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IIE Transactions on Healthcare Systems Engineering
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/uhse20

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Ozgur M. Araz[a], John W. Fowler[b] & Adrian Ramirez Nafarrate[c]

[a] Health Promotion, Social and Behavioral Health, College of Public Health University of Nebraska Medical Center, Omaha, NE, USA

[b] Supply Chain Management, WP Carey School of Business, Arizona State University, Tempe, AZ, USA

[c] Department of Industrial and Operations Engineering, Instituto Tecnologico Autonomo de Mexico, Mexico City, Mexico

Published online: 04 Nov 2014.

To cite this article: Ozgur M. Araz, John W. Fowler & Adrian Ramirez Nafarrate (2014) Optimizing service times for a public health emergency using a genetic algorithm: Locating dispensing sites and allocating medical staff, IIE Transactions on Healthcare Systems Engineering, 4:4, 178-190, DOI: 10.1080/19488300.2014.965394

To link to this article: http://dx.doi.org/10.1080/19488300.2014.965394

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IIE Transactions on Healthcare Systems Engineering (2014) **4**, 178–190
Copyright © "IIE"
ISSN: 1948-8300 print / 1948-8319 online
DOI: 10.1080/19488300.2014.965394

Optimizing service times for a public health emergency using a genetic algorithm: Locating dispensing sites and allocating medical staff

OZGUR M. ARAZ[1,*], JOHN W. FOWLER[2] and ADRIAN RAMIREZ NAFARRATE[3]

[1]*Health Promotion, Social and Behavioral Health, College of Public Health University of Nebraska Medical Center, Omaha, NE, USA*
E-mail: ozgur.araz@unmc.edu
[2]*Supply Chain Management, WP Carey School of Business, Arizona State University, Tempe, AZ, USA*
[3]*Department of Industrial and Operations Engineering, Instituto Tecnologico Autonomo de Mexico, Mexico City, Mexico*

Received March 2012 and accepted July 2014

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We formulate a *p-median* facility location model with a queuing approximation to determine the optimal locations of a given number of dispensing sites (Point of Dispensing-PODs) from a predetermined set of possible locations and the optimal allocation of staff to the selected locations. Specific to an anthrax attack, dispensing operations should be completed in 48 hours to cover all exposed and possibly exposed people. A nonlinear integer programming model is developed and it formulates the problem of determining the optimal locations of facilities with appropriate facility deployment strategies, including the amount of servers with different skills to be allocated to each open facility. The objective of the mathematical model is to minimize the average transportation and waiting times of individuals to receive the required service. The mathematical model has waiting time performance measures approximated with a queuing formula and these waiting times at PODs are incorporated into the *p-median* facility location model. A genetic algorithm is developed to solve this problem. Our computational results show that appropriate locations of these facilities can significantly decrease the average time for individuals to receive services. Consideration of demographics and allocation of the staff decreases waiting times in PODs and increases the throughput of PODs. When the number of PODs to open is high, the right staffing at each facility decreases the average waiting times significantly. The results presented in this paper can help public health decision makers make better planning and resource allocation decisions based on the demographic needs of the affected population.

Keywords: Location-allocation, genetic algorithms, queuing, public health, mass dispensing

1. Introduction

For responding to a major disease outbreak or to a bioterrorist attack, county health departments plan mass dispensing and vaccination operations using Point of Dispensing sites (PODs). Pandemic influenza has been a major public health concern in today's global world and may require mass vaccination and medication distribution under severe scenarios. On the other hand, anthrax and smallpox are among the most feared biological agents that may also require mass dispensing of antibiotics and antiviral (Craft *et al.,* 2005). Large-scale bioterrorist attacks using any bacterial and viral agents would require immediate mass prophylaxis campaigns to prevent a massive loss of lives. Any mass dispensing operation may require rapid establishment of a distribution network with dispensing sites and healthcare facilities. The capacity of these facilities should be flexible for various scenarios to provide medical treatment and prophylaxis for affected populations (Lee *et al.,* 2009). Optimizing the throughput of PODs with scarce resources is an important public health problem which needs to be addressed for effective delivery of required medical services.

Any large-scale emergency event, e.g., infectious disease outbreaks or bioterrorist attacks, can lead to a huge demand for medical supplies in a short amount of time. Responding to such an emergency in a timely manner requires optimally locating medical supplies and then rapid distribution. Decisions such as determining which of the possible sites should be open under different scenarios can play an important role in reducing casualties as the number of casualties depends on the affected region, the availability of resources, and the demographic characteristics of the region. An important criterion in selecting the locations

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of PODs is being able to dispense medication at demand points with minimum service times at the facilities. For this purpose, we formulate a facility location (*p-median*) model to minimize the average total time for individuals to reach to service facilities and receive the services in PODs with staff allocation considerations.

In the next section, we present a literature review of facility location problems for emergency response. Next, we formulate our problem and present the solution methodology. We then present an experimental case study with our computational results. Lastly, we conclude with our findings and a future research discussion.

2. Literature review

Locating facilities for responding to an emergency is a critical and complex problem (Daskin and Dean, 2004). Owen and Daskin (1998) present a comprehensive literature review on strategic facility location problems. In a more recent study, Snyder (2006) presents a review on facility location problems under uncertainty. Facility location problems with uncertain parameters and decision variables are formulated with mathematical programming techniques, such as stochastic programming, robust optimization and also with several hybrid methods such as simulation-optimization. In a typical facility location problem, travel times, construction costs, locations and magnitude of demand over time may not be known with certainty. In addition to these parameters, the capacity of facilities can also be variable. In this paper, we are interested in the throughput performance of mass dispensing facilities (i.e., PODs) with a stochastic arrival pattern.

One of the first models formulated to minimize the expected cost of facility location under uncertainty is presented in Mirchandani and Oudjit (1980). There are also several studies on supply network design with uncertainty including determining the location of facilities (Tsiakis *et al.,* 2001, Schutz *et al.,* 2008). For an emergency logistics application, Barbarosoglu and Arda (2004) present a two-stage stochastic programming model to plan transportation of first aid commodities to an area affected by an earthquake. The resource requirements at each location are modeled as random variables with a finite number of scenarios. Beraldi *et al.* (2004) use a similar modeling approach, within a probabilistic paradigm, to locate medical service facilities under emergency situations. Chang *et al.* (2007) present a scenario-based optimization model for distribution of rescue resources in urban flood disasters. Their decision variables include the structure of rescue organizations, locations of rescue resource stores, allocation of resources under capacity restrictions, and the distribution of these resources. Afshartous *et al.* (2008) present a simulation-optimization based methodology to determine robust locations of Coast Guard stations. Based on a real data set of distress calls, they develop a statistical model to simulate distress call locations. Recently, Beraldi and Bruni (2009) formulate and solve a probabilistic model for determining the optimal locations of facilities in congested emergency systems. The decision paradigm of the problem is handled with a two-stage structure of the stochastic program and different solution methods are presented to solve the problem. Several other studies consider large-scale emergencies and emergency medical services delivery with facility location and allocation decisions (Das *et al.,* 2007, Murali *et al.,* 2009, McLay, 2009).

