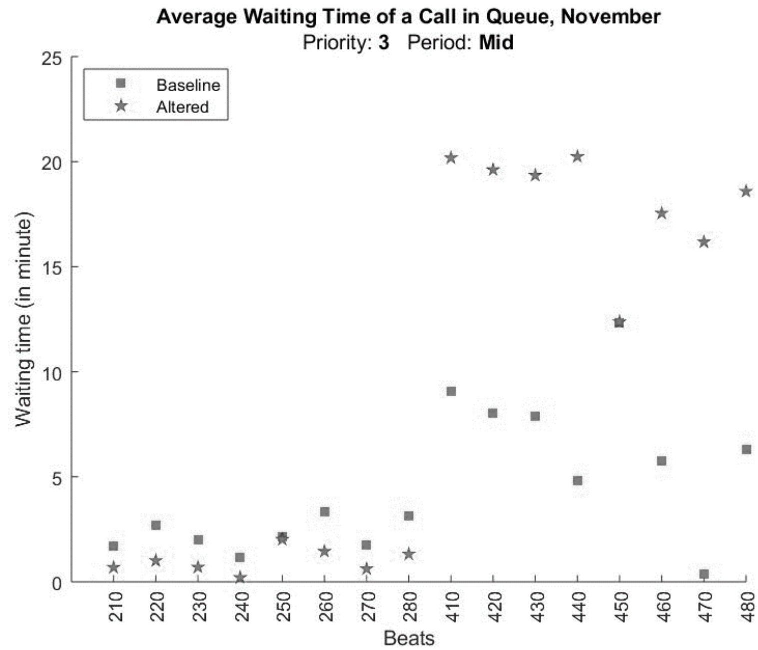


Figure 5-31 Waiting times of priority 3 call for two allocation strategies in November.

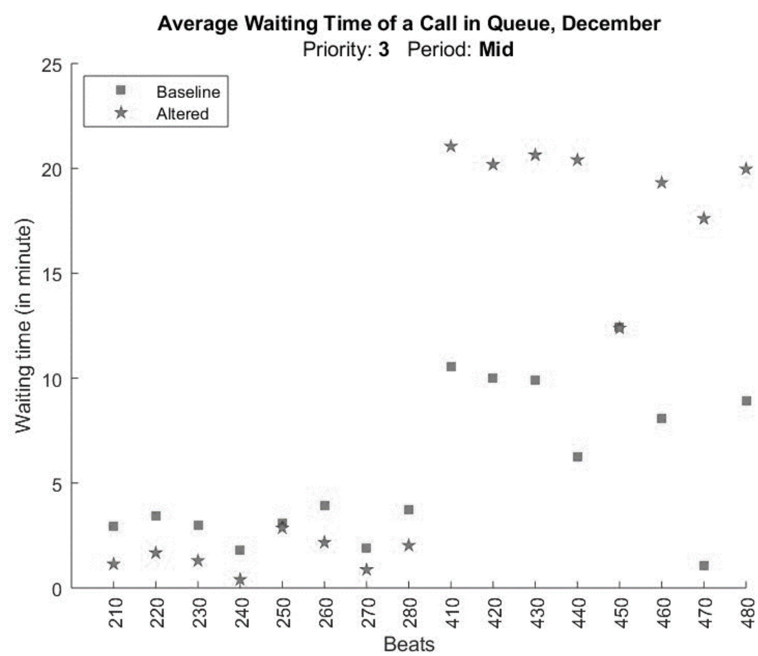


Figure 5-32 Waiting times of priority 3 call for two allocation strategies in December.

The above figures show that the waiting times of a call per beat in North decreased for the altered strategy compared to the baseline strategy and increased in East. Although there is some increase of priority 3 calls in North in November and December, waiting times still decrease because of additional officers. There are some points missing in the plots. This happens when there is no average realized calls in those corresponding beats. Hence, there no waiting time occurred. For example, in Figure 5-21, the square boxes in beats 410, 440, and 450 are missing because there was no realized priority 1 calls in those beats in the baseline scenario. However, when the number of officers is reduced from East-Mid, priority 1 calls increased in September, as shown in Figure 5-12. That is why stars are shown for those beats.

In summary, the performance of the new altered strategy could be considered better than the baseline strategy. If a lower number of higher priority calls is desirable with some increase of lower priority calls in East, then the new strategy might be a better option.

5.3.3 Deployment of DUs for Hot Beats

To study the impact of hot spot policing, two DUs have been deployed for eight hours per day for hot beats, in addition to the baseline allocation. The beats that have total predicted crime counts, regardless of priority, equal or higher than the threshold of 150 are considered as hot beats. Beats can be hot beats for some months and not other months since it depends on exceeding the threshold. All the results are given in Appendix G. The impacts of DU intervention are explained with beats 540 and 260, where 540 is identified as a hot beat at the beginning of the year, and 260 is identified in the middle of the year.

5.3.3.1 Impacts on the Criminal Environment

Figures 5-33 and 5-34 show how the total predicted crime counts change each month for beats 540 and 260, respectively. Beat 540 is identified as hot beat in January since the total predicted crime counts is 312. The crime prediction goes down to 296 due to the DU deployment. DUs continue to patrol beat 540 and keep predicted crime counts decreasing until May. In May, the predicted crime count drops to 147, which is lower than the threshold. Hence, beat 540 is no longer a hot beat, and DUs do not patrol beat 540 in May. For this reason, crime starts increasing in June and again it is considered as a hot beat and DUs again patrol this beat. Similar patterns happen in the months of October and November.

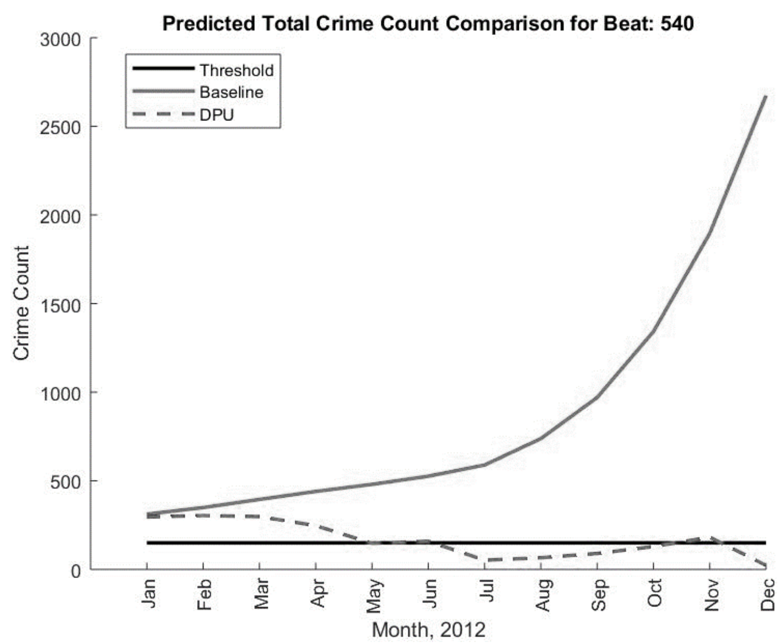


Figure 5-33 Effects of DU deployment on total crime count per month for hot beat 540.

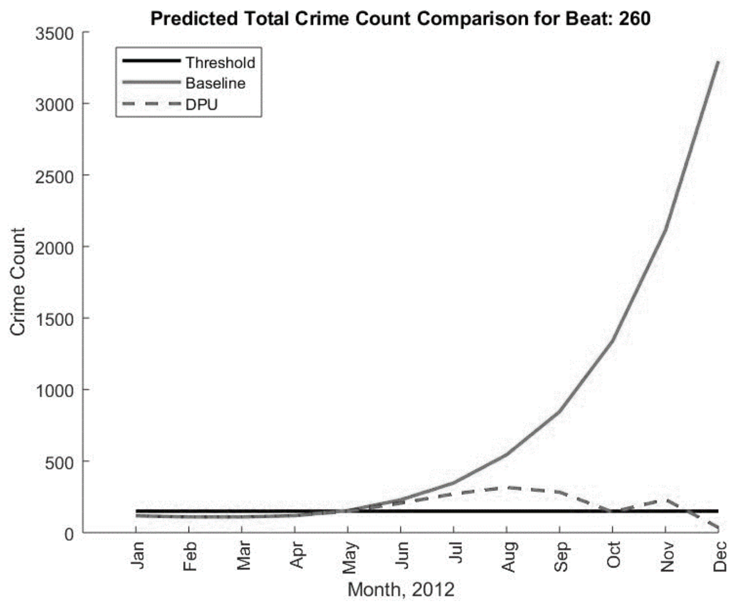


Figure 5-34 Effects of DU deployment on total crime count per month for beat 260.

Beat 260 is not a hot beat from January to April. In May, its predicted crime count reaches beyond the threshold, and Beat 260 is now considered a hot beat. DUs start rotating hot beats, including beat 260 in May. Crime decreases from 154 to 150 in beat 260. Predicted crime count continues to decrease in the following months and drops below the threshold in October. In October, DUs are withdrawn from beat 260 as it is no longer a hot beat. Again crime count starts increasing due to the absence of DUs, and it becomes a hot beat in November. Then crime goes down in December for DU deployment in November.

5.3.3.2 Impacts on Performance

Figure 5-35 compares the officers' utilization per month between the baseline allocation and DU intervention for beat 540. The figure shows that utilization decreased as crime counts decreased from the original baseline prediction. Whenever crime starts increasing the utilization starts increasing.

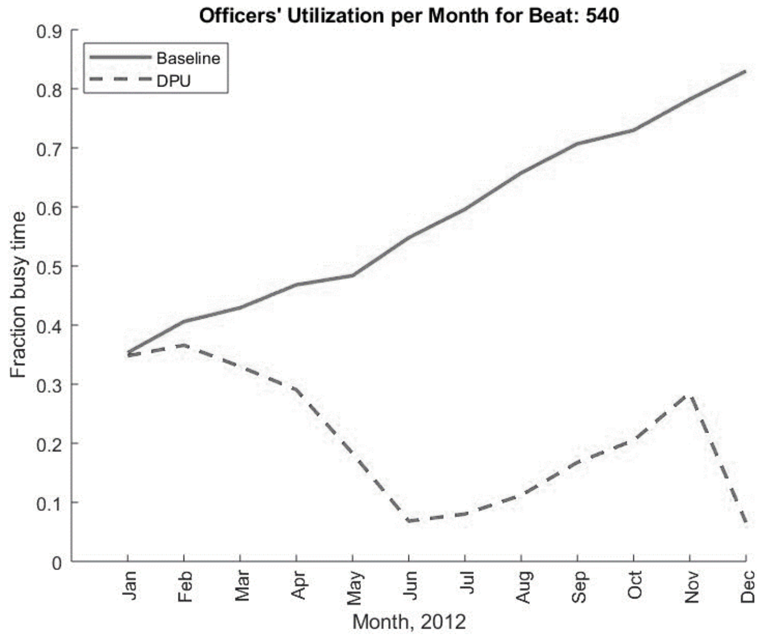


Figure 5-35 Effects of DU deployment on officers' utilization per month for hot beat 540.

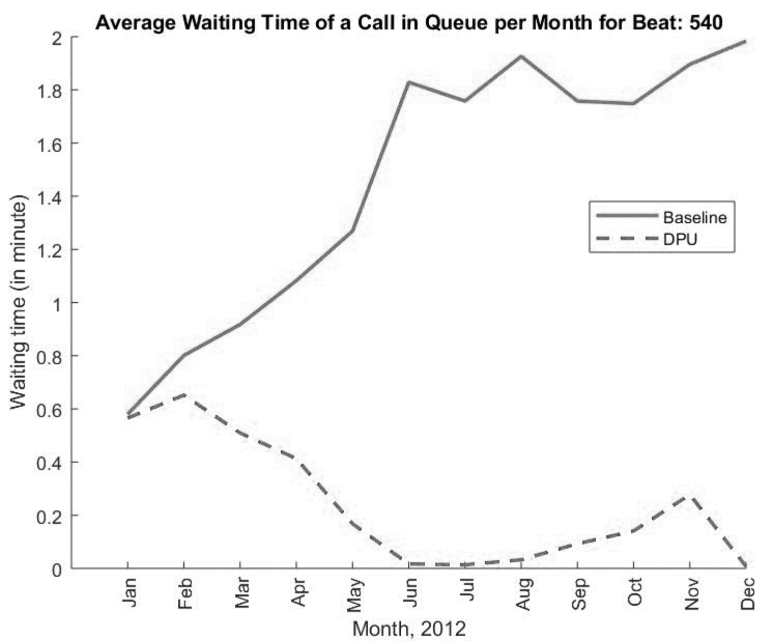


Figure 5-36 Effects of DU deployment on call waiting time per month for hot beat 540.

Figure 5-36 presents the comparison of average waiting time of a call for beat 540. This waiting time is a call waiting time in a queue regardless of priorities. Figure 5-36 shows how the average waiting time of a call is decreasing and increasing per month with predicted crime counts. The trends of waiting time should match with the trend of utilization. The trends of Figure 5-35 and 5-36 are same for beat 540.

In summary, DU deployment impacts predicted crime counts in hot beats, as well as the performance of the allocation. If some hot beats experience very low crime counts for DU deployment and officers' idle time is too high, then regular patrol officers can be reallocated from those hot beats to other beats, considering other performance measures for balanced allocation.

Chapter 6

CONCLUDING REMARKS AND FUTURE WORK

6.1 Conclusions

This dissertation developed a dynamic policing simulation framework as a novel approach to study dynamic policing strategies through an iterative process. The framework defines three modules: decision strategy module, predictive policing module, and simulation module. The framework is demonstrated with a case study based on the Arlington, TX Police Department. To implement the framework, a DES model was developed for the 911 call and deployment structure. An initial predictive model from the literature was fitted using actual crime data, unemployment, and conviction rate data, but with the artificial patrol data. A sample patrol-shift allocation provided by APD and artificial DU deployment for hot spot policing were used in the decision strategy module.

In the case study demonstration, the allocation per month for a simulated year was studied. In a shift comparison, the 10-hr shift showed effectiveness over the 8-hr shift for saving overtime, but for officers' utilization, the 8-hr shift is slightly better. The second scenario showed the impacts of different patrol allocations on predicted crimes and on performance. The third scenario provided very interesting results of hot spot policing. DUs helped hot beats by reducing crime count. Whenever DUs were withdrawn after the hot beat cooled off, crime started increasing.

The developed framework has the flexibility to study many different police intervention strategies. In this dissertation, a monthly decision strategy time scale was studied, but the framework has the ability to study allocation decisions for any time scale. It could be quarterly, seasonally, or semi-annually, etc. With the help of "what-if" scenario analysis, police departments can obtain guidance to achieve more effective policing under limited resources via dynamic strategies.

There are many studies found in the literature that seek to measure the effectiveness of different policing strategies. Most used experimental design implementations that are costly and require significant effort. Although the published results of such experiments have promising results, they are very specific to time, location, and particular strategies. The results cannot be easily generalized. It is hoped that the framework in this dissertation will encourage new directions for policing to fulfill the prediction-led policing concept via dynamic policing strategies. The simulation approach has the capability to study dynamic policing strategies for any time range with low cost and without any required real world implementation.

6.2 Future Work

Additional aspects of APD processes should be considered in future case study development. In the simulation, additional calls have been generated using a Poisson distribution. To add additional calls to each crime, a specific distribution needs to be explored by analyzing crime and call data. Currently, each call is treated separately and officers are dispatched separately to each call, even if calls arrive at the same place at the same time. More likely, the same officer can handle calls that arrive within a space range (quarter mile or half mile, etc.) or within a time limit (may be 5 minutes, 10 minutes, etc.); no additional officer will be dispatched. More accurate dispatch rules for call arrivals need to be explored. In the simulation, additional study is also needed to find distributions that more closely match that of call arrivals, response times, travel times, etc.

Criminal behavior in response to policing actions is not considered in the current simulation. This aspect can be better represented by an agent-based simulation. Integration of an agent-based simulation with the current discrete-event simulation would be a significant improvement to the present simulation framework. Additional data will be needed to inform an agent-based simulation model.

The quality of the results of the simulation are completely data-driven and dependent on the performance of the predictive policing model. Data on police allocations and actions is needed to improve the predictive policing model. The predictive policing module predicts crime using a state transition model. Building state transition models from data is an area of current research. Most existing predictive policing models in the literature are inappropriate. Some of them use uncontrollable factors to predict crime and some are too crime specific. The appropriate state transition model must relate crime with police operations. The development of appropriate state transition models for dynamic policing is an important area for future research.

The current state transition model that has been used in the case study predicts crime rate per district, per priority, per period. The predicted crime rates were then distributed into the beat levels using an algorithm discussed in Section 5.1.2, and crime rates were converted into crime counts as simulation inputs. For this reason, some information was lost because of the fractions. The inability to predict crime for multiple months in advance is a limitation of the current model. Another limitation of the current predictive model is that it did not consider DPUs for hot spot policing. If a hot spot policing component is added to the predictive policing model, then the crime prediction would be more accurate. To overcome these limitations, a state transition model that can predict crime count per beat per priority per period for any month of the year needs to be developed for the case study. The future predictive policing model should have two components: regular policing and hot spot policing.

The predictive policing model in the case study considers the number of police officers to predict crime. It only considers police presence. However, criminals might respond differently to different policing actions, such as number of stops, number of citations, number of arrests, etc. An agent-based simulation may better to study criminal behavior in response to policing actions. Incorporating criminal behavior in crime prediction would be future consideration.

The decision strategy module that can handle the complexity of the system is also needed. Since decisions on allocation are dynamically changing with time and location, and decisions are dependent on crime levels and performance criteria, a dynamic programming or multi-objective optimization could be developed for the decision strategy module. Overall, the dynamic policing simulation framework has the potential to bring together methods from statistics, analytics, and operations research to improve policing.

Appendix A

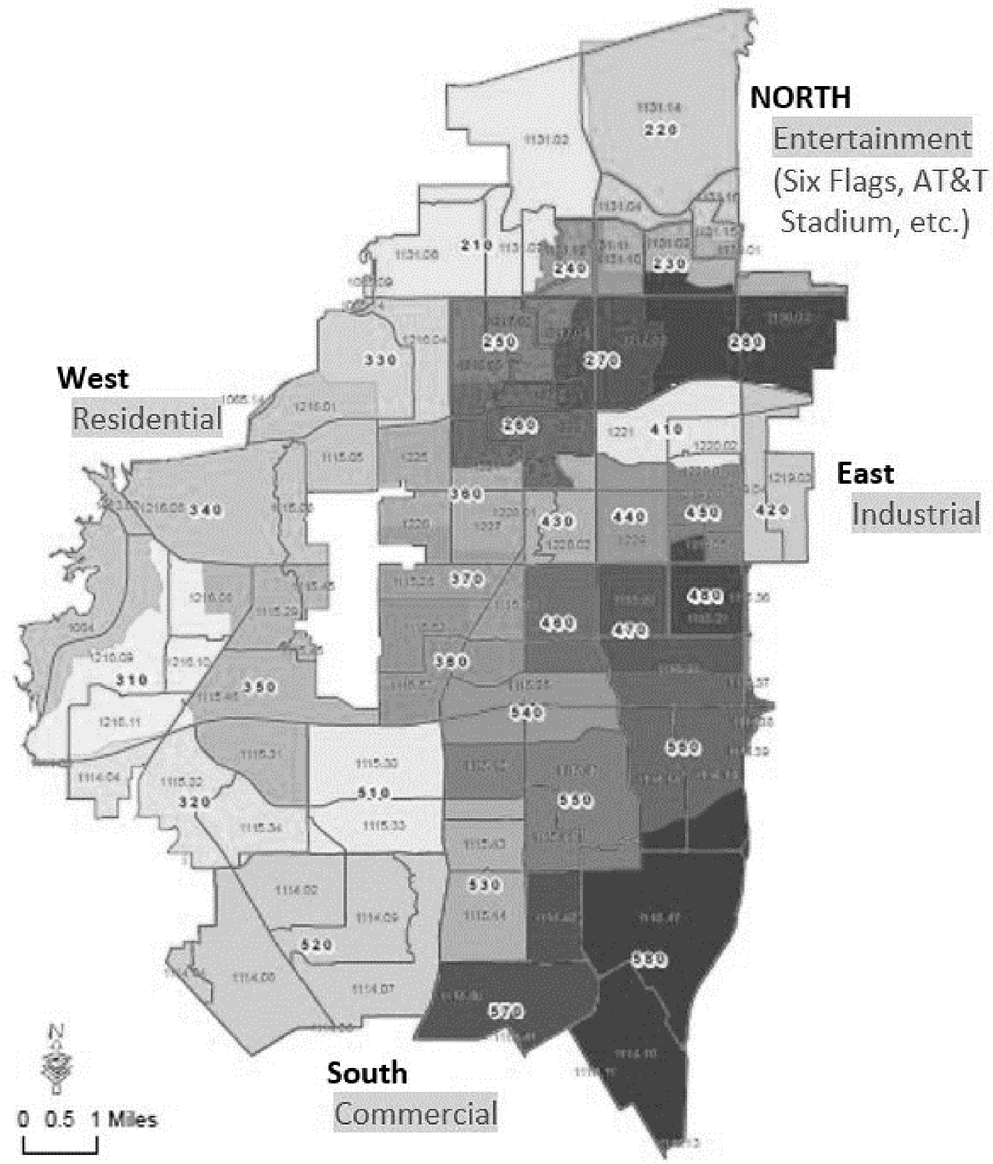


Figure A-1 Arlington, Texas police service areas, 2011.

Table A-1 List of Possible State Variables for State Transition of Predictive Policing Model.

