

MacroServ: A Route Recommendation Service for Large-Scale Evacuations

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Abstract—To respond to emergencies in a fast and an effective manner, it is of critical importance to have efficient evacuation plans that lead to minimum road congestions. Although emergency evacuation systems have been studied in the past, the existing approaches, mostly based on multi-objective optimizations, are not scalable enough when involve numerous time varying parameters, such as traffic volume, safety status, and weather conditions. In this paper, we propose a scalable emergency evacuation service, termed the *MacroServ* that recommends the evacuees with the most preferred routes towards safe locations during a disaster. Unlike many existing approaches that model systems with static network characteristics, our approach considers real-time road conditions to compute the maximum flow capacity of routes in the transportation network. The evacuees are directed towards those routes that are safe and have least congestion resulting in decreased evacuation time. We utilized probability distributions to model the real-life stochastic behaviors of evacuees during emergency scenarios. The results indicate that recommendation of appropriate routes during emergency scenarios play a critical role in quicker and safe evacuation of the population.

Index Terms—Route recommendation service, emergency evacuations, traffic modeling, scalable service



1 INTRODUCTION

Natural and man-made disasters, such as tsunamis, earthquakes, floods, and epidemics pose a significant threat to human societies. In response to the growing number of recent disasters, such as the Colorado flood, Oklahoma tornado, Japan's earth quake, Katrina hurricane, and in particular, the Red River crest that causes flood almost every year in Fargo, North Dakota, the importance and scope of emergency evacuation systems have grown tremendously over the past decade [1]. Well-planned evacuation operations and identification of appropriate rescue routes before and during a disaster play a significant role in saving lives and minimizing casualties.

1.1 Motivation

Generally, transportation planning departments consider

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the peak traffic demands during normal workdays and on special occasions [2], [3]. However, it is almost impossible to conceive transportation plans for emergency situations, due to which large volumes of traffic involved in mass evacuations is likely to exceed the capacity of road networks that may lead to the loss of human lives. For example, due to the lack of proper evacuation plan, in 1991, 25 people lost their lives within the first 30 minutes while attempting to flee their Oakland Hills (California) neighborhood during a wildfire. Moreover, reports indicate that the inefficient evacuation planning in case of the Katrina and Rita hurricanes resulted in a heavy traffic jam on the interstates. A similar traffic jam occurred for 20 hours after a winter storm in Atlanta, GA, USA, in January 2014, as the transportation network was incapable of handling the traffic congestion caused by snow and accidents. To prevent such incidents, emergency evacuation plans must be developed to ensure the availability of safest and most efficient evacuation routes for the residents of a structure, region, or city.

The objective of this paper is to develop a scalable service that can guide evacuees towards safe and least congested routes during a disaster. With the integration of Intelligent Transportation System (ITS), the proposed *MacroServ* service is capable of computing the efficient traffic flows leading to minimum congestion of the roads during an emergency evacuation.

1.2 Research Problem

Several works, such as [4]–[7], have applied multi-objective optimization in evacuation modeling. Generally,

optimization-based evacuation models consider several assumptions to optimize parameters, such as route length, shelter locations, and evacuation times. However, as discussed in [2], most of the times such assumptions are performance limiting or unrealistic, and do not precisely depict the dynamics of real-life emergency situations. Moreover, the following are the limitations of most of the optimization-based evacuation models that negatively affect the performance of such systems [2].

- A few evacuation models simulate the traffic flow with static road network characteristics that do not truly depict the real emergency scenarios [5], [8]. For instance, numerous time varying behavioral, managerial, and stochastic factors, such as number of evacuees and traffic conditions, are involved during an evacuation [8]. Such factors may lead to congestion of the paths that were otherwise suggested as optimal.
- If time factor is added to optimization problems, such that the static network is expanded over the planning horizon for every time interval, then the corresponding problem space becomes extremely large and there are no known polynomial algorithms for solving such problems [6].
- Evacuation modeling in most of the optimization-based approaches, is formulated as a network flow optimization problem [6], [9]. However, such approaches are not scalable for the real-world large-sized evacuation networks, due to the high computational complexities. Moreover, such problems are also considered to be NP-hard because of the multi-commodity nature, as evacuees are differentiated by the origin-destination pairs [7]. Therefore, solving for the travel demand rates and route flow rates requires simulation, as a closed form expression cannot be captured with optimization models [10].
- As mentioned earlier, the optimization-based evacuation models consider assumptions for various parameters, such as road capacities, traffic volumes, route distances, and population sizes [2]. However, such assumptions can become invalid during a real emergency scenario due to variations in weather conditions, unforeseen conditions of traffic, and possible destruction of transportation infrastructure.

The immediate repercussion of the above listed limitations is the suboptimal performance of optimization-based evacuation models.

1.3 Methods and Contributions

To address the abovementioned limitations, in this paper, we propose a scalable service, termed the *MacroServ*, which is capable of performing real-time simulation of dynamic large-scale transportation networks during emergency scenarios. Simulation based evacuation planning by emergency management agencies require faster execution of large-scale vehicular traffic flows. Therefore, we utilize parallel computing to achieve the required scale, size, and speed of the computations. The *MacroServ* service integrates with the ITS to obtain real-time traffic data and utilizes our proposed algorithm to compute the maximum flow of routes and route costs

among disaster sites and safety locations [11]. Based on the route costs, the *MacroServ* service redirects the traffic on alternate preferred routes before the congestion can occur. In this way, evacuees are guided towards the most preferred routes that have the minimum possible risk and the least amount of congestion.

Massive evacuations involve many stochastic factors, such as degree of compliance of evacuees to evacuation calls, rate of evacuees departing from each household/area, behavior of drivers, unforeseen traffic loads, and road conditions on transportation network. To depict such factors in our model, we make use of probability distributions, such as: **(a)** Poisson distribution [12] and **(b)** Weibull distribution [12]. The aforementioned probability distributions allow us to model emergency evacuation scenarios that closely match with the realistic scenarios.

As a case study, we performed our simulations on the real map of City of Fargo, ND, USA where the Red River crest causes flood almost every year. The gradient (slope) of the Red River averages five inches per mile of length, and drops to 1.5 inches per mile in the region of Drayton-Pembina [13]. Due to lack of slope, the Red River tends to pool and cause floods. To model our system, we obtained the data, including road capacities, traffic volumes, speed limits, contours' elevations, historic crest levels of Red River, and historic flood affected areas, from the City of Fargo [14] and North Dakota Department of Transportation (NDOT) [15]. For our simulations, we considered the population of size 108,000 living at Red River flood zones that needs to be evacuated during a flood. Moreover, the transportation network consists of 7,370 road links and 2,800 intersections.

Our simulation results indicate that the traditional evacuation plans devised by the disaster management agencies are inefficient to handle sudden loads of traffic during an emergency. The sudden evacuations result in traffic jams due to which evacuation time increases. When the evacuees are directed towards the preferred routes using our *MacroServ* service, the overall evacuation time significantly decreases. Moreover, the simulation results indicate that the evacuation performance measures are largely dependent on the highway network structure and the number of vehicles produced in an emergency planning zone. In summary, the *MacroServ* service is designed to: **(a)** act as a decision making tool that will enable transportation departments to evaluate and review the emergency evacuation plans by simulating various disaster scenarios and **(b)** recommend preferred and efficient routes to the evacuees during the course of a disaster by making use of high-end sensors and the ITS.

The remainder of this paper is organized as follows. The *MacroServ* service architecture is described in Section 2. In Section 3, we discuss the importance and role of sensors in emergency scenarios. Section 4 presents the design and modeling of our approach. Experimentation results are discussed in Section 5. In Section 6, we discuss the related work, and Section 7 concludes the paper.