In a different context, a simulation-optimization framework is presented by Vardar *et al.* (2007) for semiconductor manufacturing investment decisions including facility location and worker allocation decisions. Similar to our problem, Syam (2008) formulates a facility location model with staff allocation considerations in order to minimize the expected waiting times in the service facilities and uses a Lagrangian relaxation method to solve the problem. We use a similar optimization framework as Vardar *et al.* (2006) and Acar *et al.* (2009) to locate POD sites with uncertain performance to design a robust response system for a major public health concern.

An emergency such as an influenza outbreak or a bioterrorist attack may require PODs to perform well on several performance measures. These performance measures include average cycle time (i.e., average time an individual spends in the POD to get the service), average queue length (i.e., average number of individuals waiting to get service), and average throughput rate (i.e., total number of people that get service in a specific time period). These measures are highly dependent on available resources, e.g., number of staff allocated to bottleneck stations in a dispensing process (Washington, 2009). In a large scale emergency that is caused by anthrax, federal medical supplies from the SNS (Strategic National Stockpiles) (CDC, 2003) would be delivered to affected areas within 24 hours and it is the responsibility of the local authorities to develop efficient mass dispensing operation plans. An effective mass dispensing plan would involve setting up PODs to distribute the supplies and having easy access of individuals to the PODs. Under these conditions, the decisions about determining locations of the facilities to be opened and the amount of resources (e.g., staff) allocated to each facility are essential. In this paper, we present a mathematical model and a heuristic solution method for determining the locations of mass dispensing sites and their capacity in order to optimize service times in a public health emergency. The major contribution of the paper is incorporating the variation of demand on services, which can be due to the demographic differences of the people in the various geographic areas, into the facility location and allocation model for a specific public health problem.

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3. Problem statement and model formulation

Anthrax is an acute infectious disease caused by a spore-forming bacterium (Jia *et al.,* 2007). The logistical response strategy for an anthrax attack is planned as follows: first, the federal government will investigate the specific anthrax attack and then allocate the appropriate SNS supplies to states, then they will be sent from states to counties and finally from counties to local emergency medical service facilities, i.e., PODs (CDC, 2003). Then, local authorities are responsible for the mass distribution of these stocks within 48 hours, which is specific to anthrax attacks, to the affected population. To measure the service performance, we first present the queuing model formulation of multiple identical PODs operating at specified geographical locations. The objective is to evaluate the average performance of PODs under various staffing scenarios based on their throughput performances. Based on our discussion with public health managers and according to their bioterrorism preparedness plans, we assume that the public health emergency is occurring in one locale with a determined boundary. In addition, we also assume that SNS assets and medical countermeasures will be available in sufficient quantities for the affected region. We use a queuing approximation to save computational time of the solution algorithm, rather than simulating the operations of the entire POD network. Two of the important performance measures of POD operations are the capacity of each POD (i.e., throughput values) and the average time spent by individuals in each POD (Zaric *et al.,* 2008). These measures determine the system responsiveness during a bioterrorist attack which is highly dependent on the number of staff serving in PODs at a given time.

For formulating the *p-median* location problem with staff allocation decisions, we first identify aggregated demand locations in a pre-defined geographical area, i.e., the census block groups in Maricopa County, Arizona. Maricopa is the largest county in the state of Arizona (in terms of its population) and it includes the Phoenix Metropolitan area, one of the largest metropolitan areas in the United States. In the case of an anthrax attack to a metropolitan area, e.g., Phoenix Metro area, a large and sudden demand on medical facilities will emerge and medical agencies will be very likely to suffer from insufficient resources. Due to the nature of this public health emergency, timely response is critical in terms of saving lives and avoiding chaos.

A mass dispensing facility which is close to the center of the demand location will provide better quality of service to the demand point and it is assumed to be more easily accessible than a facility located far from the center of the demand location (Dessouky *et al.,* 2006). Here, we formulate a mathematical model to determine which PODs among candidates to open with appropriate staffing that can effectively respond to demographic needs, specified by the age distribution of the assigned demand locations given a limited time frame. The model is a nonlinear optimization model that incorporates the waiting time performance measure from the queuing formulation into the objective function of the optimization model. The overall service delivery performance measure that we evaluate in the objective function is the sum of the average waiting time in PODs and the average travel time of individuals to reach the PODs.

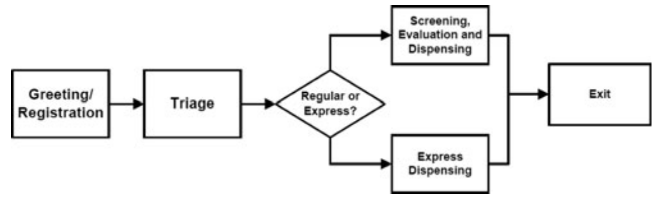

Fig. 1. POD layout and process flow diagram.

The baseline and simplified POD layout model that is considered in this paper is presented in Figure 1. The dispensing process includes basic operations and the parameters associated with these operations are assigned from the published literature (Whitworth, 2006; Lee *et al.,* 2006; Hupert *et al.,* 2002) and also based on the data we obtained from the Public Health Department of Maricopa County. The service process in a POD includes registration, triage and dispensing. After triage, individuals are directed to regular or express dispensing stations based on needs of medical screening. For example, elderly people or those with pre-existing medical conditions may need to speak with a healthcare professional (e.g., a nurse). During the triage process, individuals go through a medical evaluation and based on this evaluation they are led to the appropriate medication dispensing station.

State health officials have identified numerous alternative locations for POD sites, because there may be multiple attack locations and as a result multiple POD locations may be required to mitigate the risk on response facilities. However, opening all of these possible POD sites at the same time may not be an efficient strategy in terms of resource utilization and operating cost of PODs. The Centers for Disease Control and Prevention (CDC) has developed guidelines for county health departments to plan their response for bioterrorist events and infectious disease outbreaks (CDC, 2003).

In this paper, we use a queuing approximation model from Aaby *et al.* (2006) for calculating the average waiting times to analyze the bottleneck stations in the process. The waiting time approximations are embedded into our facility location model to minimize the average waiting time at each POD by allocating an optimal number of staff to each station. In our model, we consider a POD with a registration station, prescreening station, express dispensing station and dispensing station with screening. Since the registration and prescreening stations are very unlikely to be the bottleneck in the whole process, the time to get through these stations is assumed to be constant (Aaby *et al.,* 2006). See Table 1 for

Table 1. Queuing model parameters and values (Aaby *et al.,* 2006)

Stations	Mean Processing Time	SCV	Variance
Registration	1 minute	0	-
Prescreening	2 minutes	0	-
Express Dispensing (E)	3 minutes	0.5	4.5
Screening and Dispensing (D)	5 minutes	0.25	6.25

the parameter values, i.e., mean processing time, squared coefficient of variation (SCV), and variance of processing time at each station, used in queueing approximations of the model.

