A MODEL OF TRAFFIC IMPACTS:

POINTS OF DISPENSING AS A RESPONSE

TO A BIOLOGICAL OUTBREAK

by

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A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Master of Applied Sciences

Summer 2016

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ACKNOWLEDGMENTS

I would first and foremost like to thank my thesis advisor Dr. Sue McNeil. Her professional guidance, moral support, and endless pep talks were vital to my writing this thesis. Dr. McNeil has provided an amazing support system throughout my graduate career.

I would also like to thank Dr. Earl "Rusty" Lee, whom without I would not have come up with this thesis topic. His inspiration and input were the catalyst for this entire thesis.

I would also like to acknowledge Michael DuRoss from the Delaware Department of Transportation. Mr. DuRoss was a great teacher, mentor, and facilitator in the creation of this model. In addition, I would like to thank Scott Thompson-Graves, Ashley Tracy, and Li Li at Whitman, Requardt & Associates for the time, effort, and helpfulness in developing the POD Traffic Impact Model.

Finally, I would like to thank my parents for their continued support and love.

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ABSTRACT

A Point of Dispensing (POD) is one method to distribute medical countermeasures to a population during a biological outbreak. The POD Traffic Impact Model (POD TIM) developed in this research examines the traffic impacts of POD operations on a transportation network. The methodology utilizes a modified and enhanced travel demand forecast model based on DelDOT's Statewide Evacuation Model in Citilabs Cube to include the choice of POD location choice based on proximity. Five patient arrival scenarios are tested using six relevant measures of effectiveness: V/C ratio, average and maximum patient queue length, average and maximum waiting times (delay), and worst time to arrive.

A case study is developed based on Wilmington, Delaware under the assumptions of an aerosolized anthrax release, and five POD locations. The case study operates under several assumptions: all traffic is vehicular; 90% compliance rate; and a POD processing rate of 1000 people per hour. Results indicated that the POD choice algorithm created an uneven distribution of population between the five POD locations, with 40% at one POD and 1% at another POD. The disparity in population distribution meant that the POD TIM is insensitive to patient arrival pattern. At their busiest, PODs had maximum queues of over ten thousand people. The oversight of a parking constraint sub-model led to all patients parking their vehicles and queueing outside of PODs. In reality, parking would represent a serious concern during POD operations. In general, the PODs did not have significant traffic impacts on the surrounding networks. Recommendations for future research include updating the POD choice algorithm, implementing a parking constraint sub-model, and readdressing the patient arrival patterns.

Chapter 1

INTRODUCTION

1.1 Problem Statement

In the public health sector, emergency response plans exist for mass biological outbreaks, such as a pandemic or a bioterrorism attack. A Point of Dispensing (POD) is one method to distribute medical countermeasures. At a POD, public health personnel dispense medication to the public at predetermined locations. Public health emergency planners utilize decision support tools to prepare for the challenges and uncertainties of POD operations. However, the public health sector has not considered the potential impacts of traffic generated by PODs. When added to daily traffic, the congestion caused by this additional traffic may negatively affect POD efficiency. During a public health emergency, a decreased efficiency could mean an increased mortality rate when distributing medication to an entire population within 24 hours. This thesis performs an exploratory analysis to understand better the current gaps in public health emergency response policy, to model traffic generated by PODs, and to provide recommendations for future POD traffic models.

1.2 Motivation

Among literature focusing on planning and operation of PODs, very little focuses on the effects of external challenges. The literature on planning and operation of PODs does not recognize or address the external challenges, such as traffic congestion. The goal of a POD is to dispense medical countermeasures to a target population within 24 to 48 hours (“Cities Readiness Initiative,” 2010). Planning emphasizes internal logistics such as staffing, location, and set-up optimization (Nelson et al., 2008; Emergency Management Institute, 2008; Nelson et al., 2012).

When logistics external to the POD are considered, typically the focus is on the delivery, repackaging, and distribution of medical countermeasures from state and federal stockpiles to POD locations (Nelson et al., 2012). However, other potential issues exist because of the interface between the community in which the POD is located and the POD operations. This interface includes transportation-related challenges include vehicular and pedestrian logistics, such as arrival rates, parking availability, and traffic control. Even a well-planned POD may face unexpected congestion outside of the facility that affect its utilization rate, throughput rate, and waiting times.

I have identified a gap between public health emergency response and transportation planning and analysis in the context of POD operations. I advocate for open communication, collaboration, and coordination between Departments of Public Health and Transportation during emergency response planning. By integrating traffic modeling into the POD planning process, we create a comprehensive emergency response and an open line of communication.

1.3 Objectives

This exploratory analysis demonstrates the benefits of using travel demand software during POD planning. The primary objective is to provide evidence that the interaction between a transportation network and a POD warrants future analysis and collaboration. This study provides proof of concept for the use of travel demand models in emergency response planning. In the long term, development of a travel demand POD model may determine congestion spots, identify possible traffic control measures, and provide recommendations for emergency planners. This first attempt to model POD traffic will produce many important recommendations for future model iterations.

Many questions may be answered through a case study of traffic during POD operations. Primarily, are the traffic impacts worth considering during emergency planning? How much additional traffic does a POD generate? How is this traffic distributed throughout the network? How does POD-generated traffic affect background traffic? Where do the congestion points occur in the network? Are there identifiable reasons for this congestion that can be mitigated through traffic control? By answering these questions, I hope to demonstrate that POD traffic impacts and potential control measures should be considered during emergency response planning.

Because POD-generated traffic has not been previously considered from this perspective, the secondary objective is to provide recommendations to improve the accuracy and realism of future travel demand/traffic impact models. What issues arise from the current model? How do the assumptions shape the model results? How inaccurate or unreasonable are these assumptions? What are the limitations of this methodology? In the future, modelers should integrate realistic social behaviors, internal POD processes, and alternative performance metrics. This case study will provide guidance for future models.

The third objective is to promote communication and collaboration between emergency management and transportation agencies. The results of this analysis may be shared with emergency planners and policy makers to help them better understand the external challenges of PODs. In addition to issues caused by our model assumptions, how do POD guidelines, policies, and practices impact the process? For example, many planners assume a uniform arrival rate for patients (Ma et al., 2011).

The analysis results will shape the discussion between public health officials and transportation agencies.

1.4 Overview of Methodology

To explore the issues identified, the Point of Dispensing Traffic Impact Model (POD TIM) is created to analyze the impact of POD operations on a transportation network. The POD TIM forecasts hourly traffic demand on the Delmarva Peninsula during a public health response to a large-scale biological outbreak. The POD TIM is based on a background network model, the four-step method (Garber & Hoel, 2009), and scenarios. The Delaware Department of Transportation provides the regional network in Citilabs Cube, a transportation and land use modeling platform. The case study area and a 1-2 mile buffer zone are modeled at the census block level. The remaining regional network of the Delmarva Peninsula is modeled using transportation analysis zones.

The POD TIM utilizes the four-step method of traditional travel demand models, consisting of trip generation, trip distribution, mode choice, and route assignment. In addition to normal background traffic, the model generates POD trips based on demographic data, employment records, and compliance rate. POD locations service two populations: residents of the case study area; and non-resident workers, who live outside of but are employed within the case study area. The POD TIM runs several model scenarios, which vary residential patient arrival patterns. The model compares a uniform, stationary patient arrival pattern to four non-uniform arrival patterns. There are two sets of performance measures for the model. Network performance measures describe hourly background, evacuation, and spillover traffic volumes. POD performance measures indicate patient arrival and processing rates, queue lengths, and waiting times. A case study of Wilmington, Delaware is used to demonstrate the methodology.

1.5 Outline of the Thesis

The first chapter of this paper introduces the problem, objectives, methodology, and outline of the rest of the thesis. Chapter 2 provides a literature review of background information, related research, and relevant methodologies. Chapter 3 introduces the methodology, including describing the model process, performance measures, arrival scenarios, and data sources. Chapter 4 describes the case study of Wilmington, Delaware used to demonstrate the methodology. Results, analysis, and discussion are provided in Chapter 4 also. Chapter 5 provides conclusions, recommendations, and suggestions for future research. Appendices document a disclaimer, arrival pattern data, and POD measures of effectiveness results.

Chapter 2

LITERATURE REVIEW

2.1 Background

In this chapter, I review the literature related to POD planning, past related research, and relevant methodologies. The purpose of the literature review is to understand the operation of PODs, and determine the extent to which issues related to transportation planning and traffic analysis is included in these documents. My goal is to better understand current standards, practices, and research in disease outbreak emergency planning and response.

Motivations for this research stemming from the literature include the lack of traffic management plans and a call for interagency coordination. I define PODs and relevant terminology, such as open and closed, head of household method, and drive-through clinics. I identify transportation management plans in federal initiatives and standards, POD preparedness measures, and plans and roles for Delaware. Lessons learned from planning and field exercises involve investigating nonstationary patient arrival rates and implementing traffic control. The majority of POD models optimize internal POD processes such as location, layout, and staffing, although two publications examine the external impacts of POD operations. Lastly, I examine how the uses of travel demand forecast models for other research are relevant to this thesis.

2.1.1 Motivation from the Literature

When trying to frame the initial transportation problem, the first step was to determine where current practitioners and planners *think* that there is a problem. I review motivations found in POD exercise reports that support the need for traffic analysis and understanding the impacts of PODs in transportation planning. The largest motivation for this research is the lack of explicit planning for transportation issues during POD planning and operations based on the literature reviewed here. Much of POD research skirts around the issues of traffic, congestion, and logistical management surrounding a POD. The most direct mention comes from a study by Gupta et al. (2013), which states that "[traffic] management will also be problematic in large cities… though traffic management is outside the scope [of this research]" (p. 106). A majority of POD literature focuses on internal logistics, such as patient throughput rates, service times, and staff utilization rates.

However, planning and exercises should consider all aspects of POD operations, including external processes. The POD literature hints to the need for collaboration with transportation owners and operators, declaring that traffic control may be problematic and suggesting that future research incorporate the external processes of a POD (Gupta et al., 2013; Koh et al., 2008; Reid, 2010; Whitworth, 2005). For example, inadequate parking may lead to increased congestion, bottlenecks, and traffic accidents (Whitworth, 2005; Reid, 2010). A high-efficiency mass dispensing site may be severely underutilized "if gridlocked parking lots and access roads prevent clients and supplies from reaching the dispensing site" (Whitworth, 2005, p. 1). In extreme situations, drivers may run out of gas or abandon their vehicles in the road (Whitworth, 2005; Reid, 2010). Insufficient planning, training, and practice may lead to unprepared PODs during a public health emergency, which can lead to high death tolls (Rebmann et al., 2015). These POD publications clearly imply that future research and planning should plan for transportation issues.

A public health emergency plan requires the cooperation and coordination of many organizations, such as departments of public health, emergency response services, elected officials, and law enforcement (Koh et al,. 2008). These organizations should also include Departments of Transportation. Table and field exercises provide experience, feedback, and insight into mass dispensing situations (Banks et al., 2013). Exercises and training also help to develop cooperative relationships between participating organizations. Departments of Transportation, highway agencies, and law enforcement may provide valuable insight during training, exercises, and planning. Good planning recognizes that "the lack of an event does not mean a lack of risk" (Agócs et al., 2007, p. 266). The message the literature tells us is that if we do not consider the effects of increased traffic, congestion, and limited access points, we are setting ourselves up for failure before an event even occurs.

2.1.2 Points of Dispensing

A Point of Dispensing (POD) is a preselected location where medical operations dispense vaccines, antibiotics, or other medication to the general population during a public health emergency (Hupert et al., 2004; Emergency Management Institute, 2008). PODs may be employed in response to a variety of biological outbreaks, such as influenza, aerosolized anthrax, or smallpox. A typical POD is comprised of "areas for patient registration, triage, medical evaluation, and dispensing of appropriate prophylaxis" (Zerwekh et al., 2007, p. 8). PODs use a "pull" method that requires the affected population to gather at specified locations to receive medical countermeasures (MCMs) (Hupert et al., 2004; Koh et al., 2008). Alternatively, "push" methods involve delivering MCMs to households through the United States Postal Service or other delivery service (Reid, 2010). "Pull" methods, such as PODs, offer the advantages of medical education and evaluation, dosage modifications, and dispensing of vaccines (Reid, 2010). PODs are the most utilized method to quickly and efficiently vaccinate or distribute medication to a population (Baccam et al., 2011).

There are two types of PODs: open PODs, which dispense to the general population; and closed PODs, which provide MCMs to a specific organization, such as a hospital or corporation (Rebmann et al., 2014; Rebmann et al., 2015). For closed PODs, a formal agreement exists between a health department and a private entity to dispense MCMs to all organization members and their families (Rebmann et al., 2014). Although closed PODs can target specific groups, officials need open PODs to reach most of a community's population. Open PODs should be easily accessible to all members of a community (Rebmann et al., 2014). Open and closed PODs operate side-by-side to dispense MCMs to the entire affected population.

POD operators may use a head of household (HoH) method when distributing oral medication. In a HoH dispensing method, an individual is allowed to pick up MCMs for all members of their household (Agócs et al., 2007). The HoH method offers several benefits, such as shorter waiting times for individuals, fewer facilities, and less staff needed for each location (Agócs et al., 2007). Additionally, the HoH model allows higher risk populations such as children, senior citizens, and people with disabilities to remain at home, thus lowering their exposure risk. However, this method cannot be utilized for vaccinations, which must be administered to each individual by a qualified health professional.

2.1.3 Arrival Rates, Throughput Rates, and Service Times

When assessing the operations of a POD, there are several key characteristics to consider. The arrival rate describes the pattern in which people arrive at the site before and during operations (Baccam et al., 2011; Ma et al., 2011). Many dispensing plans assume a stationary, uniform arrival rate, where patients arrive at a constant, fixed rate (Ma et al., 2011). However, arrival patterns are much more complex in real life situations. The service time specifies how long it takes to process one patient at a POD, including registration and dispensing MCMs (Ma et al., 2011). The throughput rate indicates how many people one POD can service per hour (Baccam et al., 2011; Ma et al., 2011). Assumptions about arrival rates, service times, and throughput rates vary between studies. Waiting times and queue lengths are also very important to consider in an analysis, as these can be an indicator of inadequate staffing, high service times, or low throughput rates.

2.1.4 Walk-in versus Drive-Through PODs

There are two POD delivery methods: walk-in clinics, in which patients park their vehicles and walk through the POD set-up; and drive-through clinics, in which patients remain in their vehicles for the duration of the process. Drive-through clinics may have multiple processing lanes, with the ability to process several vehicles per lane if staffing allows. Choosing the type of delivery that best fits the situation depends on the type of MCM (e.g. antibiotic versus vaccine), available workforce, the size of the patient population, and the time available to dispense medications (Reid, 2010).

There are several advantages to dispensing MCMs via drive-through over a traditional, walk-in POD. These benefits include protection from severe weather, access for clients with limited mobility, and keeping families together (Reid, 2010; Banks et al., 2013). By secluding patients in separate vehicles, there is a decreased risk of disease transmission between patient groups and staff. Decreasing the risk of exposure may increase health care workers' willingness to participate in POD operations (Reid, 2010). Drive-through clinics also eliminate several external process limitations, such as parking constraints, excessive queues, and security issues (Zerwekh et al., 2007; Reid, 2010). Additionally, HoH methods may be used at drive-through PODs when dispensing oral MCMs. Congestion and bottlenecks along the road network may still be a concern.

There are several drawbacks to drive-through PODs. Although vehicles provide patients with protection from the elements, POD staff are exposed to the weather (Reid, 2010). There may be limited availability of restrooms for patients in processing (Zerwekh et al., 2007). Additionally, there is the potential for vehicles to run out of gas and cause a traffic jam in the queue (Reid, 2010). Costs of idling in line for hours are a negative impact for patients. Both drive-through and walk-in clinics discriminate against people without transportation or licenses. Choosing the best method for dispensing depends on the disease scenario, location, and available resources.

2.1.5 Transportation Issues in Federal Initiatives, Guidelines, and Standards for PODs

POD operations plans should have the flexibility and scalability to adapt to variety of biological threats (Lee et al., 2009). During planning and operations, public health officials must overcome many constraints, such as location choice, supply distribution, limited staff, and time (Hupert et al. 2009; Koh et al., 2008; Lee et al., 2009; Ma et al., 2011). In the event of a large-scale aerosolized anthrax release, it is critical to dispense medical countermeasures within 48 hours of exposure (Whitworth, 2005). The first 24 hours are dedicated to preparing the POD and the delivery of the medicine, leaving 24 hours to vaccinate or dispense medication to potentially affected populations (Ma et al., 2011). Speed, accuracy, security, and organization are crucial principles for a successful POD (Agócs et al., 2007; Banks et al., 2013). There are many concerns and constraints to consider during the planning and operation of PODs.

Public health emergency response occurs at the lowest level of government that can adequately manage the incident. Biological outbreak plans are generally formed at the city or county level (Rebmann et al., 2015). These plans are not standardized, which is both a strength and weakness. As a benefit, each location's plans are tailored to their unique population, geography, and resources. Unfortunately, unstandardized plans lead to an inherent variability in the vocabulary, quality, and scope of response plans. Several federal programs have provided guidelines for POD planning. These include the Cities Readiness Initiative, a planning guide from the Agency for Healthcare Research and Quality, POD standards from the Centers for Disease Control and Prevention, and guidelines from the Federal Emergency Management Agency and the U.S. Army Corps of Engineers ("Cities Readiness Initiative," 2010; Hupert et al., 2004; Nelson et al., 2008, Centers for Disease Control and Prevention, 2008; Emergency Management Institute, 2008). Additionally, two reports from the National Cooperative Highway Research Program examine the intersection of transportation and public health (Friedman et al., 2006; Fletcher et al., 2014). Upon examination, it was found that transportation-related planning is only minimally considered in federal guidelines. When transportation is considered, it is in the context of logistical delivery of MCMs to POD sites, transferring of sick patients to medical treatment facilities, and traffic control of entry/exit points and parking lots.

2.1.5.1 Cities Readiness Initiative and the Strategic National Stockpile

The CRI is a federally funded program created in 2004 by the Centers for Disease Control and Prevention (CDC) ("Cities Readiness Initiative", 2010). The CRI helps metropolitan statistical areas (MSAs) to develop response plans to large-scale biological outbreaks ("Cities Readiness Initiative", 2015). As of 2010, seventy-two metropolitan statistical areas were participating in the CRI, including Dover, Delaware ("Cities Readiness Initiative", 2010). The CRI encourages MSAs to create, implement, and update their response plans.

Initial planning scenarios stemmed from a homeland security perspective, focusing on bioterrorism events such as anthrax attacks. The CRI's original goal was to receive, distribute, and dispense medical countermeasures (MCMs) from the CDC's Strategic National Stockpile (SNS) to a target population within 48 hours of a bioterrorism event ("Cities Readiness Initiative", 2010, Ma et al., 2011). In the case of an anthrax release, the mortality rate sharply increases 48 hours post-exposure (Ma et al., 2011). The SNS contains enough medicine to protect the United States' population if supplies run out at the local level during a public health emergency, delivering to any location within twelve hours (Hupert et al., 2004; Zerwekh et al., 2007; "Strategic National Stockpile", 2015). According to the CDC, "each state has plans to receive and distribute SNS medicine and medical supplies to local communities as quickly as possible" ("Strategic National Stockpile", 2015). Since the CRI's initial implementation, scenarios have expanded to incorporate epidemics such as smallpox and influenza. The current focus emphasizes an all-hazards approach to public health preparedness. Regional transportation analysis and POD traffic management have not been explicitly considered by the initiative (Nelson et al., 2012).

2.1.5.2 CDC POD Standards

Based on research by the Department of Health and Human Services, Nelson et al. (2008) recommends a set of POD standards related to security, staffing, facility locations, and operations. The standards are based on evidence through consultation of current policy, mathematical modeling, and coordination with practitioners and key stakeholders (Nelson et al., 2008). The Centers for Disease Control and Prevention/Division of Strategic National Stockpile have adopted these standards (Centers for Disease Control and Prevention [CDC], 2008). State and local-level policymakers and emergency planners are the target audience. The standards incorporate flexibility to allow planners to meet the unique needs of their area. Nelson et al. (2008) urge local planners to plan beyond the standards to effectively service their population, stating that even full compliance with these standards may not lead to a "fully successful response" (p. 7). The standards follow the CRI goals to dispense MCMs to a population within 48 hours (Nelson et al., 2008).

The emphasis of the standards is on internal POD infrastructure, such as facility location and set-up (Nelson et al., 2008). The standards do not directly pertain to transportation-related issues such as transportation infrastructure, traffic control, and congestion management. The required number of PODs considers population size and geographical distribution (Nelson et al., 2008). The report suggests future collaboration between "public health and city planning, public works, transportation, and other departments likely to possess GIS capabilities" to aid with POD location optimization process (Nelson et al., 2008, p. 24). Potential POD optimization models may utilize travel distance as a metric, assuming people will travel to the POD nearest to them (Nelson et al., 2008). However, there is no consideration of how this influx of travel would affect the road network. Nelson et al. (2008) briefly consider transportation in POD site security, recommending guidance on vehicle traffic control immediately surrounding a POD location. Additionally, security should manage POD location ingress, egress, and parking (Nelson et al., 2008). However, security responsibilities do not include managing the larger impacts of congestion throughout a region's transportation network.

Nelson et al. (2008) recommend further development of infrastructure and operational capabilities standards. The authors suggest that current standards may leave deficits in planning, such as communicating information to the public and incident management. I suggest that these deficiencies also include regional transportation planning. A congested transportation network may impact the operational capabilities of a POD, such as throughput rate. Future iterations of POD standards should incorporate transportation management planning.

2.1.5.3 FEMA Point of Distribution Guidelines

The Emergency Management Institute is a training institute supported by the Federal Emergency Management Agency (FEMA) and the Department of Homeland Security (DHS). The institute offers an independent study course on Points of Distribution called "IS-26: Guide to Points of Distribution" (Emergency Management Institute [EMI], 2008). Compared to the CDC POD standards, the FEMA guidelines provide more detailed instructions for operations and planning. The course focuses on the functional aspects of Points of Distribution for state and local emergency planners. The course defines the roles of the local Emergency Management Agency for staffing, set-up and layout, equipment, operations, and safety. The guide defines Points of Distribution as "centralized locations where the public picks up life sustaining commodities following a disaster or emergency" (EMI, 2008, p. 6). Because a Point of

Distribution focuses on distributing a wider array of commodities to the public, the set-up, staffing, and operations instructions may differ from traditional public health Point of Dispensing (POD). In the case of a large-scale biological outbreak, we may consider "Point is Distribution" synonymous with our definition of a POD and the "commodities" as medical countermeasures.

The manual does consider transportation issues directly related to POD operations. The transportation impact surrounding a POD is mentioned when determining site layout (EMI, 2008). The guide urges planners to consider entry and exit points, traffic flow, and potential congestion when choosing POD locations. However, the guide does not suggest a methodology to assess traffic impacts of a POD. Although the manual calls for a Traffic Controller staff position, this position's duties pertain to drive-through site traffic flow, not regional mitigation (EMI, 2008). Transportation impacts of multiple PODs in a region are not considered.

2.1.5.4 Agency for Healthcare Research and Quality Planning Guide

Community-Based Mass Prophylaxis: A Planning Guide for Public Health Preparedness is a customizable framework for state, county, and local public health agencies currently developing epidemic response plans. The guide was published by the Agency for Healthcare Research and Quality, whose objective is to improve the safety, quality, and preparedness of the American Healthcare System (Hupert et al., 2004). The guide is intended for a wide audience, including public health agencies, academics, and non-governmental organizations. However, users should consider that information in the guide might be outdated, as the Public Health Emergency Preparedness program that published the guide was discontinued in 2011.

The *Planning Guide*'s purpose is to provide a response structure, common understanding, and shared vocabulary of disease outbreak response. The guide describes the vital components of outbreak response, mass dispensing, and the design, planning, and support functions for PODs (called Dispensing/Vaccination Centers in the guide). The framework provides enough flexibility to incorporate local characteristics into response plans. The planning guide discusses transportation in the context of logistical transport of supplies and medical transport for sick patients. Ironically, the guide utilizes highway traffic as an analogy for patient flow within a POD. However, the guide does not consider any external transportation challenges or traffic management of a POD.

2.1.5.5 NCHRP Report on Role of Transportation in Public Health Disasters

In 2006, The National Cooperative Highway Research Program (NCHRP) published *A Guide to Transportation's Role in Public Health Disasters* (Friedman et al., 2006). The report examines the vulnerabilities of transportation systems to chemical, biological, and radiological threats. The guide defines each threat, identifies emergency response needs, and provides emergency response plans for highway, maritime, railway, aviation, and mass transit transportation systems. The focus of transportation's role in a public health emergency relates to the transmission, contamination, and containment of a biological, chemical, or radiological threat through a transportation system.

For this project, we are interested in the performance highway transportation during the response to biological threats. Principle factors considered in response include "biological agent type and formulation, quantity and persistence, exposure route, dispersion, and population density in the area at risk" (Friedman et al., 2006, p. 20). Vulnerabilities in a transportation system include confined areas, passenger volume, contamination of ventilation and other utilities, and the decontamination process (Friedman et al., 2006). Transportation system responsibilities include routing exposed populations to "decontamination areas," evacuating non-exposed populations, and providing clear passage for first responders and medical supplies (Friedman et al., 2006). Transportation agencies have three main roles before, during, and after a public health emergency: managing traffic flow and congestion within the road network; sharing information about the network with other public agencies; and coordinating logistics for other agencies and the public (Friedman et al., 2006). These objectives directly align with the role of transportation during POD operations. Although more detailed guidelines are not provided, this report supports coordination and collaboration between public health and transportation agencies.

2.1.5.6 NCHRP Report on Public Transportation Pandemic Planning and Response

The NCHRP published *A Guide for Public Transportation Pandemic Planning and Response* in 2014 in response to the call for comprehensive pandemic planning (Fletcher et al., 2014). The report reviews pandemics, the role of transportation organizations during a pandemic, agency coordination, containment tactics, and staffing (Fletcher et al., 2014). The guide focuses on pandemic planning for rural and suburban transit organizations and human transport providers, which is outside the scope of this case study. However, this document may be useful for future research that incorporates public transportation into the POD planning process.

2.1.6 POD Preparedness

There have been several evaluations of POD preparedness, including the Technical Assistance Review (TAR) and a national study of open and closed PODs (Nelson et al., 2012; Rebmann et al., 2014; Rebmann et al., 2015). The TAR is a weighted composite score that assesses thirteen functional areas in the following categories: Strategic National Stockpile plans, management, and requests; tactical communications and security; public information; receipt, storage, distribution, and dispensing of MCMs; and training, exercise, and evaluation (Nelson et al., 2012). However, the TAR has several limitations, such as its sole focus on oral medication dispensing and its use to assess CRI participants only (Rebmann et al., 2015). No formal review exists for non-CRI jurisdictions' open PODs or for any closed PODs.

In an online survey of 456 CRI jurisdictions and 500 randomly sampled non-CRI jurisdictions, Rebmann et al. (2015) asked whether U.S. jurisdictions are prepared to operate open PODs. A total of 257 jurisdictions completed the survey, which assessed for open POD preparedness, alternative dispensing options, closed POD plans, perceived preparedness and priorities, exercise participation and scenarios, and after-action reports. Approximately 94% of jurisdictions had written and/or layout POD plans (Rebmann et al., 2015). Furthermore, approximately 74% of jurisdictions reported having at least one closed POD (Rebmann et al., 2014). Rebmann et al. (2014) and Rebmann et al. (2015) filled a hole in public health preparedness literature by recognizing gaps in readiness evaluation, analyzing shortcomings in preparedness, and identifying opportunities to increase these attributes.

