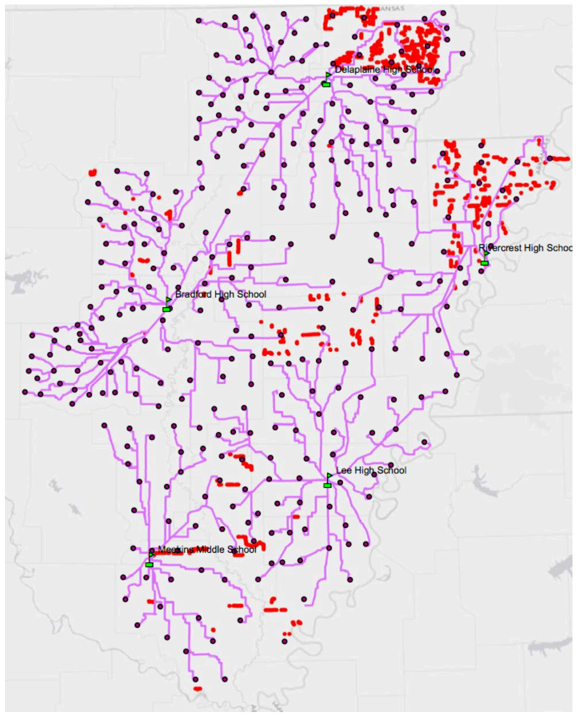
MODELS FOR DISASTER RELIEF SHELTER LOCATION AND SUPPLY ROUTING



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ABSTRACT

This project focuses on the development of a natural disaster response planning model that determines where to locate points of distribution for relief supplies after a disaster occurs. Advance planning (selecting locations for points of distribution prior to the disaster) is complicated by the expectation that buildings and transportation infrastructure in the impact zone may experience damage. For example, highway bridges in affected areas are predicted to be non-functional after an earthquake. The response planning model developed in this project specifies how points of distribution should be chosen once the specific disaster scenario, and the damage caused, is known. The model relies on real-time information regarding actual damage to transportation infrastructure and locations of persons in need of assistance. Response time is critical in saving lives after a disaster, so an approximate solution approach is developed to obtain good solutions quickly. A case study motivated by a New Madrid Seismic Zone (NMSZ) catastrophic event is used to test the model. The case study region includes nineteen counties in Northeastern Arkansas that are most likely to sustain damage in such a scenario. Given a constraint on the total budget available to open and operate points of distribution, it is demonstrated that solutions obtained using the optimal offline approach are able to serve an average of 81% of total demand across test instances considered in a computational study. Solutions obtained using the approximate online approach are able to serve an average of 63% of total demand. A number of assumptions had to be made when populating the case study with data. The solutions presented here are intended simply to illustrate the model and solution approach. The quality of conclusions that can be based on the model and solutions will increase as higher-quality data becomes available for populating the model.

1 PROJECT DESCRIPTION

One hundred years ago, a series of three magnitude eight earthquakes occurred along the New Madrid fault line. If a similar New Madrid Seismic Zone (NMSZ) catastrophic event occurred today, the impact in Arkansas, especially the Northeastern counties, would be extensive. Damage to buildings, loss of power, and shortage of water are expected to leave 285,000 Arkansans residing across a 15,000 square mile rural area in need of shelter. The anticipated resources required to support this need include: 1,400 shelters with 30,000 support staff, 285,000 cots, 572,000 blankets, 169 truckloads of water, and 93 truckloads of ready-to-eat meals. The logistics requirements of a comprehensive disaster relief plan called for by an emergency of this magnitude include determining where points of distribution for essential supplies should be located over the large region. Advance planning is complicated by the expectation that the transportation infrastructure (en route to the shelters) in the impact zone will also experience damage. For example, 700 highway bridges in the affected counties are predicted to be non-functional after a major earthquake. Relief planning models are needed that specify how supply distribution points should be chosen once the specific disaster scenario, and the damage caused, is known.

As suggested by requirements of the motivating problem, the scope of this research consists of natural disaster response models that determine where to locate points of distribution. The models rely on real-time information regarding actual damage to transportation infrastructure and locations of persons in need of assistance. While some localities have response plans in place, they may not be feasible for the specific damage scenario caused by the disaster. For example, current disaster relief plans are often developed on a per-county basis, with each county specifying a distribution location, such as a centrally located county seat or courthouse. If the remaining infrastructure along routes between impacted populations and these locations is not sufficient after the disaster, new distribution locations must be specified. Therefore, the models developed here utilize real-time infrastructure status information to create plans. The proposed models are expected to produce improved solutions that enable the provision of essential resources to more people in affected areas, because they consider a wide variety of real-time information regarding the current population and transportation infrastructure. Response time is critical in saving lives after a disaster, so an approximate solution approach for the model is developed to obtain good solutions quickly.

The primary objectives of this study are two-fold. First, a dynamic model for disaster response is developed, along with an approximate approach for its solution. Then, the model and solution approach are used to determine response plans for a number of NMSZ catastrophic event scenarios. The research tasks conducted to achieve this objective are summarized below:

Task 1: Validation of post-disaster logistics requirements

Meetings with disaster relief personnel are held in order to validate the scope of logistics decisions that should be incorporated in the model. For example, in addition to specifying shelter locations, should distribution center locations and assignments also be determined endogenously? Can shelter location decisions be modified as new information becomes available? Having a strong grasp of the underlying problem ensures the developed model is of practical value.

Task 2: Development of a real-time poster-disaster response model

Specification of a comprehensive shelter location and supply routing plan, pre-disaster, that requires no modification once the disaster occurs, is highly unlikely. It would require predicting *exactly* which roads and buildings will be damaged, and *exactly* which populations will require emergency relief. Hence, it is imperative to develop a method for specifying a response plan once the specific disaster scenario is known. Information regarding the affected populations and remaining transportation infrastructure will become known in the critical hours following a disaster, as emergency calls are placed, and as air operations complete damage assessments. A real-time model is created that considers newly revealed damage information. This model determines point of distribution locations such that *actual* (not expected) performance is optimized.

Task 3: Gathering of case study data

To develop a disaster response plan for a NMSZ catastrophic event scenario, the following data elements are collected. First, damage estimates by locality (*e.g.*, bridges destroyed, roads damaged, persons seeking shelter) are obtained from Center for Earthquake Education and Technology Transfer [1] and Mid America Earthquake Center [2]. A graph representation of road network in the impacted Arkansas counties is obtained from the Center for Advanced Spatial Technologies (CAST) at the University of Arkansas. Population estimates by zip code or census block group, available from United States Census Bureau, are collected. Additionally, a list of candidate point of distribution locations in the impacted region is determined.

Task 4: Computational experiments

A computational experiment is conducted to determine where points of distribution should be located and how demand should be allocated for the case study instances.

The remainder of this report is organized as follows. In Section 2, post-disaster logistics requirements specific to a NMSZ catastrophic event scenario are described. Section 3 formally presents the model being discussed. In Section 4, literature studying relevant disaster response location plans is reviewed. A mathematical model and offline solution approach are given in Section 5 and 6. Case study development is discussed in Section 7 with computational results provided in Section 8. Finally, Section 9 presents concluding remarks and directions for future research.

2 POST-DISASTER LOGISTICS REQUIREMENTS

In this section, expected logistics requirements following a NMSZ catastrophic event are discussed. Information compiled from documents describing emergency response plans and from conversations with emergency response personnel is presented.

The expected impacts of a 7.7 magnitude earthquake in the New Madrid Seismic Zone were assessed in a 2009 National Overview Event Summary [1]. The eight states included in the NMSZ are Arkansas, Missouri, Indiana, Ohio, Kentucky, Tennessee, Alabama, and Mississippi. There are 141 counties in these states defined as impacted counties, estimated to suffer the most damage and loss. On day one after the earthquake, 1.1 million households are expected to be without clean drinking water and 2.6 million are expected to be without power. Almost 3,500 fatalities and 85,000 injuries may result. Projected damages to infrastructure include over 32,000 collapsed buildings and 3,600 damaged bridges. The at risk population, defined as those households that are displaced or without water and/or power for 72 hours, is expected to reach

7.2 million in the NMSZ by day three. Almost 3,500 truckloads of commodities (food, water, and ready to eat meals) could be required to support the at risk population [1].

The Northeastern portion of Arkansas is expected to sustain the most damage in the state [1]. The impacted region in the state includes nineteen counties. The Arkansas Department of Emergency Management (ADEM) and the Federal Emergency Management Organization (FEMA) will "coordinate and synchronize response operations to provide support for life-saving, life-sustaining, and other resources necessary for responding to and recovering from the effects of a no notice catastrophic earthquake in the State of Arkansas" [2]. Their objectives in the immediate aftermath of a catastrophic earthquake include:

- Event to 24 hours: conduct situational awareness, provide resources and commodities to affected counties, ready logistical resources for deployment,
- 24 hours to 96 hours: maintain communications, guidance, controls; receive, stage, and integrate responders and resources,
- 96 hours to 168 hours: establish transportation corridors for movement of resources and commodities; provide sheltering, mass care, commodities,
- Beyond 168 hours: sustained response; transition to recovery operations [2].

The response resources coordinated by the joint state and federal organization to support the impacted counties in Arkansas are expected to originate from within Arkansas and other states to the Southwest. Areas to the South and West of Little Rock are prepared for the reception of evacuees. The American Red Cross, which provides mass care including shelter and commodities, plans to shelter in Little Rock and Northwest Arkansas in the event of a large magnitude NMSZ earthquake. States such as Texas, Oklahoma and Louisiana by default are to move personnel and resources to Little Rock to assist with the response effort if an earthquake of magnitude at least 6.2 occurs [3]. Assistance is not expected from states to the North and East of Arkansas, as these states are also likely to sustain severe damage, and because major Mississippi River crossings along the Eastern border of Arkansas are expected to be unavailable.

A component of the Arkansas state plan is that the National Guard will mobilize a team in each impacted county to assess needs and evacuate the critically injured. While a plan is in place to move essential resources such as personnel and mass care commodities to impacted counties as soon as possible, it is expected that it will take at least three days to begin mobilizing support [3]. This estimate is consistent with the ADEM/FEMA objectives outlined above. With 85% of bridges down, waterways unavailable, and no power, water and natural gas, impacted populations are advised to prepare to be able to survive on their own for three days at a minimum [3].

Mass care commodities should be provisioned near the locations of impacted populations as soon as possible following a catastrophic earthquake event. One common method for distributing commodities is to establish Points of Distribution (PODs), which are "centralized locations where the public picks up life sustaining commodities following a disaster or emergency" [4]. Here, commodities typically include food and water, and may also include ice, tarps, and blankets. Persons traveling by foot or vehicle arrive at POD locations and receive a set amount of supplies per person. In the POD guide published by FEMA, the operating requirements and capacities of three POD sizes are described [4]:

- Type III POD – 150 ft by 300 ft; capacity of 5,000 people per day; requires 19 daytime staff and 4 night staff,
- Type II POD – 250 ft by 300 ft; capacity of 10,000 people per day; requires 34 daytime staff and 6 night staff,
- Type III POD – 250 ft by 500 ft; capacity of 20,000 people per day; requires 78 daytime staff and 10 night staff.

While other methods of mass care commodity provision include mobile delivery, this research focuses on guiding the selection of locations for PODs.

3 PROBLEM STATEMENT

A set of demand points I representing populations in need of life-sustaining commodities such as food and water is known. Associated with each demand point i in I is a known location and magnitude, measured by the number of people requiring food and water. A set of potential POD locations J is known and each has an associated capacity. Let $G = (V, E)$ be a symmetric graph where the vertex set includes all demand points and potential POD locations, such that $V = I \cup J$, and the edge set includes edges for every pair of vertices (m,n) for which a path exists in the road network pre-disaster. The cost of edge (m,n), denoted h_{mn}, is the distance of the shortest path between m and n in G. Note that G is not necessarily connected; that is, paths may not exist between all pairs of demand points.

A planning horizon of length T is considered that begins at the time of the disaster and planning is carried out at discrete time intervals $t = 1,\ldots,T$, representing days, for example. Information is revealed at the beginning of each planning period that includes the magnitude of demand of each demand point for the current period, d_{it}, and an updated symmetric graph $G_t = (V, E_t)$ that considers new information regarding the operability of the road network in period t. Because of possible damages to infrastructure, some paths (edges) that were available pre-disaster may no longer be available, and shortest paths between pairs of demand points may change. Thus, the edge set available in period t is a subset of the edge set available in the fully operable road network E (i.e., $E_t \subseteq E$). As a result, the length of the shortest path between a pair of demand points may be longer in period t once some network components have failed than it was pre-disaster (i.e., $h_{mn}^t \geq h_{mn}$). As response operations commence after the disaster, failed portions of the road network may be returned to operable status. Edges not available in period t may become available again in a future period. That is, $E_1 \subseteq E_2 \subseteq \cdots \subseteq E_T \subseteq E$, and $h_{mn}^1 \geq h_{mn}^2 \geq \cdots \geq h_{mn}^T \geq h_{mn}$.

A total budget B is available for establishing and operating PODs. There is a fixed cost associated with establishing a POD denoted C_F and a per-period cost associated with operating a POD, denoted c_o. Once a POD has been opened, it must continue to operate throughout the duration of the planning horizon. The problem is to choose which candidate POD locations to open and when to operate them. Decisions must also be made to determine the portion of demand from each demand point that should be assigned to each opened POD. Demand from point i cannot be assigned to an operating POD j if the travel distance along the shortest path from i to j is greater than an allowable distance D. Once the decision to serve a quantity of demand from point i using POD j in period t has been made, POD j must continue to satisfy at least that quantity of demand from i in periods $t+1,\ldots,T$ as long as demand point i requires. Demand cannot be split among PODs.

POD opening and operating decisions and demand allocation decisions must be made subject to the described constraints. The primary objective when making these decisions is to maximize the total demand served during the planning horizon. The secondary objective is to minimize distance travelled between demand points and their assigned facilities.

4 LITERATURE REVIEW

Disaster operations can be categorized in four phases: mitigation, preparedness, response, and recovery [5]. The mitigation and preparedness stages occur prior to the disaster. Mitigation consists of actions that help prevent the disaster or reduce the damage caused while preparedness focuses on developing advance plans for response. The response stage begins immediately after a disaster occurs and involves activities aimed to reduce the impact to the affected population. The recovery phase commences after the response phase ends and consists of long-term activities designed to restore impacted communities [5]. Literature addressing POD location decisions during various phases of disaster operations are reviewed here. Much of the existing POD location literature focuses on choosing good locations for PODs during the mitigation and preparedness phases of disaster operations [6-10]. The studies differ based on the cost objectives considered and whether uncertainty in problem elements is explicitly modeled.

