Agent-Based Model Simulation for Police Deployment Decision-Making in Patrol Operations

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Abstract

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The University of Texas at Arlington, 2021

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Police patrolling plays a key role in responding to 911 calls and reducing crimes. The effectiveness of patrol operations heavily depends on the deployment of police officers – e.g., the number of officers assigned to specific policing districts or beats. The complex nature of the policing system – dynamic and stochastic criminal behavior, compounded with limited policing resources, render current (traditional) police operations, which are often managed in a reactive and stationary manner – often makes it very challenging to manage and control. This study develops an agent-based simulation framework to address the dynamically changing environment in police operations and provide a platform to study alternate police patrolling strategies. Moreover, this model is implemented to investigate the police patrol operation and improve its performance. A real-world case study was conducted to illustrate how this framework is used in dynamic patrol deployment planning. The findings of this research model can provide useful information to support policing decision-makers in developing more effective police deployment decision analytics and improves the dynamic patrol operational performance.

Index Terms: Agent-based modeling, Police Patrol Operation, Hot Spots Policing, Dynamic Policing

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CHAPTER 1 INTRODUCTION

Crime is an inevitable feature of every society, mostly occurring in urban areas, and is generally not understood well [1].The reasons why crime occurs widely vary, ranging from demographic and cultural circles, social and economic factors to security availability and lack of crime prevention strategies [2-5]. The effects and costs of crime are diverse and complex, developing an anomalous social life and ultimately increasing mortality rate (ultimate cost of committing a crime) [6, 7].

Through joint efforts by the government, law enforcement agencies, and researchers in crime prevention and control, the overall prevalence of crime has continued to decline over the past decade [8]. However, the actual rate of crime is still considerable. According to the FBI's Uniform Crime Reporting (UCR) Statistics, a total of 8,977,306 crimes nationwide were reported in 2017, accounting for 85.7% of property crimes (e.g., burglary, arson, motor vehicle theft, and shoplifting) and 14.3% of violent crimes (e.g., aggravated assault, murder, robbery, and rape). The property crime rate has been falling unwaveringly in the last 15 years, which showed a decline of 3% compared with 2016 data, as well as violent crime rate, which has dropped 0.2% in 2017 [9]. Each year, the estimated cost of crime victimization is more than $200 billion, and public spending on police protection exceeds $100 billion [10]. Clearly, the need to mitigate such a considerable social-economic burden is urgent, and more cost-effective solutions are called for immediately to reduce crimes.

The provision of public safety is the main responsibility of police departments, and police officers have made significant efforts to reduce crimes, fear, and disorders while protecting citizens from social and economic losses. Among various police operations, ranging from patrol, traffic law enforcement, a general call for services to crime prevention and investigation, all require joint efforts and extensive coordination among different operations units. To successfully reduce crime, rate the effectiveness of these operations is the key in terms of both planning and execution. Police patrol operations are an integral part of a complex policing system that consists of several components, including people (e.g., police officers, criminals, victims), processes (e.g., dispatching process of police officers), and environmental elements (e.g., property location). These components continuously interact with each other and collectively drive the dynamics of the underlying system.

The quality of police operations (e.g., effectiveness, efficiency, equality, cost) is a crucial determinant of the crime prevention outcome. However, despite a lot of efforts made in this area, police operations remain as a 'blind black box' system. Today's police operations confront several significant challenges, hamper our efforts to understand the dynamics of the police system properly, evaluate operations appropriately, and further enhance quality outcomes. Some of the challenges involved include the dynamics of the crime system, limited police force, 'stationary' operations and management, lack of effective performance assessment, reactive and stationary manner of traditional patrol operations, etc.

To overcome some of these challenges, understanding the complexities of police operations and planning limited resources effectively and efficiently is paramount and imperative. Researchers and policing practitioners have developed many strategic solutions in this direction, and some have been successfully implemented. For example, the traditional policing strategy of expanding police forces has been accepted as one of the most effective solutions to reduce crimes. "More police, less crime" has guided police operations, meaning police presence can reduce crime by deterring potential offenders [11-13]. However, on the opposite side, this strategy has received growing criticisms recently, as little evidence shows more police equals less crime. Prior to the decision of hiring more police officers, a more critical but underemphasized area that ought to be investigated is how police officers are deployed [11, 14]. Beyond these arguments, an important fact that may lead to the inconsistent conclusion in this strategy is the discrepancy between the police operations and crime prevention outcomes.

Traditionally, policing has been primarily concerned with responding to calls and investigating crimes. However, there has been a shift toward crime prevention in the past few decades by utilizing more proactive approaches. Predictive policing has received significant attention because of machine learning methods and data growth developments in recent years. As stated by Charlie Beck, chief of the Los Angeles Police Department (2009), "The predictive vision moves law enforcement from focusing on what already happened to what will happen and how to effectively deploy resources in front of crime, thereby changing outcomes" [15].

Although the intent of predictive policing is to use the prediction results – e.g., where and when a crime is more likely to take place in the near future– to facilitate informed policing decision-making in terms of resource use and interventions, two critical gaps in current knowledge and practice that hinder law enforcement agencies from successfully adopting predictive policing. *First*, prediction is only half of the crime prevention, and the other half is to inform decision-making strategies and appropriate police actions [16, 17]. This latter half is part of "prediction-led policing" [17]. Even if prediction capability and accuracy are enhanced, the prediction results may not produce tactical utility and crime reduction. For example, identifying a large hot spot may be accurate, but it does not provide any new information to help identify specific interventions [6]. Further, policing operations must transition from reactive to proactive and from stationary to dynamic for the prediction to influence operations. In traditional operations, police often focus on reacting to the calls, and the deployment schedule is usually static (e.g., the same weekly schedule may be used for several months) and not appropriate for handling crimes that occur dynamically.

Second, identifying the effectiveness of police interventions is a challenging task due to uncertain criminal behavior and dynamically changing environmental variables. The traditional research approach in law enforcement literature utilizes randomized controlled trials (RCTs) to evaluate police interventions. However, this approach often requires high costs (labor, time, and risk) and does not take advantage of today's data collection, analytics, and complex system modeling capabilities. Further, the evaluation of the effectiveness of a particular police intervention needs to be conducted more rigorously at a system level. For instance, an intervention of allocating more police officers to patrol in hot spots can result in a decreased number of robberies (an intended consequence). Simultaneously, a decreased number of driving while intoxicated (DWI) incidents may also be observed (an unintended consequence) due to fewer officers available for doing traffic stops. Without system level measurement and evaluation of the consequences, the effectiveness of police interventions might be amplified or diluted improperly.

To date, to better represent the dynamic nature of the policing system, simulation models of crimes have been more successful. As the first contribution of this research, an agent-based simulation (ABS), which is particularly suited for studying the behavior of complex adaptive systems at both micro- and macro-level, was developed as a core method of this research to represent the underlying dynamics of the policing system. This model improves the police operations outcome, facilitates operational decision-making, supports police deployment decision analytics, and improves the dynamic patrol operational performance based on the state of the policing system.

In the policing context, ABS, a bottom-up approach, will allow the explicit representation of the crimes and the actions of police officers, where specific behavior rules will be used to govern these operations. Most ABM studies focus on a particular type of crime (e.g., household burglary, robbery, violent crime), so the other contribution of this research is that this agent-based simulation is a more comprehensive model to represent the police operations based on various types of crimes. Moreover, the conceptual agent-based policing framework is generalizable to a broader context of policing systems for decision analytics.

Based on the research objectives, an agent-based policing framework for a model of dynamic policing was generated with a necessary and effective connection among crime dynamics, decision strategies, and police operation simulation. This framework incorporates the fundamental process (steps) and the proposed dynamic policing approach's key modules (methods/tools). It was generated with the primary intention to design a generalizable policing framework that can be applied in different local contexts.

Next, an ABS model was developed to mimic the interactive and adaptive behaviors of the core components of the dynamic policing framework in the underlying policing system at a micro-level. This agent-based (AB) model improves the police operations outcome, facilitates operational decision-making, and supports deployment decision analytics. The developed AB model investigated the police patrol operation and improved its performance. Figure 1 depicts a general process flow of the police

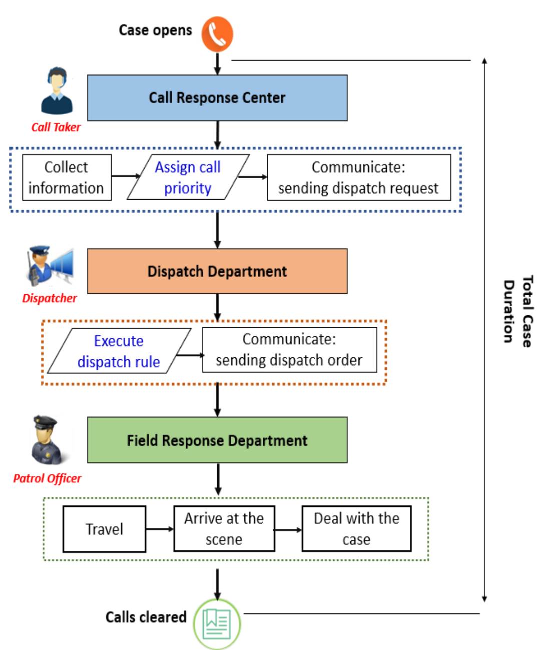


Figure 1. Process flow of the police.

operations implemented through ABS. This process starts when a call arrives (the case will be open) and ends when the officers handled the calls and the scene is cleared.

Finally, the goal of this phase was to evaluate the effectiveness of patrol unit deployment on crime dynamics under various simulated scenarios. Design of experiments methods was used to generate various experimental scenarios in ABS (e.g., different scheduling strategies, patrol sizing, and police interventions like different hotspots scenarios). The experimental outcomes, e.g., all the possible consequences of particular deployment strategies, will facilitate systematic evaluations of the police interventions. In addition to those traditional outcome measures, e.g., crime rate, call response time, new outcome variables such as call wait time in a queue for police presence, police travel time to an incident, and officers' workload and utilization per shift were established. Further, the resource optimization algorithms were incorporated into the ABS to find the optimal strategy under specific scenarios.

The remaining report is organized as follows: Chapter 2 provides a brief literature review on the relevant approaches. Chapter 3 addresses the theoretical framework being utilized in this research to fulfill the specific needs of this research. Also, an agent-based design that represents the essential components of the policing system describes in this Chapter. A case study conducts in Chapter 4 to illustrate how the agent-based model proposed in this paper. Chapter 5 provides the model validation, results, and sensitivity analysis to examine the patrol operations outcome. Moreover, some experiments investigating the effectiveness of factors may contribute to the police operations in this Chapter. Finally, Chapter 6 discusses conclusions and an overview of the future work of this research.

CHAPTER 2 LITERATURE REVIEW

Crime can be studied as a human and social phenomenon that might be affected by the motives and conduct of the criminal, victim, and other individuals as well as their connections with or attitudes toward the surrounding environment [18, 19]. These complex human elements, along with the immense complexity of the environment, make crime extremely tough to comprehend, forecast, and model. To properly establish the aims and scope of the proposed paper, a comprehensive literature review on four major themes: (1) traditional crime modeling, (2) policing simulation, (3) hot spots analysis, and (4) policing outcome evaluation.

2.1 Traditional Crime Modeling

Rising crime rates, mental and social disorders, and fear of crimes resulted in the establishment of the President's Crime Commission in 1967 for repairing the American policing system by evaluating and controlling crimes at the time. So, today's crime modeling genesis is from the decision of that commission that constructed a modern study to determine specific measures to reduce crime [20].

Crime is not random, and a large amount of research has been done to uncover the underlying factors (e.g., the spatial component and patterns of crime) needed to model the "crime system." As a result, some approaches in environmental criminology have been examined in the past decade, and consequently, significant progress has been obtained in developing methodologies for crime prediction and analysis [17, 21-23]. Even though spatial crime analysis was the first to appear in the 18th century, the phrase "environmental criminology" had its genesis in 1971 by C. Ray Jeffery (1971), a criminologist who asked for the establishment of a new school in the field of criminology focusing on the environment in which crime happens [24]. The progress of environmental criminology studies creates a new approach in modeling "crime at places" with a focus on more details (e.g., streets, shops, or houses) [25]. Following this progress, focusing more on individual's spatial-temporal behavior and their environment, instead of using spatially aggregated census data, researchers are now modeling the streets and houses at the individual-level [26].

Regression approaches that are "traditional" (e.g., traditional multivariable regression techniques, naive regression, etc.) are advanced by applying techniques from other disciplines. However, most of the "traditional" crime models are linear and are not appropriate to capture the environmental complexity and dynamics of crime systems [27]. Crime systems are a challenging system in modeling due to their dynamically changing environmental variables and complex interactions in the system. Although linear crime models proved to be critical techniques for crime analysis to support police operations, the individual-level models are thus far more suited to simulating crime systems' proactive and dynamic structure.

2.2 Policing Simulation

To gain insights into how policing strategies and attendant interventions affect crimes (e.g., reduce crimes, displace crimes, or no impact), computer simulation is deemed as the most appropriate method because it provides researchers and practitioners a method to evaluate proposed solutions with no costs and risks prior to real-world implementation. By contrast, since the local factors and local physical environment have been shown to have a large effect on crime, statistical models of crime that work at large scales would not be an effective modeling approach. This is because these models face difficulties in providing predictive analyses and incorporating human behavioral factors [2, 5, 28-34].

To address some of the shortcomings of statistical models, computer simulation has become a new and necessary analytical tool that can forecast any given system's behavior and can study "what-if" scenarios [35]. On the subject of policing, it has been used in several studies to better represent the dynamic nature of policing. A computer simulation was first introduced by Lanier et al. (1993) to predict homicide rates, one of the most challenging crimes for police to assess, and support prevention strategies development [36]. Most policing simulation literature applied three approaches to mimic crime phenomena: system dynamics (SD), discrete-event simulation (DES), and agent-based simulation (ABS).

A. System Dynamics

System dynamics (SD) is a highly abstract method of computer-aided simulation to analyze complex social systems that are hard to foresee and change. In policing, this methodology is used to model the average behavior of the policing system based on certain transition rates from one state to another [37]. Newsome (2007) developed an SD model for the West Yorkshire Police Department, UK, to study the impact of policing activity on system outcomes and inform better management decisions [38]. System dynamics modeling was also used by Carter and Moizer (2011) in Devon and Cornwall County Police Departments, UK, to better respond to emergency demands of the public by delivering policing services. This objective correlates with better performing resource management for hiring and training patrol officers [39]. In a similar type of study by Moizer et al. (2015), a system dynamics model was developed to compare different policy choices in policing for the purpose of achieving more efficient rules for resource allocation of officers [40].

In another study of using system dynamics in policing, Lee and Jung (2017) showed that the number of crimes is responded to by police patrol and is affected by civic partnership [41]. The researchers identified a strategic technique in effectively reducing and preventing crimes by constructing teamwork between the police and citizens. This method could keep the number of crimes handled by police officers stable in the increase of crimes by dynamically changing interaction between civic and the police without increasing police finances rapidly [41].