Although evaluated jurisdictions appear prepared, gaps do exist in the evaluative measures for POD preparedness (Nelson et al., 2012; Rebmann et al., 2014; Rebmann et al., 2015). Most notably, current preparedness measures do not consider the external, logistical challenges of PODs, such as accessibility, parking capacity, and vehicle congestion (Nelson et al., 2012). Few studies have examined how fundamental assumptions about patient arrival rates and dispensing capabilities affect POD preparedness, operations, and efficiency (Ma et al., 2011; Baccam et al., 2011). Additionally, Rebmann et al. (2015) identified a discrepancy between perceived and actual dispensing preparedness, in which 82% of jurisdictions claimed they could distribute to the entire population within 48 hours, despite 43% acknowledging that they had insufficient staff and volunteer numbers. This finding highlights that some jurisdictions may be less prepared than they believe. By ignoring the transportation challenges surrounding a POD, the gap between perceived and actual preparedness grows larger.

Even fewer preparedness measures have been conducted for closed PODs. The gap between CRI and non-CRI jurisdictions grows larger when considering closed POD preparedness. Rebmann et al. (2014) stated that 85% of CRI jurisdictions reported having at least one closed POD, while only 58.5% of non-CRI jurisdictions reported closed POD plans. Rebmann et al. (2014) posits that this preparedness discrepancy may be partially because of funding provided to CRI participants. Overall, a standardized, formal review process is needed to assess POD preparedness for all jurisdictions, not just CRI participants. This formal review should incorporate traffic control measures and mitigation strategies to alleviate congestion and other external challenges surrounding PODs.

2.1.7 Written Plans, Roles, and Agencies in Delaware

2.1.7.1 Neighborhood Emergency Help Center Plan

Published in 2008 by the Department of Health and Social Services for the State of Delaware, the *Neighborhood Emergency Help Center Plan* is an official document defining the emergency response plans for a crisis within the state of Delaware (Division of Public Health [DPH], 2008b). The document describes circumstances for initiating a plan, general facility set-up and operations, and agency roles and responsibilities (DPH, 2008b). Agencies involved include Delaware Health and Social Services, Delaware Emergency Management Agency, Delaware Pharmacist Society, Delaware Department of Transportation (DelDOT), Delaware State Police (DSP), and Emergency Medical Services. Additionally, volunteers from the Delaware Medical Reserve Corps or from private EMS agencies may be present.

A Neighborhood Emergency Help Center (NEHC) is a facility operated by the aforementioned agencies and the State Health Operations Center that provides "prophylaxis, medical triage and sheltering […] in the event of a disaster or public health event" (DPH, 2008b, p. 3). In many public health emergency scenarios, a NEHC is synonymous with a POD. The NEHC plan provides several key guidelines for planning and operations in Delaware. The Division of Public Health assumes a patient throughput rate of between 1000-2000 people per hour per location for medications and up to 600 people per hour per location for vaccines (DPH, 2008b). To distribute patient throughput both throughout the 24-hour operational period and to different locations, patients may be assigned to a NEHC by area, postal code, phone number, or other technique (DPH, 2008b). Lastly, the plan states that NEHCs are not limited only to Delaware residents, indicating that any person who attends a NEHC shall receive care. (DPH, 2008b).

The document does not provide explicit, formal traffic management plans. DelDOT's roles include to "assist in planning efforts with DPH[;] provide traffic control at NEHC facilities[; and] participate and/or observe in yearly exercises by DPH, if necessary" (DPH, 2008b, p. 31). The Delaware State Police shall also provide traffic support. Several transportation characteristics related to potential NEHC sites are listed below:

- "At least two main roads from different directions to access the facility.
- Secondary road or long driveway (over 500 feet) used to access the facility.
- Parking lots sufficiently illuminated.
- Number of parking areas.
- Total area enough to accommodate parking for visitors, employees, public transit vehicles (buses), police cars, and ambulances.
- Main entrance to the Initial Sorting and Screening Area easily located from the parking area(s).
- Location of overflow parking areas" (DPH, 2008b, p. 69-71).

No further guidance is offered on how to set up parking, access points, and traffic control outside of NEHCs. Lastly, the NEHC plan lists potential locations for NEHC facilities, seen in Table 1 below.

Table 1: List of Potential NEHC Sites (DPH, 2008b, p. 176)

Site	Location
Northern Health Services Area Sites	
Brandywine Senior Center	Claymont
Christiana Fire Company	Christiana
Claymont Community Center	Claymont
Del Tech – Stanton	Stanton
Del Tech – Wilmington	Wilmington
Jewish Community Center	Wilmington
Newark Senior Center	Newark
Riverfront	Wilmington
Southern Health Services Area Sites	
Blades Fire Company	Blades
Cape Henlopen Senior Center	Rehobeth Beach
Del Tech – Dover	Dover
Del Tech – Georgetown	Georgetown
Delaware National Guard (Smyrna Readiness Center)	Smyrna
Georgetown CHEER Community Center	Georgetown
Greenwood Fire Hall	Greenwood
Harrington Senior Center	Harrington
Laurel Fire Hall	Laurel Fire Hall
Modern Maturity Center Dover	Dover
Roxana Fire Company	Roxana
State Service Centers	
Appoquinimink State Service Center	Middletown
Belvedere State Service Center	Wilmington
Claymont State Service Center	Claymont
DelaWarr State Service Center	New Castle
Floyd I. Hudson State Service Center	Newark
Northeast State Service Center	Wilmington
Winder Laird Porter State Service Center	Wilmington
Anna C. Shipley State Service Center	Seaford
Bridgeville State Service Center	Bridgeville
Edward W. Pyle State Service Center	Frankford
Georgetown State Service Center	Georgetown
James W. Williams State Service Center	Dover
Laurel State Service Center	Laurel
Milford State Service Center	Milford

2.1.7.2 Delaware Influenza Pandemic Plan

The *Delaware Influenza Pandemic Plan* is an official document published in 2008 by the Department of Health and Social Services for the State of Delaware (Division of Public Health [DPH], 2008a). The *Delaware Influenza Pandemic Plan* outlines the responsibilities and procedures for all involved agencies during an influenza pandemic. Although influenza pandemic response may differ from an anthrax exposure or a smallpox outbreak, this plan is a similar scenario to an epidemic that requires mass dispensing clinics.

The pandemic plan operates in one of six phases (DPH, 2008a). Phases 1 and 2 belong to the "Inter-Pandemic Period," in which no flu viruses are present currently. Phases 3, 4, and 5 represent a "Pandemic Alert Period," in which human infections begin to spread, although transmission is localized. In phase 6, the "Pandemic Period," the flu virus poses an immediate public health emergency to the general population. During a pandemic, the state governor may declare States of Emergency (DPH, 2008a). Open and closed PODs (NEHCs, hospitals, universities, large employers, etc.) will operate to dispense antivirals and vaccinations to the population (DPH, 2008a). The plan identifies distribution protocols for various "Vaccination Priority Groups," including medical personnel and high-risk populations (DPH, 2008a). During a pandemic, DelDOT's responsibility is to "provide traffic control measure at the NEHCs and other points of dispensing" (DPH, 2008a, p. 19). No further traffic management procedures are provided.

2.1.7.3 State, County, and City Level Emergency Operations Plans

Emergency Operations Plans exist at the State, County and City levels. It is understood that these plans contain detailed information on the emergency response to a biological outbreak. However, the plans are not publically available, and despite requests to Delaware Emergency Management Agency (DEMA) access was not granted for research purposes.

2.1.7.4 Delaware Department of Transportation

There are no formally written plans detailing the Delaware Department of Transportation's role during a biological outbreak (D. Day, personal communication, April 5, 2016). DelDOT's role during a biological outbreak is as a support agency for the Division of Public Health and Delaware Emergency Management Agency, providing any necessary training and resources (D. Day, personal communication, April 5, 2016). Most likely, the responsibility will fall to DelDOT's Transportation Management Center (TMC), in conjunction with state, county, and local law enforcement and emergency services. A 2004 *Transportation Incident & Event Management Plan* provides the only indication of the potential role of DelDOT in a medical emergency (Delaware Department of Transportation [DelDOT], 2004). However, the plan is a multi-hazard evacuation procedure, with no specific strategies for a mass dispensing scenario. Additionally, the plan is a decade out of date. Thus, the plan is only marginally helpful when framing the problem.

The incident management plan names the Transportation Management Team (TMT) as the group primarily responsible, consisting of agencies such as DelDOT, Delaware Emergency Management Agency, Delaware State Police, and other essential groups (DelDOT, 2004). DelDOT would coordinate alternate routes, supply traffic control devices such as "barriers, cones, temporary signs, and sign crews," and provide information to the Delaware Emergency Operations Center during an emergency (DelDOT, 2004, p. 23). The TMC would be responsible for "transportation management, secondary incident management, providing real-time information," and deploying and staging assets (DelDOT, 2004, p. 23-4). State, county, and local law enforcement would be an essential asset for traffic control around the POD site.

2.2 Past Related Research

2.2.1 Planning, Field Exercises, and Lessons Learned

Many departments of public health, emergency services, and other organizations have published reports on their experiences in POD planning, training, and exercises. Summarized below are the assumptions, constraints, and results from these exercises.

Public health agencies in Massachusetts, Pennsylvania, Washington, Oregon, and New York have performed walk-in clinics (Koh et al., 2008; Agócs et al., 2007; Stergachis et al., 2007; Spitzer et al., 2007; Rinchiuso-Hasselmann et al., 2011). Three out of five exercises utilized the HoH dispensing method (Koh et al., 2008; Agócs et al., 2007; Stergachis et al., 2007). The remaining exercises dispensed vaccinations, which must be administered by a health professional to each individual (Spitzer et al., 2007; Rinchiuso-Hasselmann et al., 2011). Health organizations and first responders in Hawaii, Washington, New Mexico, and Kentucky held drive-through POD exercises (Zerwekh et al., 2007; Reid, 2010; Banks et al., 2013; Carrico et al., 2012). Only Hawaii utilized a HoH method, although it was not explicitly named as such (Zerwekh et al., 2007). The other three exercises administered influenza vaccines (Reid, 2010; Banks et al., 2013; Carrico et al., 2012).

The layout of each exercise was different, incorporating local needs, resources, and capacity constraints. Waiting times, service times, and throughput rates depended on POD set-up, staffing, and resource availability. For each exercise, the initial throughput rate assumption was a function of target population size and time the POD was operational. Throughput rate assumptions ranged from 360-1000 people per hour. Information collected from drills included observed throughput rates, service times, queue lengths, and wait times, which vary depending on location, staffing resources, and demand.

There are several limitations of the information learned from these exercises and drills. Several reports recognized that field exercises might not accurately represent emergency mass dispensing events (Agócs et al. 2007; Banks et al, 2013; Stergachis et al., 2007). Because vaccination clinics were voluntary, the throughput rates may not accurately reflect the true throughput capacity of each drive-through (Banks et al., 2013). In at least one case, the POD never reached full capacity, and therefore POD operations were never pushed to the limit of their capabilities (Stergachis et al., 2007). Despite these limitations, field tests can still provide valuable insights into the operational challenges for PODs. Rinchiuso-Hasselmann et al. (2011) asserted that while the lessons resulted from small-scale clinics, there are implications for larger-scale operations.

For walk-in clinics, recommended improvements related to the dispensing process, POD layout, staffing resources, operations and control, and prior and just-in-time training. Analysis of one exercise revealed that the patient arrival rate did not follow a stationary Poisson process (Spitzer et al., 2007). Typically, POD planners assume a stationary, uniform rate for patient arrivals (Baccam et al., 2011). A nonstationary arrival rate could have a large impact on both internal and external processes of a POD. Only one walk-in clinic exercise noted that issues outside of the

POD should be considered (Koh et al., 2008). A limitation of walk-in clinic exercises is the focus on internal POD process improvements. POD exercises represent the opportunity to examine and respond to external challenges in addition to internal challenges.

The drive-through clinics experienced several limitations and lessons related to public communication and traffic control. Post-exercise discussion of the Hawaiian POD revealed that drivers were confused by traffic flow patterns (Zerwekh et al., 2007). Reid (2010) acknowledged that traffic control, thinly spread security, and traffic due to queuing were limitations. Future exercises should incorporate clearer signage and increased traffic guidance. The Washington clinic only administered 250 vaccine doses at their first exercise, due to a restricted priority group, poor weather, and limited advertisement and public awareness (Reid, 2010). For their second clinic, a long queue developed before the clinic opened. For the first clinic in New Mexico, many vehicles arrived up to two hours before operations began, causing the waiting times to be longer (Banks et al., 2013). Banks et al. (2013) note that while routine clinics focus on limiting transportation effects on the public, “these concerns would be significantly different during a public health emergency or disaster and would result in different techniques for processing” (p. 180). Concerns during an emergency should focus on how transportation affects a POD’s efficiency in addition to how POD traffic affects the rest of the network’s mobility.

2.2.2 POD Models

Decision support tools help emergency managers plan for POD events. Some emergency planners utilize mathematical models to simulate, optimize, and evaluate aspects of mass dispensing events, such as staffing levels, location, and layout. The

Bioterrorism and Epidemic Outbreak Response Model, the Dynamic POD Simulator, the University of Maryland's Clinic Planning Model Generator, and an optimization model by Hernandez et al. (2015) are decision support tools that determine staffing levels and POD performance based on staffing constraints, patient flow and queueing, and layout (Hupert et al., 2009; Hernandez et al. 2015). The RealOpt model, created by Lee et al. (2009), is a decision-support software suite that models decisions about POD location, floor plans, and resource and staff allocation. In addition, RealOpt performs disease propagation analysis, investigates alternative dispensing strategies, and provides personnel training. Models by Gupta et al. (2013) and Ramirez-Nafarrate et al. (2015) optimize POD location, capacity, and layout for drive-through PODs, and can be used in conjunction with RealOpt. The inputs and outputs vary for each of these models based on their functional uses.

There are several advantages when using models during the planning process. By creating flexible, scalable, real-time tools, public health officials may overcome the challenges of making time-sensitive decisions during biological outbreaks. Users may customize input parameters based on factors like available staff, number of POD locations, and target population. These models are scalable to communities of different sizes (Gupta et al., 2013; Lee et al., 2009). Developers have validated these models using results from key operations of past clinical experience (Gupta et al., 2013; Lee et al., 2009; Hernandez et al., 2015). The greatest contribution of such models is the balance between using simulation and optimization to produce results quickly. However, there exists a trade-off between the computational time and precision of a simulation-optimization model (Lee et al., 2009). To receive the most accurate and precise solution, a model needs to portray external and internal processes realistically.

Programming a detailed, realistic simulation takes time that emergency planners may not have during a biological outbreak. A more detailed simulation requires more computation time, limiting the number of optimization iterations. A less realistic scenario computes faster, but may not have the level of detail and accuracy required to provide an optimal solution. Lee et al. (2009) claim that simulation-optimization models are a big challenge for emergency planners.

There are other potential drawbacks for these models as well. Although scientists and researchers create these models, public health officials and emergency managers use them. It is important for the user interface to be intuitive, instructive, and easy to run. Emergency managers may not understand the internal processes and inherent uncertainty within models, and thus misinterpret results as factual. Another limitation is the scope of the models. For example, Lee et al. (2009) did not demonstrate whether the RealOpt model could adapt to extremely unusual circumstances, which may potentially limit its flexibility. RealOpt and the Dynamic POD Simulator may only be used for walk-in PODs (Lee et al., 2009; Hupert et al., 2009), while the models created by Gupta et al. (2013) and Ramirez-Nafarrate et al. (2015) are explicitly for drive-through PODs. Despite these disadvantages, models provide useful decision support when planning, analyzing, and implementing POD operations.

None of the aforementioned models considers the effects of external transportation processes on a POD’s efficiency. Currently, only two publications have examined the effects of transportation (Baccam et al., 2011; Ma et al., 2011). These two publications are reviewed in the following subsection.

2.2.3 Transportation Related Models

Two publications by Baccam et al. (2011) and Ma et al. (2011) have examined external impacts of POD operations at the microscopic level. These studies consider queueing, total process time, POD utilization rate, and congestion. Ma et al. (2011) developed a demand and supply model to examine impacts on a specific POD location due to limited parking, congested roadways, and nonstationary arrival rates. The road network, developed in PTV Vissim, includes all access points to the POD and key intersections immediately surrounding the POD (Ma et al., 2011). Performance measures for the Vissim model include average and maximum waiting times, parking lot queue lengths, dispensing queue lengths, delays, total person-hours of waiting, percentage of time that parking lots are at capacity, and POD inbound and outbound volumes (Ma et al., 2011). In a complementary study, Baccam et al. (2011) examined how traffic flow, nonstationary arrival rates, and parking capacity affect POD utilization rates using Monte Carlo simulation (twenty iterations) in Visual Basic Applications for Microsoft Excel. Performance measures included total process time, number of vehicles in the parking lot, and queue lengths waiting to park (Baccam et al., 2011).

The same six arrival rates are used in both publications, based on work by Whitworth (2005), Hupert et al. (2009), Lindell and Prater (2007), and Morrow and Gladwin (2005) (Ma et al., 2011; Baccam et al., 2011). Baccam et al. (2011) and Ma et al. (2011) used a Poisson process to distribute the arrival patterns within each hour. The six arrival rates are shown in Figure 1 as the percent of patients arriving at a POD over 24 hours.

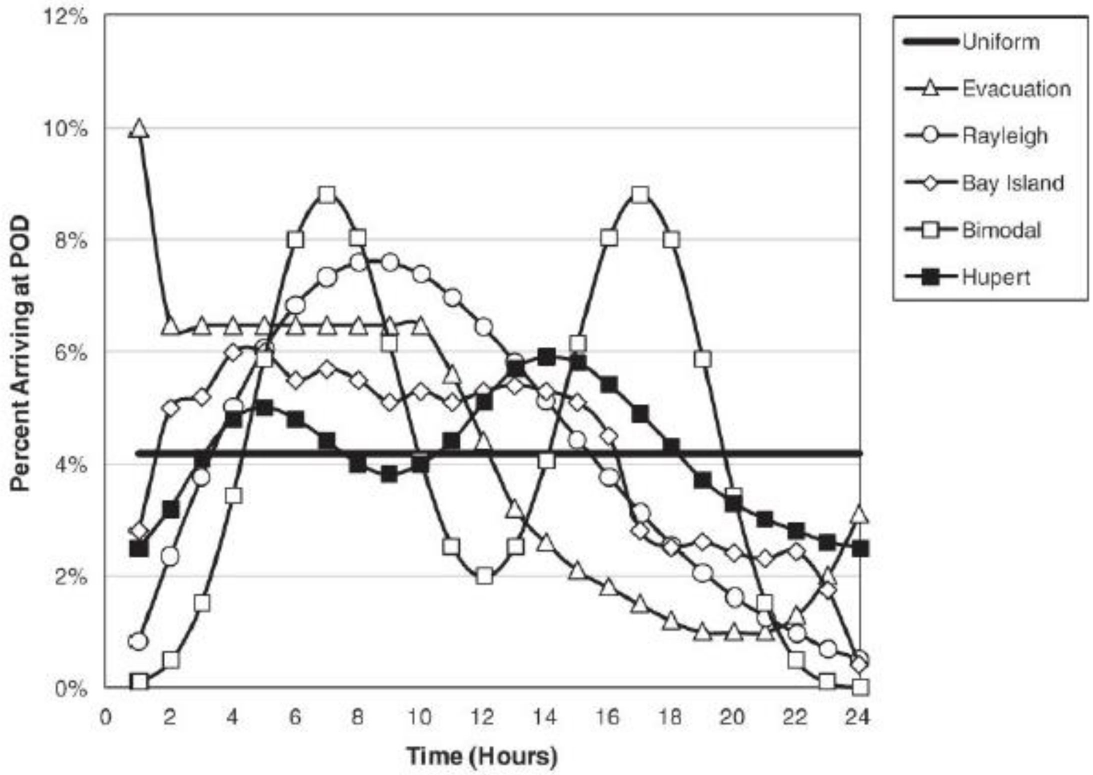

Figure 1: POD Arrival Rates (Baccam et al., 2011, p. 141)

The five nonstationary arrival rates include:

- "An evacuation rate based on observations prior to Hurricane Ivan in 2004;
- A Rayleigh distribution, which has been used to describe hurricane evacuation times;
- A distribution approximation of arrival rates in a hypothetical "Bay Island" POD study;
- A bimodal distribution based on a binomial function;
- An approximation of a bimodal arrival rate used in a study by Hupert and colleagues." (Baccam et al., 2011, p. 141-142)

There are several motivations for these two publications. The first is emergency planners' underlying assumption of a stationary, uniform arrival rate during the dispensing period. In reality, the public arrive randomly, which the authors consider "a concern, especially if it results in underuse of POD staff and lower throughput rates than planned" (Baccam et al., 2011, p. 140). Results from case studies demonstrated that total process time in a POD was much greater for nonstationary arrival rates, causing long waiting times and lengthy queues (Baccam et al., 2011; Ma et al., 2011). Secondly, Baccam et al. (2012) suggest that the POD process itself can affect parking availability and generate congestion, with increased service times creating longer queues and waiting times. The third motivation comes from the limited supply of parking spaces at a POD location, which limits the number of people who can arrive and enter the POD at a given time. In the case studied by Baccam et al. (2011), the number of parking spaces greatly influenced queue length and congestion on the road network outside of the POD.

Ma et al. (2011) and Baccam et al. (2011) emphasize the importance of integrating the medical process with transportation problems to analyze the POD process accurately. Baccam et al. (2011) conclude that "nonstationary arrival rates to the PODs will likely cause traffic challenges outside of the PODs and should receive increased attention from planners" (p. 147). These challenges included long queues to enter a POD, long queues to enter parking lots, and increased traffic congestion on the surrounding road network. Baccam et al. (2011) urge planners to consider pedestrian access, accessibility to mass transit, and parking availability when choosing a POD location. Congestion mitigation strategies include signs, barriers, and traffic control officers to guide vehicle and pedestrian traffic, indicate entry/exit points and queueing areas, and facilitate flow at surrounding intersections (Baccam et al,. 2011). Increasing available parking may reduce traffic congestion on the road network. Another alternative is to provide shuttles from satellite parking lots.

There are several disadvantages about the assumptions in these two models. The model assumes a first-in-first-out service rate between stages, which may not be the case for different interest groups (people with special needs versus families versus single individuals). The models simplifies the internal dispensing process (Ma et al., 2011). Additionally, staffing levels, service times, and service rates are fixed. These conditions may not accurately reflect POD processes during operation. Ma et al. (2011) assume a HoH dispensing method, which may only be used to administer medications, not vaccinations. Dispensing vaccinations would create a lower throughput rate and potentially increase waiting times. Baccam et al. (2011) note that there is no dynamic interaction between traffic congestion and the arrival of additional vehicles. In reality, congestion on the network surrounding the POD would prevent additional vehicles from arriving. Lastly, these studies have a very limited scope, focusing on a small study area around the POD. The microscopic analyses provide evidence that external impacts exist immediately surrounding the POD. However, no larger, regional analysis is performed to see how the congestion spreads throughout the network.

2.3 Relevant Methodologies

2.3.1 Travel Demand Forecast Model

To understand traffic impacts on a transportation network, transportation planners may utilize a demand forecast model. A travel demand model is a computer model that forecasts travel demand and behavior based on assumptions. Most commonly used is the four-step travel model, which consists of trip generation, trip distribution, mode choice, and route assignment (Garber & Hoel, 2009). First, the study region is separated into traffic analysis zones (TAZs), which have the following characteristics: similar socioeconomic features; similarly sized populations; few trips between zones; and composed of census tract, physical, political, and historical boundaries if possible (Garber & Hoel, 2009). Each TAZ features a centroid node that contains employment, socioeconomic, and other demographic information.

For trip generation, planners determine the number of trips that begin or end in each TAZ. These trips are grouped by purpose, such as work-based trips or home-based trips. Next, the generated trips are distributed within and outside of the study region. Internal trips begin and end in a TAZ. Internal-external trips begin or end outside of the study area. One method for trip distribution is the gravity model, which utilizes transportation system, land-use, and socioeconomic characteristics to distribute trips. Once the trips are distributed, the model determines the proportion of trips made by available transportation modes, such as personal vehicle or mass transit. Mode choices are based on travel times, socioeconomic factors, and availability.

At this point, transportation planners know how many trips occur, mode of transportation, and where the trips begin and end. The last step determines the routes used by these modes on these trips. Trip assignment is an iterative process that redistributes traffic based on road capacity, posted speed limits, travel times, and route availability. Trip assignment produces the expected traffic volumes on all roads across the network. Once the four steps have been completed, the model produces evaluative metrics of the traffic impacts. Evaluative metrics include volume to capacity ratio, level of service, and travel times.

In the following subsections, I review several case studies that utilize a travel demand model to analyze network-level impacts in Citilabs Cube. Cube is a software platform for travel demand forecast modeling. Within Cube, a gravity model completes an origin-destination matrix, which is a table indicating how many trips travel between two locations for all location pairs within the network (Patterson, 2013). The model then utilizes the four-step travel model to assign these trips to the network and output travel times for each road segment (Patterson, 2013).

2.3.2 Analysis of Complete Streets using Cube

The first case study examines the impacts of complete street policies in Cube. A "complete street" integrates pedestrian, cyclist, transit, and vehicle uses safely into one road (Patterson, 2013). Patterson (2013) considers the effect of implementing complete street strategies on the transportation network in Smyrna, Delaware. The model of Smyrna and the Delmarva Peninsula was provided by the Delaware Department of Transportation. Smyrna is modeled at the tax parcel level, while the surrounding area is modeled in TAZs (Patterson, 2013). Outputs include "daily volumes, volume to capacity ratios for the peak AM period, and travel times for the AM, PM, and midday peak periods, and for the off peak period" (Patterson, 2013, p. 73). Delay and emissions impacts are quantified by travel time changes across the entire network.

Patterson's model has several differences from the POD model. In Patterson's analysis of complete streets, road capacities are varied while volumes across the network remain constant. These capacity variations simulate the implementation of various "complete street" tactics. Oppositely, in the analysis of POD operations, road capacities will remain constant while volumes are varied over a 24-hour period. The analysis performed by Patterson (2013) demonstrates the flexibility and innovation of using the Cube travel demand model for nontraditional purposes.

2.3.3 DelDOT Statewide Evacuation Model

The Delaware Department of Transportation (DelDOT) utilizes a statewide travel demand model, called the Peninsula Model, in Cube Voyager (Thompson-Graves et al., 2007). As a part of their Peninsula Model, DelDOT has created a Statewide Evacuation Model, which utilizes road capacity, behavioral, policy, and operational assumptions, and their iterative traffic assignment process to model hourly evacuation impacts (Thompson-Graves et al., 2007). Behavior assumptions include the rate of evacuation, compliance, population size, and evacuation destinations (Thompson-Graves et al., 2007). Policy assumptions include determining when to declare an evacuation or a state of emergency for specific areas (Thompson-Graves et al., 2007). The evacuation assignment is an iterative, hourly process that assigns evacuation trips and background traffic to the network, determines operating capacity and demand, and assigns spillover trips to the subsequent hour when volume exceeds road capacity (A. Tracy, personal communication, February 24, 2016). The model has a thirty-hour evacuation period. This model is the base for the POD Traffic Impact Model for this thesis.

2.3.4 Accessibility-Based Network Vulnerability Analysis

A case study by Taylor (2008) proposes an alternative performance measure to the more traditional delay, travel time, volume to capacity ratio, level of service, and emissions used in travel demand models. The methodology identifies vulnerabilities in the transportation network using Cube Voyager. The case study examines the impacts of congestion “hot spots” in the network in terms of accessibility (Taylor, 2008). In this context, accessibility is based on three factors: traveler, transport system, and land use (Taylor, 2008). Accessibility may be considered both as the ease of access of point X from point Y and as the overall accessibility level of the study region.

The framework considers time of day, mode of transportation, and origin-destination trips. Accessibility is measured by social welfare costs, called “CS,” which is “the benefit … that an individual receives from a consumption choice situation” (Taylor, 2008, p. 599). Accessibility of individual locations can be aggregated into an overall accessibility level for the network. The largest drawback is the unit of study for the model. The case study divides the study area in statistical local areas, the next size above TAZs. To break these areas into smaller zones would greatly increase computational time for the model. Statistical local areas provide only a very broad representation of a town or neighborhood, and thus may exclude many local roads, intersections, and key features. An accessibility analysis at this scope may not accurately identify vulnerabilities or congestion spots within the network. Notwithstanding the method’s broad scope, the accessibility metric has the potential in future work to provide an alternative network performance metric that reflects human costs instead of vehicle impacts.