A number of papers explicitly model various types of uncertainty that may be present in location problems with application in disaster preparedness. Campbell and Jones study the problem of choosing locations to pre-position supplies and choosing the quantity of supplies to be pre-positioned, given that the locations where supplies are stored are subject to failure [7]. Various relationships between distance to the disaster and risk are examined. For example, supply locations situated near the disaster may allow for lower travel cost associated with delivering supplies from the supply location to the demand point, but also may be subject to a higher probability of failure. Costs associated with purchasing and transporting supplies are considered, as are restocking costs for goods destroyed by the disaster and salvage values for goods that are not delivered. Rawls and Turnquist also study the problem of choosing quantities of supplies to be pre-positioned at chosen locations when potential facility locations are subject to failure [8]. They develop a stochastic model that considers potential facility failures and additional uncertainties in demand locations and quantities and transportation network capacities. The objective in their two-stage model is to minimize the total expected cost incurred across all potential scenarios. Elements of total cost include transportation costs, fixed costs associated with opening facilities and resource purchase costs [8].

Other disaster preparedness facility location studies focus on novel objective functions that capture costs that may not be present in other types of facility location problems. For example, Yushimoto et al. study the problem of locating a pre-determined number of uncapacitated facilities that are intended to serve as warehouses for supply pre-positioning [6]. The objective is to minimize a function of urgency that depends on distance, and all model elements such as demand and travel time are known with certainty. Jaller and Holguín-Veras develop a model that considers facility congestion in determining how many points of distribution should be located and what their associated capacities should be [9]. A cost minimization objective is used in which costs associated with locating PODs, travel costs and costs representing waiting time of individuals are considered. Balcik and Beamon develop a model to determine the number and locations of points of distribution and the amount of supplies to allocate to each one in order to maximize the total affected population covered with budget and capacity constraints [10].

A number of disaster response models in the literature focus on the routing of vehicles to deliver supplies after a disaster occurs [*e.g.*, 11,12]. A comprehensive summary of recent disaster relief routing research efforts is available in De la Torre et al. [13]. Because location decisions are under consideration in this report, these papers are not reviewed here. The problem considered here is distinguished from previous work by its focus on post-disaster decision-making. Specifically, a model and solution approach are developed to determine where to locate PODs and how to assign demand points to them using information regarding demand requirements and transportation infrastructure status that is revealed in a rolling online fashion after the disaster occurs. Whereas previous work focused on finding good location decisions in the preparedness phase of disaster operations, this work contributes to the literature regarding the response phase.

5 MATHEMATICAL MODEL

The problem presented in Section 3 can be modeled as a mixed integer program. Table 1 summarizes decision variables and parameters used in the model. The objective is to maximize the total demand served during the planning horizon. A secondary objective is to minimize the distance between demand points and their assigned POD locations using the available road network in each period. This secondary objective is weighted according to a sufficiently large constant in order to not influence POD location and demand allocation decisions. Constraints (1) are used to ensure each demand point is served by at most one POD. Constraints (2)-(4) control the opening and operating of PODs. Constraints (2) ensure that an opened POD will continue to operate until the end of the planning horizon. Constraints (3) ensure that unopened PODs cannot be operated, and constraints (4) ensure that each POD location can be opened at most once. Constraints (5) are used to enforce that once a portion of demand from a demand point has been assigned to a POD, the same POD will continue to satisfy at least that quantity of demand from the point for the remainder of the planning horizon. Constraints (6) ensure that demand cannot be assigned to PODs in periods they are not operating. Constraint (7) ensures the total budget for opening and operating PODs is not exceeded, and constraints (8) ensure the capacities of operating PODs are not exceeded. Constraints (9) enforce the maximum allowable distance between a demand point and its assigned POD location using the accessible road network in each period.

Table 1: Model elements

Item	Type	Description
X_{ijt}	binary variable	equals 1 if demand point i is assigned to POD j in planning period t and 0 otherwise
A_{ijt}	continuous variable with range [0,1]	percentage of demand of point i satisfied by POD j in period t
Z_{jt}	binary decision variable	equals 1 if POD opened at potential POD location j in period t and 0 otherwise
Y_{jt}	binary decision variable	equals 1 if POD j operates in period t and 0 otherwise
d_{it}	input parameter	demand of point i in period t
h_{ijt}	input parameter	length of shortest path from i to j in G_t
C_F	input parameter	fixed cost to open a POD
c_o	input parameter	cost per period to operate a POD
B	input parameter	total budget for opening and operating PODs
Q	input parameter	POD capacity
D	input parameter	maximum allowable distance between a demand point and its assigned POD location
M	input parameter	sufficiently large constant

The model is given by the following objective function and constraint sets (1)-(9):

$$\text{Maximize } \sum_1^i \sum_1^j \sum_1^t (d_{it}\, \mathrm{A}_{ijt} - M h_{ijt} X_{ijt})$$

[1] $\sum_1^j X_{ijt} \leq 1 \quad \forall\, \mathrm{i} \in I, \forall\, \mathrm{t} \in T$,

[2] $Y_{jt} \geq \sum_1^t Z_{jt} \quad \forall\, \mathrm{j} \in J, \forall\, \mathrm{t} \in T$,

[3] $Y_{jt} \leq \sum_1^t Z_{jt} \quad \forall \text{ j} \in J, \forall \text{ t} \in T,$

[4] $\sum_1^t Z_{jt} \leq 1 \quad \forall \text{ j} \in J,$

[5] $A_{t-1} \leq A_t \quad \forall \text{ i} \in I, \forall \text{ j} \in J, \forall \text{ t} \in (2..t),$

[6] $A_{ijt} \leq X_{ijt} \quad \forall \text{ i} \in I, \forall \text{ j} \in J, \forall \text{ t} \in T,$

[7] $\sum_1^j \sum_1^t (Z_{jt} C_F + Y_{jt} c_{oj}) \leq B,$

[8] $\sum_1^i A_{ijt} d_{it} \leq Q Y_{jt} \quad \forall \text{ j} \in J, \forall \text{ t} \in T,$

[9] $h_{ijt} X_{ijt} \leq D \quad \forall \text{ i} \in I, \forall \text{ j} \in J, \forall \text{ t} \in T.$

6 ONLINE APPROACH

In this section, we offer a so-called online procedure for making POD location and subsequent demand allocation decision in real-time. In the online variant of our problem, new information, specifically demand levels and updated restricted barriers, is made available to the decision maker at the beginning of each period. However, information about demand and/or barriers in future periods remains unknown. Therefore, the user must weigh the benefit of opening a POD now to serve known demand, and commit to operating it for the remaining periods in the horizon, versus saving the fixed and operational costs by waiting until a future period. Also, if opened, the decision maker must determine which demand points to satisfy and at what level. Again, the commitment made in terms of delivering relief to a demand point is a commitment that must be honored throughout the remainder of the planning horizon. Therefore, as we will see in the computational results, decisions made early in the horizon in many ways serve to determine the quality of the decision maker's overall relief strategy. Unlike offline optimization that strives to find the optimal set of decisions, given perfect information, the online procedure is a rule-based approach for the decision maker to follow in real-time. Given that information is not known with certainty, the notion of optimality is not an appropriate measure of quality. Ideally, the goal of creating a 'good' online procedure would be that it would perform within specified performance bounds regardless of the information revealed in real-time. Obviously, in the worst-case, the difference from the optimal offline solution and even a 'good' online solution may be significant.

In our online approach, decision priority is given to demand points with the highest amount of relief need. That is, we begin by sorting the demand points by size in non-increasing order. Then, we begin each iteration of the algorithm by considering the largest remaining demand point. We consider assigning that demand point to its closest potential POD location. If that POD is already opened, and capacity exists to satisfy the demand point at some level, the assignment is made. If the desired POD is not open, then we use a probabilistic step to determine whether to open the POD. As shown in the detailed algorithm below, the probability of opening a desired POD is determined by the ratio of the cost to open and operate the POD for the remainder of the horizon versus the distance from the demand location under consideration to its desired POD. If the candidate demand point is not assigned to the most desirable POD location, the next most attractive POD location is considered and the process continues until either the demand is assigned, or no additional PODs are available for consideration. We continue considering demand points in this manner until either insufficient capacity is available to serve any demand in that period, the budget to open and operate PODs is depleted or all demand points have been assigned. The detailed description of our online algorithm is presented as follows.

Notation:

Let D_t be the set of available demand points in period t

Let b be the remaining budget available in each period

Let g_{pt} be the amount of remaining capacity at POD p in period t

Let F_i be the set of PODs located within 25 miles of demand location i

Let A_{pt} be the demand points assigned to POD p in period t

Let M_p be the set of minimum levels in which we must satisfy those demand points assigned to POD p

Let m_k be the minimum level at with demand point k can be satisfied

Online Algorithm:

Step 0 (Initialization): $A_{pt} = \emptyset$, $S_{pt} = \emptyset$ for all $p \in P$ and $t \in T$. Sort D_t in non-increasing order h_{it} for all $t \in T$. Set $t' = 1$.

Step 1 (Satisfy established demand): If $t' > T$, STOP, else initialize $g_{pt'} = G$ for all $p \in P$ and $b = B$. If $t' = 1$, continue to Step 2. Else, for all $p \in P$, first update $A_{pt'} = A_{p(t'-1)}$,$g_{pt'} = g_{pt'} - \sum_{k=1}^{|M_p|} m_k$ and then continue to Step 2.

Step 2 (Consider new demand): Set $D_{t'} = D_{t'}/\{\cup_{p\in P} A_{pt'}\}$ and $i'$to be the first demand point in $D_{t'}$. If $D_{t'} = \emptyset$, set $t' = t' + 1$ and return to Step 1. Else, if $D_{t'} \neq \emptyset$, let $\bar{p}$ = $\text{argmin}_{p\in F_{i'}}\, d_{i'p}$. If

$A_{\bar{p}t'} \neq \emptyset$ and $g_{\bar{p}t'} > 0$, continue to Step 2a. If $A_{\bar{p}t'} \neq \emptyset$ and $g_{\bar{p}t'} = 0$, set $F_{i'} = F_{i'}/\bar{p}$ and repeat Step 2. If $A_{\bar{p}t'} = \emptyset$, continue to Step 2b.

Step 2a (Assign new demand to open facility): Assign i' to $\bar{p}$ by updating $A_{\bar{p}t'} = A_{\bar{p}t'} \cup i'$. Set $m_{i'} = \min\{g_{\bar{p}t'}, d_{i't}\}$. Update the remaining capacity of the POD to be $g_{\bar{p}t'} = g_{\bar{p}t'} - m_{i'}$. Return to Step 2.

Step 2b (Consider opening desired POD): If $\sum_{t=t'}^{T} c_0 + C_F > b$, set $F_{i'} = F_{i'} \backslash \bar{p}$ and return to Step 2. Else, generate r = U(0,1). If r > $\frac{\sum_{t=t'}^{T} c_0 + C_F}{h_{i'\bar{p}}}$, set $F_{i'} = F_{i'} \backslash \bar{p}$ and return to Step 2. Otherwise, $A_{\bar{p}t'} = A_{\bar{p}t'} \cup i'$. Set $m_{i'} = \min\{Q, d_{i't}\}$, $b = b - \sum_{t=t'}^{T} c_0 + C_F$ and $g_{\bar{p}t'} = g_{\bar{p}t'} - m_{i'}$. Return to Step 2.

7 CASE STUDY DEVELOPMENT

In 1812, three earthquakes of magnitude 8.0 occurred in the NMSZ [14]. With almost 44 million people living along this fault line today, a similar magnitude earthquake could be devastating. This conceivable scenario motivates the case study considered here. According to the NMSZ Catastrophic Event Planning Project, nineteen counties in Arkansas will be affected if the scenario occurs [9]. A list of these counties, along with their respective populations, is given in Table 2. As described in Section 1, our model considers the number of individuals in need of relief throughout the impacted region during each day and the POD locations predetermined to be candidates to locate relief resources. To realistically construct these inputs in a manner representative of a potential NMSZ catastrophic event, careful consideration was given to the choice of methods used to generate problem instances. Each of these methods is described below.

7.1 Planning horizon

Planning for disaster response begins immediately after the catastrophic event occurs. PODs often operate for only the first three to seven days after event occurrence, and demand for relief supplies is projected to diminish after seven days [15]. Therefore, a planning horizon of seven days is considered in this study. Planning is carried out at the beginning of each of day in the study period.

Table 2: Impacted counties in Arkansas and the associated populations

County	Population
Arkansas	20,749
Clay	17,609
Craighead	82,148
Crittenden	50,866
Cross	19,526
Greene	37,331
Independence	34,233
Jackson	18,418
Lawrence	17,774
Lee	12,580
Mississippi	51,979
Monroe	10,254
Phillips	26,445
Poinsett	25,614
Prairie	9,539
Randolph	18,195
St. Francis	29,329
White	67,165
Woodruff	8,741

7.2 Points of distribution

Following an emergency or disaster, the affected population seeks sustaining commodities from centralized locations that are called PODs [1]. Suitable candidate locations for PODs include centrally located, large stable structures. Given that many schools have facilities that meet these criteria, a list of schools in the impacted counties was determined. EducationBug, a complete listing of educational resources available on line, was used to develop a list of 127 schools in the case study region [16]. The Federal Emergency Management Agency provides a manual describing how to setup and operate PODs of three different capacities [4]. Due to the known demographics associated with the likely impacted communities in Arkansas, we chose to focus on locating and operating type II PODs. A type II POD can serve 10,000 persons per day, with an average of 280 cars per hour [4].

7.3 Demand points

It is anticipated that a NMSZ catastrophic event will result in a large number of individuals needing mass care commodities such as food and water. In the nineteen impacted counties in Arkansas, the at risk population, defined as “displaced households (due to structural damage) and those without water and/or power for 72 hours," is expected to be almost 480,000 by day three after the event [1]. The shelter seeking population, defined as a subset of the at risk population, is expected to reach almost 150,000 in the same timeframe [1]. Demand estimates were generated for case study instances using the shelter seeking population by county. While we do not anticipate the provision of shelter at POD locations, the shelter seeking population estimates were chosen as the basis for demand because perhaps not all households in the at risk population would seek mass care commodities from a POD.

