International Journal of Transportation
Vol.4, No.2 (2016), pp.15-30
http://dx.doi.org/10.14257/ijt.2016.4.2.02

Infectious Disease and Hospital Surge Capacity Impacts on Urban Transportation

Evangelos I. Kaisar*, James E. Coolahan[1], Roy P. Koomullil[2]
and Peter A. Averkiou, M.D.[3]

[*]Associate Professor
Civil, Environmental and Geomatics Department, Florida Atlantic University
[1]Chief Technology Officer, Coolahan Associates, LLC
[2]Associate Professor, University of Alabama at Birmingham
[3]Assistant Professor, Charles E. Schmidt College of Medicine
Florida Atlantic University
[*]Ekaisar@fau.edu, [1]jim.cooolahan@comcast.net, [2]Rkoomul@uab.edu,
[3]Paverkiou@health.fau.edu

Abstract

Most existing hospital surge capacity models are focused on the problem of strategic planning or preparedness, i.e., predicting the resources required over the entire course of an incident based on a static set of inputs. The implicit assumption is that medical and public health response are not impacted by external situations, i.e., the existing models do not support tactical planning and preparedness. One of the external situations not considered is traffic. When modeling hospital surge capacity in response to a catastrophic event, such as treatment and vaccinations for contagious diseases during a bioterrorism crisis, the impact of dynamic traffic conditions on the arrival and departure of patients at the hospital, as well as the ability of hospital staff to arrive in a timely manner to administer medical care, must be considered. The dormant period makes monitoring normal daily traffic operations critical in creating proper response. In this paper we present a hybrid mesoscopic-microscopic model that applies microscopic simulation to areas of specific interest, while simulating a large surrounding network in lesser detail with a mesoscopic model.

Keywords: *Simulation, Mesoscopic, Microscopic, Bioterrorism, Hospital Surge Capacity, and Response*

1. Introduction

The spread of infectious disease is a major concern for urban populations worldwide. While commonly occurring in nature in the form of seasonal influenza outbreaks, these events have the potential to become major catastrophes, potentially killing millions, *e.g.*, Influenza Pandemic of 1918, which killed 20 to 50 million people. As the focus of hazard vulnerability in recent years has shifted from natural disaster to man-madedisaster, the potential for a biological terrorist attack in an urban area is a real threat. The transport of disease in cases of deliberate mass exposure takes on a unique form, whereby numerous infections occur at a single time and location (first generation). These infected populations travel to home, work and unknowing lyexpose others within their social networks (second and third generations). Depending on the biological agent, this may continue undetected for several days or weeks before officials can respond. This can ultimately result in hundreds of exposed individuals seeking care/vaccination within a small timeframe.

After the initial mass exposure, the contagion transport is conducted entirely using the transportation network. First generation victims travel from the mass exposure location to

ISSN: 2287-7940 IJT

carry out their everyday travel routine (travel to home, work, school, *etc.*). As a result, travel patterns will change as the life cycle of the disease progresses. Initially, the disease has no effect on travel, but ultimately hospital trips will increase and quarantines will be put in place. The goal of this paper is to examine the effects that infectious disease and hospital surge capacity have on traffic systems over the entire life cycle of a regional epidemic.

This paper summarizes the components used in modelling the effects of a regional epidemic on transportation operations. In this work, the authors use a disease spread model (Sparrows) developed by Johns Hopkins University Applied Physics Laboratory. It is a hospital surge capacity model which combines AHRQ Hospital Surge Model (AHRQ, 2011) and Maxi-Vac Model [1] and a hybrid traffic simulation platform AimSun N.G. to combine the model-outputs and quantify the traffic interactions. A Command and Control (C2) model was developed allowing for the testing of response strategies for the evaluation of strategic and tactical operational planning [2].

Discretised into forty 24-hour periods after the initial mass exposure, the disease spread model calculates the probability of infection for each member of a household and their associated travel for the following period (commute to work, self-quarantine, travel to hospital or seek vaccination). The Hospital Surge Model estimates the daily hospital resources needed for each facility (personnel and vaccine), hospital demand (arrivals who are infected, fatally ill, require vaccination and "worried well") and the hospital capacity. Arrivals are turned away once the daily capacity of the hospital facility is reached (no more available room or the facility is out of vaccine).The aspects of these models are combined into traffic simulation environment Aimsun N.G. where their impacts on the traffic network are quantified. Each model reports back to Command and Control where the tactical response model is updated at the end of each diurnal cycle.

The intent of this work is to simulate the interactions between the spread of an infectious disease, hospital surge capacity and the transportation system over the entire life cycle of an outbreak. Numerous biological agent scenarios and tactical response strategies can be explored using the Command and Control interface with the use of this model. Public officials and policy maker scan increase the arsenal of tools available to them, in order to plan and respond accordingly, if such an incident were to occur. The following section of this paper provides a description of the background research in disease spread followed by the biological event scenario. Next the paper describes the modeling components of traffic flow and hospital surge. The final sections provide the results from the practical application and a summary of the major findings.

2. Background of Disease Spread

Few studies exist which attempt to bridge the gap between regional transportation modeling and the spread of infectious disease. However, the spread of disease associated with bioterrorism is well documented. Many studies regarding disease focused on the spread of disease through contact rates, contact locations, and the timeline of signs and symptoms. Much of the bioterrorist models were structured to observe contact patterns inside a network [3]. A common contact mixing scheme inside a typical network is schools, work and social gathering spots. These models noted schools, neighborhoods and social gatherings as the primary breeding grounds for the spread of disease [3, 4]. In studies based on smallpox [3-7] it was very important to identify the nature of the disease because it has different characteristics than most biological weapons. This is what creates the high risk of infection and/or death because the signs and symptoms do not appear until 7 to 16 days after exposure, having a mean of 11.5 days. The timeline is well defined by [5, 7].Incubation, prodrome (early stage) and fulminant (late stages) can all be seen in Figure 1: Signs and Symptoms [7]:

- Prodrome (early-symptoms)- 2 to 5 days of fever and aches
- Fulminant (late-symptoms)- 7 to 14 days of rash