2.4 Summary of Relevant Literature

Table 2 provides a summary of the relevant literature focusing on the concepts, data, and models that are used to answer the research questions posed in Chapter 1.

Table 2: Summary of Relevant Literature

Area	Summary	Sources
Concepts	PODs dispense MCMs to population during a public health emergency	Hupert et al., 2004; Emergency Management Institute, 2008
	PODs should dispense oral antibiotics to population within 48 hours of an anthrax release	Whitworth, 2005; Ma et al., 2011
	Coordination between public health and transportation agencies is assumed in plans, but not formally written	EMI, 2008; DPH, 2008a; DPH, 2008b
	Potential transportation issues include insufficient parking, entry point bottlenecks, and congestion due to queueing	Whitworth, 2005; Reid, 2010; Ma et al., 2011; Baccam et al., 2011
POD Configurations	Open PODs dispense MCMS to general population	Rebmann et al., 2015
	An organization operates a closed POD for all employees and their families	Rebmann et al. 2014
	A head of household method allows 1 member to pick up MCMs for entire household	Agócs et al., 2007
	In walk-in clinics, patients park and walk through POD set-up	Koh et al., 2008; Agócs et al., 2007; Stergachis et al., 2007; Spitzer et al., 2007; Rinchiuso-Hasselmann et al., 2011
	Drive-through clinics allow patients to remain in vehicle for entire process	Zerwekh et al., 2007; Reid, 2010; Banks et al., 2013; Carrico et al., 2012

Table 2, continued

Area	Summary	Sources
Data	Federal initiatives, standards, and roles are provided by the Cities Readiness Initiative, CDC, FEMA, and NCHRP	"Cities Readiness Initiative," 2010; Nelson et al., 2008, CDC, 2008; EMI, 2008; Friedman et al., 2006
	Delaware's Division of Public Health assumes a processing rate of 1000-2000 people per hour for medications and up to 600 people per hour for vaccinations	DPH, 2008b
	Throughput rates, service times, and arrival patterns vary in real-time exercises	Koh et al., 2008; Agócs et al., 2007; Stergachis et al., 2007; Spitzer et al., 2007; Rinchiuso-Hasselmann et al., 2011; Zerwekh et al., 2007; Reid, 2010; Banks et al., 2013; Carrico et al., 2012
	Nonstationary patient arrival rates may be more realistic than a uniform arrival pattern	Baccam et al., 2011; Ma et al., 2011

Table 2, continued

Area	Summary	Sources
Tools	Many simulation-optimization models evaluate internal POD characteristics such as location, layout, and staffing	Hupert et al., 2009; Hernandez et al., 2015; Gupta et al., 2013; Ramirez-Nafarrate et al., 2015; Lee et al., 2009
	A microscopic-level traffic simulation in PTV Vissim models POD impacts due to traffic and parking	Ma et al., 2011
	A Monte Carlo simulation in Microsoft Excel examines POD utilization rates based on nonstationary patient arrival rates	Baccam et al., 2011
	Travel demand forecast models provide a regional analysis of traffic impacts	Garber & Hoel, 2009; Patterson, 2013; Thompson-Graves et al., 2007
Performance Measures	Average and maximum waiting times, parking lot queue lengths, dispensing queue lengths, delays, total person-hours of waiting, percentage of time that parking lots are at capacity, and POD inbound and outbound volumes	Ma et al., 2011
	Total process time, number of vehicles in the parking lot, and queue lengths waiting to park	Baccam et al. 2011
	Volume to capacity ratio, level of service, travel times	Garber & Hoel, 2009; Patterson, 2013
	Delay and emissions impacts	Patterson, 2013
	Overall accessibility level of a transportation network, calculated through social welfare costs	Taylor, 2008

Chapter 3

METHODOLOGY

3.1 Introduction

This chapter describes the general methodology used for the thesis. The POD Traffic Impact Model forecasts hourly traffic demand on the Delmarva Peninsula during a public health response to a large-scale biological outbreak. The model, adapted from the DelDOT's evacuation model, consists of the transportation network, the four-step method, and scenarios. Several model scenarios are tested, in which residential patient arrival patterns are varied. There are two sets of performance measures for the model. Network performance measures describe hourly background, evacuation (in this case traffic going to and from the POD), and spillover traffic volumes. POD performance measures indicate patient arrival and processing rates, waiting times, and queue lengths. Lastly, sources for the data used in the methodology are provided.

3.2 POD Traffic Impact Model

The POD Traffic Impact Model (POD TIM) used for this methodology is a modified and enhanced travel demand forecast model created in Citilabs Cube Voyager. Whereas a typical travel demand model predicts network usage as a function of behavior, the POD TIM examines the impacts of the network's usage during POD operations. The POD TIM does not model individual trip generation or behavior, but instead makes broad assumptions about these factors. In addition, a traditional travel demand model predicts network usage for peak and off-peak periods. The POD TIM analyzes traffic impacts in one hour increments.

The network base of the model is the Delaware Department of Transportation's Peninsula Model, which consists of the Delmarva Peninsula including Delaware and the eastern shore of Maryland (see Figure 2 below) (Patterson, 2009). The model uses the four step method (trip generation, trip distribution, mode choice, and route assignment), real-time traffic data, and a calibration process to accurately forecast travel demand across the regional transportation network (Garber & Hoel, 2009; Thompson-Graves et al., 2007). The Peninsula Model is broken into TAZs, with the case study area modeled at the census block level. The POD TIM builds upon the framework of DelDOT's Statewide Evacuation Model. The Statewide Evacuation Model utilizes road capacity and characteristics, an iterative traffic assignment process, and behavioral, policy, and operational assumptions to model hourly evacuation traffic and delay. In the Statewide Evacuation Model, traffic is assigned to destination zones outside of the study region. The POD TIM alters the destination zones to be POD locations and adds a patient processing sub-model. Unlike evacuation traffic that remains at the destination zones, POD patient traffic returns to work or home after being processed at PODs.

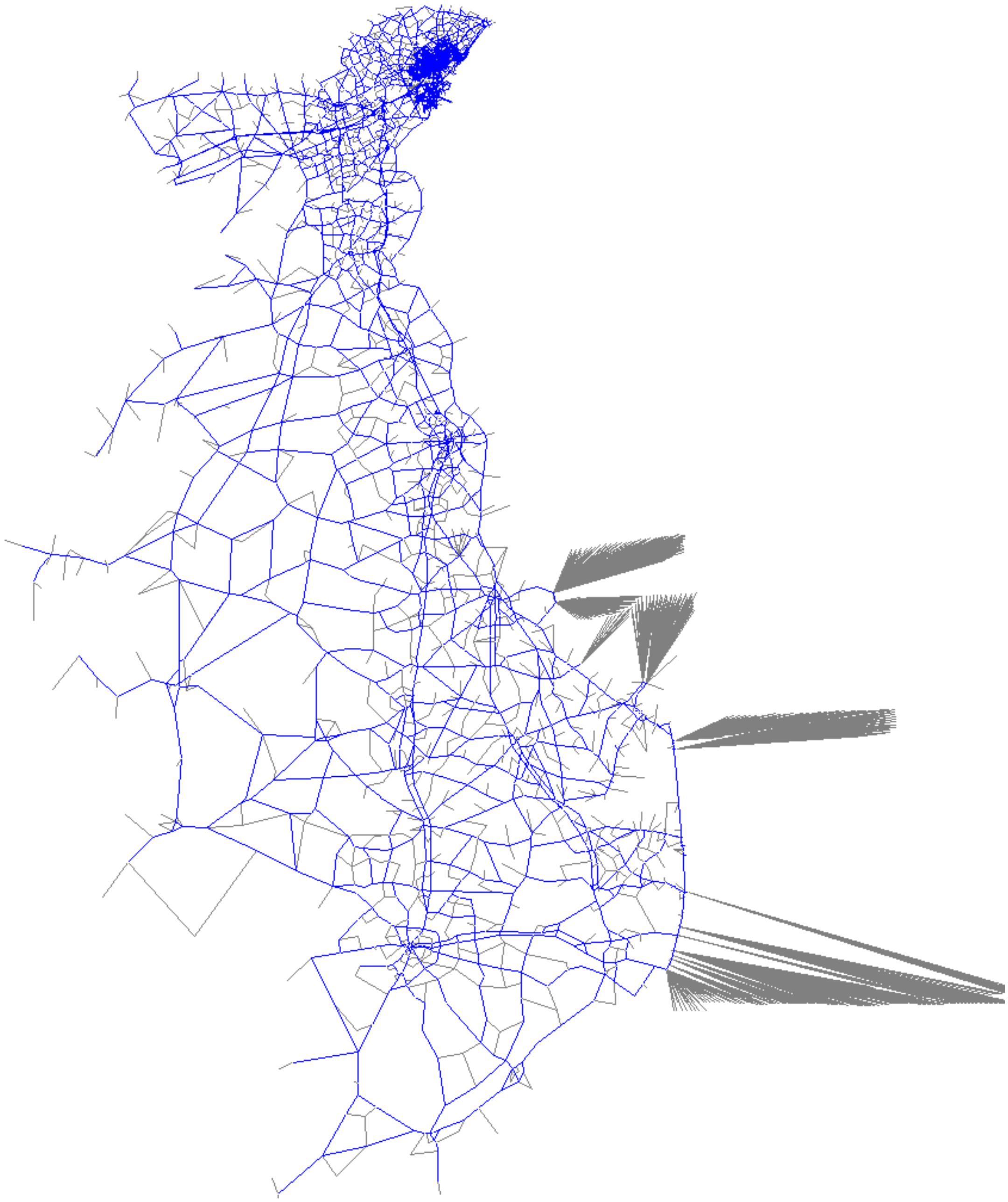

Figure 2: The Delaware Department of Transportation's Peninsula Model Road Network, in Citilabs Cube

The POD TIM operates similarly to the Statewide Evacuation Model, with an hourly, iterative trip assignment process. The POD TIM assigns POD and background traffic to the network, determines road operating capacity and demand, and assigns excess traffic to subsequent hours. Inputs include POD patient arrival patterns, POD "destination" zones, population "evacuation" zones, and compliance rate. Each input scenario is run once, as the model assumes the results are for an "average day" (A. Tracy, personal communication, February 25, 2016). The model has the capability to restrict vehicle traffic in the network with a "state of emergency" setting. POD locations are modeled as TAZs with a link connector to the network. Once patients arrive at a POD, they park, exit their vehicles, and queue to enter the POD. The PODs have fixed hourly processing rates and operate for a continuous 24 hours. However, the underlying evacuation model has a 30-hour traffic assignment period, in which all hours must have a nonzero arrival rate. A small percentage of the population (less than 1%) may arrive at the PODs after "closing." After a POD has "closed," it will continue to process patients until its queue dissipates. The model assumes that all traffic is vehicular. Pedestrian, mass transit, and other modes of transportation are not considered explicitly.

The PODs service two distinct populations within the model. For both groups, the decision of which POD to go to is proximity-based. The first group are home-based work trips for people who live outside of the case study area. These people work within the study region, may be exposed to contaminants, and therefore are required to go to the PODs. I call this group "non-resident workers." Because non-resident workers enter and exit the study region twice daily, they are most likely to go to a POD on their way to or from work. In this model, all non-resident workers stop at a

POD on their way from home to work. The decision of which POD location to go to is based on the smallest combined total travel time for the two legs of the commute: home to POD and POD to work. Thus, the POD that causes the smallest addition in commute will be chosen.

The second group are residents who live within the study area, whom I call “residents.” This population group includes adults, children, seniors, and persons with disabilities. All residents within the case study region are required (notwithstanding the compliance rate) to go to a POD. Residents may work within the study region, but will only attend PODs once as residents. Residents go to the POD closest to their homes. It is assumed that residents will travel to PODs from home, with one vehicle per household, and return to home afterwards. Households without vehicles use transit and arrive the same hour as the households with vehicles. At the POD, each vehicle break ups into the number of patients within each household for POD processing. In the case study, several resident arrival patterns are considered during POD operations.

3.3 Model Process and Scenarios

The POD TIM consists of three aspects: the base network, the four-step method, and scenarios. The base network for the POD TIM is the Peninsula Model, seen above in Figure 2. The Peninsula Model is a series of nodes, which represent road intersections and other network features, and links, the road segments that connect nodes. The base network is a catalog of physical road infrastructure characteristics, such as number of lanes, length and width, capacity, and traffic volumes. The network is broken into traffic analysis zones (TAZs) that contain demographic data for homogenous population areas. The case study area is divided into census blocks, in which all city-block level streets are modeled as links in the network.

The core of the model is the four-step process: trip generation, trip distribution, mode choice, and route assignment. The model first performs this process to background trips, applying an "hour of day factor" to derive hourly background trips. Background trips, separated from non-resident worker trips that must travel to PODs, are assigned to the network. The model then generates POD trips. The non-resident worker POD trips are derived using the "hour of day factor" also. POD destinations are chosen for non-resident workers based on combined travel time from home to the POD and from the POD to work. For residents, the model first processes demographic data to collect population per household and households with vehicles. Assuming one vehicle trip per household, the model applies the patient arrival curve to obtain hourly vehicle and population trips. POD destination choice for residents is based on proximity to home. POD locations are modeled as TAZs with a link connector to the network. Once vehicles arrive at a POD, they park, exit their vehicles, and queue to enter the POD. The model utilizes a POD Release Process sub-model to determine in which hour patients are released back into the network. A capacity constrained assignment process determines spillover traffic into subsequent hours.

The model may run different scenarios. For the POD TIM, the following factors are adjustable: patient arrival pattern, beginning arrival time, at what time POD operations begin, POD locations, affected population, compliance rate, and state of emergency. Each input scenario is run once, as the model assumes the results are for an "average day." For this thesis, patient arrival pattern is the only varied input.

3.4 Patient Arrival Scenarios

The methodology consists of five resident patient arrival scenarios. The scenarios utilize different, hourly patient arrival patterns to understand potential traffic impacts on the network due to varying patient behavior. The arrival curves only pertain to Wilmington residents. Non-resident workers arrive at PODs on their way to work from home, continuing to work afterwards. The five arrival curves used for residential arrivals are based on studies performed by Baccam et al. (2011) and Ma et al. (2011). The first rate is a uniform, stationary rate. The remaining four rates are non-uniform, non-stationary rates. The five rates, shown in Figure 3f below, are a uniform, dual uniform, AM and PM rush hour peaks, a PM rush hour peak, and a midday peak. Hourly arrival percentages of the total population for each arrival scenario are provided in Appendix B.

The uniform, stationary arrival rate reflects many POD planners' implicit assumptions that the public will arrive at the POD at a constant rate throughout operations (Ma et al., 2011). The uniform arrival curve is the base line for comparison with other POD arrival rates (see Figure 3a below).

The second arrival rate is a dual uniform rate, in which a higher, uniform percentage of patients will arrive during daytime hours between 8 AM and 8 PM (see Figure 3b). A much lower, stationary percentage of patients will arrive throughout nighttime hours (9 PM to 8 AM). The dual uniform arrival rate is based on the assumption that there will be significantly more arrivals during daytime hours than nighttime (Ma et al., 2011; Whitworth, 2005).

The third arrival rate reflects the typical weekday pattern of peak traffic during AM and PM rush hours (7-9 AM and 4-6 PM) (see Figure 3c). This scenario reflects a majority of vehicles stopping at PODs as a part of their work commute.

The fourth arrival rate is an adjusted rush hour pattern, in which the PM peak (4-8 PM) is much greater than the AM peak (see Figure 3d). This curve may reflect a pattern in which more residents go to PODs after work.

The fifth arrival rate is a midday peak (10 AM – 2 PM) (Figure 3e). The midday peak may reflect a weekend day of POD operations, a state holiday, or a declared state of emergency.

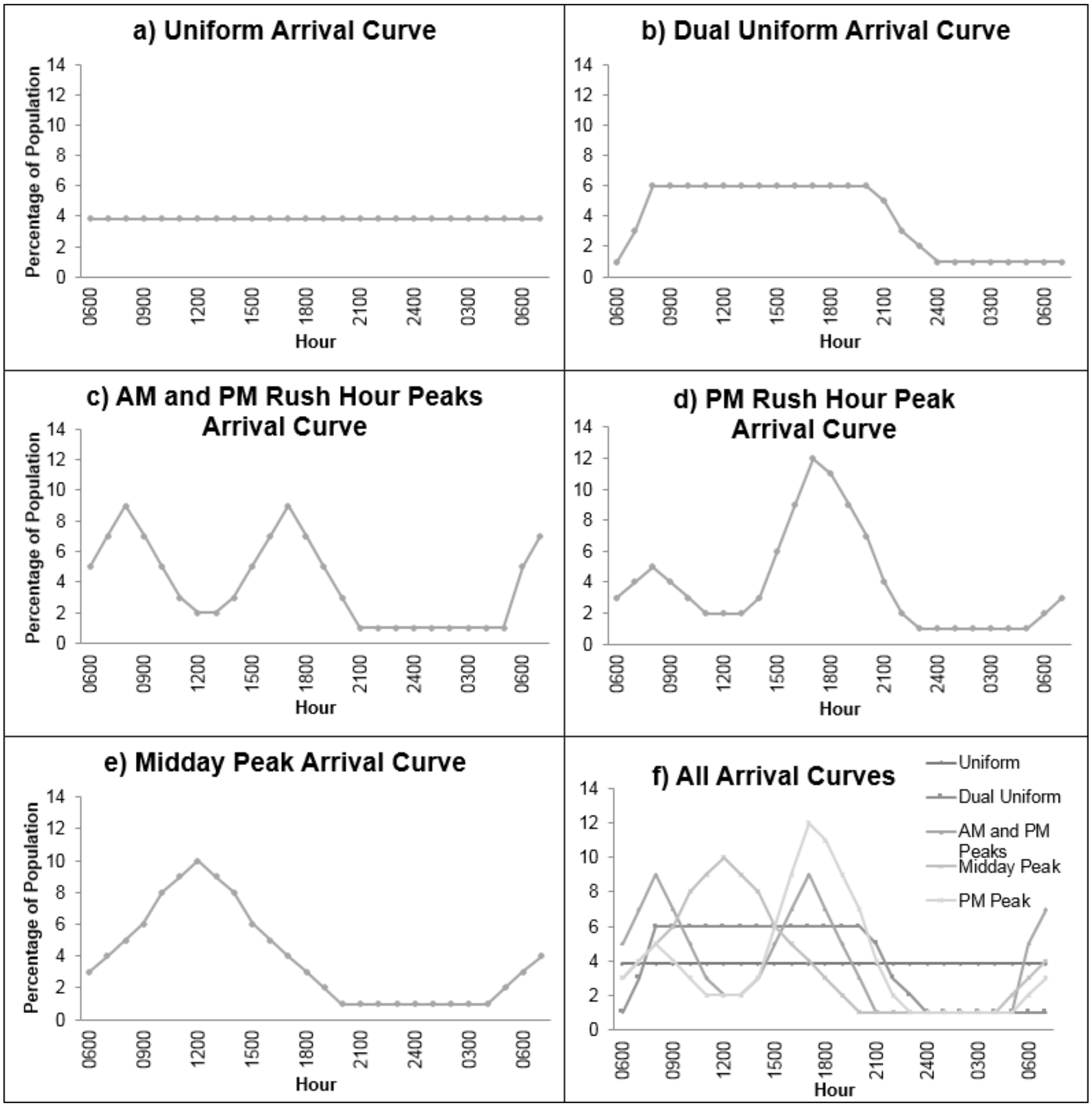

Figure 3a-f: Arrival Curve Scenarios of Percentages of Hourly Patient Arrivals at PODs

3.5 Measures of Effectiveness

The POD TIM outputs two sets of measures of effectiveness (MOEs). A summary of the measures of effectiveness are provided in Table 3 below. Network MOEs describe the hourly conditions of the transportation network and traffic. Each link in the network outputs a capacity, background volume, evacuation volume, spillover, and volume to capacity ratio for each direction for each hour. The capacity is the maximum hourly traffic volume per lane that can pass through a road segment. Capacity constraints are set within the model and do not change hourly. Background volume is all trip demand within the network not related to PODs. Evacuation volume is the non-resident worker and resident trip demand to and from POD locations. For both background and evacuation volumes, these values represent the traffic that wants to use the road for a given hour. However, due to capacity constraints, not all of this traffic may make it through the network within that hour, resulting in spillover traffic that overflows into the following hour. The volume to capacity (V/C) ratio summarizes link demand and traffic flow on a scale of 0-1. Low V/C ratios indicate healthy traffic flow, while values close to or above one indicates traffic resembling gridlock.

The second set of MOEs are POD MOEs, which describe the hourly internal process for each POD location. MOEs include patient spillover from the previous hour, new arrivals, hourly processing rate, and patient spillover to the following hour. Similar to spillover traffic demand, patients that are not processed for a given hour will be pushed to the next hour. The MOEs also calculate the number of hours that people will wait in the queue, up to the current hour. Queue lengths vary hourly based on patient arrivals, processing, and spillover. From these MOEs, I calculate maximum delay, average delay, average queue length, and maximum queue length. This information determines when the worst and best times to arrive are. For this analysis, I choose delay and V/C metrics over the social costs suggested by Taylor (2008) because it is important to understand first the technical impacts of PODs. I must understand how the network handles a large-scale emergency response before considering how the congestion may impact people socially. From these MOEs, I shall better understand the regional impacts of POD operations.

Table 3: Descriptions of Model Measures of Effectiveness

Measure of Effectiveness	Description
Network	**Hourly conditions of transportation network and traffic**
Capacity	Maximum hourly traffic volume per lane that can reasonable pass through a road segment
Background volume	Trip demand within network not related to PODs
Evacuation volume	Non-resident worker and resident trip demand to and from PODs
Spillover volume	Traffic demand that cannot be met in a given hour due to capacity constraints, resulting in traffic pushed into the following hour
Volume to capacity ratio (V/C)	Summary of link demand and traffic flow. Anything greater than 1 represents gridlock
POD	**Hourly internal processes of each POD location**
Patient spillover from previous hour	Patients who arrived in a prior hour but have not been processed yet, in queue
New arrivals	Patients who arrive in the current hour
Processing rate	Number of patients processed per hour per location
Patient spillover to next hour	Patients from prior and current hours that are not processed in current hour, pushed into next hour
Hourly average queue	Up to current hour’s arrivals, the average number of hours a patient will wait in line to be processed
Maximum delay	Maximum number of hours spent in queue, over entire operational period
Average delay	Average number of hours spent in queue, over entire operational period
Maximum queue length	Maximum number of people waiting in line at POD, over entire operational period
Average queue length	Average number of people waiting in line at POD, over entire operational period
Worst time to arrive	The worst time to arrive at a POD location, based on maximum delay

3.6 Data Sources

The data used in this methodology come from a variety of census, transportation, and public health sources, seen in Table 4: Data Sources below.

Table 4: Data Sources

Data	**Source**
Arrival rates	Baccam et al. 2011; Ma et al. 2011
Peninsula Model and background traffic data	Provided by DelDOT
POD Traffic Impact Model (POD TIM)	Created by DelDOT and WRA
Wilmington census data	U.S. Census Bureau 2015a; 2015b
Throughput rates	DPH 2008b

Chapter 4

CASE STUDY

4.1 Wilmington, Delaware

To demonstrate the feasibility of this methodology, I chose the city of Wilmington, Delaware as a case study. Wilmington is located on the Delaware and Christina Rivers in New Castle County. Washington D.C., Baltimore, Philadelphia, and New York City are located within a three-hour radius of Wilmington, accessible by Interstate 95, which bisects the city. Downtown Wilmington is a dense grid pattern of intersecting streets with limited parking. The Amtrak Station sits on the Christina River, at the mouth to Wilmington's latest development area called the Riverfront. Many Fortune 500 companies are headquartered within Wilmington, making it a large corporate hotspot ("About the City of Wilmington," 2016). In addition to its residential population of 72,000, over 40,000 people enter the city for employment daily ("About the City of Wilmington," 2016). The case study area is determined by the boundaries of the city of Wilmington (see Figure 4), except in the south where the study area extends to Interstate 295. The study area is bounded by the Delaware River to the east. A 1-2 mile buffer zone beyond these boundaries is included to capture the relevant network. The study area including the buffer zone are modeled at the census block level as shown in Figure 5. All surrounding areas are modeled as TAZs in the Peninsula Model (see Figure 2 in Section 3.2).