2 SERVICE ARCHITECTURE

The *MacroServ* is designed as a route recommendation service that computes the preferred routes on a transportation network during the emergency evacuation scenarios. To make such service scalable, the parallel computing architecture is utilized on a cluster setup. We provide details about various components of the service architecture with an illustrated example.

2.1 Major Components

2.1.1 Road Side Units

As depicted in Fig. 1, the collection of traffic information is performed by Road Side Units (RSU). The RSUs consist of sensors deployed mostly on the intersections to capture the road characteristics and disaster related information, such as average speed of vehicles, average number of vehicles, rain intensity, flood level, and road's extreme temperature conditions (See Section 3). The collected information is transferred to the route recommendation service, where the route computation takes place.

2.1.2 Route Recommendation Service

The basic purpose of route recommendation service is to perform the real-time analysis of the sensory data received through ITS and compute preferred routes for the evacuees that are least congested and at least risk. Fig. 1 depicts the high-level components of the service, and the computational details, complexity, as well as empirical evaluation of the service are thoroughly investigated in the subsequent sections of the paper. The sensory data as input workload to the service consists of current traffic and disaster related information that is relayed to the route computation algorithm. The route computation algorithm running on cluster nodes computes a subset of routes that have the sufficient capacity to allow maximum traffic flow with minimum delay. The service relays the information about the computed set of preferred routes to the emergency management department to take appropriate decisions during evacuations, as well as to the evacuees for traffic guidance through RSU, navigation devices, and other means of communication, such as radio or smart phones.

2.2 An Example Scenario

Fig. 1 also presents an example scenario of the proposed *MacroServ* service architecture. While the evacuation is in progress, the vehicles are following different routes on a city's transportation network. The road congestion information is communicated from the RSU sensors to the Traffic Control Center (TCC), as shown in Step 1 from where it is communicated to route recommendation service (Step 2). The route recommendation service utilizes computer cluster and route computation algorithm to compute the alternate routes with the maximum flow capacity (Step 3). The vehicles approaching towards congested road links are warned in advance, and are provided with alternate preferred routes on the navigation devices to prevent congestion (Step 4 and Step 5).

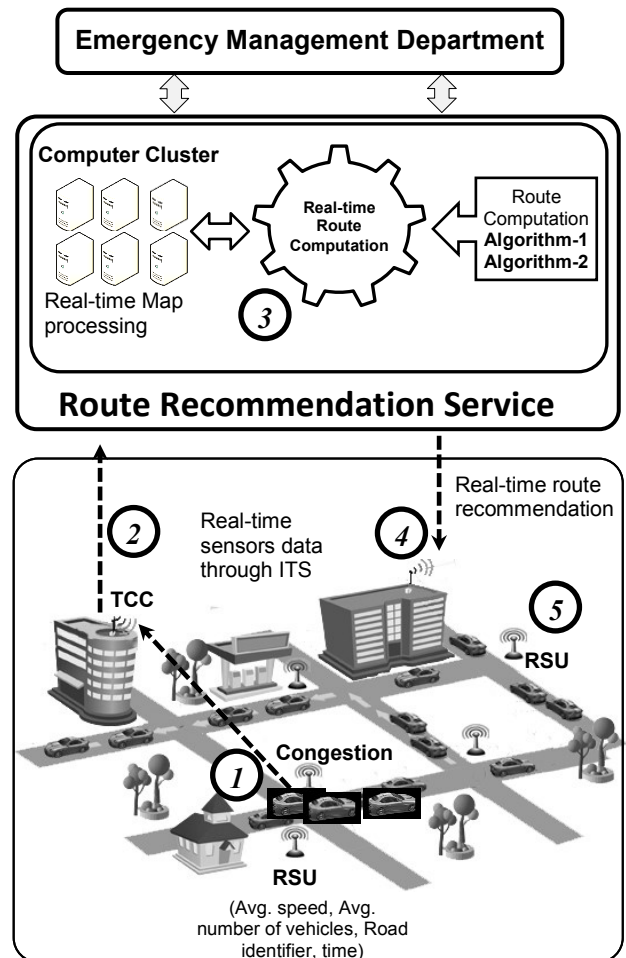


Fig. 1. A high-level architecture of the *MacroServ* route recommendation service

3 ITS AND DISASTER MANAGEMENT

An ITS is a combination of advanced sensing technologies used in transportation engineering to monitor traffic and road infrastructure, and to assist users for a better traffic management and safe travelling [16]. A basic ITS could include several essential components, such as: (a) a sensing system, (b) a communication system, (c) roadside units including traffic signal control system and movable signs, and (d) a notification system that includes car navigation and disaster warning system. In addition, advanced modeling techniques are also intensively used with a combination of an ITS for traffic predictions and guidance based on historical baseline data.

A sensing system plays a critical role and provides basis for any decisions made from the ITS. Achieving an accurate and reliable monitoring system for traffic and infrastructure behavior has attracted worldwide attention. Vehicle-based sensing systems are usually used for transportation infrastructure assessments while infrastructure-based systems can be applied for both traffic and infrastructure monitoring [19].

Infrastructure sensors can be installed either on the side or top of road, or can be embedded inside the roads also known as in-road reflectors [17], [18]. In the past decades, numerous infrastructure sensors were placed

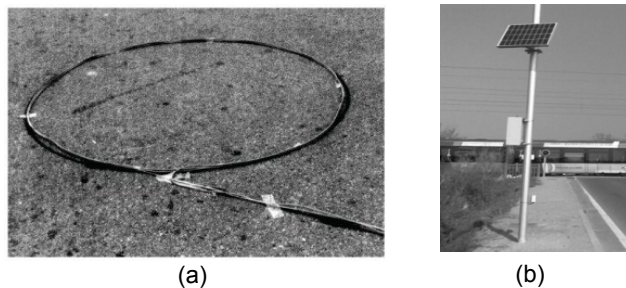


Fig. 2. Traffic and disaster sensors

around cities and towns in United States, resulting in a network of ITS for better traffic management.

The collection of road traffic information can be achieved through in-road detectors. Inductive loop sensor, as shown in Fig. 2(a) is one example of the commonly applied infrastructure traffic sensor. Fig. 2(b) shows a typical road-side communication unit.

4 DESIGN AND MODELING

In this section, we present the design and model of the proposed route recommendation service. Due to a disaster's evolution in space and time, the network characteristics, such as vehicles' speed and road capacity vary with time. Some roads may suffer blockade over time due to congestion, whereas a few roads may become inaccessible after being hit by the disaster (e.g., flood). Capturing the important time evolving variations in the road infrastructure, makes the model more realistic.

We model the traffic at macro-scale level, where the vehicles act as intelligent agents carrying evacuees from sources to destinations. The *MacroServ* service computes real-time preferred routes for the evacuees. Consequently, the autonomous agents make dynamic route choices based on the congestion level on roads, distance from the destination, road safety condition, and capacity in safety shelters. The dynamic re-routing of vehicles more closely depicts a realistic scenario, as with the advancement in ITS and sensors, most of the vehicles nowadays are equipped with radio and GPS based navigation systems [11]. Therefore, the vehicles can interpret road conditions in advance by the help of navigation systems, as well as through the updates on radio. In the following text, we discuss the various phases of our model.

4.1 Network Design

To create the transportation network, we imported the map of City of Fargo from the OpenStreetMap API [20] that has a database of world maps, and the regional maps can be exported in XML format. For each road segment (between two intersections), the information from the ITS about traffic volumes, speed limits, number of lanes, segment length, and contour elevations, has been stored in the database as indicated in Fig. 3. The aforementioned information has been obtained from NDOT [15]. Moreover, the intersections are also stored in database as nodes with unique identifiers (Fig. 3).

Based on the past records of flooding in the City of Fargo, the areas that are at higher risk of getting affected by the Red River flood are marked on the map as

Intersections	
Node ID	GPS point
N_1	P_1
N_2	P_2
...	...