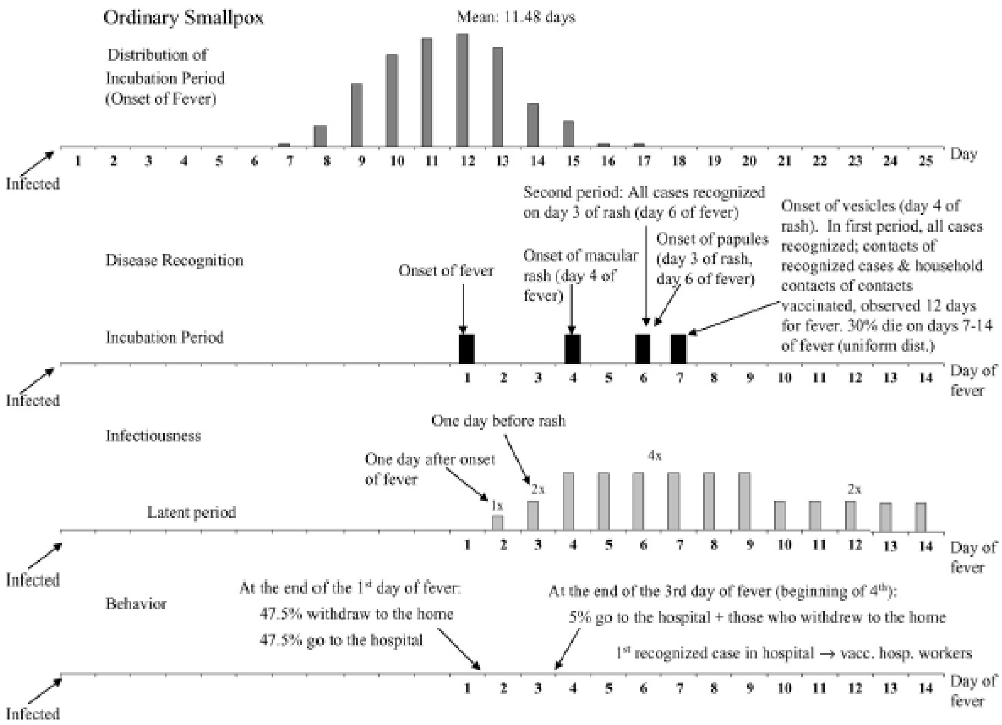


Figure 1. Signs and Symptoms Timeline [7]

Other studies by [4] and [8] focus on the impacts of vaccination both prior to and during the spread of disease. There is a consensus that healthcare workers and officials should vaccinate ahead of time. This allows them to work uninhibited and respond to those in need of treatment. Network-wide vaccinations are found unproductive and should only be implemented if the risk of an attack becomes so prevalent that it is demanded. These papers provide insight as to where and how many vaccination/emergency centers are necessary.

Response studies, [3] and [6] make it clear that effective targeting and containment of known infected areas can greatly reduce the spread and infection of disease. This reduces the overall demand for treatment at emergency centers, thus lowering travel delays. Perhaps the most important idea gathered from the bioterrorism review was that analysis of the social network's structure should be done in enough detail to understand how they interact (demographics) [7]. In the field of public safety, simulation has been applied to catastrophic events management and emergency incidents including fires, hurricanes and earthquakes [9-11]. The approaches to micro-scale crowd simulation and evacuation dynamics include the use of Cellular Automata (CA), Multi-agent Systems (MAS), and behavior-related physical models in recent research. The CA model divide the space in a uniform grid and each individual occupies a particular grid in a discrete time step. The individual behavior is dependent on the variables values of the neighboring cells at the previous time step and the behavior rules set in advance. CA has been widely used in simulation modelling [12, 13]. The ability to combine research areas regarding biological terrorism with emergency response transportation studies in an urban area is a dynamic and does not have the correct attention. The development of a biological event response plan to effectively and efficiently manage transportation travel and delay times is the main goal of this paper.

3. Simulation Model Design Overview

The bioterrorist attack scenario takes place at a concert arena in downtown Baltimore MD. Based on demographic research inside each transportation analysis zone (TAZ), a distribution of attendees is created based on TAZ origin. The attack will take place through the air duct network of the arena. The attendees of the show will be unaware of the release of smallpox and will become infected based on their location in the arena and air movement throughout. The attendees will proceed home after the show, and mixing of the population will ensue over the following days. Normal daily operations regarding trip distribution throughout the network will be monitored for approximately 12 days (based on the smallpox model for incubation) during morning peak hour driving times. After approximately 12days, the first signs and symptoms begin to arise and emergency centers will be implemented throughout the network as necessary.

Figure 2 shows the design concepts for the Bioterrorism Crisis Management (BCM) simulation, including the components to be executed prior to simulation of federation execution and the “faster than real time” components used during federation execution, along with principal data flows. Some of the aspects of the airborne transport simulation require significant run-time on dedicated multi-computer resources. Both the simulation of the airflow within the arena and the transport of the biological agent in that airflow currently require computations that cannot be performed in real time using currently available computing resources. Therefore, both the simulation of the release and transport through the arena ductwork, and the simulation of the airborne transport within the arena, must be performed in advance. Also, the generation of the local population, its age demographics, home and work/school locations, and the subset attending the concert in the arena at the time of the biological agent release can all be performed in advance.