Category	**State Variables**
Temporal	- Season (Winter, Spring, Summer, Fall) - Months of year - Weeks of month - Days of week - Major holidays - Weekend - Holiday - Non-holiday - School closed days - Lagged crime rate *t-1*
Weather	- Daily mean temperature - Temperature-humidity index - Wind speed - Humidity - Sun light hours - Precipitation - Percentage of sky cover
Demographic	- Population density - Age, sex of victims and offenders - Proportion of 17-24 age - Percentage of young male population (15-17 age) - Percent Black - Percent Latino - Racial / ethnic heterogeneity - Percent single parent households - Percent occupied units - Percent owners - Mean educational attainment - Proportion of community with no education - Presence of ex-combatants - Presence of returned refugees - Internally displaced persons per capita - Presence of seasonal labors and migrants per capita - Number of tribes - Number of males - Number of widowed - Number of divorced / divorce rate - Percentage of persons in ethnic minority groups - Membership in social, religious and cultural groups

	- Number of prisoners - Poverty level - Crime levels - Conviction rate - Median income - Real minimum wage - Count of owner occupied households - Median rent charged for all housing units that are rented - Consumer price index - Unemployment - Gini coefficient (Income inequality index) - Percentage of non-white - Median value of all housing units - GDP - Consumer's expenditure - Average asset wealth - Average household quality - Household with high disposable income (%) - Intra-communal standard deviation of average asset wealth - Intra-communal standard deviation of average household quality - Proportion of residents describing local leaders as "corrupt" - Proportion of residents describing the police and courts as "corrupt" - Proportion of residents reporting a burglary, armed robbery, or assault in the previous year - Proportion of residents reporting an ongoing land conflict in the previous year
Geographic data	- The distance to the nearest college or university from the crime location - The distance to the nearest K_12 school - The distance to the nearest interstate highway - The distance to the nearest usable road - The distance to the nearest small business - Proximity to bus stop (Units within a 330 ft radius of a bus stop are coded 1, and all others are coded 0) - Proximity to major thoroughfare (1 for areas within a two block (1,000 ft) of major roads, 0 for all others) - Proximity to likely offenders (Greater than 500 ft and less than 1,500 ft away from the residence of an arrested burglar coded as 1, 0 for athers) - Distance (logged) to US-Mexico border (miles) - Distance (logged) to US-Canada border (miles) - Distance (logged) to major port (miles)
Crime type characteristics	- 911 call type in number (Domestic, drugs, public disorder, shots fired, truancy, vice, weapons) - Offence crime type (Criminal mischief, disorderly conduct, liquor law violation, prostitution, public drunkenness, simple assault, trespass) - Drugs at arrest - Availability of handguns

	- Stolen property features (Alcohol, cigarettes, food staffs, antiques, drugs, cadrs,..etc.) - Location of entry (Wall, adjoining property, roof, window,…etc.) - Entry methods and behavior (Smash, Cut, Duplicate key, Drill, Force.etc.) - Type of dwelling (Old, Terrace, Bungalow, Flat … etc.) - Search behavior (Untidy, Downstairs only, Many rooms.. etc.) - Location of exit (Wall, Adjoining property, Exit same as entry.. etc.) - Alarm/Phone (Cut phone, Tamper with alarm, Alarm activated) - Bogus official crime (Social service, Home help, Gardener..etc.) - Land use (1 for residential, 0 for all others) - Housing tenure (1 for renter occupied, 0 for owner occupied) - Vacant unit (1 for vacant unit, 0 for occupied) - Substandard housing (1 if it had a reported housing code violation, 0 if not) - Nuisance violation (1 if it had a reported nuisance violation, 0 if not) - Street lighting (1 for dark areas, 0 for illuminated areas) - Corner lots served (1 for corner lot, 0 for noncorner lot) - Wooded areas and vacant lots (1 for areas adjacent to a wooded area or vacant lot, 0 for all other areas) - Felony arrest rate - Total misdemeanor arrests
Others	- Number of police officers - Police workload (# of diff. crimes per full time sworn officer) - Presence of a police station or magistrate - Strength of cell network coverage - Strength of radio reception - Vehicle density (per mile^2 in 1,000s) - Household with no vehicles (%) - Adult male property offender pool (Arrest rate per 1,000 population) - Auto/parts dealer and repair establishment (# per 1,000 vehicles) - Multiunit housing (% of housing with 5or more units) - MVT clearance rate (%) - MVT specialized unit (1 or 0) - Stolen vehicle tracking system (1 or 0) - License plate reader (1 or 0) - Droughts and floods - Insects and other pest infestations - Livestock diseases - Human diseases

Appendix B

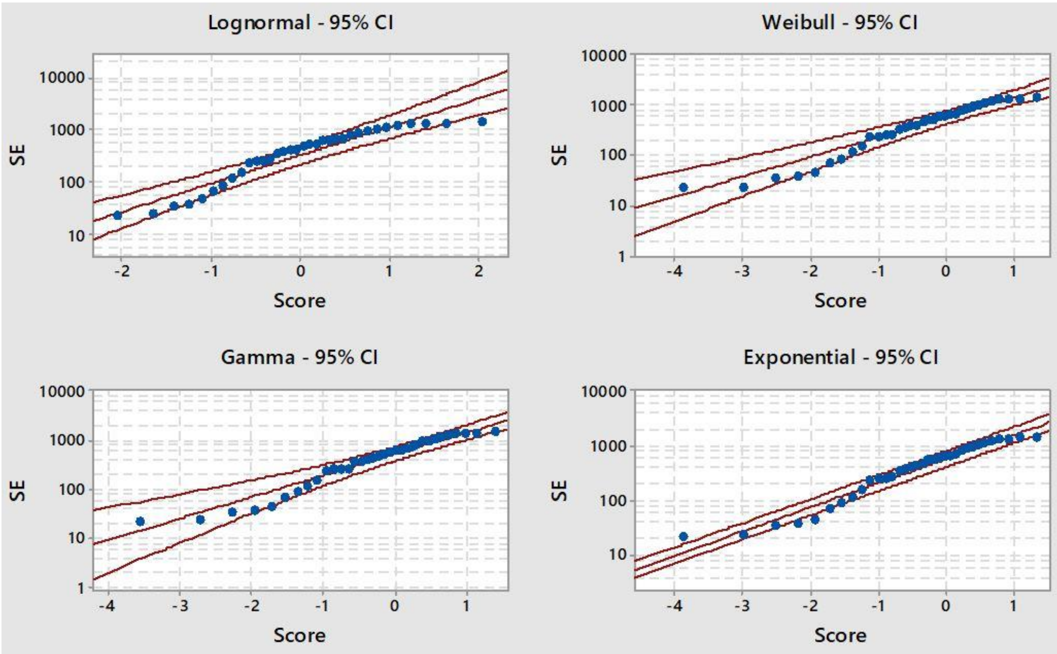


Figure B-1 Q-Q plots for CFS interarrival time for South_Priority_E for February 2011.

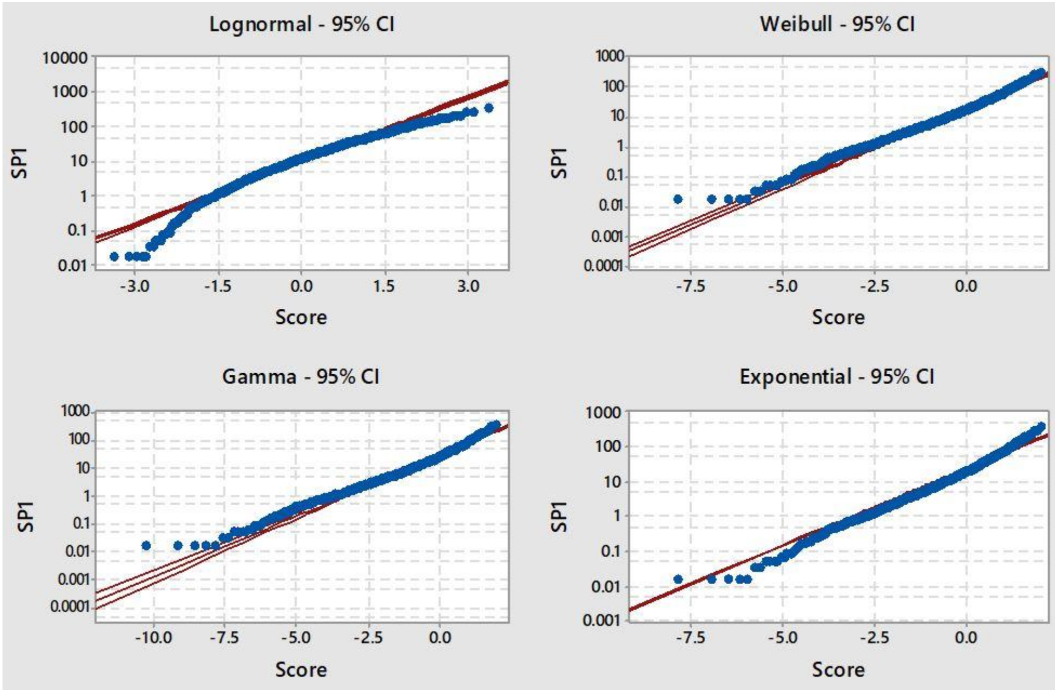


Figure B-2 Q-Q plots for CFS interarrival time for South_Priority_1 for February 2011.

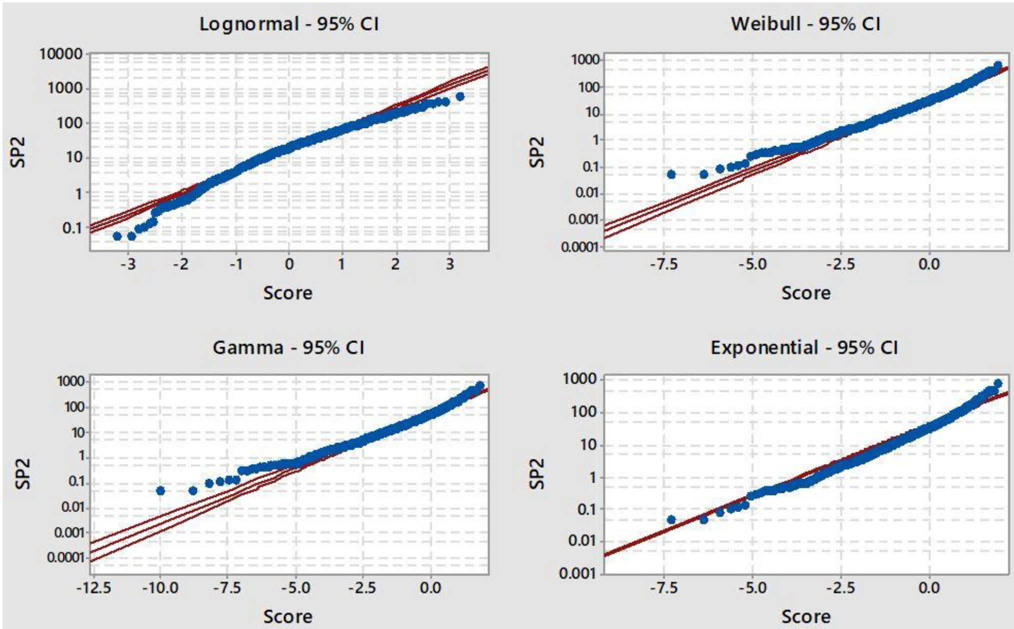


Figure B-3 Q-Q plots for CFS interarrival time for South_Priority_2 for February 2011.

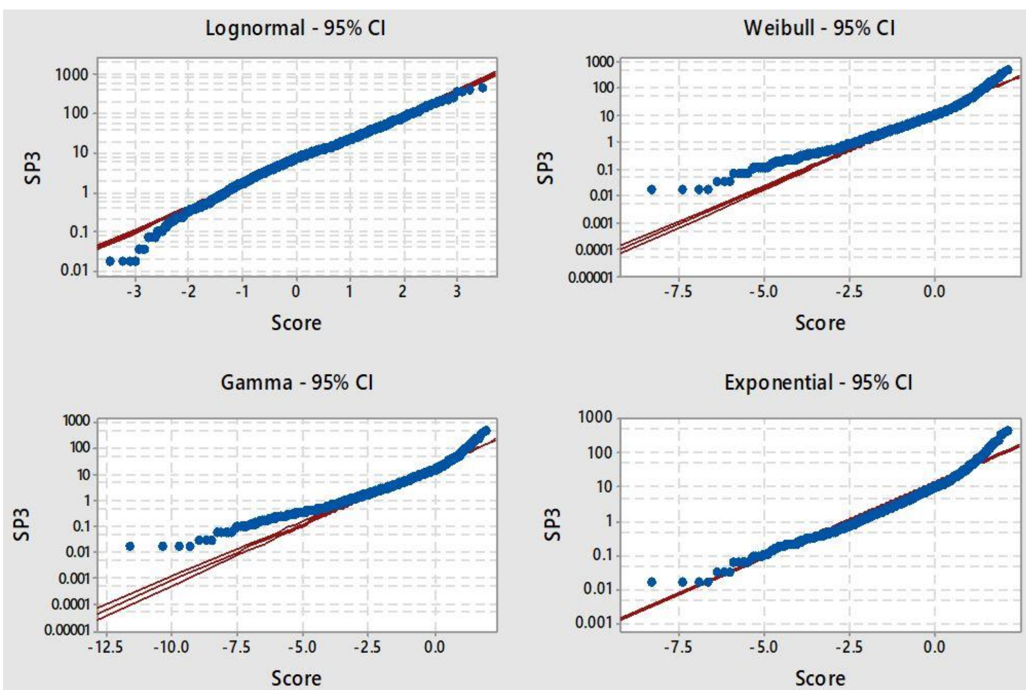


Figure B-4 Q-Q plots for CFS interarrival time for South_Priority_3 for February 2011.

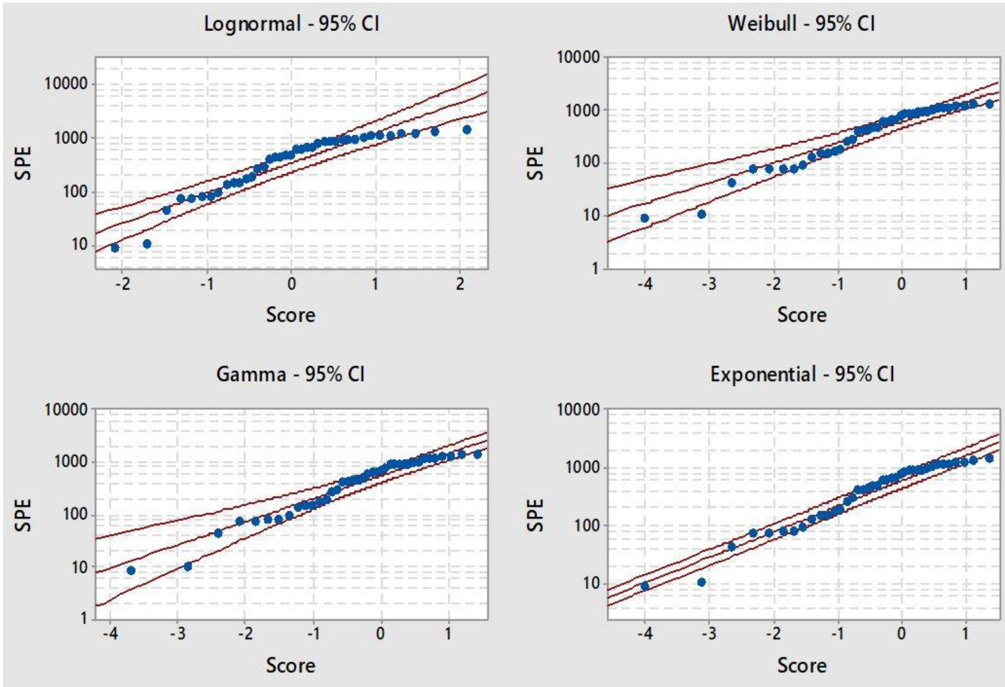


Figure B-5 Q-Q plots for CFS interarrival time for South_Priority_E for November 2011.

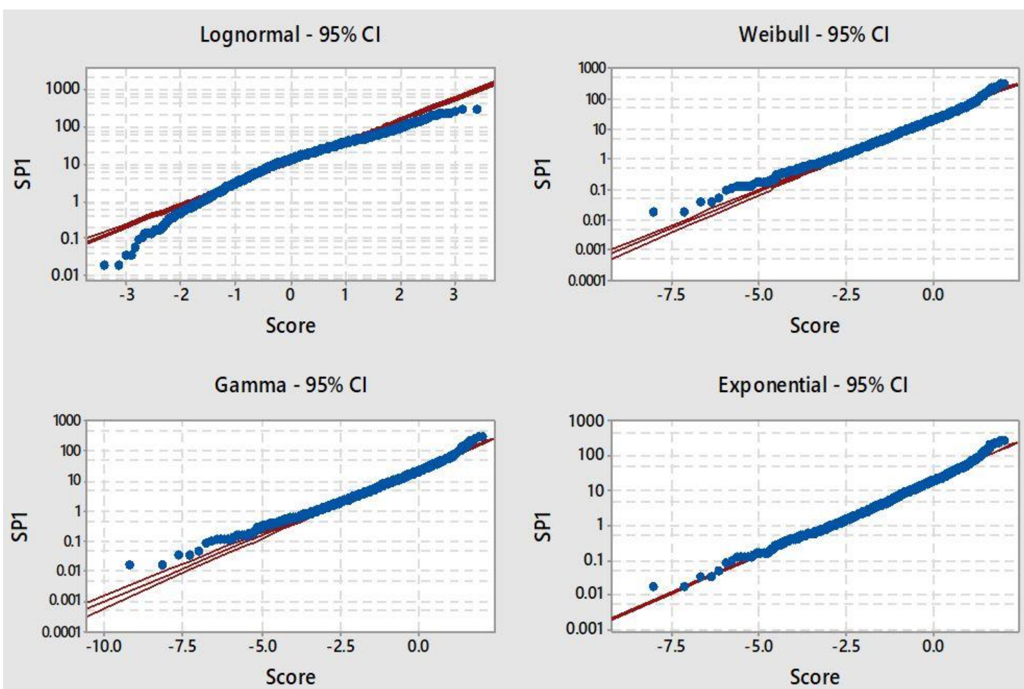


Figure B-6 Q-Q plots for CFS interarrival time for South_Priority_1 for November 2011.

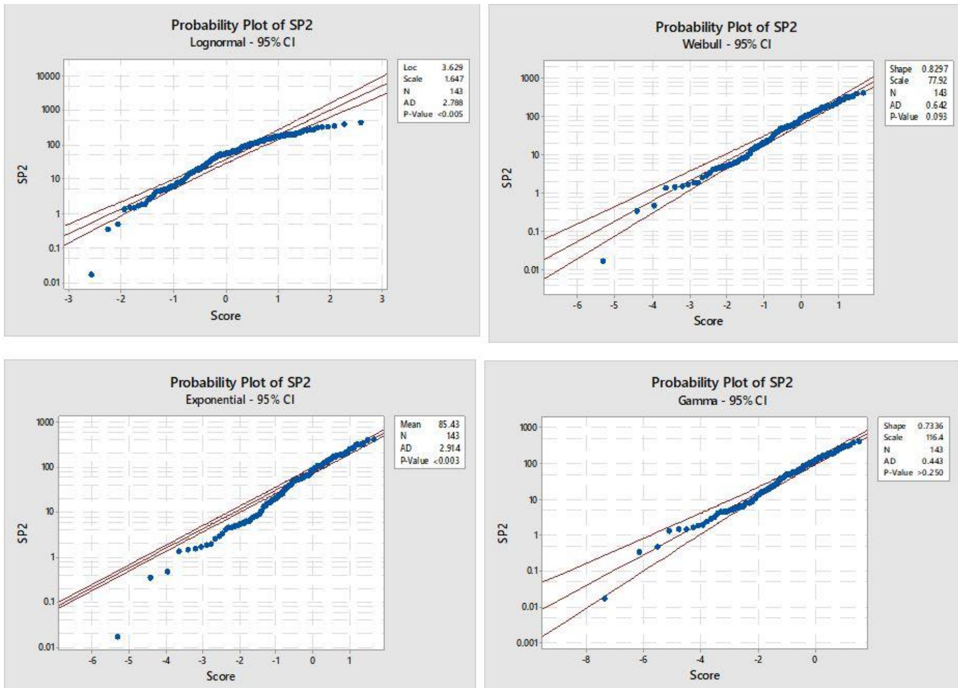


Figure B-7 Q-Q plots for CFS interarrival time for South_Priority_3 for November 2011.

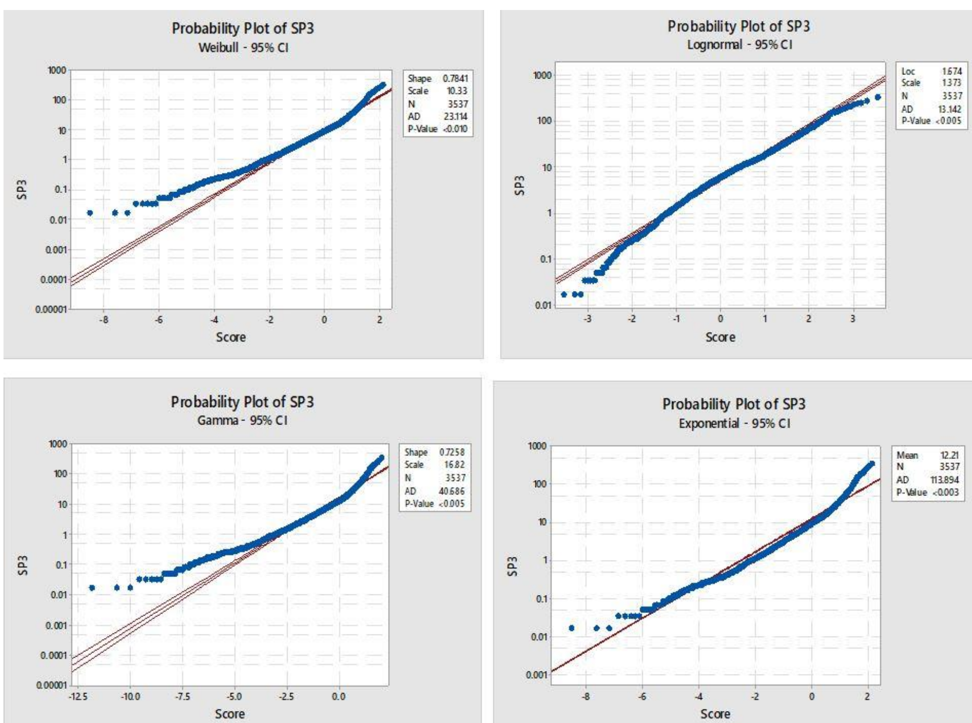


Figure B-8 Q-Q plots for CFS interarrival time for South_Priority_3 for November 2011.

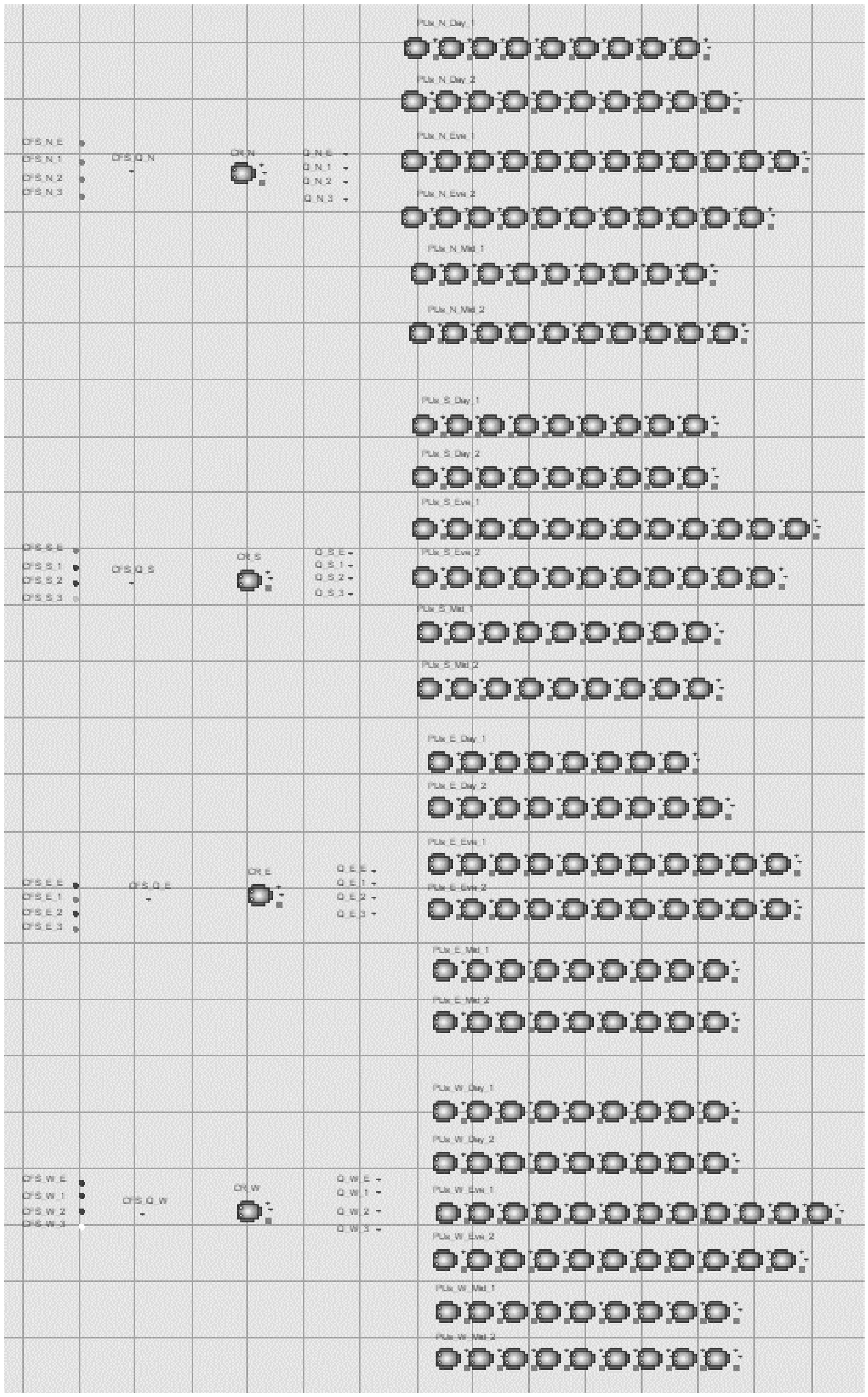


Figure B-9 Screenshot of the WITNESS discrete-event simulation model for 8-hr shift.

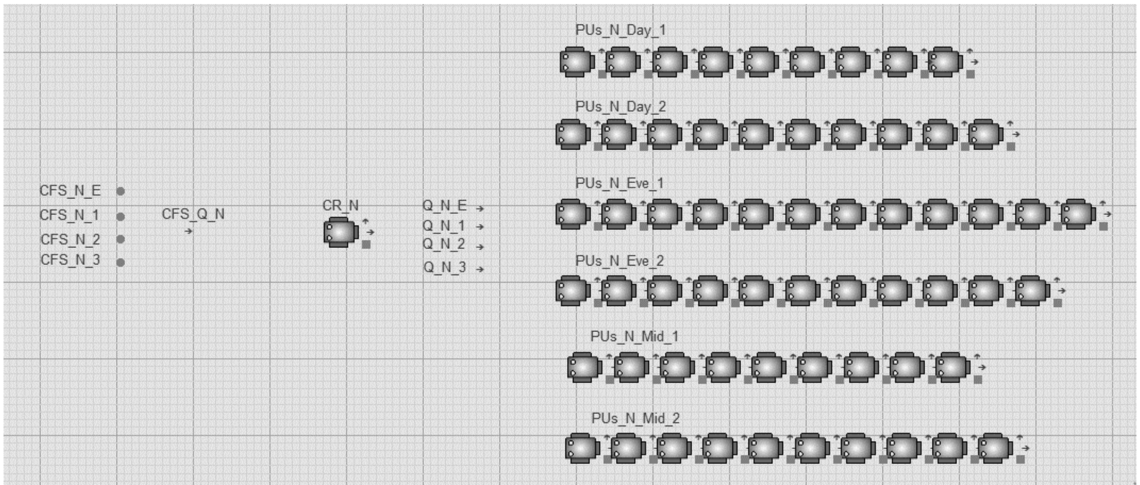


Figure B-10 Screenshot of North in the WITNESS discrete-event simulation model for 8-hr shift.