Roads						
Route ID	Start point	End point	Length	Speed limit	No. of lanes	Traffic volume
R1	P_1	P_{10}	1500	30	1	14,212
R2	P_7	P_{15}	800	35	2	21,200
...

Fig. 3. Database of transportation network

evacuation zones. Safety shelters are defined on the map locations that are not at risk of flooding.

4.2 Evacuee's Departure Rate

In this phase, we present a way of estimating the average number of vehicles departing from each home within a disaster affected area. Specifically, we need to find the time distribution of the evacuating vehicles. To make such estimations, it is important to know the population size of the particular area under consideration. However, the population size is a random factor that varies between day and night. People are more likely to be at work places during the day and at home during night time or weekends. In our model, we intend to introduce the maximum traffic load on the transportation network from the disaster affected area. Therefore, we assume that the people are at home when the disaster warning is announced. Moreover, we also assume that in a given time interval, vehicles originating from the homes make a discrete count, such as 0, 1, 2, ..., or n number of vehicles. Therefore, to represent the vehicle departure rate, we utilized Poisson distribution [12] given as:

$$P[X = q] = \frac{\lambda^q \cdot e^{-\lambda}}{q!}. \quad (1)$$

The above equation indicates the probability that there would be q number of vehicle departures, where λ is the mean number of departures per time interval. The Poisson distribution is commonly used in queuing theory, and describes the probability that q events will occur within a time period, given that the time between two events is a random number that is independent of the time of the previous events [12]. For our given scenario, at a given time interval, some houses have no or a few vehicles coming out, most have some vehicles emerging, and a few houses have most vehicles departing. Moreover, the vehicle departures are also independent of each other. Under such circumstances, we considered the Poisson distribution to be more appropriate to depict the vehicular departures during an evacuation scenario. The primary reason for such selection is that just a single parameter, mean value λ , needs to be configured in simulations to evaluate the effect of varying number of departing vehicles during an evacuation depending on the number of residents at home.

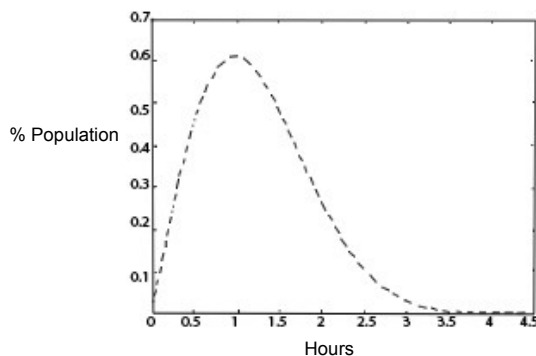


Fig. 4. Evacuees departure times in response to emergency

4.3 Departure Times

The purpose of this phase is to model the rate of vehicles entering the transportation network following the evacuation instructions. For model accuracy, it is imperative to consider the evacuees' behavior in response to the evacuation orders. The evacuees' decision about when to leave depends on factors, such as, severity of the disaster, social status, and the availability of information and transport. Some people may prefer to stay behind to look after their property. In general, it is more likely that a few people leave initially, then the evacuations reach the peak value, and gradually slow down as most of the population have already evacuated. Such an evacuation behavior can be depicted with a response curve as stated in Fig. 4 that indicates the percentage of people departing in each time interval. The evacuation response curve can be expressed with probability density function of Weibull distribution [12], given as:

$$f(x; \alpha, \beta) = \begin{cases} \frac{\beta}{\alpha} \left(\frac{x}{\alpha}\right)^{\beta-1} \times e^{-\left(\frac{x}{\alpha}\right)^\beta}, & x \geq 0, \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

In above equation, the parameter $\alpha > 0$ is the scale parameter, and $\beta > 0$ is the shape parameter of the distribution. If the parameter x represents the time taken in departure, then the Weibull gives a distribution that has departure rate proportional to a power of time. The values of α and β can be configured to analyze the impact of evacuees' compliance behavior during the emergency evacuations. Compared to the Poisson and Uniform distributions, the Weibull distribution more closely depicts the evacuee's behavior due to the asymmetric nature of the curve, as indicated in Fig. 4.

4.4 Safety Shelter Selection

This step computes the set of safety shelters for evacuating vehicles. The simplest approach is to assign safety shelters that are at the shortest distances from the vehicles. However, this may result in overcrowding of shelters when most of the vehicles prefer to reach the nearest shelters. An alternate approach is to manually designate shelters for the evacuees in various areas. However, the aforementioned approach is not efficient, as the roads leading to manually designated shelters may become inaccessible due to congestion or other factors.

In our model, we adopt a probabilistic approach of assigning shelters to evacuees. We consider the real-time varying factors, such as road traffic, congestion, distance, risk level, and capacity of the shelter. In this way, evacuees are recommended a set of shelters that are most preferable in the current time interval.

4.5 Route Selection

In this step, the route recommendation service computes the preferred routes for the vehicles during evacuation. The service allows individuals to take decisions about route selection at road intersections. For an intersection, the service maintains a route table that contains least travel costs from the intersection to each of the destinations. Cost is based on flow capacity, maximum speed limit, density of traffic, length, and travel time of the road link. The total cost of a route between an intersection and the destination shelter is the sum of the costs of individual road segments. As a disaster has tendency to expand outwards from the epicenter, such as in the case of wild fire, tornado, and floods, the roads which are not affected by disaster yet may get hit by the disaster at a later time. Therefore, costs are computed by also taking into consideration the disaster affected roads. The information about road damage is provided at real-time by the high-end ITS sensors. As indicated in Table 1, if a vehicle is heading for Shelter 2, then at the intersection, the least cost towards Shelter 2 is 13 that is for the Route 3. Moreover, the costs indicated in Table 1 are dynamic and are adjusted at real-time according to the road congestions. Therefore, when more vehicles enter a road segment, the overall speed of the vehicles decrease and the cost is recalculated. In the following subsections, we present the cost calculation and route recommendation algorithm.

4.5.1 Route Cost Calculation

The route cost is the time it will take a vehicle to traverse a route to reach the destination shelter. When traffic capacity of a route is greater, then the vehicles will take lesser time in traversing the route, and smaller will be the route cost. Let L_k be the length of a road segment k , which has N_k number of lanes, and ℓ be the average length of vehicles passing through the road segment. The maximum possible traffic flow capacity of the road segment k is:

$$f_k = \frac{L_k \times N_k}{\ell} \quad (3)$$

Equation (3) computes the maximum number of vehicles that can traverse the road segment without congestion at a given time interval. In normal situations, inter-vehicular distance depends on speed of vehicles. More the speed,

TABLE 1
ROUTE COST TABLE MAINTAINED BY EACH INTERSECTION

Route ID	Shelter 1	Shelter 2	Shelter 3	Shelter 4	...
1	11	65	32	35	...
2	43	34	54	31	...
3	23	13	31	33	...
4	24	21	45	36	...
...

higher would be the inter-vehicular distance. However, we assume that during the time of disaster, it is almost impossible for the vehicles to maintain appropriate inter-vehicular distance, because, evacuees are trying to save their lives, so traffic laws are difficult to apply. Suppose, the number of vehicles currently travelling through the road segment k is denoted by τ_k . Thereafter, the extent of congestion experienced by the road segment k is:

$$c_k = \frac{\tau_k}{f_k}. \quad (4)$$

If we let s_k^{max} denote the maximum allowed speed limit of the road segment k , then the free flow (F_k) of vehicles currently traversing the road segment is given as:

$$F_k = f_k \times s_k^{max}. \quad (5)$$

With τ_k number of vehicles travelling through the link, the maximum possible speed can be computed as:

$$S_k = \frac{F_k}{\tau_k}. \quad (6)$$

Finally, we compute the travel cost of road segment k as:

$$C_k = \frac{L_k}{S_k}. \quad (7)$$

The cost in the above equation is dynamic and varies with time as the numbers of vehicles on the road segment vary.