B. Discrete-Event Simulation

Discrete-event simulation (DES) is commonly utilized to observe a dynamic decision strategy performance during a period of time based on some linear processes or sequential events. DES was used by Srinivasan et al. (2013) to study the staffing strategies and scheduling scenarios of the Richmond, Virginia Police Department to estimate the number of patrol officers, as well as where and when they needed to staff the department in order to improve the patrol operational performance. In a similar study, Haque et al. (2017) applied DES to develop dynamic patrol deployment strategies at the Arlington, Texas, Police Department [42, 43].

Similar to the study done by Haque et al., Zhang et al. (2013) found a police patrol design includes two primary operation outcomes: minimizing call response time and patrol officers' workload using DES. However, this was different in that it did focus on the condition where the number of accessible patrol officers is less than the number of calls for service (CFS) within districts [44]. In another study by Zhang and Brown (2014), the two districting plans' performance metrics -average response time and officer workload- were evaluated for the Charlottesville Police Department, VA, to find the optimal solution for police patrol district design applying DES [45].

C. *Agent-Based Simulation*

Agent-based simulation (ABS) or micro-simulation is a more advanced simulation approach that can explicitly represent the micro-behavior of individuals and their interactions in any spatial-temporal context [46]. ABS is a class of computational models that have been used extensively in several fields, such as social science, biology, epidemiology, transportation, business, criminology, etc. It is well acknowledged as a powerful tool particularly suited for studying complex adaptive systems (e.g., policing systems) that are stochastic and have many nonlinear and dependent interactions with each other and with their environment [46-49].

In the context of policing, ABS, with an integration of the Geographic Information System (GIS), will enable explicit representations of the behavior of criminals and police officers at both the micro-level and macro-level, as well as the environmental settings such as the spatial context [49]. Overall, ABS plays a significant role in policing modeling from three major perspectives: (1) it represents the dynamics of the crime system and predicts the police operations outcomes; (2) it facilitates the risk assessment of various contributing factors to the policing operations; and (3) it helps a decisionmaker evaluate the effect of different intervention strategies under varied "what-if" scenarios [47, 48].

Much attention has been paid to the utilization of ABMs in criminological literature [27, 50-52]. Malleson et al. (2009) utilized ABS to model household burglaries and evaluate the effectiveness of police interventions. Victim and offender behaviors, as well as detailed environmental components, were incorporated into this ABS to explore unique attributes and behaviors of the underlying policing system [47, 48]. In another study by Malleson and Evans (2009), agent-based modeling (ABM) was used to predict the burglary rates in the City of Leeds, UK. This model represents the behavioral factors of burglars at the individual level to forecast the location of potential burglaries. Also, it shows that the environmental components in the city affect on where burglars will travel to commit a crime [47]. In contrast to Malleson et al., Birks, Townsley, and Stewart (2012) developed another agent-based simulation modeling of residential burglary to study the impact of the propositions such as routine activity approach, rational choice perspective, and crime pattern theory on patterns of offending under several simulation experiments [53].

In their recent review, Weisburd et al. (2017) used an ABM under several different sets of assumptions to examine the effectiveness of hotspot policing strategy on street robbery rates [6]. Further studies taking agent-based simulation into account showed the significant impact of hotspot policing as an effective crime-prevention approach (Eck and Liu (2008), Groff and Birks (2008), Sherman and Weisburd, (1995) [50, 54, 55]. Similar work has been done by Liu et al. (2005) using a crime simulation of street robbery to support the routine activity (RA) theory, wherein delinquent, targets, and locations of crime are represented as agents and characterized based on a set of pre-specified attributes [56]. Overall, various scholars have pointed out that agent-based modeling is a mighty approach in crime reduction process assessment [54, 57-60].

D. Evaluate "What-If" Analysis in Simulation

What-if scenarios, which are input constraints to the simulation, will be considered from the crime pattern change's perspective by both giving simulations of different scenarios to realize the developed operation response to crime and giving current crime situations and looking for the most effective operations. So, by what-if analysis, the modifications to police resources can be explored. It is also combined with some theory-driven behavioral models like rational choice models, which are bounded rational models that examine the effectiveness of police operations to determine if they are rational behaviors vs. non-rational behaviors to see how the model will change.

Moreover, the optimization will be used to manage system behavior under certain conditions, as well as improve system performance. Dynamic optimization will derive the optimal combination of conditions resulting in the best possible strategy and optimal resource plan that can help better manage crimes.

2.3 Hot Spots Analysis

Hot spots analyses are a family of crime prediction methods that focus on identifying areas of high crime risk in the future – i.e., where the crime is most likely to occur – based on relevant data (e.g., historical crime data) [61]. In current literature, the majority of the hot spots analyses are retrospective, including a variety of univariate methods ranging from "naïve" ones (e.g., random walk, Naïve Lag 12) to more sophisticated ones (e.g., different exponential smoothing techniques) and a number of crime mapping techniques (e.g., grid mapping, covering ellipses, kernel density) [62-64]. Due to the major shortcoming of such retrospective analyses – i.e., presuming future criminal phenomenon would follow the same patterns that happened in the past, recent studies have paid growing attention to prospective hot spots methods, such as leading indicators, point process modeling, and artificial neural networks, to identify early warning signs across space and time, and inform a proactive approach to police problem solving and crime prevention [62, 65-67].

2.4 Policing Outcome Evaluation

Randomized controlled trial (RCT) and quasi-experiment are two common approaches to evaluate police interventions [68, 69]. The method of RCT is potent for discovering associations between an intervention and an outcome through randomly assigning the intervention under study to two groups of study areas – i.e., treatment group and control group. In literature, numerous studies have been conducted using a randomized trial technique to investigate hot spots policing effects on preventing crime and disorderly conduct in crime hot spots [70-75]. For example, through RTC implementation in Dallas, Texas, Weisburd et al. (2015) found that augmenting patrol at crime hot spots can cause remarkable crime reductions at hot spots [76]. Another study by Taylor et al. (2011) included randomized controlled trials to examine the effects of two hot spots policing strategies, directed patrol and problem-oriented policing (POP), in Jacksonville, Florida, on violent crime hot spots [77].

Different from RCT's random assignment, the quasi-experiment approach allows researchers to control the assignment to the environmental conditions. For example, Sherman et al. (1995) implemented a quasi-experiment in Kansas City, Missouri, to solve the gun violence problem by controlling beat (smaller sub-division of a district) with nearly identical levels of drive-by shootings [55, 78]. Moreover, some studies included results from a meta-analysis of some quasi-experimental designs to test and contrast the effectiveness of closed-circuit television (CCTV) on preventing crime in a large-scale environment [79-81].

With the rapid advancement of computer simulation techniques, conducting experiments in a simulated setting has recently gained more attention. Compared to the field experiments, simulation-based experiments provide a cost-effective solution to assess the outcomes of various interventions with no risks [47, 50].

CHAPTER 3 DESIGN AND IMPLEMENTATION

3.1 Agent-Based Policing Framework

To fulfill the specific needs of this research (i.e., bridge the gaps in predictive policing for police patrol operations), a comprehensive and explicit agent-based policing framework was devised. This framework is developed based on two established policing frameworks, prediction-led policing framework [17] and dynamic policing simulation framework [82]. By intention, it will address the core components, basic processes, key method modules, and meaningful data needed to formalize the concept of dynamic policing. The underlying framework of agent-based policing represented in Figure 2 comprises operations and decisions stages: crime dynamics, decision strategies, and police operation simulation. The development of processes and modules are discussed in the following section.

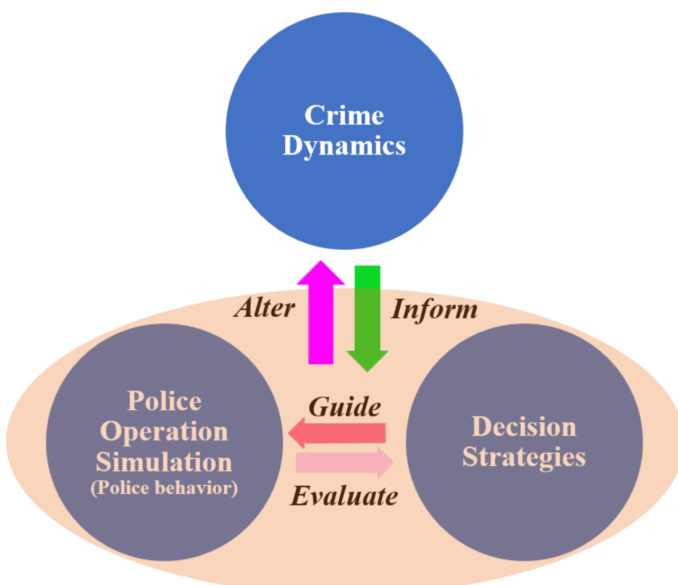


Figure 2. Agent-Based policing framework.

Crime dynamics represent where and when crimes occur (crime patterns in time and space), which changes as conditions change. For instance, changes in the social (e.g., families and neighborhoods support, inaccessibility to services, population density, individual well-being) and environmental conditions (e.g., weather, holiday season, property location, absence of police officer) may affect the dynamics of crime. Identifying the dynamic nature of the crime can be used to objectively inform police decisions, strategies, and tactical operations by identifying and predicting the crime data.

In this research, in order to develop a better dynamic policing model, the 911 call information was used to analyze the dynamics of crime (crime trends) more accurately, visualize potential criminal activities in a timely manner, and understand crime hot spots. This analysis enables us to better understand how to classify crimes, sort priorities, and identify controllable actions and strategies as opposed to uncontrollable factors (weather or location) by policing.

Understanding the dynamic structure of criminal activities is fundamental for implementing police decision strategies. Some examples of these decision strategies consist of police patrol allocation (e.g., assigning the appropriate number of officers to each district/beat during a specific shift), hot spot policing (e.g., specify the hot spots and allocate Hotspot Enforcement and Assistance Team [HEAT] officers to those hot spots), body worn cameras, installing surveillance equipment, and establishing community watch schemes, etc. Since the policing framework is dynamic, decision strategies should develop dynamically. For instance, in patrol allocation, the number of police patrol could differ due to the adaptive criminal environment or diverse time scale (e.g., monthly, holiday season, seasonally, or weekly). Or location, time, and size of hot spots can differ in hot spot policing.

For informing decision-making, limited law enforcement resources, one of the police operations challenges, need to be considered, and decisions must be made using the available resources. As a constraint in patrol allocation strategies, the limited police workforce creates significant barriers to developing more effective policing operations and the dynamic policing system.

The decision strategy component could guide police operations (police deployment strategies) to develop and evaluate at a micro-level using agent-based simulation. Agent-based simulation (ABS) that can explicitly represent the agents' behavior at the micro-level and their interactions in any spatial-temporal context is considered an appropriate micro-simulation in this research. Police operations are the responsibilities and activities that law enforcement agencies perform in their designated environment, including communication, patrolling, responding to calls for service, etc. ABS can effectively evolve the policing system over time, with the potential to study "what-if" scenarios by utilizing and testing various police operations. For example, the agent-based simulation could help evaluate the effectiveness of policing interventions like hot spot policing by using different scenarios for patrolling (randomly, uniformly, mix, etc.).

Additionally, by applying the ABS, the police operations assess the decision strategies like patrol allocation strategies or selecting efficient intervention strategies by optimizing available resources. For instance, while officers are patrolling in hot spots, there might be a need to assign more HEAT officers to those hot spots due to high crime risk. Further, this proposed framework emphasizes which police operations also directly influence the dynamics of crime. For example, police patrolling at the spatial where the crime is most likely to occur can reduce crime by allocating heat officers. Therefore, the loop in the proposed framework iterates from crime dynamics that lead to efficient police decision strategies, implementing police operations, and then updating the crime dynamics that yield new actions for police operations.

3.2 Agent-Based Simulation

An agent-based simulation is a class of computational models that has been applied extensively in several fields, such as social science, biology, epidemiology, transportation, business, criminology, etc. It is especially suited for representing complex adaptive systems that have several nonlinear interactions and dependent happenings. ABS is an object-oriented modeling approach that achieves a near-realistic representation of the real-world system based on numerous and heterogeneous agents' unique characteristics and behaviors. Collectively, the aggregate behavior of the system is autonomously driven by the behaviors of these individual agents.

In the context of policing, ABS, with an integration of the GIS, will enable explicit representations of the behavior of criminals and police officers at both the micro-level and macro-level, as well as the environmental settings such as the spatial context [49]. Overall, ABS plays a significant role in policing systems modeling from three major perspectives: (1) it represents the dynamics of the crime system and predicts the police operations outcomes; (2) it facilitates the risk assessment of various contributing factors to the policing operations; and (3) it helps a decisionmaker evaluate the effect of different intervention strategies under varied "what-if" scenarios [47, 83].

The proposed AB design for this research has formulated the characteristics and behaviors of agents, a spatially explicit context, and the police operations process. Correspondingly, four primary types of agents, police, location (district/beat), call, and self-initiated activity, are generated to represent the individuals, location, and operations, respectively.

3.3 Model Agents and Attributes

By the design principles of the agent-based modeling approach, four types of agents include: call, self-initiated activity, police, and beat/district agents, were created and characterized based on a set of attributes, and their specific behaviors were governed by certain rules (logic). These modules are used to represent three operational processes explicitly, i.e., 911 call-taking process, police dispatching process, and incident/accident handling process. Table 1 provides a list of all the agent attributes specified in the design.

Table 1. Agent attributes of AB model.

Agent	Attribute	Description	Source
CALL	ID	A randomly generated number, e.g., 1, 2, . . .	Some assumptions
	Priority	Level of importance of crime (E-emergent, 1-high, 2-medium, 3-low).	Police department data
	Type	Incident/call type (rape, burglary, fraud, robbery, drug dealing, etc.).	Police department data
	Location	Incident/call location (GIS coordinates, district, beat).	Police department data
	Reported time	Incident/call report time (date, day of week, hour).	Police department data
	Time on call	Cumulative time calculated from the first patrol unit to arrive on scene thru the last patrol to clear.	Police department data
SELF-INITIATED ACTIVITY	ID	A randomly generated number, e.g., 1, 2, ….	
	Priority	Level of importance of crime (E-emergent, 1-high, 2-medium, 3-low).	Police department data
	Type	Incident/call type (rape, burglary, fraud, robbery, drug dealing, etc.).	Police department data

	Self-initiated time on call	Cumulative time calculated from the first patrol unit initiating activity thru the last patrol to clear.	Police department data
POLICE	Demographic	Officers gender, education level, etc.	Police department data
	Role	Officers assigned role (dispatch officer, HEAT officer).	Police department data & some assumptions
	Shift	Working schedule (Arlington police department has 4x10 hours shifts per day that officers are randomly assigned to a shift based on a set of rules).	Police department data & some assumptions
	Mobility	Patrolling route (district, beat).	Some rules & assumptions
BEAT/DISTRICT	ID	A randomly generated number, e.g., 1, 2, ….	Police department data
	Boundary	The beat or district region (e.g., north, south, west, or south district)	Police department data
	Number of officers	Number of regular officers or HEAR officers designated to each district/beat.	Some rules & assumptions

3.4 Model Agent Behaviors

The AB simulation design has been modeled based on two agents' behaviors: the call agent and the police agent. For each particular type of behavior, the corresponding attributes discussed in section 3.2 are used to generate specific rules for governing this behavior. Figure 3 shows the 911 call for service process flow used to represents the behavior of the call and police agents.