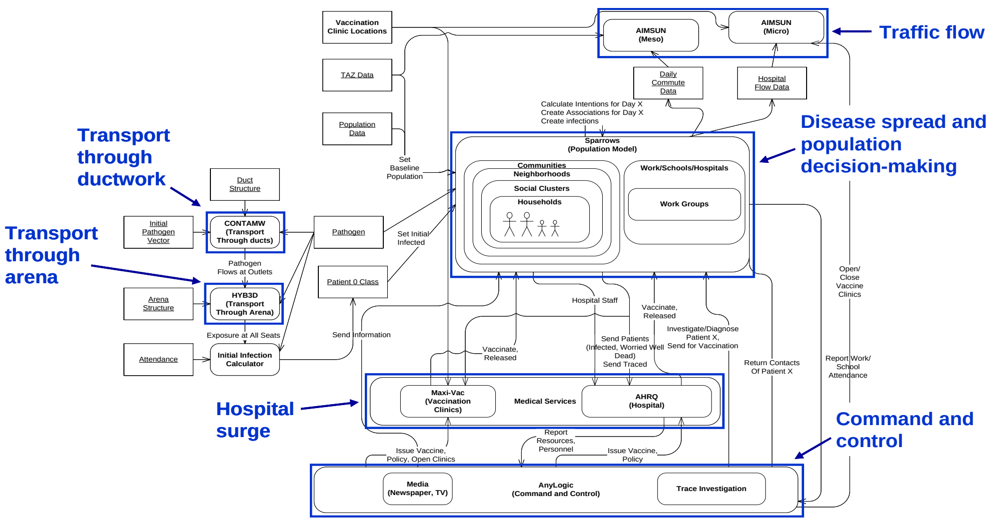


Figure 2. Simulation System Framework [14]

Once all of the computations required to be done in advance have been performed, the “faster than real time” simulation can be executed. There are four principal simulation components in the “faster than real time” simulation (in addition to simulation management, data logging, and visualization):

1. The spread of the disease through the local population and the population’s reactions;
2. The flow of traffic, both in daily home-work-school patterns and to treatment centers;
3. The Command and Control of response actions, including risk communications;
4. The surge of persons to be treated at hospitals and vaccination centers.

3.1. Population Generation and Sparrows Model

Households were grouped into Social Groups with a mean of four households and a standard deviation of one household, to approximate the (fixed) Social Group size of four used in [7]. Social Groups were grouped into Neighborhoods of a size as close to 500 persons as was possible, based on the number of persons in each TAZ. The initial exposure at the music hall resulted in a total of 2809 seats in the arena receiving a cumulative dosage above the infection threshold.

Operating on a diurnal cycle, each household decides what actions each member of that household will take during the next day. In a normal case, this involves each household member proceeding to his/her daily commute. Each household member has a normal commute destination: a School, a Work Group, a Hospital or the household's Home. A normal commute would then involve an individual residing at their commute destination as well as all the locations in their household's Home hierarchy (*i.e.*, the Home, Social Group, Neighborhood and Community) with a possibility of exposure and infection at each. At each cycle, households can change the travel behavior of their members. They can change their destination to a Hospital if they feel an individual needs to seek treatment (or vaccination). They can also self-quarantine and spend both the daytime and evening in their household.

The decision-making process for households was driven by the risk communications sent from the Command and Control simulation. Every day, individuals react to the most recent risk communications. Individuals may correctly self-quarantine or seek vaccination, or may exhibit counterproductive behaviors such as queuing at medical facilities as "worried well", based upon the communications, their own disease state (*e.g.*, vaccinated, infected, contagious) and that of their household (*e.g.*, at-risk due to infected household members).

3.2. Emergency Response Command and Control

The Command and Control (C2) simulation supports analysis of strategic, tactical and operational planning and activities, including deployment of resources, maintenance of situational awareness, and public communications. The U.S. Department of Homeland Security (DHS) has released, and continues to update, a set of documents that provide guidance for emergency response agencies (Office of Naval Research, 2005). The C2 simulation exchanges data between the simulations models (Sparrow, Traffic and Hospital Surge) and provides initialization and shutdown services for this federation. The C2 simulation subscribes to data published by the population disease spread simulation. Daily data was received for each school and each hospital. The data was processed to plot the number of new cases and fatalities, cumulative student and teacher absences from all schools, medical staff and bed shortages, and the number of people vaccinated each day.

The C2 simulation published data to represent daily public communications. This data includes parameters to enable the population disease spread simulation to simulate the behavioral effects of the communications. The C2 simulation modeled the intensity and frequency of risk communications based on an internally maintained alert level. An order to vaccinate medical staff is published at the first indication of the crisis. The alert level was raised based on rules that can include factors for the rate of new cases, fatalities, school absences and vaccination facility capacity utilization (Office of Naval Research, 2005). The C2 simulation can issue an order to close schools as the alert level rises. The scenario used for the initial prototype raises the alert level when the five-day moving average of new cases increases more than 20%. Each time the level was raised, the simulated effectiveness of the risk communications increased. The messages included instructions for the infected, at-risk, normal and recovered members of the population. The preferred behavior was for the infected to be isolated, the at-risk to seek vaccination, and the normal and recovered to continue with their daily routine of attending school or going to work.

3.3. Traffic Flow Modeling

Resources play a vital role in the execution of an emergency response plan. Accessto and the ability to move through the transportation infrastructure is often just as important as the availability of medical supplies and the operation of treatment centers, although it is often overlooked. With the ability to simulate real-time, dynamic traffic assignment scenarios, one can effectively locate conflict points (areas with high density and high delay-time), which can assist in establishing where emergency response centers are located and how the population will reach them. Two levels of simulation, mesoscopic and microscopic, are meshed for enhanced analysis, with the use of a hybrid simulation technique. The hybrid allows for simulation of small networks or areas (microscopic) while simulating the surrounding area through mesoscopic simulation. One can study the effects of signal controls, network origin-destination (O/D) travel routes/times and the redistribution effects with the hybrid model. This network and simulation were performed using the meso/micro-simulation traffic Simulation platform Aimsun NG.

The simulation took place over 40 days to model proper response and movement of the population across the network prior to, during, and at the downfall of the disease outbreak. Figure 2: Simulation System Framework, outlines the major aspects of the simulation systems and how they interact with one another. Emergency response consists of multiple origin-destination (O/D) matrices, which have the capacity to be opened, closed and/or recalculated, based on the situational awareness and surge capacity information from command control. Due to the nature of the disease in the bioterrorist attack (delayed onset of signs and symptoms), the traffic management perspective will have the capability to evolve alongside the changes in demand for emergency centers. Coding scripts were modeled in order to accurately visualize and manage the driver behavioral aspects of real-life scenarios. Due to the uncertain nature of human behavior in emergency situations, it was important to have the ability to manage abnormal actions taken by drivers to arrive at emergency centers.