An Illustrative Example: We present an example of the cost computation with the support of Table 2 and Fig. 5. Suppose, at the time interval T_1 , the road segment CD has maximum capacity of four vehicles ($f_{CD} = 4$) and the maximum speed limit $s_{CD}^{max} = 50$ km/h. The free flow of vehicles according to (5) is given as $F_{CD} = 200$. As indicated in Fig. 5(a), the current number of vehicles on link is $\tau_{CD} = 4$, so by using (6), we get the maximum possible speed as $S_{CD} = 200/4 = 50$. If the length of the link is $L_{CD} = 300m$, then the travel time cost is given as $C_{CD} = 300/50 = 6$ (Table 2, Column 1). As one more vehicles enter the link CD, the total number of vehicles becomes $\tau_{CD} = 5$ (Fig. 5(b)), and the travel cost is increased to 7.5. In Fig. 5(c), when the number of vehicles on link CD reaches 7, then the link cost becomes 10.5 (Table 2, Column 3), which is an indication of road

TABLE 2
ROAD CONGESTION EXAMPLE

T_1	T_2	T_3
$F_k = 4 \times 50 = 200$	$F_k = 4 \times 50 = 200$	$F_k = 4 \times 50 = 200$
$S_k = 200/4 = 50$	$S_k = 200/5 = 40$	$S_k = 200/7 = 28.5$
$C_k = 300/50 = 6$	$C_k = 300/40 = 7.5$	$C_k = 300/28.5 = 10.5$

TABLE 3
NOTATIONS AND THEIR DESCRIPTION

G	Graph representing the transportation network
$H^{(r)}$	Sub-graph, representing a region r
X_{xz}	Set of routes between an intersection x and destination z
g	A group of people
l^m	Location of person m
Z	Set of shelters

congestion, and consequently the vehicles are travelling with reduced speeds. Therefore, the incoming vehicles are redirected to other routes with the smaller cost (indicated by arrows in Fig. 5(c)). In the following subsection, we present our algorithm that computes the preferred routes for the evacuating vehicles.

4.5.2 Route Computation Algorithm

Fig. 6 depicts a portion of the map of City of Fargo that we considered as a case study in this paper. The three main items on the map are disaster risk areas, intersections, and safety shelters. During the evacuation, the residents in affected areas flee towards safety shelters, and are guided about the routes on intersections. We denote the road network with a graph notation: $G = (V, E)$, where V is the set of vertices representing intersections, and E is the set of links that represent roads. Table 3 indicates the set of notations used in this subsection. The real-time processing of graph of up to the scale of a city is very resource intensive task and is not feasible to be performed by a single computational node. Therefore, the graph G is logically split into several sub-graphs, and each sub-graph is processed on a separate node using MPI on the HPC cluster. We denote a sub-graph by $H^{(r)}$, $r = 1, 2, 3, \dots, n$, such that $H^{(1)} \cup H^{(2)} \cup H^{(3)} \cup \dots \cup H^{(n)} = G$. Between any two regions $H^{(a)}$ and $H^{(b)}$, we define a set of overlapping points as *boundary points* B_{ab} . The boundary points are the intersection nodes

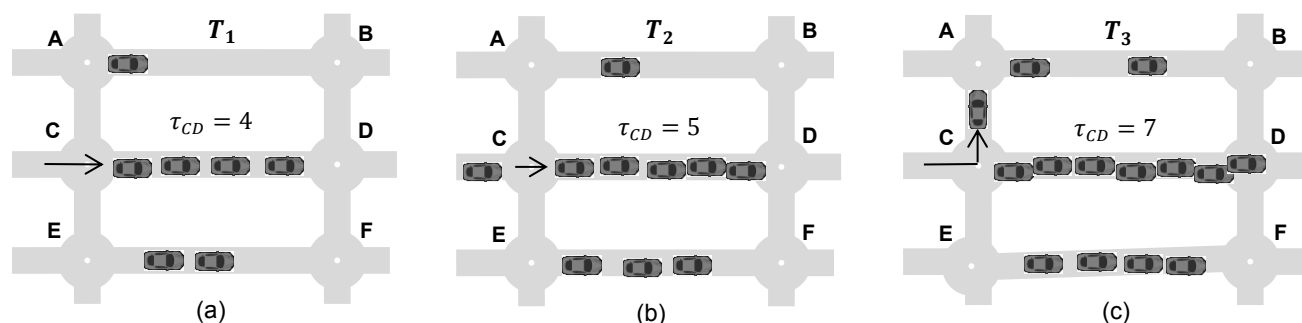


Fig. 5. Route cost update: (a) no congestion, (b) slight congestion, and (c) alternate route selection due to high congestion. The arrow sign shows the directions to the next intersection during evacuation at intersection C.