The NMSZ Catastrophic Event Planning Report provides estimates for the total population in each of nineteen counties and the shelter seeking population in each county for day one and day three [1]. Ratios of shelter seeking population estimates to total population estimates were computed to approximate the percentage of people in each county presenting demand for mass care commodities at PODs on days one and three. These demand percentages by county are given in Table 3. Because shelter seeking population data was not available for other days in the planning horizon, simple assumptions were used to make estimations. The day two shelter seeking population was assumed to be equal to day one, and day four was assumed to be equal to day three. Estimates for days five through seven were developed considering the pattern of demand for food, water, and ice following Hurricane Katrina. According to a report that analyzed requests for resources after Hurricane Katrina, the temporal distributions for requests for food, water, and ice were as shown in Figure 1 [17]. Requests for these goods peaked on day five and began to decrease on days six and seven. To approximate a maximum demand percentage for days five and six, it was assumed that half of the remaining population that had not presented demand on day three would additionally require mass care commodities on day five. Demand for day six was assumed to be equal to day five. Demand for day seven was approximated as the average of demand for days one and three, to resemble the temporal distribution of demand in Figure 1 that indicates demand returns to its initial day one and three levels before completely diminishing.

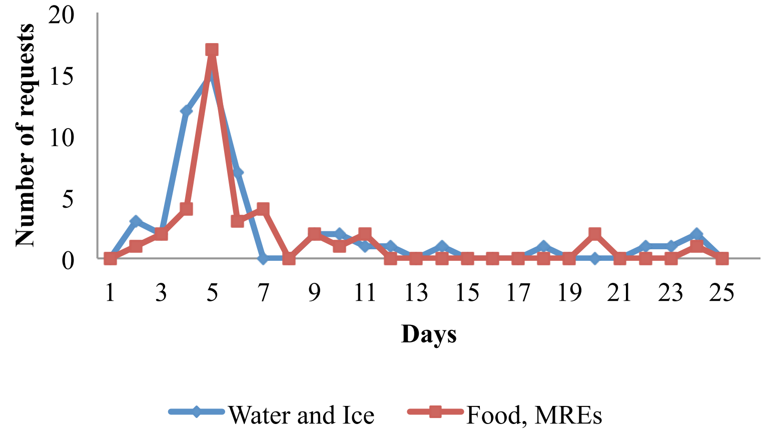

Figure 1: Number of requests per day for ice, water, and food

Table 3: Demand percentages by county

	Demand percentage			
County	Day 1	Day 3	Day 5	Day 7
Arkansas	3.60%	20.60%	60.30%	12.10%
Clay	6.10%	30.73%	65.36%	18.42%
Craighead	7.65%	27.88%	63.94%	17.76%
Crittenden	10.23%	31.57%	65.78%	20.90%
Cross	7.47%	31.12%	65.56%	19.29%
Greene	6.86%	27.29%	63.64%	17.07%
Independence	3.41%	16.25%	58.13%	9.83%
Jackson	6.25%	30.14%	65.07%	18.20%
Lawrence	4.12%	25.12%	62.56%	14.62%
Lee	7.37%	37.02%	68.51%	22.19%
Mississippi	12.15%	31.97%	65.99%	22.06%
Monroe	4.34%	25.04%	62.52%	14.69%
Phillips	4.69%	24.92%	62.46%	14.80%
Poinsett	10.70%	30.70%	65.35%	20.70%
Prairie	3.65%	20.41%	60.21%	12.03%
Randolph	1.60%	20.93%	60.47%	11.27%
St. Francis	6.82%	35.69%	67.84%	21.25%
White	1.36%	14.39%	57.20%	7.88%
Woodruff	7.28%	33.67%	66.83%	20.47%

To determine origination points of the demand seeking population, a list of subdivisions in the nineteen county region and their populations was developed based on a census report that divided each county to numerous subdivisions [18]. The populations were multiplied with the percentages given in Table 3 to produce daily demand estimates by subdivision. The latitude-longitude coordinates of the centroid of each subdivision were collected from census 2000 U.S Gazetteer files [19]. All demand of each subdivision is assumed to be located at the centroid.

Four demand points in the case study region were determined to have a maximum daily demand greater than 10,000, the capacity of a type II POD. In the model developed in this report, a demand point can be allocated to at most one POD. Because it would not be possible to serve all demand from these four demand points using a single POD, they were divided into subregions and a new demand location was associated with each subregion as follows. Let n_i be the maximum daily demand of demand point i, and let $k_i = \lceil n_i/10{,}000 \rceil$. For any demand point for which $k_i > 1$, eliminate demand point i and create k_i new demand points, each having demand n_i/k_i. Manually select latitude-longitude coordinates for these k_i points such that they are approximately equally spaced throughout the original subdivision. This process led to 343 total demand points considered in the case study region.

7.4 Road network

The road network in the case study region and the operational status of its individual elements are explicitly considered when determining the connectivity of and distances between pairs of demand points and potential POD locations. The operational status of network elements and shortest path determinations are discussed in Sections 7.5 and 7.6 below. First, the software used in determining the underlying road network is described. ArcGIS software from ESRI is a "complete system for designing and managing solutions through the application of geographic knowledge" [20]. ArcMap is considered to be the main functionality of ArcGIS. ArcMap is used to work with maps, perform analysis, compile, edit, and modify datasets, and many other tasks [20]. StreetMap North America is a dataset from Tele Atlas (a company that provides ESRI with digital maps) that provides street display and routing for the United States and Canada [20]. Specifically, "StreetMap North America - Detailed Streets" was used to determine the underlying road network in the case study region. The dataset integrates a connectivity model representing transportation networks, including points, lines and turns [21]. A layer in ArcMap was created from the original StreetMap file that contained only the road network for the nineteen counties in the case study region, as using the full file exceeded our computational resources. The term layer in ArcMap refers to an "integrated set of spatial data usually representing entity instances within one theme, or having one common attribute or attribute value in an association of spatial objects" [22]. The created layer contains all highways, avenues, circle roads, county roads, interstates, roads, county line routes, rues, state highways, and US numbered highways in the case study region. This created layer is referred to as the Road file in the remainder of this report. An example section of the road file is provided in Figure 2.

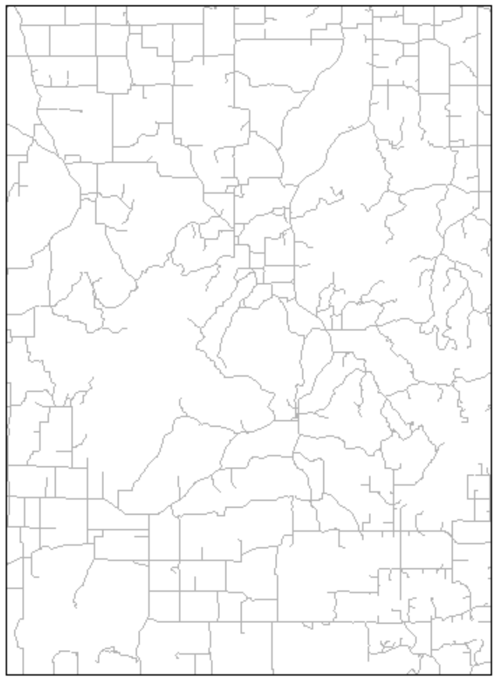

Figure 2: Visual representation of a section of the road file

7.5 Network element status

After an earthquake, the transportation infrastructure may not all be operable. Failed infrastructure components may present barriers that render elements of the underlying road network non-traversable. Bridges, being especially susceptible to failure when earthquakes occur, are modeled as the sole source of road network disruption in this case study. It is assumed that bridges may fail during the earthquake, and then may be restored to operable status over time as they are inspected and/or repaired. A list of 3513 bridges in the case study region was taken from the National Bridge Inventory [23]. The NMSZ report gives the percentage of bridges in each impacted county expected to be functional on days one, three and five following an earthquake [1]. This information is summarized in Table 4.

The values in Table 4 were used directly to determine probabilities of failure for each bridge in the case study region for day one of the planning horizon. Additionally, the values were used indirectly to determine the probability that a bridge failed on day one remains inoperable on day two, the probability that a bridge that was inoperable on day two remains inoperable on day three, and so on. Formally, the process of identifying failed bridges can be described by the following procedure. A description of how shortest paths between pairs of points are updated based on failed bridges is described in Section 7.6.

Table 4: Bridge functionality percentages by county

	Day 1	Day 3	Day 5
Arkansas	81.82%	86.35%	88.94%
Clay	61.81%	65.98%	68.46%
Craighead	42.82%	46.41%	49.13%
Crittenden	30.48%	34.61%	37.61%
Cross	40.59%	44.45%	47.25%
Greene	57.96%	62.25%	64.73%
Independence	94.97%	95.84%	96.10%
Jackson	60.41%	64.37%	66.77%
Lawrence	73.85%	76.82%	78.04%
Lee	63.73%	67.33%	69.47%
Mississippi	11.42%	13.54%	15.39%
Monroe	78.43%	83.51%	86.50%
Phillips	74.92%	78.54%	80.68%
Poinsett	19.01%	21.53%	23.68%
Prairie	76.53%	81.13%	83.9%
Randolph	80.31%	83.79%	84.77%
St. Francis	45.59%	50.8%	54.37%
White	83.83%	85.32%	85.97%
Woodruff	62.95%	66.39%	68.48%

Failed Bridge Identification Procedure:

Let k_{it} be the percentage of bridges functional in county i on day t of the planning horizon. Let Z_{jit} be a random variable indicating whether bridge j in county i is inoperable on day t of the planning horizon, where Z_{jit} is equal to 1 if the bridge is inoperable and 0 otherwise. Then, $P(Z_{ji1}=1)=1-k_{i1}$. Because estimates regarding the percentage of bridges functional are not available for day two, it is assumed that any bridge inoperable on day one remains inoperable on day two. That is, $P(Z_{ji2}=1|Z_{ji1}=1) = 1$. Between days two and three, some bridges may come back online, but no new bridges are expected to fail. Therefore, $P(Z_{ji3}=1|Z_{ji2}=0) = 0$. The probability that a bridge remains inoperable in period three after being inoperable in periods one and two is:

$$P(Z_{ji3} = 1|Z_{ji1} = 1) = 1 - \frac{k_{i3} - k_{i1}}{1 - k_{i1}}.$$

Estimates regarding the percent of bridges functional are not available for day four, so it is again assumed that any bridge that was inoperable on day three remains inoperable on day four. Some bridges may again come back online between days four and five. The probability that a bridge remains inoperable in period five after being inoperable in periods three and four is:

$$P(Z_{ji5} = 1|Z_{ji3} = 1) = 1 - \frac{k_{i5} - k_{i3}}{1 - k_{i3}}.$$

Finally, bridges that are inoperable on day five are assumed to remain inoperable on days six and seven.

7.6 Shortest path determinations

Travel distances between demand points and potential POD locations are determined for each period in the planning horizon by considering failed bridges impacting the operability of the underlying road network. Figure 3 illustrates the connectivity between demand points and PODs and is used to describe how failed bridges may affect the shortest distance between a demand point and POD location pair. Prior to a catastrophic event, there are three possible paths connecting the demand point and POD; each uses a single edge and each is operable. This is illustrated in the left-most figure. The length of the shortest path between the demand point and POD location is 10, using the middle edge. In time period one after the catastrophic event, two bridges have failed, presenting barriers to the traversal of the top-most two edges connecting the demand point and POD location. There is only one operable path between the demand point and POD and it has length 25. By time period two after the catastrophic event, the bridge along the top edge is repaired so that no barrier to its traversal remains in the network. Therefore there are two operable paths between the demand point and POD location and the shortest one has length 20.

ArcGIS was used to create a matrix of distances between each demand point and potential POD location pair in each planning period. Latitude-longitude coordinates of potential POD locations and demand points were uploaded to ArcGIS. For each period a modified Road file was uploaded to ArcGIS as a layer. The Road file was modified by adding a barrier for each failed bridge in each period. A barrier is the mechanism used by ArcGIS to render any road segment directly impacted by a bridge failure as non-traversable. A python script was created and used to generate distances between each potential POD location-demand point pair considering the Road and barrier information in ArcGIS. The output of the python script is an excel file containing a list of the required distances. Visual Basic for Applications was then used to transform the distances to a matrix format.

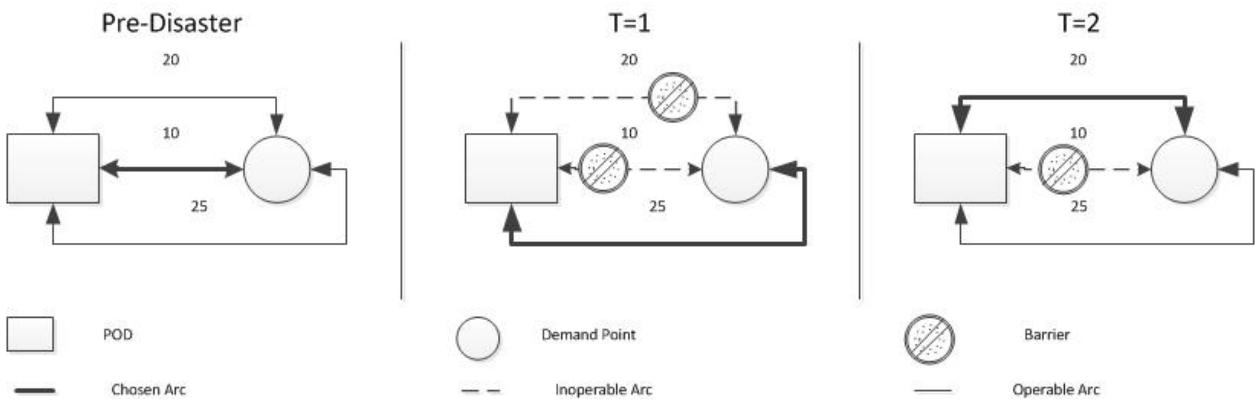

Figure 3: Effect of failed bridges on shortest paths between a demand point and POD

8 COMPUTATIONAL RESULTS

This section investigates solutions generated by solving the offline mixed-integer program via commercial optimization solver and those generated via the online procedure described previously. Our analysis considers four different test instances. For each instance the solution procedures determines the POD locations and subsequent relief demand that should be satisfied by each opened location over a seven-day post-disaster planning horizon. The demand in these experiments was generated according the procedure detailed in Section 7. This demand is the same for each of the four instances. The result of the demand generation was done with respect to 343 potential demand points. In addition, there were 127 potential PODs that could be located in each of the instances. The cost to open a POD is one unit and the cost/period to operate an opened POD is also one unit. The total budget available is 184 units. The only differentiating characteristics in each of the four instances are the barriers disrupting the transportation network. In each instance, a different set of barriers was randomly chosen. The method outlined in Section 7 is designed in such a way that the number of barriers in each instance is of the same magnitude. However, due to the random nature of the barrier selection, the number of barriers in each instance is not equivalent.