Appendix C

Table C-1 Estimated coefficients using 2011 APD data for state transition models.

District	Priority	Period	γ	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8
north	E	Mid	0.005848425	1.637649	-0.6376485	-1.16E-05	5.78E-06	0.0538477	0.09151173	-0.001018051	-0.000250473
		Day	0.01972274	2.127591	-1.127591	-9.74E-06	9.89E-06	-0.3841408	0.3457018	-0.000600939	0.000861898
		Eve	0.05729144	2.141277	-1.141277	8.55E-06	-9.21E-06	0.4627658	-0.5251798	-0.001391311	0.00105984
	1	Mid	4.980752	2.575749	-1.575749	4.46E-05	-0.000233	-2.460113	-0.2140557	-0.03298505	0.00684844
		Day	2.722401	2.735696	-1.735696	6.52E-05	-6.41E-05	-1.096101	-3.208585	-0.004976255	0.0157968
		Eve	1.937012	2.453592	-1.453592	1.85E-05	-7.67E-05	-0.2236686	-1.584619	0.02316207	-0.01382309
	2	Mid	-0.8834884	2.214865	-1.214865	-5.44E-05	7.12E-05	1.150833	-0.3063839	-0.0112963	0.01575005
		Day	0.00579803	1.996851	-0.996851	7.32E-05	-7.31E-05	6.528754	-6.540238	0.01448416	-0.01441683
		Eve	-1.092241	2.451561	-1.451561	2.25E-05	-4.21E-05	3.417421	-1.455673	0.0005985	0.003277457
	3	Mid	-0.4965161	2.489034	-1.489034	0.000162393	-0.000148	0.4665154	-0.1841521	-0.006929129	0.01492347
		Day	6.054433	2.811649	-1.811649	0.000980631	-0.001242	1.763548	-6.091959	-0.05717221	0.1191944
		Eve	-3.813984	1.837026	-0.8370258	0.000823805	-0.000753	-6.565836	10.74806	-0.00468084	-0.001384678
west	E	Mid	0.05825104	2.518333	-1.518333	-3.45E-06	3.575841e-08	-0.041137	0.04218849	4.62E-05	-0.000654543
		Day	0.0208341	2.204875	-1.204875	4.11E-07	9.33E-08	0.0446452	-0.0946328	0.000619114	-0.00026143

		Eve	0.09095164	2.45115	-1.45115	2.51E-06	-6.23E-08	-0.0851633	-0.0868045	-0.000554363	-0.000154555
	1	Mid	2.26306	2.884485	-1.884485	0.000136787	-0.000169	-2.683248	0.1078198	-0.01374878	0.01226369
		Day	0.1446205	2.397843	-1.397843	-1.49E-05	1.41E-06	1.704607	-1.567558	0.00651581	-0.009228162
		Eve	-0.1000551	2.790938	-1.790938	3.78E-05	-4.58E-05	0.5105003	-0.1478818	-0.001619734	-0.000387895
	2	Mid	-0.1032029	2.326541	-1.326541	1.46E-05	-1.77E-05	-0.2131945	0.4633441	-8.17E-05	-0.001525903
		Day	0.01187746	1.990259	-0.990259	-1.55E-05	1.55E-05	1.070032	-1.088573	-0.000715426	0.000807885
		Eve	0.2959049	2.746641	-1.74664	-1.38E-06	3.14E-05	-0.2760008	-0.7212403	-0.001186386	-0.003463068
	3	Mid	0.8607281	2.515759	-1.515759	5.71E-05	-6.84E-05	-3.070888	2.108967	-0.01325723	0.01206944
		Day	0.8373208	2.588487	-1.588487	7.39E-05	-9.93E-05	-3.861233	2.659508	-0.008855314	0.0344702
		Eve	7.67959	2.750096	-1.750096	0.000307518	-0.000352	-6.327212	-4.244712	0.001666311	0.008232842
east	E	Mid	-0.3102376	1.569671	-0.569671	1.53E-05	-8.89E-06	0.3897667	-0.0880999	4.54E-05	0.000721005
		Day	0.01659674	2.479313	-1.479313	4.32E-06	-6.56E-06	-0.0905072	0.11866	-0.001093806	0.000999986
		Eve	0.03252187	2.695197	-1.695197	-7.20E-06	7.32E-06	-0.0620397	0.01611063	1.84E-05	-0.000216557
	1	Mid	-1.554293	1.705933	-0.7059333	0.000120711	-7.49E-05	-2.501291	3.649352	-0.01501006	0.02090348
		Day	-2.39561	3.175423	-2.175423	-4.95E-05	7.08E-05	0.8053574	1.877077	0.001706414	0.01503856
		Eve	1.370333	2.847279	-1.847279	1.66E-05	-3.81E-05	-1.205161	-0.2921437	-0.005660173	0.003573624

	2	Mid	0.158764	2.760377	-1.760377	3.52E-06	-1.15E-05	0.0299496	-0.0541242	-0.001671055	-0.000120663
		Day	-0.08441471	2.33857	-1.33857	3.52E-05	-3.50E-05	1.34558	-1.216876	0.003341676	-0.003668952
		Eve	0.02102286	2.881483	-1.881483	1.19E-05	-1.85E-05	0.2876297	-0.2325833	-0.000836927	0.003686722
	3	Mid	-0.2641827	2.091981	-1.091981	5.07E-05	-5.04E-05	-3.026571	3.39007	-0.0282666	0.02938911
		Day	-3.121932	2.922843	-1.922843	5.90E-05	-0.000107	0.9205362	3.974661	-0.005890083	0.04265546
		Eve	0.9578783	1.856811	-0.8568114	-0.000117532	9.60E-05	-0.2312839	-0.8108195	0.004743397	-4.17E-05
south	E	Mid	-0.07807211	2.620824	-1.620824	2.32E-07	2.33E-06	0.03841	0.01218421	-1.11E-05	0.000413719
		Day	-0.009301924	2.572328	-1.572328	-2.66E-06	3.68E-06	0.0503001	-0.0556023	6.73E-05	-0.000220356
		Eve	-0.02990495	2.906043	-1.906043	-2.12E-06	4.84E-06	0.0383468	-0.046466	-0.000506692	0.000159748
	1	Mid	0.5109175	2.48979	-1.48979	-3.17E-06	-5.14E-06	-0.5480895	-0.0291329	-0.005654139	0.005914306
		Day	-2.397704	3.537432	-2.537432	-3.92E-05	0.000114	0.6382959	1.119269	0.00179368	0.002817747
		Eve	0.1087267	2.371075	-1.371075	-2.04E-05	2.68E-05	0.593551	-0.8603106	0.000646456	-0.002458498
	2	Mid	-1.019049	0.8870392	0.1129608	3.12E-05	1.07E-05	0.4801856	-0.043445	1.36E-05	0.007168049
		Day	-0.6230177	2.65575	-1.65575	7.71E-06	-7.57E+00	0.252978	0.6707496	0.000132758	-0.000583642
		Eve	0.1248052	2.581449	-1.581449	-3.45E-06	1.06E-05	-0.201261	-0.1040038	-0.000924663	-0.000550981
	3	Mid	0.1210597	2.450595	-1.450595	2.79E-05	-3.03E-05	-0.8615817	0.7242629	-0.007028482	0.007754466

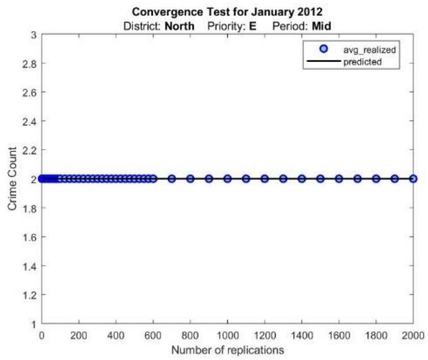
		Day	0.882179	2.513845	-1.513845	4.24E-05	-5.94E-05	-3.758727	2.664518	-0.01656108	0.02343457
		Eve	0.3117349	2.343863	-1.343863	2.27E-05	-4.27E-05	0.4166705	-0.5559529	-0.002694624	0.007794482

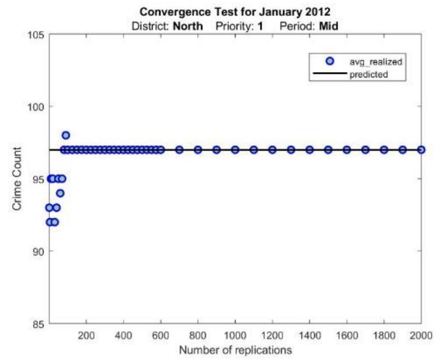
Table C-2 Mean travel time in minutes from one beat to other beats using Google Maps.

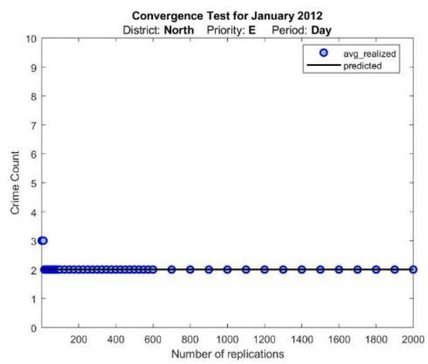
Beat	210	220	230	240	250	260	270	280	310	320	330	340	350	360	370	380	410	420	430	440	450	460	470	480	510	520	530	540	550	560	570	580
210	-	10	8	5	7	8	9	13	17	23	9	14	17	10	16	16	13	14	11	14	13	17	18	17	20	26	23	22	21	20	26	20
220	10	-	12	11	15	16	14	16	25	30	15	23	30	21	26	30	21	25	22	21	25	26	26	24	33	38	36	29	35	26	30	27
230	8	12	-	6	8	12	6	8	20	23	11	15	21	13	16	19	9	10	14	12	9	15	12	11	15	20	19	13	16	15	20	15
240	5	11	6	-	7	10	8	9	19	22	10	14	19	11	15	16	11	12	12	11	12	15	16	15	20	22	23	18	19	18	24	19
250	7	15	8	7	-	4	5	10	17	20	5	11	17	6	9	12	9	14	7	9	12	13	14	15	16	21	19	13	16	19	20	19
260	8	16	12	10	4	-	7	10	18	17	8	11	16	6	7	9	7	12	5	7	10	10	13	13	13	19	16	11	14	17	17	18
270	9	14	6	8	5	7	-	6	19	20	10	12	19	11	13	14	6	9	10	7	9	11	13	11	15	21	19	14	16	15	20	15
280	13	16	8	9	10	10	6	-	18	18	12	16	16	14	14	15	6	7	13	9	6	13	10	8	13	19	17	10	13	12	18	12
310	17	25	20	19	17	18	19	18	-	8	14	8	6	14	12	11	18	17	15	19	16	15	16	16	8	11	15	11	14	15	17	17
320	23	30	23	22	20	17	20	18	8	-	18	12	7	16	13	10	18	16	15	18	15	14	15	16	7	7	11	11	13	15	14	16
330	9	15	11	10	5	8	10	12	14	18	-	9	15	7	10	14	13	15	9	13	15	15	17	17	15	21	21	16	19	21	23	22
340	14	23	15	14	11	11	12	16	8	12	9	-	9	8	8	12	16	18	10	14	16	14	16	16	12	15	18	14	17	19	21	21
350	17	30	21	19	17	16	19	16	6	7	15	9	-	13	11	9	16	15	14	16	13	12	13	14	7	9	12	9	12	14	15	16
360	10	21	13	11	6	6	11	14	14	16	7	8	13	-	4	8	11	13	4	7	10	9	11	12	10	16	15	10	13	16	16	19
370	16	26	16	15	9	7	13	14	12	13	10	8	11	4	-	6	12	13	5	8	10	7	9	10	8	14	11	8	11	14	15	15
380	16	30	19	16	12	9	14	15	11	10	14	12	9	8	6	-	14	13	6	11	12	8	10	12	5	12	9	7	10	11	13	13
410	13	21	9	11	9	7	6	6	18	18	13	16	16	11	12	14	-	6	10	6	6	11	10	10	13	18	17	10	12	12	19	12

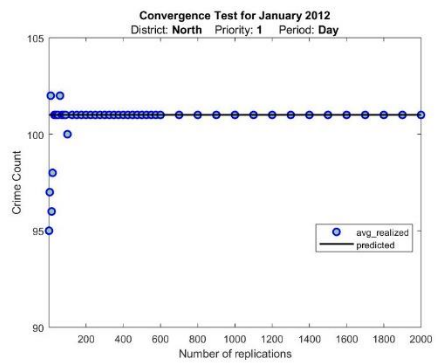
420	14	25	10	12	14	12	9	7	17	16	15	18	15	13	13	13	6	-	12	7	4	12	9	8	12	17	15	9	12	11	17	11
430	11	22	14	12	7	5	10	13	15	15	9	10	14	4	5	6	10	12	-	7	10	8	10	10	10	16	13	9	13	14	15	17
440	14	21	12	11	9	7	7	9	19	18	13	14	16	7	8	11	6	7	7	-	4	7	7	8	13	18	17	11	13	12	19	14
450	13	25	9	12	12	10	9	6	16	15	15	16	13	10	10	12	6	4	10	4	-	9	7	6	11	17	15	9	12	11	16	11
460	17	26	15	15	13	10	11	13	15	14	15	14	12	9	7	8	11	12	8	7	9	-	5	8	9	14	13	7	9	9	14	12
470	18	26	12	16	14	13	13	10	16	15	17	16	13	11	9	10	10	9	10	7	7	5	-	3	10	16	14	8	9	6	15	11
480	17	24	11	15	15	13	11	8	16	16	17	16	14	12	10	12	10	8	10	8	6	8	3	-	11	16	16	9	10	8	17	11
510	20	33	15	20	16	13	15	13	8	7	15	12	7	10	8	5	13	12	10	13	11	9	10	11	-	7	7	6	9	10	11	13
520	26	38	20	22	21	19	21	19	11	7	21	15	9	16	14	12	18	17	16	18	17	14	16	16	7	-	7	12	12	16	9	12
530	23	36	19	23	19	16	19	17	15	11	21	18	12	15	11	9	17	15	13	17	15	13	14	16	7	7	-	9	7	10	6	9
540	22	29	13	18	13	11	14	10	11	11	16	14	9	10	8	7	10	9	9	11	9	7	8	9	6	12	9	-	7	8	10	11
550	21	35	16	19	16	14	16	13	14	13	19	17	12	13	11	10	12	12	13	13	12	9	9	10	9	12	7	7	-	5	7	6
560	20	26	15	18	19	17	15	12	15	15	21	19	14	16	14	11	12	11	14	12	11	9	6	8	10	16	10	8	5	-	12	8
570	26	30	20	24	20	17	20	18	17	14	23	21	15	16	15	13	19	17	15	19	16	14	15	17	11	9	6	10	7	12	-	7
580	20	27	15	19	19	18	15	12	17	16	22	21	16	19	15	13	12	11	17	14	11	12	11	11	13	12	9	11	6	8	7	-

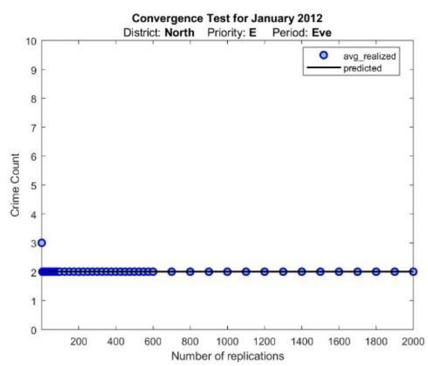
Appendix D

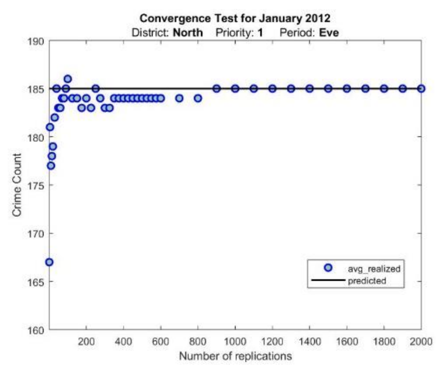

Convergence Test for January 2012
District: North Priority: E Period: Mid
avg_realized
predicted
Crime Count
Number of replications

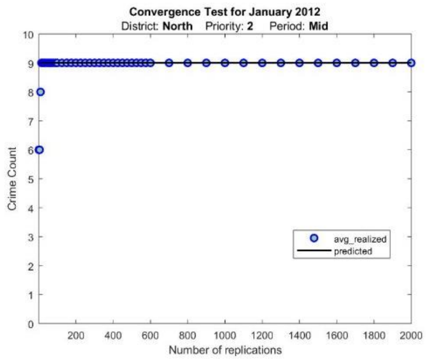

Convergence Test for January 2012
District: North Priority: 1 Period: Mid
avg_realized
predicted
Crime Count
Number of replications

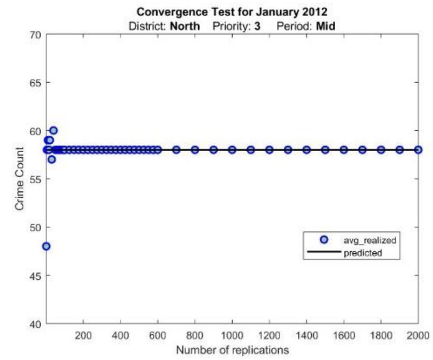

Convergence Test for January 2012
District: North Priority: E Period: Day
avg_realized
predicted
Crime Count
Number of replications

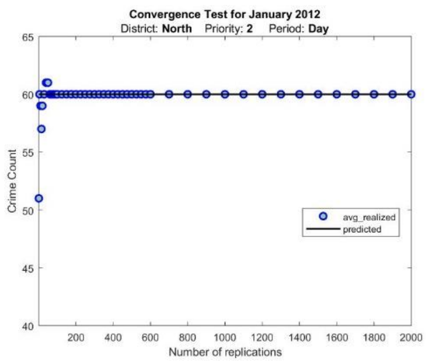

Convergence Test for January 2012
District: North Priority: 1 Period: Day
avg_realized
predicted
Crime Count
Number of replications

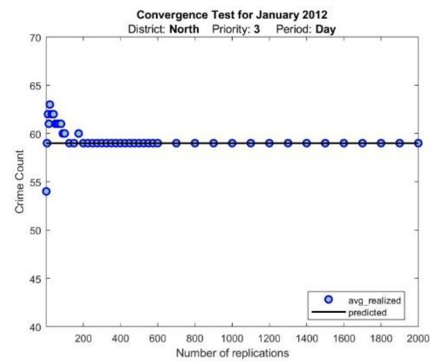

Convergence Test for January 2012
District: North Priority: E Period: Eve
avg_realized
predicted
Crime Count
Number of replications

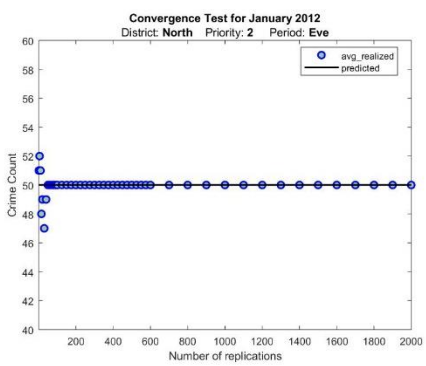

Convergence Test for January 2012
District: North Priority: 1 Period: Eve
avg_realized
predicted
Crime Count
Number of replications

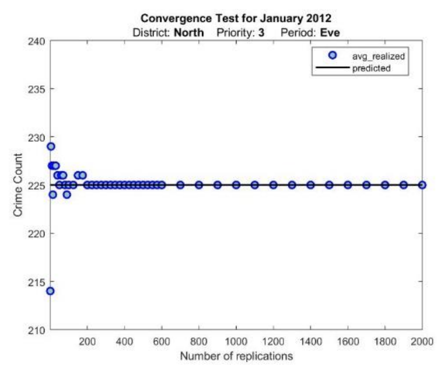

Convergence Test for January 2012
District: North Priority: 2 Period: Mid
Crime Count
Number of replications
avg_realized
predicted

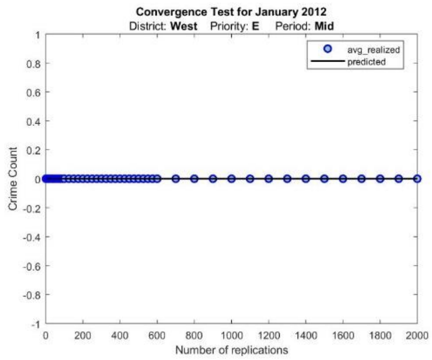

Convergence Test for January 2012
District: North Priority: 3 Period: Mid
Crime Count
Number of replications
avg_realized
predicted

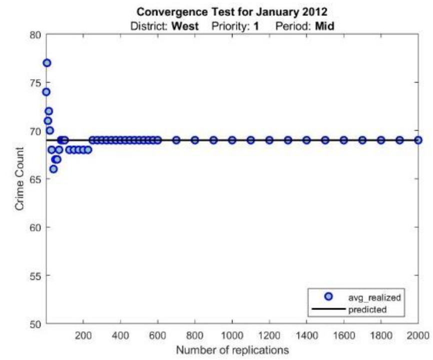

Convergence Test for January 2012
District: North Priority: 2 Period: Day
Crime Count
Number of replications
avg_realized
predicted

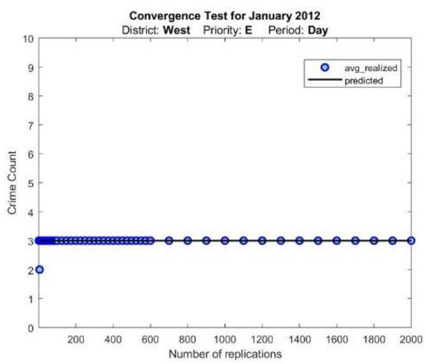

Convergence Test for January 2012
District: North Priority: 3 Period: Day
Crime Count
Number of replications
avg_realized
predicted

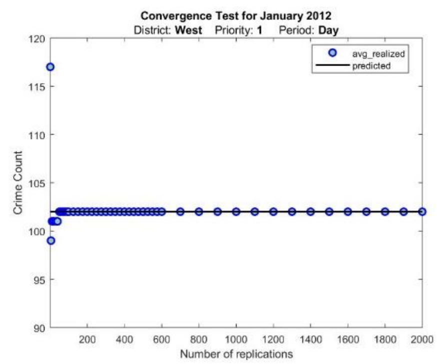

Convergence Test for January 2012
District: North Priority: 2 Period: Eve
Crime Count
Number of replications
avg_realized
predicted

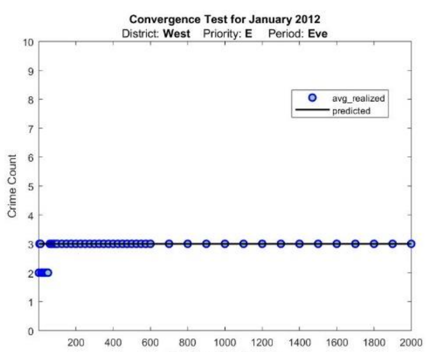

Convergence Test for January 2012
District: North Priority: 3 Period: Eve
Crime Count
Number of replications
avg_realized
predicted

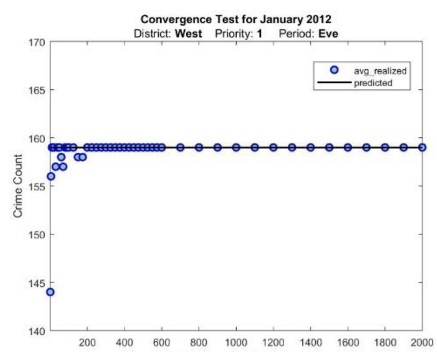

Convergence Test for January 2012
District: West Priority: E Period: Mid
avg_realized
predicted
Crime Count
Number of replications

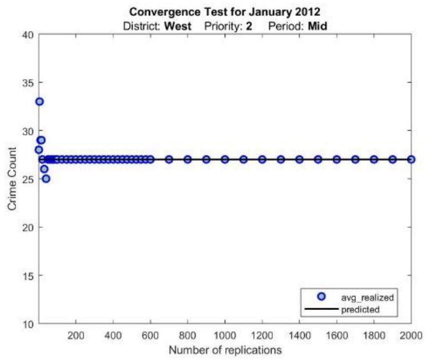

Convergence Test for January 2012
District: West Priority: 1 Period: Mid
avg_realized
predicted
Crime Count
Number of replications