3.3.1. Traffic Simulation Breakdown: The system was broken down into steps to help analyze the processes that were working inside the traffic simulation environment.

1. Modeling of current network to reproduce mixing conditions of the general population due to the contact-based spreading of disease.
- Using demographics and trip distribution
- Mesoscopic modeling of traffic flow and trips, through speed-density relationship and queuing theories.

2. The emergency centers are assigned a TAZ once command control establishes an emergency response scenario.
- Microscopic simulation regarding travel near emergency centers (hospitals and vaccination locations).
- Network allows visualization and situational awareness during real-time response in regard to fluctuations in demand and surge capacity.

3. Rates of demand were skewed through stochastic simulations based on the day of the simulation, actual contact and “worried well” rates, due to the nature of the disease (delayed onset of signs and symptoms).
- These extensions were used to dynamically modify the current simulation by changing things such as driver parameters and control timing, and implementing powerful traffic management actions, through the Application Programming Interface (API) script.

4. The mesoscopic and microscopic networks were intertwined in a hybrid meso-micro traffic simulation.
- Allowed analysis of specific areas of interest (near emergency centers), while monitoring the flows of a greater surrounding network.

3.3.2. Trip Generation and Distribution: The origin-destination matrix is composed of TAZs (area of homogenous socio-economic structure) through Baltimore City and parts of Baltimore and Anne Arundel Counties. The trip data for the entire day was provided by the Baltimore Metropolitan Council (BMC) and was converted to peak-hour trips using a peak-hour factor (PHF). The trip generation model was applied with the matrices provided by BMC. The model generates a total of 300,000 vehicles in the study area.

The O/D matrices for the trip distribution regarding TAZ to emergency centers were constantly changing and updated during the 40-day simulation. Businesses and schools were being opened and closed, quarantines set up and vaccination centers implemented, based on command and control's oversight. Measures were taken to prevent the population from flooding to the same hospital, since there were many more TAZ zones than emergency centers. A probabilistic model was used in order to allow vehicles to distribute themselves from their origin to several destination emergency centers. The emergency centers were assigned a probability based on the distance it was away from the origin TAZ. The closer the emergency center was to the origin, the higher the probability that vehicles would travel there. The probabilities for all the hospitals summed to 1, therefore routes permitting, vehicles could theoretically travel to any emergency centers from any TAZ.

3.3.3. Loading Rate of Trips: The trip generation for each simulation was based on the time interval between two consecutive vehicle arrivals at the origin. When the O/D matrices were loaded into the simulation model there were various loading rates which affect the headway model. Initially the first 12 days of simulation were set to a normal distribution loading rate to monitor normal daily traffic operations across the network. The headways at input sections in the network were sampled from a truncated normal distribution.

Once signs and symptoms of smallpox were identified by Command and Control, the loading rate was modified to "ASAP". Vehicles under duress entered the system through their loading points "as soon as possible", when there was space in the input section. This model makes the best use of the network entrance capacity, thereby making it a proper choice when modeling emergency scenarios. The total flow to be input at each section was put into a queue and the waiting vehicle entered the network as soon as they had enough space.

3.3.4. Dynamic Traffic Assignment Algorithm: Optimization of the network became critical to employ the most efficient response strategy. The optimization was two-fold. The designated emergency center routing strategy and the optimal Command and Control strategy together allowed access to the simulation interface during real-time simulation to account for surge capacity in the form of traffic delays of back-up times at the centers. The basis of this traffic simulation model is the movement of people from one point to another through an O/D matrix. This matrix is run under what is known as the User Equilibrium. This model suggests that travellers will try to minimize their travel time. This is achieved through travellers choosing routes that they feel are the shortest under current traffic conditions. Routing and re-routing throughout the network is performed based on this ideology. The model uses per-link cost-based functions to determine the paths or links based on the traffic demand. Therefore, dynamic traffic assignment (DTA) enables the description of traffic flow pattern evolution throughout the network. This simulation process is expressed in these steps:

1. Calculate initial shortest routes for each O/D pair, Home-Work and Home-School.

2. Simulate for peak-hour trip distribution, assigning to the available routes the fraction of the trips between each O/D pair for that time interval according to the model. Obtain new average link travel times as a result of the simulation.

3. Recalculate shortest routes, taking into account the current average link travel times.

4. Relay information from step 3 back to the simulation for dynamic re-routing.

This process allowed the simulation to be fully optimized, with focus not only on network loading but also the traffic assignment processes associated with the microscopic paradigm.

The shortest path calculation was based on a series of cost functions. The link-node representation of the network was the basis for calculation of shortest routes. The cost function defines link travel time in seconds. There were many variables that could influence the travel time such as initial cost, link capacity, capacity weight parameter, length of link and user defined cost of section.

Initial Cost of link j per vehicle type vt, calculated as follows:

$$InitCost_{j\,vt} = TravelTFF_{j\,vt} + TravelTFF_{j\,vt} * \varphi * (1 - CL_j / CL_{max}) + \tau * UserDefinedCost_s \quad (1)$$

Where:
TravelTFF – estimated travel time of link j in free flow conditions
$TravelTFF_j$= $Legnth_s$ / $SpeedLimit_s$ + Length / $SpeedLimit_t$
$Length_s$ and $SpeedLimit_s$ are the length and speed limit respectively of section s which belongs to link j. Length and $SpeedLimit_t$ are the length and speed limit respectively of the turning t, which belongs to link j.
φ - User-definedcapacity weight parameter that allows the user to influence the link capacity on the cost in relation to travel time. To avoid the dependency of link attraction with respect to the length of the link the default cost function “5.1” was selected which is related to the travel time per kilometer.

3.3.5. Mesoscopic-Microscopic Interface: The microscopic simulation process becomes important once the incident management command and control system model establishes the hospital/emergency center locations. There are 16 hospitals that will be used for treatment of the infected population. TAZs are associated with a specific hospital based on locality. Discretion was used to attempt to balance the amount of trips that could arrive at each in a worst-case scenario. These two levels are intertwined at the interface of arterial roads (microscopic level) leading to the hospitals from the main interstate highway infrastructure that runs throughout the city. Both levels are simultaneously going through the process explained above regarding routing. This routing alters the home-school and home-work matrices, because some of the trips are now being diverted to the hospitals based on the infection rates and need for treatment. This give-and-take relationship regarding trips between the two models will exhibit a response situation (microscopic) while normal daily operations are continuing to operate around the city (mesoscopic).