8.1 Offline solution

We begin our analysis by considering the solution obtained via an offline model. Recall that the offline approach implies that all demand and road network functionality data is available to the decision maker *before* making any decision. In this case, the offline solution can be viewed as decisions made with so-called perfect information or a best-case solution. Our analysis begins by looking at the computational challenges posed by the offline model. Table 5 demonstrates that problem instances of the magnitude described earlier in this section cannot be solved to optimality within our user-specified maximum time limit of ten hours. After ten hours, the commercial solver, CPLEX, was consistently able to identify a solution within approximately 8.5% of optimality for all of our instances.

Table 5: Runtimes associated with offline models

Instance	Runtime (sec.)	Optimality Gap
1	36000	8.20 %
2	36000	8.50 %
3	36000	8.44 %
4	36000	8.45 %

Though the solutions did differ only slightly from instance to instance in the offline case, we can identify important differences between each instance that may be significant in accounting for these distances. In particular, for each instance, there were some demand points that were completely isolated. A descriptive table for the number of isolated demand points per day for each instance is given in Table 6.

Table 6: Number of isolated demand points per instance per day

Instance	Day 1,2	Day 3,4	Day 5,6,7
1	11	10	9
2	11	8	8
3	10	10	9
4	12	11	10

A more detailed look at the offline decisions made for each of the four instances is available in Tables 7-10. It is clear from these tables that there is a consistent tendency to not open any facility on day one or day two. This is most likely due to the low *known* demand requirements during the first two days of post-disaster relief. Specifically, days one and two have less than 25% of the demand requirements seen during each of days three through six. We see that a majority of PODs are *opened* on day three with the upturn in demand. During day five, the maximum number of facilities is reached for the first time in all 4 instances. This peak in available PODs corresponds in the peak in relief demand on day five. The maximum percentage of demand served is reached on day seven, while the maximum demand served is reached on days five and six. Across all instances, the selected PODs are able to serve approximately 80% of demand known to the decision maker over the relief horizon, given the specified budget. It is also apparent that the percentage of demand fulfilled notably exceeds the percentage of demand points served. This suggests that our offline solution places priority on satisfying demand points associated with more populated areas. As anticipated, after the infrastructures of the PODs are put in place a higher percentage of demand is served in the latter days of the relief efforts.

Table 7: Offline results for Instance 1

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	0	0	27	29	32	32	32	32
Num. of demand points served	0	0	210	246	282	283	312	1333
% of demand points served	0%	0%	61%	72%	82%	83%	91%	56%
Total people served	0	0	113913	120554	306317	306337	83205	930326
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	0%	0%	78%	83%	88%	88%	92%	81%

Table 8: Offline results for Instance 2

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	0	0	26	26	33	33	33	33
Num. of demand points served	0	0	213	213	288	289	308	1311
% of demand points served	0%	0%	62%	62%	84%	84%	90%	55%
Total people served	0	0	113358	113358	318483	318531	85454	949184
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	0%	0%	78%	78%	92%	92%	94%	83%

Table 9: Offline results for Instance 3

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	0	0	28	0	32	32	32	32
Num. of demand points served	0	0	243	243	296	296	311	1389
% of demand points served	0%	0%	71%	71%	86%	86%	91%	58%
Total people served	0	0	113627	113627	301953	301953	80625	911785
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	0%	0%	78%	78%	87%	87%	89%	79%

Table 10: Offline results for Instance 4

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	0	0	25	27	33	33	33	33
Num. of demand points served	0	0	203	229	294	294	300	1320
% of demand points served	0%	0%	59%	67%	86%	86%	87%	55%
Total people served	0	0	105366	111571	308045	308045	81278	914305
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	0%	0%	72%	77%	89%	89%	90%	80%

Figure 4 graphically confirms that the trend in demand served is consistent across each of the four instances. The budget available allows for a majority of the demand points to be open during day three and remain open during the peak of demand in days five and six. This relationship is clear when comparing Figures 4 and 5 below.

Additional analysis of our offline solutions revealed that 264 of the 343 demand points were serviced at least one day across the four instances. Also, 43 of the 127 PODs were utilized at some point in the four instances studied. Given that only approximately thirty PODs were opened in each instance, this suggests that the PODs selected varied only moderately with the change in barriers considered. Interestingly, there were only six demand points that were never serviced throughout the four instances. One of the demand points was not serviced because of the distance constraint, as the closest PODs to it was not within 25 miles.

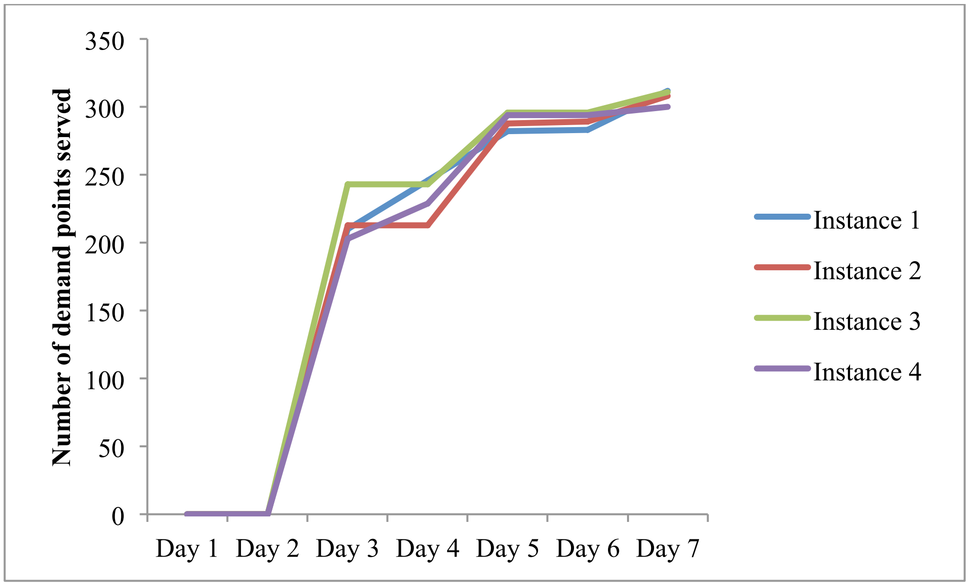

Figure 4: Total demand points served in offline solutions

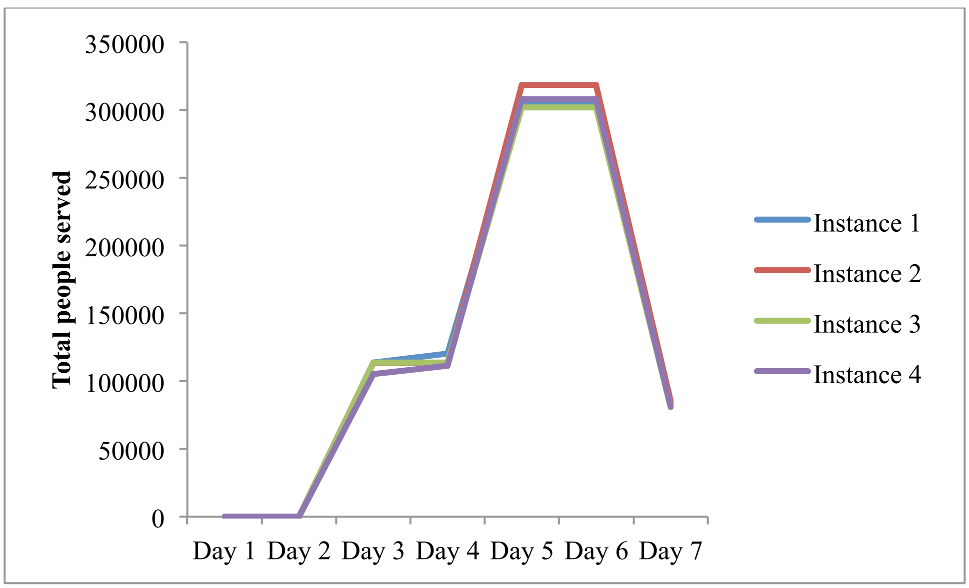

Figure 5: Total people served in offline solutions

Because our instances are based on the impact to a specified geographic region (i.e. Eastern/Central Arkansas), it is interesting to visualize both the POD locations chosen and demand points satisfied on a representative map. Figure 6 presents the frequency in which each demand point is satisfied in our four offline solutions. Clearly, a majority of the demand points are satisfied during at least one day of the planning horizon in all instances. Interestingly, three of the six demand points that are not serviced in any instance are geographically grouped in the northern area of the region. A majority of the other less frequently served demand points are found in less populated areas.

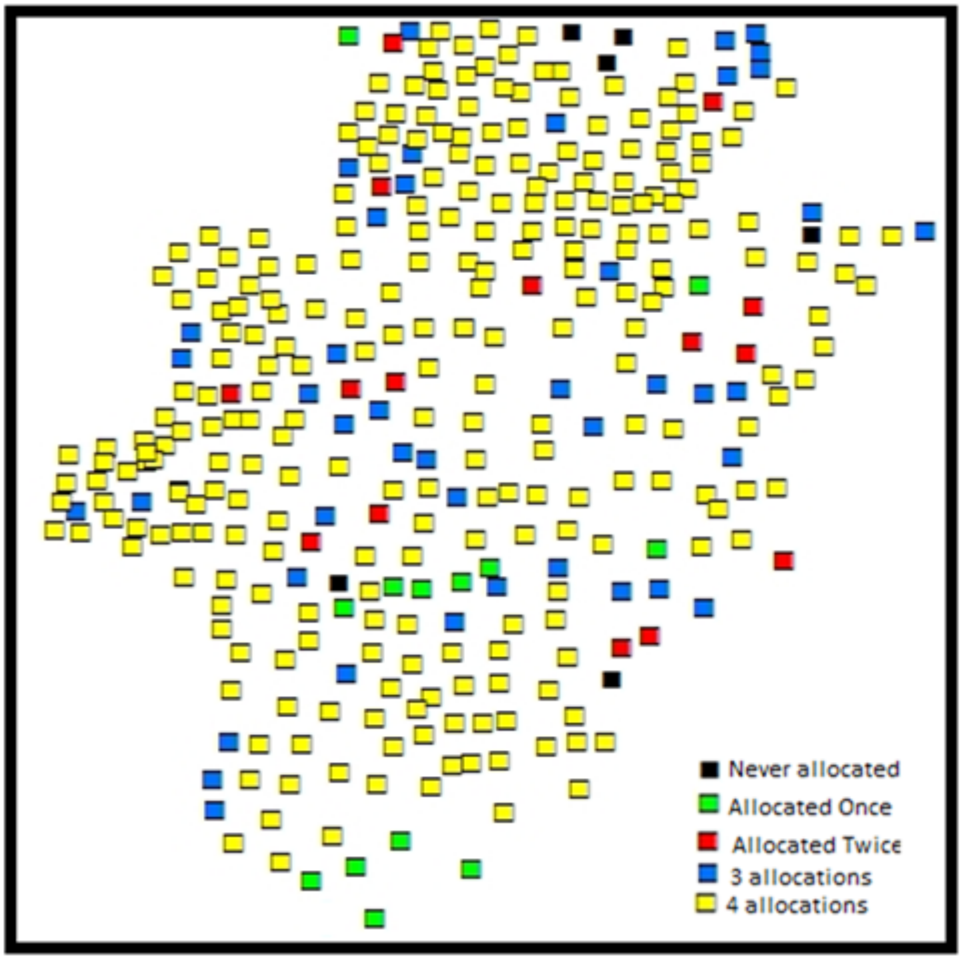

Figure 6: Num. offline solutions (out of 4) in which demand points are assigned to PODs

From the perspective of how POD decisions are made, Figure 7 displays how frequently each POD is utilized in the four instances considered. The number of PODs opened in no instances, one instance, and so on is given in Table 11. For example, there are 58 candidate POD locations that are not utilized in the offline solutions for any of the four instances studied. There are, on average, sixteen demand points in the near vicinity of those POD locations. From this information it can be concluded that, on average, the *number* of surrounding demand points has little to do with how likely a POD is to be opened. Though not universally true, Figure 7 suggests that a subset of the candidate POD locations that were never chosen are found in areas where a number of PODs locations are available for selection within a relatively small radius.

Also, the PODs that were opened in all instances are either geographically central to an area with fewer POD options or in areas with very dense populations.

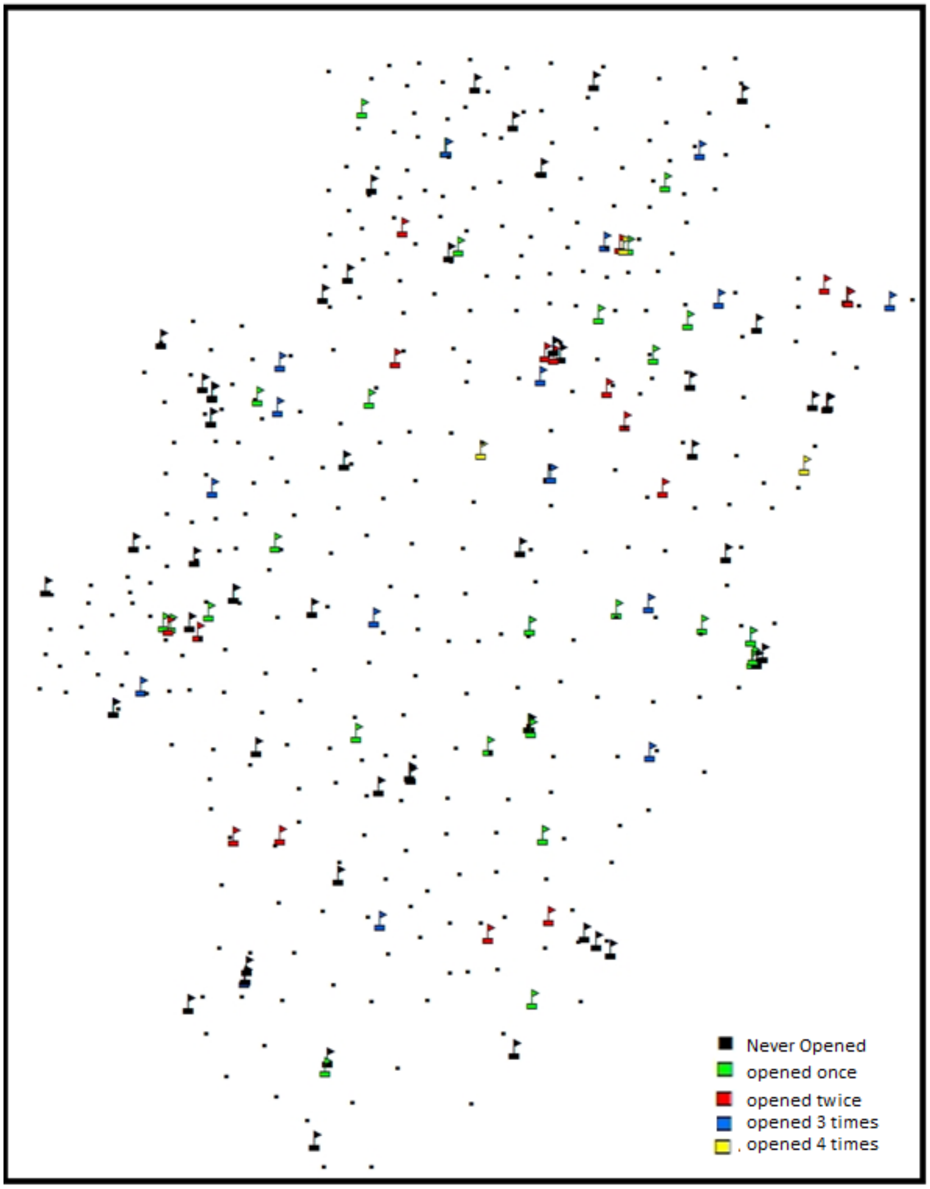

Figure 7: Num. offline solutions (out of 4) in which POD locations chosen

Table 11: Number of PODs based on number of instances they are open (online)

Num. instances	Num. PODs	Avg. num. of surrounding demand points
0	58	16
1	30	19
2	20	19
3	16	20
4	3	20

Finally, a time-expanded interpretation of the decisions made in an offline solution can be seen by collectively studying Figures 8-10. It is clear that the regions with dense barriers (e.g. roads blocked by bridge damage) contain PODs that serve relatively few demand points when compared with PODs in regions less impacted by transportation infrastructure damage. In addition, though there are regions with demand that have no PODs opened to serve them, areas with dense populations often have numerous PODs within a relatively small radius. Similarly, those regions with less relief demand requirements are often required to travel the most distance to get to their nearest POD. If we consider the changes from day-to-day in the offline solution, the most interesting difference is the amount and location of demand served when comparing days three and five. Interestingly, as additional demand information becomes available in day five, an entire area in the western region of the impacted area is serviced for the first time.