We now present mathematical details of the queuing model that we use to approximate several performance measures in a single POD and also the *p-median* location-allocation model.

3.1. *Queuing approximation of waiting times in PODs*

We model each POD as an open queuing network (Aaby *et al.,* 2006). In our POD model, we have two different service lines and these lines are express dispensing and regular dispensing. At a station k, ($k = E$ or D), in POD j, we assume the number of servers is represented by z_{kj}. Let N_j be the number of individuals per unit time arriving to POD j and assume N_j has a Poisson distribution with parameter λ_j. The service times at each station k, are assumed to have a general distribution with mean μ_k and standard deviation σ_k. For a given POD j, based on the demographic needs of the assigned demand locations, i.e. characterized by the age distribution which may be high correlated with the medical complications, the proportion of the individuals who require the regular dispensing process varies and this variability can significantly affect the throughput performance of the PODs. Here we present the notation and variables for the model.

Decision Variables

$$x_{ij} = \begin{cases} 1 \textit{ If demand point } i \textit{ is assigned to POD } j \\ 0 \textit{ otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 \textit{ If a POD is open at location } j \\ 0 \textit{ otherwise} \end{cases}$$

$z_{D,j}$: Number of staff allocated to regular dispensing station at POD j

$z_{E,j}$: Number of staff allocated to express dispensing station at POD j

Model Parameters:

d_{ij}: Distance between the centroid of the demand location (i.e. census block group) i and POD location j

t_{ij} : average travel time from demand point i to POD j

v_{ij}: average travel speed from the centroid of the demand location i to POD j

$t_{ij} = d_{ij} / v_{ij}$

M: Total number of PODs decided to be opened (defined *a priori*)

K_k: Maximum number of resource units of type k available

τ :Targeted total time for completing the dispensing of medicines (minutes)

P_i: Population of demand point (i.e., census block group) i

TP: Total population in the service area

$$TP = \sum_i P_i \tag{1}$$

γ: Compliance rate (i.e., proportion of the population that will be going to dispensing sites)

$$(0 < \gamma < 1)$$

λ: Expected arrival rate to PODs during the anthrax bioterrorist event

$$\lambda = \frac{TP}{\tau}\gamma \tag{2}$$

N_j : Number of individuals arriving to POD j (Poisson distribution) per unit time

λ_j: Arrival rate to POD j

$$\gamma_j = \left(\frac{\sum_i P_i x_{ij}}{TP}\right)\lambda = \left(\sum_i P_i x_{ij}\right)\frac{\gamma}{\tau} \tag{3}$$

θ_i: Proportion of the population that requires regular dispensing from demand location i

α_j: Proportion of arrivals that require regular dispensing at POD j

$$\alpha_j = \left(\sum_i x_{ij}\theta_i P_i\right) \Big/ \left(\sum_i x_{ij} P_i\right) \tag{4}$$

$\lambda_{D,j}$: Arrival rate to regular dispensing station in POD j

$$\lambda_{D,j} = \alpha_j \lambda_j \tag{5}$$

$\lambda_{E,j}$: Arrival rate to express dispensing station in POD j

$$\lambda_{E,j} = (1 - \alpha_j)\lambda_j \tag{6}$$

μ_D : Mean service rate at regular dispensing stations

μ_E : Mean service rate at express dispensing stations

$\sigma_D{}^2$: = Variance of service times at regular dispensing stations

$\sigma_E{}^2$: = Variance of service times at express dispensing stations

$c_D{}^2$: = Squared coefficient of variation for service times at regular dispensing stations

$c_E{}^2$: = Squared coefficient of variation for service times at express dispensing stations

Let $\overline{W}_{E,j}$ be the average waiting time in the express dispensing station and let $\overline{W}_{D,j}$ be the average waiting time

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in the regular dispensing station at POD j. Given that the queue structure in our model is assumed to form an $M/G/s$ queuing model, from Aaby *et al.* (2006) we can calculate the average waiting times at any POD j with the equation given in (7).

$$\overline{W}_j = \alpha_j \overline{W}_{D,j} + (1-\alpha_j)\overline{W}_{E,j} \tag{7}$$

Equation (8), which is an expansion of Equation (7), approximates the overall average waiting time for POD j. It is worth noting that the quality of this approximation increases as the utilization of servers increases (Whitt, 1992).

$$\begin{aligned}\overline{W}_j = {} & \alpha_j \left(\frac{1+c_D^2}{2}\right)\left[\frac{\left(\lambda_{D,j}/\mu_D z_{D,j}\right)^{\sqrt{2z_{D,j}+2}-1}}{z_{D,j}\left(1-\left(\lambda_{D,j}/\mu_D z_{D,j}\right)\right)}\right]\frac{1}{\mu_D} \\ & +(1-\alpha_j)\left(\frac{1+c_E^2}{2}\right) \\ & \times\left[\frac{\left(\lambda_{E,j}/\mu_E z_{E,j}\right)^{\sqrt{2z_{E,j}+2}-1}}{z_{E,j}\left(1-\left(\lambda_{E,j}/\mu_E z_{E,j}\right)\right)}\right]\frac{1}{\mu_E}\end{aligned} \tag{8}$$

3.2. *POD location model and resource allocation*

In this section we formulate the facility location and (staff) resource allocation problem. This model incorporates traveling and waiting times at each facility into the objective function. The sum of average waiting times in PODs is minimized by allocating the appropriate number of staff. In the presented model the total number of PODs to be open is fixed, i.e., M. Finally, the average travel speed in the county is assumed to be constant. These assumptions can easily be relaxed to make the presented model more robust. Now, the mathematical notation of the model is given as follows.