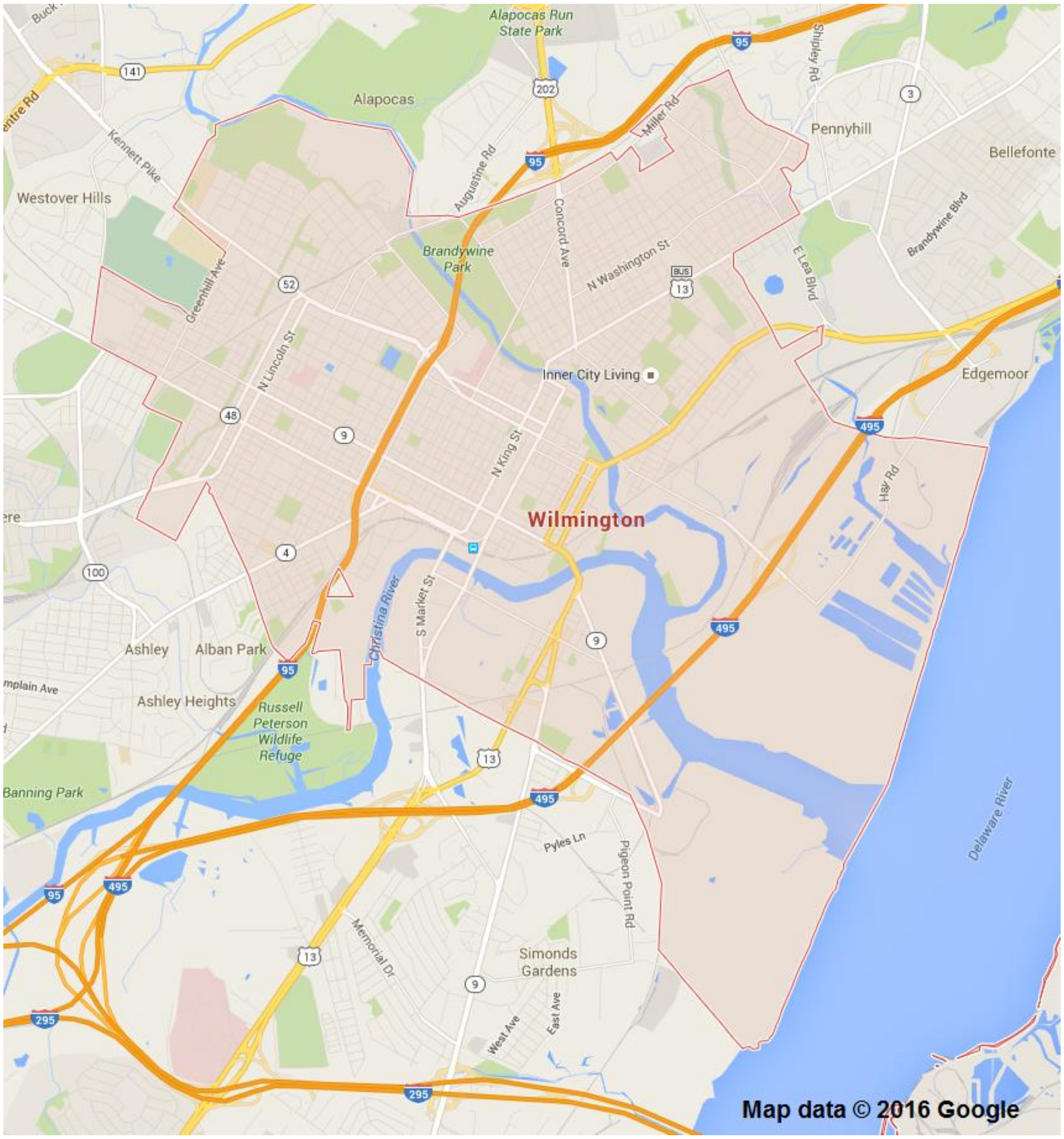

Figure 4: Wilmington City Limits (Google Inc., 2016)

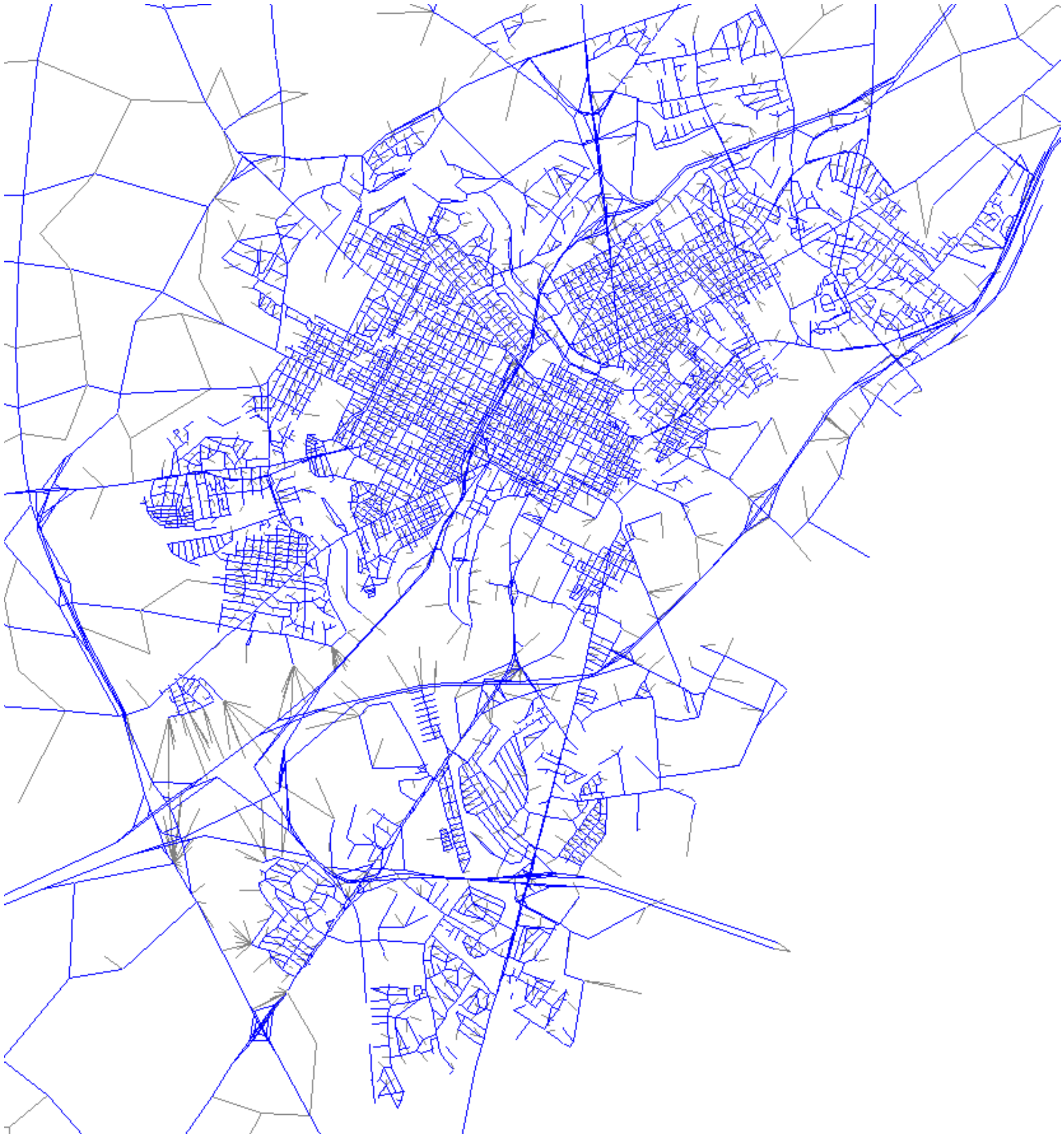

Figure 5: Case Study Area of Wilmington, Modeled at the Census Block Level

4.2 Case Study Scenario

This case study examines the transportation network impacts of a citywide dispensing effort in Wilmington, DE. The case study operates under the assumption of an aerosolized anthrax release throughout Wilmington. In the event of an anthrax attack, it is critical to dispense oral antibiotics within 48 hours of exposure, after which the mortality rate increases drastically (Whitworth, 2005; Ma et al., 2011). The Cities Readiness Initiative originally based planning on this scenario, founded on evidence that receiving antibiotics within 48 hours prevents 95% of anthrax outbreaks (CDC, 2008). The first 24 hours are dedicated to POD preparations and medication delivery, leaving 24 hours to dispense oral antibiotics to potentially infected populations (Ma et al., 2011). The response for Wilmington, DE is based on the typical planning scenario to a citywide anthrax release.

4.3 POD Locations

To service the entire residential and working populations of Wilmington, I must first discuss several relevant assumptions. According to the Point of Dispensing Standards created by Nelson et al. (2008) and adopted by the CDC (2008), the affected region should estimate how many PODs are needed to service the region's entire population. According to the most recent census data, Wilmington has a residential population of 71,817 and a non-resident worker population of 43,647 (U.S. Census Bureau, 2015a; U.S. Census Bureau, 2015b). Together, an estimated population of 115,464 people live and work in Wilmington.

Delaware's *Neighborhood Emergency Help Center Plan* indicates that a POD location may dispense between 1,000-2,000 oral antibiotics per hour per location (DPH, 2008b). For the purposes of this study, I assume the lower throughput rate of 1,000 people per hour per location. Thus, one POD may process 24,000 people over its 24 hours of operation. Approximately five POD locations are needed to service Wilmington's working and residential populations within a 24-hour period.

POD locations were chosen through several methods. The *NEHC Plan* provides a list of suggested locations throughout Delaware (DPH, 2008b). Four locations in Wilmington were chosen from this list (seen in Table 1 in Section 2.1.7.1):

- Jewish Community Center (JCC) and YWCA Delaware, located at 709 N Madison Street, Wilmington, DE 19801;
- George Campus of the Delaware Technical Community College (DelTech) in downtown Wilmington, located at 300 N. Orange Street, Wilmington, DE 19801;
- Northeast State Service Center (NESSC), located at 1624 Jessup St, Wilmington, DE 19802; and
- Frawley Stadium at the Riverfront, home to the Wilmington Blue Rocks baseball team, located at 801 Shipyard Drive, Wilmington, DE 19801.

The remaining location was chosen because of plentiful parking, ease of access, and relatively well-known location:

- Department of Motor Vehicles (DMV) south of Wilmington near the I-495/US-13 exchange, located at 2230 Hessler Blvd, New Castle, DE 19720.

The combination of these five locations is not officially endorsed. DPH is not willing to share potential POD locations for strategic reasons. The five locations were chosen to give a wider geographical coverage of the city of Wilmington, in addition to the limited guidelines for location choice. See Figure 6 below for a map of POD locations.

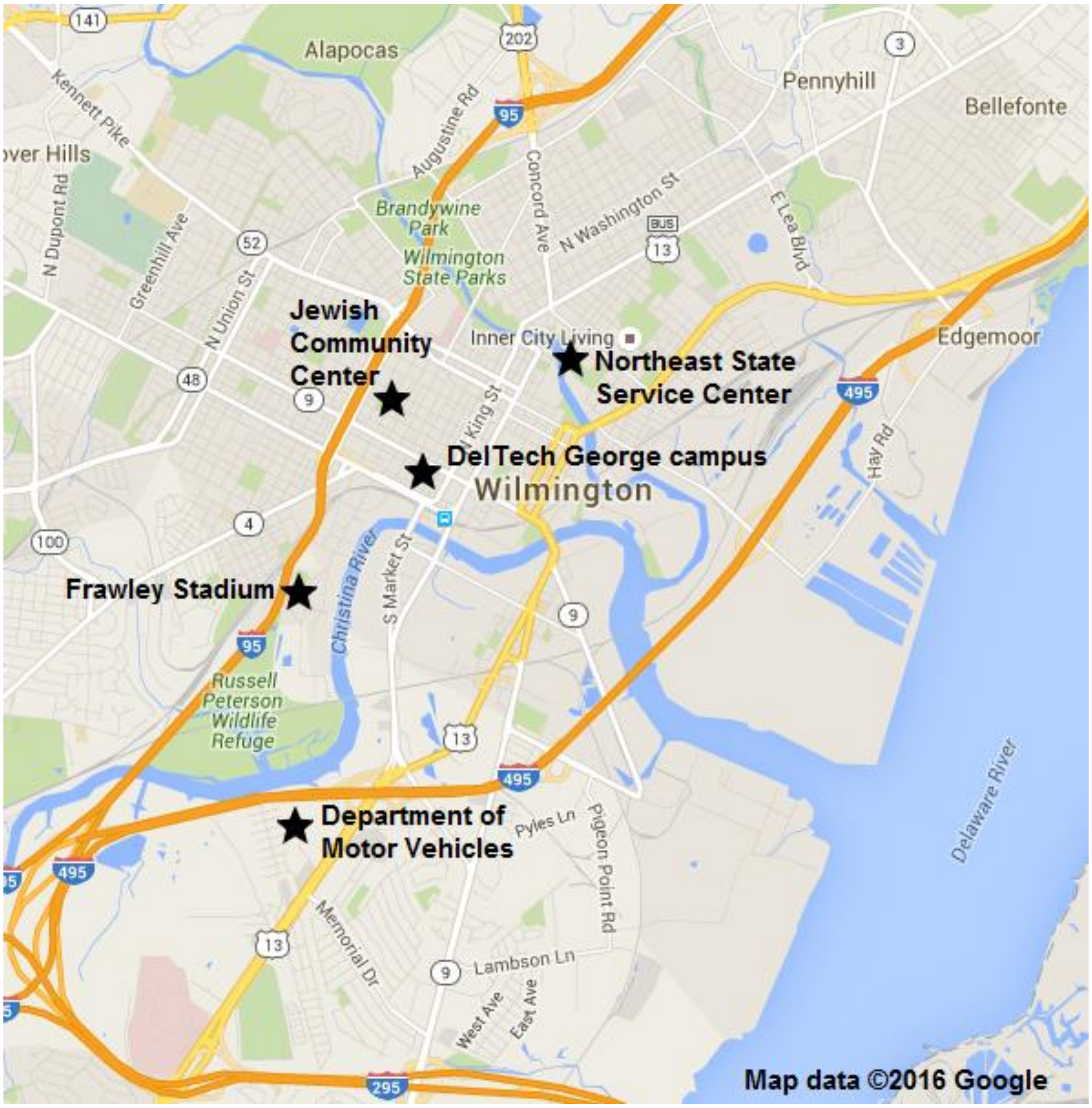

Figure 6: POD Locations in Wilmington (Google Inc., 2016)

4.4 Assumptions

In this section, I discuss the remaining assumptions utilized for the case study of Wilmington, DE. The POD system is activated in response to a citywide, aerosolized anthrax release. The process does not operate under a declared state of emergency. PODs operate for a continuous 24-hour period, opening at 8 AM and operating until 8 AM the following day. However, PODs will continue to process patients after 8 AM on the second day until all patient queues have dissipated. Patients may begin to arrive at the POD up to two hours before operations begin. This behavior reflects patient actions and assumptions in exercises and research (Ma et al., 2011; Banks et al., 2013). Each POD location has a processing rate (or throughput rate) of 1,000 people per hour (DPH, 2008b). Patient processing is first-in first-out, i.e. the system does not utilize priority groups. The number of PODs needed to service Wilmington's population was calculated from Standards 1.1 and 1.2 of the Point of Dispensing Standards (Nelson et al., 2008; CDC, 2008). The remaining standards focused on internal processes, which are not relevant to this study. The purpose of these PODs is solely to dispense oral antibiotics to the population. No triage or medical treatment is provided at POD locations.

All traffic headed to PODs is vehicular. Pedestrian, mass transit, and other transportation modes are not considered explicitly. There is a 90% compliance rate, meaning that 90% of the affected population will head to the PODs. Non-resident workers will head to PODs on their way from home to work, continuing the journey to work afterwards. Wilmington residents will follow hourly arrival rate patterns, beginning and ending at home. These arrival curves are varied to test emergency planners' assumption of a uniform patient arrival rate. There is no formal assignment process issued by the Delaware Division of Public Health to assign the population to specific PODs. Both non-resident workers and residents choose POD locations based on proximity. Non-resident workers will choose the POD that least increases their commute distance. Residents will choose the POD closest to their home. For residents, one vehicle per household travels to the POD. Households without vehicles use transit and arrive the same hour as the households with vehicles. No news outlets or social media provide real-time updates of POD status, waiting times, or traffic conditions to the public, which might influence POD location choice.

The POD TIM is adapted from the Delaware Statewide Evacuation Model. The adaptation required understanding how PODs function and how users use the POD. Two assumptions resulted from oversights when setting up the model and should be corrected in future model iterations. First, the model assumes an unlimited parking capacity for each POD location. Once a vehicle clears the road capacity and arrives at the POD TAZ, the vehicle parks and patients line up in the queue to enter the POD. In reality, parking would be a major constraint on the transportation network. The second assumption is that there is no service time within the POD. Once a patient enters the POD, they are immediately processed and released. A more realistic model would include the time to service a patient within the POD.

4.5 Analysis, Results, and Discussion

In this section, I analyze and discuss the results from the five model scenarios. Performance measures of the POD TIM are separated into POD and transportation network MOEs. The raw data for POD MOEs are available in the Appendices C through G.

4.5.1 POD Performance Measures

The results from the five arrival scenarios are first discussed in general terms, as several concepts are common to all arrival scenarios. The performance measures for each of the specific arrival scenarios are then discussed.

Overall, the PODs processed approximately 100,000 patients. The initial population estimate of residents and non-resident workers in Wilmington was 115,464 people. The model implemented a 90% compliance rate. The proximity algorithm for POD location choice was the same for each scenario. Approximately 39.7% of the serviced population arrived at the Jewish Community Center, 29.6% at the Northeast State Service Center, 16.7% at the Department of Motor Vehicles, 13.2% at the DelTech George campus, and 0.8% at Frawley Stadium (see Figure 7 below). The disparity between patient populations at the PODs causes several issues, including underutilized staff, long queues, and dangerously long waiting times.

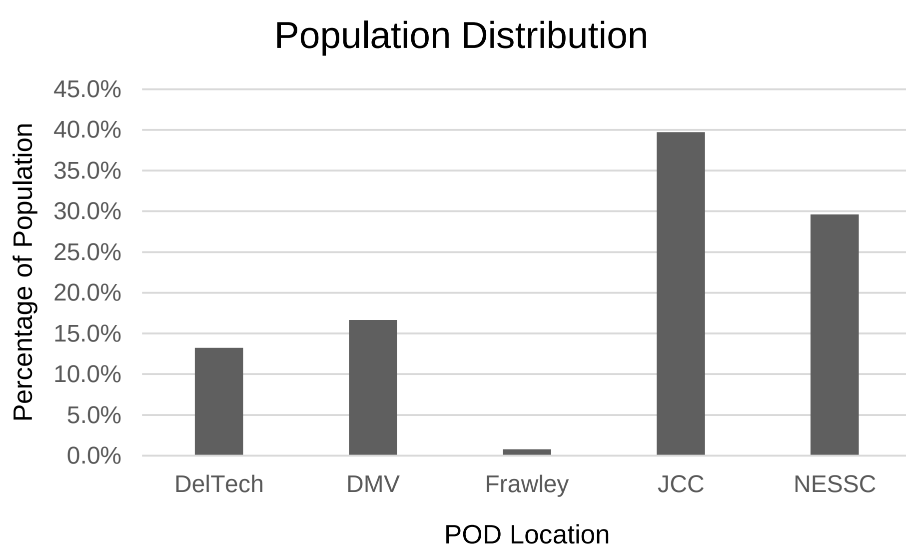

Figure 7: Population Distribution Amongst POD Locations

In all scenarios, the Frawley POD is severely underutilized due to the POD choice algorithm by closest proximity. Despite its abundant parking, the facility is closest for the least number of both residents and non-resident workers. The Frawley POD services less than 800 people during its entire operation. This facility underutilizes staff, medical, and parking resources and reserve roadway capacity. Although the stadium location develops a queue of approximately 490 people, the queue occurs because a majority of patients arrives before 8 AM. In all scenarios, the worst time to arrive is 6 AM, due to the two-hour delay for the POD to open.

The DMV and DelTech PODs are also underutilized in every scenario. Both locations receive a surge in the morning due to the incoming non-resident worker population. The DMV POD has the largest AM surge of all POD locations. This immense surge is most likely due to the DMV's close proximity to several major highways, including Interstates 95, 495, and 295, and US Route 13, which are utilized by non-resident workers on the commute to Wilmington. However, the influx of patients drastically lowers after the initial AM peak. Maximum and average queue lengths and delays between scenarios were similar for both the DMV and DelTech PODs. For the DMV POD, maximum and average queue lengths were around 7,000 and 2,000 people respectively. Maximum and average delay were about 8 and 2 hours respectively. The worst time to arrive at the DMV POD was 8 AM for all scenarios. The queue lengths and delays were much smaller for the DelTech POD, with maximum queue lengths around 3,000 people and average queue lengths less than 1,000 people. The maximum and average delays were about 4 and 1 hours respectively. The worst time to arrive varied between 7 AM and 8 AM for all scenarios.

In contrast, the JCC POD was completely overwhelmed by patients, receiving over 1.6 times the volume of patients it could service in 24 hours. The JCC's close proximity to both residential homes and places of employment made it a prime POD location. In all scenarios, the maximum queue is over 15,000 people in length. The maximum delay is over 20 hours. The worst times to arrive vary more than other POD locations, with the earliest time at 6 PM and the latest at 7 AM the following morning. This worst time varies due to the arrival patterns of residential patients. However, with an average queue of at least 9,000 people and an average delay of over 10 hours, the patient arrival patterns are insignificant when considering the long waiting times experienced by all patients. A long waiting time could become dangerous for patients, due to fatigue and exhaustion, limited access to food, water, and bathrooms, and the short timeframe within which to receive antibiotics. The JCC POD operates at 100% capacity, perhaps running out of medical supplies or causing POD worker fatigue and burnout.

The NESSC POD also operates at full capacity, although not to the same extent as the JCC POD. For all scenarios with the exception of the uniform arrival curve, the maximum and average queue lengths were above 11,000 and 6,000 people respectively. The maximum and average delays were above 12 and 7 hours respectively. The uniform arrival scenario had smaller queue lengths and delays by a third. The assumption of a uniform arrival rate in POD planning and operations may lead to a lack of preparedness for a non-uniform arrival pattern. The worst time to arrive varied between 5 PM and 11 PM.

Due to the nature of the evacuation model, a small percentage of patients (cumulatively less than 1%) arrive after the initial 24 hours of operation. With the exception of this small number of patients, all patients at the Frawley, DMV, and DelTech PODs are processed within the 24 hours. However, in all scenarios, patient processing continues past 8 AM on the second day at the NESSC and JCC PODs. The NESSC POD operates for an additional six hours, closing at 2 PM on the second day. The JCC POD operates for an additional sixteen hours to service its extreme backlog of patients, closing at 12 AM.

Overall, the biggest impact on the PODs was the morning surge of non-resident workers, which caused queues to form immediately. When POD processing capacity is underwhelmed, the worst time to arrive is at the beginning of the day. This was true for the DMV, Frawley, and DelTech PODs. When POD processing capacity is overwhelmed, the worst time to arrive is in the evening. The JCC and NESSC PODs never recovered from the initial surge, with more patients arriving hourly.

At this stage of the model, the transportation network and PODs are insensitive to patient arrival patterns for three reasons. First, the huge influx of non-resident workers in the morning causes patient queues for all locations, regardless of residential arrival pattern. Secondly, the proximity algorithm for choosing POD locations creates an enormous disparity in population distribution. For the overcrowded PODs, it is impossible to tell if the patient queues and long waiting times are due to varying arrival patterns or the proportion of population who arrive. The Frawley POD received so little traffic that the arrival patterns are insignificant. Thirdly, the lack of a parking capacity constraint at POD locations represents an inaccurate description of traffic behavior on the road network. There is one exception to patient arrival insensitivity, seen at the NESSC POD. The difference in queue lengths and delay between the uniform and non-uniform arrival scenarios suggests that a non-uniform arrival pattern could directly impact POD operations. Patient arrival patterns should be reconsidered in future research, addressing the above-mentioned reasons for insensitivity in this analysis.

The following subsections contain the POD MOEs for each arrival scenario. The relevant MOEs relate to population, queue length, and delay for each POD location. The population served and percentage of total population are provided. The maximum and average queue lengths are measured as number of people waiting to be serviced at a POD. The maximum and average delay are the number of hours that people waited to be serviced at a POD. The worst time to arrive at each POD location is based on the time at which the maximum delay occurs.

4.5.1.1 Uniform Arrival Scenario

The POD measures of effectiveness for the uniform arrival scenario are shown below in Table 5.

Table 5: POD MOEs for the Scenario Assuming Uniform Arrivals

POD	Pop. Served	% of Total Pop.	Max Queue Length	Average Queue Length	Max Delay	Average Delay	Worst Time to Arrive
DelTech	13,261	13.3%	3,330	456.13	4.33	1.00	7:00
DMV	16,659	16.7%	7,098	1,850.83	8.1	2.51	8:00
Frawley	767	0.8%	491	27.35	2.2	0.17	6:00
JCC	39,710	39.7%	15,576	9,501.83	16.57	10.52	31:00
NESSC	29,615	29.6%	5,539	4,687.50	6.54	5.71	23:00

4.5.1.2 Dual Uniform Arrival Scenario

The POD measures of effectiveness for the dual uniform arrival scenario are shown below in Table 6.

Table 6: POD MOEs for the Scenario Assuming Dual Uniform Arrivals

POD	Pop. Served	% of Total Pop.	Max Queue Length	Average Queue Length	Max Delay	Average Delay	Worst Time to Arrive
DelTech	13,232	13.2%	2,951	543.43	3.95	1.08	7:00
DMV	16,668	16.7%	6,969	2,336.97	7.97	2.99	8:00
Frawley	768	0.8%	482	37.28	2.19	0.25	6:00
JCC	39,728	39.7%	21,199	12,007.52	22.2	13.03	22:00
NESSC	29,609	29.6%	12,206	7,108.78	13.21	8.13	21:00

4.5.1.3 Rush Hour Peaks Arrival Scenario

The POD measures of effectiveness for the AM and PM rush hour peaks arrival scenario are shown below in Table 7.

Table 7: POD MOEs for the Scenario Assuming AM and PM Rush Hour Peaks for Arrivals

POD	Pop. Served	% of Total Pop.	Max Queue Length	Average Queue Length	Max Delay	Average Delay	Worst Time to Arrive
DelTech	13,226	13.2%	3,955	724.80	4.96	1.27	8:00
DMV	16,671	16.7%	7,919	2,425.23	8.92	3.08	8:00
Frawley	764	0.8%	501	26.92	2.2	0.17	6:00
JCC	39,672	39.7%	19,282	11,595.17	20.28	12.61	20:00
NESSC	29,687	29.7%	11,380	6,785.00	12.38	7.80	19:00

4.5.1.4 PM Rush Hour Peak Arrival Scenario

The POD measures of effectiveness for the PM rush hour peak arrival scenario are shown below in Table 8.

Table 8: POD MOEs for the Scenario Assuming PM Rush Hour Peak Arrivals

POD	Pop. Served	% of Total Pop.	Max Queue Length	Average Queue Length	Max Delay	Average Delay	Worst Time to Arrive
DelTech	13,208	13.2%	3,261	468.27	4.26	1.01	7:00
JCC	39,725	39.7%	20,786	10,995.07	21.79	12.01	21:00
NESSC	29,635	29.6%	11,963	6,138.78	12.96	7.16	21:00
Frawley	767	0.8%	489	26.27	2.19	0.17	6:00
DMV	16,671	16.7%	7,143	2,059.17	8.14	2.72	8:00

4.5.1.5 Midday Peak Arrival Curve Scenario

The POD measures of effectiveness are the midday peak arrival scenario are shown below in Table 9.

Table 9: POD MOEs for the Scenario Assuming Midday Peak Arrivals

POD	Pop. Served	% of Total Pop.	Max Queue Length	Average Queue Length	Max Delay	Average Delay	Worst Time to Arrive
DelTech	13,232	13.2%	3,261	886.93	4.26	1.43	7:00
JCC	39,698	39.7%	21,605	12,568.81	22.6	13.59	18:00
NESSC	29,640	29.6%	13,542	7,681.41	14.54	8.70	17:00
Frawley	765	0.8%	489	25.35	2.19	0.17	6:00
DMV	16,672	16.7%	7,143	2,666.67	8.14	3.32	8:00

4.5.2 Network Performance Measures

The network MOE results are fundamentally the same for each arrival scenario because the transportation network is insensitive to the arrival patterns of Wilmington residents and workers at the PODs. Therefore, I review the performance measures for the uniform arrival scenario only. The most relevant metric is the volume to capacity (V/C) ratio, which summarizes the level of congestion on each segment of road. The Highway Capacity Manual identifies congestion using Levels of Service (LOS), with a scale of A through F (Transportation Research Board, 2010). Generally, road segments with LOS A, B, or C represent acceptable levels of congestion. The Highway Capacity Manual defines LOS C as a V/C less than a threshold between 0.62 and 0.74, depending on free flow speed, for basic freeway segments and multilane highways (Transportation Research Board, 2010). As an approximation, I assume V/C less than 0.7 as an acceptable level of congestion. A V/C value above 0.7 demonstrates potential congestion due to heavy traffic volumes.

Overall, the network does not experience heavy congestion, in part because of the absence of a parking capacity constraint at POD locations. Once vehicles clear the capacity of the roads surrounding a POD, the vehicles may "park" and queue outside of the POD on foot. It is noted that in this model the transportation network does not display the realistic conditions that would arise from limited parking.

I focus on the AM and PM peak periods when traffic is greatest. Figures 8, 9, 10, 11, 12, and 13 below illustrate the overall level of congestion in V/C. In the figures, black links represent V/C values greater than 0.7 and gray links represent V/C values less than 0.7. High levels of congestion occur where black is present. Figures 8, 9, and 10 illustrate the overall level of congestion in the 6, 7, and 8 AM hours respectively. Figures 11, 12, and 13 illustrate the overall level of congestion in the 4, 5, and 6 PM hours respectively.