4. Hospital Surge Modeling

The hospital surge model (HSM) is responsible for predicting the necessary hospital capacity required based on the number of casualties and “worried well”. In this context, hospital capacity includes beds in each of three types of units, the emergency department

(ED), the intensive care unit (ICU), and the floor, as well as two types of personnel: physicians and other medical personnel. This version of the model does not include other expendable hospital supplies or non-medical personnel.

New individuals are presented to the HSM at the beginning of each diurnal cycle. The HSM models both vaccination and treatment, passing all individuals presented to it by the population model first through a triage/vaccination process. Infected individuals are admitted, if hospital capacity exists for them, and moved through the various hospital units as their disease progresses.

At the end of each diurnal cycle, the HSM reports hospital status to the Command and Controlmodel in support of decisions on the need for more vaccination and treatment clinics and personnel. The HSM also returns recovered (immune) individuals to the population model and removes fatalities, recovering renewable hospital resources such as beds and staff. Finally, it reports the individuals who are rejected, either because they are “worried well”, *i.e.*, not infected, or because the hospital has insufficient resources to accommodate them. This last capability is unique among extant hospital surge models as will be explained below.

Rather than develop a new hospital model from scratch, a review ofmore than a dozen extant hospital models was conducted. This yielded the discovery of two limiting factors:

1. No single extant model adequately modeled both treatment and vaccination as required by our scenario.
2. Most extant hospital surge capacity models are focused on the problem of strategic planning or preparedness, i.e., predicting the resources required over the entire course of an incident based on a static set of inputs. In the language of DHS, most extant models are focused on the “pre-incident” end of the preparedness continuum while our efforts are focused in the middle of the continuum, the “incident” itself (McCracken, 2009). The implicit assumption is that medical and public health responses based on situational awareness do not impact the evolution of the incident, *i.e.*, the extant models don’t support tactical planning and preparedness.

To address these problems the following solutions were implemented:

1. We selected two separate extant models, AHRQ and MaxiVac, respectively, and reverse-engineered their mathematical models into a single HSM federate. The results of this reverse engineering are hospital personnel-to-patient ratios for each of the hospital units for admitted individuals (derived from AHRQ), and limits on the number of patients that can be seen based on the clinic size and available personnel, based on MaxiVac.
2. The resulting HSM calculates the resources needed on a daily basis rather than for the whole incident, allowing dynamic allocation and reallocation of medical personnel. Unlike extant models, it models the possibility that all individuals seeking treatment will not receive it in a timely manner due to hospital overload. It was for this reason that we had to reverse-engineer the mathematical models of AHRQ and MaxiVac rather than reuse the models directly.

The HSM federate models all 16 hospitals in the selected geographic area of interest within the greater Baltimore area that have licensed, acute care beds as necessary to treat smallpox. This includes 15 civilian hospitals as well as the Baltimore Veterans Administration (VA) Medical Center. Each hospital is initialized with its number of beds per unit [15] which does not change throughout the scenario. The HSM daily cycle begins with receiving the number of medical personnel allocated and the number of arrivals, including infected, “worried well”, fatally ill, and those requiring vaccination. Based on these inputs, each hospital calculates its ability to deliver treatment and reports shortages of personnel and beds to theCommand and Control model. Vaccinated and "worried well" individuals are returned to the population model. As mentioned earlier, individuals can be rejected in this model, unlike other models. This can happen at two points:

1. Individuals can be rejected "at the hospital door", *i.e.*, they never get to the triage/vaccination clinic because there are simply too many individuals in line seeking treatment.
2. Individuals can be identified as infected and needing treatment, but there are simply no available beds in the hospital, so they can't be admitted. This is one area where more data is required to determine how such situations would be handled in an actual bioterrorism crisis.

Note that both categories of rejected individuals are highly likely to attempt to return to the hospital on subsequent days seeking treatment. The more times they are rejected and have to return, the larger their impact on the traffic model.