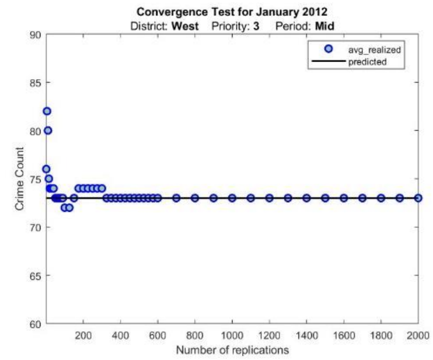

Convergence Test for January 2012
District: West Priority: E Period: Day
avg_realized
predicted
Crime Count
Number of replications

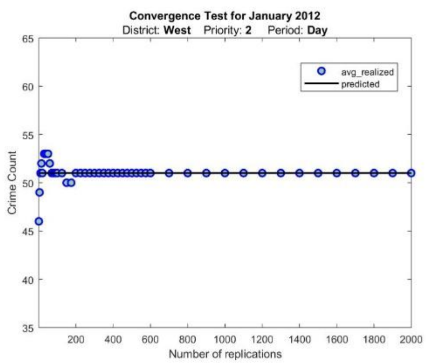

Convergence Test for January 2012
District: West Priority: 1 Period: Day
avg_realized
predicted
Crime Count
Number of replications

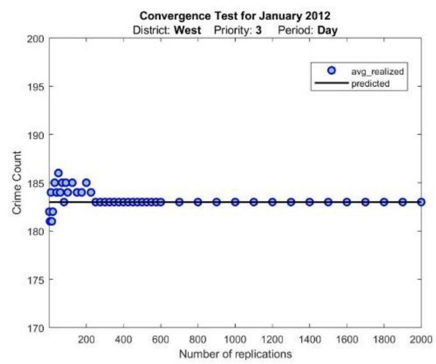

Convergence Test for January 2012
District: West Priority: E Period: Eve
avg_realized
predicted
Crime Count
Number of replications

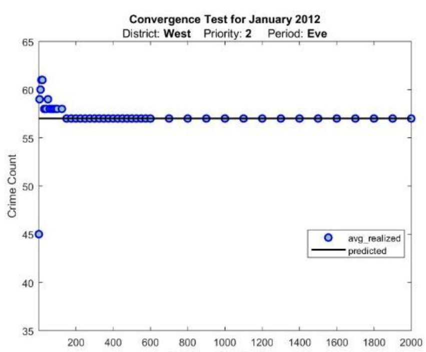

Convergence Test for January 2012
District: West Priority: 1 Period: Eve
avg_realized
predicted
Crime Count
Number of replications

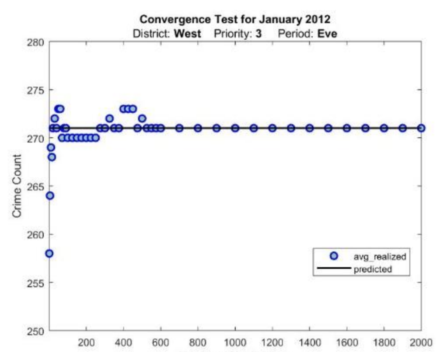

Convergence Test for January 2012
District: West Priority: 2 Period: Mid
Crime Count
Number of replications
avg_realized
predicted

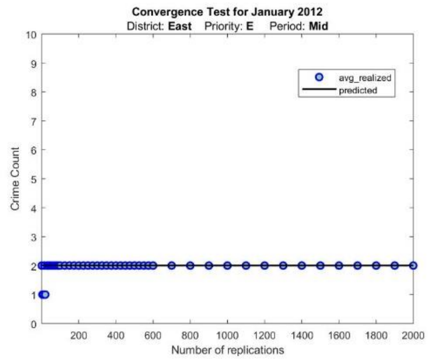

Convergence Test for January 2012
District: West Priority: 3 Period: Mid
Crime Count
Number of replications
avg_realized
predicted

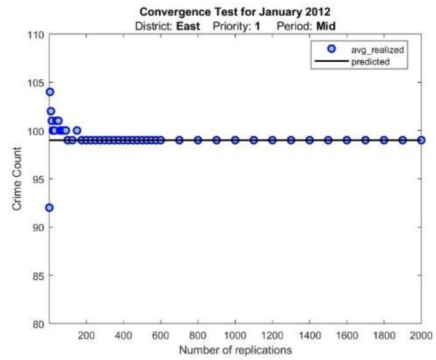

Convergence Test for January 2012
District: West Priority: 2 Period: Day
Crime Count
Number of replications
avg_realized
predicted

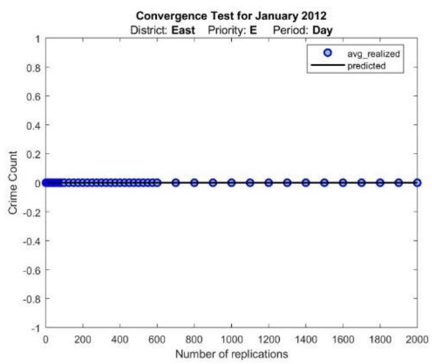

Convergence Test for January 2012
District: West Priority: 3 Period: Day
Crime Count
Number of replications
avg_realized
predicted

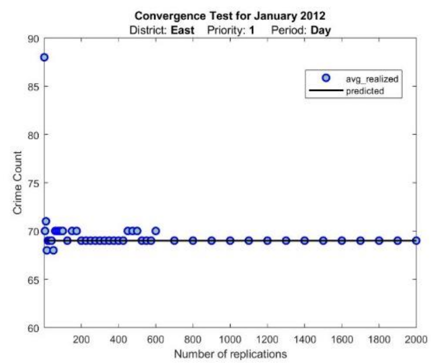

Convergence Test for January 2012
District: West Priority: 2 Period: Eve
Crime Count
Number of replications
avg_realized
predicted

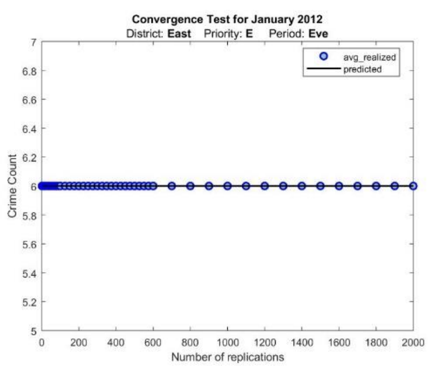

Convergence Test for January 2012
District: West Priority: 3 Period: Eve
Crime Count
Number of replications
avg_realized
predicted

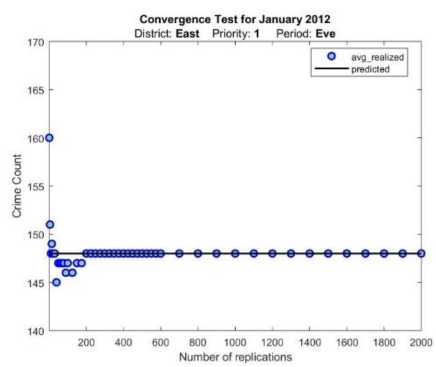

Convergence Test for January 2012
District: East Priority: E Period: Mid
avg_realized
predicted
Crime Count
Number of replications

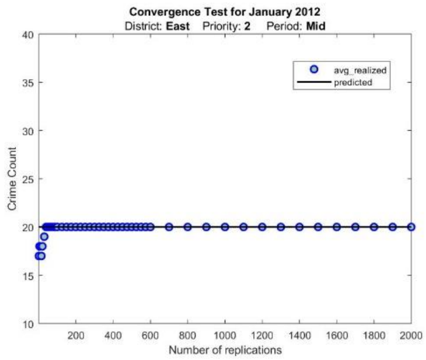

Convergence Test for January 2012
District: East Priority: 1 Period: Mid
avg_realized
predicted
Crime Count
Number of replications


Convergence Test for January 2012
District: East Priority: E Period: Day
avg_realized
predicted
Crime Count
Number of replications

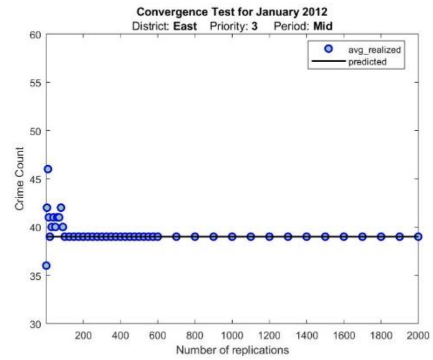

Convergence Test for January 2012
District: East Priority: 1 Period: Day
avg_realized
predicted
Crime Count
Number of replications


Convergence Test for January 2012
District: East Priority: E Period: Eve
avg_realized
predicted
Crime Count
Number of replications

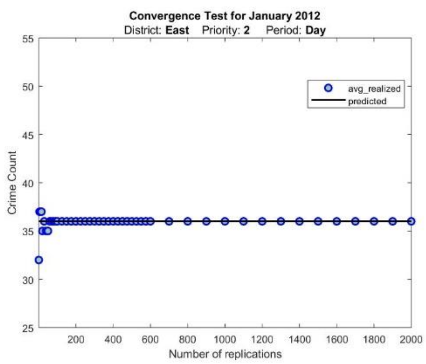

Convergence Test for January 2012
District: East Priority: 1 Period: Eve
avg_realized
predicted
Crime Count
Number of replications



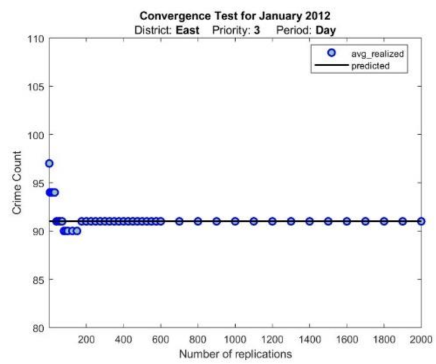
Convergence Test for January 2012
District: **East** Priority: **2** Period: **Mid**
avg_realized
predicted
Crime Count
Number of replications



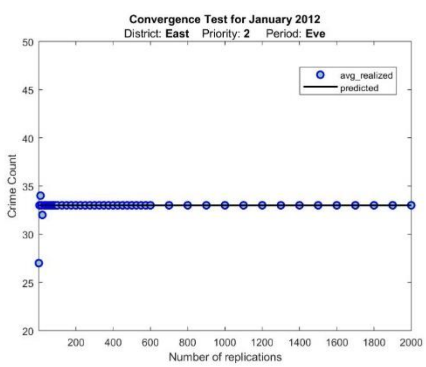
Convergence Test for January 2012
District: **East** Priority: **3** Period: **Mid**
avg_realized
predicted
Crime Count
Number of replications



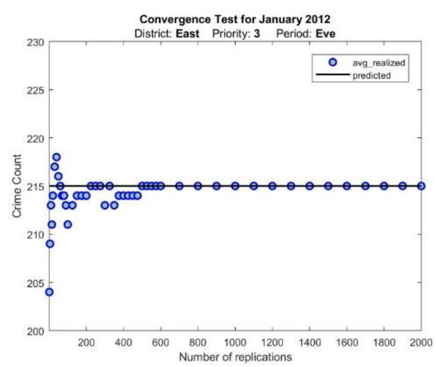
Convergence Test for January 2012
District: **East** Priority: **2** Period: **Day**
avg_realized
predicted
Crime Count
Number of replications



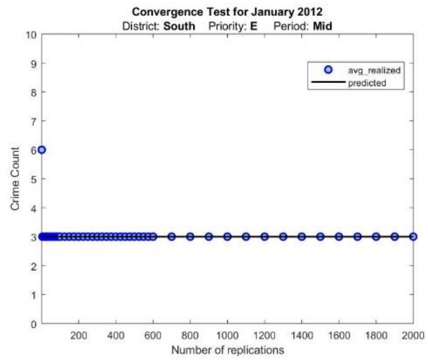
Convergence Test for January 2012
District: **East** Priority: **3** Period: **Day**
avg_realized
predicted
Crime Count
Number of replications

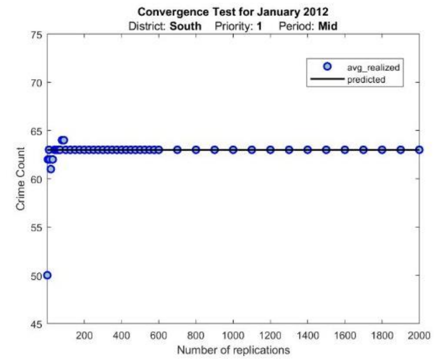


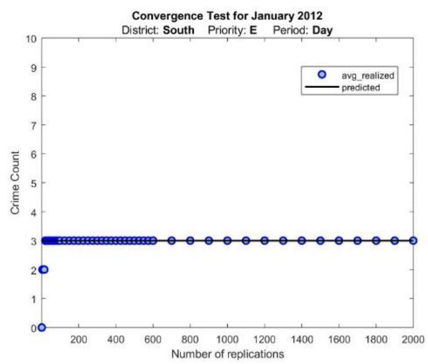
Convergence Test for January 2012
District: **East** Priority: **2** Period: **Eve**
avg_realized
predicted
Crime Count
Number of replications

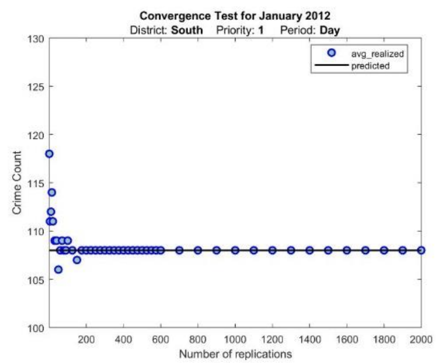


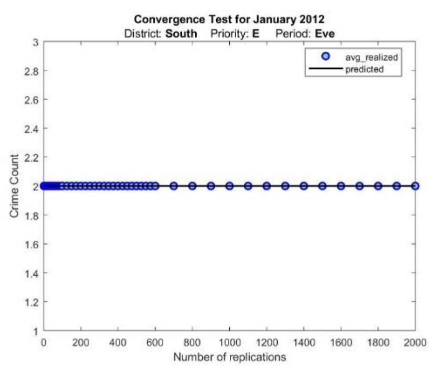
Convergence Test for January 2012
District: **East** Priority: **3** Period: **Eve**
avg_realized
predicted
Crime Count
Number of replications

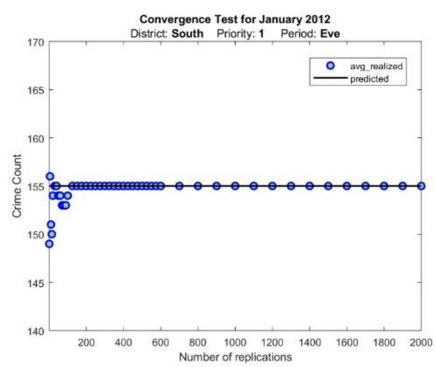

Convergence Test for January 2012
District: South Priority: E Period: Mid
avg_realized
predicted
Crime Count
Number of replications

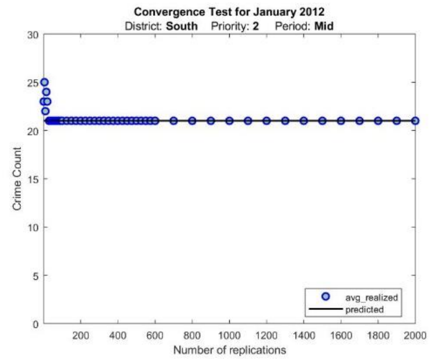

Convergence Test for January 2012
District: South Priority: 1 Period: Mid
avg_realized
predicted
Crime Count
Number of replications

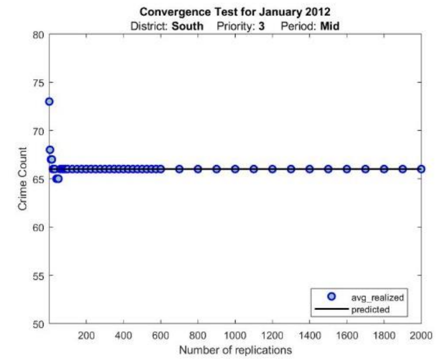

Convergence Test for January 2012
District: South Priority: E Period: Day
avg_realized
predicted
Crime Count
Number of replications

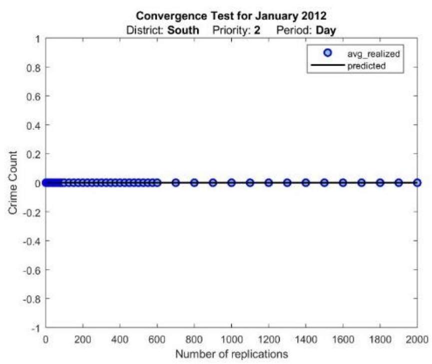

Convergence Test for January 2012
District: South Priority: 1 Period: Day
avg_realized
predicted
Crime Count
Number of replications

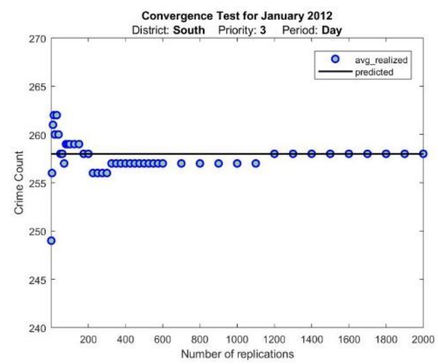

Convergence Test for January 2012
District: South Priority: E Period: Eve
avg_realized
predicted
Crime Count
Number of replications

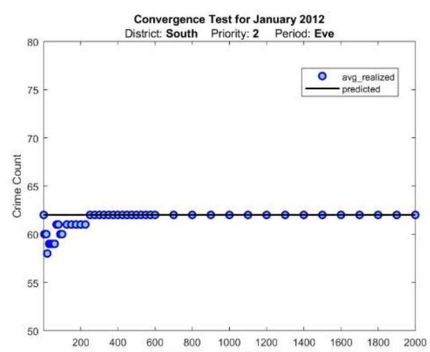

Convergence Test for January 2012
District: South Priority: 1 Period: Eve
avg_realized
predicted
Crime Count
Number of replications

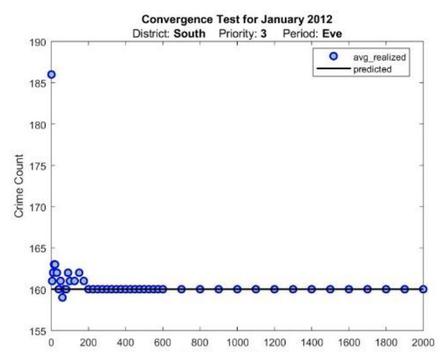

Convergence Test for January 2012
District: South Priority: 2 Period: Mid
Crime Count
Number of replications
avg_realized
predicted


Convergence Test for January 2012
District: South Priority: 3 Period: Mid
Crime Count
Number of replications
avg_realized
predicted


Convergence Test for January 2012
District: South Priority: 2 Period: Day
Crime Count
Number of replications
avg_realized
predicted


Convergence Test for January 2012
District: South Priority: 3 Period: Day
Crime Count
Number of replications
avg_realized
predicted


Convergence Test for January 2012
District: South Priority: 2 Period: Eve
Crime Count
Number of replications
avg_realized
predicted


Convergence Test for January 2012
District: South Priority: 3 Period: Eve
Crime Count
Number of replications
avg_realized
predicted

Appendix E

Table E-1 Predicted crime count per month of a simulated year from past prediction.

District	Priority	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
north	E	Mid	2	2	2	3	4	4	4	4	5	6	7	8
		Day	2	2	3	4	5	6	7	9	12	15	19	23
		Eve	2	1	0	0	0	0	0	0	0	0	0	1
	1	Mid	97	113	138	183	265	403	618	956	1488	2339	3693	5842
		Day	101	105	109	114	121	132	150	179	226	307	445	683
		Eve	185	227	291	390	541	766	1096	1578	2282	3313	4819	7017
	2	Mid	9	1	0	1	1	0	0	1	6	12	20	30
		Day	60	71	77	86	100	112	127	136	140	146	150	163
		Eve	50	58	70	93	134	197	293	433	637	938	1379	2028
	3	Mid	58	39	6	0	0	9	25	49	76	116	173	261
		Day	59	0	0	10	94	320	752	1541	2935	5499	10166	18682
		Eve	225	213	171	101	55	57	54	46	0	0	0	0
west	E	Mid	0	0	0	0	0	0	0	0	0	0	0	0
		Day	3	4	5	6	7	8	9	10	11	12	13	14
		Eve	3	2	0	0	0	0	0	0	0	0	0	0
	1	Mid	69	88	117	165	263	464	841	1551	2875	5374	10083	18960
		Day	102	113	128	153	190	239	309	404	539	731	1002	1387
		Eve	159	203	278	411	652	1087	1866	3259	5748	10206	18189	32489
	2	Mid	27	32	37	42	49	60	74	92	113	140	175	221
		Day	51	53	55	60	65	67	70	72	76	81	87	95
		Eve	57	63	67	66	53	20	0	0	0	0	0	0
	3	Mid	73	70	65	52	35	20	0	0	0	0	1	0
		Day	183	181	187	201	238	321	461	698	1078	1694	2685	4267
		Eve	271	345	455	631	946	1521	2521	4264	7283	12572	21821	38006
east	E	Mid	2	2	0	0	1	3	5	6	4	2	0	0
		Day	0	0	0	0	1	4	9	17	28	45	71	110
		Eve	6	7	9	13	19	28	43	69	114	190	319	537
	1	Mid	99	89	73	44	22	21	18	18	0	0	0	0
		Day	69	29	0	0	4	16	50	133	325	745	1664	3666
		Eve	148	149	149	148	147	147	144	137	122	97	52	0
	2	Mid	20	27	39	60	98	166	285	494	861	1508	2648	4656
		Day	36	41	43	46	54	66	83	103	125	155	194	251
		Eve	33	29	23	15	5	0	0	2	7	20	48	106
	3	Mid	39	14	0	0	2	17	32	54	71	87	103	114
		Day	91	39	0	0	43	170	441	989	2057	4140	8177	15981

		Eve	215	226	250	285	314	331	349	371	412	457	509	559
south	E	Mid	3	5	8	13	21	34	55	89	144	232	374	603
		Day	3	5	8	13	20	30	46	71	111	174	273	428
		Eve	2	0	0	0	0	0	0	0	0	0	0	0
	1	Mid	63	62	62	63	65	69	74	82	96	119	156	212
		Day	108	113	122	128	115	59	0	0	0	0	0	0
		Eve	155	156	155	153	143	118	80	22	0	0	0	0
	2	Mid	21	22	17	10	6	6	9	9	1	0	0	0
		Day	0	0	0	0	0	0	0	0	0	0	0	0
		Eve	62	64	65	63	54	35	2	0	0	0	0	0
	3	Mid	66	65	62	54	45	41	35	29	15	0	0	0
		Day	258	272	296	323	368	458	591	803	1118	1597	2327	3425
		Eve	160	153	148	152	174	217	283	377	507	696	962	1338

Table E-2 Predicted crime count per month of a simulated year from past average realized crime counts.