Figure 8: Congestion Levels in V/C for 6 AM Hour

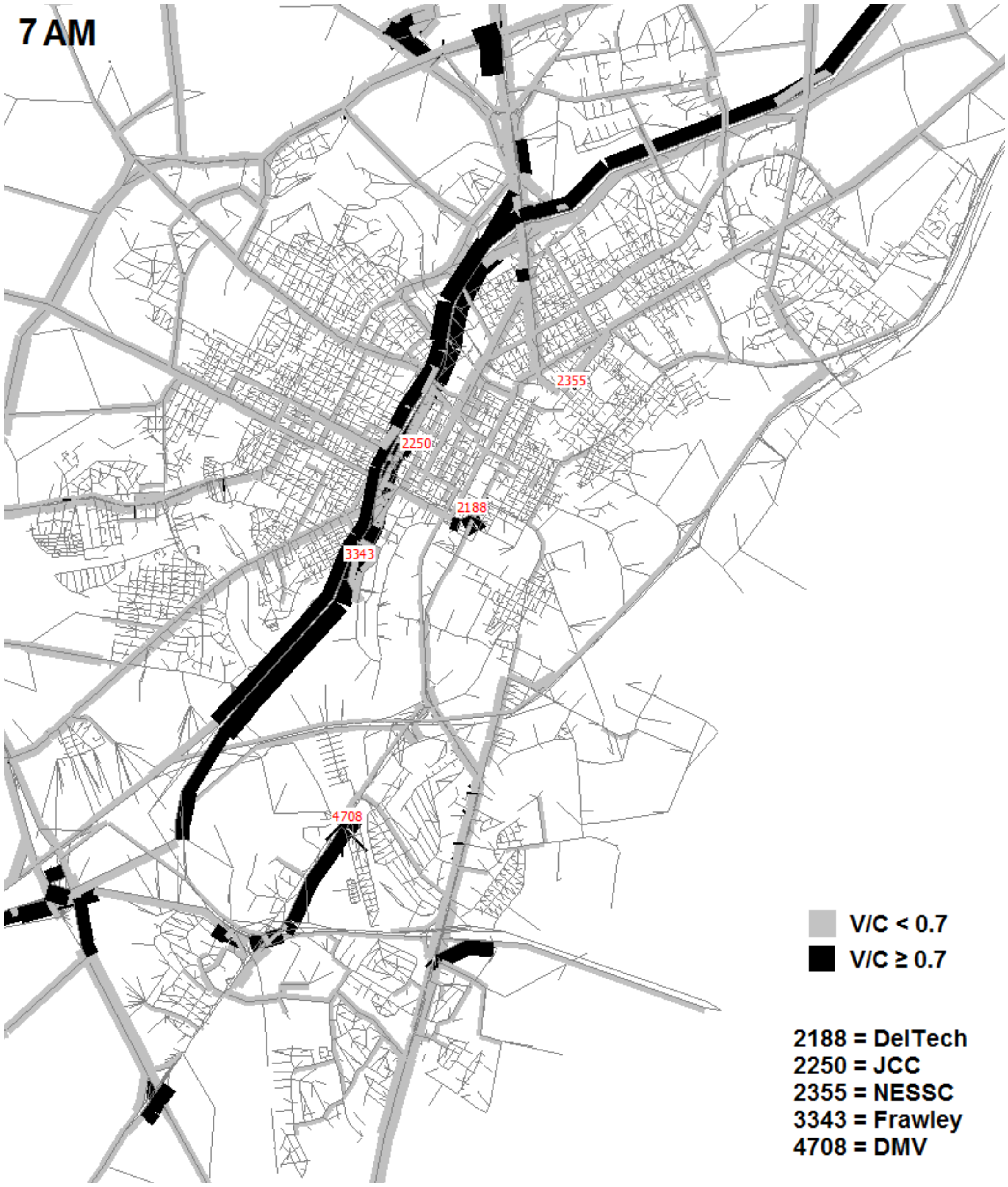

Figure 9: V/C Congestion Levels for 7 AM Hour

Figure 10: V/C Congestion Levels for 8 AM Hour

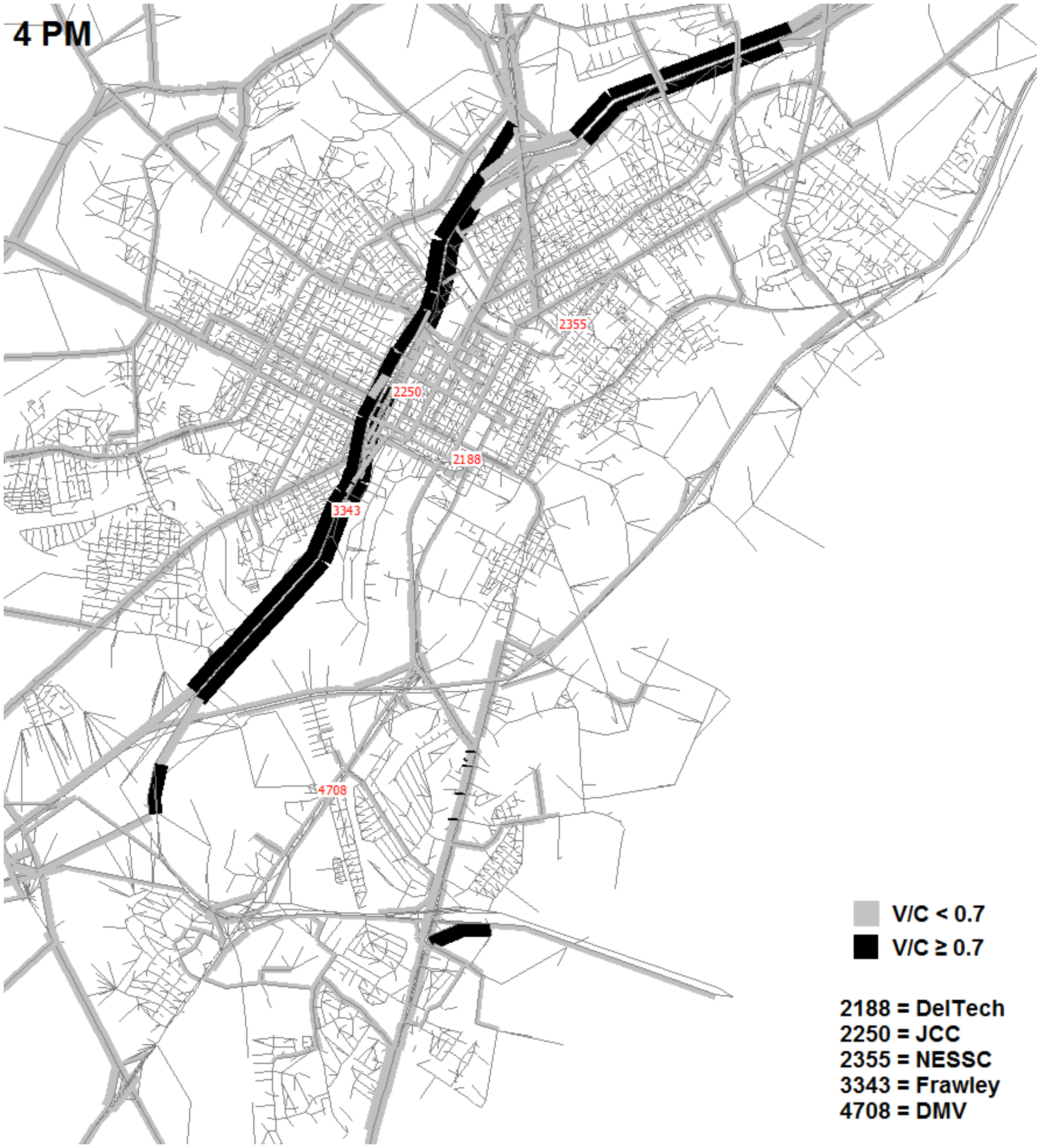

Figure 11: V/C Congestion Levels for 4 PM Hour

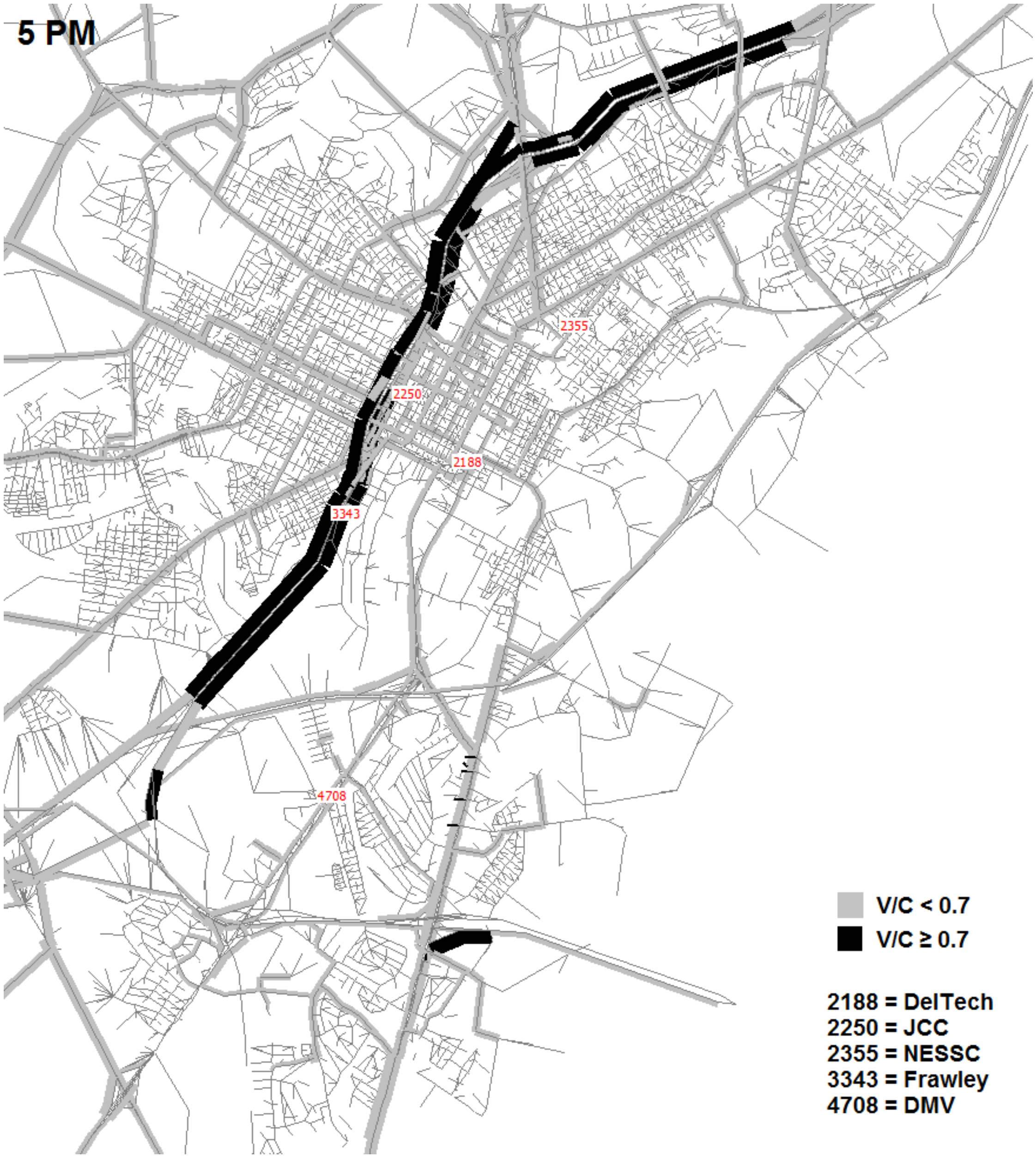

Figure 12: V/C Congestion Levels for 5 PM Hour

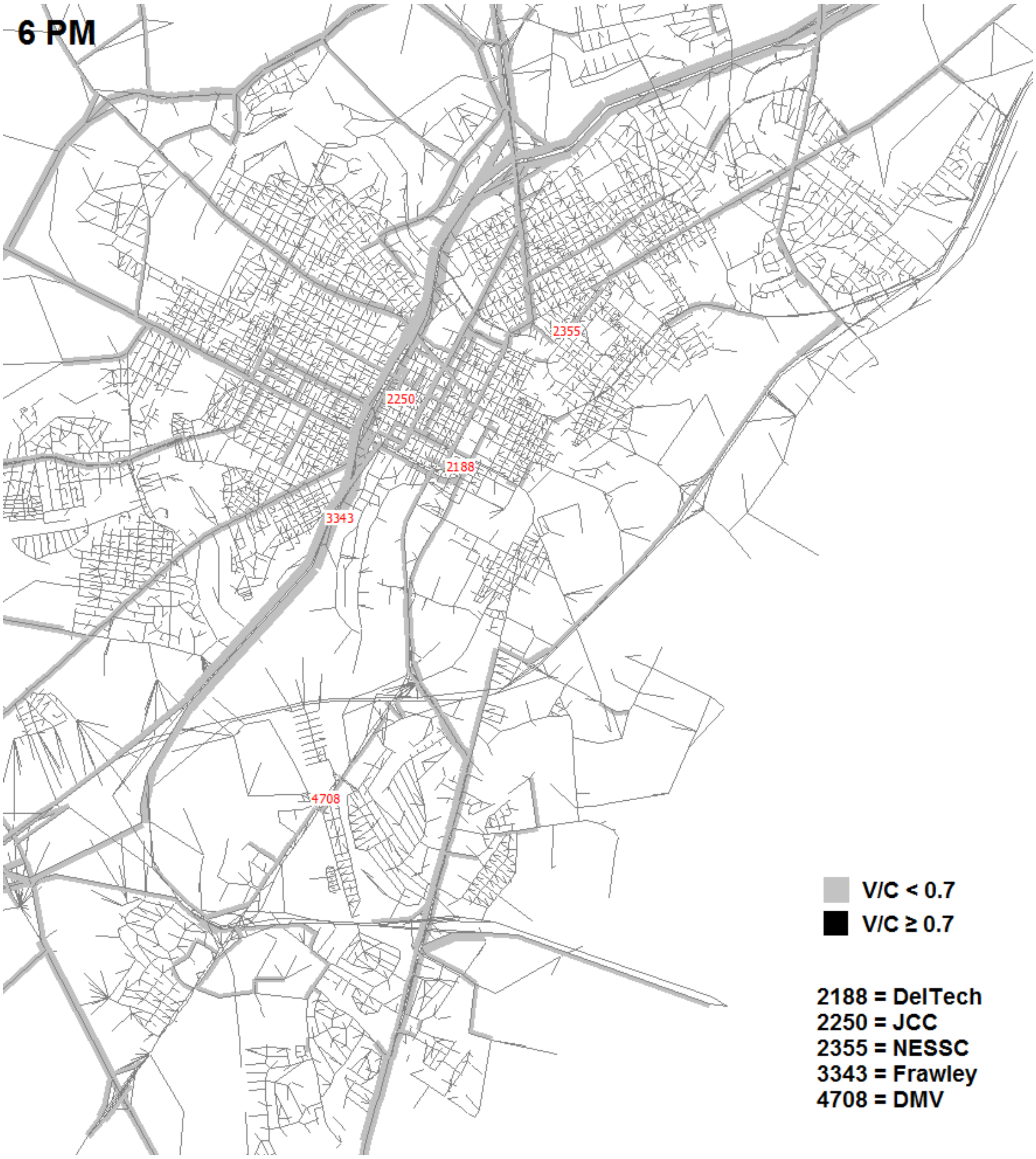

Figure 13: V/C Congestion Levels for 6 PM Hour

Overall, traffic is acceptable with a limited number of links exhibiting high levels of congestion. The main source of congestion is Interstate 95, which bisects Wilmington. Interstate 95 is congested with commuters during rush hours on a typical workday, and therefore this congestion is not unusual. There are several areas of localized congestion outside of the DMV, DelTech, and JCC POD locations during the AM rush hour. There are no areas of localized congestion surrounding PODs during the PM rush hour. There are no areas of high congestion surrounding the NESSC or Frawley PODs for any hour.

During the AM rush hour, there is congestion surrounding the DMV POD. A more detailed map of the area shown in Figure 14 shows the proximity to Interstate 295, Interstate 495 and State Route 13. In the 6 AM and 8 AM hours, the congestion is only located at the entrance to the DMV POD (Figures 15 and 17). During the 7 AM hour, the congestion extends down US Route 13 to the interchange with Interstate 295 (Figure 16). During the PM rush hour, there are no road segments with V/C greater than 0.7, indicating acceptable traffic conditions.

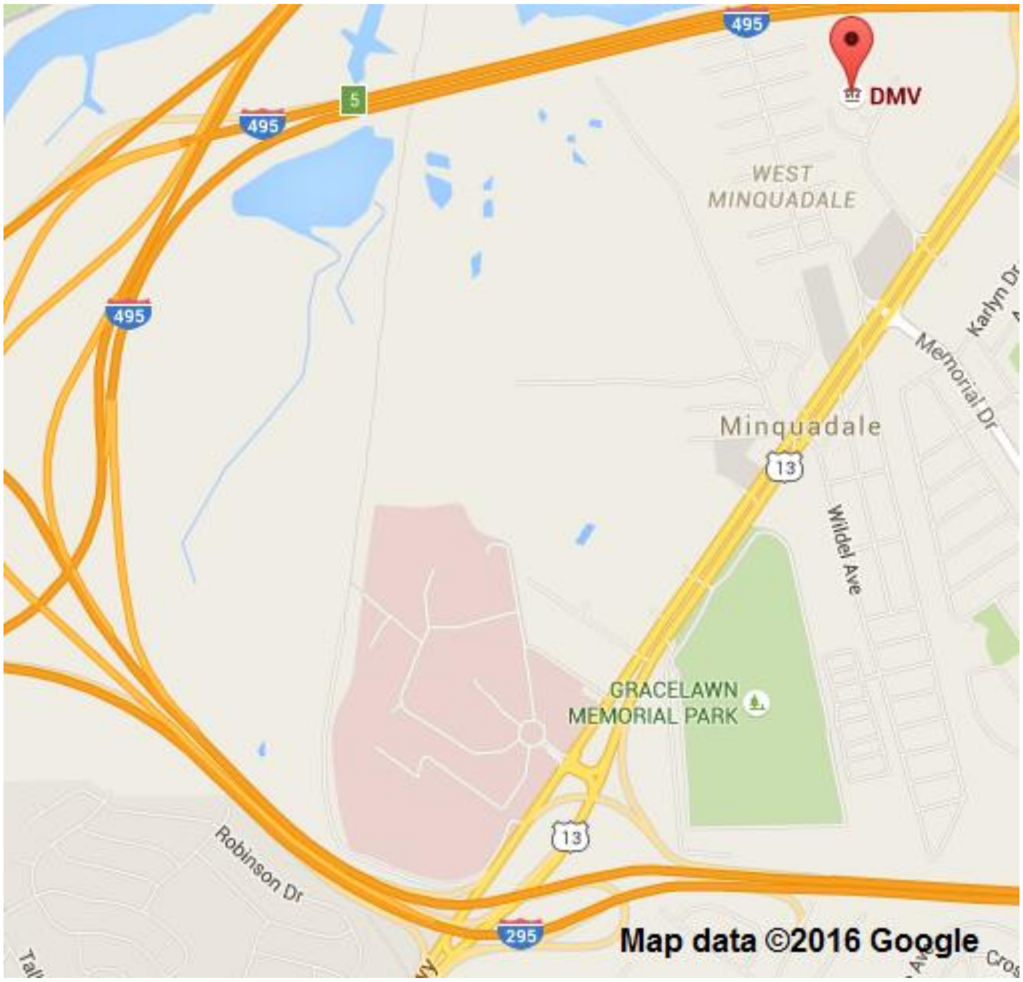

Figure 14: Map of Area Surrounding the DMV POD (Google Inc. 2016)

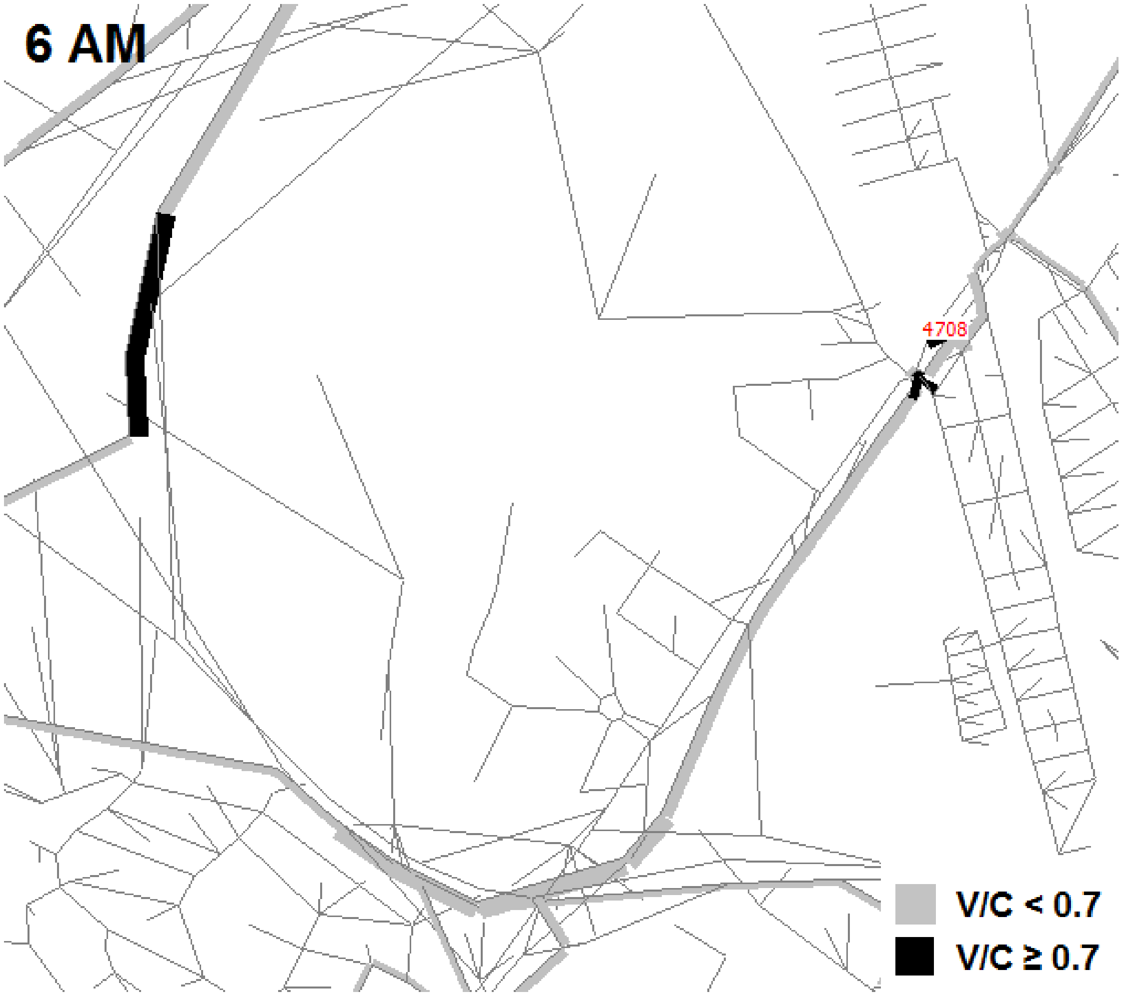

Figure 15: V/C Congestion Levels for the 6 AM Hour Surrounding the DMV POD

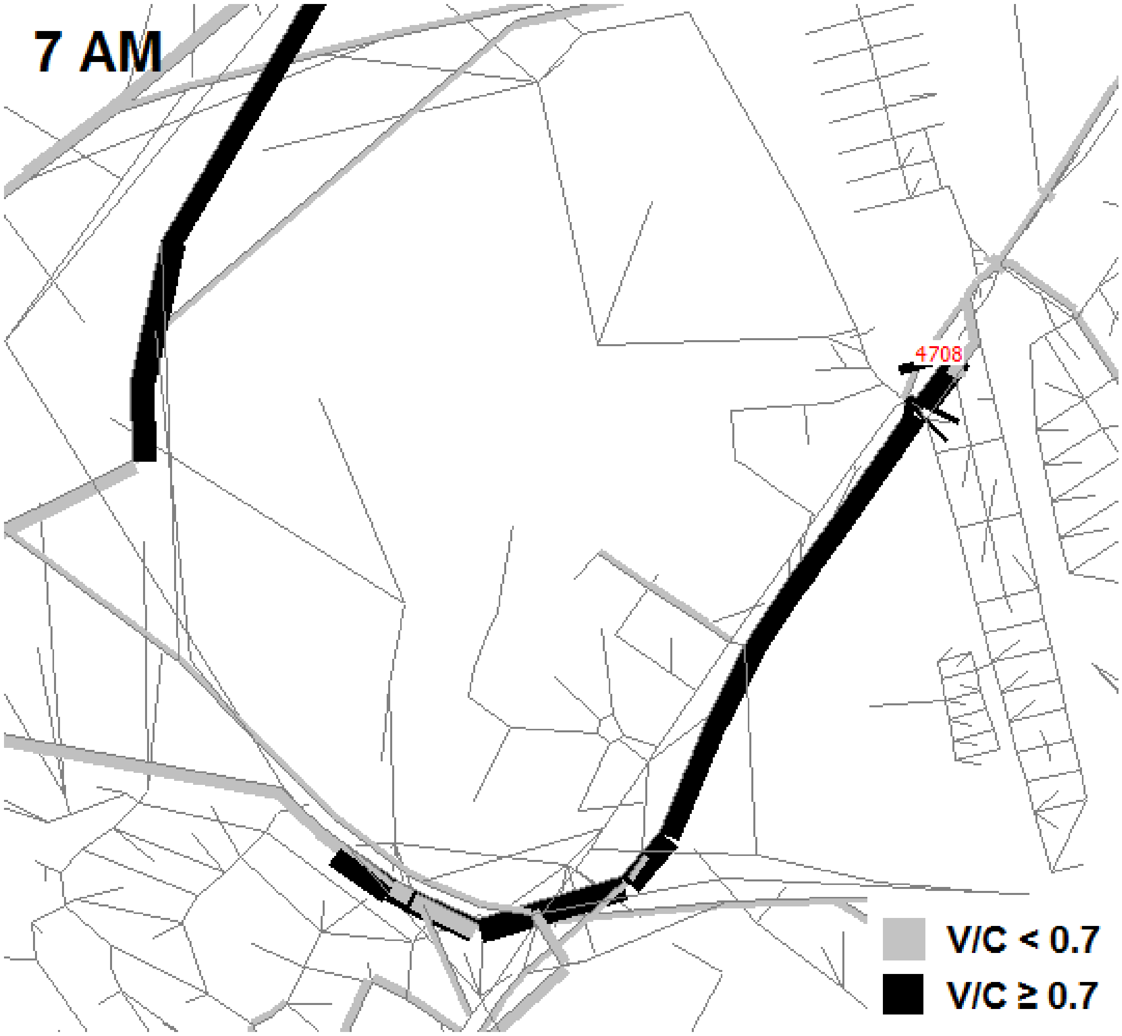

Figure 16: V/C Congestion Levels for the 7 AM Hour Surrounding the DMV POD

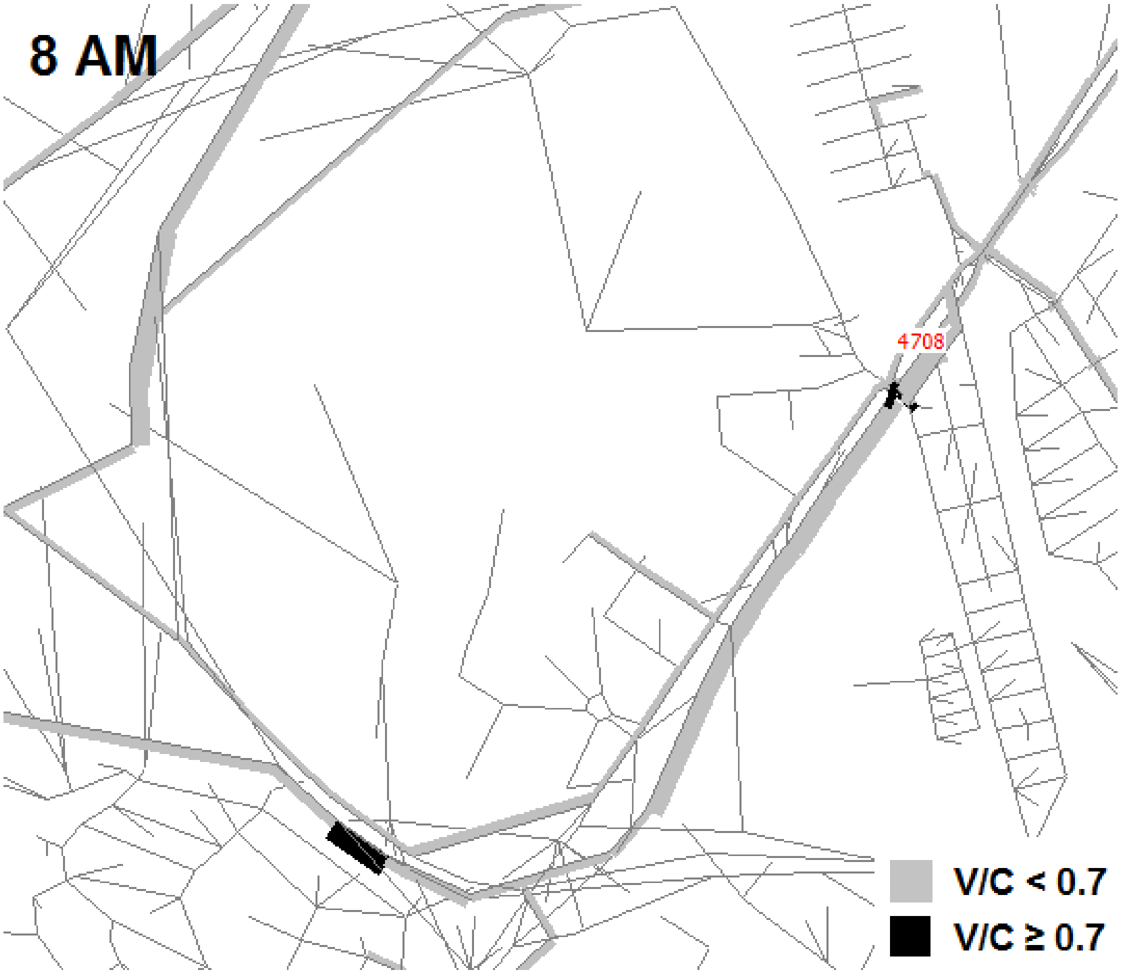

Figure 17: V/C Congestion Levels for the 8 AM Hour Surrounding the DMV POD

There was a small amount of congestion on the bend of E. Front Street near the DelTech POD. A more detailed map of the area is shown in Figure 18. This congestion occurred for the 6, 7 and 8 AM hours (Figure 19). There was no congestion during the PM hours.