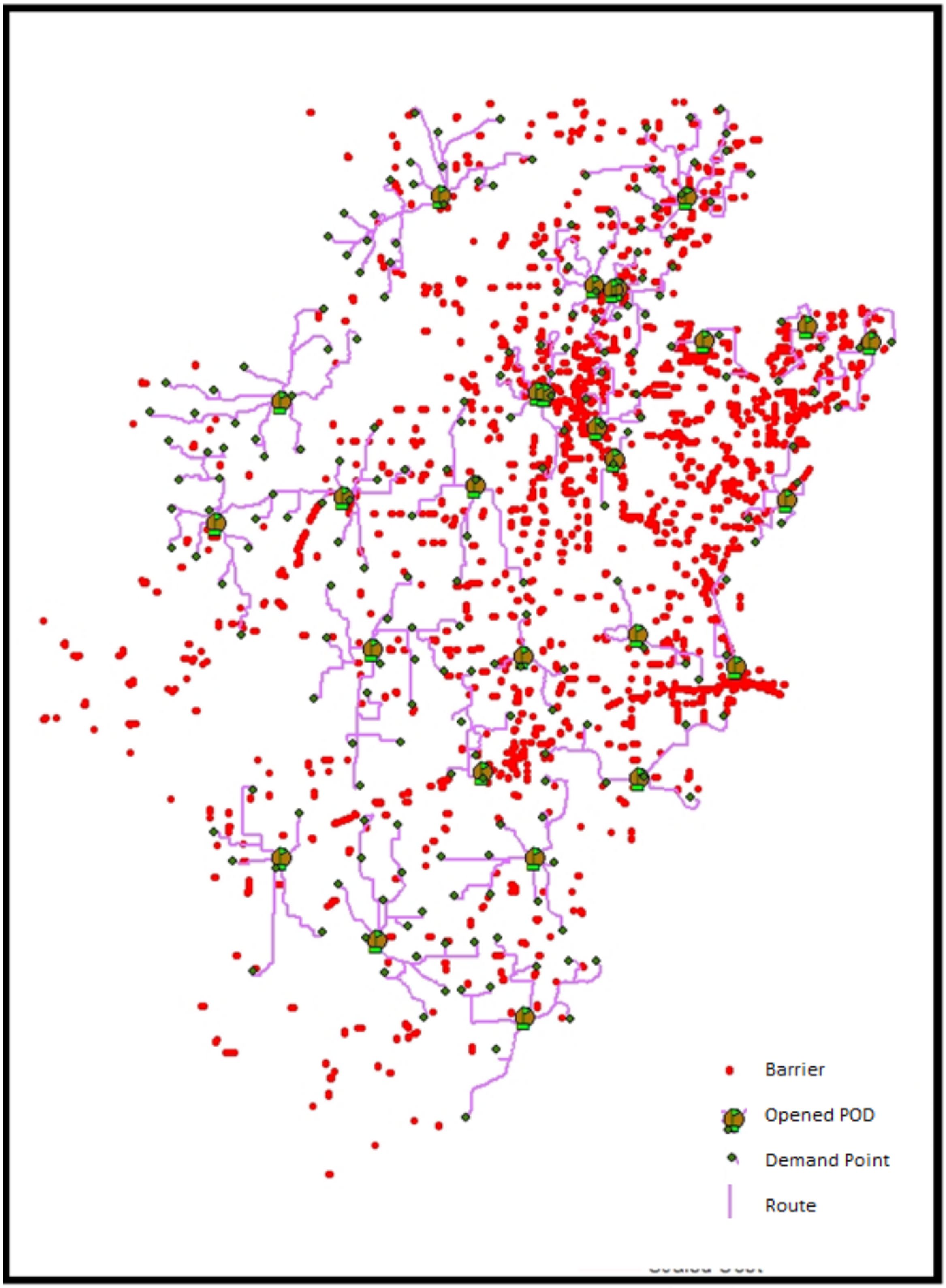

Figure 8: Offline map day 3 – Instance 1

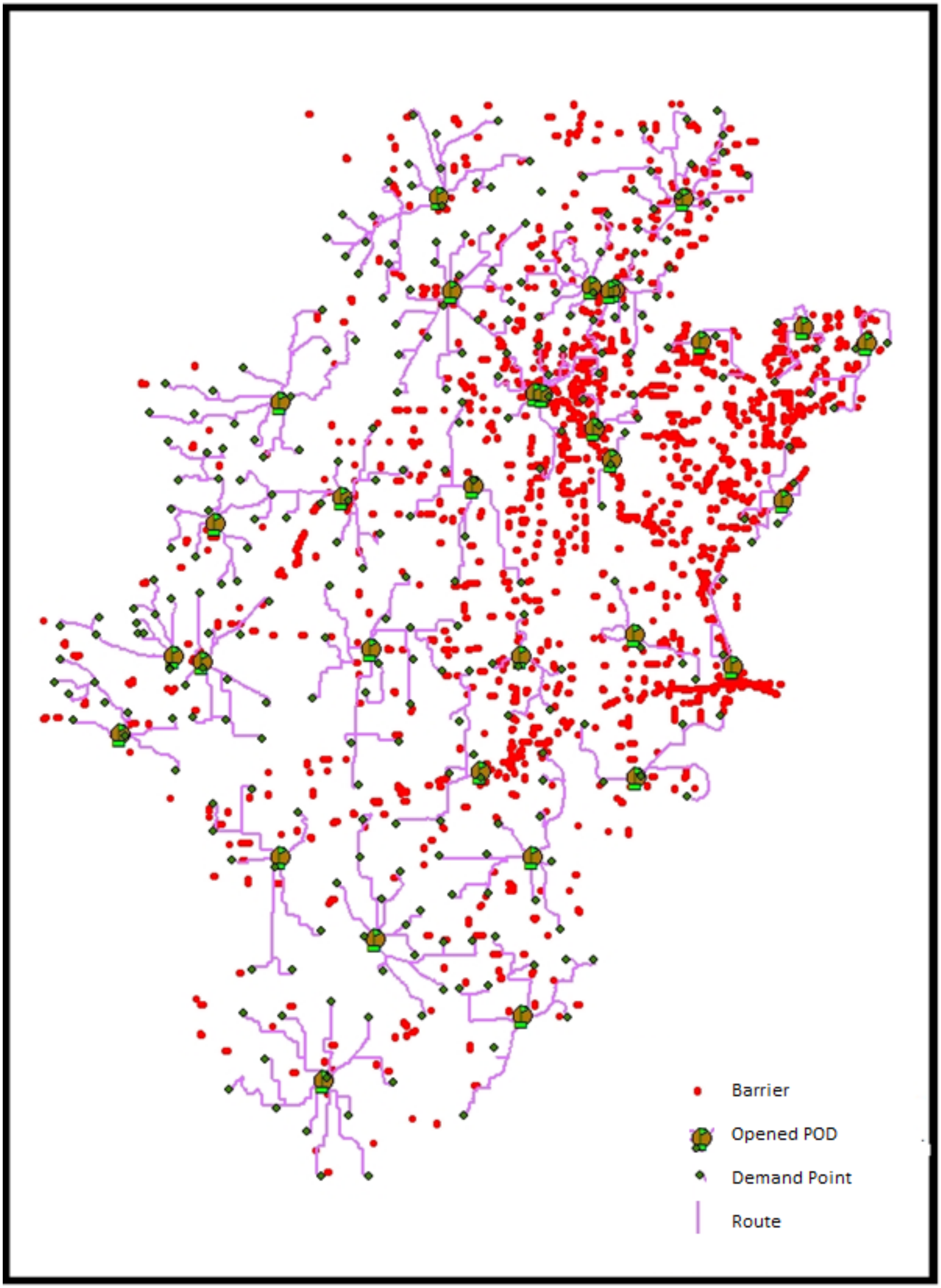

Figure 9: Offline map day 5 – Instance 1

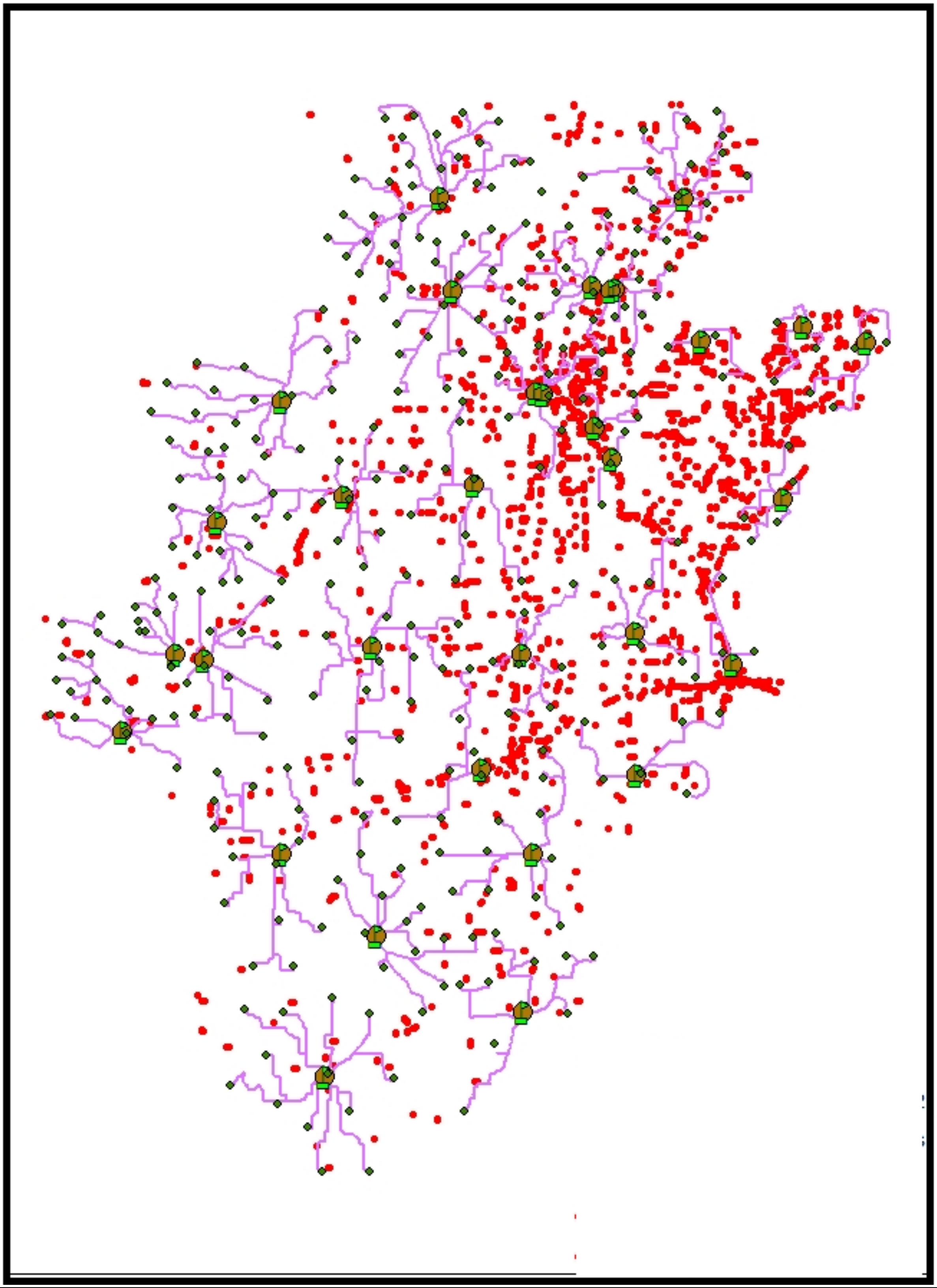

Figure 10: Offline map day 7 – Instance 1

8.2 Online solution

The online variant of our problem requires that decisions be made period-by-period as information is revealed. Compared to Section 8.2, the solutions in this section can be thought of as suffering from lack of perfect, or complete information, much like the restrictions placed on decision-makers in practice. We are interested in how the choices made in the online solutions vary from those made offline in Section 8.2. Tables 12-15 offer a significant contrast as to when PODs get opened. In the online scenario, more than 20 PODs are opened on day one. Recall that PODs did not open until day three in the offline solution. The reason for this is the online algorithm does not benefit from knowing that a large majority of demand is going to arrive in day five. Therefore, having the most facilities open during that portion of the planning horizon is paramount. Instead, the online solution is has almost the same amount of PODs open in days one through seven. This leads to a decrease in overall demand fulfilled of approximately 20% when compared to the amount of demand fulfilled in the offline solution. Similarly, over 10% less demand points, on average, are satisfied in the online solution. These results suggest that the quality of the online solution is highly restricted by the decisions made only with information available at the beginning of the post-disaster horizon. Perhaps more conservative triggers for opening a POD in days one and two would lead to solutions with more demand served. Again, all these observations are consistent throughout the four instances studied in this section. These results are confirmed graphically in Figures 11 and 12.