Location Allocation Model:

$$Min\left[\left(\sum_{i\in I}\sum_{j\in J} P_i\left(t_{ij}+\overline{W}_j\right)\right)x_{ij}\right] \tag{9}$$

Subject to:

$$\sum_{j\in J} x_{ij} = 1 \ \forall i \in I \tag{10}$$

$$\sum_{j\in J} y_j \le M \tag{11}$$

$$x_{ij} \le y_j \ \forall i \in I, \forall j \in J \tag{12}$$

$$\sum_{j\in J} z_{kj} \le K_k \ \forall k \in K \tag{13}$$

$$\overline{W}_j = f(\alpha_j, \lambda_{E,j}, \lambda_{D,j}, \mu_E, \mu_D, z_{E,j}, z_{D,j}) \tag{14}$$

$$\begin{aligned}& x_{ij}, y_j \in \{0,1\} \ \forall i \in I, \forall j \in J \\ & z_{kj} \in Z^+ \ \forall j \in J, \forall k \in K\end{aligned} \tag{15}$$

In this model, we use rectilinear distances between the center of the census block groups and the POD locations, since it is the most appropriate distance measure for calculating the travel time in the considered area, i.e., Maricopa County, Arizona (Wyman and Kuby, 1995). The objective function (9) minimizes the total travel time from demand points to PODs plus the average waiting times at PODs. The presented model is extensible enough to consider cost minimization related to POD operations (see Appendix for the generic formulation). Constraint set (10) assures that each demand point i is assigned to a POD and constraint (11) guarantees that a maximum of M facilities are opened as POD sites. In (12) we guarantee that a demand point i can only be served by facility j if facility j is open and (13) guarantees that the maximum availability of staff resources is not exceeded. In (14) we formulate the average waiting times in each POD as a function of resources allocated to each POD (equation 8), the arrival of the individuals to them and the service times at each station. Constraints in (15) are the binary and integrality constraints on the decision variables.

4. Solution approach: Genetic algorithm for POD location-allocation

The *p-median* facility location problem is an NP-hard combinatorial optimization problem (Alp *et al.,* 2003). In addition, our problem formulation has nonlinearity in constraint (14), i.e., the definition of the waiting times in the PODs. This constraint could be relaxed and linearized; however, the computational time for finding the optimal solution would likely increase significantly. Hence to solve this problem, we develop a heuristic method based on a genetic algorithm (GA). Here, we describe the implementation of our genetic algorithm.

A genetic algorithm (GA) is a local search algorithm based on the biological evolution paradigm (Holland, 1975). In a GA, first a set of feasible solutions, called the initial population, is generated and genetic operators are used to search the neighborhood of the initial population. Next, a selection is made based on the *survival of the fittest* rule to determine the members of the next generation. This mechanism continues until a stopping criterion is met (e.g., after a fixed number of iterations, or if the solution has not improved sufficiently after a certain number of iterations). Members of the population are called *chromosomes* and each chromosome represents a solution to the problem. The chromosomes evolve through successive iterations called *generations*. In each generation, chromosomes are evaluated using the measure of fitness. To create the next generation, new chromosomes called *offspring* are formed by merging two chromosomes from the current generation using a *crossover operation* and/or modifying a chromosome using a *mutation operator*. A new generation is formed from this intermediate population by selecting

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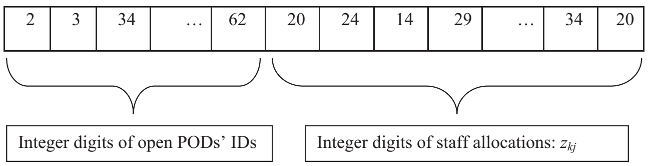

Fig. 2. Demonstration of the encoding scheme with a chromosome.

according to the fitness values, some of the parents and offspring and rejecting others so as to keep the population size constant. Fitter chromosomes have higher probability of being selected. After several generations the fitness of the solutions improves. Genetic algorithms have been used for solving various types of facility location problems (Alp *et al.,* 2003; Bozkaya *et al.,* 2002; Salhi and Gamal, 2003). In our context, a solution is an integer code representing the index of each open POD, and number of staff for two types (express staff and regular staff) allocated to each facility. It is also worth noting that we used a generational approach for the GA; an alternative approach would be the steady state approach (Vavak and Fogarty, 1996).

4.1. *GA-based heuristic for solving p-median problem*

In this section, we describe the implementation of our genetic algorithm to solve the facility location problem with staff allocation decisions.

4.1.1. *Chromosome encoding*

Each chromosome represents a feasible solution to the problem. Genes of the chromosome represent the elements of a feasible solution. We first form a numbered list of the potential facilities to open and the chromosomes have the integer digits representing open facilities in each solution. Our algorithm fixes M, as decision makers often determine how many PODs to open and the model assumes a fixed number of resources for both staff types. With the input of number of PODs to open (i.e., M), the chromosomes size is fixed. In our GA, the chromosomes representing the solutions consist of two parts. The first part has M integer values, each integer representing an open facility. The second part is formed with $2M$ integer digits that represent the number of express staff and regular staff allocated to each open POD, respectively. An example of a chromosome with the encoding scheme is given in Figure 2. In this example, the POD with ID 2 is opened and 20 staff members are allocated to the express dispensing station and 24 are allocated to the regular dispensing station.

4.1.2. *Fitness function (fitness evaluation)*

In our genetic algorithm we evaluate the fitness of the chromosomes by the value of the objective function (Equation 9). The fitness calculation assumes that every demand point is assigned to one facility, specifically the closest open facility.

4.1.3. *Chromosome population and initialization*

The GA has a fixed population size of $N = 500$ chromosomes, which was determined to be large enough to increase the chances of obtaining the global optimum solution at the expense of computational time, based on published literature (Alp *et al.,* 2003). For all different number of PODs open problem instances we calculated the suggested population size based on Alp *et al.* (2003). Even 200–250 would be sufficient as the population size; we doubled it to be safe in our computations. A greedy method is applied to generate the initial population of the algorithm (see Fig. 3). In the greedy algorithm, M randomly chosen facilities are opened (there is an equal probability of each facility being opened) and each census block group is assigned to the closest open POD site. For each open POD, the algorithm assigns a random number of staff, from a uniform distribution of which parameters are set based on the open PODs and total servers available, by utilizing all the available resources and checking if the queue feasibility conditions are

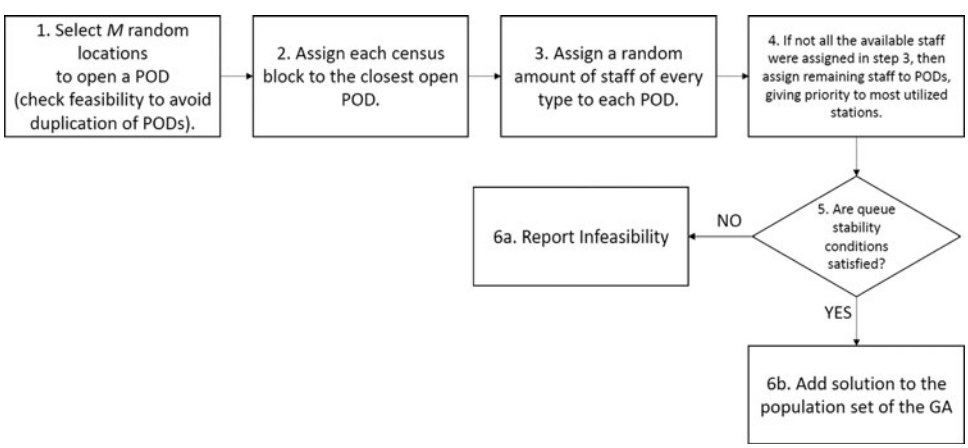

Fig. 3. Greedy algorithm for generating solutions.