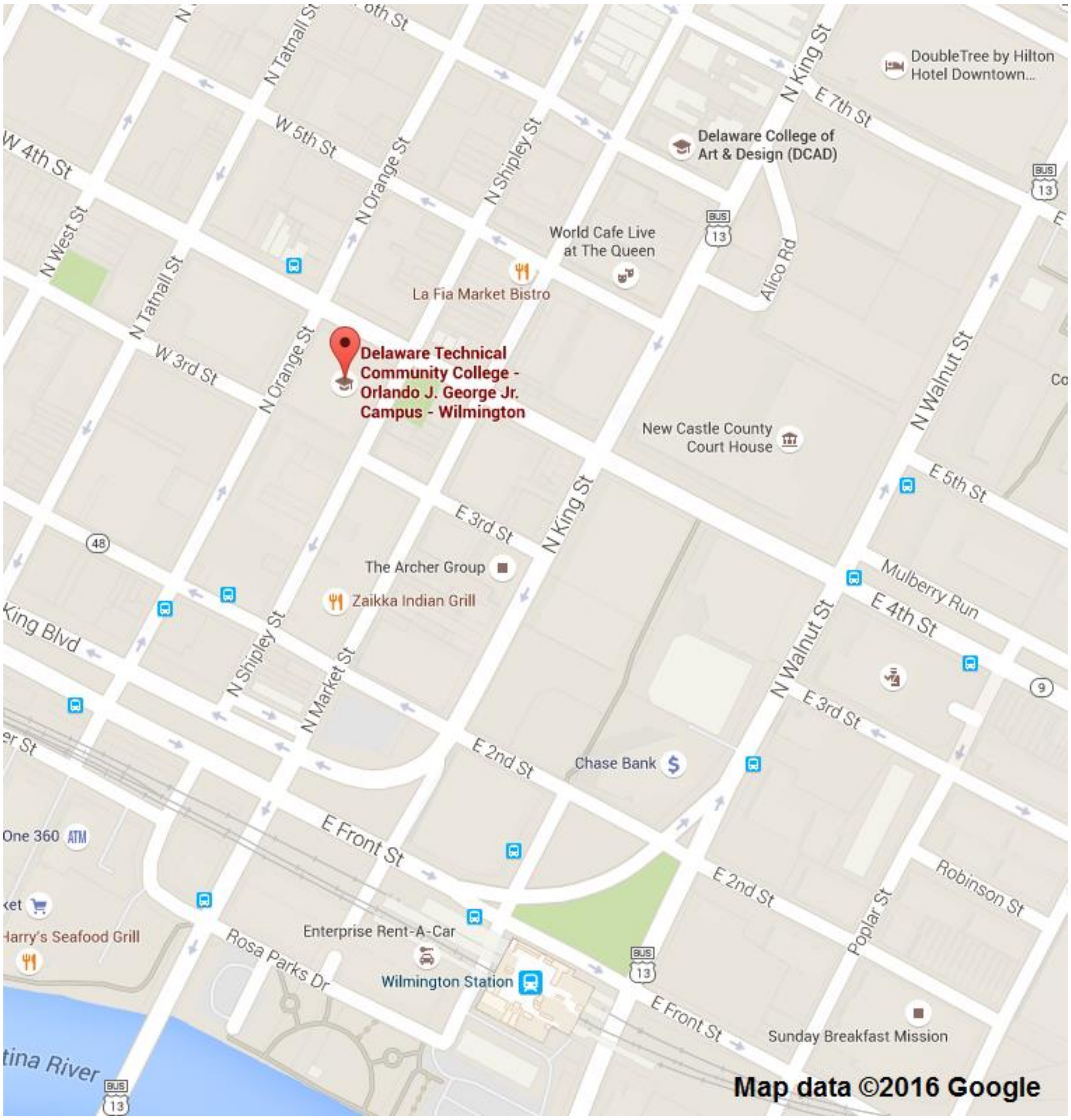

Figure 18: Map of Area Surrounding the DelTech POD (Google Inc., 2016)

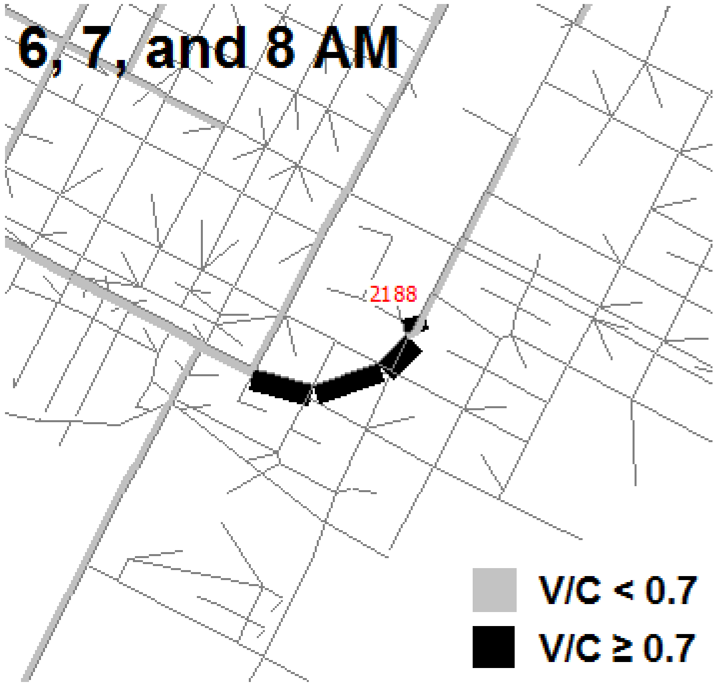

Figure 19: V/C Congestion Levels for 6, 7 and 8 AM Hours Surrounding the DelTech POD

Lastly, the block of W. 7^{th} Street immediately before the JCC POD experienced congestion. A more detailed map of the area is shown in Figure 20. This block was only congested during the 7 AM hour (Figure 21). The surrounding network was not congested during the 6 or 8 AM hours or the PM rush hours.

Figure 20: Map of Area Surrounding the JCC POD (Google Inc., 2016)

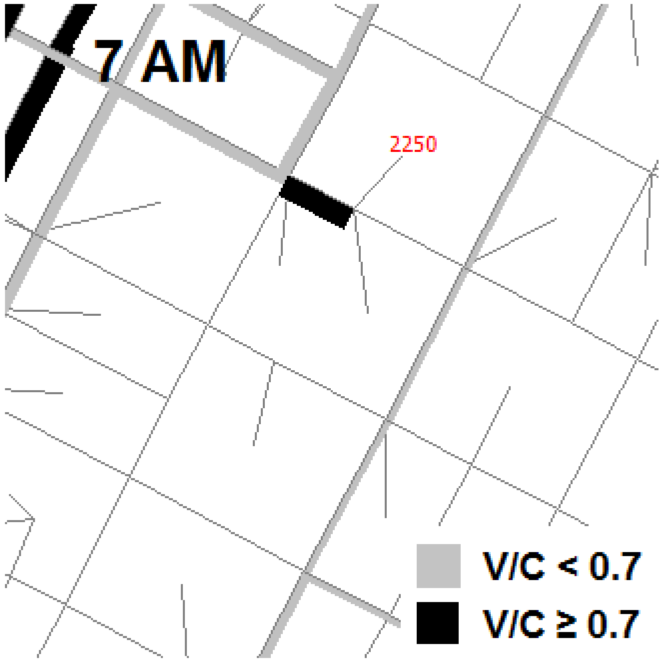

Figure 21: V/C Congestion Levels for 7 AM Hour Surrounding the JCC POD

Beyond these small areas of congestion, the network was clear throughout the AM and PM rush hours. However, I would like to reiterate that the low levels of congestion are caused, in part, by the assumption within the model of an infinite parking capacity. A more realistic model would also consider the impacts of limited parking availability. Parking constraints are discussed in the following section.

4.5.3 Parking Availability

Although parking was not considered as a constraint for this case study, parking would represent a serious concern during POD operations (Ma et al., 2011; Baccam et al., 2011). An estimate of the available parking for each POD location is based on counting spaces or available curb parking using images from Google Earth (Google Inc., 2015). I perform approximate calculations to determine how many curb parking spaces would be necessary to accommodate the maximum queue lengths experienced by each POD. A household survey by the Wilmington Area Planning Council (2009) reported an average work trip occupancy of 1.3 persons per vehicle and an average school trip occupancy of 2.6 persons per vehicle. Because the POD scenario operates under the assumption that families travel together, I assume an upper estimate of 2.5 persons per vehicle. Additionally, I assume a length of 20 feet per parking space for curb or parallel parking. A web search indicated that 20 feet would be a reasonable assumption. To provide some intuition to how much parking is needed, I provide curb miles of parking required to accommodate the maximum queues.

Frawley Stadium, located in the Riverfront in Wilmington, has by far the largest amount of available parking spaces. The area offers over 3,500 spots in both painted and unpainted asphalt areas. The surrounding retail area parking is included in the count. Additionally, surrounding fields and unpaved areas may be used for excess parking. However, such a large area for parking would require traffic control mechanisms to facilitate flow and order. Despite the abundance of parking, the Frawley POD requires only a maximum of 200 parking spaces to accommodate a maximum queue length of 501 patients. The parking availability at Frawley Stadium is severely underutilized.

The DMV parking lot has approximately 225 parking spaces. However, several drive-through lanes and other paved areas could be converted into temporary parking, providing approximately 50 additional spaces. Nearby, there are several other large parking lots within 1/2 mile that could be appropriated for an added 1,000 spaces. This is a total of 1,275 available parking spaces at the DMV. With a maximum queue of

7,919 patients, the DMV requires approximately 3,168 parking spaces, or 12 miles of curbside parking. The DMV has a shortage of 1,893 spaces, or 7 miles of parking, to accommodate the maximum number of patients present at one time.

Unlike the Riverfront and the DMV, both the JCC and DelTech campus are located in the heart of Wilmington and therefore have very limited parking. The majority of parking is on street. The Wilmington Parking Authority operates six parking garages and two surface lots within Wilmington, shown below in Figure 22 (Wilmington Parking Authority, n.d.). These lots offer a total of 4,413 parking spaces. Within a ¼-mile radius of the DelTech George campus on Orange Street, there are an additional 8 medium-sized parking lots with approximately 800 spaces. However, these lots may be dedicated to other corporate, retail, or private entities. The parking lots would have to be lawfully appropriated in the event of a POD.

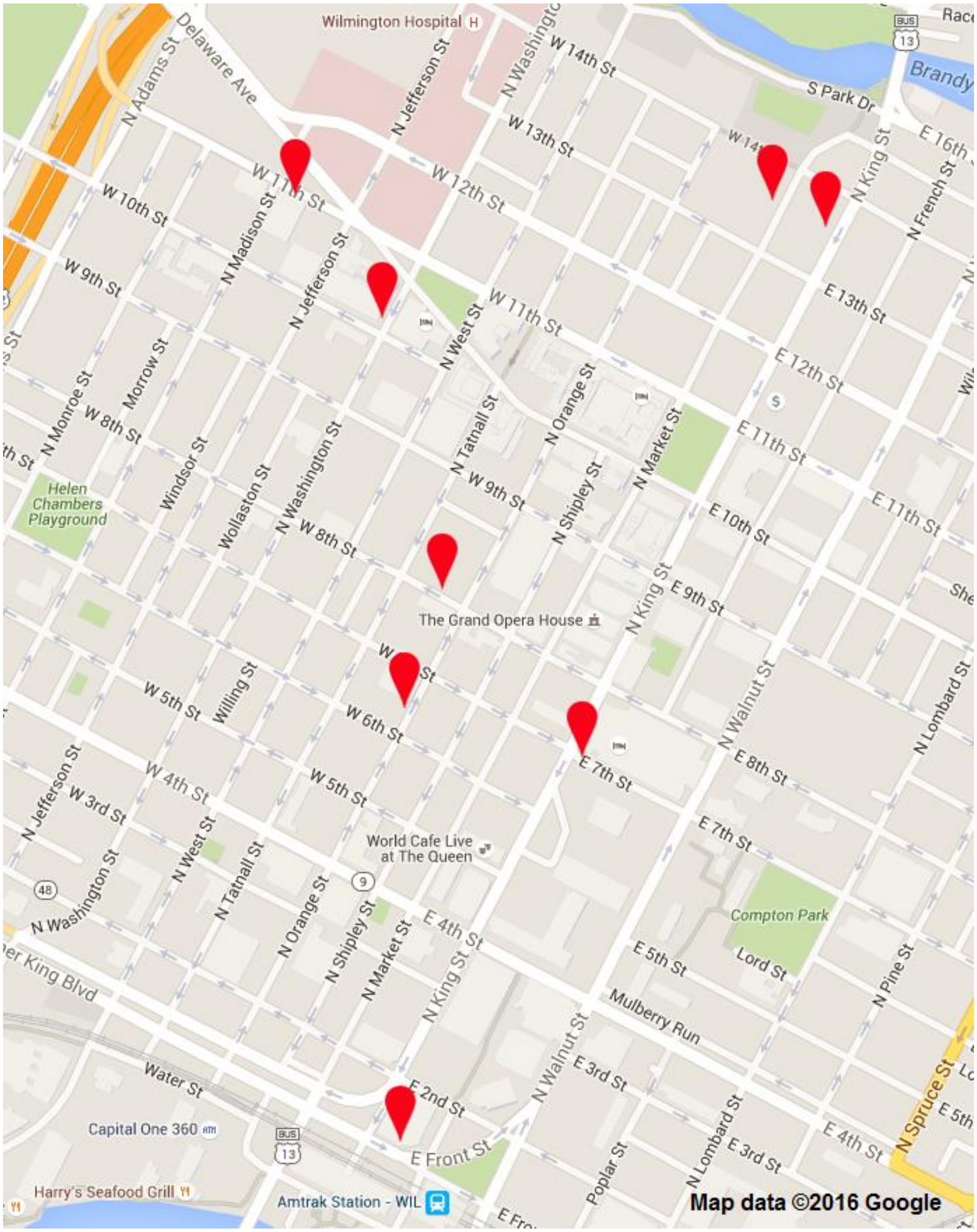

Figure 22: Map of Parking Garages and Surface Lots Operated by the Wilmington Parking Authority (Google Inc., 2016)

Despite these parking facilities and surrounding on-street parking, there is not nearly enough parking to accommodate the JCC POD's maximum queue length of 21,605 patients. Such a vast accumulation of people would require 8,642 parking spaces, or 33 miles of parking. The DelTech POD has a maximum queue of 3,955 patients, requiring 1,582 spaces, or 6 miles of parking.

There are approximately 225 spaces in the parking lot and on the street immediately in front of the NESSC. In addition, there is street parking in the surrounding neighborhood. However, the NESSC POD requires approximately 4,882 parking spaces, or 18 miles of parking, to accommodate its maximum queue length of 12,206 patients.

For all locations with the exception of Frawley Stadium, there is woefully inadequate parking to accommodate the large crowds waiting at each POD. The long queues waiting to enter parking lots would create gridlock surrounding POD locations. Additionally, vehicles circling the area in search of parking would create more traffic. Future research should quantify the impacts of limited parking capacity on the network during POD operations.

4.5.4 POD TIM Computational Performance

The POD TIM ran in Citilabs Cube version 6.1.1. The run time for each scenario was approximately thirty hours on a Dell desktop computer with Intel® Core™ 2 Quad processing and Microsoft Windows 7 64-bit operating system.

Chapter 5

CONCLUSIONS, RECOMMENDATIONS, AND FUTURE RESEARCH

5.1 Conclusions

The POD TIM demonstrated that for the Wilmington case study large queues and delays can occur at selected PODs but in general, the transportation network is able to handle the additional traffic. Overall, the goal of the POD TIM is to provide an understanding of the impact of the traffic generated by PODs on the performance of the transportation network. The first iteration of the POD TIM only partially achieved this goal. However, the primary objective of this thesis is to obtain evidence that future analysis is warranted. The thesis meets the primary objective because the POD TIM demonstrates that it is possible to model traffic surrounding PODs. The first iteration of the POD TIM has provided a foundation on which to build future models. The second objective is to provide recommendations to improve the accuracy and realism of a traffic impact model. I discuss recommendations and future research in the following sections. The third objective is to promote collaboration and communication between Emergency Management Agencies, Divisions of Public Health, and Departments of Transportation. Although this thesis does not directly address the third objective, the POD TIM provides a common goal, shared vocabulary, and a starting point for interagency coordination.

Below, I draw conclusions based on the case study results. The algorithm used to determine the POD visited, patient arrival patterns, and lack of parking constraints limited the realism of traffic behavior on the network. Within the POD choice algorithm, all POD patients go to the POD location closest to them. For residents, this location was the POD closest to their home. Non-resident workers choose the POD that added the least distance to their normal work commute. The proximity algorithm caused a vast discrepancy in population distribution between POD locations. The JCC POD received nearly 40% of the population, while the Frawley POD received less than 1%. Realistically, patients may choose to go to a POD that is a farther distance, due to familiarity, convenience, or knowledge about waiting times. The location choice algorithm is an important determinant of congestion for each POD.

Due to the POD choice algorithm, the POD TIM was insensitive to patient arrival patterns. The discrepancy in population distribution overwhelmed several PODs. Queue lengths and waiting times were extensive for the JCC and NESSC PODs, regardless of arrival pattern. The worst time to arrive was the only factor that patient arrival patterns affected. So few people utilized the Frawley POD that the arrival patterns were inconsequential. In addition, the patient arrival patterns were inconsistent between non-resident workers and residents. Non-resident workers traveled to PODs on their commutes to work, with a majority arriving during the AM rush hour. Residents followed several arrival curves, including a uniform, dual uniform, and several rush hour peak scenarios. Overall, the patient arrival patterns were insensitive and inconsistent.

The lack of a parking constraint sub-model within the POD TIM was a large disadvantage. Without a parking constraint sub-model, infinite parking is assumed to be available at each POD location. The only network constraints were road capacities. Once vehicles arrived at PODs, the vehicles parked and patients queued to enter the PODs. In reality, PODs may have inadequate parking to accommodate the number of patients waiting to be serviced. The only notable exception was the Frawley POD. For all other locations, limited parking and large patient queues would result in lines of vehicular traffic waiting to park. The long queues of vehicles waiting to enter parking lots would create gridlock surrounding POD locations. Additionally, vehicles circling the area in search of parking would create more traffic. Parking availability would be a significant restriction of POD operations.

There are other limitations of the POD TIM as well. The POD internal processes were modeled simplistically, with first-in-first-out processing, no additional service time, and no consideration of patient queue storage. The POD TIM utilized a uniform set of behavioral assumptions, with no regard to the inherent diversity and complexity of human actions. The model only considers vehicular traffic, neglecting pedestrian, mass transit, and other forms of transportation. Additionally, the computational time to run a model scenario is a disadvantage in emergency planning. Each model scenario ran for approximately thirty hours. With a thirty-hour run time, public health officials may only use the POD TIM as a preemptive planning measure to identify potential congestion areas for POD scenarios. The model may not be used during an ongoing emergency to identify where traffic management resources should be distributed. Future iterations of the POD TIM should incorporate solutions to its many limitations.

5.2 Recommendations

Based on the results and conclusions from the previous sections, I recommend which model assumptions and processes should be refined in future iterations. Opportunities for future work include the POD choice algorithm, patient arrival patterns, and parking constraints. Additionally, recommendations related to internal processing, behavioral assumptions, and model capabilities are provided.

The POD TIM requires a more sophisticated POD choice algorithm to balance the population distribution while accurately modeling patients' behaviors. Possible options include official POD location assignment or POD status updates through social media or news outlets. Planners may use traffic impact models to determine to which PODs patients will go based on behavioral assumptions. Emergency managers may utilize patient distribution results, in conjunction with other POD models, to distribute staff and supplies to best meet demand. Planners may also use the POD TIM to contrast several patient-location assignment strategies, such as by postal code or phone number.

Although the POD TIM was insensitive to patient arrival patterns in the first model attempt, arrival scenarios should be considered with a different location choice algorithm. The POD TIM results displayed evidence that different patient arrival rates could affect queue lengths, delay, and worst times to arrive. For the NESSC POD, the uniform arrival rate had smaller queue lengths and delays by a third than the non-uniform rates. The assumption of a uniform arrival rate in POD planning and operations may lead to a lack of preparedness for a non-uniform arrival pattern. In the current model, the AM surge of non-resident workers created long queues and waiting times early in the day. Researchers should also consider a variety of non-resident worker arrival patterns. Arrival patterns may have an impact on staffing, parking availability, and traffic control. Future model iterations may examine uniform and non-uniform patient arrival patterns for both residents and non-resident workers.

Future models should represent the available parking surrounding each POD location. I hypothesize that implementing a parking constraint sub-model would greatly increase congestion throughout the transportation network. Information about available parking may be acquired from Google Earth or visual inspection of the area. The parking sub-model may also include the physical locations of these parking spots and accurately demonstrate the traffic effects of vehicles circling the block looking for parking.

Other recommendations for model improvements include internal processing, behavioral assumptions, and model capabilities. The internal processes of PODs should incorporate dynamic processing rates, priority patient groups, waiting areas, and possible triage and evaluation operations. Future model iterations should integrate complex behavioral assumptions, such as turn away rates due to long waiting times, POD status updates, and individuals' reactions to a biological outbreak. A more comprehensive traffic impact model may include pedestrian and mass transit volumes in addition to vehicular traffic. Future models should reduce computational time to make the model usable in emergency situations.

5.3 Future Research

In this section, I suggest specific methods for the above recommendations. Future iterations of the POD TIM should incorporate realistic social behaviors in the POD choice algorithm and patient arrival patterns. The challenges of a realistic parking sub-model are reviewed. In addition, I consider possible directions for future work. Opportunities for future work include alternative modes of transportation, behavioral assumptions in other contexts, and the internal POD process. Lastly, I discuss the model itself, including alternative performance metrics, the limitations of the software platform, and possible uses in POD planning and operations.

I suggest two options for an updated POD choice algorithm. The first option is a public information updating system in addition to the current least-distance choice algorithm. The information would provide incoming patients with status updates on waiting times, available parking, and other POD statistics. Therefore, patients may choose to go to a POD location other than the closest POD based on current demand. The information may be disseminated through either social media, news outlets, or direct messages from the Division of Public Health. The second option is POD location assignment. The Delaware Division of Public Health's *NEHC Plan* (2008b) suggests location assignment based on postal codes or telephone numbers. Because location assignment is only relevant to residents with home addresses in the case study area, several alternatives may be considered for non-resident workers. The first alternative is the operation of closed PODs at large, corporate firms in the study area. The operation of closed PODs would require coordination between the Division of Public Health and corporations. Non-resident workers employed at smaller companies would attend open PODs based on the location proximity algorithm. The second alternative would assign places of employment to open PODs by address. The POD choice algorithm is a challenge to consider in future work.

Patient arrival patterns may also integrate realistic behavior assumptions for residents and non-resident workers. Many complex factors determine when patients go to PODs, such as number of dependents, work schedules, number of vehicles per household, and available information about a POD's status. Arrival scenarios may be separated into non-resident worker patterns and resident patterns. For non-resident workers, arrival patterns should not be fixed in the morning commute. Non-resident workers may choose to go to PODs after work instead to avoid missing work hours. I suggest three non-resident worker arrival scenarios: all workers on their way to work from home, all workers on their way to home from work, and a 50-50 split before and after work. The five existing residential arrival scenarios are sufficient for the next iteration of the model. The POD TIM should consider every combination of non-resident worker and resident arrival patterns. Future research may examine dynamic arrival patterns, where patients make the decision to go to a POD based on a complex set of human behaviors. Survey-based research may be used to define more realistic arrival patterns.

The implementation of a parking constraint sub-model represents a challenge for researchers. There is a trade-off between realism and complexity when modeling parking availability. The most simplistic version of a parking sub-model creates a parking space constraint at the entrance of each POD location. Vehicles arrive at a POD, wait for available parking, park, and then dispatch to the POD. If no parking is available, vehicles queue on the roads surrounding the POD. A more complex version may include the physical locations of parking spaces, such as the garages owned by the Wilmington Parking Authority. In this version, vehicles arrive at parking space locations instead of the PODs. However, patients must be “linked” to their parking spaces, i.e. a parking space remains occupied until the patients occupying that space have been serviced in the POD and return to their vehicle. This version is vastly more complex to model because the POD TIM must keep track of each individual patient within the PODs. Computational time may also increase with complexity. However, it is vital for future researchers to include a parking constraint sub-model.

Researchers may consider other factors of parking availability as well. The model may demonstrate the traffic effects of vehicles circling the network looking for parking. Future research should determine how far away a distance is acceptable to park. If parking is tightly constrained, vehicles may park several miles away and walk to PODs. Constraints on available parking also include permit-only parking, pay-for-parking, handicapped parking, and loading zones. Researchers may consider the availability of handicap parking spaces, as physically disadvantaged populations might be unable to walk long distances to PODs. There may be parking facilities shared by two or more POD locations, such as with the JCC and DelTech PODs. Many challenges of parking availability should be considered in future model iterations.

Future models should incorporate all available modes of transportation for a region. Most notably, pedestrian volumes may comprise a large percentage of POD crowds in densely populated, urban areas. The Division of Public Health may urge patients to walk instead of drive in areas with limited parking. Planners should note that large swarms of pedestrians might require traffic control at intersection crossings. POD patients may also use mass transit options, such as buses, subways, or streetcars. Patients may combine walking and mass transit use in a single trip. Patients who chose to walk or take public transportation may reduce network congestion.

There are many aspects of behavior that should be considered in future work. First, human behaviors are complex. The POD TIM's fixed compliance rate and proximity-based location choice algorithm do not realistically model patient decision processes. Many factors determine if, when, and where to go to a POD. Researchers must understand the components of an individual's decision to go to a POD, including understanding of the severity of the biological outbreak, time sensitivity of the event, and transportation mode choices. People's reactions to a large-scale biological outbreak may not be rational. Individuals may be noncompliant with a mandatory order to receive MCMs. Groups may continue their normal routine, work on an altered schedule, or completely change plans. A realistic model should compare multiple behavior scenarios.

Secondly, future models should evaluate a population's reactions to POD operations, such as waiting times at queues, available sources of information, and the potential for turn-away patients. The current model assumes that patients will wait in queues for over ten hours. Researchers should investigate how the availability of POD status updates, through channels such as social media or local news stations, may affect location choice, arrival time, and compliance. Patients who are aware of long waiting times may choose a different arrival time or location. Additionally, patients waiting in long lines may leave a POD before being serviced. Future research should consider the impacts of patient turn-away on fatality rate, spread of infection, and other public health factors. It is also possible that sick patients waiting in long queues will succumb to illness before receiving MCMs. In the case of an anthrax release, the mortality rate increases drastically after the first 48 hours. Patients who do not receive MCMs within this period may become fatally ill. Future models should consider the potential impacts of extremely long queue lengths, such as patient turn-away and death.