District	Priority	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
north	E	Mid	2	2	2	3	4	4	4	4	5	6	7	8
		Day	2	2	3	4	5	6	7	9	12	15	19	23
		Eve	2	1	0	0	0	0	0	0	0	0	0	1
	1	Mid	97	113	138	185	269	411	627	964	1477	2269	3460	5201
		Day	101	105	109	114	121	132	152	180	227	303	441	673
		Eve	185	222	284	383	524	734	1031	1462	2075	2910	4026	5490
	2	Mid	9	1	0	1	1	0	0	1	6	12	20	30
		Day	60	71	77	86	100	112	127	134	137	142	145	157
		Eve	50	58	70	93	134	197	290	425	618	899	1298	1867
	3	Mid	58	39	6	0	0	9	25	49	76	114	170	256
		Day	59	0	0	10	94	317	743	1512	2829	5121	8920	14722
		Eve	225	213	173	102	56	58	55	47	0	0	0	0
west	E	Mid	0	0	0	0	0	0	0	0	0	0	0	0
		Day	3	4	5	6	7	8	9	10	11	12	13	14
		Eve	3	2	0	0	0	0	0	0	0	0	0	0
	1	Mid	69	88	117	165	266	471	850	1559	2843	5173	9271	15982
		Day	102	113	130	159	196	248	324	424	565	757	1021	1398
		Eve	159	203	278	411	652	1084	1837	3139	5366	9038	14740	22712
	2	Mid	27	32	37	42	49	60	74	92	113	140	175	224

		Day	51	53	55	60	65	67	70	72	76	81	87	95
		Eve	57	63	67	66	53	20	0	0	0	0	0	0
	3	Mid	73	73	71	63	53	49	42	35	19	0	0	0
		Day	183	181	187	195	223	296	421	625	947	1477	2295	3550
		Eve	271	345	455	631	941	1508	2460	4062	6635	10686	16609	24286
east	E	Mid	2	2	0	0	1	3	5	6	4	2	0	0
		Day	0	0	0	0	1	4	9	17	28	45	71	108
		Eve	6	7	9	13	19	28	43	69	111	181	299	503
	1	Mid	99	89	73	44	22	21	18	18	0	0	0	0
		Day	69	29	0	0	4	16	50	133	325	745	1655	3568
		Eve	148	149	149	148	147	150	151	152	152	151	153	154
	2	Mid	20	27	39	58	94	155	264	447	765	1328	2275	3838
		Day	36	41	43	46	56	70	90	114	141	178	228	298
		Eve	33	29	23	15	5	0	0	2	7	20	48	109
	3	Mid	39	14	0	0	2	17	32	54	71	87	101	111
		Day	91	39	0	0	43	170	438	974	2001	3924	7343	12854
		Eve	215	222	248	284	311	329	347	363	394	430	476	521
south	E	Mid	3	5	8	13	21	34	55	89	141	226	363	579
		Day	3	5	8	13	20	30	46	71	111	174	270	419
		Eve	2	0	0	0	0	0	0	0	0	0	0	0
	1	Mid	63	62	62	63	67	70	73	80	95	118	155	211
		Day	108	113	122	128	112	50	0	0	0	0	0	0
		Eve	155	156	157	156	147	123	84	24	0	0	0	0
	2	Mid	21	22	17	10	6	6	9	9	1	0	0	0
		Day	0	0	0	0	0	0	0	0	0	0	0	0
		Eve	62	64	65	63	54	35	2	0	0	0	0	0
	3	Mid	66	65	62	54	45	41	35	29	15	0	0	0
		Day	258	267	286	301	326	389	476	609	800	1077	1487	2044
		Eve	160	153	148	150	170	213	276	365	482	655	889	1205

Table E-3 Average fraction busy time of officers per beat per month for a simulated year.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.12	0.11	0.08	0.08	0.09	0.17	0.27	0.38	0.51	0.62	0.72	0.81
220	0.13	0.11	0.09	0.09	0.12	0.20	0.32	0.45	0.58	0.67	0.79	0.86
230	0.13	0.11	0.09	0.09	0.10	0.20	0.29	0.42	0.55	0.64	0.74	0.83
240	0.12	0.10	0.07	0.08	0.10	0.18	0.29	0.42	0.55	0.65	0.76	0.84
250	0.11	0.08	0.06	0.06	0.09	0.14	0.23	0.36	0.48	0.58	0.70	0.79
260	0.21	0.18	0.16	0.14	0.18	0.30	0.43	0.57	0.68	0.77	0.86	0.91
270	0.16	0.18	0.17	0.19	0.25	0.44	0.61	0.73	0.82	0.89	0.94	0.96
280	0.18	0.18	0.14	0.13	0.16	0.28	0.38	0.54	0.66	0.75	0.84	0.9
310	0.20	0.24	0.25	0.29	0.34	0.41	0.50	0.60	0.70	0.82	0.91	0.95
320	0.28	0.40	0.46	0.55	0.60	0.71	0.78	0.85	0.92	0.96	0.98	0.99
330	0.20	0.24	0.25	0.31	0.35	0.43	0.52	0.60	0.72	0.83	0.91	0.96
340	0.13	0.15	0.15	0.19	0.24	0.34	0.42	0.53	0.63	0.75	0.87	0.93
350	0.20	0.21	0.21	0.27	0.31	0.43	0.52	0.63	0.75	0.85	0.92	0.96
360	0.27	0.32	0.33	0.36	0.42	0.51	0.58	0.68	0.79	0.88	0.94	0.97
370	0.11	0.14	0.16	0.18	0.23	0.32	0.40	0.49	0.59	0.71	0.84	0.92
380	0.26	0.30	0.32	0.37	0.41	0.51	0.59	0.68	0.79	0.88	0.94	0.97
410	0.18	0.16	0.13	0.13	0.16	0.21	0.31	0.45	0.55	0.66	0.77	0.82
420	0.14	0.12	0.08	0.09	0.12	0.17	0.25	0.36	0.51	0.61	0.73	0.81
430	0.14	0.13	0.10	0.12	0.13	0.17	0.24	0.38	0.50	0.60	0.71	0.77
440	0.13	0.10	0.09	0.09	0.11	0.15	0.23	0.37	0.50	0.61	0.72	0.8
450	0.20	0.24	0.20	0.26	0.36	0.55	0.72	0.83	0.89	0.92	0.95	0.96
460	0.14	0.11	0.08	0.10	0.09	0.12	0.18	0.27	0.40	0.51	0.62	0.7
470	0.06	0.05	0.03	0.04	0.04	0.06	0.09	0.15	0.25	0.37	0.48	0.57
480	0.14	0.11	0.10	0.10	0.10	0.14	0.21	0.31	0.46	0.55	0.66	0.74
510	0.15	0.16	0.14	0.13	0.13	0.15	0.16	0.21	0.25	0.32	0.42	0.54
520	0.13	0.13	0.11	0.11	0.11	0.11	0.12	0.14	0.17	0.22	0.31	0.38
530	0.15	0.17	0.13	0.14	0.13	0.15	0.15	0.18	0.24	0.29	0.39	0.49
540	0.35	0.41	0.43	0.47	0.48	0.55	0.60	0.66	0.71	0.73	0.78	0.83
550	0.15	0.17	0.15	0.14	0.14	0.15	0.18	0.20	0.25	0.31	0.41	0.5
560	0.18	0.19	0.18	0.15	0.16	0.17	0.17	0.21	0.27	0.34	0.43	0.54
570	0.07	0.06	0.05	0.06	0.05	0.05	0.05	0.06	0.07	0.10	0.16	0.26
580	0.20	0.21	0.18	0.18	0.18	0.20	0.20	0.23	0.29	0.35	0.46	0.54

Table E-4 Average waiting time (in minutes) of a call in queue per beat per month for priority 1 for a simulated year.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.55	0.43	0.30	0.21	0.20	0.76	2.02	3.68	5.87	7.12	8.21	8.69
220	0.34	0.22	0.12	0.10	0.18	0.92	2.23	3.91	5.59	6.48	7.21	7.51
230	0.58	0.48	0.36	0.22	0.23	1.06	2.18	4.27	6.29	7.33	8.23	8.68
240	0.04	0.04	0.01	0.01	0.02	0.19	0.85	2.11	3.24	4.01	4.45	4.75
250	0.20	0.09	0.04	0.03	0.11	0.57	1.53	3.01	4.46	5.58	6.32	6.80
260	1.32	1.09	0.82	0.48	0.63	1.84	3.97	5.96	7.46	8.25	8.84	8.88
270	0.06	0.12	0.09	0.09	0.15	0.81	2.16	3.00	3.46	3.75	3.80	3.73
280	1.10	1.13	0.69	0.41	0.48	1.82	3.27	5.73	7.22	8.03	8.75	8.89
310	1.37	1.84	1.85	2.63	3.21	4.40	5.29	6.28	6.90	7.72	8.18	8.22
320	1.51	2.93	3.51	4.55	5.22	6.15	6.63	6.70	6.78	6.75	6.61	6.48
330	1.26	1.86	1.94	2.85	3.38	4.61	5.61	6.26	7.06	7.89	8.27	8.26
340	0.08	0.11	0.12	0.24	0.47	1.05	1.69	2.28	2.79	3.26	3.97	4.37
350	0.84	0.85	0.76	1.18	1.43	2.57	3.38	4.32	5.27	5.95	6.39	6.54
360	2.08	2.70	2.93	3.54	4.46	5.66	6.12	6.93	7.63	7.99	8.14	8.12
370	0.01	0.05	0.08	0.14	0.37	0.87	1.32	1.70	2.00	2.36	2.88	3.30
380	2.08	2.51	2.77	3.69	4.28	5.42	6.30	7.02	7.54	7.93	8.18	8.06
410	1.06	1.03	0.82	0.93	1.09	1.39	2.75	5.30	5.96	6.58	7.00	6.38
420	0.42	0.31	0.17	0.21	0.28	0.67	1.39	3.11	4.26	5.06	5.11	4.78
430	0.68	0.76	0.63	0.78	0.79	1.14	1.85	3.98	5.50	6.29	6.45	6.07
440	0.07	0.04	0.04	0.05	0.05	0.13	0.44	1.47	2.49	3.09	3.20	2.92
450	0.74	0.80	0.59	0.97	1.97	4.56	7.34	9.10	5.97	5.57	4.97	4.25
460	0.76	0.60	0.38	0.56	0.43	0.61	1.21	2.47	4.13	5.48	6.02	5.90
470	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.08	0.48	1.36	2.12	2.21
480	0.68	0.47	0.58	0.59	0.58	0.89	1.47	3.16	4.74	5.90	6.22	5.99
510	0.90	0.89	0.72	0.62	0.72	0.84	0.29	0.55	0.07	0.07	0.17	0.30
520	0.49	0.49	0.43	0.45	0.46	0.49	0.08	0.08	0.02	0.04	0.08	0.16
530	0.90	1.00	0.59	0.82	0.72	0.90	0.31	0.54	0.04	0.04	0.09	0.20
540	0.97	1.37	1.57	1.84	2.20	3.12	1.38	2.09	0.29	0.26	0.33	0.42
550	0.73	0.82	0.79	0.65	0.63	0.86	0.11	0.10	0.06	0.10	0.19	0.30
560	1.09	1.17	1.12	0.79	0.98	1.28	0.43	0.52	0.06	0.07	0.15	0.28
570	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
580	1.35	1.50	1.15	1.13	1.30	1.70	0.60	0.87	0.07	0.09	0.17	0.27

Table E-5 Average waiting time (in minutes) of a call in queue per beat per month for priority 2 for a simulated year.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.42	0.44	0.26	0.19	0.20	0.78	2.03	3.69	5.73	7.06	25.00	8.79
220	0.33	0.16	0.11	0.09	0.19	0.91	2.18	3.81	5.34	6.50	21.72	7.65
230	0.58	0.42	0.36	0.22	0.22	1.05	2.18	4.19	6.03	7.17	25.10	8.92
240	0.05	0.03	0.02	0.01	0.02	0.19	0.84	2.07	3.19	4.05	13.75	4.90
250	0.14	0.05	0.02	0.02	0.10	0.57	1.50	2.94	4.29	5.26	19.32	6.95
260	1.31	0.95	0.78	0.48	0.63	1.82	3.91	5.82	6.98	8.34	27.06	9.00
270	0.06	0.12	0.09	0.10	0.16	0.83	2.16	3.07	3.58	3.85	11.74	3.84
280	1.15	1.08	0.69	0.42	0.46	1.77	3.18	5.66	6.88	8.21	26.79	9.06
310	1.37	1.92	1.84	2.64	3.25	4.42	1.45	2.29	3.27	4.47	16.58	5.90
320	1.54	3.01	3.60	4.63	5.26	6.32	4.01	4.45	4.84	5.19	15.71	5.18
330	1.25	1.84	1.90	2.85	3.43	4.64	1.69	2.28	3.42	4.66	16.87	5.96
340	0.09	0.10	0.10	0.25	0.49	0.97	0.30	0.57	1.07	1.76	8.01	3.22
350	0.79	0.83	0.76	1.14	1.46	2.46	1.62	2.41	3.35	4.34	14.93	5.33
360	2.20	2.72	2.96	3.56	4.44	5.66	2.12	3.14	4.29	5.08	17.20	5.97
370	0.02	0.05	0.08	0.14	0.38	0.90	0.09	0.19	0.44	0.93	5.07	2.24
380	2.16	2.58	2.85	3.70	4.27	5.55	2.32	3.25	4.19	5.09	17.12	5.96
410	1.04	1.04	0.68	1.01	0.14	0.56	1.74	3.74	5.89	8.49	29.97	9.84
420	0.38	0.33	0.12	0.19	0.14	0.39	1.22	2.79	4.59	6.56	22.99	8.05
430	0.65	0.79	0.65	0.73	0.09	0.36	1.25	3.19	5.13	7.66	26.97	9.31
440	0.06	0.04	0.05	0.07	0.01	0.06	0.31	1.39	2.64	3.86	14.07	4.94
450	0.81	0.88	0.64	1.06	1.98	3.50	6.12	9.08	9.75	9.52	27.04	8.36
460	0.76	0.60	0.49	0.61	0.07	0.18	0.76	2.10	4.05	6.44	23.14	8.53
470	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.08	0.47	1.38	6.74	2.58
480	0.71	0.51	0.53	0.54	0.06	0.30	0.90	2.39	4.53	6.98	25.09	8.86
510	0.39	0.37	0.25	0.18	0.21	0.31	0.00	0.00	0.00	0.00	0.00	0.00
520	0.12	0.12	0.04	0.03	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00
530	0.38	0.43	0.24	0.23	0.26	0.39	0.00	0.00	0.00	0.00	0.00	0.00
540	0.36	0.44	0.49	0.59	0.65	1.04	1.42	0.29	0.32	0.00	0.00	0.00
550	0.17	0.12	0.14	0.02	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00
560	0.54	0.48	0.51	0.23	0.34	0.37	0.00	0.00	0.00	0.00	0.00	0.00
570	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
580	0.58	0.60	0.48	0.38	0.40	0.63	0.00	0.00	0.00	0.00	0.00	0.00

Table E-6 Average waiting time (in minutes) of a call in queue per beat per month for priority 3 for a simulated year.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.55	0.45	0.25	0.18	0.21	0.77	2.01	3.81	5.03	6.03	6.67	7.05
220	0.34	0.20	0.09	0.10	0.18	0.92	2.28	4.05	5.10	5.76	6.26	6.45
230	0.58	0.48	0.35	0.20	0.24	1.07	2.27	4.38	5.18	6.13	6.69	7.01
240	0.05	0.04	0.01	0.01	0.02	0.21	0.87	2.14	3.01	3.62	3.94	4.13
250	0.19	0.09	0.02	0.02	0.11	0.58	1.51	3.06	4.37	5.32	5.94	6.28
260	1.36	1.04	0.74	0.45	0.64	1.93	4.01	6.13	6.08	6.67	7.13	7.08
270	0.07	0.13	0.09	0.10	0.16	0.86	2.22	3.11	2.85	3.06	3.08	2.99
280	1.10	1.12	0.65	0.42	0.48	1.82	3.39	5.97	5.95	6.54	7.03	7.11
310	1.39	1.84	1.88	2.66	3.29	4.41	5.37	6.35	6.98	6.77	6.95	6.90
320	1.58	3.03	3.55	4.66	5.27	6.31	6.74	6.83	6.92	5.43	5.26	5.12
330	1.24	1.87	1.95	2.88	3.49	4.63	5.68	6.34	7.16	6.91	7.08	6.96
340	0.08	0.10	0.11	0.25	0.49	1.07	1.75	2.32	2.84	2.92	3.40	3.65
350	0.86	0.85	0.76	1.20	1.44	2.63	3.44	4.47	5.39	4.91	5.17	5.22
360	2.19	2.74	2.98	3.63	4.46	5.68	6.20	7.06	7.76	6.91	6.88	6.78
370	0.01	0.05	0.09	0.14	0.37	0.90	1.36	1.74	2.07	2.22	2.61	2.85
380	2.14	2.52	2.80	3.75	4.32	5.49	6.39	7.13	7.68	6.85	6.91	6.73
410	1.07	1.01	0.75	0.87	1.06	1.46	2.74	5.23	7.15	8.60	10.02	9.92
420	0.44	0.30	0.15	0.17	0.26	0.64	1.47	3.08	5.16	6.69	7.81	8.12
430	0.70	0.79	0.63	0.74	0.79	1.05	1.93	4.11	6.34	7.83	9.16	9.43
440	0.06	0.04	0.04	0.05	0.05	0.11	0.41	1.52	2.87	3.90	4.80	5.01
450	0.78	0.87	0.37	0.64	2.02	4.61	7.38	9.16	9.85	9.60	9.10	8.43
460	0.76	0.59	0.38	0.53	0.43	0.67	1.21	2.66	4.59	6.49	7.96	8.58
470	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.08	0.49	1.39	2.25	2.58
480	0.73	0.49	0.55	0.54	0.49	0.74	1.48	3.22	5.55	7.08	8.30	9.00
510	0.87	0.89	0.77	0.62	0.67	0.89	0.94	1.64	1.91	2.86	4.25	6.19
520	0.52	0.49	0.46	0.44	0.52	0.50	0.57	0.78	1.15	1.66	2.78	3.63
530	0.88	0.97	0.63	0.86	0.75	1.00	1.01	1.51	2.61	3.21	5.13	6.75
540	0.99	1.40	1.61	1.90	2.23	3.15	4.23	5.32	6.42	6.73	7.25	7.48
550	0.73	0.81	0.80	0.65	0.56	0.86	1.21	1.43	2.04	2.49	3.54	4.53
560	1.06	1.11	1.14	0.83	0.99	1.26	1.37	1.97	2.88	4.10	5.67	7.70
570	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.13	0.40
580	1.38	1.47	1.13	1.15	1.29	1.71	1.69	2.34	3.37	4.55	6.79	8.22

Table E-7 Average total overtime (in minutes) per beat per month for a simulated year.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	1354.82	917.08	724.67	620.58	752.22	1250.20	1998.58	2618.12	3066.38	3510.15	3691.01	4041.307
220	1797.40	1308.29	1005.73	875.07	1030.86	1736.37	2520.26	3271.60	3663.71	4024.87	4198.98	4452.393
230	1339.63	950.52	802.86	606.83	807.36	1471.02	2083.45	2824.18	3200.64	3599.60	3753.83	4041.173
240	2463.44	1786.54	1316.26	1128.33	1373.72	2324.37	3529.64	4670.31	5273.45	5973.54	6176.17	6607.993
250	1773.90	1275.69	949.87	737.55	1055.87	1414.80	2235.34	2997.81	3512.08	4067.43	4356.31	4792.707
260	2009.91	1473.21	1192.09	940.11	1203.71	1924.34	2755.67	3345.88	3570.89	3844.50	3936.02	3996.573
270	3564.36	3180.94	3025.19	2737.82	3520.37	5584.75	7244.51	7876.87	7756.16	8220.56	7873.64	7889.547
280	1764.06	1456.04	1099.22	823.06	1067.53	1844.68	2464.87	3213.41	3496.89	3869.74	3902.00	3999.993
310	2138.69	2256.21	2320.90	2499.32	2851.25	3074.50	3488.99	3838.24	3839.52	4159.00	3992.03	3988.42
320	3259.30	4019.23	4679.38	4959.87	5238.86	5338.23	5635.41	5301.40	4764.45	4620.47	4143.71	4131.16
330	2091.66	2267.26	2369.14	2661.40	2882.85	3193.70	3659.74	3826.32	3928.11	4173.65	4029.24	3995.96
340	2875.12	2963.40	3204.14	3629.96	4238.45	5087.35	5918.79	6556.35	6729.88	7113.21	6976.66	7008.45
350	2997.05	2998.50	3180.57	3845.00	4338.05	5129.86	5806.67	6047.03	6088.79	6093.13	5723.62	5553.99
360	2651.10	2764.03	2938.07	2982.02	3310.26	3563.28	3810.48	4106.20	4108.87	4146.39	3903.42	3872.61
370	2935.38	3296.68	3805.59	3884.55	4593.12	5534.01	6435.53	7184.33	7610.40	8240.72	8256.08	8494.41
380	2670.67	2608.35	2919.17	3051.72	3257.49	3553.63	3894.27	4046.25	4034.80	4164.83	3865.20	3897.597
410	1852.56	1422.06	1259.45	1272.04	1641.25	2067.41	2960.56	3856.98	4131.05	4647.89	4900.19	5005.343
420	1978.78	1574.66	1219.23	1347.81	1757.48	2194.11	2870.37	3583.26	4220.30	4744.37	4885.89	5145.887
430	1499.05	1258.57	1056.13	1161.88	1444.42	1840.31	2500.07	3369.29	3940.44	4430.57	4678.67	4750.723
440	2692.52	1933.77	1994.56	2009.76	2413.41	2946.86	4336.68	5654.73	6449.83	7395.08	7608.67	8074.647
450	2904.56	3293.37	3096.91	3641.81	4780.78	5949.59	7043.51	7728.71	7615.71	7804.75	7322.47	7173.053
460	1458.64	1059.00	821.77	1016.10	1080.03	1387.45	2001.87	2735.74	3300.57	3948.07	4185.43	4507.897
470	1551.14	1290.94	933.78	1029.32	1253.85	1596.76	2525.75	3732.98	5028.69	6533.80	7375.53	8099.96
480	1511.02	1022.57	981.40	1008.34	1145.53	1578.46	2283.68	2951.73	3631.49	4196.05	4353.96	4622.437
510	1697.84	1675.30	1541.34	1402.29	1507.74	1546.42	1641.42	2107.54	2152.54	2630.87	3027.69	3826.913
520	1850.99	1700.45	1536.12	1447.09	1581.25	1564.06	1718.06	1996.71	2204.85	2818.36	3468.47	4005.47
530	1806.10	1719.03	1511.91	1557.21	1546.03	1666.26	1827.73	2100.06	2460.34	2823.01	3332.88	3853.327
540	5748.55	5808.18	6397.52	6467.37	6902.91	7602.06	8504.92	9124.77	9304.31	9438.81	9376.04	9796.66
550	2307.76	2206.90	2221.47	2018.04	2212.47	2220.85	2709.98	2866.29	3322.25	4022.09	4630.39	5493.303
560	1947.67	1829.17	1906.82	1613.34	1772.96	1909.25	1972.40	2354.87	2607.58	3124.60	3568.30	4209.037
570	1881.48	1682.77	1577.61	1681.13	1346.75	1609.84	1643.03	1923.68	2156.17	2790.65	3574.84	4706.01
580	2107.64	2100.41	1919.38	1861.07	1985.02	2176.70	2173.14	2542.11	2859.49	3373.88	3860.54	4397.263

Appendix F

Table F-1 Average fraction busy time of officers per beat per month for 8-hr shift.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.12	0.10	0.07	0.08	0.09	0.17	0.25	0.37	0.51	0.60	0.71	0.80
220	0.13	0.12	0.08	0.08	0.11	0.18	0.30	0.44	0.54	0.67	0.77	0.85
230	0.13	0.11	0.09	0.09	0.10	0.17	0.28	0.42	0.53	0.64	0.74	0.82
240	0.12	0.10	0.08	0.07	0.10	0.17	0.27	0.40	0.53	0.64	0.75	0.83
250	0.10	0.09	0.07	0.07	0.08	0.14	0.23	0.36	0.47	0.58	0.70	0.79
260	0.21	0.18	0.14	0.14	0.17	0.28	0.42	0.55	0.67	0.75	0.85	0.90
270	0.17	0.19	0.19	0.21	0.28	0.46	0.62	0.73	0.83	0.89	0.94	0.96
280	0.18	0.17	0.14	0.13	0.16	0.29	0.40	0.52	0.65	0.74	0.84	0.90
310	0.20	0.22	0.25	0.29	0.33	0.40	0.47	0.57	0.67	0.78	0.88	0.94
320	0.29	0.39	0.44	0.53	0.59	0.67	0.74	0.83	0.91	0.95	0.97	0.98
330	0.20	0.24	0.25	0.28	0.34	0.40	0.48	0.57	0.69	0.80	0.90	0.95
340	0.13	0.15	0.15	0.19	0.24	0.32	0.40	0.50	0.61	0.73	0.84	0.92
350	0.20	0.20	0.22	0.27	0.30	0.41	0.50	0.59	0.71	0.82	0.90	0.95
360	0.27	0.30	0.31	0.36	0.40	0.47	0.55	0.63	0.76	0.85	0.92	0.96
370	0.12	0.14	0.16	0.18	0.23	0.31	0.38	0.48	0.58	0.70	0.83	0.90
380	0.26	0.30	0.33	0.36	0.40	0.47	0.54	0.64	0.75	0.85	0.92	0.96
410	0.17	0.15	0.13	0.14	0.15	0.22	0.32	0.44	0.58	0.69	0.80	0.87
420	0.14	0.11	0.10	0.09	0.10	0.16	0.24	0.37	0.51	0.63	0.77	0.85
430	0.14	0.13	0.11	0.12	0.12	0.16	0.24	0.34	0.48	0.59	0.71	0.79
440	0.12	0.10	0.09	0.09	0.12	0.16	0.23	0.37	0.51	0.63	0.75	0.84
450	0.20	0.22	0.21	0.25	0.37	0.56	0.72	0.84	0.91	0.93	0.96	0.97
460	0.13	0.10	0.08	0.08	0.09	0.14	0.18	0.28	0.40	0.52	0.64	0.74
470	0.06	0.05	0.04	0.04	0.04	0.06	0.08	0.14	0.25	0.36	0.49	0.59
480	0.15	0.11	0.09	0.11	0.11	0.17	0.24	0.35	0.48	0.58	0.70	0.79
510	0.16	0.15	0.14	0.14	0.11	0.14	0.15	0.18	0.25	0.30	0.41	0.51
520	0.13	0.13	0.11	0.11	0.09	0.10	0.11	0.12	0.15	0.19	0.27	0.35
530	0.16	0.16	0.15	0.13	0.13	0.13	0.13	0.15	0.19	0.25	0.34	0.42
540	0.35	0.41	0.42	0.46	0.47	0.52	0.59	0.65	0.70	0.73	0.78	0.83
550	0.16	0.17	0.15	0.14	0.12	0.15	0.16	0.18	0.23	0.31	0.41	0.51
560	0.17	0.19	0.17	0.17	0.15	0.15	0.17	0.22	0.26	0.32	0.42	0.52
570	0.07	0.07	0.06	0.06	0.04	0.04	0.05	0.06	0.07	0.10	0.15	0.22
580	0.20	0.21	0.18	0.19	0.17	0.18	0.20	0.23	0.29	0.34	0.46	0.52