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Fig. 4. Demonstration of the cross over operator.

satisfied, i.e., $\lambda_{D,j}/\mu_D z_{D,j} < 1$ and $\lambda_{E,j}/\mu_E z_{E,j} < 1$ for all open PODs.

If these utilization constraints cannot be achieved in any of the PODs for any service line, then the algorithm reports infeasibility. In addition, the algorithm ensures all staff are used after staff feasibility is checked, by allocating additional staff to open PODs based on the utilizations computed in both lines. Priority is always given to the highly utilized lines.

We use randomly selected solutions from the current generation and generate a candidate set consisting of *2N* new solutions (*N* current chromosomes and *N* offspring chromosomes). These solutions then go through the selection procedure based on their fitness values. We keep the best solution from the candidate solution set (elitism) into the next generation and tournament selection is used as our selection mechanism to select the remaining members of the next generation (Gen and Cheng, 2000). We generate new solutions via a mutation operator and a crossover operator as described below.

4.1.4. *Genetic operators and offspring generation*

Crossover: One point crossover is applied to selected parent chromosomes as follows: a predefined crossover point is selected and between two adjacent elements two new chromosomes are generated by swapping all elements in the head of the chromosomes (Gen and Cheng, 2000). An example of a cross over operation is represented in Figure 4. This crossover point can be in both location and allocation parts of the chromosomes. Therefore, since the resource allocation part of the chromosomes is twice the size of facility location part, this operator is twice as likely to be operating on the allocation portion of the problem as the location portion of the problem. Crossover rate was chosen as 0.5 after parameter tuning.

Mutation: Our mutation operator is a random mutation operator and it picks a random gene in a selected chromosome and changes the value of the gene by enforcing a different value. If the gene being mutated is a location gene, the operator ensures that an already open POD is not selected. If it is an allocation gene, it changes the number of servers assigned as necessary for satisfying queue feasibilities and avoiding the situations exceeding the available capacity. A mutation rate of 0.1 was used; determined after parameter tuning which yielded the best results in most experiments. An example of a mutation operator is given in Figure 5.

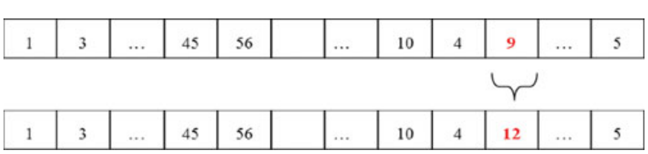

Fig. 5. Demonstration of the mutation operator.

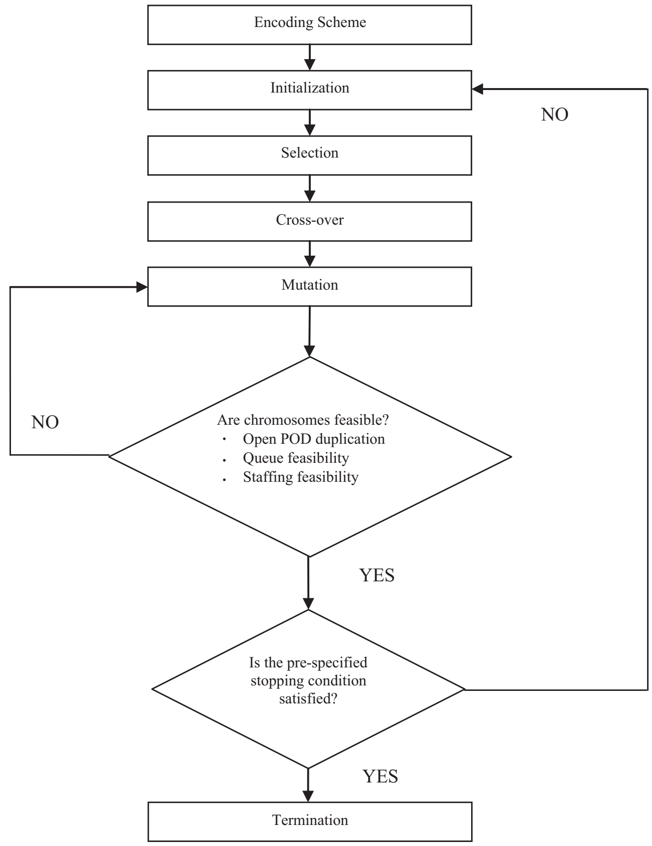

Fig. 6. Simple schematic representation of the GA.

4.1.5. *GA termination*

The heuristic terminates once a pre-specified number of iterations, i.e., 500 iterations, is executed. A simple schematic representation of the GA is presented in Figure 6.

5. Experimental studies and computational results

We solve the described problem by using the developed GA for determining the POD locations in Maricopa County, Arizona. Based on Maricopa County's preparedness plan, we consider the case of having 105 predetermined possible POD locations in the area and perform computations for the scenarios of opening 1, 2, 3, 4, 5, 10, 15, 25, 35, 45, 55, 65, 75, 85, and 95 PODs.

In our computations, we used a county-wide fixed travel speed (i.e., $v_{ij} = v$) and we assume the geographical centers of the census block groups represent the aggregated discrete demand locations. Each demand location has its

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Table 2. Staff availability for each scenario

Normal Staffing	Regular	500
	Express	1000
Low Staffing	Regular	250
	Express	500
High Staffing	Regular	1000
	Express	2000

population as the demand quantity. In addition, based on the demographic structure of the demand locations, i.e., the proportion of the population older than certain age and thus may have more medical complications; each demand point is characterized by its proportion of the population that requires regular dispensing.