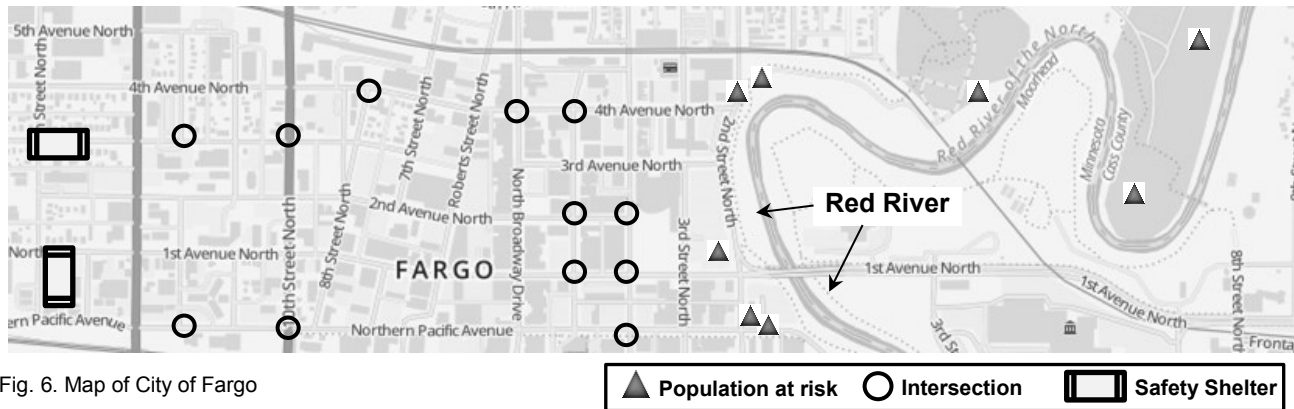


Fig. 6. Map of City of Fargo

Algorithm 1. Route Recommendation

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1: while time interval  $t \leq T_{end}$  do
2:   PARFOR region  $H^{(r)} \in G$  do
3:     PARFOR intersection  $x \in H^{(r)}$  do
4:       for each shelter  $z \in Z$  do
5:         if  $z \in H^{(r)}$  then
6:           Route cost  $\xi^{(xz)} = \min\{\sum_{e \in j} C_e\}, \forall j \in X_{xz}$ 
7:         else
8:           Route cost  $\xi^{(xpi)} = \min\{\sum_{e \in j} C_e\}, \forall j \in X_{xpi}$ 
9:         end if
10:       end for
11:     end PARFOR
12:   for each  $g$  in area  $A \in H^{(r)}$  do
13:      $D = GetDestination(g)$ 
14:     for each  $m \in g$  do
15:        $move(m, D)$ 
16:     end for
17:   end for
18: end PARFOR
19: end while

```

Algorithm 2. Get Destination Shelter

Input: A group g of people
Output: A shelter \mathcal{S} that is preferred by every member of group

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1:  $Q \leftarrow$  Retrieve group members from  $g$ 
2:  $V' \leftarrow getShelters()$  // shelters that have space
3: for each member  $m \in Q$  do
4:   for each shelter  $v \in V'$  do
5:      $P[m][v] = \min c^{(j)}(l^m, v), \forall j \in X_{l^m, v}$ 
6:   end for
7: end for
8:  $Rank[v] \leftarrow avg(P)$ 
9:  $\mathcal{S} = v_{min(Rank)}$ 
10: return  $\mathcal{S}$ 

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that are common to both the regions, such that $B_{ab} = H^{(a)} \cap H^{(b)}$. Suppose, evacuees in region $H^{(a)}$ are recommended a shelter that is located in the region $H^{(r)}$, where $r \neq a$. As a first step, the evacuees are routed towards a boundary point $p_i \in \{B_{ak} = H^{(a)} \cap H^{(k)}\}$ that has the minimum congestion and risk at the current time interval (determined through ITS). Here, $H^{(k)}$ is the region adjacent to $H^{(a)}$, and located on the shortest and safest path towards the target shelter. On reaching the boundary point p_i using least cost paths, as the next step, vehicles are routed within the same region $H^{(k)}$ based on route cost computations. If $k=r$, then the vehicles have reached the desired region, where the target shelter is located. Otherwise, the aforementioned procedure will be repeated to further route the vehicles towards new boundary point.

As indicated in Algorithm 1, the PARFOR loop executes in parallel for each of the regions (Line 2). Within a region, route cost tables are updated in parallel

using (7) for every intersection and shelter (Line 3–Line 11). There can be more than one route possible between an intersection and a safety shelter, and each route consists of numerous road segments. If the destination shelter lies within the same region, then the Line 6 filters out a route that has the minimum travel cost between an intersection x and shelter z . Otherwise, the minimum travel cost is calculated between the shelter x and the boundary point p_i as indicated in Line 8. For various groups of evacuees in the disaster affected area (A), the preferred destination shelters are selected using *GetDestination* function in Line 13 that is defined in Algorithm 2. Algorithm 2 selects only those shelters from the set of shelters that still have space to accommodate more people (Line 2). We assume that shelter space information is available by the help of sensors installed at each shelter. The Line 3 to Line 7 of Algorithm 2 computes the minimum travel cost of each evacuee in the group g from each shelter. The shelter whose average travel cost is minimum from all the group members is considered as the one satisfying the group members and is selected as the destination shelter (Algorithm 2, Line 8 to Line 10). An example scenario of the aforementioned destination selection is when members of a family are at different locations in a city during the time of disaster, and they want to gather at a place that is at shortest travel costs for each member. On selection of the destination

shelter, the Line 14 to Line 16 of the Algorithm 1 moves each group member towards destination shelter. More precisely, in the real emergency scenario, the *move* function is meant to recommend the evacuees with least cost route towards the destination. The *move* function also handles the boundary condition, such that when a vehicle reaches the boundary of a region $H^{(r)}$, the current region hands over the vehicular details to the new region. Such a case may arise when the destination shelter is not located in the same region from where the vehicle has initiated evacuation.

4.5.2.1 Time Complexity

The time complexity of the *MacroServ* is based on the time complexity of the Algorithm 1. From the Line 4 to Line 9, the Algorithm 1 calculates the cost of all the routes from a single intersection to all of the shelters and boundary points. For z shelters and j routes from an intersection to a shelter, the time complexity is $O(z \times j)$ and for p boundary points, the time complexity is $O(p \times j)$. The time complexity of the Algorithm 1 from the Line 4 to Line 9 is $O(z \times j + p \times j)$. The number of boundary points p is much larger than the number of shelters. Therefore, the time complexity is equivalent to $O(p \times j)$. For i intersections, the time complexity is $O(i \times p \times j)$. For h regions the time complexity is $O(h \times i \times p \times j)$. In Line 13, the destination is selected for each group by calling the Algorithm 2.

In Line 1 of the Algorithm 2, all the members of the group are retrieved with time complexity $O(1)$. All the shelters having space are selected in the Line 2 that takes $O(z)$. The time complexity of the Algorithm 2 from Line 3 to Line 7 is $O(m \times z)$, where m is the number of the users in the group. The time complexity of the Line 8 is $O(m)$. Therefore, the total time complexity of the Algorithm 2 is $O(z + m \times z + m + 1)$ that is equivalent to $O(m \times z)$.

The Line 13 in the Algorithm 1 uses Algorithm 2 so its time complexity is $O(m \times z)$. For g number of groups, the time complexity increases to $O(g \times m \times z)$. The time complexity of the Line 14 to Line 16 is $O(m)$ that increases to $O(g \times m)$ for g number of groups. For Line 2 to Line 18, the time complexity becomes $O(h \times (i \times p \times j + g \times m \times z))$. The algorithm iterates T_{end} times. Therefore, the total time complexity of the Algorithm 1 is $O(T_{\text{end}} \times h \times (i \times p \times j + g \times m \times z))$. By executing the algorithm in parallel, the time complexity is reduced to $O(T_{\text{end}} \times (p \times j + g \times m \times z))$.

5 PERFORMANCE EVALUATION

We implemented the route cost computation algorithm in C++ using OpenMPI library [21]. The experiments are performed on HPC cluster established in North Dakota State University (NDSU), Fargo, ND, USA [22]. The cluster nodes have the following specifications: quad-core Intel X5550 @ 2.67GHz with 48GB ECC DDR3 1333MHz (8GB DIMMs), 160GB 7.2K RPM SATA HDD, 1x Myri-10G port, and dual Gigabit Ethernet ports. Fig. 6 indicates

the scenario considered in the simulations. The population settled at the Red River's bank needs to be evacuated towards the safety shelter locations. The road intersections are equipped with ITS sensors to send alerts to the vehicles during the evacuations. The map is divided into 3 regions (zones). The total number of evacuees is about 108,000. If the given map is converted to a graph representation, then the graph has 2,800 vertices with 7,370 edges.

5.1 Performance Metrics