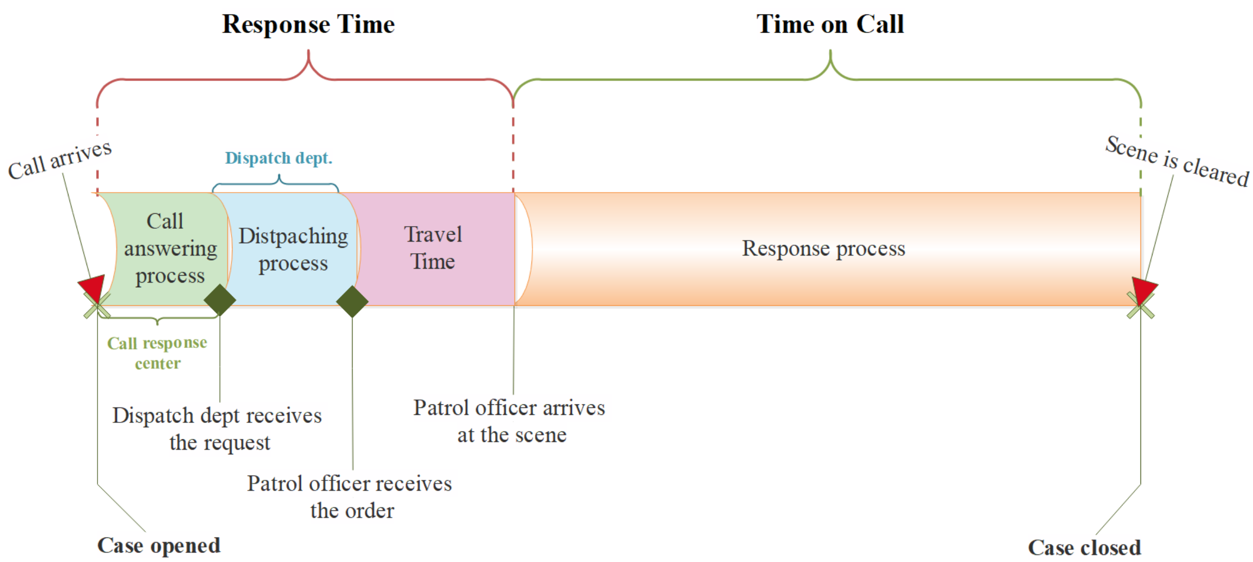


Figure 3. Call agent behavior.

For call process flow, when a call arrives, the case will be open. After collecting the information and assigning the priority to the call, the call response center will send a dispatch request to the dispatch department. The call answering process by the call agent will take less than a minute.

When the dispatch department receives the request, after executing the dispatch rule, the case will be closed if they realize that there is no need to dispatch. Otherwise, the dispatch department will go through the dispatch process to find the nearest available officer in the call district to respond to the call and then send a dispatch order to that officer. When the dispatch department receives the request until finding the available police patrol is called **wait for police present time,** which is based on the call priority (the level of crime importance).

To identify how officers' diverse responsibilities translate into movement and presence at a shift structure, developing a different formalized model of officers' behavior based on their assigned roles is essential. During the specified shifts, officers are designated to cover an appropriate service area (two jurisdiction layers - policing district and beat) and respond to the dynamic policing demands. In this research, the behavior of regular officers' agent who have been assigned to patrolling in a designated location and responding to both calls for service and self-initiated activities was investigated. Further, the behavior of Hotspot Enforcement and Assistance Team (HEAT) officers who have been designated to hot spot policing tasks such as patrolling in hot areas (a small geographic area where crime concentrates) and focusing on crime prevention was formalized.

The officer's movement follows the paths using a Geographic Information System (GIS) coordination, enabling the simulation model to track their activities within their shifts. The structure of officers' operations (regular patrol officers and HEAT officers) is formalized and presented as flowcharts in Figures 4 and 5.

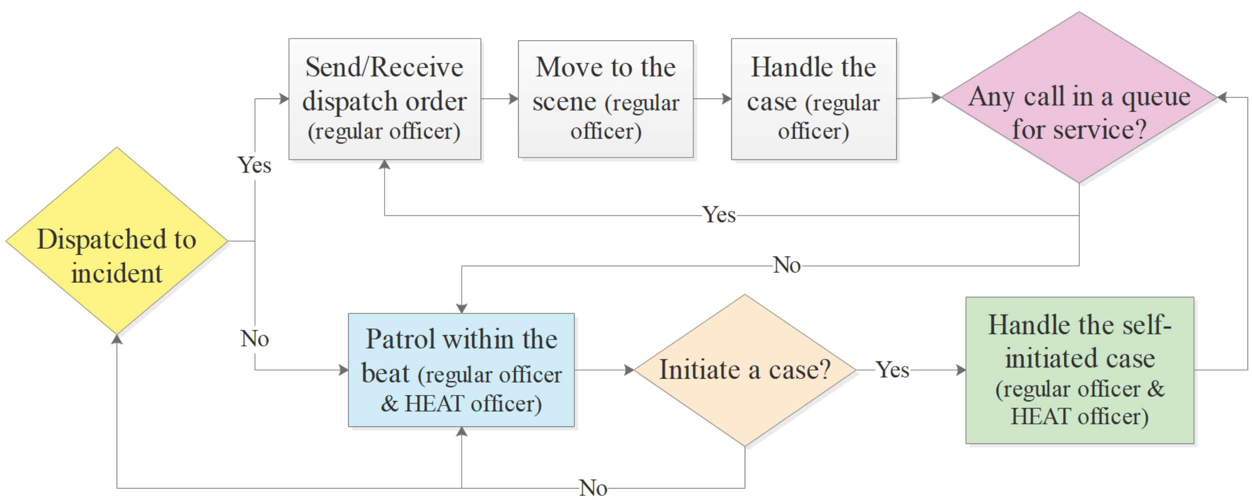


Figure 4. Flowchart of responding behavior of police agent. The rectangular used to represent operations, and the diamond display decision points in the operations process.

The flow chart in Figure 4 indicates that the patrol officers respond to the calls for service (all the priorities) when there is a need to dispatch for an incident. The dispatch department sends the dispatch order to patrol officers, who, after receiving the order, move to the scene of the incident to deal with the incident. After arriving on the scene, patrol officers will handle the call, and then the case will be closed. So, the *c*umulative time calculated from the first patrol unit to arrive on scene thru the last patrol to clear is called **time on call**. Moreover, the time from when the call initiated to the first unit arrives on the scene is known as the **call response time**. In other words, call response time is the summation of the call answering process, dispatching process, and travel times. For the movement (move to the scene or patrol cross the beat), officers proceed to their planned assignments using the "fastest" route through GIS. In the agent-based model, the fastest route, which takes the least time, is selected instead of the shortest route because the shortest route may not be the quickest one, particularly the routes in a city.

The first responsibility of officers is to respond to the calls for service if any incident needs to be dispatched. Otherwise, officers are patrolling within their designated beat if there is no need to dispatch or any call waiting for service. Officers who are patrolling will pick XY coordinates of a place in the beat area assigned to them at random and then move to the location. Once they arrive at their patrol destination, they will pick new random coordinates and repeat the patrolling process.

During the patrolling, officers may open a self-initiated case that will be handled immediately at the scene. Officers are handling a variety of self-initiated duties intending to prevent crime at the control area. A self-initiated case can be triggered by ongoing crime, suspicious behavior, community-based activity, and traffic stops. The use of an agent-based model allows generating self-initiated cases at the individual level. If officers do not encounter any suspicious and risky cases in their control area, they continue to patrol using a random patrolling strategy within their assigned beat.

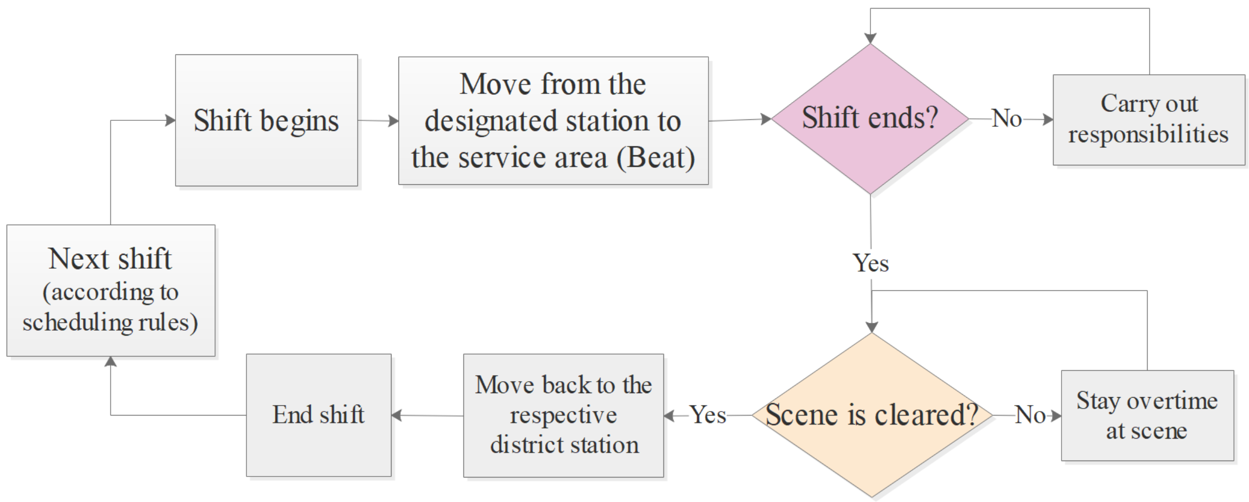


Figure 5. Flowchart of working behavior by shift schedule. The rectangular used to represent operations, and the diamond display decision points in the operations process.

The set of officers' behaviors that shows how they choose their next activity based on their shift schedule is shown in Figure 5. Based on their assigned shift structure, officers make decisions about what actions they should take. The high-level decision flow diagram that shows the structure of officers' movements at the beginning of their shifts represents movement from the designated district station to the service area (Beat) to begin their specific set of tasks. While performing tasks, if the shift has ended and the scene has cleared, the officers are moved back to their respective district station, and the shift will end, and officers will wait for the next shift to be scheduled based on the rules.

Officers are responsible for performing their tasks until their shift schedule is running. If the corresponding shift has ended but the scene is not cleared, officers need to stay overtime at the scene to clear the call. So, overtime is triggered when a call for service requires more time to respond than the current shift's remaining time.

CHAPTER 4 CASE STUDY

4.1 Data

The Arlington Police Department (APD) serves about 400,000 residents, excluding tourists and commuters of the nation's 48th largest city. The city has approximately 100 square miles and proliferates with new constructions, including Texas Live!, Global Life Park. These places and other entertainment venues like Six Flags Over Texas, AT&T Stadium, Texas Rangers Ballpark, and world-class shopping venues became the city a destination for nearly 14 million visitors a year. With the primary mission of accrediting public safety, the Arlington Police Department that the Commission accredited on Accreditation for Law Enforcement Agencies (CALEA) in November 1989, responds to a Dispatched Priority "1" Calls for services by an average of 10 minutes. APD is a full-service law enforcement agency consisting of sworn officers, professional staff employees, and reserve officers. The APD service area shown in Figure 6 is separated into the four largest city divisions, the North, West, East, and South police districts, and each district consists of 8 smaller spatial units called beats.

The 911 call data contains all incidents reported to the 911 call center between January 1, 2013, and December 31, 2017 (5 years) that have been collected from the Arlington Police Department for this research. This data set can be grouped into two primary types of information.

(1) Incident data: *location* (i.e., policing district, beat, police reporting area -PRA, GIS coordinates), *time* (i.e., date, day of the week, time), *type* (e.g., burglary, motor vehicle theft, rubbery, etc.), and *priority* (i.e., E-emergent, 1-high, 2-medium, 3-low).

(2) Operations outcome: *call response time* (i.e., time from when the call is initiated to the first unit arrives on the scene) and *time on call* (Cumulative time calculated from the first patrol unit to arrive on scene thru the last patrol to clear).

Further, we gathered some relevant data on police operations to gain a deeper understanding of how patrol operations are planned and executed. Some quantitative data include *allocated officers* (both regular patrol and HEAT officers) *by district per shift* and *police schedule* (shift, capacity, off time, etc.). In addition, *administrative task time* (e.g., reporting) and *benchmark values of operations outcomes* were also collected. Some qualitative data was collected during the research meetings with APD representatives on various aspects of police operations, such as goals, procedures, processes, daily policing tasks (e.g., dispatched or self-initiated), communication, rules, travel routes of officers, and coordination, etc. The primary data source will be the Intergraph Computer-Aided Dispatch (I/CAD) system utilized by APD for call handling and dispatching.

The data gathered from APD to improve their quality and integrity and ensure their consistency with the AB model was enhanced and preprocessed in three steps: **(1)** *missing data handling* – using specific techniques to handle the missing data (e.g., removal, imputation). **(2)** *data transformation* – converting data to the appropriate formats required by the model implementation (e.g., convert x and y coordinates to latitude and longitude to be suitable for the simulation software); and **(3)** *data cleaning* – removing inappropriate data (e.g., duplicated calls).

Further, in order to be some data challenges in this research (e.g., unavailability, incompleteness), a *literature-informed simulation technique* was used, where publications served as another important data source. From the existing knowledge by literature, some police operation rules, logic, and theories data were informed. Data or theories that the literature cannot inform were generated by some randomized assignment (based on some assumptions).

Moreover, to support our research development and the consistency of our proposed model, we used proper simulation techniques to generate 911 call arrivals for our AB model. So, in this way, we developed an adaptive data structure with common data modules to adjust the data values readily.

4.2 Simulation Development

A novel agent-based simulation model was developed to systematically investigate the police patrol operation, support deployment decision analytics, and improve the patrol operational performance. The ABS model was constructed in AnyLogic® (*AnyLogic Company, Professional Researcher Edition 8.5.2*), a featured multi-method, Java-based computer simulation toolkit. AnyLogic provides the built-in modules for constructing the model, such as input parameters, variables, control, function, and statechart.