We first solve the formulated *p*-median problem without considering any staff allocation decisions or the demographics of the census blocks. Again, the census block groups are assigned to their closest PODs as it was in the population initialization of the solution. We determine the optimal facility locations in terms of minimizing the average travel time for individuals to reach a POD. Then, we calculate the expected waiting times for individuals in each POD by assuming the total available staff are equally allocated to each open POD. We call this approach the *naïve staff allocation approach*, which is a process

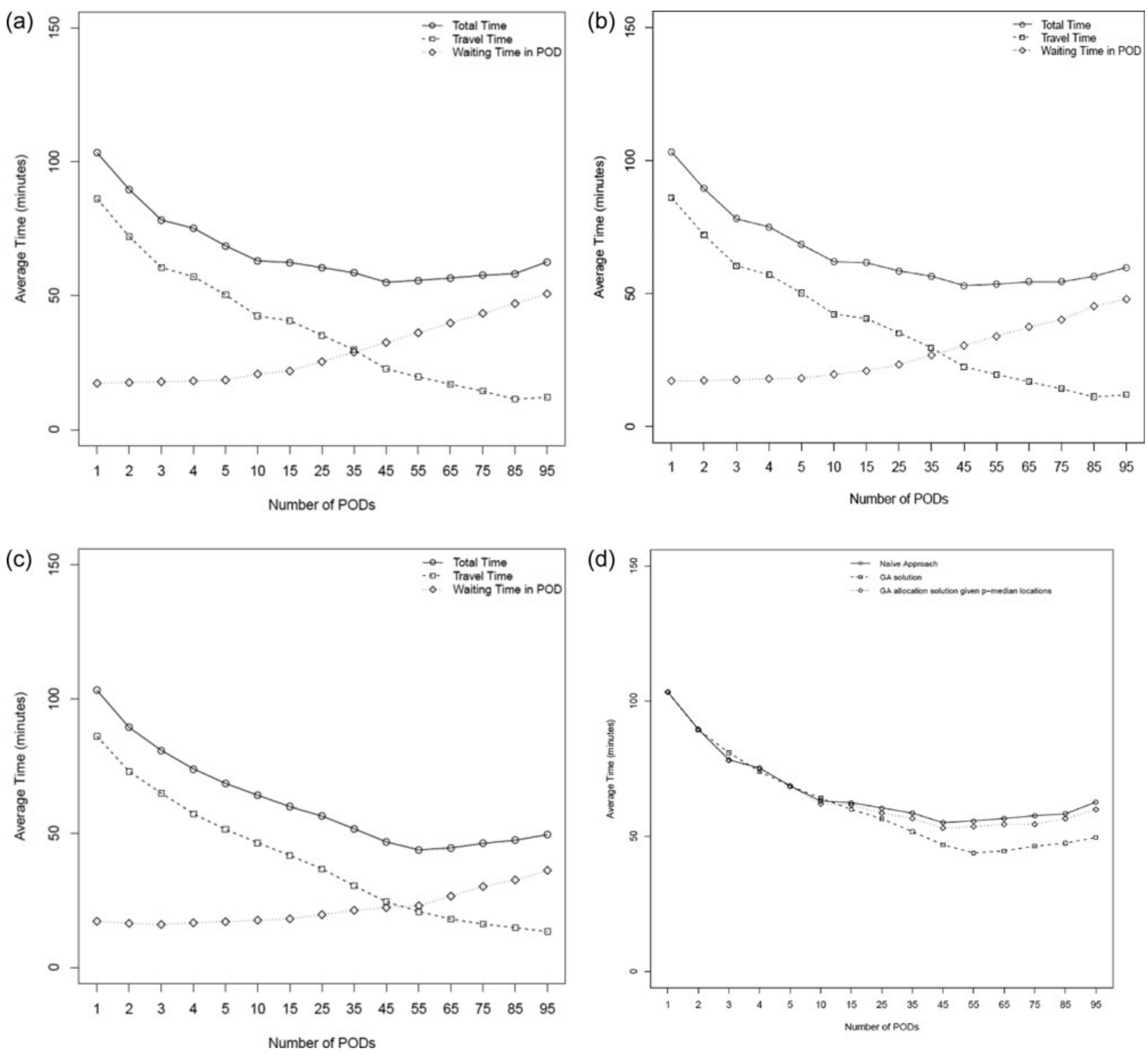

Fig. 7. (a) Average total service time to receive service for different number of PODs open in the *naïve approach.* (b) Average total service time to receive service for different number of PODs open in *with GA allocation solution given p-median locations.* (c) Average total service time to receive service for different number of PODs open in the *GA solution.* (d) Comparison of total times for receiving services in three scenarios.

Table 3. Results for naïve approach and GA approach for different number of PODs open

No. of PODs	Naïve Staff Allocation			Fixed Location & GA Allocation		GA Sol. for Location & Allocation			GA Comparison with Naïve Approach
	Total Time	Travel Time	Waiting Time	Total Time	Waiting Time	Total Time	Travel Time	Waiting Time	Overall Improvement (%)
1	103.31	86.11	17.20	103.31	17.20	103.31	86.11	17.20	0
2	89.56	72.10	17.46	89.45	17.35	89.44	73.02	16.42	0.13
3	78.28	60.50	17.78	78.08	17.58	80.88	64.89	15.99	−3.32
4	75.22	57.12	18.10	75.12	18.00	73.97	57.33	16.64	1.66
5	68.63	50.23	18.40	68.42	18.19	68.54	51.51	17.03	0.14
10	63.01	42.36	20.65	62.00	19.64	64.11	46.50	17.61	−1.75
15	62.40	40.63	21.77	61.61	20.98	59.91	41.79	18.12	3.99
25	60.49	35.20	25.29	58.56	23.36	56.47	36.79	19.68	6.64
35	58.54	29.68	28.86	56.55	26.87	51.72	30.43	21.29	11.65
45	55.02	22.56	32.46	53.03	30.47	46.82	24.50	22.32	14.9
55	55.70	19.62	36.08	53.56	33.94	43.85	20.85	23.00	21.27
65	56.56	16.85	39.71	54.38	37.53	44.58	18.00	26.58	21.18
75	57.59	14.23	43.36	54.42	40.19	46.29	16.14	30.15	19.62
85	58.24	11.23	47.01	56.51	45.28	47.44	14.81	32.63	18.54
95	62.63	11.96	50.67	59.87	47.91	49.54	13.34	36.20	20.9

Note. The time unit in the table is minutes.

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considered by local officers for exercise planning scenario. We perform additional computations to have comparisons for the county's plan with different strategies that may perform better. Based on the county's plans, a number of PODs will be opened and a pre-determined number of staff for the express and regular dispensing stations will be equally distributed to these PODs. Staff in PODs would be reallocated in real time based on backlogs in the system. In our problem, we first assume the county has a total of 1000 express dispensing staff and 500 regular dispensing staff. We also consider different scenarios with high and low staff availability, using the county numbers as the base case (normal) staffing. The numbers of staff that we use for each case are displayed in Table 2.

We solve the 1, 2, 3, 4, 5, 10, 15, 25, 35, 45, 55, 65, 75, 85, and 95 median problems (normal staffing levels) using the naïve approach and report the average travel time for reaching the PODs in the county and the average waiting time in the PODs. As the number of PODs opened increases, the average time for individuals to reach a POD decreases (as expected). In addition, the average waiting time for individuals to get the required medication in PODs increases dramatically when the total number of PODs opened in the county is higher than 15. The results for average total time for individuals to get service with different numbers of PODs open are presented in Figure 7a. After our naïve approach analysis, we fixed POD locations to the optimal sets found as p-median solutions in all scenarios, and used the GA to determine staff allocations for open PODs. The results are presented in Figure 7b. With this approach waiting time results can be improved in comparison to the waiting time results obtained in the naïve approach (up to 7.6% in the 25 PODs scenario). The total average times for receiving service and average waiting times in PODs for various scenarios can be also found in Table 3 (see Fixed Location and GA Allocation columns).