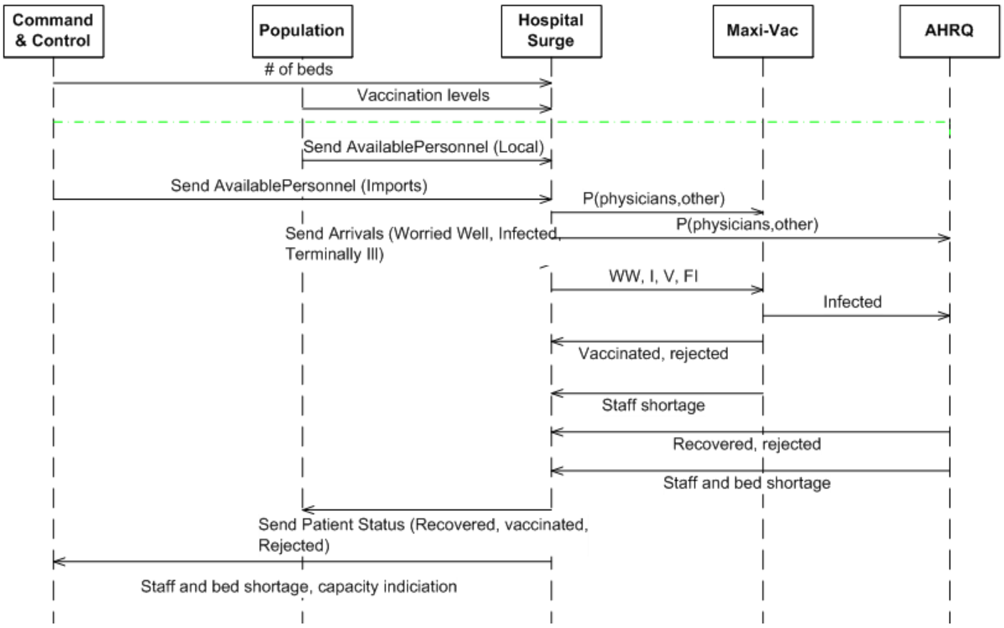


Figure 3. Health Care Sequence Model

4.1. The "Worried Well" Problem

Very little quantifiable data is available about the causes and magnitude of the "worried well" problem, although the little data available suggests that the "worried well" can be anywhere from 5 to 900 times the actual affected population [16]. Factors that impact this number are social norms, accuracy and timeliness of government data, accuracy and timeliness of media reporting, personal beliefs about the veracity of government and media reports, and individual tendency to follow directions. Again, very little quantifiable data exists about the impact these factors have on the magnitude of the "worried well" problem. What is clear is that a factor of only a few times the actual affected population has the potential to overload the medical infrastructure during an incident where the affected population itself is large. The result is that the infected population competes with the "worried well" for scarce medical resources, including the "worried well" possibly preventing infected individuals from even getting in the door of the hospital. This is one of the effectsof HSM models that other extant models do notexhibit.

4.2. Relationship of Traffic and Hospital Surge Capacity Modeling

One must consider the impact of dynamic traffic conditions on the arrival and departure of patients at the hospital, as well as the ability of hospital staff to arrive in a timely manner to administer medical care, when modeling hospital surge capacity in response to a catastrophic event, such as treatment and vaccinations for contagious diseases during a bioterrorism crisis.Because most hospital surge models are static and predictive, rather than dynamic and reactive, they assume that exactly the right set of patients who need treatment will arrive at the hospital in a timely manner. Furthermore, most don't account for the impact of "worried well" on either the hospital or the rest of the infrastructure. Such is not the reality of contemporary urban environments. Not only can the "worried well" overwhelm the triage function of the hospital as we have discussed, their migration in large numbers to the hospitals can overwhelm the routes to the hospitals, blocking the arrival of those individuals actually infected.

By modeling the expected number of vehicle trips to a finite number of hospital treatment/vaccination centers that is triggered by a population decision model, as is done here, it is possible to account for the traffic load presented by the combination of truly ill individuals, those seeking vaccination, and the "worried well". This allows for the possibility that traffic conditions on any given day could modulate the arrival rate at the treatment facility. Similarly, the rejection of potential patients at the entrance of the hospital due to an over-capacity condition can generate additional repeat traffic on the following day to the same or**to**a different facility.

5. Simulation Results and Analysis

The consortiums biological terrorist attack model and the 40-day trip distribution monitoring provided many pertinent details as to how an optimized plan should transpire. Access to information such as traffic flows, corridor densities and capacities, travel times, queuing delay, all while ensuring the most efficient paths/routes for vehicles within the network are in use (DTA), gives an in-depth look as to where, why and when incidents are occurring and how they can be mitigated. Incidents can be thought of as traffic back-ups or extreme delay for any reason. Travel time for days 12 through 15 can be seen in Figure 3a.

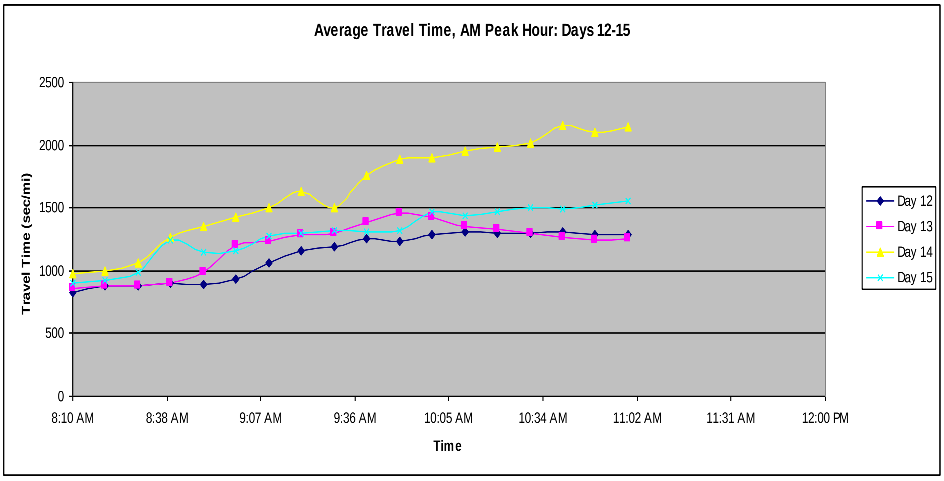


Figure 3a. Average Travel Time, Am Peak Hour: Days 12-15

It is during these times that significant changes within the network regarding traffic operations are taking place. Home based work and school trips are still continuing as perusual but signs and symptoms of the disease are rapidly occurring, therefore an influx in trips to emergency centers impacted the network and drastically changed travel and delay time values. Figure 3b shows the travel time of the network nearly 3 weeks after the release of the agent. It was reflected in the travel time of days 19 and 20 that Command and Control had a greater grasp on the situation at hand and mitigation of the spread.