The model implementation adopted in this research followed two sequential steps: **(1)** create a multi-layer geographic information system map of the area under study. The City of Arlington, located in North Texas, as a case study region in this research, includes layers such as policing districts, beats, road structures of the city, police stations in each district, and other specialized sections and units that support patrol operations. For police operations, the city is divided into four patrol districts (the largest division of a city): North, West, East, and South, and each district further

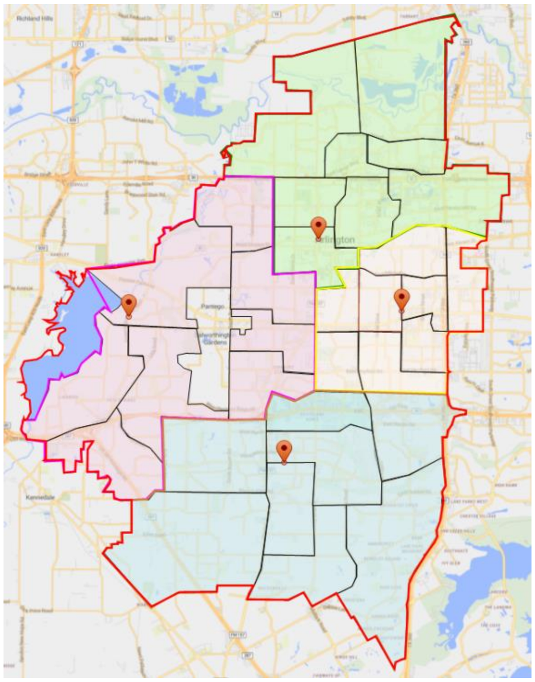


Figure 6. The city of Arlington police department service area.

encompasses eight beats which are the smaller sub-divisions of a district. Figure 6 depicts a detailed policing district map of the research case study (The City of Arlington) implemented for the simulation model using AnyLogic to mimic and visualize the dynamics of the underlying patrolling system at a micro-level.

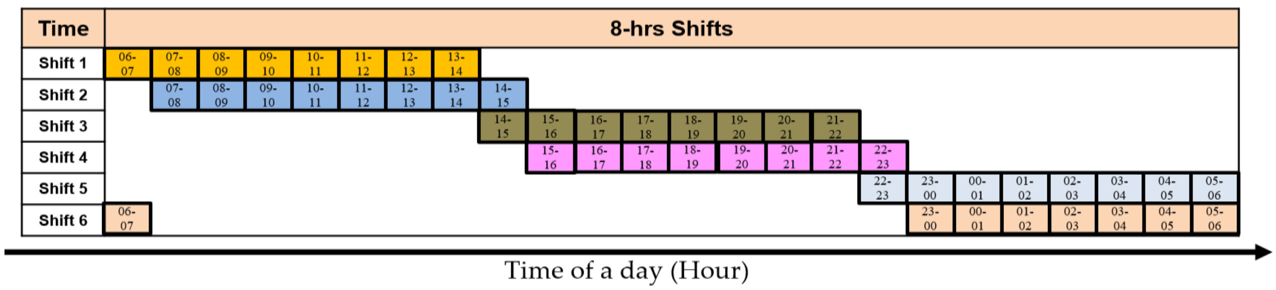
(2) implement ABS, following the micro-level design and explore the relationships between the pre-specified factors (e.g., characteristics of calls for service, police patrol operations design) and two patrol performance metrics (i.e., response time and officer workload). The proposed agent-based model is created to find the solution for police patrol decision analytics.

Generalization is a common issue in simulation studies. Although this research utilized the APD data to design the AB model and address the research goals under specific local circumstances, our primary intention was to create a generalizable policing model that can be applied in different local contexts. Therefore, in conjunction with the adaptive data structure, a generalizable model structure was developed to increase the generality and scalability of the policing simulation model.

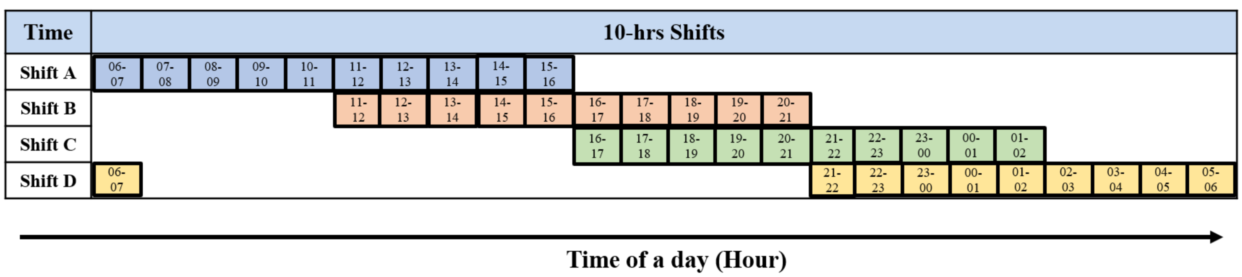
4.3 Shift Structure

Police scheduling is an important decision strategy for law enforcement agencies to cover their service area constantly. Traditionally, most police departments used an 8-hour scheduling framework in which their patrol officers deployed on their service area for five days, 8-hour shifts in each day, followed by two days off. Recently, many agencies offered an alternative work schedule that affords officers an opportunity to work four 10-hour shifts. In this scheduling program, while the officers' shift time is extended, their work weeks are shortened. The alternative program was successful by mitigating the officers' levels of fatigue and causing a better work life quality. Therefore, recognizing the importance of this alternative work schedule by the Arlington

(TX) Police Department (APD) led to an offer to officers to work 10-hour shifts in all four patrol districts on January 1, 2017. Since 2017, officers started to work 40-hours a week in 10-hour shifts, a situation where multiple shifts overlap during the day. Figure 7 is a representation of the 8-hour and 10-hour shifts.



(a) 6x8 hours overlap shifts during a day.



(b) 4x10 hours overlap shifts during a day.

Figure 7. Representation of officers' shift.

Panel (a) of Figure 7 presents an 8-hour shift where all the shifts have overlap (7 hours with the next shift and 1 hour with the previous shift). Researchers noted the number of challenges during these overlapping periods, such as patrol car shortages, problems in managing the schedule, and high levels of fatigue in officers that increase the risk of inappropriate service area coverage [84-86].

Panel (b) shows a 10-hour shift where each shift has 4 hours overlap with the previous shift and 4 hours overlap with the next shift, except shift A and D (first and last shift) that they only have 1-hour overlap with each other from 6 to 7 am.

4.4 Simulation Modules

To formulate a detailed (micro-level) design of Agent-Based Simulation construction, the specific modeling elements and behaviors rules of agents are needed to get considered.

Call/incident responding modules:

- Calls are responded to by the nearest officer in the call district (the nearest officer could be the beat officer or the district officer, which means the beat officer may not be busy but not the nearest one).
- Calls are prioritized for a police presence (higher priority calls have precedence, and calls with the same priority are handled following First-In-First-Out logic).
- Calls are answered through the fastest road chosen by GIS.

Officers' designating & dispatching rules:

In the construction of the AB simulation, some assumptions for officer's designation and dispatching are considered, such as:

- Two units are doing patrolling: (1) Regular patrol units (237 regular patrol officers citywide), (2) HEAT officers (4 officers per district).

- HEAT officers have designated tasks (hot spot policing).
- Regular patrol officers are responsible for taking the call first.
- Officers are allowed to patrol cross their service area (beat) if needed, but not allowed to cross the respective district.
- Officers start and finish their shift at the police station of their designated district.
- In the construction of the AB simulation, some assumptions for officer's designation and dispatching are considered such as:

(1) Once the patrol officer is dispatched for a specific call, he/she would not be diverted for responding to another call. **(2)** Officers are designated to a specific district but randomly assigned to different beats within the district (at least one officer per beat). **(3)** Officers are using a random patrolling strategy for traveling within their beats.

Staffing and scheduling rules:

- Each regular patrol officer works 40-hour a week (4-days workweek, each shift 10-hour long). Panel (b) of Figure 7 represents 4x10 hours shifts, a situation where multiple shifts overlap during the day.
- Officers are assigned to a 10-hour shift randomly.
- The minimum gap allowed between two officers' shifts in 24 hours is 8 consecutive hours.
- Shifts are overlapped during the day, and they run without any break.
- Overtime is considered when any call requires additional time to serve after the officers' work shift.

The composition of APD's field operations allocated officers by the district for 2017 is represented in Figure 8.

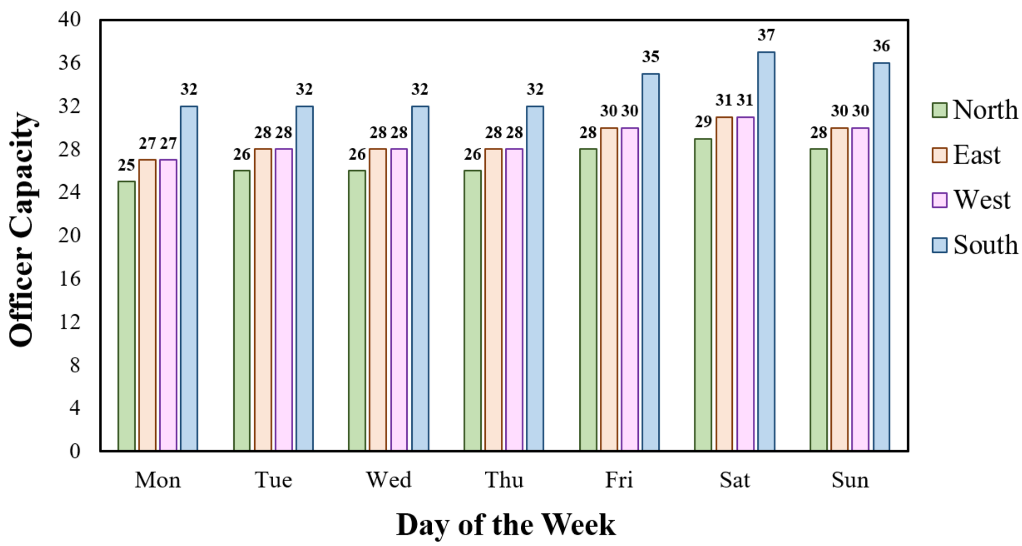


Figure 8. Daily Distribution Summary of the Staffing by District.

(Based on the 2018, APD bid summary packet).

4.5 Hot Spot Policing Simulating Steps

Many policing strategies have been developed to improve police operations toward better outcomes, i.e., reduced crime and more efficient call response. One of the most well-known, widely implemented strategies is the hot spots policing – a policing strategy focuses on small areas where crime is concentrated. In the ABM, deployment of HEAT officers at hot spots follows four hot spot policing decision strategy steps; they are implemented as follows [82]. As shown in Figure 9, during the first step, hot spot areas are identified and targeted with crime prevention and crime level control efforts. In this regard, dynamic units will be allocated to those hot spot areas where crime is being focused in the second step. Next, the available HEAT officers will determine the intervention strategy for those hot spots from the two *fundamentally different* directed patrol or Problem-Oriented Policing (POP) strategies in the third step. Finally, the adjusted crime reduction variable per hour will be used to estimate the crime reduction.

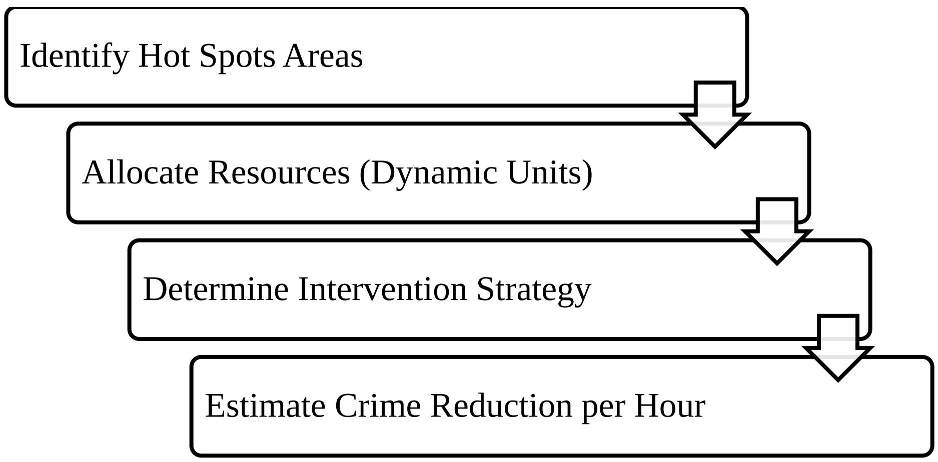


Figure 9. Hot spot policing simulating steps.

For a detailed design of the hot spot policing ABM construction, some specific modeling elements and behavior rules of HEAT officers, including staffing and scheduling rules, need to address.

Staffing Rules of Hot Spot Policing Simulation:

- HEAT officers have designated tasks (hot spot policing).
- 16 HEAT officers (dynamic policing units) are deployed across hot beats in addition to regular patrol.

- HEAT officers are randomly assigned to different hot beats within the district (at last one officer per hot beat).
- HEAT officers will be deployed across heat beats on other districts when there are no heat beats identified for a particular district.
- HEAT officers (dynamic policing units) are rotated randomly across hot beats.

Scheduling rules of Hot Spot Policing Simulation:

- HEAT officers will be randomly assigned to a 6-hr shift if they are eligible.
- HEAT officers will be deployed across heat beats for a 6-hrs shift per day.
- There is no off time between two shifts.
- Each HEAT officer works a maximum of 40 hours per week.

Figure 10 shows a 6-hour HEAT shift schedule during the day in which none of the shifts overlap, and there is no gap between the two shifts.

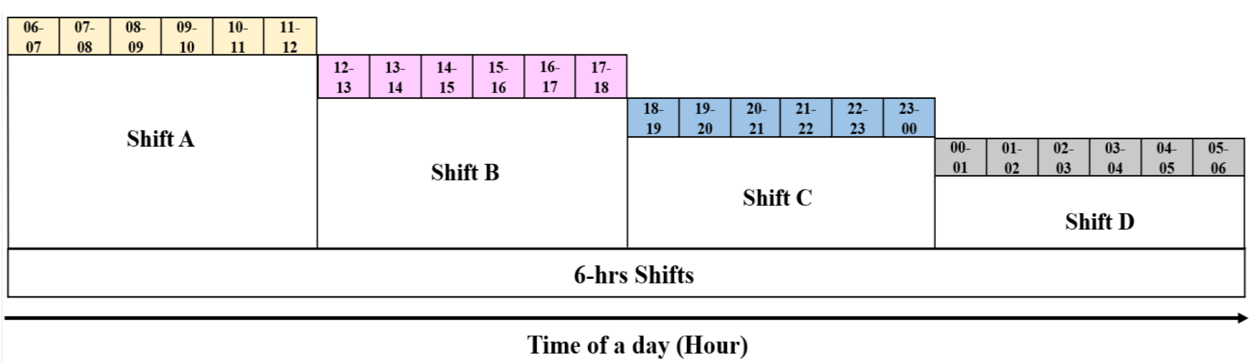


Figure 10. Representation of HEAT shift schedule.

An Example of Directed Patrol Strategy for Hot Spots Policing

The following example presents how hot spot policing works in an ABM implemented in this research study. In this regard, the week one crime volume (sum of all the priorities crime volume) per beat is shown in Table 2. The hot beats of crime which are identified by analyzing this week's crime volume applying two different scenarios, are displayed in Tables 3 and 4 (with and without threshold on crime volume). Further, a HEAT (a dynamic policing unit) is randomly assigned to each of those hot beats in addition to regular patrol officers starting from the next week. So, HEAT officers are randomly rotated across those hot spots for a 6-hour shift. Finally, at the last step of the decision strategy, the crime volume per hot beat will be adjusted by the crime reduction variable per hour to make those hot beats cold areas.

Table 3. The week one crime volume by beat.