The performance metrics considered in the simulations include: (a) evacuation times, (b) average travel time, (c) road congestion, and (d) population evacuated. The evacuation time indicates the time spent between the start of evacuation and when the last person evacuates the affected area. The average travel time computes the average of travel times of all the evacuees. The road congestion is computed by (4) and indicates the amount of congestion experienced by a road segment at a given time interval. The population evacuated indicates the number of people who have fled from disaster area in a certain time interval. The performance of the system is observed by varying the parameters of the Poisson and Weibull distributions.

5.2 Comparison Techniques

To compare the performance of the *MacroServ* service, we considered two other evacuation approaches: (a) *Dedicated* and (b) *Shortest-Path*. In the first approach, the evacuating population follows only those routes that are predefined by the Fargo department of transportation [15]. The criterion of selection of dedicated routes is set by department of transportation, and the primary factor is the road capacity. Therefore, we considered the dedicated routes as a set of the interstates and main roads [14]. We developed the shortest-path model (based on Dijkstra algorithm) that allows the evacuees to take the shortest routes from disaster site towards safety locations. The information about the changes in the road conditions is made available to both the aforementioned approaches to provide a fair comparison with the *MacroServ*.

5.3 Evaluation Results

In this subsection, we present the evacuation performance of our proposed scheme in comparison to the abovementioned approaches. For each data point, the simulation is repeated 20 times to obtain the statistical significance of the results. In our experiments, we also introduced the damage to the roads by the disaster to analyze the impact on total evacuation and average travel time. For that purpose, we utilized Bernoulli distribution [12] to randomly mark roads as damaged beginning with destroying initially those roads that are geographically near to the disaster site, and as the simulation time proceeds, the road destruction is expanded outwards to mimic damage caused by the floods.

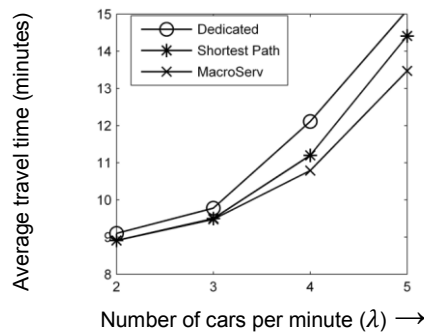


Fig. 7. Average travel times with varying number of departing vehicles from each intersection ($\alpha=6$ and $\beta=2$)

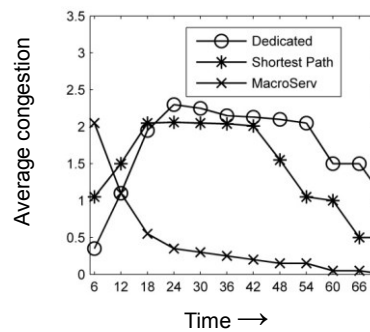


Fig. 8. Average congestion with respect to time with damaged road network $\alpha=6$, $\beta=2$, and $\lambda=5$

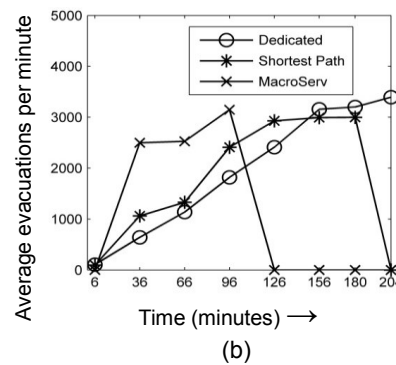
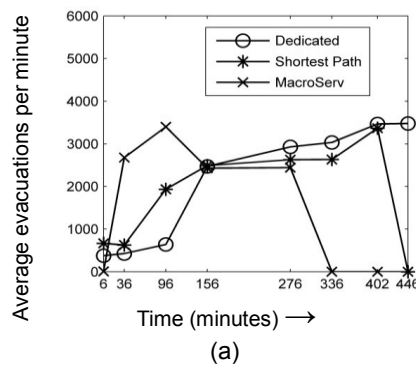


Fig. 9. Average evacuations per minute with varying shape parameter in Weibull distribution: (a) $\alpha=6$, $\beta=1$, and $\lambda=5$, and (b) $\alpha=6$, $\beta=2$, and $\lambda=5$

5.3.1 Impact of departure rate

Figure 7 depicts average travel time of the vehicles by varying the departure rate of vehicles from the intersections. When the departure rate is lower, less than 3 vehicles per minute, the average travel time taken is almost same for all the three approaches. However, as the departure rate increases, the average travel time of *Dedicated* and *Shortest-Path* turns out to be higher than the *MacroServ*. This is an expected outcome, as the aforementioned approaches do not take into account the current traffic flow rate on roads. As people tend to adopt the shortest route for evacuations, the roads become congested and road's traffic flow rate is dropped. Same is the reason for *Dedicated* approach as arrival of too many vehicles on limited set of roads results in congestion.

5.3.2 Impact of congestion

Figure 8 compares the three approaches for congestion on the roads near the shelters with respect to time. Initially, due to heavy congestion in case of *Dedicated* and *Shortest-Path*, very few cars are able to reach the roads leading towards shelters. Therefore, the congestion on the roads is shown lesser for *Dedicated* and *Shortest-Path* in the Fig. 8. Alternatively, the vehicles quickly reached the roads near shelters for the *MacroServ* scheme, which resulted in higher congestion in the first few minutes. However, the congestion decreases subsequently as most of the vehicles have reached the shelters. Moreover, congestion level decreases relatively at lower rate in the case of *Dedicated* and *Shortest-Path*. This is due to the fact that both the approaches do not consider traffic flow capacity while

computing routes, and as a result evacuees are guided towards short but congested roads.

5.3.3 Impact of shape (β) of Weibull distribution

In this simulation setup, we inspect the impact of evacuations with respect to time. The $\beta=1$ in Fig. 9(a) indicates that most of the people have departed immediately after disaster warning from the affected site. The sudden significant increase in departing population resulted in an overall increase in the evacuation times. The $\beta=2$ (Fig. 9(b)) is the approximate mean around the scaling parameter, which creates the similar curve indicated in Fig. 4. As reflected from Fig. 9(b), the total evacuation time with $\beta=2$ is lesser than the evacuation time with $\beta=1$ in Fig. 9(a). The most probable reason is that with $\beta=2$, few people are expected to be evacuated initially, then evacuations go to a peak value and gradually decrease, which results in the less congestion of roads. The slow departure puts less load on the road network and results in lesser evacuation time. Fig. 9 indicates that an organized evacuation with gradual departure performs much better than a random immediate evacuation approach. However, whether the evacuation is organized or otherwise, the *MacroServ* scheme yields shorter evacuation time and evacuates more population per minute as compared to the other approaches. Especially, within one hour of issuing evacuation comments, the *MacroServ* service doubles the amount of evacuees when compared with the other two approaches. This accounts for the fact that the evacuees are directed towards the roads with maximum flow rate.

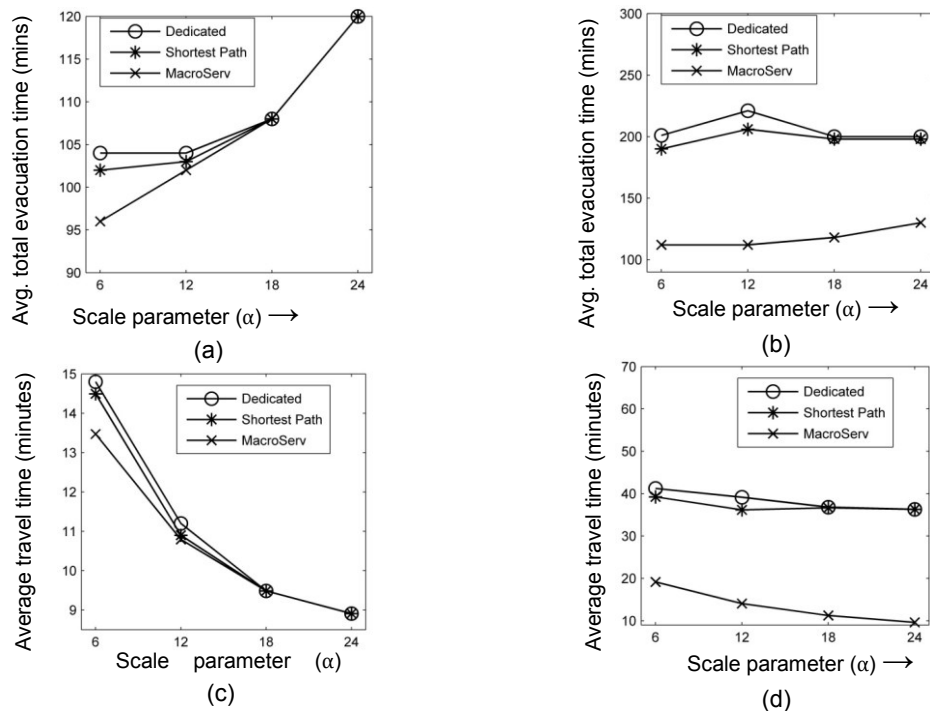


Fig. 10. Effect of road damage by varying departure time (scale parameter α) with $\beta=2$: (a) average total evacuations under normal conditions, (b) average total evacuations under damaged conditions, (c) average travel time under normal condition, and (d) average travel time under damaged conditions.

5.3.4 Impact of average departure time

Figure 10 presents the results for varying the departure time that is determined by the parameter α . As it can be seen in Fig. 10(a), under normal road conditions, when the average departure time of the evacuees increases, the average total evacuation times become similar for *MacroServ*, *Dedicated*, and *Shortest-path*. The similarity in evacuation times of the three approaches is due of the low density of traffic on roads. As inter-arrival times of vehicles entering road network have increased, this leads to the lesser congestion on roads. Moreover, increased departure time also results into the increased evacuation times. Fig. 10(b) depicts the evacuation times under damaged road conditions. The *MacroServ* takes half of the time for evacuations as compared to the time taken by the other approaches. Alternatively, *Shortest-Path* does not consider the road condition and congestion while computing the routes. This may lead to traffic jams when vehicles move towards the damaged roads, resulting in increased congestion and total evacuation times. Fig. 10(c) shows the average travel time versus departure time, α . The average travel time decreases as the departure time increases under normal road conditions. Similar to Fig. 9, it can be seen from Fig. 10(c) that as people are taking more time in departure, there would be less congestion on the roads, and average travel times for the three approaches becomes similar. Under damaged road network (Fig. 10(d)), *MacroServ* outperforms the other two schemes because of the most preferred route recommendation strategy.