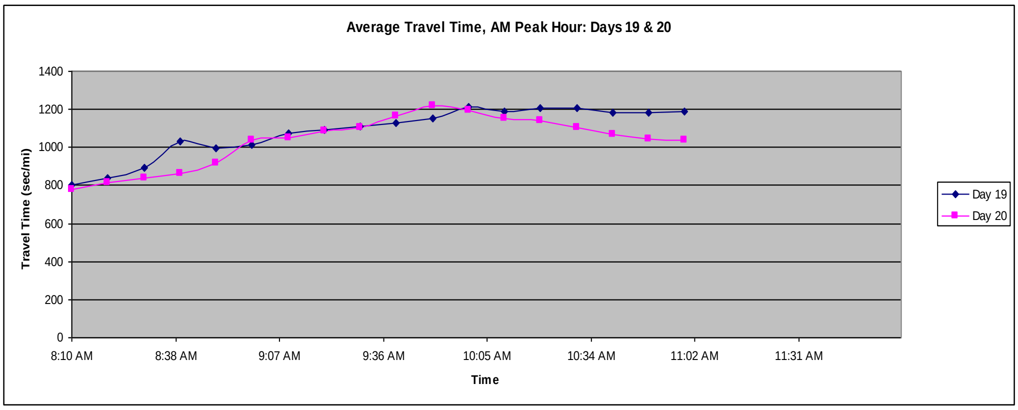


Figure 3b. Average Travel Time, AM Peak Hour: Days 19 and 20

Command and control has effectively identified the point of release, set up the proper emergency centers, and since the identity of the disease is nowapparent**,** proper facility closures have taken place to rapidly eliminate the spread. The facility closures within an urban metropolitan network include the closing of schools, commerce centers and other organizations where close contact was endured. The closing of these locations along with command and controls orders for quarantine/ vaccination/ treatment lower the volume of trips being made throughout the network. The success of the consortium was reflected back in the final day of the case study, Day 40, where the travel time was back near pre-outbreak daily AM peak hour travel times (Figure 3c).

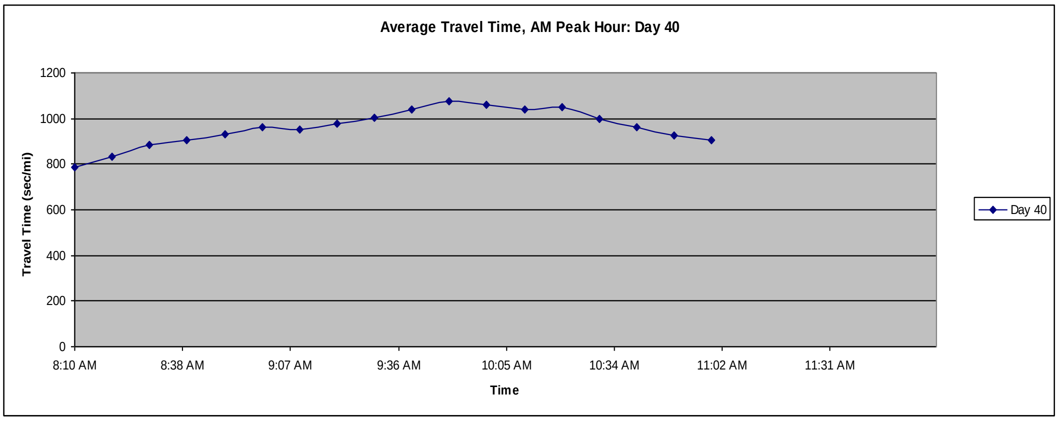


Figure 3c. Average Travel Time, AM Peak Hour: Day 40

The results produced are from multiple replications of the simulation shown in Figure 4. Both the flow and harmonic speed of the traffic were detailed for the 3-hour peak time simulation. The results concluded that the highways capacity was quickly reached and their ability for travelers to make it to their arterial road exit ramps was inhibited by the congestion. For future modification to the model, more access points should be provided to the highway infrastructure, providing more routing opportunities.

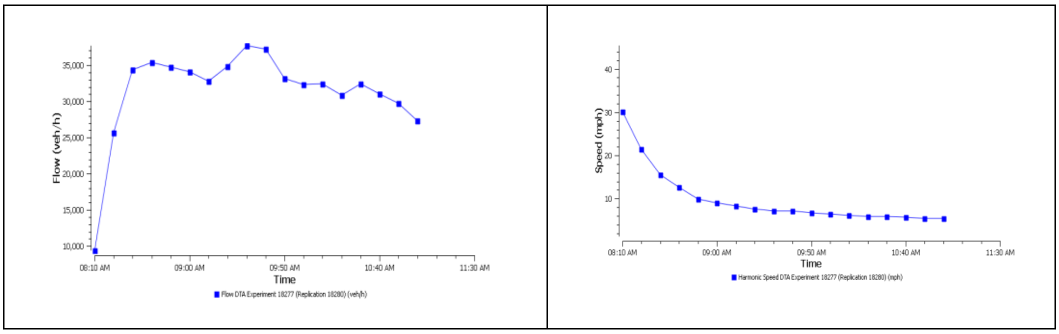


Figure 4. Mesoscopic Results of Multiple Replications

The most intriguing information from the simulation comes not only from the data, but also fromthe visualization of the animated simulation. The animation showed that this type of scenario could be treated similarly to an evacuation with contra-flow traffic routing. Since Command and Control had minimized traffic movements through the network effecting not only treatment centers but all areas near the centers, increasing the infrastructures capacity with contra-flow would be greatly beneficial.

6. Conclusion

This paper has presented a discussion of traffic modeling and hospital surge capacity modeling as implemented in the Bioterrorism Crisis Management simulation constructed by the National Center for the Study of Preparedness and Catastrophic Event Response (PACER). By implementing a diurnal cycle of the mixing of the population, and the travel of individuals to hospitals, it is possible to explore the dynamic nature of relationships between traffic flow to the hospitals, and the hospitals' capabilities to accommodate the surge in the number of individuals seeking treatment.

The proposed simulation and optimization allows for effectiveness in monitoring the mixing of the population and the management of treatment centers, through routing of real-time behaviors and demands: two levels of simulation meshed into an optimal hybrid simulation. Acritical response plan was successfully modeled, in conjunction with O/D matrices, optimal signal timing and real-time routing manipulation. A complete and critical understanding of a smallpox release, spread and treatment was accomplished, throughthe integration of the multilevel computer simulation systems. The focus of traffic routing and optimization was effectively performed with variables from the Dynamic Traffic Assignment algorithm that was included inside the simulation platform. The 40-day simulation provided different matrices and trip distributions, which were developed by command and control in order to effectively treat the population at emergency centers. The worst-case scenario was found and analyzed to enhance the infrastructures capabilities. Results from this research have lead to the need for more exploration into access points for a meso level simulation and the need for signal optimization near treatment centers in the micro level simulation. This type of influx in traffic can be accommodated by an evacuation technique such as contra-flow, increasing the unidirectional capacity of the network. An important aspect of the entire project was the capability to visualize the movements through the animation. This integral part of the simulation allows for precise identification of the location, and in some cases, the causes of problem areas within the network.