District	Beat	Call vol. week 1
North	210	18.8
North	220	31.2
North	230	20.5
North	240	22.1
North	250	24.6
North	260	15.9
North	270	22.8
North	280	24.5
West	310	16.6
West	320	25.4
West	330	18.2
West	340	17.6
West	350	16.2
West	360	13.2
West	370	15.2
West	380	19.6
East	410	18.8
East	420	13.9
East	430	12.4
East	440	22.1

Table 2. Hot beats of crime not using threshold.

District	Heat Beat	Call vol. week 1
North	220	31.2
North	250	24.6
West	320	25.4
West	380	19.6
East	440	22.1
East	450	26.3
South	540	34.6
South	580	27

Scenario 1. The threshold is not considered. So, based on crime volume (λ) on week one, the two first hot beats of crime per district were identified.

East	450	26.3
East	460	11.9
East	470	12.6
East	480	16.8
South	510	13
South	520	12.2
South	530	20.3
South	540	34.6
South	550	16.8
South	560	19.2
South	570	12.8
South	580	27

Table 4. Hot beats of crime using threshold.

District	Heat Beat	Call vol. week 1
North	220	31.2
East	450	26.3
South	540	34.6
South	580	27

Scenario 2. The threshold is considered for hot beats based on crime volume (λ).

CHAPTER 5 MODEL VALIDATION, EXPERIMENTS, AND RESULTS

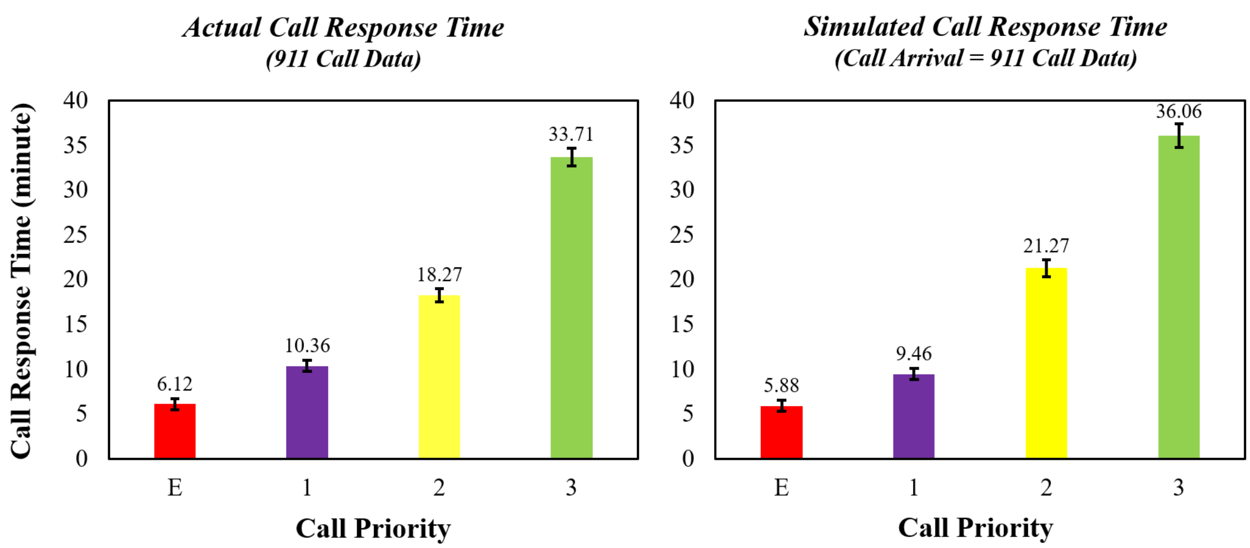
5.1 Model Validation

Model validation plays a critical role in modeling and simulation studies. Validating a simulation builds the credibility of the developed model in terms of the reliability of simulated results. Model validation is described by Schlesinger et al. in 1979 as a "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" [87]. In other words, the validity and accuracy of the model results are assessed by comparing the model results to known data. Different types of tests and methods can be applied for validating agent-based models [88, 89]. Every simulation model is a new subject for determining its degree of accuracy and validity.

A. Validation with Historical Data

Our study intends to use the data collected from the APD to validate the simulated results. In this way, the model was calibrated and validated by comparing the average call response time by the call priority level provided by the APD as the historical data with the average call response time as the AB model's output. In this model design, some of ABS's input parameters, including the attributes of the call agent, were informed by the APD collected data. In other words, the model call data as input were generated based on the APD raw data.

Figure 11 is shown as a process of demonstrating that the model results are valid by comparing the response time achieved from the actual data, Figure 11 (a) with the simulated response time derived from the AB model that used the actual 911 call data as input data, Figure 11 (b).



(a) Actual call response time

(911 call data)

(b) Simulated call response time

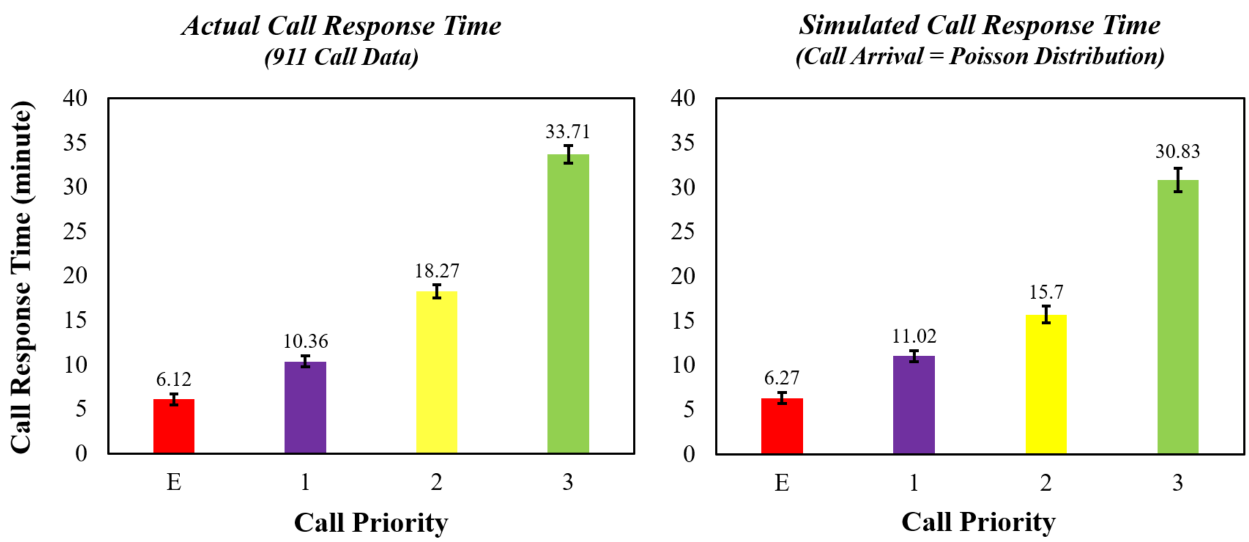
(911 call data)

Figure 11. ABM validation using actual data (mean; standard error of the mean).

The t-test run indicates no significant difference is found between the average response time derived from the simulation model and the observation data (p-value $> \alpha = 0.05$). Thus, the proposed model design was successfully validated.

B. Validation by Generating Data Using Distribution

In this validation scenario, to assure reliable performance of the simulation, the response time achieved from the actual data (911 call data) was calibrated using the response time results derived from the simulation model, Figure 12 (b). In this scenario, some simulation techniques are utilized to generate the call arrival by the Poisson distribution. According to the paired t-test conducted, there is not enough statistically significant difference between the average response time achieved from the simulation model utilizing Poisson distribution for generating the call arrivals and the 911 actual data (p-value > α = 0.05).



(a) Actual call response time

(911 call data)

(b) Simulated call response time

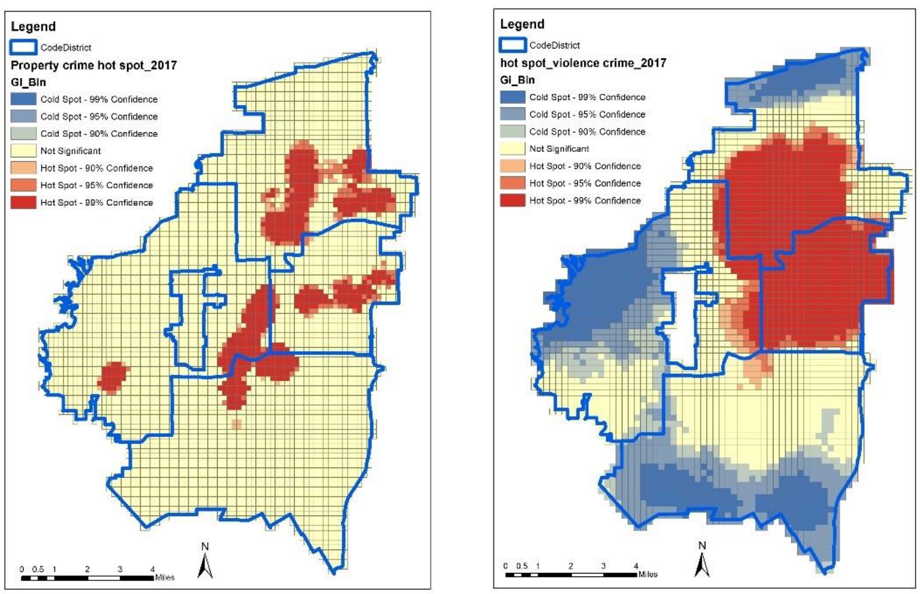
(Poisson distribution)

Figure 12. ABM validation using distribution data (mean; standard error of the mean).

In general, all the figures above (Figures 11 and 12) show that if the incident priority increases, the average response time to calls for service decreases. In other words, calls with a higher level of importance (i.e., calls with priority Emergent and 1) have precedence and are responded to very rapidly. On the other hand, less significant calls (i.e., priority 2 and 3 calls) have a lengthier delay before police response. Correspondingly, they have a higher response time. Furthermore, the results of conducted t-tests confirm that this agent-based model is a robust design for studying the patrol operations decisions.

5.2 Results

Based on the preliminary analysis and GIS mapping that was conducted on the 5-year data (2013-2017), 911 call data provided four outcomes: (1) a typology of incidents; (2) incident frequency distributions; (3) incident temporal patterns; and (4) hot spots maps. Figure 13 demonstrates the hot spot clusters of crimes (911 call data) reported to APD using the kernel density method. Among the four police districts of APD, the high volume of violent crimes is centralized in North and East districts, whereas the property crimes are scattered in all four districts.

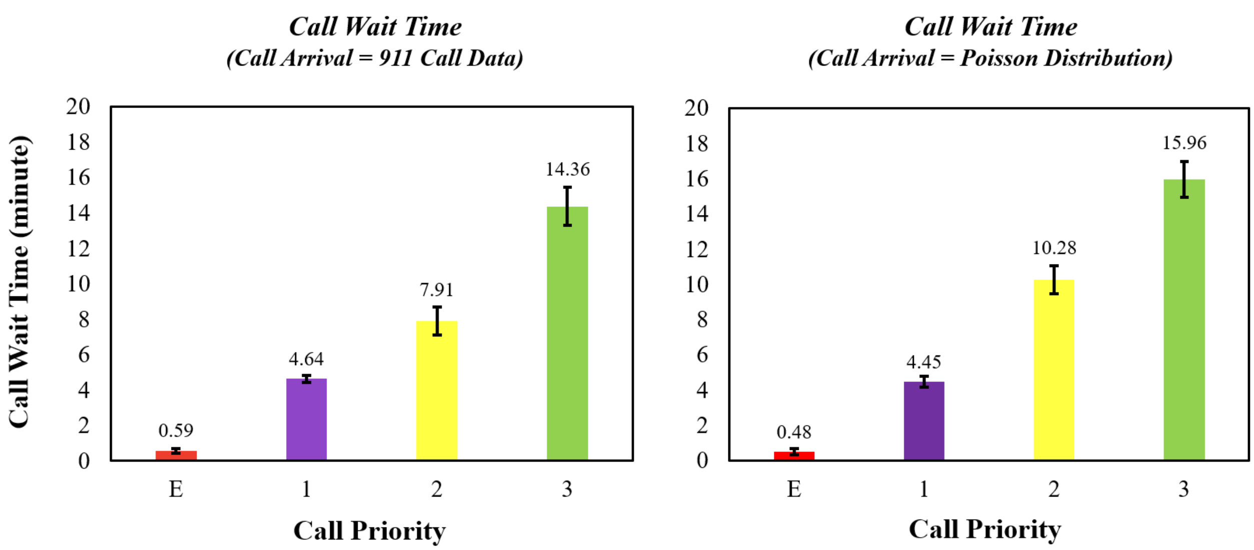


(a) Property crime (b) Violent crime

Figure 13. Hot spot clusters of crimes reported to APD in 2017.

The ABS simulation was developed to capture the interactions between crime dynamics and police actions at an individual level and investigate police resource sharing for crime prevention with call response. From the weekly simulation runs (i.e., simulation run length), some results were obtained for handling both calls for service and self-initiated activities on the 10-hours shift. Figures 11 and 12 show the average of an outcome variable, call response time, by the call priority level (E-emergent, 1-high, 2-medium, 3-low) as the first result derived from the simulation used in Section 4.5 for validating the established model in this research.

The second result of the agent-based model is shown in Figure 14. This figure demonstrates another outcome variable, call wait time, achieved from the model. These results achieved from both call arrival by the 911 call data and call arrival by distribution are expressed that when an incident occurs, the district dispatcher allocates the nearest accessible officer to that call by using the GIS coordinates. If all patrol officers are busy in that district at that minute, the call will be waiting in a queue for police to be present and responded to based on priority.

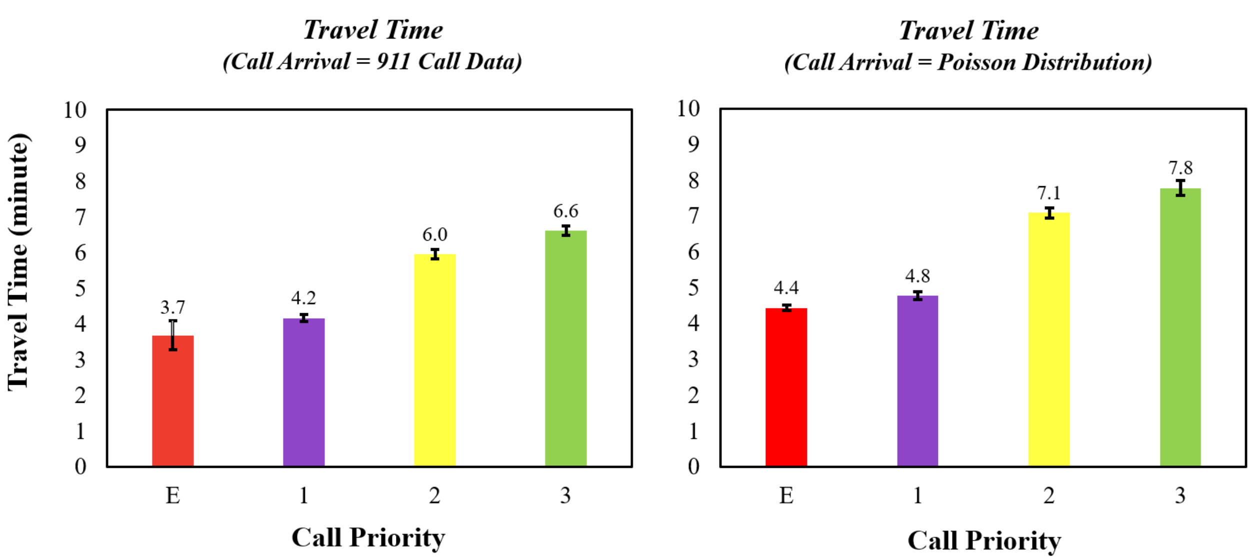


(a) Call wait time (911 call data)　　(b) Call wait time (Poisson distribution)

Figure 14. ABM calls wait time in a queue by priority (mean; standard error of the mean).