The current version of the POD TIM simplifies internal processes to a first-in-first-out operation with no added service time. However, POD internal processes are dynamic, with variable staffing, layout, and supplies that may affect hourly processing rates. PODs may incorporate priority groups, which identify specific population such as children, pregnant women, and senior citizens as a higher priority for MCMs. PODs may utilize head of household methods to distribute several types of MCMs. PODs may operate as triage and evaluation centers in addition to MCM dispensing centers, such as in the *NEHC Plan* (DPH, 2008b). Opportunities for future research include employing a dynamic processing rate, incorporating triage and evaluation procedures, and considering different dispensing techniques.

The flexibility of the POD TIM is key to its successful use in planning. A flexible model is adaptable for use in many disease scenarios. The POD TIM may have future applications as a scenario comparison. I have already discussed comparing location choice strategies, patient arrival patterns, and other behavioral factors above. Other scenario characteristics include type of biological outbreak, walk-in versus drive-through PODs, and implementation of closed PODs. In addition, researchers may use the model to compare traffic mitigation techniques. Future work should consider the rigidity of the model's assumptions. The current POD TIM is an inflexible model that considers an anthrax release with open PODs and limited behavior options. An improved model would incorporate general planning concepts and accommodate ongoing emergency characteristics. Researchers may also create a traffic impact model that is compatible with existing POD models, such as the Bioterrorism and Epidemic Outbreak Response Model, the Dynamic POD Simulator, or the RealOpt model (Hupert et al., 2009; Lee et al., 2009). Future research should balance the rigidity of the model's assumptions and outputs with the needs of emergency planners.

Researchers should consider if the current model uses the best tools to analyze the traffic impacts of PODs. I use the term "tools" to refer to two distinct aspects of the model: the performance measures within the model and the modeling software itself. The current model's performance measures quantify network and POD impacts. Network measures of effectiveness compare background, POD, and spillover traffic volumes to road capacity. POD measures of effectiveness describe patient arrivals, processing rates, spillover volumes, queue lengths, and delay. Both sets of performance measures examine the infrastructure impacts. However, it may be equally important to examine social costs to the population as well. A publication by Taylor (2008) measures impacts in accessibility to users, in which accessibility is the ease of access from point X to point Y. Accessibility of individual locations may be aggregated into an overall accessibility level for the network. A user-based performance metric may more directly relate POD traffic impacts to POD planning and operations.

The second aspect of the model to be considered is the software platform. The POD TIM is modeled in Citilabs Cube Voyager, a macroscopic level software often used for travel demand models. Future research should consider if Citilabs Cube is the best software to analyze POD traffic impacts on a transportation network. I ask the question, is a travel demand forecast model the best type of model to represent the interaction between PODs and the transportation network? A macroscopic level model is needed to understand the impacts across a regional network. However, a complimentary, detailed examination of POD locations may be performed at a microscopic level. Researchers may model parking availability in a microscopic level software, such as the model by Ma et al. (2011). This model type would examine each POD location individually, since modeling the entire case study region at the microscopic level would be extreme. A microscopic level POD model may also be useful when determining traffic mitigation techniques. Future research should explore microscopic and macroscopic traffic modeling software to ensure the best fit for the model.

The last, and arguably most important, suggestion for future research is to promote communication, coordination, and collaboration between Emergency Management Agencies, Divisions of Public Health, Departments of Transportation, and academic research institutions. Currently, two large issues stand between researchers and interdisciplinary collaboration. The first issue is security guidelines that prevent sharing official documents between agencies and institutions. The second issue is differing vocabulary between agencies, particularly between researchers and practitioners. We may overcome these prohibitive issues through compromise and discussion between organizations. In *A National Strategic Plan for Public Health Preparedness and Response*, the CDC states that "it is essential that partners and stakeholders across public health, healthcare, bio-defense, emergency management, and the private sector, work together" (2011, p. 4). I advocate extending interagency collaboration to Departments of Transportation as well. The goal of future POD traffic impact models is to facilitate interagency coordination between the emergency management sector and Departments of Transportation.

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Appendix A

DISCLAIMER

This research uses a model created by the Delaware Department of Transportation and the data associated within that model. However, the views and opinions expressed through this research are those of the author, and do not reflect policies or programs of the Delaware Department of Transportation. The Delaware Department of Transportation does not endorse the processes or findings of this research.

Appendix B

HOURLY ARRIVAL PERCENTAGES OF TOTAL POPULATION FOR ARRIVAL CURVE SCENARIOS

Table 10 presents the hourly arrival percentages of the total population for the five arrival scenarios. The five patient arrival rates are a uniform, dual uniform, AM and PM rush hour peaks, a PM rush hour peak, and a midday peak arrival curves. The model has a two-hour waiting period before the PODs open, followed by 24 hours of continuous patient arrivals. However, the underlying evacuation model has a 30-hour traffic assignment period, in which all hours must have a nonzero arrival rate. Therefore, a small percentage of the population (cumulatively less than 1%) may arrive at the PODs for four hours after "closing."

Table 10: Hourly Arrival Percentages of Total Population for Arrival Curve Scenarios (in percentages)

Time of Day	Uniform	Dual Uniform	AM and PM Rush Hour Peaks	PM Rush Hour Peak	Midday Peak
6:00	3.83	1	5	3	3
7:00	3.83	3	7	4	4
8:00	3.84	6	9	5	5
9:00	3.83	6	7	4	6
10:00	3.83	6	5	3	8
11:00	3.83	6	3	2	9
12:00	3.83	6	2	2	10
13:00	3.83	6	2	2	9
14:00	3.83	6	3	3	8
15:00	3.83	6	5	6	6
16:00	3.83	6	7	9	5
17:00	3.83	6	9	12	4
18:00	3.83	6	7	11	3
19:00	3.83	6	5	9	2
20:00	3.83	6	3	7	1
21:00	3.83	5	1	4	1
22:00	3.83	3	1	2	1
23:00	3.83	2	1	1	1
24:00	3.83	1	1	1	0.9
25:00	3.84	1	1	0.9	0.9
26:00	3.83	1	1	0.9	0.9
27:00	3.83	1	1	0.9	0.9
28:00	3.83	0.9	1	0.9	1
29:00	3.83	0.9	1	1	2
30:00	3.83	0.9	5	2	3
31:00	3.83	0.9	6.6	3	4
32:00	0.1	0.1	0.1	0.1	0.1
33:00	0.1	0.1	0.1	0.1	0.1
34:00	0.1	0.1	0.1	0.1	0.1
35:00	0.1	0.1	0.1	0.1	0.1

Appendix C

POD MOES FOR UNIFORM ARRIVAL CURVE SCENARIO

Tables 11 through 15 contain the POD MOEs for each POD location for the uniform arrival scenario. The model provided time of day, residents from previous hour, new arrivals, POD processing rate, spillover to next hour, and hourly average queue. For descriptions, see Table 3 in Section 3.5. Cumulative arrivals and cumulative processed were calculated after each scenario run. Due to rounding errors within matrices in the model, cumulative arrivals and cumulative processed may not be equal.

Table 11: Raw Hourly Data for DelTech POD for Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1426	0	1426	3.43	1426	0
7:00	1426	1904	0	3330	4.33	3330	0
8:00	3330	644	1000	2974	3.97	3974	1000
9:00	2974	398	1000	2372	3.37	4372	2000
10:00	2372	414	1000	1787	2.79	4786	3000
11:00	1787	407	1000	1194	2.19	5193	4000
12:00	1194	418	1000	612	1.61	5611	5000
13:00	612	403	1000	15	1.01	6014	6000
14:00	15	410	425	0	0.43	6424	6425
15:00	0	387	387	0	0.39	6811	6812
16:00	0	414	414	0	0.41	7225	7226
17:00	0	415	415	0	0.42	7640	7641
18:00	0	421	421	0	0.42	8061	8062
19:00	0	411	411	0	0.41	8472	8473
20:00	0	397	397	0	0.4	8869	8870
21:00	0	397	397	0	0.4	9266	9267
22:00	0	401	401	0	0.4	9667	9668
23:00	0	400	400	0	0.4	10067	10068
24:00	0	395	395	0	0.39	10462	10463
25:00	0	396	396	0	0.4	10858	10859
26:00	0	395	395	0	0.39	11253	11254
27:00	0	395	395	0	0.39	11648	11649
28:00	0	395	395	0	0.39	12043	12044
29:00	0	395	395	0	0.39	12438	12439
30:00	0	395	395	0	0.39	12833	12834
31:00	0	395	395	0	0.39	13228	13229
32:00	0	8	8	0	0.01	13236	13237
33:00	0	9	9	0	0.01	13245	13246
34:00	0	8	8	0	0.01	13253	13254
35:00	0	8	8	0	0.01	13261	13262

Table 12: Raw Hourly Data for JCC POD for Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2842	0	2842	4.84	2842	0
7:00	2842	3517	0	6358	7.36	6359	0
8:00	6358	1734	1000	7092	8.09	8093	1000
9:00	7092	1359	1000	7451	8.45	9452	2000
10:00	7451	1391	1000	7841	8.84	10843	3000
11:00	7841	1378	1000	8219	9.22	12221	4000
12:00	8220	1397	1000	8616	9.62	13618	5000
13:00	8616	1370	1000	8986	9.99	14988	6000
14:00	8986	1385	1000	9371	10.37	16373	7000
15:00	9371	1364	1000	9735	10.74	17737	8000
16:00	9735	1416	1000	10152	11.15	19153	9000
17:00	10152	1418	1000	10570	11.57	20571	10000
18:00	10570	1405	1000	10975	11.98	21976	11000
19:00	10975	1387	1000	11362	12.36	23363	12000
20:00	11362	1355	1000	11717	12.72	24718	13000
21:00	11717	1357	999	12074	13.07	26075	13999
22:00	12074	1364	1000	12439	13.44	27439	14999
23:00	12439	1364	1000	12803	13.8	28803	15999
24:00	12803	1349	1000	13152	14.15	30152	16999
25:00	13152	1352	1000	13504	14.5	31504	17999
26:00	13504	1349	999	13853	14.85	32853	18998
27:00	13854	1349	1000	14203	15.2	34202	19998
28:00	14203	1349	1000	14552	15.55	35551	20998
29:00	14552	1349	1000	14901	15.9	36900	21998
30:00	14901	1337	1000	15238	16.24	38237	22998
31:00	15238	1337	1000	15575	16.57	39574	23998
32:00	15575	34	1000	14609	15.61	39608	24998
33:00	14609	34	1001	13643	14.64	39642	25999
34:00	13642	34	1000	12676	13.68	39676	26999
35:00	12676	34	1000	11710	12.71	39710	27999
36:00	11710	0	1000	10710	11.71	39710	28999

Table 12, continued

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
37:00	10710	0	1000	9710	10.71	39710	29999
38:00	9709	0	1000	8709	9.71	39710	30999
39:00	8709	0	1000	7709	8.71	39710	31999
40:00	7709	0	1000	6709	7.71	39710	32999
41:00	6710	0	1000	5710	6.71	39710	33999
42:00	5710	0	1000	4710	5.71	39710	34999
43:00	4710	0	1000	3710	4.71	39710	35999
44:00	3710	0	1000	2710	3.71	39710	36999
45:00	2710	0	1000	1710	2.71	39710	37999
46:00	1710	0	1000	710	1.71	39710	38999
47:00	710	0	710	0	0.71	39710	39709

Table 13: Raw Hourly Data for NESSC POD for Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2160	0	2160	4.16	2160	0
7:00	2160	2665	0	4825	5.83	4825	0
8:00	4825	1333	1000	5159	6.16	6158	1000
9:00	5159	1002	1000	5161	6.16	7160	2000
10:00	5161	1041	1000	5202	6.2	8201	3000
11:00	5202	1030	1000	5232	6.23	9231	4000
12:00	5232	1046	1000	5278	6.28	10277	5000
13:00	5278	1011	1000	5288	6.29	11288	6000
14:00	5288	1021	1000	5309	6.31	12309	7000
15:00	5309	1019	1000	5328	6.33	13328	8000
16:00	5328	1069	1000	5397	6.4	14397	9000
17:00	5397	1071	1000	5468	6.47	15468	10000
18:00	5468	1036	1000	5504	6.5	16504	11000
19:00	5504	1022	1000	5526	6.53	17526	12000
20:00	5526	1000	1000	5525	6.53	18526	13000
21:00	5525	1001	1000	5526	6.53	19527	14000
22:00	5526	1006	1000	5532	6.53	20533	15000
23:00	5532	1006	1000	5538	6.54	21539	16000
24:00	5538	993	1000	5531	6.53	22532	17000
25:00	5531	996	1000	5526	6.53	23528	18000
26:00	5526	993	1000	5519	6.52	24521	19000
27:00	5519	993	1000	5512	6.51	25514	20000
28:00	5512	993	1000	5505	6.5	26507	21000
29:00	5505	993	1000	5498	6.5	27500	22000
30:00	5497	1006	1000	5503	6.5	28506	23000
31:00	5504	1006	1000	5510	6.51	29512	24000
32:00	5510	26	1000	4535	5.54	29538	25000
33:00	4535	25	1000	3561	4.56	29563	26000
34:00	3561	26	1000	2586	3.59	29589	27000
35:00	2586	26	1000	1612	2.61	29615	28000
36:00	1612	0	1000	612	1.61	29615	29000
37:00	612	0	612	0	0.61	29615	29612

Table 14: Raw Hourly Data for Frawley POD for Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	196	0	196	2.2	196	0
7:00	196	295	0	491	1.49	491	0
8:00	491	48	538	0	0.54	539	538
9:00	0	9	9	0	0.01	548	547
10:00	0	11	11	0	0.01	559	558
11:00	0	10	10	0	0.01	569	568
12:00	0	12	12	0	0.01	581	580
13:00	0	10	10	0	0.01	591	590
14:00	0	10	10	0	0.01	601	600
15:00	0	9	9	0	0.01	610	609
16:00	0	12	12	0	0.01	622	621
17:00	0	13	13	0	0.01	635	634
18:00	0	12	12	0	0.01	647	646
19:00	0	11	11	0	0.01	658	657
20:00	0	9	9	0	0.01	667	666
21:00	0	9	9	0	0.01	676	675
22:00	0	10	10	0	0.01	686	685
23:00	0	9	9	0	0.01	695	694
24:00	0	9	9	0	0.01	704	703
25:00	0	9	9	0	0.01	713	712
26:00	0	9	9	0	0.01	722	721
27:00	0	9	9	0	0.01	731	730
28:00	0	9	9	0	0.01	740	739
29:00	0	9	9	0	0.01	749	748
30:00	0	9	9	0	0.01	758	757
31:00	0	9	9	0	0.01	767	766

Table 15: Raw Hourly Data for DMV POD for Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2936	0	2936	4.94	2936	0
7:00	2936	4090	0	7027	8.03	7026	0
8:00	7027	1072	1000	7098	8.1	8098	1000
9:00	7098	350	1000	6448	7.45	8448	2000
10:00	6448	425	1000	5874	6.87	8873	3000
11:00	5873	401	1000	5275	6.27	9274	4000
12:00	5274	437	1000	4711	5.71	9711	5000
13:00	4711	369	1000	4081	5.08	10080	6000
14:00	4080	393	1000	3473	4.47	10473	7000
15:00	3473	359	1000	2832	3.83	10832	8000
16:00	2832	458	1000	2291	3.29	11290	9000
17:00	2291	462	1000	1753	2.75	11752	10000
18:00	1753	424	1000	1177	2.18	12176	11000
19:00	1177	396	1000	573	1.57	12572	12000
20:00	573	344	917	0	0.92	12916	12917
21:00	0	347	347	0	0.35	13263	13264
22:00	0	360	360	0	0.36	13623	13624
23:00	0	359	359	0	0.36	13982	13983
24:00	0	330	330	0	0.33	14312	14313
25:00	0	331	331	0	0.33	14643	14644
26:00	0	330	330	0	0.33	14973	14974
27:00	0	330	330	0	0.33	15303	15304
28:00	0	330	330	0	0.33	15633	15634
29:00	0	330	330	0	0.33	15963	15964
30:00	0	330	330	0	0.33	16293	16294
31:00	0	330	330	0	0.33	16623	16624
32:00	0	9	9	0	0.01	16632	16633
33:00	0	9	9	0	0.01	16641	16642
34:00	0	9	9	0	0.01	16650	16651
35:00	0	9	9	0	0.01	16659	16660

Appendix D

POD MOES FOR DUAL UNIFORM ARRIVAL CURVE SCENARIO

Tables 16 through 20 contain the POD MOEs for each POD location for the dual uniform arrival scenario. The model provided time of day, residents from previous hour, new arrivals, POD processing rate, spillover to next hour, and hourly average queue. For descriptions, see Table 3 in Section 3.5. Cumulative arrivals and cumulative processed were calculated after each scenario run. Due to rounding errors within matrices in the model, cumulative arrivals and cumulative processed may not be equal.

Table 16: Raw Hourly Data for DelTech POD for Dual Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1133	0	1133	3.13	1133	0
7:00	1133	1818	0	2951	3.95	2951	0
8:00	2951	867	1000	2818	3.82	3818	1000
9:00	2818	623	1000	2441	3.44	4441	2000
10:00	2441	637	1000	2077	3.08	5078	3000
11:00	2078	630	1000	1708	2.71	5708	4000
12:00	1708	641	1000	1348	2.35	6349	5000
13:00	1348	628	1000	976	1.98	6977	6000
14:00	976	635	1000	611	1.61	7612	7000
15:00	611	604	1000	215	1.22	8216	8000
16:00	215	631	846	0	0.85	8847	8846
17:00	0	632	632	0	0.63	9479	9478
18:00	0	646	646	0	0.65	10125	10124
19:00	0	636	636	0	0.64	10761	10760
20:00	0	621	621	0	0.62	11382	11381
21:00	0	519	519	0	0.52	11901	11900
22:00	0	315	315	0	0.31	12216	12215
23:00	0	211	211	0	0.21	12427	12426
24:00	0	102	102	0	0.1	12529	12528
25:00	0	102	102	0	0.1	12631	12630
26:00	0	102	102	0	0.1	12733	12732
27:00	0	102	102	0	0.1	12835	12834
28:00	0	91	91	0	0.09	12926	12925
29:00	0	91	91	0	0.09	13017	13016
30:00	0	91	91	0	0.09	13108	13107
31:00	0	91	91	0	0.09	13199	13198
32:00	0	8	8	0	0.01	13207	13206
33:00	0	9	9	0	0.01	13216	13215
34:00	0	8	8	0	0.01	13224	13223
35:00	0	8	8	0	0.01	13232	13231

Table 17: Raw Hourly Data for JCC POD for Dual Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1854	0	1854	3.85	1854	0
7:00	1854	3226	0	5081	6.08	5080	0
8:00	5081	2488	1000	6569	7.57	7568	1000
9:00	6569	2123	1000	7692	8.69	9691	2000
10:00	7692	2153	1000	8845	9.84	11844	3000
11:00	8845	2140	1000	9985	10.99	13984	4000
12:00	9985	2159	1000	11144	12.14	16143	5000
13:00	11145	2134	1000	12279	13.28	18277	6000
14:00	12280	2149	1000	13428	14.43	20426	7000
15:00	13429	2130	1000	14559	15.56	22556	8000
16:00	14559	2182	1000	15741	16.74	24738	9000
17:00	15740	2184	1000	16924	17.92	26922	10000
18:00	16925	2169	1000	18094	19.09	29091	11000
19:00	18094	2151	1001	19245	20.24	31242	12001
20:00	19244	2119	1001	20363	21.36	33361	13002
21:00	20363	1769	1000	21131	22.13	35130	14002
22:00	21132	1071	1000	21203	22.2	36201	15002
23:00	21203	719	1001	20922	21.92	36920	16003
24:00	20922	352	1000	20274	21.27	37272	17003
25:00	20274	352	999	19626	20.63	37624	18002
26:00	19626	352	1001	18978	19.98	37976	19003
27:00	18977	352	1000	18330	19.33	38328	20003
28:00	18329	317	1001	17646	18.65	38645	21004
29:00	17646	317	1001	16963	17.96	38962	22005
30:00	16962	315	1001	16277	17.28	39277	23006
31:00	16276	315	999	15590	16.59	39592	24005
32:00	15591	34	999	14625	15.62	39626	25004
33:00	14625	34	1000	13659	14.66	39660	26004
34:00	13659	34	1000	12693	13.69	39694	27004
35:00	12693	34	1000	11727	12.73	39728	28004

Table 17, continued

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
36:00	11726	0	1000	10726	11.73	39728	29004
37:00	10726	0	1000	9726	10.73	39728	30004
38:00	9727	0	1000	8727	9.73	39728	31004
39:00	8727	0	1000	7727	8.73	39728	32004
40:00	7727	0	1000	6727	7.73	39728	33004
41:00	6727	0	1000	5727	6.73	39728	34004
42:00	5726	0	1000	4726	5.73	39728	35004
43:00	4727	0	1000	3727	4.73	39728	36004
44:00	3726	0	1000	2726	3.73	39728	37004
45:00	2727	0	1000	1727	2.73	39728	38004
46:00	1727	0	1000	727	1.73	39728	39004
47:00	727	0	727	0	0.73	39728	39731

Table 18: Raw Hourly Data for NESSC POD for Dual Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1417	0	1417	3.42	1417	0
7:00	1417	2446	0	3863	4.86	3863	0
8:00	3863	1900	1000	4764	5.76	5763	1000
9:00	4764	1565	1000	5328	6.33	7328	2000
10:00	5329	1606	1000	5935	6.93	8934	3000
11:00	5934	1595	1000	6529	7.53	10529	4000
12:00	6529	1611	1000	7141	8.14	12140	5000
13:00	7140	1573	1000	7713	8.71	13713	6000
14:00	7713	1583	1000	8296	9.3	15296	7000
15:00	8296	1586	1000	8882	9.88	16882	8000
16:00	8882	1637	1000	9519	10.52	18519	9000
17:00	9519	1638	1000	10157	11.16	20157	10000
18:00	10156	1598	1000	10755	11.75	21755	11000
19:00	10754	1585	1000	11339	12.34	23340	12000
20:00	11339	1562	1000	11901	12.9	24902	13000
21:00	11901	1304	1000	12205	13.21	26206	14000
22:00	12205	791	1000	11996	13	26997	15000
23:00	11997	531	1001	11528	12.53	27528	16001
24:00	11528	260	999	10787	11.79	27788	17000
25:00	10788	260	1000	10047	11.05	28048	18000
26:00	10047	260	1000	9307	10.31	28308	19000
27:00	9307	260	1000	8567	9.57	28568	20000
28:00	8567	233	1000	7801	8.8	28801	21000
29:00	7801	233	1000	7034	8.03	29034	22000
30:00	7034	236	1000	6270	7.27	29270	23000
31:00	6270	236	1000	5507	6.51	29506	24000
32:00	5506	26	1000	4532	5.53	29532	25000
33:00	4532	25	1000	3557	4.56	29557	26000
34:00	3558	26	1000	2583	3.58	29583	27000
35:00	2583	26	1000	1609	2.61	29609	28000
36:00	1609	0	1000	609	1.61	29609	29000
37:00	609	0	609	0	0.61	29609	29609

Table 19: Raw Hourly Data for Frawley POD for Dual Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	189	0	189	2.19	189	0
7:00	189	293	0	482	1.48	482	0
8:00	482	53	535	0	0.53	535	535
9:00	0	14	14	0	0.01	549	549
10:00	0	16	16	0	0.02	565	565
11:00	0	16	16	0	0.02	581	581
12:00	0	17	17	0	0.02	598	598
13:00	0	15	15	0	0.01	613	613
14:00	0	16	16	0	0.02	629	629
15:00	0	15	15	0	0.01	644	644
16:00	0	18	18	0	0.02	662	662
17:00	0	18	18	0	0.02	680	680
18:00	0	17	17	0	0.02	697	697
19:00	0	16	16	0	0.02	713	713
20:00	0	14	14	0	0.01	727	727
21:00	0	12	12	0	0.01	739	739
22:00	0	8	8	0	0.01	747	747
23:00	0	5	5	0	0.01	752	752
24:00	0	2	2	0	0	754	754
25:00	0	2	2	0	0	756	756
26:00	0	2	2	0	0	758	758
27:00	0	2	2	0	0	760	760
28:00	0	2	2	0	0	762	762
29:00	0	2	2	0	0	764	764
30:00	0	2	2	0	0	766	766
31:00	0	2	2	0	0	768	768

Table 20: Raw Hourly Data for DMV POD for Dual Uniform Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2692	0	2692	4.69	2692	0
7:00	2692	4019	0	6712	7.71	6711	0
8:00	6712	1258	1000	6970	7.97	7969	1000
9:00	6970	537	1000	6507	7.51	8506	2000
10:00	6507	613	1000	6119	7.12	9119	3000
11:00	6119	589	1000	5708	6.71	9708	4000
12:00	5708	624	1000	5332	6.33	10332	5000
13:00	5332	557	1000	4889	5.89	10889	6000
14:00	4889	580	1000	4469	5.47	11469	7000
15:00	4469	547	1000	4016	5.02	12016	8000
16:00	4017	646	1000	3663	4.66	12662	9000
17:00	3663	649	1000	3312	4.31	13311	10000
18:00	3312	612	1000	2924	3.92	13923	11000
19:00	2924	583	1000	2507	3.51	14506	12000
20:00	2507	531	1000	2038	3.04	15037	13000
21:00	2038	448	1000	1486	2.49	15485	14000
22:00	1486	289	1000	774	1.77	15774	15000
23:00	774	201	975	0	0.98	15975	15975
24:00	0	87	87	0	0.09	16062	16062
25:00	0	86	86	0	0.09	16148	16148
26:00	0	86	86	0	0.09	16234	16234
27:00	0	86	86	0	0.09	16320	16320
28:00	0	78	78	0	0.08	16398	16398
29:00	0	78	78	0	0.08	16476	16476
30:00	0	78	78	0	0.08	16554	16554
31:00	0	78	78	0	0.08	16632	16632
32:00	0	9	9	0	0.01	16641	16641
33:00	0	9	9	0	0.01	16650	16650
34:00	0	9	9	0	0.01	16659	16659
35:00	0	9	9	0	0.01	16668	16668

Appendix E

POD MOES FOR AM AND PM RUSH HOUR PEAKS ARRIVAL CURVE SCENARIO

Tables 21 through 25 contain the POD MOEs for each POD location for the AM and PM rush hour peaks arrival scenario. The model provided time of day, residents from previous hour, new arrivals, POD processing rate, spillover to next hour, and hourly average queue. For descriptions, see Table 3 in Section 3.5. Cumulative arrivals and cumulative processed were calculated after each scenario run. Due to rounding errors within matrices in the model, cumulative arrivals and cumulative processed may not be equal.