Table F-2 Average fraction busy time of officers per beat per month for 10-hr shift.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.12	0.10	0.07	0.08	0.09	0.18	0.26	0.38	0.49	0.59	0.71	0.79
220	0.17	0.15	0.10	0.10	0.13	0.22	0.33	0.48	0.61	0.71	0.80	0.88
230	0.13	0.10	0.09	0.09	0.11	0.19	0.28	0.41	0.53	0.62	0.73	0.81
240	0.12	0.10	0.08	0.07	0.11	0.17	0.28	0.41	0.53	0.65	0.76	0.84
250	0.12	0.10	0.08	0.07	0.11	0.18	0.26	0.37	0.50	0.59	0.71	0.80
260	0.22	0.18	0.15	0.14	0.17	0.30	0.42	0.54	0.64	0.73	0.83	0.89
270	0.17	0.18	0.18	0.20	0.28	0.47	0.62	0.75	0.84	0.90	0.95	0.97
280	0.18	0.17	0.13	0.12	0.17	0.28	0.40	0.54	0.64	0.74	0.84	0.89
310	0.21	0.23	0.24	0.27	0.32	0.42	0.51	0.61	0.73	0.83	0.91	0.95
320	0.34	0.43	0.50	0.58	0.64	0.73	0.79	0.86	0.93	0.96	0.98	0.99
330	0.21	0.24	0.25	0.31	0.34	0.43	0.53	0.63	0.75	0.84	0.92	0.96
340	0.14	0.16	0.17	0.21	0.25	0.34	0.43	0.52	0.64	0.75	0.86	0.92
350	0.23	0.25	0.25	0.30	0.34	0.42	0.51	0.60	0.72	0.82	0.91	0.95
360	0.28	0.31	0.30	0.37	0.42	0.49	0.56	0.67	0.76	0.86	0.93	0.96
370	0.13	0.14	0.16	0.19	0.22	0.31	0.40	0.51	0.62	0.74	0.86	0.92
380	0.27	0.32	0.31	0.35	0.43	0.51	0.58	0.70	0.81	0.88	0.94	0.97
410	0.17	0.13	0.10	0.12	0.15	0.22	0.34	0.47	0.59	0.67	0.77	0.84
420	0.17	0.13	0.11	0.12	0.13	0.21	0.28	0.42	0.58	0.68	0.78	0.86
430	0.14	0.10	0.08	0.09	0.11	0.18	0.25	0.37	0.49	0.59	0.70	0.76
440	0.13	0.10	0.09	0.09	0.10	0.16	0.25	0.37	0.52	0.63	0.75	0.83
450	0.23	0.25	0.24	0.29	0.39	0.59	0.75	0.85	0.91	0.94	0.96	0.97
460	0.13	0.10	0.07	0.08	0.09	0.13	0.18	0.30	0.41	0.51	0.62	0.70
470	0.06	0.05	0.03	0.04	0.04	0.06	0.10	0.15	0.25	0.37	0.49	0.59
480	0.15	0.10	0.09	0.09	0.11	0.16	0.24	0.36	0.48	0.60	0.68	0.75
510	0.17	0.17	0.17	0.15	0.15	0.15	0.17	0.20	0.26	0.32	0.41	0.53
520	0.15	0.16	0.14	0.12	0.12	0.12	0.13	0.16	0.17	0.22	0.31	0.38
530	0.17	0.18	0.15	0.15	0.14	0.15	0.15	0.16	0.21	0.27	0.35	0.44
540	0.36	0.41	0.44	0.47	0.47	0.53	0.60	0.66	0.71	0.74	0.80	0.85
550	0.18	0.19	0.17	0.17	0.15	0.16	0.19	0.22	0.27	0.36	0.45	0.57
560	0.19	0.20	0.19	0.18	0.16	0.18	0.19	0.22	0.29	0.35	0.43	0.53
570	0.08	0.07	0.06	0.06	0.05	0.06	0.06	0.07	0.09	0.12	0.17	0.25
580	0.21	0.24	0.20	0.19	0.17	0.19	0.21	0.24	0.30	0.35	0.44	0.52

Table F-3 Average total free time gain (day) of officer in 10_hr shift for a simulated year.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	-0.05	0.08	0.04	0.16	-0.05	-0.31	-0.24	-0.48	0.32	0.41	0.21	0.23
220	-1.08	-0.84	-0.53	-0.57	-0.62	-1.21	-1.14	-1.39	-1.82	-1.12	-0.99	-0.89
230	-0.07	0.16	0.05	-0.05	-0.15	-0.53	-0.22	0.30	0.12	0.57	0.37	0.28
240	-0.27	-0.05	0.13	-0.05	-0.28	-0.25	-0.28	-0.25	-0.03	-0.27	-0.27	-0.05
250	-0.57	-0.45	-0.43	-0.17	-0.69	-1.00	-0.81	-0.38	-0.74	-0.33	-0.12	-0.30
260	-0.18	0.02	-0.35	0.17	0.12	-0.55	-0.03	0.57	0.69	0.57	0.52	0.46
270	-0.18	0.18	0.35	0.36	0.06	-0.29	-0.18	-0.66	-0.35	-0.28	-0.15	-0.08
280	0.02	-0.05	0.40	0.32	-0.18	0.16	-0.06	-0.43	0.31	0.29	0.11	0.11
310	-0.24	-0.48	0.41	0.47	0.31	-0.64	-0.95	-1.35	-1.74	-1.35	-0.87	-0.38
320	-1.54	-1.09	-1.68	-1.75	-1.39	-1.52	-1.29	-0.99	-0.56	-0.25	-0.13	-0.09
330	-0.26	-0.07	-0.04	-0.85	0.08	-0.85	-1.53	-1.87	-1.91	-1.39	-0.66	-0.33
340	-0.22	-0.16	-0.41	-0.45	-0.24	-0.35	-0.79	-0.80	-0.80	-0.61	-0.48	-0.19
350	-0.89	-1.33	-0.91	-0.74	-1.23	-0.51	-0.29	-0.45	-0.16	-0.16	-0.18	-0.18
360	-0.33	-0.24	0.27	-0.11	-0.47	-0.71	-0.47	-1.01	-0.06	-0.36	-0.18	-0.11
370	-0.17	-0.23	0.25	-0.13	0.33	0.29	-0.50	-0.71	-1.17	-1.29	-0.98	-0.48
380	-0.27	-0.51	0.44	0.07	-0.72	-1.19	-1.40	-1.79	-1.70	-0.87	-0.48	-0.30
410	-0.02	0.61	0.73	0.66	0.19	0.02	-0.76	-1.08	-0.45	0.74	0.99	0.85
420	-0.96	-0.58	-0.48	-0.68	-0.86	-1.49	-1.52	-1.54	-2.14	-1.67	-0.34	-0.53
430	0.00	0.80	1.02	0.85	0.33	-0.76	-0.49	-0.86	-0.23	0.05	0.32	1.07
440	-0.27	-0.01	0.02	-0.07	0.58	-0.09	-0.67	-0.23	-0.51	-0.15	0.14	0.35
450	-0.79	-0.93	-0.89	-1.04	-0.79	-1.16	-0.83	-0.17	-0.14	-0.26	-0.16	-0.12
460	-0.16	-0.03	0.25	0.19	0.11	0.38	-0.20	-0.65	-0.18	0.13	0.37	1.03
470	-0.05	-0.05	0.04	-0.11	-0.03	0.11	-0.42	-0.34	-0.06	-0.39	-0.12	0.17
480	-0.18	0.34	0.12	0.50	0.24	0.12	0.16	-0.31	0.03	-0.52	0.68	1.17
510	-0.50	-0.56	-0.87	-0.30	-1.15	-0.54	-0.51	-0.52	-0.44	-0.58	0.02	-0.54
520	-0.74	-0.75	-0.89	-0.56	-0.79	-0.41	-0.73	-1.28	-0.84	-1.02	-1.16	-1.14
530	-0.52	-0.60	0.13	-0.48	-0.41	-0.59	-0.73	-0.05	-0.62	-0.58	-0.42	-0.40
540	-0.48	-0.05	-0.47	-0.41	-0.02	-0.54	-0.37	-0.17	-0.31	-0.39	-0.44	-0.57
550	-0.67	-0.67	-0.67	-0.85	-0.64	-0.39	-0.78	-1.26	-1.22	-1.56	-1.39	-1.83
560	-0.53	-0.29	-0.64	-0.57	-0.34	-0.77	-0.66	-0.02	-0.80	-1.12	-0.33	-0.37
570	-0.13	0.00	-0.09	-0.04	-0.24	-0.34	-0.24	-0.27	-0.45	-0.48	-0.57	-0.82
580	-0.44	-0.84	-0.64	-0.20	-0.12	-0.29	-0.31	-0.13	-0.24	-0.44	0.62	0.04

Table F-4 Average total overtime (in minutes) per beat per month for 8-hr shift.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	1342.73	945.45	629.90	579.94	715.48	1265.89	1932.96	2526.59	2934.58	3541.97	3657.39	4006.85
220	1750.89	1446.83	1001.33	784.15	994.41	1555.43	2312.78	3144.03	3440.38	4067.61	4159.90	4429.12
230	1357.25	971.52	772.67	618.11	747.77	1274.76	1997.35	2810.67	3147.12	3642.00	3709.17	3989.18
240	2331.78	1890.72	1438.60	1036.76	1356.37	2220.42	3341.90	4534.43	5163.92	5829.77	6153.76	6492.52
250	1736.77	1302.52	1021.21	741.72	905.14	1441.75	2196.58	3068.09	3530.71	4087.48	4378.02	4773.37
260	1966.15	1422.94	1081.06	953.21	1146.71	1803.99	2683.41	3289.82	3486.41	3811.96	3831.09	3970.18
270	3458.92	3256.95	3031.68	2673.58	3263.83	4665.24	6128.25	6624.86	6664.55	6818.62	6581.91	6565.02
280	1744.42	1343.91	1087.52	864.62	1184.77	1902.17	2585.41	3145.50	3472.04	3779.86	3817.72	3929.94
310	2104.26	2047.99	2351.83	2483.43	2651.31	2872.20	3321.92	3472.84	3628.80	3978.02	3797.90	3929.40
320	3400.47	3919.87	4511.64	4775.39	5145.59	4997.13	5101.55	4993.97	4573.04	4513.86	4028.16	3971.31
330	2183.85	2292.99	2430.11	2442.06	2769.03	2776.31	3244.36	3521.55	3655.30	3954.65	3888.97	3839.53
340	2798.97	2963.99	3112.62	3549.39	4250.64	4673.21	5617.06	5987.31	6411.48	6792.61	6601.04	6706.30
350	3165.03	2950.01	3485.62	3737.53	4343.60	5028.90	5496.70	5689.07	5754.00	5974.49	5514.16	5407.00
360	2647.45	2638.10	2840.70	2856.53	3053.14	3158.76	3524.94	3747.24	3884.53	3907.03	3755.37	3752.54
370	2776.00	2876.25	3724.38	3673.25	4376.70	4810.88	5487.32	6224.32	6450.33	7022.52	6957.72	7163.72
380	2599.11	2589.38	2928.03	2825.16	3070.97	3286.05	3542.14	3778.16	3703.72	3974.51	3735.36	3736.93
410	1760.15	1270.27	1278.96	1291.28	1545.97	2184.31	2977.58	3728.24	4292.52	4881.31	4882.78	5024.60
420	1908.68	1404.53	1428.94	1323.28	1556.89	2100.35	2807.52	3569.64	4185.49	4789.74	5064.44	5205.41
430	1525.54	1192.57	1094.34	1173.41	1296.16	1711.57	2412.63	3214.97	3789.09	4344.23	4499.96	4806.18
440	2537.24	1926.31	2014.51	1856.95	2606.20	3118.61	4291.56	5588.77	6467.69	7408.84	7688.30	8039.22
450	2889.39	2920.70	3192.76	3513.30	4838.69	6097.54	7228.27	7619.94	7575.25	7562.06	6799.92	6289.03
460	1436.01	966.71	852.39	894.42	1046.10	1525.01	1938.00	2744.78	3326.11	3909.02	4227.84	4534.81
470	1538.80	1039.17	914.08	987.83	1075.33	1580.36	2048.80	2979.73	4090.21	5089.52	6306.09	7008.18
480	1628.37	1079.17	958.33	1053.88	1224.95	1814.30	2521.20	3147.54	3767.69	4301.44	4540.00	4675.31
510	1744.27	1597.63	1581.98	1560.27	1342.01	1509.82	1663.76	1828.48	2153.27	2415.04	2982.18	3573.02
520	1728.98	1681.84	1629.94	1481.31	1353.82	1484.74	1617.83	1807.48	2075.27	2458.72	3069.45	3742.54
530	1753.08	1624.77	1738.87	1509.32	1529.98	1605.83	1563.07	1773.47	2042.53	2589.56	2903.01	3453.07
540	5639.56	5971.02	6354.92	6535.85	7048.41	7420.76	8486.10	9219.89	9259.71	9374.78	9376.41	9842.07
550	2365.62	2382.12	2197.69	2111.19	2040.62	2133.04	2577.81	2762.52	3212.88	3980.58	4657.45	5614.31
560	1894.81	1924.32	1924.96	1804.83	1794.31	1768.80	1956.46	2357.44	2558.70	3023.68	3472.05	4024.03
570	1717.96	1603.91	1340.45	1354.34	1092.02	1043.88	1332.21	1493.76	1721.38	2306.49	2750.58	3458.50
580	2121.75	2127.43	2047.73	1958.10	1955.83	2024.21	2216.88	2533.38	2905.33	3204.36	3822.31	4202.50

Table F-5 Average total overtime (in minutes) per beat per month for 10-hr shift.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	890.49	632.77	414.61	327.62	370.71	677.06	1012.72	1381.27	1659.38	2053.56	2267.78	2553.19
220	1280.97	959.06	611.55	474.93	600.07	917.43	1336.53	1837.68	2002.67	2420.62	2563.85	2805.79
230	892.70	603.19	479.45	386.78	422.59	702.40	1078.34	1514.06	1778.19	2154.34	2230.32	2613.39
240	1651.83	1182.02	763.47	576.44	846.71	1367.08	2163.61	2965.25	3476.96	4094.31	4270.41	4655.39
250	1100.87	863.58	595.42	406.14	504.83	819.10	1169.53	1629.23	1942.51	2455.55	2605.19	2977.89
260	1298.43	904.28	634.62	509.48	583.07	1012.28	1492.49	1803.38	2085.00	2421.52	2475.46	2711.31
270	2413.08	2044.63	1837.44	1542.94	2006.44	3175.61	4268.72	4750.54	4835.92	5201.19	5096.56	5090.90
280	1163.21	973.02	598.19	457.36	611.33	986.43	1454.87	1819.30	2042.45	2297.92	2500.31	2733.81
310	1271.05	1393.49	1405.64	1479.82	1598.00	1730.83	1984.97	2182.62	2366.11	2601.10	2579.31	2660.03
320	2283.66	2645.48	3030.61	3256.09	3464.27	3469.05	3421.30	3326.96	3107.22	2922.42	2599.66	2551.85
330	1432.19	1357.73	1471.55	1614.43	1593.30	1746.55	2034.51	2261.08	2369.12	2605.93	2613.83	2661.43
340	1814.44	1943.95	2121.74	2258.04	2574.52	2823.63	3468.83	3832.45	4168.45	4660.58	4629.78	4744.56
350	1990.19	1941.97	1965.35	2245.94	2489.62	2696.62	2987.58	3233.92	3297.06	3484.75	3310.51	3267.74
360	1678.54	1622.63	1632.54	1787.46	1891.93	1891.91	2059.68	2290.89	2380.39	2546.16	2470.79	2482.37
370	1866.20	1896.79	2271.92	2422.33	2584.19	2885.64	3465.59	3946.21	4300.50	4877.64	4989.84	5177.78
380	1649.45	1756.30	1717.58	1741.43	1906.26	2077.70	2142.68	2420.88	2479.85	2705.27	2514.97	2560.94
410	1088.38	733.61	696.52	769.31	1018.51	1348.15	1895.49	2500.51	2957.82	3381.64	3643.37	3894.31
420	1261.55	946.17	914.71	927.14	1052.97	1519.98	1721.93	2319.76	2757.63	3163.53	3239.80	3627.32
430	972.32	647.51	561.57	601.41	807.60	1138.02	1519.46	1972.94	2511.14	2975.98	3423.32	3669.12
440	1702.41	1175.34	1127.63	1169.00	1406.69	2005.83	2994.51	3888.19	4785.82	5645.76	6010.11	6321.60
450	1887.58	1890.60	1979.31	2127.36	2941.57	3856.54	4748.25	5159.78	5221.22	5308.54	4946.98	4769.91
460	915.48	600.79	483.94	527.65	622.69	871.90	1175.97	1750.61	2131.72	2690.87	3032.90	3462.66
470	984.03	708.14	602.93	721.39	769.14	929.39	1427.29	1962.02	2749.94	3782.50	4599.55	5424.17
480	1092.52	679.39	669.90	632.66	806.39	1057.21	1413.31	1966.82	2398.83	3077.68	3259.12	3661.28
510	1147.15	1049.11	1080.94	880.06	922.07	899.88	918.55	990.75	1123.75	1287.19	1486.48	1887.49
520	1070.56	1064.48	990.55	859.80	847.37	840.46	984.08	1183.73	1123.80	1418.14	1763.94	2096.02
530	1125.51	1101.76	924.35	898.02	926.14	928.84	986.13	984.62	1136.62	1369.52	1530.87	1850.80
540	4158.74	4048.88	4518.58	4690.23	4682.47	5079.16	5655.88	5910.02	5797.93	5726.27	5728.73	6058.61
550	1464.08	1455.79	1240.47	1300.50	1131.36	1192.37	1365.30	1562.37	1769.12	2153.66	2460.89	2962.78
560	1151.06	1203.27	1169.36	1073.80	978.95	1065.40	1120.01	1205.09	1359.77	1610.63	1787.29	2126.39
570	1167.50	1045.62	930.81	864.38	828.12	849.88	824.97	906.54	1074.02	1383.71	1593.56	2009.06
580	1321.11	1386.88	1290.51	1172.71	1067.11	1081.32	1290.07	1326.47	1540.11	1733.11	1943.31	2255.55

Table F-6 Additional total overtime (in minutes) incurred in 8-hr shift compared to 10-hr shift.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	452.24	312.68	215.29	252.32	344.77	588.83	920.24	1145.32	1275.20	1488.41	1389.62	1453.66
220	469.92	487.78	389.78	309.22	394.34	638.00	976.25	1306.35	1437.71	1647.00	1596.05	1623.33
230	464.55	368.33	293.22	231.33	325.19	572.36	919.02	1296.61	1368.93	1487.67	1478.86	1375.79
240	679.96	708.70	675.14	460.33	509.67	853.34	1178.29	1569.18	1686.96	1735.47	1883.36	1837.13
250	635.91	438.94	425.79	335.58	400.32	622.66	1027.05	1438.86	1588.21	1631.94	1772.84	1795.48
260	667.73	518.66	446.44	443.74	563.64	791.71	1190.92	1486.44	1401.41	1390.44	1355.63	1258.87
270	1045.85	1212.32	1194.24	1130.64	1257.39	1489.63	1859.53	1874.32	1828.63	1617.43	1485.36	1474.12
280	581.21	370.90	489.33	407.27	573.44	915.75	1130.54	1326.21	1429.59	1481.95	1317.42	1196.13
310	833.21	654.51	946.20	1003.61	1053.31	1141.37	1336.96	1290.22	1262.69	1376.92	1218.59	1269.38
320	1116.81	1274.39	1481.03	1519.31	1681.33	1528.09	1680.25	1667.01	1465.82	1591.44	1428.51	1419.46
330	751.66	935.27	958.56	827.63	1175.74	1029.76	1209.85	1260.48	1286.18	1348.73	1275.14	1178.10
340	984.54	1020.04	990.88	1291.36	1676.12	1849.58	2148.23	2154.86	2243.04	2132.03	1971.26	1961.74
350	1174.84	1008.04	1520.27	1491.60	1853.98	2332.28	2509.12	2455.16	2456.94	2489.75	2203.65	2139.26
360	968.92	1015.47	1208.17	1069.08	1161.22	1266.85	1465.27	1456.35	1504.14	1360.87	1284.58	1270.17
370	909.80	979.47	1452.46	1250.92	1792.51	1925.24	2021.73	2278.11	2149.83	2144.88	1967.88	1985.95
380	949.66	833.09	1210.45	1083.74	1164.71	1208.35	1399.46	1357.28	1223.88	1269.25	1220.40	1175.99
410	671.77	536.66	582.44	521.97	527.46	836.17	1082.09	1227.74	1334.71	1499.67	1239.42	1130.30
420	647.13	458.37	514.23	396.14	503.93	580.37	1085.59	1249.89	1427.87	1626.21	1824.65	1578.09
430	553.23	545.06	532.77	572.01	488.56	573.55	893.18	1242.03	1277.95	1368.26	1076.65	1137.06
440	834.83	750.97	886.88	687.95	1199.51	1112.78	1297.06	1700.58	1681.87	1763.08	1678.19	1717.63
450	1001.81	1030.10	1213.45	1385.94	1897.13	2241.00	2480.02	2460.16	2354.03	2253.53	1852.94	1519.13
460	520.53	365.92	368.45	366.78	423.42	653.12	762.04	994.17	1194.40	1218.15	1194.94	1072.15
470	554.77	331.03	311.15	266.44	306.19	650.97	621.51	1017.72	1340.27	1307.02	1706.54	1584.02
480	535.85	399.78	288.43	421.22	418.56	757.09	1107.90	1180.72	1368.86	1223.76	1280.89	1014.03
510	597.12	548.52	501.04	680.21	419.94	609.94	745.21	837.73	1029.52	1127.86	1495.71	1685.53
520	658.42	617.37	639.40	621.51	506.46	644.28	633.75	623.75	951.47	1040.58	1305.52	1646.53
530	627.57	523.01	814.52	611.31	603.84	676.99	576.94	788.85	905.91	1220.05	1372.14	1602.27
540	1480.82	1922.15	1836.34	1845.62	2365.94	2341.61	2830.22	3309.88	3461.79	3648.51	3647.68	3783.47
550	901.55	926.34	957.22	810.70	909.26	940.67	1212.51	1200.16	1443.77	1826.93	2196.57	2651.53
560	743.75	721.05	755.60	731.04	815.36	703.40	836.45	1152.35	1198.94	1413.05	1684.77	1897.64
570	550.46	558.30	409.64	489.97	263.90	194.01	507.25	587.22	647.36	922.78	1157.02	1449.45
580	800.64	740.55	757.22	785.40	888.72	942.89	926.81	1206.91	1365.22	1471.26	1879.00	1946.95