5.3.5 Impact of road damage probability

The simulations are performed to analyze the effect of

road infrastructure damage on the three evacuation schemes. Fig. 11(a) indicates that with the increase in road damage probability, the average travel time also increases. However, the *MacroServ* scheme has lesser increase in travel time as compared to the other two approaches. The reason for the aforementioned behavior is that the evacuees are not directed towards damaged routes in the case of *MacroServ*, and consequently, the vehicle speeds are not reduced. Fig. 11(b) depicts the effect of damage recovery time of roads on the average travel time. When damage to the road network occurs, the vehicles are diverted towards paths that are slightly longer than the damaged ones. When the recovery time is smaller, such as 12 minutes, more vehicles arrive back on the shortest paths and cause congestion that causes more delay. With increase in the recovery time (18 to 30 minutes), more cars were diverted to longer paths, and few remaining cars came back on the shortest path, and traveled with less congestion. Overall average travel time decreases slightly in case of *Shortest-Path*. The *MacroServ* approach is already using the road network efficiently and is not allowing congestion on the road, so effect of road damage is not observed in *MacroServ*. Fig. 11(c) shows the effect of the percentage of road damages on average travel time. The *Dedicated* fails to complete the simulation with even small number of road damages. Therefore, we have not listed the *Dedicated* approach in the figure. However, *MacroServ* and *ShortestPath* approaches have shown resilient to the road damages upto 55% overall road damages on a grid like road network of Fargo city on an average. For road damages more than 55%, the vehicles cutt off from the road networks and simulations fails to stop.

5.3.6 Impact of population growth

In this simulation run, we evaluate the effect of damaged road network if the population is increased by 2% in each

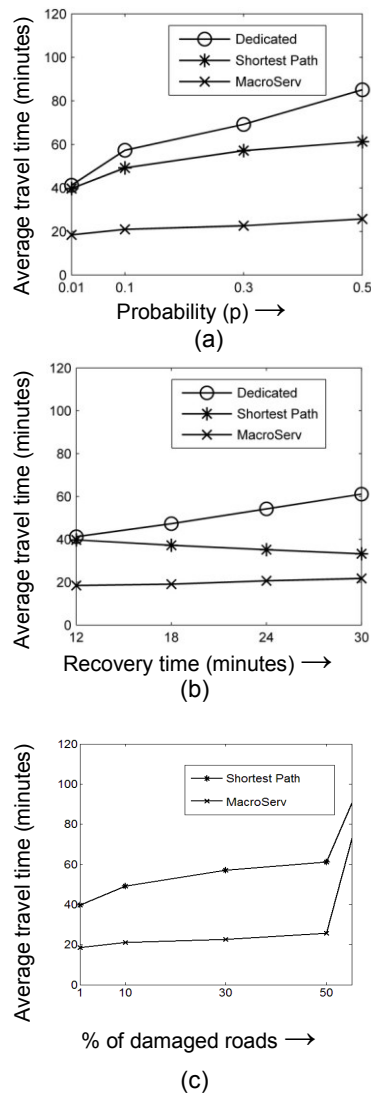


Fig. 11. Impact of (a) road damage probability, (b) recovery time, (c) percentage of damaged roads, on average travel time with $\alpha=6$, $\beta=2$, $\lambda=5$, and $p=0.01$

coming year [23]. Fig. 12 indicates that there would be very slight effect of increase in population on the average travel time for all the approaches. However, in contrast to the *Dedicated* and *Shortest-Path* the proposed *MacroServ* evacuation strategy is exhibiting the least average travel times in the future years. Therefore, we may conclude that *MacroServ* is capable of efficiently handling the evacuations with increased population size.

5.3.7 Scalability analysis

The simulations are performed to analyze the scalability of the *MacroServ* framework. An algorithm is known to be scalable if the algorithm can maintain the execution time in desirable limits even in case of large increase in workload by using additional processors.

We split the map into smaller regions using two

Quadtree [32]. Quadtree is a data structure technique most often used to partition a two-dimensional space by recursively subdividing it into four quadrants or regions. The procedure of creating the Quadtree-based partitioning begins with decomposing the region into four equal quadrants, subquadrants, and so on with each leaf node containing data corresponding to a specific sub-region based on a criteria. Each node in the tree either has exactly four children, or has no children (a leaf node) [32].

We varied the number of partitions in our simulations and observed the effects of such variation on parameters, such as recommendation generation time and inter-message exchange among the computational nodes. Both the aforementioned parameters are most significant as they determine the efficiency of the proposed framework. We considered the maximum of 16 partitions, as increasing the number of partitions results in some partitions becoming empty (carrying no nodes). In Fig. 13 and Fig. 14, we evaluated the aforementioned metrics for our proposed scheme *MacroServ* by varying the number of vertices in the map. We utilized Quadtree for map partitioning.

Fig. 13 presents the effect of increasing the number of partitions (one partition per processor) as well as the size of map on the recommendation generation time. Results indicate that doubling the size of the region increases the recommendation generation time by an average of 26%. The increase in single processor results in decrease in the recommendation generation time by an average of 9%. Moreover, it can be observed from the results that by increasing the number of processors, the *MacroServ* framework can efficiently provide recommendations for the large-scale datasets with little effect on the recommendation generation time.

Fig. 14 shows the effect of increasing the number of partitions and map size on the average number of vehicles that travel from one zone to another (i.e., number of messages passed between processors). The results indicate that the increase in a single processor increases the average number of vehicles travelling from one zone to another by 39%. However, doubling the size of the map decreases the average number of vehicle crossing from one zone to another by 76%.

Figure 15 represents the communication versus computation cost of the *MacroServ*. The communication versus computation cost is the measure of calculating the performance of parallelized solutions [34], [35]. The computational time of the *MacroServ* decreases with the increase of number of partitions. However, the communication time increases with the increase in number of partitions. The ratio of communication and computation remains at 0.8 on an average with four partitions. However, the ratio increases sharply with the increase of partitions due to increase in number of messages being passed and delayed the overall execution time. Our thorough experimental results show that for the Fargo road network size, the ideal case is to have four partitions of up to 700 vertices to ensure fast and efficient execution of the *MacroServ* framework. Based on the results presented in Fig. 13, Fig. 14, and Fig. 15, we

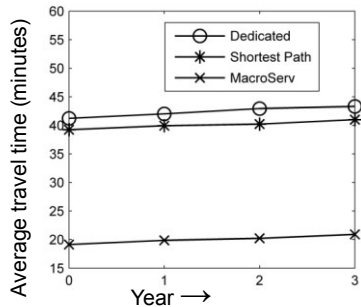


Fig. 12. Effect of population increase in future 3 years on average car travel time on damaged network ($\alpha=6$ $\beta=2$, and $\lambda=5$)

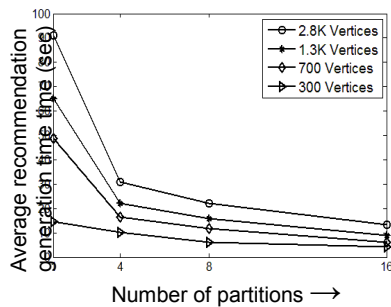


Fig. 13. Effect of increase in number of partitions

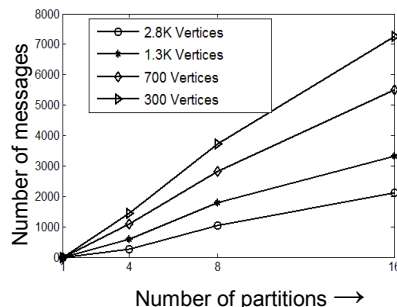


Fig. 14. Effect of increase in number of partitions

concluded that the *MacroServ* is a scalable service, as it can efficiently handle the large sized map by increasing the number of processors.

6 RELATED WORK

Numerous studies conducted in the past addressed various perspectives of emergency evacuation modeling, such as route finding [6], shelter site selection [5], evacuees' behavior [10], and traffic control strategies [24]. In recent years, there has been a growing interest in the multi-objective optimization techniques for the evacuation route finding problem.