Figure 14 (a) shows the average call wait time in a queue (min) by the priority level achieved from the simulation model using the actual 911 call data. Furthermore, Figure 14 (b) shows the average wait time (min) by the call priority obtained from the model using the Poisson distributed data as a call arrival. The results are highlighted that the average call wait time followed an upward trend, along with a decrease in the call priorities. Specifically, the average call wait time for calls with the highest priority level (priority E) in both figures is less than 36 seconds. In contrast, calls with priority 3, the lowest priority level, are placed in a queue for patrol officer availability for about 14 to 16 minutes.

The following ABM result displays the time for the police to reach the incident scene. As shown in Figure 15 (a) and (b), the results reported that calls' priority Emergency and "1" have a shorter travel time since they have precedence to other priority calls and as the nearest officers are dispatched for the calls. Calls with priority "2" and "3" have a longer travel time compared to the call with the higher priority since calls are responded to based on their preference. Therefore, the travel time depends on the number of calls waiting in line for the police to respond.



(a) Travel time (911 call data) (b) Travel time (Poisson distribution)

Figure 15. ABM police travel time to the scene (mean; standard error of the mean).

Another operation outcome, officer workload, was derived from the AB model to represent better the dynamic nature of policing and the patrol operational performance. Figure 16 indicates the average number of cases (both calls for service and self-initiated activities) responded to per shift per district by officers designated to those shifts at a specific district. This result found that, in almost all the districts, the average response cases for shift 3 from 4 pm to 2 am are greater than the other shifts. This means more calls are handled during this shift by officers.

Consequently, looking at the level of cases responded by officers per shift, it is logical that the officers' workload per shift shown in Figure 17 presents the higher workload for officers assigned to shift 3. It can be concluded that the greater the number of calls for service per shift, the greater the workload of officers assigned to that shift.

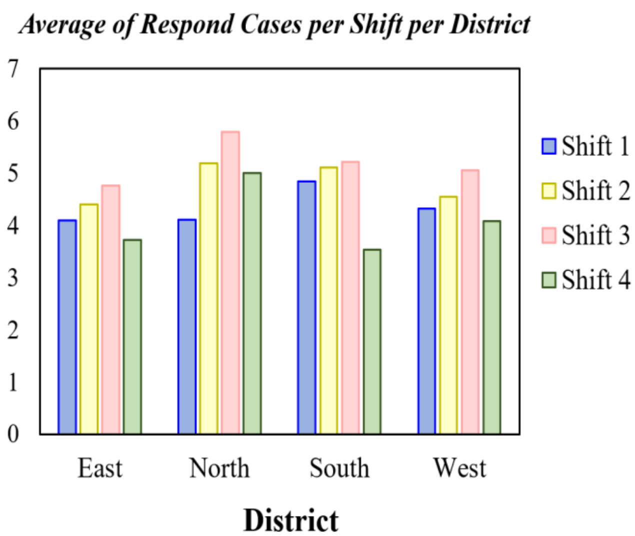


Figure 17. Avg. of response cases by officers per shift per district.

Figure 16. Officers' workload by shift.

The average utilization of officers per shift reached from the model and shown in Figure 18 address that the officers' utilization increases as the number of calls for service increases. In other words, as crime (both calls for service and self-initiated activities) decreases, officer utilization will also decrease.

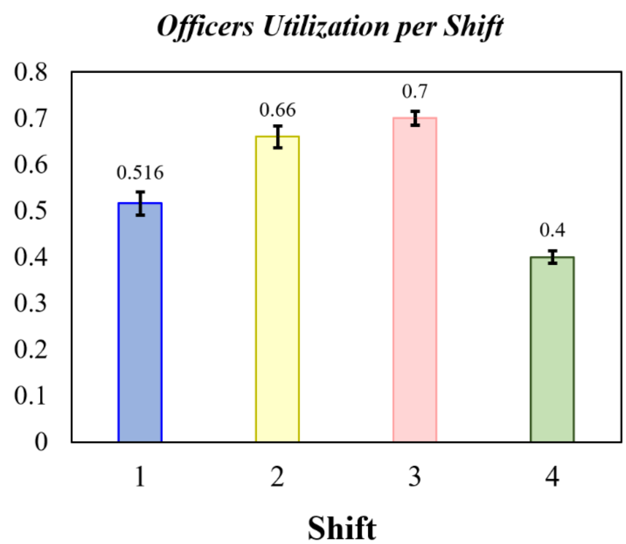


Figure 18. Officers' utilization per shift.

5.3 Sensitivity Analysis

In this section, a sensitivity analysis of some key model results is presented. Figure 19 depicts the results of a sensitivity analysis of call response time and call wait time under two scenarios: Officers use the fastest route to proceed to their planned assignments or use the shortest route. For the shortest route, the distance is measured by GIS, and officers travel the shortest route between the two coordinates, but with the fastest route, time is measured, and officers select the route that takes the least amount of time.

When officers choose the fastest route to perform their duties (responding to both calls for service and self-initiated activities), the response time and call wait time will be less than the shortest route. Since time is a critical factor in responding to calls as a major driver for crime prevention, in this AB model, the fastest route is chosen for officers to accomplish their planned tasks in less time.

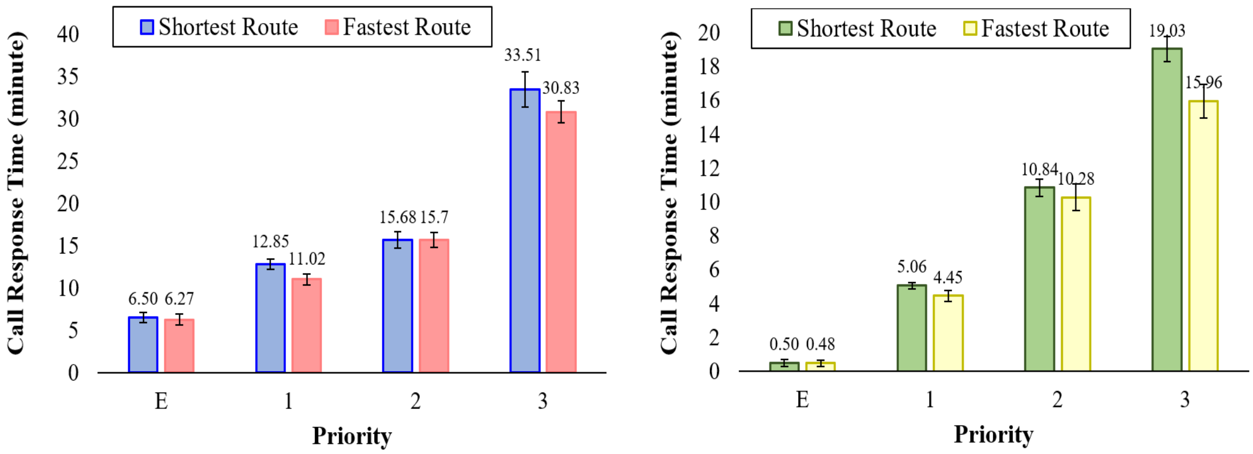


Figure 19. Sensitivity results of call response & wait time by priority under different scenarios.

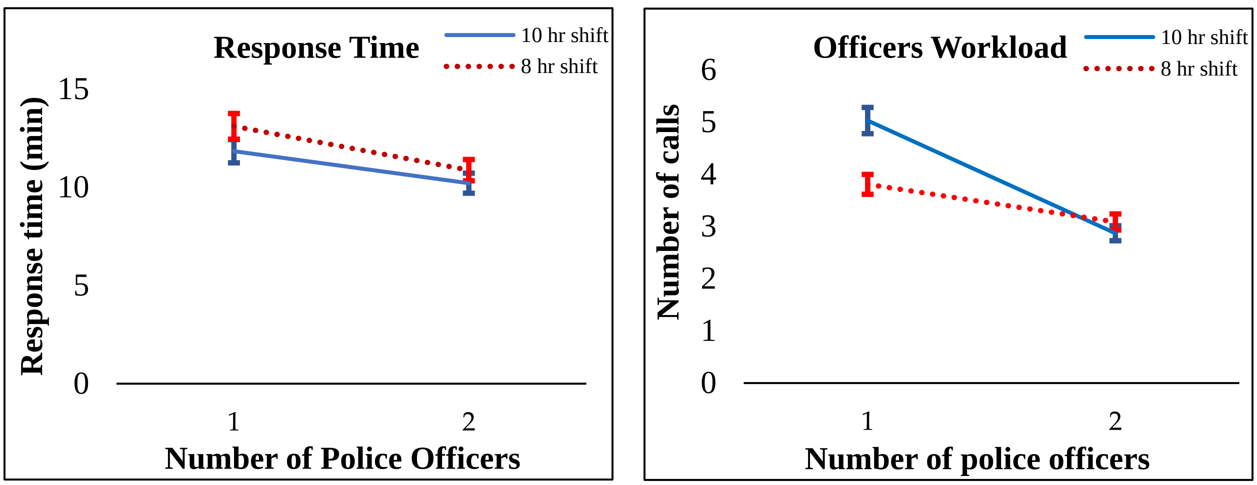
5.4 Experiments

In this section, experimental studies of certain key parameters of the model are conducted to prove the effectiveness of the agent-based model. These experiments are performed to examine the impacts of factors that contributed to the response time, the major driver for crime prevention.

A. Scenario for Shift Schedule & Patrol Sizing

A baseline scenario is developed for current operations based on several pre-specified explanatory factors: characteristics of police officers, patrol district design, and operational factors. In the baseline scenario, officers are randomly assigned to a 10-hour shift, 4 days a week, with a low patrol size of at least one police officer per beat. Officers travel randomly within their beats and respond to calls that have been assigned to them or handle self-initiated cases during their shift.

The first experiment scenario is to find the effectiveness of two different scheduling strategies [82]; 8-hour vs. 10-hour shifts, and to investigate the impact of two different patrol sizes (one police officer per beat vs. two police officers per beat) on response time and officers' workload (number of calls handled per police officer per shift). Figure 20 (a, b) illustrates the main effect of these two scheduling scenarios on the response time and the number of cases handled by each officer per shift.



(a) *Scenarios:* Impact of different shift schedules and patrol sizing on the 911 call response time (mean; 95% C.I.).

(b) *Scenarios:* Impact of different shift schedules and patrol sizing on officers' workload (mean;95% C.I.).

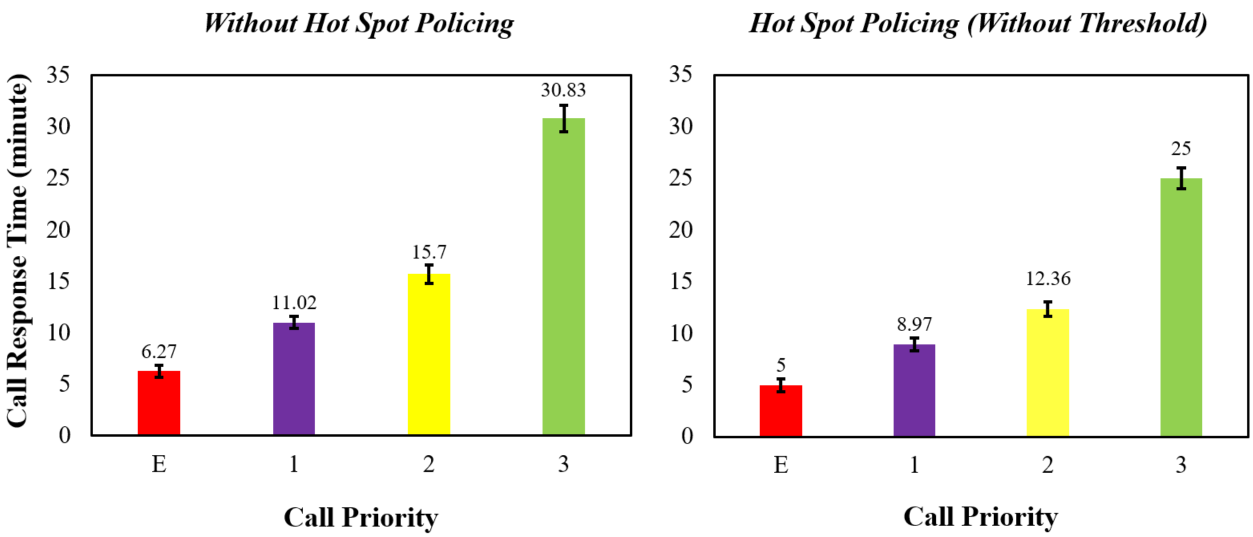
Figure 20. Scenarios for Shift Schedule & Patrol Sizing.

The results of the tests for these parameters found that a 10-hour shift is more efficient than an 8-hour shift in call response time in both patrol sizing scenarios. So, Figure 20 (a) proves that officers answering calls more quickly in a 10-hour shift, and the 911 calls have less call response time compared to an 8-hour shift.

Quasi-experimental studies typically document that police patrolling plays a vital role in reducing crime, although the estimated magnitudes vary [79-81, 90]. However, scholars estimate that the effects of police deployments on decreasing neighborhood crime may be offset by displacing the crime and shifting to other areas or neighborhoods [91-93]. Also, Sherman et al. (1989) concluded that manipulating the policing intensity had no detectable impact on crime deduction [94]. In conclusion to these studies, the results of this experiment shown in Figure 20 (a) indicated that doubling the number of officers did not significantly affect response time. So, this suggests that more cops were not always the answer. In contrast, as exhibited in Figure 20 (b), doubling the number of officers causing the reduction in the number of cases handled by each officer per shift (officers' workload) in both shifts.