References

[1] M. Washington, J. Mason, M. Meltzer, "Maxi-Vac: planning mass smallpox vaccination clinics", Journal of Public Health Management & Practice, 11 (6),**(2005)** 542–9.
[2] Transport Simulation Systems, "Aimsun 6.0 User's Manual: Microsimulator and Mesosimulator in Aimsun 6." **(2008)**, pp. 1-387.
[3] J. W. Glasser, S. Foster, D. Millar and M. Lane, "Evaluating Public Health Responses to Reintroduced Smallpox via Dynamic, Socially Structured, and Spatially Distributed Metapopulation Models", Clinical Infectious Disease, **(2008)**.
[4] S. A. Bozzette, R. Boer, V. Bhatnagar, "A Model for a Smallpox-Vaccination Policy", Journal of Medicine, **(2003)**.
[5] Chen, Li-Chiou, Kaminsky, "Aligning Simulation Models of Smallpox Outbreaks", Journal of Medicine, **(2004)**.
[6] N. M. Ferguson, M. MaKeeling, J. Edmunds, R. Gani, "Planning for Smallpox Outbreaks", Journal of Medicine, **(2003)**.
[7] I. Longini, E. Halloran, A. Nizam, Y. Yang, S. Burke, D. Cummings and J. Epstein, "Containing a large bioterrorist smallpox attack: a computer simulation approach". International Journal of Infectious Diseases, **(2006)**.
[8] S. Eubank, V. Hasan Guclu, A. Kumar, "Modeling Disease Outbreaks in Realistic Urban Social Networks". Journal of Science, **(2004)**.
[9] X. Chen, J. Meaker, and F. Zhan, "Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys", Natural Hazards, **(2006)** pp. 321–338.
[10] R. Peacock, J.D. Kuligowski, "Averill Pedestrian and Evacuation Dynamics", Springer, Verlag, **(2011)**.
[11] E. I. Kaisar, W.Degnan, J.Coolahan and R. Koomullil,"A Hybrid Meso-Microscopic Model for Catastrophic Event Management", CICTP-2014, **(2014)** pp. 3678-3690
[12] Thalmann, S. Musse, "Crowd Simulation", e-book, Kindle edition **(2007)**.
[13] R. Alizadeh, "A dynamic cellular automaton model for evacuation process with obstacles", Safety Science, 49, **(2011)**, pp. 315–323.
[14] J. E. Coolahan, M. T. Kane, R. P. Koomullil, E. I. Kaisar and K. K. Walsh, "Results of a Federated Simulation of Urban Chemical Disaster Response," Interservice/Industry Training, Simulation & Education Conference, Orlando, FL, **(2008)**.
[15] Griffin, Maryland Healthcare Commission 2009 report, **(2009)**.
[16] F. Stone, "The 'Worried Well' Response to CBRN Events: Analysis and Solutions," TheCounterproliferation Papers, Future Warfare Series, No. 40, USAF Counterproliferation Center.

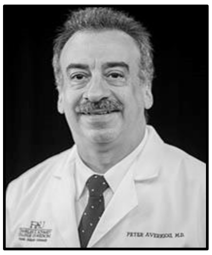
Authors

Evangelos I. Kaisar, Ph.D. is anAssociate Professor & Director at Multimodal Intelligent Transportation Laboratory Systems and Director of Geomatics and Transportation Engineering Program at Florida Atlantic University. He received his Ph. D. at University of Maryland at College Park, MD. Dr. Kaisar's area of expertise includes preparedness and catastrophic events management, Logistics and Transportation System Design, Transportation System Security and Efficiency, Mathematical and Large Scale Simulation Modelling and Freight Logistics

James E. Coolahan, is the Chief Technology Officer of Coolahan Associates, LLC, having retired from full-time employment at the Johns Hopkins University Applied Physics Laboratory (JHU/APL) in December 2012 after 40 years of service. His technical activities have included modeling and simulation (M&S), test and evaluation, and data acquisition system development. In 2000-02, he served on the National Research Council Committee on M&S Enhancements for 21st Century Manufacturing and Acquisition. In 2006-2009, he served as the Principal Investigator for the Modeling and Simulation Integration Framework project that was conducted as part of the National Center for the Study of Preparedness and Catastrophic Event

Response (PACER) for the Department of Homeland Security (DHS). He currently chairs the M&S Committee of the Systems Engineering Division of the National Defense Industrial Association (NDIA), and teaches courses in M&S for Systems Engineering in the JHU Engineering for Professionals M.S. program. He holds B.S. and M.S. degrees in aerospace engineering from the University of Notre Dame and the Catholic University of America, respectively, and M.S. and Ph.D. degrees in computer science from JHU and the University of Maryland, respectively.

Roy P. Koomullilis an Associate Professor of Mechanical Engineering at the University of Alabama at Birmingham (UAB). Dr. Koomullil received his doctoral degree in Aerospace Engineering from Mississippi State University in 1997. Before joining UAB, he worked as an Assistant Research Professor at the NSF Engineering Research Center (ERC) at Mississippi State University (MSU). Dr. Koomullil's area of expertise includes compressible and incompressible flows, computational fluid dynamics, finite volume upwind schemes on generalized grids, unsteady flow simulation, six-degreeof-freedom (6-DOF) rigid body simulations, overset meshes, and high performance computing.



Peter A. Averkiou, M.D., F.A.A.P., is a board certified pediatrician, who was in private practice for 20 years in Boca Raton, Florida. In 2012, he joined the faculty of the Charles E. Schmidt College of Medicine at Florida Atlantic University as an Assistant Professor of Clinical Biomedical Science. Dr. Averkiou is the Co-Director of M1 and M2 Clinical Education. He is also the Director of the Newborn Nursery Clinical Rotation and the Director of the Service Learning Projects. Dr. Averkiou serves as a Learning Community/Portfolio Advisor. He is also on the Interprofessional Education Development Sessions Committee and the YMCA Diabetes Prevention Program Advisory Board. Dr. Averkiou is a Diplomate of the American Board of Pediatrics and a Fellow of the American Academy of Pediatrics.