Then, we solve the problem by using the GA for determining the POD locations in terms of minimizing the average travel times to PODs while also determining the optimal staffing configurations in each POD based on the census block group assignments. We call this case the *GA approach* and observe significant improvement in the waiting times in the PODs, especially, when the total number of PODs is relatively larger. We note that average total traveling times do not change significantly from those in the naïve approach with any of these cases. The total time for receiving service could be improved up to 21.27% (i.e., opening 55 PODs scenario) with the use of GA for solving the problem for location and staff allocation simultaneously and significant improvements can be achieved for scenarios of opening 35 and more PODs. We present the results for the GA approach in Figure 7c. As stated earlier, our objective is minimizing the average total time that an individual spends in a POD in addition to the travel time that is spent to reach a POD. The results show that allocating the staff to each POD based on the demographics of the demand locations assigned to them with the GA, reduces the average cycle time (i.e., time spent by an individual in the facility to receive the service) of the PODs. We observe significant improvements in the average travel times to PODs with both naïve approach and GA approach as more PODs are open, and when the total number of PODs open is relatively larger (i.e., >25) we observe significant reductions in total service delivery time. Figure 7d compares the objective function

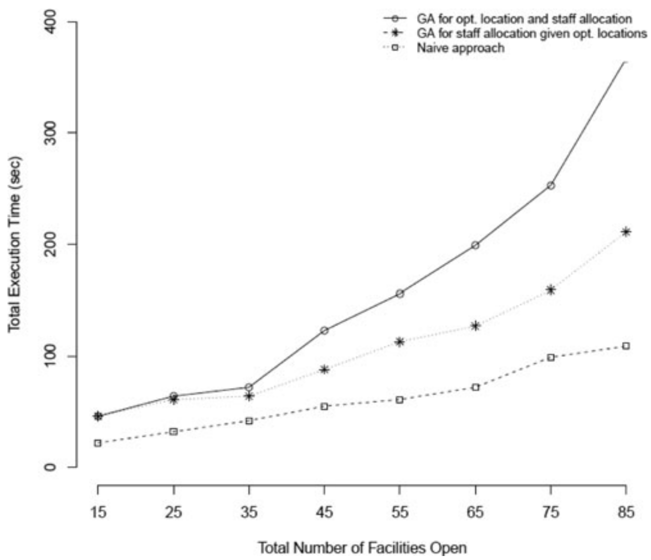

Fig. 8. Comparison of algorithm execution times for three cases.

values for all scenarios obtained with all three approaches. It is clear from the figure that, solving the problem with GA simultaneously for both objectives can generate improved total time results for scenarios with 15 or more open PODs. This improvement is maximized at 55 open PODs scenario with 21.27% in comparison to the naïve approach and with 18.12% in comparison to the fixed p-median locations and the GA allocation approach.

By using the GA for determining which POD sites to be open and determining the amount of staff to allocate to each POD based on the demographics of the assigned demand locations, one can find solutions to the problem that require less time for individuals to receive their required medication in response to an anthrax attack. However, optimizing the staff allocations simultaneously with the location-allocation model in the GA, increases the computational time significantly (see Fig. 8). Nevertheless, the GA still generated solutions in a reasonable amount of time (worst case is less than 7 minutes).

In Table 3, we show the details of the solutions that are obtained for problem instances with a different number of PODs open. These results are presented for the naïve approach, the GA approach, and also for the fixed location and GA allocation approach. We report the total time spent by an individual to get service, i.e., the sum of the average travel time and the average waiting time in PODs. The naïve approach presents the results of locating facilities with the GA but without considering staff allocations. On the other hand, the GA approach presents the results for solving the problem with the genetic algorithm both for facility location and staff allocations simultaneously. As it is seen from the table after opening more than 55 PODs in the area, the objective function value starts increasing again, even though the travel times continue to decrease.

Table 4. Comparison of total times and waiting times for normal and high staffing scenarios

	Normal Staffing (GA Approach)		High Staffing (GA Approach)	
No. of PODs	Total Time	Waiting Time	Total Time	Waiting Time
1	103.31	*17.20*	90.22	*4.11*
2	89.44	*16.42*	80.29	*8.19*
3	80.88	*15.99*	68.78	*8.28*
4	73.97	*16.64*	66.02	*8.90*
5	68.54	*17.03*	59.44	*9.21*
10	64.11	*17.61*	51.94	*9.58*
15	59.91	*18.12*	50.57	*9.94*
25	56.47	*19.68*	46.13	*10.93*
35	51.72	*21.29*	41.62	*11.94*
45	46.82	*22.32*	35.13	*12.57*
55	43.85	*23.00*	33.04	*13.42*
65	44.58	*26.58*	31.62	*14.77*
75	46.29	*30.15*	30.54	*16.31*
85	47.44	*32.63*	30.08	*18.85*
95	49.54	*36.20*	31.05	*19.09*

We also consider different staffing scenarios. The normal staffing scenario uses the planned staffing numbers for the county and results show that for regular dispensing the utilization rates are very high in PODs. For the low staffing scenario, the GA could not find any feasible solution that could keep the utilization rates less than or equal to 1 for the regular servers. In the high staffing scenario the utilzation rates significantly decreased for both, regular and express dispensing stations. In Table 4, the objective function values are compared for both normal staffing and high staffing scenarios with the GA solutions for various number of PODs opened. For the low staffing scenario, as it was mentioned before, no feasible solution was found that could satisfy the queue feasiblity conditions, therefore we do not report waiting time for that scenario. On the other hand, in the scenario with a higher number of staff, the average waiting times are decreased significantly when it is compared to normal staffing scenario. These results are consistent for all of the cases of number of PODs open. For demonstration, we present the details of the scenario of opening 10 PODs in the appendix with a figure of optimal locations of open PODs and a table presenting the assigned number of regular and express individuals and the number of regular and express staff assigned to each open POD (see Fig. A1 and Table A1 for details).

6. Conclusions and future work

An important problem in responding to public health emergencies is determining the location of mass dispensing facilities to open to provide the required service in a reasonable

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amount of time. In this paper, we not only investigate the problem of finding the optimal locations of service facilities (PODs), but also search for effective (staff) resource allocation levels for each open facility in terms of satisfying a certain quality of service. The quality of the service at each POD can be measured in various ways, but the time to get the service is one of the most important performance measures for anthrax bioterrorism. Previous simulation studies show that the right level of staffing in PODs can significantly reduce the waiting times and this minimizes the total time to get service in each POD (Washington, 2009). For this reason, we investigate the problem of facility location with the staff allocation of two types of servers in order to minimize the average total time to get the right medication. We use queuing approximations to calculate the waiting times and solve the problem with a genetic algorithm.