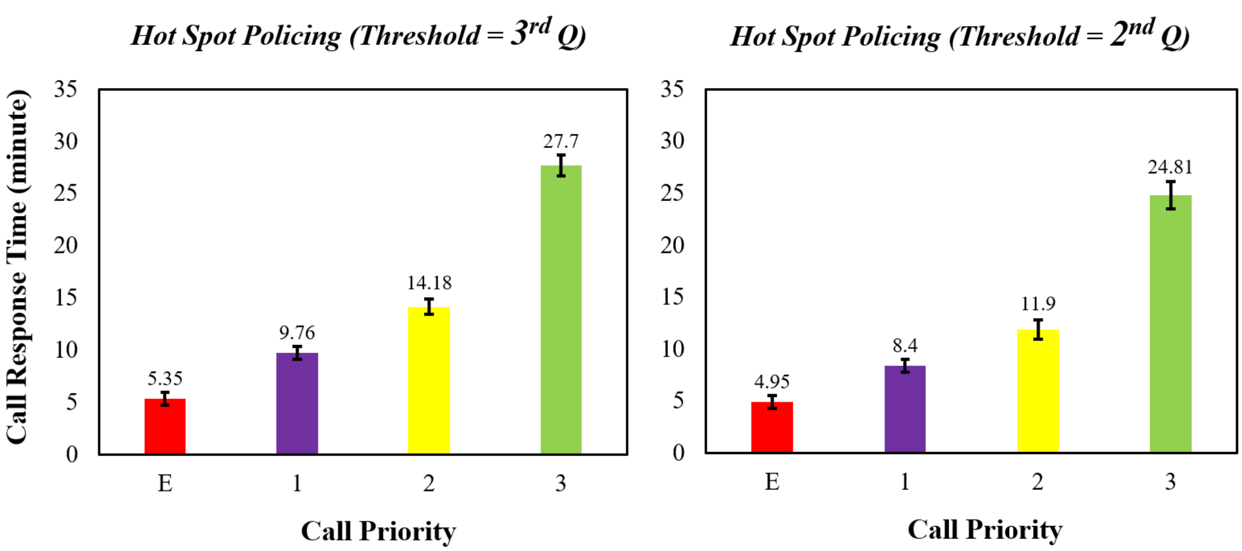
B. Scenarios for Hot Spot Policing

The second scenario is conducted to use the simulation model to test two different hot spots policing strategies in crime reduction on hot spots. Figure 21 (a) exhibits the baseline scenario for call response time derived from the simulation by different call priority levels (E-emergent, 1-high, 2-medium, 3-low). In the baseline scenario, HEAT officers are not deployed. Further, Figures 21 (b-d) present the call response time by deploying HEAT officers on hot beats in which those hot spots are identified using different criteria on crime volume.



(a) Call response time without hot spot policing (b) Call response time with hot spot policing

(*Scenario1*: Identifying hot spots not using threshold)



(c) Call response time with hot spot policing (d) Call response time with hot spot policing

(*Scenario2:* Identifying hot spots using threshold)

Figure 21. Call response time under different hot spots policing scenarios.

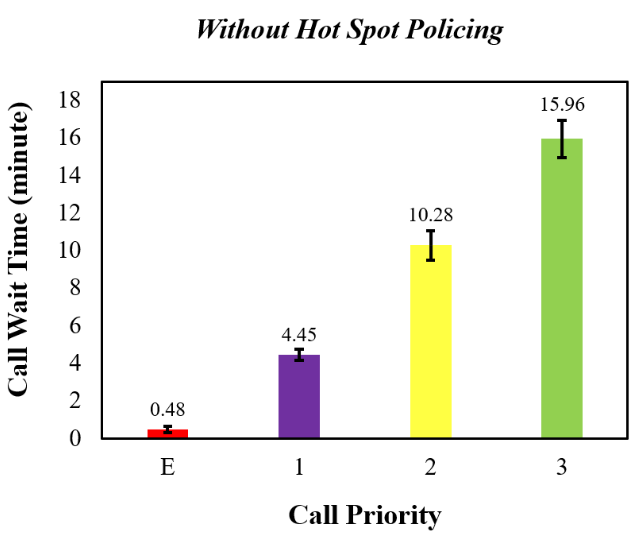
In the first scenario, two hot beats of crime per district (2*4 districts = 8 hot beats for all districts per week) are identified by analyzing crime volume (λ) per week. In this scenario, hot beats of crime were identified by not using a threshold on crime volume. Instead, each week the first two hot beats of crime per district would be selected by sorting the previous week's crime volume (λ). Correspondingly, the number of hot spots per district is fixed each week. Then, four Dynamic HEAT officers would be deployed for a 6-hrs shift per day on those hot beats per district in addition to regular patrol officers (4*4 = 16 HEAT officers). Figure 21 (b) demonstrates the average call response time (minute) by the call priority level with hot spot policing deployment on hot beats that are recognized without using the threshold.

In the second scenario, the threshold on crime volume (λ) is used to find the hot beats of crime. So, the number of hot beats per week per district varies based on the previous week's crime volume (λ). The hot beats will be selected using the two different quantiles (3rd Q and 2nd Q). Then, in addition to regular patrol officers, dynamic HEAT officers will be deployed for a 6-hrs shift per day on those hot beats per district. But in this scenario, the HEAT officers might also deploy on heat beats on other districts than they are assigned if no heat beats are identified for a particular district.

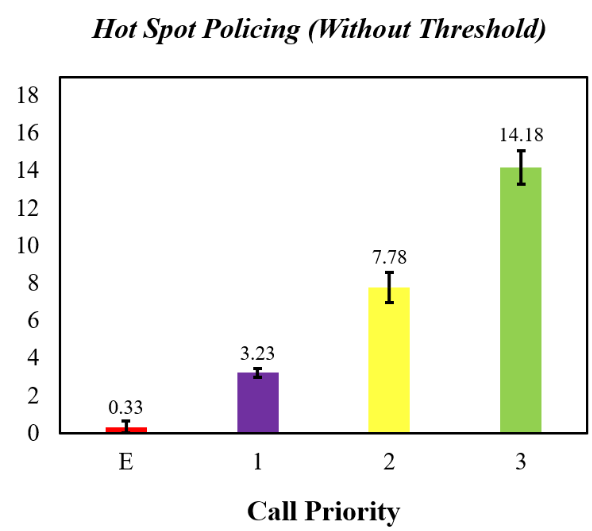
Figure 21 (c) shows how the hot spots are identified using the third quartile (Q3) threshold. This means by looking at the call volume per week, those beats whose call volume is greater than 75 percent of the data points are identified as hot spots. Further, Figure 21 (d) explains how hot spots are recognized by using the second quartile (Q2) as a threshold on crime volume, which means that those beats whose call volume is more than half of the data point are considered as hot spots. Comparing these two situations demonstrated using the second quartile as a threshold found more hot beats than the third quartile.

The comparison of Figures 21 (b-d) with Figure 21 (a) as the baseline scenario shows that due to the Heat officers' deployment on hot beats, the average response time (minute) by the call priority level is decreased on those plots. For instance, the response time for calls with priority 3, which is the lowest priority level, decreased by about 3 to 6 minutes compared to the priority 3 call response without hot spot policing strategies. For emergency calls, call response time is reduced 1 to 2 minutes which is critical in policing system to respond to calls in a very efficient manner. Thus, based on the results, hot spot policing seems to influence the efficiency of call response time positively.

To further indicate that hot spots policing improves the efficiency in the policing system, Figures 22 (b-d) display that the deployment of HEAT officers on hot beats reduces the average call wait in a queue for police present. On the other hand, Figure 22 (a) displays the average call wait time in a queue (min), by the call priority level achieved from the simulation model without the deployment of HEAT officers.

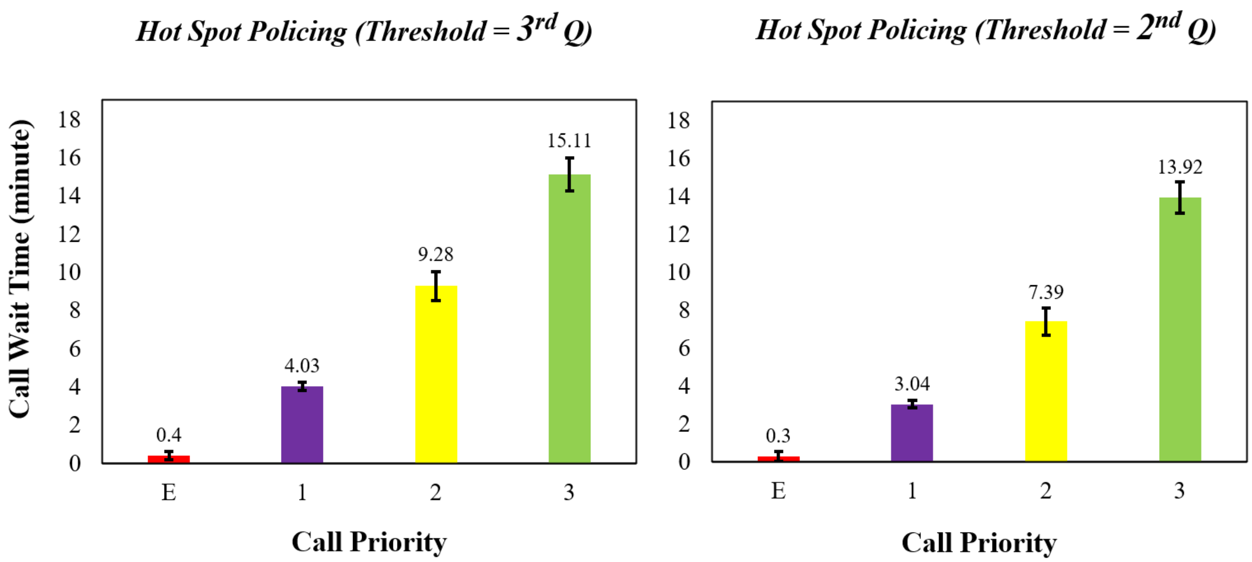


(a) Call wait time without hot spot policing



(b) Call wait time with hot spot policing

(*Scenario1*: Identifying hot spots not using threshold)



(c) Call wait time with hot spot policing (d) Call wait time with hot spot policing

(*Scenario2:* Identifying hot spots using threshold)

Figure 22. Call wait time in a queue for police present under different hot spots policing scenarios.

The above plots demonstrate that the average call wait time for police present followed an upward trend while the call priorities decrease. Further, the comparison of Figure 22 (a) with (b-d) reveals that the call wait time in a queue for police present is reduced due to the HEAT officers' deployment on hot beats. For example, the average call wait time for priority Emergency, which is the highest priority, is reduced by 5 to 10 seconds. Further, calls with priority 3, which is the lowest priority level, are placed in a queue for patrol officer availability for about 1 to 2 minutes less than when there was no hot spot policing deployment.

In literature, several experiments were conducted to present the efficiency of hot spots policing on crime reduction. For instance, Sherman & Weisburd (1995) run a hot spots experiment in Minneapolis in which police officers deployed for seven days a week, 3 hours at a time, during two dosage periods [55, 78]. This increment of police presence at hot spots reduced calls for service (crime) by about 13%. Further, in 2011, Ratcliffe et al. implemented a foot patrol experiment in Philadelphia where the officer pairs were assigned to 8-hours shifts either morning or evening, five days a week. The existence of foot patrol at hot spots produced a 23% reduction in street violent crime [75]. Other hot spot experiments have been conducted in California, London, or Florida, which show a decline in calls for service by assigning teams of officers to visit hot spots [61, 77, 95]. Therefore, by testing the results achieved from the simulation model using hot spot strategies with the results from the existing literature, the agent-based simulation outcomes present the effectiveness and influence of hot spot strategies on reducing crime and control at hot spots.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

This research developed an agent-based policing framework as a proactive and cost-effective policing solution to address the dynamically changing complexities and uncertainties in police operations and improve patrol operational performance. The framework integrates three modules: Crime Dynamics, Decision Strategies, and Police Operation Simulation (police behavior). To illustrate how this framework is used to represent the interactive crime dynamics, dynamic police patrol operations at a micro-level, and simulation of a complex system of regular patrol and HEAT officers' movement and behavior, an agent-based simulation (ABS) model was developed.

Through collaboration with the Arlington Police Department (APD), Texas, a real-world case study was conducted to verify this concept. Hot spot policing and police patrol allocation strategy modules were implemented to estimate impacts on crime volume, call response time, and call wait time. Moreover, the validity and accuracy of the model results are assessed by comparing the model results to actual data.

A design of experiments approach is used to inspect how police actions affect the operational outcomes under a set of system constraints. Different experiments were performed to examine the impacts of factors, such as the number of patrol officers, shift schedule (8-hour vs. 10-hour shifts), and hot spot policing, on officers' workload and response time, which are primary metrics for police departments. Furthermore, a sensitivity analysis is performed on the response time and call wait time under two different route scenarios.

The future goals of this research study will first be to incorporate the adaptive criminals' behavior and study the policing actions to find better police intervention methods. In addition, more experimental scenarios could run to evaluate operational performance and identify the optimal model. This is called a simulation-based optimal solution. For instance, different deployment strategies for patrolling can implement to adapt to crime dynamics. A dynamic policing simulation framework could be developed to explore how officers can move and behave within different environments with various characteristics and time scales (e.g., semi-annually, seasonally, quarterly, etc.). Further, what-if scenario analysis can be implemented to study how other aspects of police operations can help obtain more effective policing.

REFERENCES

[1] (2018 Annual Report). *APD Annual Reports*.

[2] L. E. Cohen and R. Machalek, "A general theory of expropriative crime: An evolutionary ecological approach," *American Journal of Sociology,* vol. 94, pp. 465-501, 1988.

[3] C. R. Shaw and H. D. McKay, "Juvenile delinquency and urban areas," 1942.

[4] R. Hood and K. Joyce, "Three generations: oral testimonies on crime and social change in London's East End," *British journal of criminology,* vol. 39, pp. 136-160, 1999.

[5] R. T. Wright and S. H. Decker, *Burglars on the job: Streetlife and residential break-ins*: UPNE, 1996.

[6] D. Weisburd, A. A. Braga, E. R. Groff, and A. Wooditch, "Can hot spots policing reduce crime in urban areas? An agent-based simulation," *Criminology,* vol. 55, pp. 137-173, 2017.

[7] E. Durkheim, "The normal and the pathological," 1895.

[8] L. T. Hoover, "Crime-Specific Policing," *Police and Policing: Contemporary Issues,* p. 281, 1999.

[9] (2017). *Crime in the United States (FBI: UCR)*. Available: https://ucr.fbi.gov/crime-in-the-u.s/2017/crime-in-the-u.s.-2017/topic-pages/property-crime

[10] A. Chalfin, "Economic costs of crime," *The encyclopedia of crime and punishment,* pp. 1-12, 2015.

[11] S. Mello, "More COPS, less crime," *Journal of Public Economics,* vol. 172, pp. 174-200, 2019.

[12] W. N. Evans and E. G. Owens, "COPS and Crime," *Journal of Public Economics,* vol. 91, pp. 181-201, 2007.

[13] S. Weisburd, "Police presence, rapid response rates, and crime prevention," *Review of Economics and Statistics,* pp. 1-45, 2016.

[14] J. E. Guffey, Larson, J.G. and Kelso, C., "Police officer staffing: analyzing the commonly held belief that more cops equals less crime. ," *Professional Issues in Criminal Justice,* vol. 5, pp. 29-41, 2010.

[15] C. Beck and C. McCue, "Predictive policing: what can we learn from Wal-Mart and Amazon about fighting crime in a recession?," *Police Chief,* vol. 76, p. 18, 2009.

[16] J. Hollywood, S. Smith, C. Price, B. McInnis, and W. Perry, "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,* vol. 539, 2012.