Table 12: Online results for Instance 1

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	22	23	23	23	23	23	23	23
Num. of demand points served	131	147	151	151	155	155	155	1045
% of demand points served	38%	43%	44%	44%	45%	45%	45%	44%
Total people served	25540	26195	99083	99083	211865	211865	63393	737024
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	71%	73%	68%	68%	61%	61%	70%	64%

Table 13: Online results for Instance 2

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	22	23	23	23	23	23	23	23
Num. of demand points served	131	146	152	152	154	154	154	1043
% of demand points served	38%	43%	44%	44%	45%	45%	45%	43%
Total people served	27102	27759	102381	102381	209463	209463	65467	744016
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	76%	78%	70%	70%	60%	60%	72%	65%

Table 14: Online results for Instance 3

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	22	23	23	23	23	23	23	23
Num. of demand points served	126	143	147	147	149	149	150	1011
% of demand points served	37%	42%	43%	43%	43%	43%	44%	42%
Total people served	25580	26244	94974	94974	198318	198318	60804	699212
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	72%	73%	65%	65%	57%	57%	67%	61%

Table 15: Online results for Instance 4

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Number of facilities open	22	23	23	23	23	23	23	33
Num. of demand points served	120	136	142	142	144	144	144	972
% of demand points served	35%	40%	41%	41%	42%	42%	42%	40%
Total people served	25393	26055	94105	94105	213245	213245	61398	727546
Total demand	35735	35735	145375	145375	348051	348051	90566	1148888
% demand fulfilled	71%	73%	65%	65%	61%	61%	68%	63%

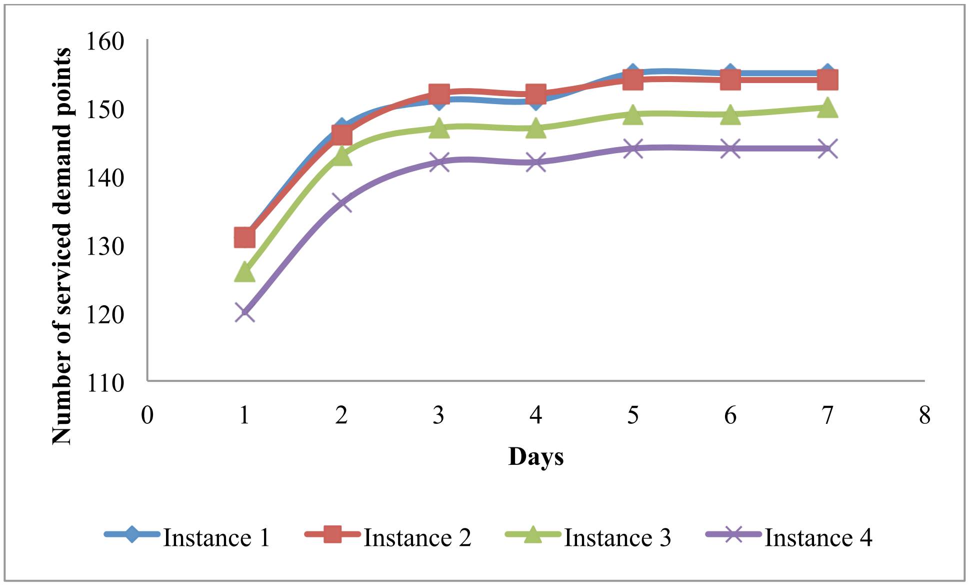

Figure 11: Total demand points served in online solutions

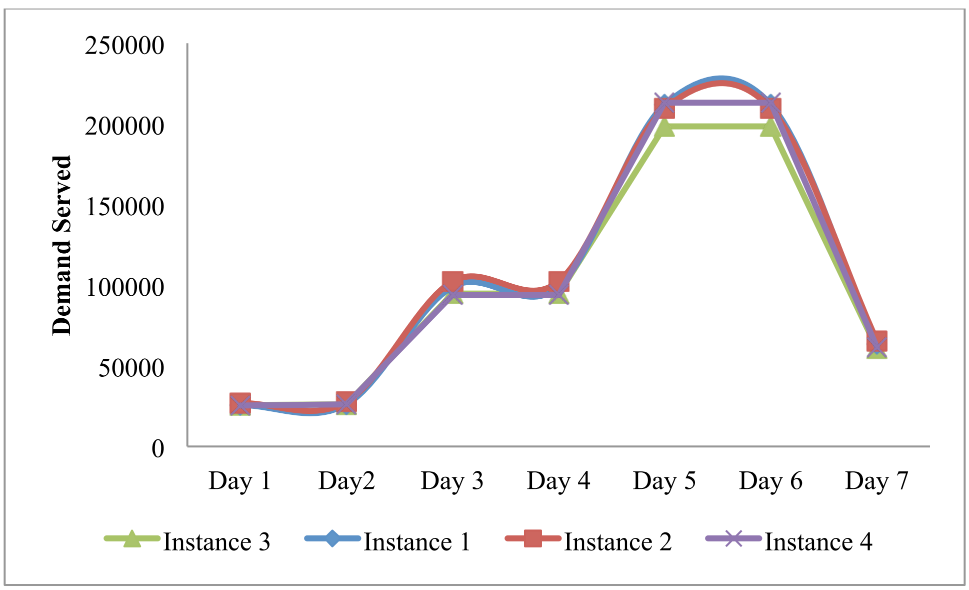

Figure 12: Total demand served in online solutions

Figure 13 and Table 16 provide additional insight into the perceived significance of each demand point in the online solutions. First, it is clear that far more demand points are never serviced in the online solutions, as compared to the offline solutions. Interestingly, many of these points lie on the periphery of the impacted area. Recall that the percentage of the impacted population decreases as we get further from the epicenter of the disaster in the northeast corner of the region. This suggests that the online solution is driven heavily by the size of a demand and a particular location. In fact, given the small snapshot of information available to the online procedure in each period, these solutions suggest that total demand satisfied is perhaps sacrificed in order to satisfy fewer demand points with higher relief needs. It is also interesting that, in Table 16, a majority of demand points are either not served at all or served in all four instances considered in this study. Again, this suggests that exact subset of barriers specified in each instance had minimal impact on the demand points satisfied.

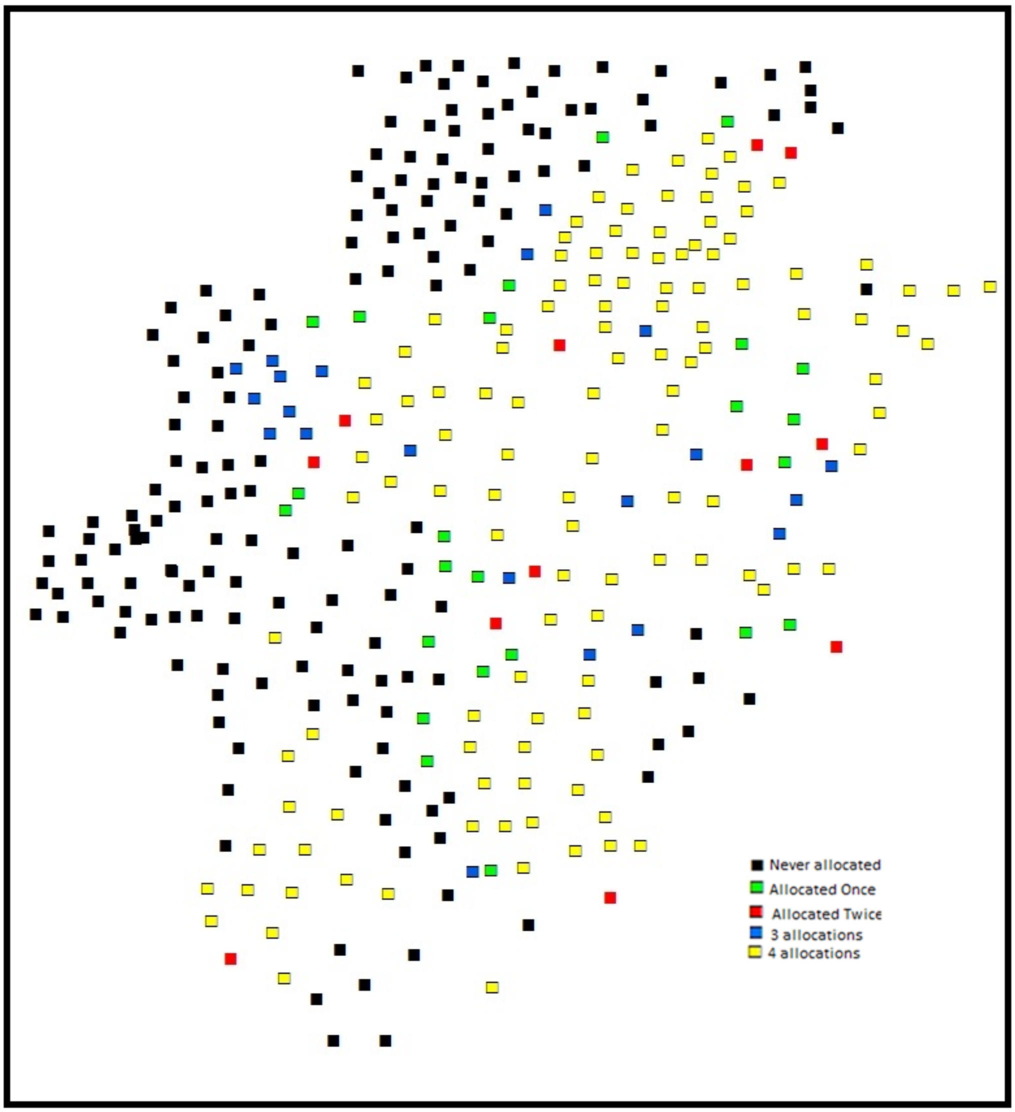

Figure 13: Num. online solutions (out of 4) in which demand points are assigned to PODs

Table 16: Avg. demand of demand points based on frequency of POD assignments (online)

Num. instances	Num. demand points	Average daily demand 1	3	5	7
0	162	33.4	216.1	646.0	124.8
1	25	76.6	314.2	679.4	195.5
2	13	170.5	581.2	1231.0	376.0
3	20	118.6	472.1	1051.2	295.5
4	123	193.6	695.2	1539.7	448.0

Table 17 and Figure 14 offer insight into how the POD location decisions differ between instances in the online solution. Unlike in the offline solution, a majority of PODs opened in the online solutions were utilized in all of the four instances. Far more variability in POD selection was seen between the four solutions obtained by the offline procedure. Again, as in the offline case, the frequency that a POD was located did not directly increase with the average number of demand points surrounding that POD. In fact, those PODs used in all four instances had, on average, a low number of demand points in the surrounding area. However, it is important to note that those few demand points in the surrounding area were often those with the highest requested demand levels amongst the available demand points.

Table 17: Number of PODs based on number of instances they are open (online)

Num. instances	Num. PODs	Avg. num. of surrounding demand points
0	95	18
1	8	13
2	3	22
3	6	23
4	15	14

Finally, a time-expanded visualization is available for the online solution to Instance 1 through Figures 15-17. At first glance, it appears that demand is satisfied almost identically from period-to-period. In terms of PODs opened and demand points served, this is a valid observation. However, it is important to note that the amount of demand served increases sharply in days five and seven. It is clear that the POD locations are far more concentrated in the areas with the highest percentage of impacted population as compared to the offline POD location decisions. However, much like in the offline solutions, the number of demand points served per POD in areas with a dense amount of barriers is far fewer than those located in areas where the amount of infrastructure damage is reduced. Again, it is clear that the online demand satisfaction solution consistently chooses not to satisfy demand in both the northern and western regions of the impacted area.