Appendix G

Table G-1 Total predicted crime counts per beat per month from average realized crime for baseline allocation.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	70	64	64	68	85	123	183	284	437	693	1101	1730
220	92	87	87	95	121	180	275	425	660	1049	1667	2611
230	75	69	68	73	96	141	215	333	517	819	1299	2045
240	113	106	105	115	148	219	331	512	798	1260	1994	3111
250	81	75	73	78	99	146	223	342	531	840	1331	2086
260	118	110	110	119	154	229	347	544	845	1338	2112	3295
270	192	213	252	318	456	723	1152	1828	2865	4510	6972	10380
280	109	103	103	115	149	219	335	519	809	1282	2030	3170
310	99	111	129	160	217	324	513	841	1397	2335	3831	6071
320	178	240	326	456	673	1061	1721	2855	4701	7614	11923	17479
330	107	118	138	172	239	359	568	931	1542	2566	4204	6648
340	111	124	144	178	243	361	572	934	1548	2579	4235	6688
350	123	135	159	200	272	409	649	1066	1774	2950	4819	7569
360	133	150	178	221	299	451	716	1175	1943	3219	5241	8204
370	114	129	151	190	260	390	621	1019	1689	2812	4600	7229
380	133	150	177	221	302	456	727	1197	1981	3289	5358	8373
410	103	82	71	72	79	103	149	236	398	708	1281	2286
420	90	71	60	59	65	84	121	189	318	563	1015	1824
430	84	67	57	56	60	76	108	172	289	513	929	1664
440	113	94	81	82	88	116	169	269	456	811	1459	2602
450	160	173	181	208	276	410	653	1101	1904	3378	5954	10079
460	68	53	44	43	44	55	78	120	200	352	633	1133
470	65	51	42	41	42	53	74	114	190	335	602	1082
480	75	57	48	47	51	66	95	148	244	431	776	1394
510	77	73	68	62	59	56	56	64	80	109	152	214
520	75	72	68	62	59	56	56	63	78	103	144	203
530	80	75	73	70	65	63	63	72	91	122	170	240
540	312	349	395	440	480	526	589	738	970	1342	1896	2673
550	102	99	97	95	93	89	90	106	134	182	256	362
560	92	88	84	79	76	72	74	86	109	147	207	292
570	64	61	59	54	51	47	47	54	65	85	116	162
580	99	95	91	89	85	82	81	93	118	160	223	312

Table G-2 Total predicted crime counts per beat per month from average realized crime when 2 DUs are deployed for hot beats.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	70	64	64	68	85	123	180	258	354	429	399	213
220	92	87	87	95	121	176	240	325	383	353	187	31
230	75	69	68	73	96	141	204	282	388	477	455	255
240	113	106	105	115	148	195	254	295	255	124	199	26
250	81	75	73	78	99	146	209	288	393	478	456	252
260	118	110	110	119	150	206	271	316	283	145	231	36
270	181	183	175	153	106	168	63	100	166	12	21	32
280	109	103	103	115	149	211	284	389	467	441	246	47
310	99	111	129	159	190	244	288	264	136	230	34	56
320	166	204	234	236	176	71	119	198	21	36	58	85
330	107	118	138	168	204	264	314	294	158	26	44	71
340	111	124	144	169	206	266	318	293	152	23	40	65
350	123	135	152	173	199	219	191	91	154	21	35	59
360	133	148	150	157	144	107	171	64	109	180	14	24
370	114	129	144	162	188	209	181	88	149	249	34	59
380	133	141	152	163	157	123	201	89	149	16	28	46
410	103	82	71	72	79	103	149	222	333	520	735	801
420	90	71	60	59	65	84	121	183	275	424	596	631
430	84	67	57	56	60	76	108	170	271	419	586	625
440	113	94	81	82	88	116	172	242	361	485	508	302
450	149	150	136	155	144	215	181	82	148	19	33	61
460	68	53	44	43	44	55	78	120	195	325	520	731
470	65	51	42	41	42	53	74	114	190	318	503	706
480	75	57	48	47	51	66	95	148	241	381	609	854
510	77	73	68	62	59	56	56	64	80	109	152	192
520	75	72	68	62	59	56	56	63	78	103	144	193
530	80	75	73	70	65	63	63	72	91	122	170	223
540	296	304	298	247	147	159	52	66	90	129	182	23
550	102	99	97	95	93	89	90	106	134	170	216	266
560	92	88	84	79	76	72	74	86	109	147	203	257
570	64	61	59	54	51	47	47	54	65	85	116	156
580	99	95	91	89	85	82	81	93	118	160	205	254

Table G-3 Average fraction busy time of officers per beat per month for a simulated year when two DUs are deployed for hot beats.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.12	0.11	0.08	0.08	0.09	0.17	0.27	0.35	0.45	0.50	0.48	0.36
220	0.13	0.11	0.09	0.09	0.12	0.20	0.28	0.38	0.44	0.42	0.30	0.06
230	0.13	0.11	0.09	0.09	0.10	0.20	0.28	0.37	0.47	0.51	0.51	0.38
240	0.12	0.10	0.07	0.08	0.10	0.16	0.23	0.27	0.27	0.16	0.03	0.05
250	0.11	0.08	0.06	0.06	0.09	0.14	0.22	0.32	0.40	0.45	0.45	0.33
260	0.21	0.18	0.16	0.14	0.18	0.27	0.36	0.41	0.41	0.28	0.06	0.10
270	0.16	0.15	0.12	0.10	0.07	0.12	0.05	0.10	0.17	0.02	0.03	0.05
280	0.18	0.18	0.14	0.13	0.16	0.27	0.36	0.46	0.52	0.51	0.39	0.11
310	0.20	0.24	0.25	0.29	0.34	0.36	0.38	0.35	0.24	0.05	0.08	0.11
320	0.28	0.35	0.38	0.36	0.30	0.13	0.22	0.03	0.06	0.09	0.15	0.19
330	0.20	0.24	0.25	0.31	0.32	0.37	0.38	0.37	0.25	0.04	0.08	0.13
340	0.13	0.15	0.15	0.19	0.21	0.26	0.30	0.28	0.17	0.02	0.05	0.07
350	0.20	0.21	0.23	0.23	0.23	0.27	0.21	0.10	0.19	0.03	0.04	0.06
360	0.27	0.30	0.30	0.30	0.29	0.24	0.33	0.18	0.29	0.06	0.10	0.13
370	0.11	0.14	0.14	0.16	0.18	0.19	0.16	0.09	0.15	0.02	0.04	0.06
380	0.26	0.29	0.29	0.29	0.28	0.23	0.32	0.20	0.29	0.05	0.09	0.14
410	0.18	0.16	0.13	0.13	0.16	0.21	0.31	0.42	0.53	0.57	0.64	0.61
420	0.14	0.12	0.08	0.09	0.12	0.17	0.25	0.34	0.44	0.53	0.57	0.55
430	0.14	0.13	0.10	0.12	0.13	0.17	0.24	0.36	0.48	0.54	0.58	0.55
440	0.13	0.10	0.09	0.09	0.11	0.15	0.25	0.31	0.43	0.47	0.47	0.35
450	0.20	0.19	0.17	0.21	0.18	0.34	0.31	0.16	0.29	0.05	0.10	0.16
460	0.14	0.11	0.08	0.10	0.09	0.12	0.18	0.27	0.40	0.49	0.55	0.59
470	0.06	0.05	0.03	0.04	0.04	0.06	0.09	0.15	0.25	0.33	0.42	0.46
480	0.14	0.11	0.10	0.10	0.10	0.14	0.21	0.31	0.43	0.52	0.61	0.63
510	0.15	0.16	0.14	0.13	0.13	0.15	0.16	0.21	0.25	0.32	0.42	0.38
520	0.13	0.13	0.11	0.11	0.11	0.11	0.12	0.14	0.17	0.22	0.31	0.35
530	0.15	0.17	0.13	0.14	0.13	0.15	0.15	0.18	0.24	0.29	0.39	0.43
540	0.35	0.37	0.33	0.29	0.18	0.07	0.08	0.11	0.17	0.20	0.29	0.07
550	0.15	0.17	0.15	0.14	0.14	0.15	0.18	0.20	0.25	0.30	0.36	0.40
560	0.18	0.19	0.18	0.15	0.16	0.17	0.17	0.21	0.27	0.34	0.41	0.46
570	0.07	0.06	0.05	0.06	0.05	0.05	0.05	0.06	0.07	0.10	0.16	0.20
580	0.20	0.21	0.18	0.18	0.18	0.20	0.20	0.23	0.29	0.35	0.43	0.47

Table G-4 Average waiting time (in minutes) of a call in queue per beat per month for priority 1 for a simulated year when 2 DUs are deployed for hot beats.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.56	0.53	0.28	0.14	0.22	0.56	2.13	3.55	5.06	6.19	6.13	4.83
220	0.38	0.24	0.16	0.11	0.19	0.81	1.80	3.40	4.29	4.37	2.94	0.00
230	0.57	0.57	0.36	0.19	0.28	0.81	2.07	3.69	5.49	6.18	6.35	5.05
240	0.05	0.03	0.01	0.01	0.03	0.14	0.53	0.98	1.18	0.50	0.00	0.00
250	0.20	0.12	0.04	0.03	0.14	0.53	1.30	2.70	3.87	4.63	4.68	3.48
260	1.36	1.09	0.78	0.50	0.68	1.72	3.14	4.20	4.60	3.32	0.02	0.87
270	0.05	0.08	0.04	0.01	0.00	0.02	0.00	0.04	0.23	0.00	0.00	0.00
280	1.11	1.07	0.57	0.44	0.51	1.64	3.04	4.81	5.97	6.18	4.96	0.69
310	1.18	1.76	1.72	2.63	3.04	3.74	3.94	3.68	2.30	0.14	0.40	0.60
320	1.44	2.22	2.59	2.34	1.80	0.41	1.09	0.03	0.08	0.20	0.50	0.77
330	1.31	1.57	2.17	2.75	2.89	3.82	4.01	3.96	2.25	0.07	0.30	0.82
340	0.05	0.11	0.12	0.23	0.32	0.63	0.91	0.78	0.24	0.00	0.01	0.02
350	0.86	0.95	0.95	0.88	0.85	1.09	0.68	0.16	0.56	0.01	0.02	0.05
360	2.17	2.52	2.76	2.74	2.74	2.21	3.35	1.49	2.73	0.21	0.50	0.83
370	0.02	0.05	0.05	0.12	0.19	0.26	0.19	0.03	0.17	0.00	0.00	0.01
380	2.05	2.33	2.36	2.54	2.44	2.12	3.37	1.66	2.73	0.16	0.40	0.99
410	1.02	0.98	0.88	0.97	0.95	1.59	2.73	4.83	5.81	6.03	6.22	5.74
420	0.45	0.29	0.20	0.24	0.32	0.51	1.44	2.97	3.86	4.64	4.78	4.55
430	0.75	0.58	0.74	0.78	0.78	1.35	1.79	3.88	5.36	5.91	5.95	5.58
440	0.07	0.04	0.03	0.06	0.04	0.11	0.53	1.11	2.15	2.64	2.68	1.95
450	0.71	0.55	0.40	0.59	0.46	2.19	2.37	0.89	2.53	0.12	0.55	1.32
460	0.70	0.32	0.41	0.47	0.40	0.76	0.96	2.31	4.29	5.36	5.83	5.55
470	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.08	0.43	1.07	1.81	2.02
480	0.80	0.52	0.46	0.61	0.55	0.82	1.43	2.82	4.65	5.72	5.99	5.62
510	0.75	0.88	0.62	0.68	0.64	0.88	0.28	0.59	0.03	0.05	0.06	0.10
520	0.47	0.46	0.45	0.47	0.43	0.48	0.06	0.05	0.02	0.03	0.06	0.13
530	0.83	0.97	0.74	0.85	0.71	0.92	0.31	0.56	0.02	0.06	0.09	0.16
540	0.94	1.11	0.89	0.74	0.30	0.02	0.00	0.01	0.00	0.00	0.02	0.00
550	0.77	0.81	0.72	0.70	0.79	0.73	0.05	0.11	0.06	0.10	0.14	0.21
560	1.02	1.11	1.07	1.07	0.86	1.25	0.57	0.57	0.06	0.06	0.16	0.20
570	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
580	1.29	1.23	1.26	1.11	1.36	1.52	0.48	0.76	0.08	0.07	0.18	0.18

Table G-5 Average waiting time (in minutes) of a call in queue per beat per month for priority 2 for a simulated year when 2 DUs are deployed for hot beats.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.49	0.45	0.29	0.15	0.23	0.60	2.02	3.46	5.09	6.08	6.10	4.63
220	0.33	0.17	0.14	0.09	0.19	0.86	1.81	3.32	4.17	4.13	2.73	0.00
230	0.54	0.53	0.33	0.18	0.25	0.83	2.03	3.69	5.27	6.13	6.45	5.24
240	0.05	0.03	0.01	0.01	0.02	0.15	0.55	0.91	1.25	0.42	0.00	0.00
250	0.15	0.07	0.02	0.03	0.13	0.51	1.26	2.72	3.86	4.40	4.62	3.15
260	1.32	0.97	0.77	0.46	0.70	1.79	3.12	4.09	4.49	3.19	0.01	0.03
270	0.06	0.08	0.03	0.01	0.00	0.02	0.00	0.03	0.26	0.00	0.00	0.00
280	1.09	0.94	0.54	0.47	0.50	1.64	3.01	4.67	5.87	6.27	4.65	0.06
310	1.17	1.74	1.83	2.67	3.28	0.75	0.77	0.45	0.00	0.00	0.00	0.00
320	1.42	2.31	2.67	2.37	1.98	0.18	0.34	0.00	0.00	0.00	0.00	0.00
330	1.52	1.68	1.99	2.83	2.86	0.89	0.71	0.63	0.00	0.00	0.00	0.00
340	0.04	0.11	0.13	0.27	0.32	0.09	0.11	0.07	0.00	0.00	0.00	0.00
350	0.89	1.02	0.97	0.92	0.78	0.53	0.21	0.00	0.00	0.00	0.00	0.00
360	2.25	2.62	2.87	2.77	2.55	0.26	0.52	0.00	0.00	0.00	0.00	0.00
370	0.02	0.05	0.05	0.12	0.18	0.02	0.01	0.00	0.00	0.00	0.00	0.00
380	2.05	2.40	2.35	2.55	2.45	0.25	0.43	0.00	0.00	0.00	0.00	0.00
410	0.95	1.03	1.00	0.86	0.12	0.62	1.70	3.49	5.41	6.19	8.18	7.52
420	0.43	0.31	0.18	0.22	0.12	0.31	1.33	2.72	4.44	5.42	6.05	6.07
430	0.71	0.56	0.68	0.58	0.07	0.35	1.17	2.98	4.96	5.90	6.63	7.12
440	0.06	0.04	0.04	0.06	0.01	0.06	0.50	1.00	2.26	2.82	3.01	1.98
450	0.68	0.59	0.43	0.69	0.48	1.71	2.16	1.00	2.92	0.00	0.01	1.45
460	0.66	0.34	0.36	0.61	0.06	0.23	0.66	1.92	3.99	5.32	6.35	7.36
470	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.07	0.43	1.04	1.77	2.20
480	0.94	0.56	0.47	0.75	0.06	0.32	0.86	2.28	4.46	5.70	6.76	7.79
510	0.41	0.39	0.25	0.28	0.20	0.31	0.00	0.00	0.00	0.00	0.00	0.00
520	0.10	0.10	0.08	0.04	0.03	0.08	0.00	0.00	0.00	0.00	0.00	0.00
530	0.35	0.38	0.27	0.19	0.26	0.28	0.00	0.00	0.00	0.00	0.00	0.00
540	0.34	0.36	0.25	0.17	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00
550	0.08	0.14	0.09	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00
560	0.52	0.48	0.38	0.19	0.35	0.35	0.00	0.00	0.00	0.00	0.00	0.00
570	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
580	0.63	0.53	0.43	0.37	0.49	0.53	0.00	0.00	0.00	0.00	0.00	0.00

Table G-6 Average waiting time (in minutes) of a call in queue per beat per month for priority 3 for a simulated year when 2 DUs are deployed for hot beats.

Beat	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
210	0.55	0.55	0.27	0.14	0.23	0.58	2.05	3.43	4.41	5.32	5.36	4.29
220	0.36	0.23	0.10	0.09	0.16	0.85	1.85	3.50	3.97	4.15	2.91	0.28
230	0.61	0.56	0.33	0.17	0.26	0.83	2.16	3.78	4.64	5.30	5.63	4.57
240	0.05	0.03	0.01	0.01	0.03	0.15	0.55	0.96	1.13	0.41	0.01	0.05
250	0.22	0.12	0.02	0.01	0.13	0.53	1.28	2.69	3.86	4.54	4.65	3.65
260	1.37	1.08	0.72	0.48	0.71	1.73	3.10	4.19	4.03	2.81	0.24	0.70
270	0.06	0.08	0.04	0.01	0.00	0.03	0.00	0.04	0.20	0.00	0.00	0.01
280	1.10	1.02	0.50	0.42	0.51	1.74	3.09	4.92	5.03	5.35	4.42	0.76
310	1.24	1.75	1.83	2.64	3.10	3.79	3.71	3.43	2.20	0.16	0.37	0.61
320	1.49	2.33	2.72	2.40	1.86	0.44	1.06	0.02	0.06	0.17	0.44	0.65
330	1.43	1.64	2.22	2.76	2.91	3.90	3.85	3.71	2.14	0.08	0.33	0.79
340	0.06	0.12	0.11	0.25	0.33	0.65	0.87	0.75	0.21	0.00	0.00	0.02
350	0.89	1.02	0.97	0.92	0.84	1.17	0.53	0.11	0.44	0.01	0.01	0.03
360	2.13	2.60	2.73	2.72	2.68	2.22	3.39	1.41	2.59	0.19	0.53	0.74
370	0.02	0.05	0.05	0.13	0.19	0.26	0.19	0.03	0.16	0.00	0.00	0.01
380	2.07	2.47	2.46	2.62	2.52	2.16	3.31	1.60	2.57	0.17	0.38	0.98
410	1.02	1.01	0.89	0.93	0.95	1.58	2.71	4.75	6.89	7.44	8.24	7.62
420	0.42	0.29	0.16	0.17	0.24	0.52	1.49	2.94	4.70	5.81	6.40	6.08
430	0.78	0.64	0.63	0.74	0.75	1.24	1.93	3.91	6.18	7.10	7.59	7.06
440	0.07	0.04	0.03	0.06	0.05	0.12	0.56	1.12	2.37	2.96	3.05	2.04
450	0.72	0.63	0.26	0.38	0.35	2.10	2.29	0.99	2.83	0.22	0.51	1.24
460	0.70	0.35	0.38	0.46	0.41	0.83	1.03	2.46	4.73	6.23	7.25	7.39
470	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.08	0.44	1.09	1.89	2.17
480	0.85	0.53	0.45	0.60	0.50	0.73	1.42	2.87	5.23	6.72	7.81	7.90
510	0.74	0.85	0.57	0.65	0.62	0.77	0.99	1.09	1.71	3.13	4.30	4.93
520	0.48	0.54	0.45	0.46	0.37	0.54	0.62	0.84	1.23	1.65	2.53	3.44
530	0.87	0.96	0.75	0.84	0.64	0.96	1.13	1.66	2.56	3.30	4.78	6.01
540	0.98	1.13	0.90	0.74	0.30	0.05	0.05	0.12	0.37	0.56	1.09	0.03
550	0.77	0.80	0.67	0.72	0.82	0.84	1.16	1.46	2.04	2.63	3.33	3.78
560	1.06	1.10	1.12	1.05	0.86	1.26	1.41	2.09	2.84	3.76	5.57	6.60
570	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.10	0.23
580	1.43	1.25	1.28	1.14	1.29	1.47	1.64	2.33	3.29	4.37	6.06	6.88

REFERENCES

1. Hoover, L.T., *Crime-Specific Policing.* Police and Policing: Contemporary Issues, 1999: p. 281.
2. FBI. *FBI Releases 2015 Crime Statistics*. 2016 [cited 2017 December, 26]; Available from: https://www.fbi.gov/news/pressrel/press-releases/fbi-releases-2015-crime-statistics.
3. McLaughlin, M., et al., *The economic burden of incarceration in the US*. 2016: St. Louis, MO: Washington University in St. Louis.
4. NIJ. *Predictive Policing [Internet]*. [cited 2017 December 26]; Available from: https://www.nij.gov/topics/law-enforcement/strategies/predictive-policing/Pages/welcome.aspx.
5. Lynch, C., *Is predictive policing the law-enforcement tactic of the future? The Wall Street Journal*. 2016.
6. Justice, N.I.o., *Predictive Policing Symposium, November 18-20, 2009.* 2009.
7. Wiki_1. *Predictive Policing [Internet]*. [cited 2017 December 26]; Available from: https://en.wikipedia.org/wiki/Predictive_policing#cite_ref-RR_1-0.
8. Perry, W.L., *Predictive policing: The role of crime forecasting in law enforcement operations*. 2013: Rand Corporation.
9. Deadman, D. and D. Pyle, *Forecasting recorded property crime using a time-series econometric model.* British Journal of Criminology, 1997. **37**(3): p. 437.
10. Lim, H., H. Lee, and S.J. Cuvelier, *The impact of police levels on crime rates: A systematic analysis of methods and statistics in existing studies.* Pacific Journal of Police & Criminal Justice, 2010. **8**(1): p. 49-82.
11. Marvell, T.B. and C.E. Moody, *Specification problems, police levels, and crime rates.* Criminology, 1996. **34**(4): p. 609-646.
12. Johnson, S.D., et al., *Predictive mapping of crime by ProMap: accuracy, units of analysis, and the environmental backcloth*, in *Putting crime in its place*. 2009, Springer. p. 171-198.
13. Berk, R., *Asymmetric loss functions for forecasting in criminal justice settings.* Journal of Quantitative Criminology, 2011. **27**(1): p. 107-123.
14. Braga, A.A. and D. Weisburd, *Policing problem places: Crime hot spots and effective prevention*. 2010: Oxford University Press.
15. Brown, D., J. Dalton, and H. Hoyle, *Spatial forecast methods for terrorist events in urban environments*, in *Intelligence and Security Informatics*. 2004, Springer. p. 426-435.
16. Canter, D., et al., *Predicting serial killers' home base using a decision support system.* Journal of Quantitative Criminology, 2000. **16**(4): p. 457-478.

17. Caplan, J.M., L.W. Kennedy, and J. Miller, *Risk terrain modeling: brokering criminological theory and GIS methods for crime forecasting.* Justice Quarterly, 2011. **28**(2): p. 360-381.
18. Mohler, G.O., et al., *Self-Exciting Point Process Modeling of Crime.* Journal of the American Statistical Association, 2011. **106**(493): p. 100-108.
19. Wang, X. and D. Brown, *The spatio-temporal modeling for criminal incidents.* Security Informatics, 2012. **1**(1): p. 1-17.
20. Wang, X. and D.E. Brown. *The spatio-temporal generalized additive model for criminal incidents*. in *Intelligence and Security Informatics (ISI), 2011 IEEE International Conference on*. 2011. IEEE.
21. Yu, C.-H., et al., *Crime forecasting using spatio-temporal pattern with ensemble learning*, in *Advances in Knowledge Discovery and Data Mining*. 2014, Springer. p. 174-185.
22. Qian, C., et al., *Weighted-traffic-network-based geographic profiling for serial crime location prediction.* Epl, 2011. **93**(6).
23. Hashemian, M., *Optimizing Police Resources Deployment*. 2016, Université d'Ottawa/University of Ottawa.
24. Mukhopadhyay, A., et al. *Optimal allocation of police patrol resources using a continuous-time crime model*. in *International Conference on Decision and Game Theory for Security*. 2016. Springer.
25. Leemis, L.M. and S.K. Park, *Discrete-event simulation: A first course*. 2004.
26. Lynch, M.J., P.B. Stretesky, and M.A. Long, *What Is Crime?*, in *Defining Crime*. 2015, Springer. p. 27-55.
27. FreeAdvice. *What is a Crime? [Internet]*. February, 2013 [cited 2017 December 27]; Available from: https://criminal-law.freeadvice.com/criminal-law/criminal-law/crime_law.htm.
28. Reference. *How does crime affect society? [Internet]*. [cited 2017 December 28]; Available from: https://www.reference.com/world-view/crime-affect-society-e062b2c8ee3c2466.
29. Taylor, R.B., *The impact of crime on communities.* The Annals of the American Academy of Political and Social Science, 1995. **539**(1): p. 28-45.
30. Glaeser, E.L., B. Sacerdote, and J.A. Scheinkman, *Crime and social interactions.* The Quarterly Journal of Economics, 1996. **111**(2): p. 507-548.
31. Quetelet, A., *Sur l'homme et le développement de ses facultés ou essai de physique sociale*. Vol. 1. 1835: Bachelier.
32. Ludwig, J. and J.R. Kling, *Is crime contagious?* The Journal of Law and Economics, 2007. **50**(3): p. 491-518.
33. MacDonald, J.W., *Classification of Crimes.* Cornell LQ, 1932. **18**: p. 524.