[17] W. L. Perry, *Predictive policing: The role of crime forecasting in law enforcement operations*: Rand Corporation, 2013.

[18] P. Brantingham and P. Brantingham, "Nodes, Paths, and Edges: Considerations on the Complexity of Crime and the Physical Environment (1993)," in *Classics in Environmental Criminology,* ed: Routledge, 2010, pp. 289-326.

[19] L. E. Cohen and M. Felson, "Social change and crime rate trends: A routine activity approach," *American sociological review,* pp. 588-608, 1979.

[20] A. Blumstein, "Crime Modeling1," *Operations Research,* vol. 50, pp. 16-24, 2002.

[21] J. M. Caplan, Kennedy, L.W. and Miller, J., "Risk terrain modeling: brokering criminological theory and GIS methods for crime forecasting," *Justice Quarterly,* vol. 28, pp. 360-381, 2011.

[22] G. O. Mohler, M. B. Short, P. J. Brantingham, F. P. Schoenberg, and G. E. Tita, "Self-Exciting Point Process Modeling of Crime," *Journal of the American Statistical Association,* vol. 106, pp. 100-108, Mar 2011.

[23] X. a. B. Wang, D.E., "The spatio-temporal generalized additive model for criminal incidents," in *Intelligence and Security Informatics (ISI), 2011 IEEE International Conference on*, 2011, pp. 42-47.

[24] T. K. Anderson, "Kernel density estimation and K-means clustering to profile road accident hotspots," *Accident Analysis and Prevention,* vol. 41, pp. 359-364, May 2009.

[25] J. E. Eck and D. Weisburd, *Crime and place* vol. 4: Criminal Justice Press Monsey, NY, 1995.

[26] A. Tseloni, "Multilevel modelling of the number of property crimes: Household and area effects," *Journal of the Royal Statistical Society: Series A (Statistics in Society),* vol. 169, pp. 205-233, 2006.

[27] J. Eck and L. Liu, "Varieties of artificial crime analysis: Purpose, structure, and evidence in crime simulations," in *Artificial crime analysis systems: Using computer simulations and geographic information systems*, ed: IGI Global, 2008, pp. 413-432.

[28] J. Baldwin, A. E. Bottoms, and M. A. Walker, *The urban criminal: A study in Sheffield* vol. 159: Taylor & Francis, 1976.

[29] A. E. Bottoms, A. Claytor, and P. Wiles, "Housing markets and residential community crime careers," *Crime, Policing, and Place: Essays in Environmental Criminology,* pp. 118-144, 1992.

[30] J. A. Carr, "The geographies of young people, crime and social exclusion," University of Leeds, 2003.

[31] E. G. Cohn, "The effect of weather and temporal variations on calls for police service," *American Journal of Police,* vol. 15, pp. 23-43, 1996.

[32] M. B. Robinson and C. E. Robinson, "Environmental characteristics associated with residential burglaries of student apartment complexes," *Environment and Behavior,* vol. 29, pp. 657-675, 1997.

[33] A. van Nes, "The burglar as a space explorer in his own neighborhood," *WIT Transactions on Ecology and the Environment,* vol. 93, 2006.

[34] P. Wiles and A. Costello, "The 'road to nowhere': the evidence for travelling criminals," *Home Office Research Study,* vol. 207, 2000.

[35] D. Line and N. White, "Effects of development on runoff and pollutant export," *Water Environment Research,* vol. 79, pp. 185-190, 2007.

[36] M. M. a. C. Lanier, D.L., "Applying Computer-Simulation to Forecast Homicide Rates," *Journal of Criminal Justice,* vol. 21, pp. 467-479, 1993 1993.

[37] M. Hoard, J. Homer, W. Manley, P. Furbee, A. Haque, and J. Helmkamp, "Systems modeling in support of evidence-based disaster planning for rural areas," *International journal of hygiene and environmental health,* vol. 208, pp. 117-125, 2005.

[38] I. M. Newsome, "Using system dynamics to model the impact of policing activity on performance," *Journal of the Operational Research Society,* vol. 59, pp. 164-170, Feb 2008.

[39] D. Carter and J. D. Moizer, "Simulating the impact of policy on patrol policing: introducing the emergency service incident model," *System Dynamics Review,* vol. 27, pp. 331-357, 2011.

[40] J. Moizer, D. Carter, and S. Liu, "Planning robust policing futures: modelling using multimethodology," *Industrial Management & Data Systems,* 2015.

[41] S. Lee and W. Jung, "System Dynamics Approach to Ability of the Police for Solving Crime: Testing the Effect of Civic Cooperation with the Police," *The International Journal of Advanced Culture Technology,* vol. 5, pp. 1-8, 2017.

[42] K. M. Haque, V. C. Chen, and B. L. Huff, "A Discrete-Event Simulation Model for Adaptive Allocation of Police Patrol," in *IIE Annual Conference. Proceedings*, 2017, pp. 1169-1174.

[43] S. Srinivasan, T. P. Sorrell, J. Paul Brooks, D. J. Edwards, and R. Diehl McDougle, "Workforce assessment method for an urban police department," *Policing: An International Journal of Police Strategies & Management*, vol. 36, pp. 702-718, 2013/11/04 2013.

[44] Y. Zhang, S. H. Huddleston, D. E. Brown, and G. P. Learmonth, "A comparison of evaluation methods for police patrol district designs," in *2013 Winter Simulations Conference (WSC)*, 2013, pp. 2532-2543.

[45] Y. Zhang and D. E. Brown, "Simulation optimization of police patrol district design using an adjusted simulated annealing approach," in *SpringSim (TMS-DEVS)*, 2014, p. 18.

[46] J. B. Dunham, "An agent-based spatially explicit epidemiological model in MASON," *Journal of Artificial Societies and Social Simulation*, vol. 9, 2005.

[47] N. Malleson, A. Evans, and T. Jenkins, "An agent-based model of burglary," *Environment and Planning B-Planning & Design*, vol. 36, pp. 1103-1123, Nov 2009.

[48] N. Malleson and M. Birkin, "Analysis of crime patterns through the integration of an agent-based model and a population microsimulation," *Computers, Environment and Urban Systems*, vol. 36, pp. 551-561, 11// 2012.

[49] J. O. Gutierrez-Garcia, H. Orozco-Aguirre, and V. Landassuri-Moreno, "Agent-based simulation of crime," in *2013 12th Mexican International Conference on Artificial Intelligence*, 2013, pp. 24-29.

[50] J. E. Eck and L. Liu, "Contrasting simulated and empirical experiments in crime prevention," *Journal of Experimental Criminology*, vol. 4, pp. 195-213, 2008.

[51] L. Liu and J. Eck, "Artificial crime analysis systems: Using computer simulations and geographic information systems," 2008.

[52] S. D. Johnson and E. R. Groff, "Strengthening theoretical testing in criminology using agent-based modeling," *Journal of Research in Crime and Delinquency*, vol. 51, pp. 509-525, 2014.

[53] D. Birks, M. Townsley, and A. Stewart, "Generative explanations of crime: Using simulation to test criminological theory," *Criminology*, vol. 50, pp. 221-254, 2012.

[54] E. Groff and D. Birks, "Simulating crime prevention strategies: A look at the possibilities," *Policing: A journal of Policy and Practice*, vol. 2, pp. 175-184, 2008.

[55] L. W. Sherman and D. Weisburd, "General deterrent effects of police patrol in crime “hot spots”: A randomized, controlled trial," *Justice quarterly,* vol. 12, pp. 625-648, 1995.

[56] L. Liu, X. Wang, J. Eck, and J. Liang, "Simulating crime events and crime patterns in a RA/CA model," in *Geographic information systems and crime analysis*, ed: IGI Global, 2005, pp. 197-213.

[57] E. Groff and L. Mazerolle, "Simulated experiments and their potential role in criminology and criminal justice," *Journal of Experimental Criminology,* vol. 4, p. 187, 2008.

[58] S. D. Johnson, "Potential uses of computational methods in the evaluation of crime reduction activity," ed: Criminal Justice Press, 2009.

[59] D. Verma, S. Gartner, D. Felmlee, D. Braines, and R. Yarlagadda, "Using AI/ML to predict perpetrators for terrorist incidents," in *Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications II*, 2020, p. 114130G.

[60] A. Verma, R. Ramyaa, and S. Marru, "Validating distance decay through agent based modeling," *Security Informatics,* vol. 2, p. 3, 2013.

[61] C. W. Telep, 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,* vol. 31, pp. 905-933, 2014.

[62] K. J. Bowers, S. D. Johnson, and K. Pease, "Prospective hot-spotting: the future of crime mapping?," *British Journal of Criminology,* vol. 44, pp. 641-658, 2004.

[63] E. R. Groff and N. G. La Vigne, "Mapping an opportunity surface of residential burglary," *Journal of Research in Crime and Delinquency,* vol. 38, pp. 257-278, Aug 2001.

[64] W. Gorr and R. Harries, "Introduction to crime forecasting," *International Journal of Forecasting,* vol. 19, pp. 551-555, 10// 2003.

[65] E. R. Groff and N. G. La Vigne, "Forecasting the future of predictive crime mapping," *Crime Prevention Studies,* vol. 13, pp. 29-58, 2002.

[66] W. L. Gorr, "Research prospective on neural network forecasting," *International Journal of Forecasting,* vol. 10, pp. 1-4, 1994.

[67] S. D. Johnson and K. J. Bowers, "The burglary as clue to the future: The beginnings of prospective hot-spotting," *European Journal of Criminology,* vol. 1, pp. 237-255, 2004.

[68] M. L. Dennis and R. F. Boruch, "Randomized experiments for planning and testing projects in developing countries: Threshold conditions," *Evaluation Review,* vol. 13, pp. 292-309, 1989.

[69] W. R. Shadish, T. D. Cook, and D. T. Campbell, *Experimental and quasi-experimental designs for generalized causal inference/William R. Shedish, Thomas D. Cook, Donald T. Campbell*: Boston: Houghton Mifflin, 2002.

[70] A. A. Braga, "Effects of hot spots policing on crime," *Campbell Systematic Reviews,* vol. 3, pp. 1-36, 2007.

[71] A. A. Braga and B. J. Bond, "Policing crime and disorder hot spots: A randomized controlled trial," *Criminology,* vol. 46, pp. 577-607, 2008.

[72] A. A. Braga, "Hot spots policing and crime prevention: A systematic review of randomized controlled trials," *Journal of experimental criminology,* vol. 1, pp. 317-342, 2005.

[73] T. R. Kochel and D. Weisburd, "Assessing community consequences of implementing hot spots policing in residential areas: findings from a randomized field trial," *Journal of Experimental Criminology,* vol. 13, pp. 143-170, 2017.

[74] L. G. Mazerolle, J. F. Price, and J. Roehl, "Civil remedies and drug control: A randomized field trial in Oakland, California," *Evaluation review,* vol. 24, pp. 212-241, 2000.

[75] J. H. Ratcliffe, T. Taniguchi, E. R. Groff, and J. D. Wood, "The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots," *Criminology,* vol. 49, pp. 795-831, 2011.

[76] D. G. Weisburd, Elizabeth R; Jones, Greg; Cave, Breanne; Amendola, Karen L; Yang, Sue-ming; Emison, Rupert F, "The Dallas patrol management experiment: can AVL technologies be used to harness unallocated patrol time for crime prevention?," *Journal of Experimental Criminology,* vol. 11, pp. 367-391, Sep 2015.

[77] B. Taylor, 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,* vol. 7, pp. 149-181, 2011.

[78] L. W. Sherman, Rogan, D.P., Edwards, T., Whipple, R., Shreve, D., Witcher, D., Trimble, W., The Street Narcotics Unit, Velke, R., Blumberg, M. and Beatty, A., "Deterrent effects of police raids on crack houses: A randomized, controlled experiment.," *Journal of Justice Quarterly,* vol. 12, pp. 755-781, 1995.

[79] D. P. Farrington, M. Gill, S. J. Waples, and J. Argomaniz, "The effects of closed-circuit television on crime: Meta-analysis of an English national quasi-experimental multi-site evaluation," *Journal of Experimental Criminology,* vol. 3, pp. 21-38, 2007.

[80] J. M. Caplan, L. W. Kennedy, and G. Petrossian, "Police-monitored CCTV cameras in Newark, NJ: A quasi-experimental test of crime deterrence," *Journal of Experimental Criminology,* vol. 7, pp. 255-274, 2011.

[81] A. Cerezo, "CCTV and crime displacement: A quasi-experimental evaluation," *European Journal of Criminology,* vol. 10, pp. 222-236, 2013.

[82] K. M. A. Haque, "A Dynamic Policing Simulation Framework," 2018.

[83] N. a. B. Malleson, M., "Analysis of crime patterns through the integration of an agent-based model and a population microsimulation," *Computers, Environment and Urban Systems,* vol. 36, pp. 551-561, 11// 2012.

[84] C. C. Caruso, "Overtime and extended work shifts; recent findings on illnesses, injuries, and health behaviors," 2004.

[85] W. W. Stenzel and R. M. Buren, "POLICE WORK SCHEDULING-AN IMPORTANT AND MANAGEABLE FUNCTION," *POLICE CHIEF,* vol. 50, pp. 54-56, 1983.

[86] S. Folkard and D. A. Lombardi, "Modeling the impact of the components of long work hours on injuries and “accidents”," *American journal of industrial medicine,* vol. 49, pp. 953-963, 2006.

[87] S. Schlesinger, "Terminology for model credibility," *Simulation,* vol. 32, pp. 103-104, 1979.

[88] F. Klügl, "A validation methodology for agent-based simulations," in *Proceedings of the 2008 ACM symposium on Applied computing*, 2008, pp. 39-43.

[89] X. Xiang, R. Kennedy, G. Madey, and S. Cabaniss, "Verification and validation of agent-based scientific simulation models," in *Agent-directed simulation conference*, 2005, p. 55.

[90] E. F. McGarrell, S. Chermak, A. Weiss, and J. Wilson, "Reducing firearms violence through directed police patrol," *Criminology & Public Policy,* vol. 1, pp. 119-148, 2001.

[91] T. A. Reppetto, "Crime prevention and the displacement phenomenon," *Crime & Delinquency,* vol. 22, pp. 166-177, 1976.

[92] J. J. Donohue, D. Ho, and P. Leahy, "Do police reduce crime? A reexamination of a natural experiment," *Empirical Legal Analysis: Assessing the Performance of Legal Institutions,* pp. 125-143, 2013.

[93] D. Hall and L. Liu, "Cops and robbers in Cincinnati: a spatial modeling approach for examining the effects of aggressive policing," *Annals of GIS,* vol. 15, pp. 61-71, 2009.

[94] L. W. Sherman, P. R. Gartin, and M. E. Buerger, "Hot spots of predatory crime: Routine activities and the criminology of place," *Criminology*, vol. 27, pp. 27-56, 1989.

[95] B. Ariel and H. Partridge, "Predictable policing: Measuring the crime control benefits of hotspots policing at bus stops," *Journal of Quantitative Criminology*, vol. 33, pp. 809-833, 2017.