Our results show that as the number of PODs that are open increases, the total travel time to reach a POD decreases, but on the other hand the waiting times at each POD will increase due to limited staffing resources. In addition, considering the demographics at each demand location and allocating the staff accordingly decreases waiting times in PODs and increases the throughput values. Especially, when the number of PODs to open is high, the right staffing at each facility decreases the average waiting times significantly. Also, having multiple servers reduces the variability at the service stations and therefore it reduces the cycle time. The solutions that our solution method (GA) generates can be used to develop better dispensing strategies by public health officials to deliver medications during a public health crisis. The results we present in this paper can help public health decision makers to make better planning and resource allocation decisions by considering the demographics of the related populations.

Finally, in our future work we plan on relaxing several assumptions that we made in our model and computational analyses. The model can be modified to determine the optimal number of PODs to be opened, rather than assuming it as fixed by the policy makers. The travel speed can be also be made to be more robust and realistic in terms of travel times by considering the population density of each census block (e.g., lower travel speeds in densely populated areas). In addition, the embedded queuing model allows us to run the model in a reasonable time for decision makers (i.e., less than 5 minutes). A discrete event simulation model could include more realistic assumptions about process of dispensing; however, it might not give the results in an acceptable time frame. A future work of developing a simulation-optimization framework can potentially improve both drawbacks. Also linearization of constraints and solving the linear program can be performed in the future work a for solution quality benchmark. Lastly, the compliance rate used in our model may depend on socio-economic characteristics which may be geographically dependent and also may depend on the health status of the individual with more vulnerable people more likely to comply. The model can be extended to capture this heterogeneity in individuals' behaviors.

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Appendix

A Generic Formulation of the POD Location- Allocation Model

$$Min\ C_1\left[\left(\sum_{i\in I}\sum_{j\in J}P_i\left(t_{ij}+\overline{W}_j\right)\right)x_{ij}\right]$$
$$+C_2\left[\left(\sum_{j\in J}\sum_{k\in K}S_k z_{kj}\right)+\left(\sum_{j\in J}f_j y_j\right)\right]$$

Subject to:

$$\sum_{j\in J}x_{ij}=1\ \forall i\in I \tag{A.1}$$

$$\sum_{j\in J}y_j\le M \tag{A.2}$$

$$\begin{aligned}&x_{ij}\le y_j\ \forall i\in I,\forall j\in J\\&\sum_{j\in J}z_{kj}\le K_k\ \forall k\in K\end{aligned} \tag{A.3}$$

$$\overline{W}_j=f(\alpha_j,\lambda_{E,j},\lambda_{D,j},\mu_E,\mu_D,z_{E,j},z_{D,j}) \tag{A.4}$$

$$\begin{aligned}&x_{ij},y_j\in\{0,1\}\ \forall i\in I,\forall j\in J\\&z_{kj}\in Z^+\ \forall j\in J,\forall k\in K\end{aligned} \tag{A.5}$$

S_k: Cost of resource type k, $k\in$ {regular staff, express staff}

C_i: Importance factor of objective i

Table A1. Solution for the 10 open POD scenario with staff allocations and population assignments

POD	POD ID	Map Label	Total Individuals Assigned	Regular Individuals Assigned	Express Individuals Assigned	Regular Staff Allocated	Express Staff Allocated
1	3	A	124,107	32,395	91,712	58	100
2	11	B	131,350	29,816	101,535	53	115
3	92	C	97,822	21,211	76,611	38	89
4	24	D	110,512	25,489	85,022	46	100
5	28	E	32,268	6,956	25,312	13	29
6	96	F	132,848	32,623	100,225	58	108
7	17	G	99,450	26,674	72,776	48	82
8	47	H	131,405	30,180	101,224	54	110
9	48	I	147,896	35,164	112,732	63	127
10	46	J	166,389	38,813	127,577	69	140

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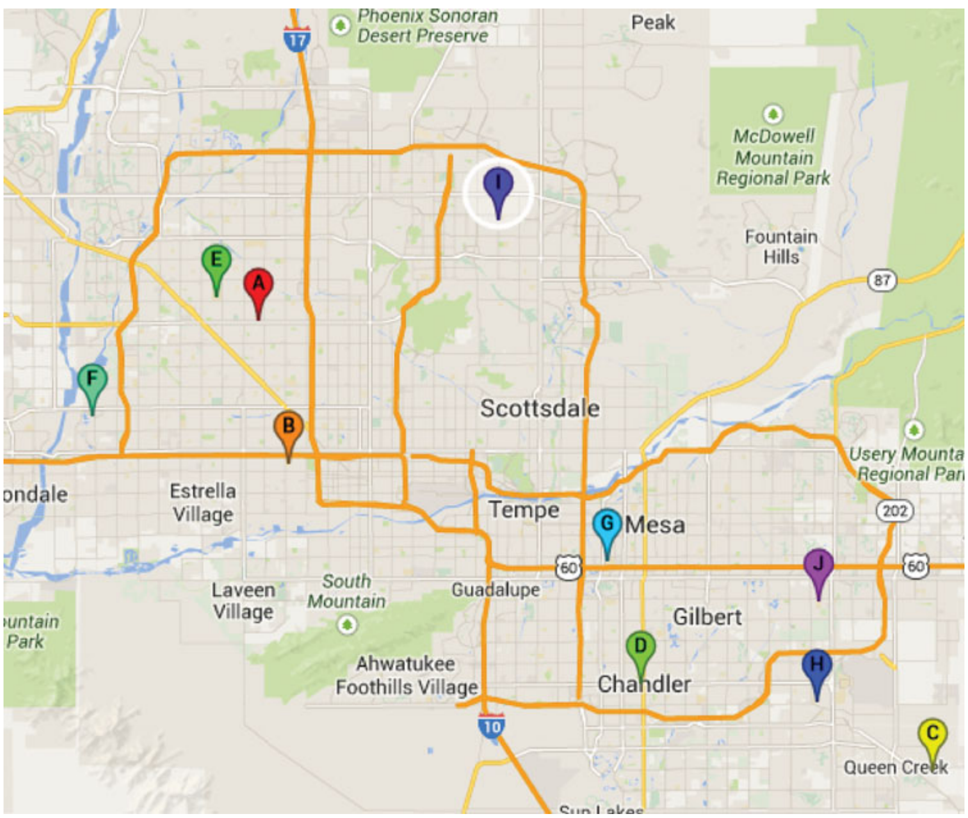

Fig. A1. Locations for the 10 open POD scenario.