34. Dale, R.W., *Felony and Misdemeanor*. 1917: Indiana University.
35. CYR, R. *Criminal Law Cyber Crimes [Internet]*. 2009 [cited 2017 December 28]; Available from: https://www.slideshare.net/verifast1/business-law-chater-6?qid=9d630e3c-d868-457d-b1e8-8353b361f5cc&v=&b=&from_search=2.
36. Wiki_2. *Violent Crime [Internet]*. [cited 2017 December 28]; Available from: https://en.wikipedia.org/wiki/Violent_crime.
37. FBI_2. *Property crime [Internet]*. [cited 2017 December 28]; Available from: https://ucr.fbi.gov/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/property-crime.
38. Nelken, D., *White-collar crime*. 1994: Dartmouth Aldershot,, England.
39. Halder, D., K. Jaishankar, and K. Jaishankar, *Cyber crime and the victimization of women: laws, rights and regulations*. 2012: Information Science Reference.
40. Srinivasan, S., et al., *Workforce assessment method for an urban police department.* Policing: An International Journal of Police Strategies & Management, 2013. **36**(4): p. 702-718.
41. Andresen, M.A., *Crime measures and the spatial analysis of criminal activity.* British Journal of criminology, 2005. **46**(2): p. 258-285.
42. Brantingham, P.L. and P.J. Brantingham, *Mapping crime for analytic purposes: location quotients, counts, and rates.* Crime mapping and crime prevention, 1998. **8**: p. 263-288.
43. Leong, K. and A. Sung, *A review of spatio-temporal pattern analysis approaches on crime analysis.* International E-journal of Criminal Sciences, 2015. **9**: p. 1-33.
44. Short, M.B., et al., *A statistical model of criminal behavior.* Mathematical Models & Methods in Applied Sciences, 2008. **18**: p. 1249-1267.
45. Short, M.B., et al., *Dissipation and displacement of hotspots in reaction-diffusion models of crime.* Proceedings of the National Academy of Sciences, 2010. **107**(9): p. 3961-3965.
46. Chainey, S., S. Reid, and N. Stuart, *When is a hotspot a hotspot? A procedure for creating statistically robust hotspot maps of crime*. 2002: Taylor & Francis, London, England.
47. Wilson, J.Q. and G.L. Kelling, *Broken windows.* Atlantic monthly, 1982. **249**(3): p. 29-38.
48. Wickes, R., *Social Disorganization Theory: Its History and Relevance to Crime Prevention*, in *Preventing Crime and Violence*, B. Teasdale and M.S. Bradley, Editors. 2017, Springer International Publishing: Cham. p. 57-66.
49. Cohen, L.E. and M. Felson, *Social change and crime rate trends: A routine activity approach.* American sociological review, 1979: p. 588-608.

50. Gorman, D.M., P.J. Gruenewald, and L.A. Waller, *Linking places to problems: geospatial theories of neighborhoods, alcohol and crime.* GeoJournal, 2013. **78**(3): p. 417-428.
51. Clarke, R.V., *" situational" Crime Prevention: Theory and Practice.* The British Journal of Criminology, 1980. **20**(2): p. 136-147.
52. Clarke, R.V.G., *Situational crime prevention*. 1997: Criminal Justice Press Monsey, NY.
53. Wortley, R. and L. Mazerolle, *Environmental criminology and crime analysis: Situating the theory, analytic approach and application.* Environmental criminology and crime analysis, 2008: p. 1-18.
54. Hollywood, J., et al., *Predictive Policing: What It Is, What It Isn't, and Where It Can Be Useful.* NLECTC Information and Geospatial Technologies Center Big Data and Smart (Equitable) Cities, 2012. **539**.
55. Clarke, R.V.G. and J.M. Hough, *The effectiveness of policing*. 1980: Gower Farnborough.
56. Goldstein, H., H. Goldstein, and M. Hill, *Problem-oriented policing*. 1990: McGraw-Hill New York.
57. Mazerolle, L., D.W. Soole, and S. Rombouts, *Crime prevention research reviews No. 1: Disrupting street-level drug markets.* Washington, DC: US Department of Justice Office of Community Oriented Policing Services, 2007.
58. Ferguson, A.G., *Predictive policing and reasonable suspicion.* Emory Law Journal, 2012. **62**(259).
59. Pearsall, B., *Predictive policing: The future of law enforcement.* National Institute of Justice Journal, 2010. **266**(1): p. 16-19.
60. Ioimo, R., *Introduction to Criminal Justice Information Systems*. 2016: CRC Press.
61. Ridgeway, G., *The pitfalls of prediction.* NIJ Journal, 2013. **271**: p. 34-40.
62. Johnson, C. *Crime mapping and analysis using GIS*. in *Geomatics Conference on Geomatics in Electronic Governance, January*. 2000.
63. Chainey, S. and J. Ratcliffe, *GIS and crime mapping*. 2013: John Wiley & Sons.
64. Eck, J., et al., *Mapping crime: Understanding hotspots.* USA: National Institute of Justice, 2005.
65. Eghteabs, C., et al. *Effects of Color and Threshold on User Perception of Heat Maps*. in *Proceedings of the 2016 ACM Conference Companion Publication on Designing Interactive Systems*. 2017. ACM.
66. Kennedy, L., J. Caplan, and E. Piza, *Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies.* Journal of Quantitative Criminology, 2011. **27**(3): p. 339-362.

67. Gale, R. and D. Holleran, *An application of risk terrain modeling to residential burglary.* TCNJ Journal of Student Scholarship, 2013. **15**: p. 1-9.
68. Osgood, D.W., *Poisson-based regression analysis of aggregate crime rates.* Journal of quantitative criminology, 2000. **16**(1): p. 21-43.
69. Meera, A.K. and M.D. Jayakumar, *Determinants of crime in a developing country: a regression model.* Applied Economics, 1995. **27**(5): p. 455-460.
70. Brown, M.A., *Modelling the spatial distribution of suburban crime.* Economic Geography, 1982. **58**(3): p. 247-261.
71. Bellair, P.E., *Social interaction and community crime: Examining the importance of neighbor networks.* Criminology, 1997. **35**(4): p. 677-704.
72. Cho, Y.H., *A multiple regression model for the measurement of the public policy impact on big city crime.* Policy sciences, 1972. **3**(4): p. 435-455.
73. Gamble, J.L. and J.J. Hess, *Temperature and violent crime in dallas, Texas: relationships and implications of climate change.* The western journal of emergency medicine, 2012. **13**(3): p. 239-46.
74. Chen, P., et al., *Assessing temporal and weather influences on property crime in Beijing, China.* Crime, Law & Social Change, 2011. **55**(1): p. 1-13.
75. Tonkin, M., et al., *A comparison of logistic regression and classification tree analysis for behavioural case linkage.* Journal of Investigative Psychology and Offender Profiling, 2012. **9**(3): p. 235-258.
76. Cahill, M. and G. Mulligan, *Using geographically weighted regression to explore local crime patterns.* Social Science Computer Review, 2007. **25**(2): p. 174-193.
77. Ngai, E., et al., *The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature.* Decision Support Systems, 2011. **50**(3): p. 559-569.
78. Corcoran, J., et al., *Data clustering and rule abduction to facilitate crime hot spot prediction*, in *Computational Intelligence: Theory and Applications, Proceedings*, B. Reusch, Editor. 2001. p. 807-821.
79. Grubesic, T.H. and A.T. Murray. *Detecting hot spots using cluster analysis and GIS*. in *Annual conference of CMRC, Dallas*. 2001.
80. Tayal, D.K., et al., *Crime detection and criminal identification in India using data mining techniques.* AI & society, 2015. **30**(1): p. 117-127.
81. Keyvanpour, M.R., M. Javideh, and M.R. Ebrahimi, *Detecting and investigating crime by means of data mining: a general crime matching framework.* Procedia Computer Science, 2011. **3**: p. 872-880.
82. Townsley, M., R. Homel, and J. Chaseling, *Infectious burglaries. A test of the near repeat hypothesis.* British Journal of Criminology, 2003. **43**(3): p. 615-633.

83. IFMPT. *Near Repeat Prediction [Internet]*. [cited 2017 December 30]; Available from: http://www.ifmpt.com/prognostik/.
84. Ratcliffe, J.H. and G.F. Rengert, *Near-repeat patterns in Philadelphia shootings.* Security Journal, 2008. **21**(1): p. 58-76.
85. Block, S. and S. Fujita, *Patterns of near repeat temporary and permanent motor vehicle thefts.* Crime Prevention and Community Safety, 2013. **15**(2): p. 151-167.
86. Wells, W., L. Wu, and X. Ye, *Patterns of near-repeat gun assaults in Houston.* Journal of Research in Crime and Delinquency, 2011: p. 0022427810397946.
87. Haberman, C.P. and J.H. Ratcliffe, *The predictive policing challenges of near repeat armed street robberies.* Policing: A Journal of Policy and Practice, 2012. **6**(2): p. 151-166.
88. Lanier, M.M. and D.L. Carter, *APPLYING COMPUTER-SIMULATION TO FORECAST HOMICIDE RATES.* Journal of Criminal Justice, 1993. **21**(5): p. 467-479.
89. Kohtz, S.J., et al. *Crime Patterns in Chicago Using Agent Based Modeling*. in *IIE Annual Conference. Proceedings*. 2017. Institute of Industrial and Systems Engineers (IISE).
90. Cohn, E.G. and J. Rotton, *WEATHER, SEASONAL TRENDS AND PROPERTY CRIMES IN MINNEAPOLIS, 1987–1988. A MODERATOR-VARIABLE TIME-SERIES ANALYSIS OF ROUTINE ACTIVITIES.* Journal of Environmental Psychology, 2000. **20**(3): p. 257-272.
91. Law, J., M. Quick, and P. Chan, *Bayesian spatio-temporal modeling for analysing local patterns of crime over time at the small-area level.* Journal of quantitative criminology, 2014. **30**(1): p. 57-78.
92. Chandra, B., M. Gupta, and M. Gupta. *A multivariate time series clustering approach for crime trends prediction*. in *Systems, Man and Cybernetics, 2008. SMC 2008. IEEE International Conference on*. 2008. IEEE.
93. Leitner, M. and M. Helbich, *The impact of hurricanes on crime: a spatio-temporal analysis in the city of Houston, Texas.* Cartography and Geographic Information Science, 2011. **38**(2): p. 213-221.
94. Peng, C., et al., *Assessing temporal and weather influences on property crime in Beijing, China.* Crime, Law and Social Change, 2011. **55**(1): p. 1-13.
95. Ratcliffe, J.H., *Aoristic Signatures and the Spatio-Temporal Analysis of High Volume Crime Patterns.* Journal of Quantitative Criminology, 2002. **18**(1): p. 23-43.
96. Mandracchia, J.T. and R.D. Morgan, *Predicting offenders' criminogenic cognitions with status variables.* Criminal Justice and Behavior, 2012. **39**(1): p. 5-25.

97. Stalans, L.J., et al., *Identifying three types of violent offenders and predicting violent recidivism while on probation: a classification tree analysis.* Law and human behavior, 2004. **28**(3): p. 253.
98. Chaiken, J., M. Chaiken, and W. Rhodes, *Predicting violent behavior and classifying violent offenders.* Understanding and preventing violence, 1994. **4**: p. 217-295.
99. Bernasco, W., *Them again? Same-offender involvement in repeat and near repeat burglaries.* European Journal of Criminology, 2008. **5**(4): p. 411-431.
100. Le Comber, S.C., et al., *Geographic profiling and animal foraging.* Journal of Theoretical Biology, 2006. **240**(2): p. 233-240.
101. Gruenewald, P.J., et al., *Ecological models of alcohol outlets and violent assaults: crime potentials and geospatial analysis.* Addiction, 2006. **101**(5): p. 666-677.
102. Holt, L. and D. Holleran, *A GEOSPATIAL ASSESSMENT OF DOMESTIC VIOLENCE.* 2014.
103. Adderley, R. and P.B. Musgrove. *Data mining case study: Modeling the behavior of offenders who commit serious sexual assaults*. in *Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*. 2001. ACM.
104. Hall, M., *Victims of crime*. 2012: Routledge.
105. Malleson, N. and M. Birkin, *Analysis of crime patterns through the integration of an agent-based model and a population microsimulation.* Computers, Environment and Urban Systems, 2012. **36**(6): p. 551-561.
106. Malleson, N., et al., *Using an agent-based crime simulation to predict the effects of urban regeneration on individual household burglary risk.* Environment and Planning B-Planning & Design, 2013. **40**(3): p. 405-426.
107. Montgomery, D.C., *Design and analysis of experiments*. 2017: John Wiley & Sons.
108. Sherman, L.W. and D. Weisburd, *General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial.* Justice quarterly, 1995. **12**(4): p. 625-648.
109. Ratcliffe, J.H. and E.T. Sorg, *The Philadelphia Experience*, in *Foot Patrol*. 2017, Springer. p. 21-41.
110. Ratcliffe, J.H., et al., *The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots.* Criminology, 2011. **49**(3): p. 795-831.
111. Headley, A.M., R.T. Guerette, and A. Shariati, *A field experiment of the impact of body-worn cameras (BWCs) on police officer behavior and perceptions.* Journal of Criminal Justice, 2017. **53**(Supplement C): p. 102-109.

112. Ariel, B., W.A. Farrar, and A. Sutherland, *The effect of police body-worn cameras on use of force and citizens' complaints against the police: A randomized controlled trial.* Journal of quantitative criminology, 2015. **31**(3): p. 509-535.
113. Telep, C.W., R.J. Mitchell, and D. Weisburd, *How much time should the police spend at crime hot spots? Answers from a police agency directed randomized field trial in Sacramento, California.* Justice Quarterly, 2014. **31**(5): p. 905-933.
114. Weisburd, D., *Randomized experiments in criminal justice policy: Prospects and problems.* Crime & Delinquency, 2000. **46**(2): p. 181-193.
115. Saladin, B.A., *Goal programming applied to police patrol allocation.* Journal of Operations Management, 1982. **2**(4): p. 239-249.
116. Green, L., *A multiple dispatch queueing model of police patrol operations.* Management Science, 1984. **30**(6): p. 653-664.
117. Curtin, K.M., K. Hayslett-McCall, and F. Qiu, *Determining optimal police patrol areas with maximal covering and backup covering location models.* Networks and Spatial Economics, 2010. **10**(1): p. 125-145.
118. Oghovese, O. and O. Olaniyi, *On optimal allocation of crime preventing patrol team using dynamic programming.* International Journal of Mathematics and Statistics Invention (IJMSI), 2014. **2**(8): p. 7-17.
119. GetRevising. *Advantages and disadvantages of mathematical models [Internet]*. [cited 2017 Decenber 31]; Available from: https://getrevising.co.uk/grids/advantages-and-disadvantages-of-mathematical.
120. Golomb, S.W., *Mathematical models: Uses and limitations.* IEEE Transactions on Reliability, 1971. **20**(3): p. 130-131.
121. Baudrillard, J., *Simulacra and simulations*. M. Poster ed. 1988: Palo Alto, CA: Stanford University Press.
122. Bogard, W., *The simulation of surveillance: Hypercontrol in telematic societies*. 1996: Cambridge University Press.
123. De Lint, W., S. Virta, and J.E. Deukmedjian, *The simulation of crime control: A shift in policing?* American Behavioral Scientist, 2007. **50**(12): p. 1631-1647.
124. Quijada, S.E., et al., *A spatio temporal simulation model for evaluating delinquency and crime policies*. Proceedings of the 2005 Winter Simulation Conference, Vols 1-4, ed. M.E. Kuhl, et al. 2005. 1328-1334.
125. Malleson, N., A. Evans, and T. Jenkins, *An agent-based model of burglary.* Environment and Planning B-Planning & Design, 2009. **36**(6): p. 1103-1123.

126. Malleson, N., A. Heppenstall, and L. See, *Crime reduction through simulation: An agent-based model of burglary*. Computers, Environment and Urban Systems, 2010. **34**(3): p. 236-250.
127. Devia, N. and R. Weber, *Generating crime data using agent-based simulation.* Computers, Environment and Urban Systems, 2013. **42**(0): p. 26-41.
128. Weisburd, D., et al., *Can hot spots policing reduce crime in urban areas? An agent-based simulation.* Criminology, 2017. **55**(1): p. 137-173.
129. Yonas, M.A., et al., *Dynamic Simulation of Crime Perpetration and Reporting to Examine Community Intervention Strategies.* Health Education & Behavior, 2013. **40**: p. 87S-97S.
130. Ortiz, F. and T.C. Sharkey. *Modeling the Impact of User Rehabilitation on Illegal Drug Trafficking Operations*. in *IIE Annual Conference. Proceedings*. 2017. Institute of Industrial and Systems Engineers (IISE).
131. Braga, A.A., *The effects of hot spots policing on crime.* The ANNALS of the American Academy of Political and Social Science, 2001. **578**(1): p. 104-125.
132. Braga, A.A., A.V. Papachristos, and D.M. Hureau, *The effects of hot spots policing on crime: An updated systematic review and meta-analysis.* Justice Quarterly, 2014. **31**(4): p. 633-663.
133. Ratcliffe, J.H., *Detecting Spatial Movement of Intra-Region Crime Patterns Over Time.* Journal of Quantitative Criminology, 2005. **21**(1): p. 103-123.
134. de Melo, S.N., et al., *Spatial/temporal variations of crime: a routine activity theory perspective.* International journal of offender therapy and comparative criminology, 2017: p. 0306624X17703654.
135. Weisburd, D. and L.G. Mazerolle, *Measuring immediate spatial displacement: Methodological issues and problems.* 1995: p. 349-359.
136. Weisburd, D., et al., *Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits.* Criminology, 2006. **44**(3): p. 549-592.
137. Bowers, K.J., et al., *Spatial displacement and diffusion of benefits among geographically focused policing initiatives: a meta-analytical review*. Journal of Experimental Criminology, 2011. **7**(4): p. 347-374.
138. Bowers, K.J. and S.D. Johnson, *Measuring the geographical displacement and diffusion of benefit effects of crime prevention activity.* Journal of Quantitative Criminology, 2003. **19**(3): p. 275-301.
139. Guerette, R.T. and K.J. Bowers, *Assessing the extent of crime displacement and diffusion of benefits: A review of situational crime prevention evaluations.* Criminology, 2009. **47**(4): p. 1331-1368.

140. Pitcher, A.B. and S.D. Johnson, *Exploring theories of victimization using a mathematical model of burglary.* Journal of Research in Crime and Delinquency, 2011. **48**(1): p. 83-109.
141. Yang, Z., et al., *A Decision-Making Framework for Ozone Pollution Control.* Operations Research, 2009. **57**(2): p. 484-498.
142. Jang, H., C.-B. Lee, and L.T. Hoover, *Dallas' disruption unit: efficacy of hot spots deployment.* Policing: An International Journal of Police Strategies & Management, 2012. **35**(3): p. 593-614.
143. Taylor, B., C.S. Koper, and D.J. Woods, *A randomized controlled trial of different policing strategies at hot spots of violent crime.* Journal of Experimental Criminology, 2011. **7**(2): p. 149-181.
144. Stevens, K.D., *Problem-oriented Policing.* The Encyclopedia of Criminology and Criminal Justice, 2014: p. 1-5.
145. Eck, J. and W. Spelman, *Problem oriented policing.* Washington, DC, 2016.
146. Ariel, B. and H. Partridge, *Predictable policing: Measuring the crime control benefits of hotspots policing at bus stops.* Journal of Quantitative Criminology, 2017. **33**(4): p. 809-833.
147. Koper, C.S., *Just enough police presence: Reducing crime and disorderly behavior by optimizing patrol time in crime hot spots.* Justice Quarterly, 1995. **12**(4): p. 649-672.
148. Braga, A.A., D.M. Hureau, and A.V. Papachristos, *An ex post facto evaluation framework for place-based police interventions.* Evaluation review, 2011. **35**(6): p. 592-626.
149. Braga, A.A. and B.J. Bond, *Policing crime and disorder hot spots: A randomized controlled trial.* Criminology, 2008. **46**(3): p. 577-607.
150. Cohen, J., W. Gorr, and P. Singh, *Estimating intervention effects in varying risk settings: Do police raids reduce illegal drug dealing at nuisance bars?* Criminology, 2003. **41**(2): p. 257-292.
151. Mazerolle, L.G., J.F. Price, and J. Roehl, *Civil remedies and drug control: A randomized field trial in Oakland, California.* Evaluation review, 2000. **24**(2): p. 212-241.
152. Reppetto, T.A., *Crime prevention and the displacement phenomenon.* Crime & Delinquency, 1976. **22**(2): p. 166-177.
153. Clarke, R.V. and D. Weisburd, *Diffusion of crime control benefits: Observations on the reverse of displacement.* Crime prevention studies, 1994. **2**: p. 165-184.
154. Thomas, T.A., *Quantifying crime displacement after a hot-spot intervention*. 2013.
155. Draca, M., S. Machin, and R. Witt, *Crime Displacement and Police Interventions: Evidence from London's" Operation Theseus"*, in *The*

Economics of Crime: lessons for and from latin America. 2010, University of Chicago Press. p. 359-374.
156. Schmidt, J.W. and R.E. Taylor, *Simulation and analysis of industrial systems*. 1970: Richard D. Irwin.
157. Law, A.M., *Simulation modeling and analysis*. 2015, New York, NY: McGraw-Hill Education.
158. DES. *Discrete event simulation [Internet]*. [cited 2017 December 31]; Available from: https://en.wikipedia.org/wiki/Discrete_event_simulation.
159. Next_event. *Discrete-event simulatio: A first course [Internet]*. [cited 2018 January 1]; Available from: http://www.cs.wm.edu/~esmirni/Teaching/cs526/section5.1.pdf.
160. Christos. *General Simulation Principles [Internet]*. [cited 2018 January 1]; Available from: https://www2.isye.gatech.edu/~sman/courses/6644/Module04-GeneralPrinciples_171016.pdf.
161. Robinson, S., *Discrete-event simulation: from the pioneers to the present, what next?* Journal of the Operational Research Society, 2005. **56**(6): p. 619-629.
162. Law, A.M. and M.G. McComas. *Simulation-based optimization*. in *Proceedings of the Winter Simulation Conference*. 2002.
163. Amaran, S., et al., *Simulation optimization: a review of algorithms and applications.* 4OR, 2014. **12**(4): p. 301-333.
164. SO. *Simulation-based optimization [Internet]*. [cited 2018 January 1]; Available from: https://en.wikipedia.org/wiki/Simulation-based_optimization.
165. Carson, Y. and A. Maria. *Simulation optimization: methods and applications*. in *Proceedings of the 29th conference on Winter simulation*. 1997. IEEE Computer Society.
166. Prasetio, Y.M., *Simulation-based optimization for complex stochastic systems.* 2003.
167. Deng, G., *Simulation-based optimization*. 2007, University of Wisconsin--Madison.
168. Bellman, R. and C. Rand, *Dynamic programming*. 1957, Princeton U6 - ctx_ver=Z39.88-2004&ctx_enc=info%3Aofi%2Fenc%3AUTF-8&rfr_id=info:sid/summon.serialssolutions.com&rft_val_fmt=info:ofi/fmt:kev:mtx:book&rft.genre=book&rft.title=Dynamic+programming&rft.au=Bellman%2C+Richard&rft.date=1957-01-01&rft.pub=Princeton+University+Press&rft.externalDocID=125086&paramdict=en-US U7 - Book: Princeton University Press.

169. Yang, Z., et al., *Mining and modeling for a metropolitan Atlanta ozone pollution decision-making framework.* Iie Transactions, 2007. **39**(6): p. 607-615.
170. Tauxe, G.W., R.R. Inman, and D.M. Mades, *Multiobjective dynamic programing with application to a reservoir.* Water Resources Research, 1979. **15**(6): p. 1403-1408.
171. Deb, K., *Multi-objective optimization*, in *Search methodologies*. 2014, Springer. p. 403-449.
172. Caramia, M. and P. Dell´Olmo, *Multi-objective optimization*. 2008: Springer.
173. Tsitsiklis, J.N. and B. Van Roy. *Analysis of temporal-diffference learning with function approximation*. in *Advances in neural information processing systems*. 1997.
174. Siebert, U., et al., *State-transition modeling: a report of the ISPOR-SMDM modeling good research practices task force–3.* Medical Decision Making, 2012. **32**(5): p. 690-700.
175. Murphy, K.P. and S. Russell, *Dynamic bayesian networks: representation, inference and learning.* 2002.
176. Azzalini, A., *Logistic regression for autocorrelated data with application to repeated measures.* Biometrika, 1994. **81**(4): p. 767-775.
177. Haque, K.M., V.C. Chen, and B.L. Huff. *A Discrete-Event Simulation Model for Adaptive Allocation of Police Patrol*. in *IIE Annual Conference. Proceedings*. 2017. Institute of Industrial and Systems Engineers (IISE).

BIOGRAPHICAL INFORMATION

Khan Md Ariful Haque was born in Mymensingh, Bangladesh. He received his B.Sc. and M.Sc. degrees in Industrial & Production Engineering from Bangladesh University of Engineering & Technology (BUET), Dhaka, Bangladesh in 2005 and 2010, respectively. In Spring 2014, he started his Doctor of Philosophy degree in Industrial, Manufacturing, & Systems Engineering (IMSE) department at the University of Texas at Arlington, TX and started working in the Center on Stochastic Modeling, Optimization, & Statistics (COSMOS) research lab. His dissertation topic was “A Dynamic Policing Simulation Framework” and Dr. Victoria Chen was his supervising professor. During his doctoral study, he got a grant as a National Institute of Justice (NIJ) graduate research fellow. His current research interests are discrete-event simulation, statistical modeling, and data analytics.