The authors in [25] studied demand-based strategies for aggregate-level routing with and without congestion. The authors proposed a network flow model that optimized an evacuation specific lexicographic objective function. The function computes the time dependent evacuation routes for each of the source. However, being a combinatorial optimization problem, the proposed approach is difficult to be solved for large realistic networks. Therefore, the authors utilized two heuristics to solve the problem, but with a tradeoff of solution quality. Lim *et al.* [6] modeled evacuation problem as network flow optimization problem. The static network is expanded over the planning horizon for each time interval. However, this makes the optimization problem extremely large to solve. Therefore, the authors proposed a heuristic based solution that utilized Dijkstra's algorithm to compute evacuation paths, and a greedy algorithm to find the maximum flow and exit schedule for each path at each time interval. In a similar study, the authors in [9] utilized mixed integer programming for a dynamic network flow optimization problem. The authors proposed a heuristic solution that was applied over the time expanded transportation network, where the time horizon was divided into intervals of equal length. However, time expansion of the network made optimization problem infeasible for large scale evacuation scenarios. Coutinho-Rodrigues *et al.* [5] proposed a multi-objective optimization problem to find evacuation paths and the location of shelters for urban evacuation planning. The authors considered many objectives for optimization, such as path lengths, path risks, evacuation times, lengths of backup paths, and number of shelters.

The set of primary routes between disaster site and

shelter locations were generated with a bi-objective shortest path approach by considering the path lengths and path risks. The model was tested on a smaller network with limited roads and intersections.

Stepanov *et al.* [7] proposed an integer programming formulation for route assignment that utilized M/G/c/c state dependent queues to address congestion and time delays on road links. The authors computed a set of evacuation routes with *k*th shortest path algorithm, and then utilized M/G/c/c model to evaluate the travel time along the shortest paths. A drawback in such approach is that the shortest paths may become congested during real evacuation scenarios due to the presence of numerous unforeseen random factors, such as traffic accidents and weather conditions. The authors in [10] developed a traffic simulation framework that assigns evacuees with the predefined routes at the beginning of evacuations. During the journey the evacuees were able to change the routes. The authors studied the effect of non-compliance of evacuation orders by evacuees during evacuations. However, the architectures and implementation details of the proposed framework were not discussed. El-Sergany *et al.* [31] proposed a framework for flood disaster management and a transport distribution model for evacuations. The authors utilized linear programming on a small scale scenario with trip distribution matrix among the affected sites and destination shelters.

Huang *et al.* [26] presented a centralized traffic control framework for emergency vehicles. The authors utilized A* algorithm to compute three types of paths: (a) primary path between source and destination, (b) secondary path that is disjoint of the primary path, and (c) a path that

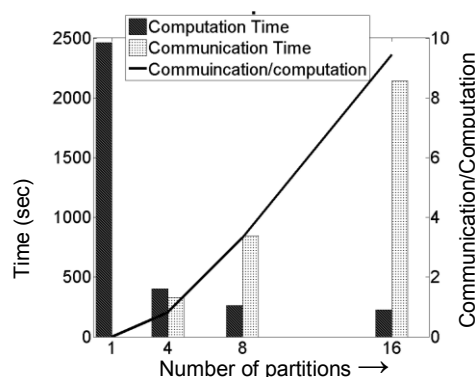


Fig. 15. Communication/Computation Cost

connects both the primary and the secondary paths. However, authors did not mention any details about the implementation and test data of their framework.

Abdelgawad *et al.* [33] presented a multi-objective optimization framework that combines the vehicular traffic and mass transit system for emergency evacuation. The paper investigated the three objectives: (a) minimum in-vehicle travel time, (b) minimum at-origin waiting time, and (c) minimum fleet cost in case of mass transit. However, the authors have not included the real-time changing parameter such as road conditions that affect the real-world evacuation.

It is noteworthy to mention that most of the aforementioned optimization-based evacuation models are unable to scale well for large-scale evacuation scenarios. Therefore, most of the techniques employ various heuristics to reduce the solution space, which results in sub-optimal route recommendations. In contrast to the optimization-based approaches, there also exist some commercial/non-commercial traffic simulation packages, such as INDY [27], PARAMICS [28], DynusT [29], and TransCAD [30]. Among the aforementioned, the PARAMICS [28] is commercial software and has been utilized mostly for micro-scale simulations. However, a common problem that most of such packages suffer from is the lack of scalability, especially when the network size is large and different from the network under normal conditions. Therefore, to address scalability, we utilized parallel computing in our proposed framework.

7 CONCLUSIONS

In this paper, we presented a service architecture *MacroServ* that performs the real-time route recommendations for the evacuees at the time of a disaster. The proposed service utilizes the live information extracted from the ITS and the road side sensors to calculate preferred evacuation paths that have maximum traffic flow capacity, least congestion, and travel cost. Unlike our approach, most of the existing work on disaster route recommendations is based on optimization techniques that compute a set of optimal routes under a specific set of parameters. However, optimization techniques are unable to precisely capture the effect of numerous stochastic and time-varying factors, which have significant influence on evacuations. Moreover, incorporating the stochastic factors in optimization models significantly increases the problem space and computation times. Therefore, to test the performance of the *MacroServ* service, we developed a scalable traffic simulation model that can be configured to simulate evacuations under different conditions and parameters. To achieve the desired level of scalability and speed we utilized parallel computing on a computer cluster that runs parallel instances of the real-time route computation algorithm. The evacuation simulations were performed on a real map of City of Fargo, USA consisting of 2,800 intersections, 7,370 roads, and a population size of 108,000. The simulation results indicated that by not routing the traffic towards the least congested routes during an emergency, the evacuations can suffer from

massive traffic jams, which increases the evacuation times and waiting times. Moreover, the results provided best case estimates for the evacuation times under a given set of parameters and stochastic factors. The evacuation simulations can allow the disaster management bodies to plan and optimize the traffic operations during a possible evacuation. Moreover, it provides a way to better analyze the critical network elements, the effect of evacuees' behavior, and managerial factors on evacuations.

In future, we intend to extend our model by incorporating more number of parameters to address the uncertain factors during emergency scenarios. For instance, a driver's behavior may vary due to stress and fear. Moreover, evacuees' compliance to the recommended routes and time of disaster also plays an important role in the road congestions. All such real-life parameters have significance and must be considered in the design of emergency evacuation models.

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