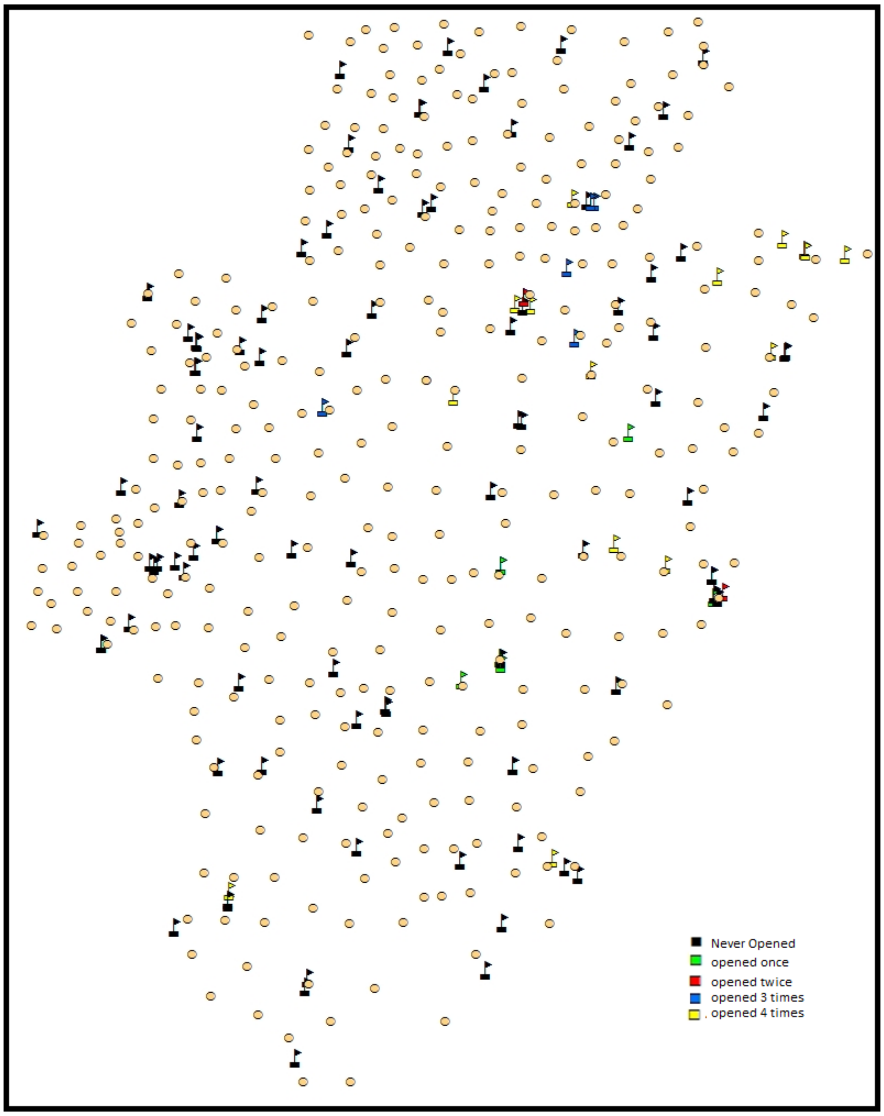

Figure 14: Num. online solutions (out of 4) in which POD locations chosen

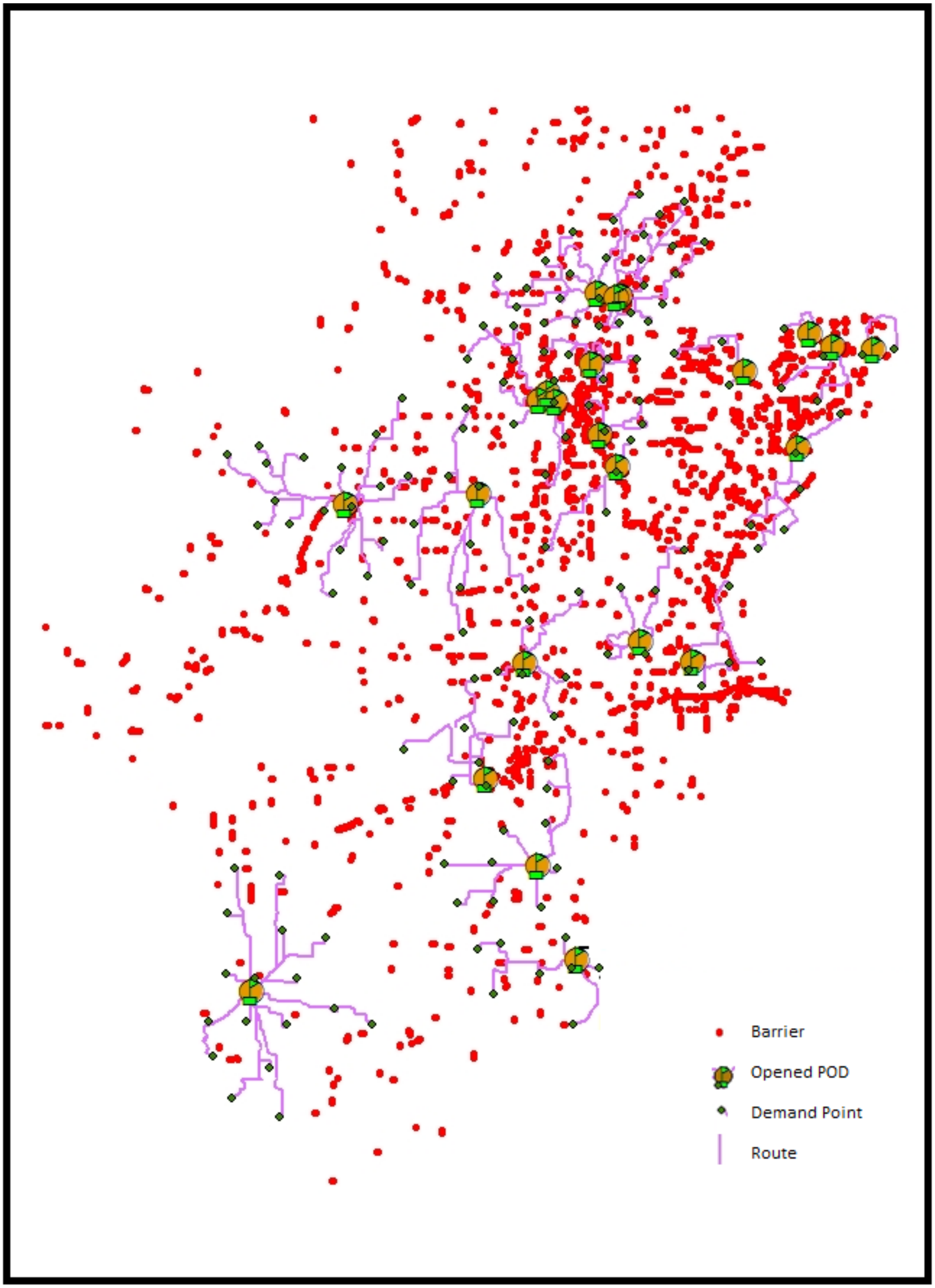

Figure 15: Online map day 3 – Instance 1

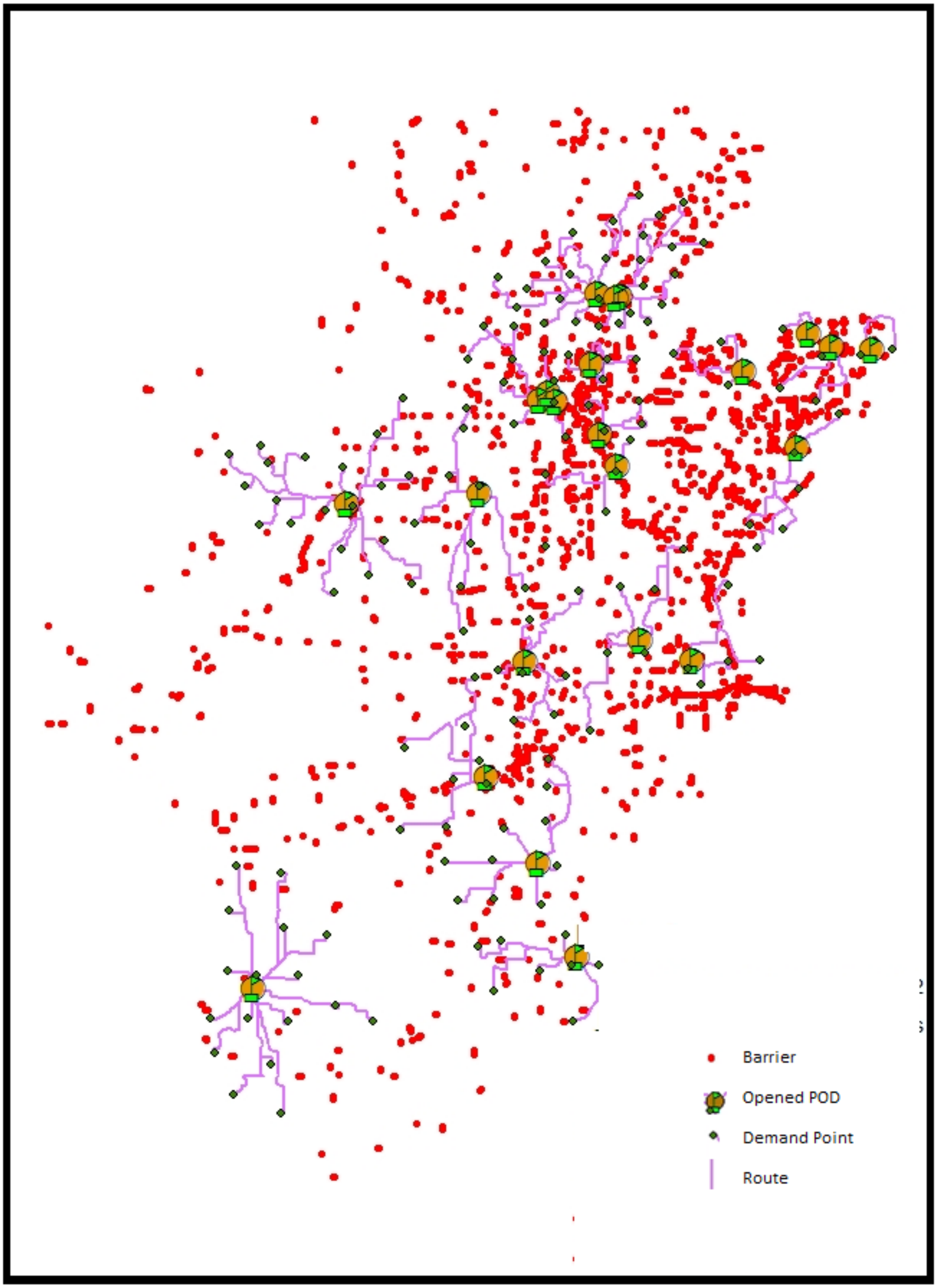

Figure 16: Online map day 5 – Instance 1

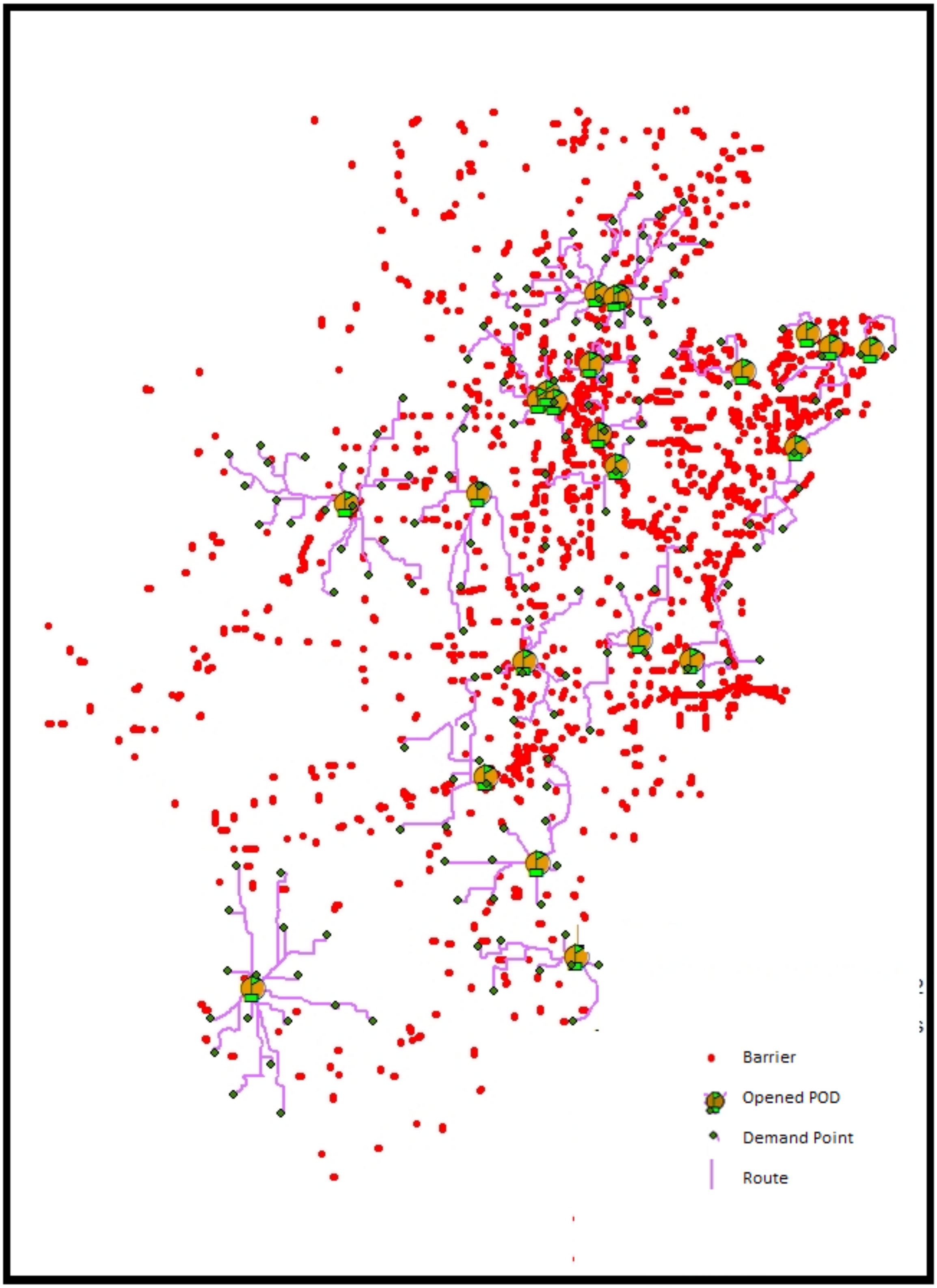

Figure 17: Online map day 7 – Instance 1

9 CONCLUSIONS AND FUTURE WORK

The work on this project focused specifically on the post-disaster delivery of relief across a region devastated by a NMSZ catastrophic event. Providing disaster relief in an efficient manner is extraordinarily challenging since much of the relief need and documented damage is not available to the user in the critical hours following the event. Stated simply, critical decisions regarding location of relief distribution points is not strategic and must be done with very little real information. For that reason, much of our study emphasized the ability to make real-time solutions in a fashion consistent with what responders are faced with. Of course, judging the quality of a real-time solution is challenging, unless compared against a describable metric. In our case, we utilized the best known offline solution to establish a bound on how effectively relief demand can be satisfied over a seven-day recovery period. This effort resulted in a mixed-integer program that, while computationally challenging to solve, was able to provide reasonable solutions within ten hours. These 'best case' solutions demonstrated that, given perfect information and a limiting budget, it may be wise not to open points of distribution immediately following the disaster. Instead, waiting to until peak demand is realized after day two allows more demand to be delivered using the given budget.

While we explored the impact of varying the barriers used to represent a disrupted road network, this change had minimal impact on the overall amount of demand satisfied. However, it did result in changes in the PODs located to satisfy that level of demand. From an online perspective, opening PODs on day one was attractive due to the fact that demand could be satisfied in a manner in which individuals in need could travel small distances to obtain aid immediately. Unfortunately, with the lack of information to indicate that future demand would be much higher in later periods, the POD location decisions made by the online solution on day one ultimately inhibited the decision maker's ability to satisfy larger amounts over the entire horizon. In addition, due to the short-term demand-focused bias of the online approach, the both the number of demand points and the PODs used to satisfy them varied minimally when altering the impacted road network. The online solutions consistently served approximately 20% less demand than those obtained with complete information. In many online scenarios, this quality of online solution would be extraordinarily encouraging. However, our observations of the quality of the online procedure are purely based on empirical observation.

Additional work is needed to obtain theoretical bounds between the worst-case online solution and best-case offline solution. Work in this area requires that the probabilistic approach to determining whether a facility is opened be carefully considered. In standard facility location scenarios, online approaches with known worst-case bounds are established via the expression determining the ‘decision probability’ and the underlying assumption of the data that is received in real-time.

In addition to further theoretical work needed in association with the online algorithm, investigation into the impact of budget level, POD opening cost and POD operating costs would provide additional insights to decisions makers. Also, the number of barriers considered in our study was varied little across all experiments. The impact of the amount of infrastructure destruction would also provide important information as to how much relief can be delivered as a function of road/bridge availability. Finally, consideration of objective measure outside of total demand satisfied, or a multi-objective approach that collectively consider demand satisfied and distance traveled would an important aspect of any future research.