Table 21: Raw Hourly Data for DelTech POD for AM and PM Rush Hour Peaks Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1546	0	1546	3.55	1546	0
7:00	1546	2231	0	3778	4.78	3777	0
8:00	3778	1178	1000	3955	4.96	4955	1000
9:00	3956	727	1000	3682	4.68	5682	2000
10:00	3682	534	1000	3217	4.22	6216	3000
11:00	3217	322	1000	2538	3.54	6538	4000
12:00	2538	229	1000	1767	2.77	6767	5000
13:00	1767	213	1000	981	1.98	6980	6000
14:00	980	324	1000	305	1.3	7304	7000
15:00	305	505	810	0	0.81	7809	7810
16:00	0	732	732	0	0.73	8541	8542
17:00	0	933	933	0	0.93	9474	9475
18:00	0	750	750	0	0.75	10224	10225
19:00	0	533	533	0	0.53	10757	10758
20:00	0	311	311	0	0.31	11068	11069
21:00	0	104	104	0	0.1	11172	11173
22:00	0	107	107	0	0.11	11279	11280
23:00	0	107	107	0	0.11	11386	11387
24:00	0	102	102	0	0.1	11488	11489
25:00	0	102	102	0	0.1	11590	11591
26:00	0	102	102	0	0.1	11692	11693
27:00	0	102	102	0	0.1	11794	11795
28:00	0	102	102	0	0.1	11896	11897
29:00	0	102	102	0	0.1	11998	11999
30:00	0	515	515	0	0.52	12513	12514
31:00	0	680	680	0	0.68	13193	13194
32:00	0	8	8	0	0.01	13201	13202
33:00	0	9	9	0	0.01	13210	13211
34:00	0	8	8	0	0.01	13218	13219
35:00	0	8	8	0	0.01	13226	13227

Table 22: Raw Hourly Data for JCC POD for AM and PM Rush Hour Peaks Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	3250	0	3250	5.25	3250	0
7:00	3250	4623	0	7874	8.87	7873	0
8:00	7874	3535	1000	10409	11.41	11408	1000
9:00	10409	2475	1000	11884	12.88	13883	2000
10:00	11884	1802	999	12686	13.69	15685	2999
11:00	12687	1086	1000	12773	13.77	16771	3999
12:00	12773	753	1000	12526	13.53	17524	4999
13:00	12526	726	1000	12252	13.25	18250	5999
14:00	12252	1091	1000	12344	13.34	19341	6999
15:00	12344	1778	1000	13121	14.12	21119	7999
16:00	13122	2535	1000	14656	15.66	23654	8999
17:00	14657	3243	1000	16900	17.9	26897	9999
18:00	16900	2522	1000	18422	19.42	29419	10999
19:00	18421	1799	1000	19220	20.22	31218	11999
20:00	19220	1062	999	19282	20.28	32280	12998
21:00	19282	360	1001	18642	19.64	32640	13999
22:00	18641	368	999	18009	19.01	33008	14998
23:00	18010	367	1000	17377	18.38	33375	15998
24:00	17377	352	999	16729	17.73	33727	16997
25:00	16730	352	1000	16082	17.08	34079	17997
26:00	16082	352	1000	15434	16.43	34431	18997
27:00	15434	352	1000	14786	15.79	34783	19997
28:00	14786	352	1000	14138	15.14	35135	20997
29:00	14138	352	1000	13490	14.49	35487	21997
30:00	13491	1745	1000	14236	15.24	37232	22997
31:00	14237	2304	999	15541	16.54	39536	23996
32:00	15541	34	999	14575	15.57	39570	24995
33:00	14576	34	1000	13609	14.61	39604	25995
34:00	13609	34	1000	12643	13.64	39638	26995

Table 22, continued

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
35:00	12643	34	1000	11677	12.68	39672	27995
36:00	11677	0	1000	10677	11.68	39672	28995
37:00	10677	0	1000	9677	10.68	39672	29995
38:00	9677	0	1000	8677	9.68	39672	30995
39:00	8677	0	1000	7677	8.68	39672	31995
40:00	7678	0	1000	6678	7.68	39672	32995
41:00	6678	0	1000	5678	6.68	39672	33995
42:00	5678	0	1000	4678	5.68	39672	34995
43:00	4678	0	1000	3678	4.68	39672	35995
44:00	3678	0	1000	2678	3.68	39672	36995
45:00	2678	0	1000	1678	2.68	39672	37995
46:00	1678	0	1000	678	1.68	39672	38995
47:00	678	0	678	0	0.68	39672	39673

Table 23: Raw Hourly Data for NESSC POD for AM and PM Rush Hour Peaks Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2467	0	2467	4.47	2467	0
7:00	2467	3498	0	5965	6.97	5965	0
8:00	5965	2689	1000	7654	8.65	8654	1000
9:00	7654	1825	1000	8479	9.48	10479	2000
10:00	8479	1346	1000	8825	9.82	11825	3000
11:00	8825	813	1000	8638	9.64	12638	4000
12:00	8638	569	1000	8207	9.21	13207	5000
13:00	8206	536	1000	7742	8.74	13743	6000
14:00	7742	806	1000	7547	8.55	14549	7000
15:00	7547	1325	1000	7872	8.87	15874	8000
16:00	7872	1899	1000	8770	9.77	17773	9000
17:00	8771	2423	1000	10194	11.19	20196	10000
18:00	10194	1858	1000	11052	12.05	22054	11000
19:00	11052	1326	1000	11378	12.38	23380	12000
20:00	11378	784	1000	11162	12.16	24164	13000
21:00	11162	267	1000	10430	11.43	24431	14000
22:00	10429	273	1000	9703	10.7	24704	15000
23:00	9702	273	1000	8975	9.98	24977	16000
24:00	8975	260	1000	8235	9.23	25237	17000
25:00	8235	260	1000	7494	8.49	25497	18000
26:00	7495	260	1000	6754	7.75	25757	19000
27:00	6755	260	1000	6014	7.01	26017	20000
28:00	6015	260	1000	5274	6.27	26277	21000
29:00	5274	260	1000	4534	5.53	26537	22000
30:00	4534	1313	1000	4847	5.85	27850	23000
31:00	4847	1734	1000	5581	6.58	29584	24000
32:00	5581	26	1000	4607	5.61	29610	25000
33:00	4607	25	1000	3632	4.63	29635	26000
34:00	3632	26	1000	2657	3.66	29661	27000
35:00	2657	26	1000	1683	2.68	29687	28000
36:00	1683	0	1000	683	1.68	29687	29000
37:00	683	0	683	0	0.68	29687	29683

Table 24: Raw Hourly Data for Frawley POD for AM and PM Rush Hour Peaks Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	199	0	199	2.2	199	0
7:00	199	302	0	501	1.5	501	0
8:00	501	60	561	0	0.56	561	561
9:00	0	17	17	0	0.02	578	578
10:00	0	14	14	0	0.01	592	592
11:00	0	8	8	0	0.01	600	600
12:00	0	7	7	0	0.01	607	607
13:00	0	5	5	0	0.01	612	612
14:00	0	8	8	0	0.01	620	620
15:00	0	12	12	0	0.01	632	632
16:00	0	20	20	0	0.02	652	652
17:00	0	25	25	0	0.02	677	677
18:00	0	19	19	0	0.02	696	696
19:00	0	13	13	0	0.01	709	709
20:00	0	7	7	0	0.01	716	716
21:00	0	2	2	0	0	718	718
22:00	0	3	3	0	0	721	721
23:00	0	3	3	0	0	724	724
24:00	0	2	2	0	0	726	726
25:00	0	2	2	0	0	728	728
26:00	0	2	2	0	0	730	730
27:00	0	2	2	0	0	732	732
28:00	0	2	2	0	0	734	734
29:00	0	2	2	0	0	736	736
30:00	0	12	12	0	0.01	748	748
31:00	0	16	16	0	0.02	764	764

Table 25: Raw Hourly Data for DMV POD for AM and PM Rush Hour Peaks Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	3038	0	3038	5.04	3038	0
7:00	3038	4364	0	7402	8.4	7402	0
8:00	7402	1517	1000	7918	8.92	8919	1000
9:00	7918	623	1000	7542	8.54	9542	2000
10:00	7542	527	1000	7068	8.07	10069	3000
11:00	7068	330	1000	6398	7.4	10399	4000
12:00	6398	279	1000	5677	6.68	10678	5000
13:00	5677	212	1000	4889	5.89	10890	6000
14:00	4889	322	1000	4210	5.21	11212	7000
15:00	4211	461	1000	3672	4.67	11673	8000
16:00	3672	732	1000	3404	4.4	12405	9000
17:00	3404	909	1000	3312	4.31	13314	10000
18:00	3312	698	1000	3010	4.01	14012	11000
19:00	3010	497	1000	2507	3.51	14509	12000
20:00	2507	273	1000	1780	2.78	14782	13000
21:00	1780	103	1000	883	1.88	14885	14000
22:00	883	116	999	0	1	15001	14999
23:00	0	115	115	0	0.12	15116	15114
24:00	0	87	87	0	0.09	15203	15201
25:00	0	86	86	0	0.09	15289	15287
26:00	0	86	86	0	0.09	15375	15373
27:00	0	86	86	0	0.09	15461	15459
28:00	0	86	86	0	0.09	15547	15545
29:00	0	86	86	0	0.09	15633	15631
30:00	0	432	432	0	0.43	16065	16063
31:00	0	570	570	0	0.57	16635	16633
32:00	0	9	9	0	0.01	16644	16642
33:00	0	9	9	0	0.01	16653	16651
34:00	0	9	9	0	0.01	16662	16660
35:00	0	9	9	0	0.01	16671	16669

Appendix F

POD MOES FOR PM RUSH HOUR PEAK ARRIVAL CURVE SCENARIO

Tables 26 through 30 contain the POD MOEs for each POD location for the PM rush hour peak arrival scenario. The model provided time of day, residents from previous hour, new arrivals, POD processing rate, spillover to next hour, and hourly average queue. For descriptions, see Table 3 in Section 3.5. Cumulative arrivals and cumulative processed were calculated after each scenario run. Due to rounding errors within matrices in the model, cumulative arrivals and cumulative processed may not be equal.

Table 26: Raw Hourly Data for DelTech POD for PM Rush Hour Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1340	0	1340	3.34	1340	0
7:00	1340	1921	0	3261	4.26	3261	0
8:00	3261	764	1000	3025	4.03	4025	1000
9:00	3025	416	1000	2441	3.44	4441	2000
10:00	2441	328	1000	1769	2.77	4769	3000
11:00	1769	218	1000	988	1.99	4987	4000
12:00	988	229	1000	217	1.22	5216	5000
13:00	217	213	430	0	0.43	5429	5430
14:00	0	324	324	0	0.32	5753	5754
15:00	0	604	604	0	0.6	6357	6358
16:00	0	933	933	0	0.93	7290	7291
17:00	0	1234	1000	234	1.23	8524	8291
18:00	234	1164	1000	398	1.4	9688	9291
19:00	398	947	1000	345	1.35	10635	10291
20:00	345	725	1000	71	1.07	11360	11291
21:00	71	415	486	0	0.49	11775	11777
22:00	0	211	211	0	0.21	11986	11988
23:00	0	107	107	0	0.11	12093	12095
24:00	0	102	102	0	0.1	12195	12197
25:00	0	91	91	0	0.09	12286	12288
26:00	0	91	91	0	0.09	12377	12379
27:00	0	91	91	0	0.09	12468	12470
28:00	0	91	91	0	0.09	12559	12561
29:00	0	102	102	0	0.1	12661	12663
30:00	0	205	205	0	0.2	12866	12868
31:00	0	309	309	0	0.31	13175	13177
32:00	0	8	8	0	0.01	13183	13185
33:00	0	9	9	0	0.01	13192	13194
34:00	0	8	8	0	0.01	13200	13202
35:00	0	8	8	0	0.01	13208	13210

Table 27: Raw Hourly Data for JCC POD for PM Rush Hour Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2551	0	2551	4.55	2551	0
7:00	2551	3575	0	6126	7.13	6126	0
8:00	6126	2140	1000	7266	8.27	8266	1000
9:00	7266	1418	1000	7684	8.68	9684	2000
10:00	7684	1098	1000	7783	8.78	10782	3000
11:00	7783	735	1000	7517	8.52	11517	4000
12:00	7517	753	1000	7271	8.27	12270	5000
13:00	7271	726	1000	6996	8	12996	6000
14:00	6997	1091	1000	7088	8.09	14087	7000
15:00	7088	2130	1000	8219	9.22	16217	8000
16:00	8218	3241	1000	10460	11.46	19458	9000
17:00	10460	4302	1000	13762	14.76	23760	10000
18:00	13762	3931	1000	16693	17.69	27691	11000
19:00	16693	3208	1000	18901	19.9	30899	12000
20:00	18901	2471	1000	20372	21.37	33370	13000
21:00	20372	1416	1000	20788	21.79	34786	14000
22:00	20788	720	1000	20507	21.51	35506	15000
23:00	20508	367	1001	19875	20.87	35873	16001
24:00	19874	352	1000	19226	20.23	36225	17001
25:00	19226	317	1000	18543	19.54	36542	18001
26:00	18543	317	999	17860	18.86	36859	19000
27:00	17861	317	1000	17178	18.18	37176	20000
28:00	17178	317	1000	16495	17.49	37493	21000
29:00	16495	352	1000	15847	16.85	37845	22000
30:00	15847	698	1000	15545	16.54	38543	23000
31:00	15545	1046	1000	15591	16.59	39589	24000
32:00	15592	34	999	14625	15.63	39623	24999
33:00	14626	34	1000	13660	14.66	39657	25999
34:00	13659	34	1000	12693	13.69	39691	26999

Table 27, continued

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
35:00	12693	34	1000	11727	12.73	39725	27999
36:00	11727	0	1000	10727	11.73	39725	28999
37:00	10727	0	1000	9727	10.73	39725	29999
38:00	9727	0	1000	8727	9.73	39725	30999
39:00	8727	0	1000	7727	8.73	39725	31999
40:00	7727	0	1000	6727	7.73	39725	32999
41:00	6727	0	1000	5727	6.73	39725	33999
42:00	5727	0	1000	4727	5.73	39725	34999
43:00	4727	0	1000	3727	4.73	39725	35999
44:00	3727	0	1000	2727	3.73	39725	36999
45:00	2727	0	1000	1727	2.73	39725	37999
46:00	1727	0	1000	727	1.73	39725	38999
47:00	727	0	727	0	0.73	39725	39726

Table 28: Raw Hourly Data for NESSC POD for PM Rush Hour Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1941	0	1941	3.94	1941	0
7:00	1941	2710	0	4651	5.65	4651	0
8:00	4651	1638	1000	5289	6.29	6289	1000
9:00	5289	1046	1000	5335	6.34	7335	2000
10:00	5335	824	1000	5159	6.16	8159	3000
11:00	5159	552	1000	4711	5.71	8711	4000
12:00	4712	569	1000	4280	5.28	9280	5000
13:00	4280	536	1000	3816	4.82	9816	6000
14:00	3816	806	1000	3622	4.62	10622	7000
15:00	3622	1586	1000	4208	5.21	12208	8000
16:00	4208	2422	1000	5630	6.63	14630	9000
17:00	5629	3208	1000	7837	8.84	17838	10000
18:00	7837	2895	1000	9733	10.73	20733	11000
19:00	9733	2363	1000	11096	12.1	23096	12000
20:00	11096	1822	1000	11918	12.92	24918	13000
21:00	11918	1045	1000	11963	12.96	25963	14000
22:00	11963	532	1000	11495	12.49	26495	15000
23:00	11495	273	1000	10768	11.77	26768	16000
24:00	10767	260	1000	10027	11.03	27028	17000
25:00	10027	233	1000	9260	10.26	27261	18000
26:00	9261	233	1000	8494	9.49	27494	19000
27:00	8494	233	1000	7727	8.73	27727	20000
28:00	7727	233	1000	6961	7.96	27960	21000
29:00	6961	260	1000	6220	7.22	28220	22000
30:00	6220	525	1000	5745	6.74	28745	23000
31:00	5745	787	1000	5532	6.53	29532	24000
32:00	5532	26	1000	4558	5.56	29558	25000
33:00	4557	25	1000	3583	4.58	29583	26000
34:00	3583	26	1000	2608	3.61	29609	27000
35:00	2608	26	1000	1634	2.63	29635	28000
36:00	1634	0	1000	634	1.63	29635	29000
37:00	634	0	634	0	0.63	29635	29634

Table 29: Raw Hourly Data for Frawley POD for PM Rush Hour Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	194	0	194	2.19	194	0
7:00	194	295	0	489	1.49	489	0
8:00	489	50	540	0	0.54	539	540
9:00	0	10	10	0	0.01	549	550
10:00	0	9	9	0	0.01	558	559
11:00	0	6	6	0	0.01	564	565
12:00	0	7	7	0	0.01	571	572
13:00	0	5	5	0	0.01	576	577
14:00	0	8	8	0	0.01	584	585
15:00	0	15	15	0	0.01	599	600
16:00	0	25	25	0	0.02	624	625
17:00	0	32	32	0	0.03	656	657
18:00	0	29	29	0	0.03	685	686
19:00	0	23	23	0	0.02	708	709
20:00	0	17	17	0	0.02	725	726
21:00	0	10	10	0	0.01	735	736
22:00	0	5	5	0	0.01	740	741
23:00	0	3	3	0	0	743	744
24:00	0	2	2	0	0	745	746
25:00	0	2	2	0	0	747	748
26:00	0	2	2	0	0	749	750
27:00	0	2	2	0	0	751	752
28:00	0	2	2	0	0	753	754
29:00	0	2	2	0	0	755	756
30:00	0	5	5	0	0	760	761
31:00	0	7	7	0	0.01	767	768

Table 30: Raw Hourly Data for DMV POD for PM Rush Hour Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2865	0	2865	4.87	2865	0
7:00	2865	4106	0	6971	7.97	6971	0
8:00	6971	1172	1000	7143	8.14	8143	1000
9:00	7142	365	1000	6507	7.51	8508	2000
10:00	6507	354	1000	5862	6.86	8862	3000
11:00	5862	243	1000	5105	6.1	9105	4000
12:00	5105	279	1000	4384	5.38	9384	5000
13:00	4384	212	1000	3595	4.6	9596	6000
14:00	3595	322	1000	2917	3.92	9918	7000
15:00	2917	547	1000	2464	3.46	10465	8000
16:00	2464	905	1000	2370	3.37	11370	9000
17:00	2370	1168	1000	2538	3.54	12538	10000
18:00	2538	1043	1000	2581	3.58	13581	11000
19:00	2581	842	1000	2423	3.42	14423	12000
20:00	2423	617	1000	2040	3.04	15040	13000
21:00	2040	362	1000	1402	2.4	15402	14000
22:00	1402	202	1000	604	1.6	15604	15000
23:00	604	115	719	0	0.72	15719	15719
24:00	0	87	87	0	0.09	15806	15806
25:00	0	78	78	0	0.08	15884	15884
26:00	0	78	78	0	0.08	15962	15962
27:00	0	78	78	0	0.08	16040	16040
28:00	0	78	78	0	0.08	16118	16118
29:00	0	86	86	0	0.09	16204	16204
30:00	0	172	172	0	0.17	16376	16376
31:00	0	259	259	0	0.26	16635	16635
32:00	0	9	9	0	0.01	16644	16644
33:00	0	9	9	0	0.01	16653	16653
34:00	0	9	9	0	0.01	16662	16662
35:00	0	9	9	0	0.01	16671	16671

Appendix G

POD MOES FOR MIDDAY PEAK ARRIVAL CURVE SCENARIO

Tables 31 through 35 contain the POD MOEs for each POD location for the midday peak arrival scenario. The model provided time of day, residents from previous hour, new arrivals, POD processing rate, spillover to next hour, and hourly average queue. For descriptions, see Table 3 in Section 3.5. Cumulative arrivals and cumulative processed were calculated after each scenario run. Due to rounding errors within matrices in the model, cumulative arrivals and cumulative processed may not be equal.

Table 31: Raw Hourly Data for DelTech POD for Midday Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1340	0	1340	3.34	1340	0
7:00	1340	1921	0	3261	4.26	3261	0
8:00	3261	764	1000	3025	4.03	4025	1000
9:00	3025	623	1000	2648	3.65	4648	2000
10:00	2648	842	1000	2490	3.49	5490	3000
11:00	2490	939	1000	2429	3.43	6429	4000
12:00	2429	1051	1000	2480	3.48	7480	5000
13:00	2480	939	1000	2419	3.42	8419	6000
14:00	2419	842	1000	2261	3.26	9261	7000
15:00	2261	604	1000	1865	2.87	9865	8000
16:00	1865	532	1000	1397	2.4	10397	9000
17:00	1397	432	1000	829	1.83	10829	10000
18:00	829	335	1000	164	1.16	11164	11000
19:00	164	222	386	0	0.39	11386	11386
20:00	0	103	103	0	0.1	11489	11489
21:00	0	104	104	0	0.1	11593	11593
22:00	0	107	107	0	0.11	11700	11700
23:00	0	107	107	0	0.11	11807	11807
24:00	0	91	91	0	0.09	11898	11898
25:00	0	91	91	0	0.09	11989	11989
26:00	0	91	91	0	0.09	12080	12080
27:00	0	91	91	0	0.09	12171	12171
28:00	0	102	102	0	0.1	12273	12273
29:00	0	205	205	0	0.21	12478	12478
30:00	0	309	309	0	0.31	12787	12787
31:00	0	412	412	0	0.41	13199	13199
32:00	0	8	8	0	0.01	13207	13207
33:00	0	9	9	0	0.01	13216	13216
34:00	0	8	8	0	0.01	13224	13224
35:00	0	8	8	0	0.01	13232	13232

Table 32: Raw Hourly Data for JCC POD for Midday Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2551	0	2551	4.55	2551	0
7:00	2551	3575	0	6126	7.13	6126	0
8:00	6126	2140	1000	7266	8.27	8266	1000
9:00	7266	2123	1000	8389	9.39	10389	2000
10:00	8389	2857	1000	10246	11.25	13246	3000
11:00	10246	3196	1000	12443	13.44	16442	4000
12:00	12443	3566	1000	15009	16.01	20008	5000
13:00	15009	3192	1000	17200	18.2	23200	6000
14:00	17201	2854	999	19054	20.05	26054	6999
15:00	19055	2130	1000	20185	21.19	28184	7999
16:00	20185	1829	999	21014	22.01	30013	8998
17:00	21015	1477	1000	21492	22.49	31490	9998
18:00	21492	1112	999	21604	22.6	32602	10997
19:00	21605	742	1000	21347	22.35	33344	11997
20:00	21346	358	999	20704	21.7	33702	12996
21:00	20705	360	1000	20065	21.07	34062	13996
22:00	20065	368	999	19433	20.43	34430	14995
23:00	19433	367	1001	18801	19.8	34797	15996
24:00	18800	317	1000	18117	19.12	35114	16996
25:00	18116	317	1000	17433	18.43	35431	17996
26:00	17433	317	1001	16750	17.75	35748	18997
27:00	16750	317	1000	16067	17.07	36065	19997
28:00	16067	352	999	15419	16.42	36417	20996
29:00	15419	704	1001	15124	16.12	37121	21997
30:00	15123	1046	1000	15169	16.17	38167	22997
31:00	15170	1395	1000	15565	16.56	39562	23997
32:00	15565	34	999	14599	15.6	39596	24996
33:00	14599	34	1000	13633	14.63	39630	25996
34:00	13633	34	1001	12667	13.67	39664	26997
35:00	12666	34	1001	11700	12.7	39698	27998

Table 32, continued

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
36:00	11699	0	1000	10699	11.7	39698	28998
37:00	10699	0	1000	9699	10.7	39698	29998
38:00	9699	0	1000	8699	9.7	39698	30998
39:00	8699	0	1000	7699	8.7	39698	31998
40:00	7698	0	1000	6698	7.7	39698	32998
41:00	6698	0	1000	5698	6.7	39698	33998
42:00	5698	0	1000	4698	5.7	39698	34998
43:00	4698	0	1000	3698	4.7	39698	35998
44:00	3698	0	1000	2698	3.7	39698	36998
45:00	2698	0	1000	1698	2.7	39698	37998
46:00	1698	0	1000	698	1.7	39698	38998
47:00	698	0	698	0	0.7	39698	39696

Table 33: Raw Hourly Data for NESSC POD for Midday Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	1941	0	1941	3.94	1941	0
7:00	1941	2710	0	4651	5.65	4651	0
8:00	4651	1638	1000	5289	6.29	6289	1000
9:00	5289	1565	1000	5854	6.85	7854	2000
10:00	5854	2128	1000	6981	7.98	9982	3000
11:00	6982	2377	1000	8359	9.36	12359	4000
12:00	8359	2654	1000	10013	11.01	15013	5000
13:00	10014	2351	1000	11365	12.36	17364	6000
14:00	11364	2102	1000	12467	13.47	19466	7000
15:00	12467	1586	1000	13053	14.05	21052	8000
16:00	13053	1375	1000	13428	14.43	22427	9000
17:00	13428	1115	1000	13544	14.54	23542	10000
18:00	13543	820	999	13364	14.36	24362	10999
19:00	13364	548	1000	12912	13.91	24910	11999
20:00	12912	266	999	12178	13.18	25176	12998
21:00	12179	267	1000	11446	12.45	25443	13998
22:00	11447	273	1000	10720	11.72	25716	14998
23:00	10719	273	1000	9992	10.99	25989	15998
24:00	9992	233	1000	9225	10.23	26222	16998
25:00	9225	233	1000	8458	9.46	26455	17998
26:00	8458	233	1000	7692	8.69	26688	18998
27:00	7692	233	1000	6925	7.93	26921	19998
28:00	6925	260	1000	6185	7.19	27181	20998
29:00	6185	518	1000	5703	6.7	27699	21998
30:00	5703	787	1000	5490	6.49	28486	22998
31:00	5491	1051	1000	5541	6.54	29537	23998
32:00	5541	26	1000	4567	5.57	29563	24998
33:00	4567	25	1000	3592	4.59	29588	25998
34:00	3592	26	1000	2618	3.62	29614	26998
35:00	2618	26	1000	1643	2.64	29640	27998
36:00	1643	0	1000	643	1.64	29640	28998
37:00	643	0	643	0	0.64	29640	29641

Table 34: Raw Hourly Data for Frawley POD for Midday Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	194	0	194	2.19	194	0
7:00	194	295	0	489	1.49	489	0
8:00	489	50	540	0	0.54	539	540
9:00	0	14	14	0	0.01	553	554
10:00	0	21	21	0	0.02	574	575
11:00	0	23	23	0	0.02	597	598
12:00	0	26	26	0	0.03	623	624
13:00	0	22	22	0	0.02	645	646
14:00	0	20	20	0	0.02	665	666
15:00	0	15	15	0	0.01	680	681
16:00	0	15	15	0	0.02	695	696
17:00	0	13	13	0	0.01	708	709
18:00	0	10	10	0	0.01	718	719
19:00	0	6	6	0	0.01	724	725
20:00	0	2	2	0	0	726	727
21:00	0	2	2	0	0	728	729
22:00	0	3	3	0	0	731	732
23:00	0	3	3	0	0	734	735
24:00	0	2	2	0	0	736	737
25:00	0	2	2	0	0	738	739
26:00	0	2	2	0	0	740	741
27:00	0	2	2	0	0	742	743
28:00	0	2	2	0	0	744	745
29:00	0	5	5	0	0	749	750
30:00	0	7	7	0	0.01	756	757
31:00	0	9	9	0	0.01	765	766

Table 35: Raw Hourly Data for DMV POD for Midday Peak Arrival Curve Scenario

Time of Day	Patients from Previous Hour	New Arrivals	POD Processing Rate	Spillover to Next Hour	Hourly Average Queue (hours)	Cumulative Arrivals	Cumulative Processed
6:00	0	2865	0	2865	4.87	2865	0
7:00	2865	4106	0	6971	7.97	6971	0
8:00	6971	1172	1000	7143	8.14	8143	1000
9:00	7142	537	1000	6679	7.68	8680	2000
10:00	6680	786	1000	6465	7.47	9466	3000
11:00	6465	848	1000	6313	7.31	10314	4000
12:00	6313	970	1000	6283	7.28	11284	5000
13:00	6283	815	1000	6098	7.1	12099	6000
14:00	6098	753	1000	5850	6.85	12852	7000
15:00	5850	547	1000	5397	6.4	13399	8000
16:00	5398	560	1000	4958	5.96	13959	9000
17:00	4957	477	1000	4434	5.43	14436	10000
18:00	4434	353	1000	3788	4.79	14789	11000
19:00	3788	238	1000	3026	4.03	15027	12000
20:00	3026	100	1000	2126	3.13	15127	13000
21:00	2126	103	1000	1229	2.23	15230	14000
22:00	1229	116	1000	345	1.35	15346	15000
23:00	345	115	460	0	0.46	15461	15460
24:00	0	78	78	0	0.08	15539	15538
25:00	0	78	78	0	0.08	15617	15616
26:00	0	78	78	0	0.08	15695	15694
27:00	0	78	78	0	0.08	15773	15772
28:00	0	86	86	0	0.09	15859	15858
29:00	0	172	172	0	0.17	16031	16030
30:00	0	259	259	0	0.26	16290	16289
31:00	0	346	346	0	0.35	16636	16635
32:00	0	9	9	0	0.01	16645	16644
33:00	0	9	9	0	0.01	16654	16653
34:00	0	9	9	0	0.01	16663	16662
35:00	0	9	9	0	0.01	16672	16671