REFERENCES

1. Elnashai AS, Cleveland LJ, Jefferson T and Harrald J. 2009. Impact of New Madrid Seismic Zone earthquakes on the central USA volume I. MAE Center Report No. 09-03. Available from http://mae.cee.illinois.edu/publications/2009/09-03.htm.

2. Arkansas Department of Emergency Management. 2010. New Madrid planning executive brief.

3. Arkansas Red Cross. 2011. Phone interview with Arkansas State Disaster Officer.

4. Federal Emergency Management Agency. 2008. IS-26 guide to Points of Distribution. Available from http://training.fema.gov/EMIWeb/IS/is26.asp.

5. Celik M, Ergun O, Johnson B, Keskinocak P, Lorca A, Pekgun P and Swann J. 2012. Humanitarian logistics. In *Tutorials in Operations Research: New Directions in Informatics, Optimization, Logistics, and Production*. Hanover, MD: Institute for Operations Research and the Management Sciences.

6. Yushimito W, Jaller M and Ukkusuri S. 2012. A Voronoi-Based Heuristic Algorithm for Locating Distribution Centers in Disasters. *Networks and Spatial Economics* **10**(3), p. 1-19.

7. Campbell AM and Jones PC. 2011. Prepositioning supplies in preparation for disasters. *European Journal of Operational Research* **209**, p. 156-165.

8. Rawls CG and Turnquist MA. 2010. Pre-positioning of emergency supplies for disaster response. *Transportation Research Part B: Methodological* **44**(4), p. 521-534.

9. Jaller M and Holguín-Veras J. 2011. Locating points of distribution with social costs considerations. Submitted to the *90th Transportation Research Board Annual Meeting*.

10. Balcik B and Beamon BM. 2008. Facility location in humanitarian relief. *International Journal of Logistics: Research and Applications* **11**(2), p. 101-121.

11. Balcik B, Beamon BM and Smilowitz K. 2008. Last mile distribution in humanitarian relief. *Journal of Intelligent Transportation Systems* **12**(2), p. 51-63.

12. Perez N, Holguín-Veras J, Mitchell JE and Sharkey TC. 2010. Integrated vehicle routing problem with explicit consideration of social costs in humanitarian logistics. Submitted.

13. De la Torre LE, Dolinskaya IS and Smilowitz KR. 2012. Disaster relief routing: integrating research and practice. *Socio-Economic Planning Sciences* **46**(1), p. 88-97.

14. Stewart D and Knox R. 1995. The earthquake America forgot: 2,000 temblors in five months – and it will happen again. N.p.: Gutenberg-Richter. Print.

15. Hagan, C. 2010. County Points of Distribution (PODs) Course. Florida Department of Emergency Management. Available from http://www.floridadisater.org.

16. Educationbug. 2012. Public schools by county. Available from http://arkansas.educationbug.org/public-schools/

17. Holguín-Veras J, Jaller M and Brom M. Immediate resource requirements after Hurricane Katrina: policy implications for disaster response. Submitted to *Natural Hazards Review*.

18. U.S. Census Bureau. 2003. Arkansas: 2000 population and housing unit counts. Retrieved from http://www.census.gov/prod/cen2000/phc-3-5.pdf.

19. U.S Department of Commerce. National County Subdivisions Gazetteer. Available from www.census.gov/tiger/tms/gazetteer/cousub2k.txt; accessed January 2012.

20. ESRI. 2010. ESRI Data & Maps. Available from http://www.esri.com/data/data-maps/j9974esridataandmaps10.pdf. Accessed January 2013.

21. ESRI. ArcGIS Desktop 9.3 Help. Available from http://webhelp.esri.com/arcgisdesktop. Accessed December 2012.

22. Federal Geographic Data Committee. Content standard for digital geospatial metadata: glossary. Available from: http://www.fgdc.gov/metadata/csdgm/glossary.html. Accessed December 2012.

23. U.S. Department of Transportation, Federal Highway Administration. 2011. National Bridge Inventory (NBI) ASCII Files – Arkansas. Available from http://www.fhwa.dot.gov/bridge/nbi/ascii.cfm?year=2011. Accessed May 2012.

APPENDIX: CASE STUDY DEMAND

Table 18: Demand associated with demand points per day

	Daily demand					Daily demand			
Township	1	3	5	7	Township	1	3	5	7
Arkansas	3	16	48	10	Brookland	194	706	1619	450
Barton	9	50	146	29	Buffalo	152	555	1274	354
Bayou Meto	8	44	128	26	Gilkerson	251	915	2099	583
Brewer	2	11	33	7	Greenfield	168	612	1403	390
Chester	11	64	188	38	Herndon	92	336	770	214
Crockett	5	31	90	18	Jonesboro	3647	13295	30490	8471
Garland	6	32	94	19	Lake City	168	612	1404	390
Gum Pond	353	2021	5916	1187	Lester	38	138	316	88
Henton	23	132	387	78	Little Texas	19	68	156	43
Keaton	37	211	619	124	Maumelle	175	639	1466	407
La Grue	176	1011	2959	594	Nettleton	625	2278	5225	1452
McFall	5	28	81	16	Powell	158	575	1319	366
Mill Bayou	21	119	347	70	Prairie	11	39	90	25
Morris	24	136	398	80	Promised Land	17	61	139	39
Point Deluce	9	51	151	30	Taylor	20	72	166	46
Prairie	24	140	409	82	Texas	28	100	230	64
Stanley	31	177	517	104	Black Oak	50	154	322	102
Bennett-Lemmons	40	204	433	122	Bob Ward	121	373	778	247
Bradshaw-Haywood	11	58	123	35	Fogleman	157	485	1010	321
Brown-Carpenter	14	73	155	44	Jackson	140	432	901	286
Cache-Wilson	31	156	332	94	Jasper	1221	3770	7857	2496
Chalk Bluff-Liddell	16	80	170	48	Lucas	85	261	545	173
Clark	18	88	188	53	Mississippi	2834	8748	18230	5791
Cleveland-North Kilgore	37	185	393	111	Mound City	33	100	209	66
East Oak Bluff-B	14	72	152	43	Proctor	90	279	581	185
Gleghorn-South Kilgore	10	50	107	30	Tyronza	386	1191	2483	789
Johnson	33	164	348	98	Wappanocca	85	262	547	174
Knob	15	76	161	45	Bedford	40	167	352	104
Nelson	16	81	173	49	Brushy Lake	33	139	293	86
North St. Francis	160	808	1718	484	Coldwater	35	144	304	90
Payne-Swain	6	33	69	20	Ellis	39	162	342	101
Pollard	36	179	381	107	Fair Oaks	17	70	148	44
South St. Francis	105	529	1124	317	Hickory Ridge	49	206	433	128
West Oak Bluff	166	838	1782	502	Mitchell	94	391	823	242
Big Creek	330	1202	2756	766	Searcy	109	454	957	281
Black Oak	194	707	1621	450	Smith	154	644	1356	399
Arkansas	3	16	48	10	Brookland	194	706	1619	450

Table 19: Demand associated with demand points per day (cont.)

	Daily demand					Daily demand			
Township	1	3	5	7	Township	1	3	5	7
Twist	3	12	25	7	Greenbrier	56	266	952	161
Tyronza	148	615	1296	381	Hill	12	58	209	35
Wynne	735	3063	6453	1899	Huff	22	103	369	62
Blue Cane	5	19	45	12	Jefferson	8	37	133	22
Breckenridge	85	339	792	212	Liberty	27	128	459	78
Bryan	17	66	154	41	McHue	131	625	2236	378
Cache	77	305	712	191	Magness	15	73	260	44
Clark	1170	4652	10851	2911	Moorefield	77	368	1317	223
Collier	30	120	281	75	Oil Trough	23	109	389	66
Crowley	21	84	196	53	Relief	13	64	228	39
Evening Shade	5	19	45	12	Rosie	20	93	334	57
Friendship	53	211	491	132	Ruddell	331	1578	5642	954
Hays	10	40	94	25	Salado	34	161	575	97
Hopewell	21	85	199	53	Washington	33	155	554	94
Hurricane	117	466	1087	292	White River	31	147	525	89
Jones	35	138	323	87	Barren	53	256	554	155
Lake	19	77	181	48	Bateman	3	14	31	9
Main Shore	19	77	181	48	Bird	141	680	1469	411
Poland	79	314	732	196	Breckenridge	34	164	353	99
Reynolds	6	23	53	14	Bryan	6	29	62	17
St. Francis	67	268	625	168	Cache	19	92	198	56
Salem	68	270	629	169	Cow Lake	29	137	297	83
Shady Grove	14	55	127	34	Glaize	51	247	534	149
Spring Grove	416	1654	3858	1035	Glass	76	367	792	221
Sugar Creek	48	191	446	120	Grubbs	40	192	414	116
Union	170	677	1578	423	Jefferson	67	322	696	195
Walnut Corner	9	34	80	22	Richwoods	24	114	246	69
Ashley	47	224	800	135	Union	503	2424	5234	1464
Barren	43	205	732	124	Village	106	509	1100	308
Big Bottom-Wycou	47	223	796	135	Annieville	16	95	236	55
Black River-Marshell	7	35	127	21	Ashland	12	71	176	41
Cushman-Union	34	161	574	97	Black River	23	139	347	81
Departee	9	44	156	26	Black Rock	51	312	778	182
Dota	27	130	465	79	Boas	125	763	1900	444
Fairview	49	231	827	140	Cache	7	41	101	24
Gainsboro	33	158	566	96	Campbell	230	1400	3488	815
Twist	3	12	25	7	Greenbrier	56	266	952	161

Table 20: Demand associated with demand points per day (cont.)

Township	Daily demand 1	3	5	7	Township	Daily demand 1	3	5	7
Dent	40	243	605	141	Hector	102	268	552	185
Dowell	14	88	219	51	Little River	142	374	771	258
Duty	23	143	355	83	McGavock	88	233	480	161
Eaton	12	71	176	41	Monroe	1220	3209	6624	2215
Flat Creek	5	32	80	19	Neal	317	834	1721	575
Jesup	7	41	101	24	Scott	78	206	426	142
Lawrence	11	68	170	40	Whitton	47	123	254	85
Marion	16	96	240	56	Brinkley	189	1093	2728	641
Morgan	25	153	380	89	Brown	0	1	3	1
Promised Land	23	138	344	80	Cache	95	551	1375	323
Reeds Creek	37	225	561	131	Cleburne	6	33	82	19
Richwoods	5	33	82	19	Cypress Ridge	16	91	226	53
Spring River	17	104	260	61	Dixon	12	71	177	42
Strawberry	15	89	221	52	Duncan	48	275	688	162
Thacker	20	119	296	69	Greenfield	12	70	176	41
Big Creek	6	33	60	20	Hindman	5	28	69	16
Council	6	31	58	19	Jackson	10	56	139	33
Fleener	27	137	253	82	Keevil	11	64	159	37
Hampton	66	331	612	198	Mont-Smalley	8	46	114	27
Hardy	0	1	3	1	Pine Ridge	5	27	67	16
Independence	473	2377	4399	1425	Raymond	4	22	56	13
Oak Forest	31	154	285	92	Richland	8	47	118	28
Richland	64	323	597	194	Roc Roe	16	94	236	55
St. Francis	142	712	1317	427	Big Creek	26	139	349	83
Spring Creek	45	228	422	137	Cleburne	35	186	467	111
Texas	35	177	327	106	Cleveland	11	57	143	34
Union	31	154	286	93	Cypress	10	52	129	31
Big Lake	505	1329	2744	917	Hickory Ridg.	85	452	1134	269
Bowen	563	1481	3056	1022	Hicksville	11	56	141	33
Burdette	39	104	214	71	Hornor	515	2741	6871	1628
Canadian	59	155	319	107	Lake	4	19	47	11
Carson	41	107	221	74	Marion	35	184	462	110
Chickasawba	2461	6474	13361	4467	Mooney	21	110	275	65
Dyess	113	298	616	206	St. Francis	298	1586	3974	942
Fletcher	213	561	1158	387	Spring Creek	92	489	1226	291
Golden Lake	132	347	716	239	Tappan	97	518	1299	308
Half Moon Lake	80	211	436	146	Bolivar	474	1361	2897	918

Table 21: Demand associated with demand points per day (cont.)

	Daily demand					Daily demand			
Township	1	3	5	7	Township	1	3	5	7
Dobson	24	69	147	47	Little Black	10	130	375	70
Greenfield	133	382	813	258	O'Kean	5	68	198	37
Greenwood	303	869	1850	586	Reyno	9	119	345	64
Little River	453	1301	2768	877	Richardson	12	158	458	85
Lunsford	43	124	264	84	Running Lk	1	19	54	10
Owen	80	229	488	155	Shiloh	16	212	613	114
Scott	118	340	723	229	Siloam	7	88	255	47
Tyronza	125	359	764	242	Spring Riv	5	70	201	38
W Prairie	101	291	620	196	Union	2	26	74	14
Willis	885	2539	5405	1712	Warm Spr	4	56	162	30
Belcher	4	20	60	12	Water Vall	5	70	202	38
Bullard	7	37	110	22	W Roanoke	15	190	550	102
Calhoun	13	71	210	42	Wiley	2	26	75	14
Center	17	97	285	57	Black Fish	9	47	90	28
Des Arc	10	55	163	33	Franks	61	319	606	190
Hazen	74	413	1217	243	Garland	147	772	1467	460
Hickory Pl.	21	118	347	69	Goodwin	41	214	406	127
Lower Hill	27	152	449	90	Griggs	66	345	656	206
Roc Roe	16	88	260	52	Heth	53	275	522	164
Tyler	9	51	151	30	Johnson	128	670	1274	399
Union	3	18	52	10	L'Anguille	53	278	529	166
Upper Hill	3	18	53	11	Madison	1167	6106	11607	3636
Watensaw	52	292	860	172	Prairie	93	488	928	291
White Riv	92	517	1526	305	Telico	152	797	1516	475
Baker	1	11	33	6	Wheatley	30	156	296	93
Bristow	4	58	169	31	Albion	4	42	169	23
Butler	1	10	28	5	Antioch	7	70	279	38
Columbia	14	187	541	101	Bald Knob	61	645	2562	353
Current Riv	8	107	308	57	Big Creek	20	207	823	113
Dalton	5	59	172	32	Cadron	5	55	219	30
Demun	123	1606	4638	864	Cane	17	182	722	99
E Roanoke	8	104	302	56	Chrisp	11	116	459	63
Eleven Pt	5	62	179	33	Clay	9	91	363	50
Foster	9	118	340	63	Cleveland	1	13	51	7
Ingram	4	52	149	28	Coffey	13	133	527	73
Jackson	4	56	163	30	Coldwell	8	81	321	44
Janes Creek	11	145	420	78	Crosby	7	74	293	40