Evacuation and Emergency Management Using a Federated Cloud

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A federated cloud computing architecture combines multiple private and public clouds to perform damage assessment, determine victim locations, and coordinate rescue efforts.

Natural disasters are becoming more frequent and cataclysmic every year. Some of the deadliest natural disasters, both in terms of fatalities and cost, have occurred over the last decade. The 2010 earthquake in Haiti and the 2004 tsunami in the Pacific belt, both causing more than 220,000 fatalities, were among the deadliest.[1,2] According to Munich RE, the average number of disasters throughout the 1980s was 400; this increased to 630 in the 1990s, and to 730 in the last decade.[3] Even in this modern-day world with its advanced technology, major natural disasters, such as earthquakes, landslide, cyclones, tsunamis, and floods, take a toll upon the human race.

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Contemporary disaster relief and evacuation strategies still need loads of enhancement and optimization. For example, in August 2005, Hurricane Katrina affected large parts of Louisiana, Mississippi, and Florida. With a death count of more than 1,800 and estimated damages of $108 billion, Katrina proved to be the costliest natural disaster in US history. However, officials lacked a definitive plan of action following the event. Local rescue teams, overwhelmed by the destruction, weren't in a position to evaluate and analyze the storm's effects and severity. Even after a partial damage assessment, constant communication failures led to ongoing pandemonium. Worst was that many of the already insufficient number of deployed military troops remained unutilized because they weren't briefed and exercised in a timely manner.

Today, disaster-hit environments face the following major challenges[4]:

- Officials lack a clear plan for distributing rescue teams over the affected area, which impedes the emergency response.
- It becomes increasingly difficult for rescue troops arriving from outside the disaster-affected zone (neighboring states or countries), because the existing structure lacks a proper scientific approach to regulate the rescue routine.
- Traditional techniques fail to distinguish between zones in which people require immediate help from zones in which most of the people are already dead.
- Most importantly, the lack of a proper communication backbone leads to collapse of the electronic communication medium—ranging from emergency phone calls to social media.

Clearly, contemporary disaster relief infrastructure and methods are inadequate, time-consuming, and certainly not optimally designed—especially given that the first 24 to 72 hours (the "golden 72")—are critical to the rescue of disaster victims. Thus, we need an efficient and decisive emergency management and evacuation policy. To optimize such policies, it's important to analyze huge volume of data generated from different sources.[5]

We propose using federated cloud computing to manage and govern the data generated in huge volumes and high velocity from various data sources. Federated cloud computing involves multiple private, public, and/or community clouds collaborating to achieve a common goal. Our proposed disaster relief approach also involves acquiring raw data in situ, and processing and aggregating this sensor data within the federated cloud framework to arrive at a consolidated and dependable analysis of a disaster's affects.

System Architecture

Figure 1 shows the high-level architecture of the proposed federated cloud computing platform. The architecture is comprised of three tiers: heterogeneous sensor nodes on the bottom tier, legacy systems in the middle, and the federated cloud computing tier on the top. The architecture involves both primary data sources, which provide the raw data from the disaster-affected areas, and secondary data sources, which combine composite data from diverse data sources.

Primary Data Sources or Onsite Sensors

Contemporary sensor technology aims at complete sensor coverage and control (see www.sensorsmag.com/about-sensors). Thus, without loss of generality, we assume predeployment of several heterogeneous sensor nodes across the disaster-affected regions. Heterogeneity of sensors ensures a multiparametric supervision of the regions.

Vibration sensors. Vibration sensors can be highly useful in disasters such as earthquakes, tsunamis, and landslides. In a postdisaster scenario, data received from these vibration sensors supports disaster assessment and evaluation of region-specific severity.

Environmental sensors. Environmental sensors collect rainfall amounts, temperature, pressure, fluid velocity, and other environmental data. Such deployments help the rescue personnel acquire an overall projection of the area's condition following any natural calamity. The information provided also help in determining the disaster spread pattern.

Thermographic camera sensors. Also known as infrared camera sensors, thermographic camera sensors function irrespective of ambient light.[6,7] In a postdisaster scenario, these sensors periodically capture and transmit frames (generated through thermal imaging) to the onsite sensor cloud storage. These frames are analyzed within the cloud servers in real time to determine the location and number of live victims in the affected regions.

Wireless body sensors. Contemporary healthcare strategies envision body sensor nodes as a vital component of advanced healthcare systems. Patients could wear these body sensors for both regular and

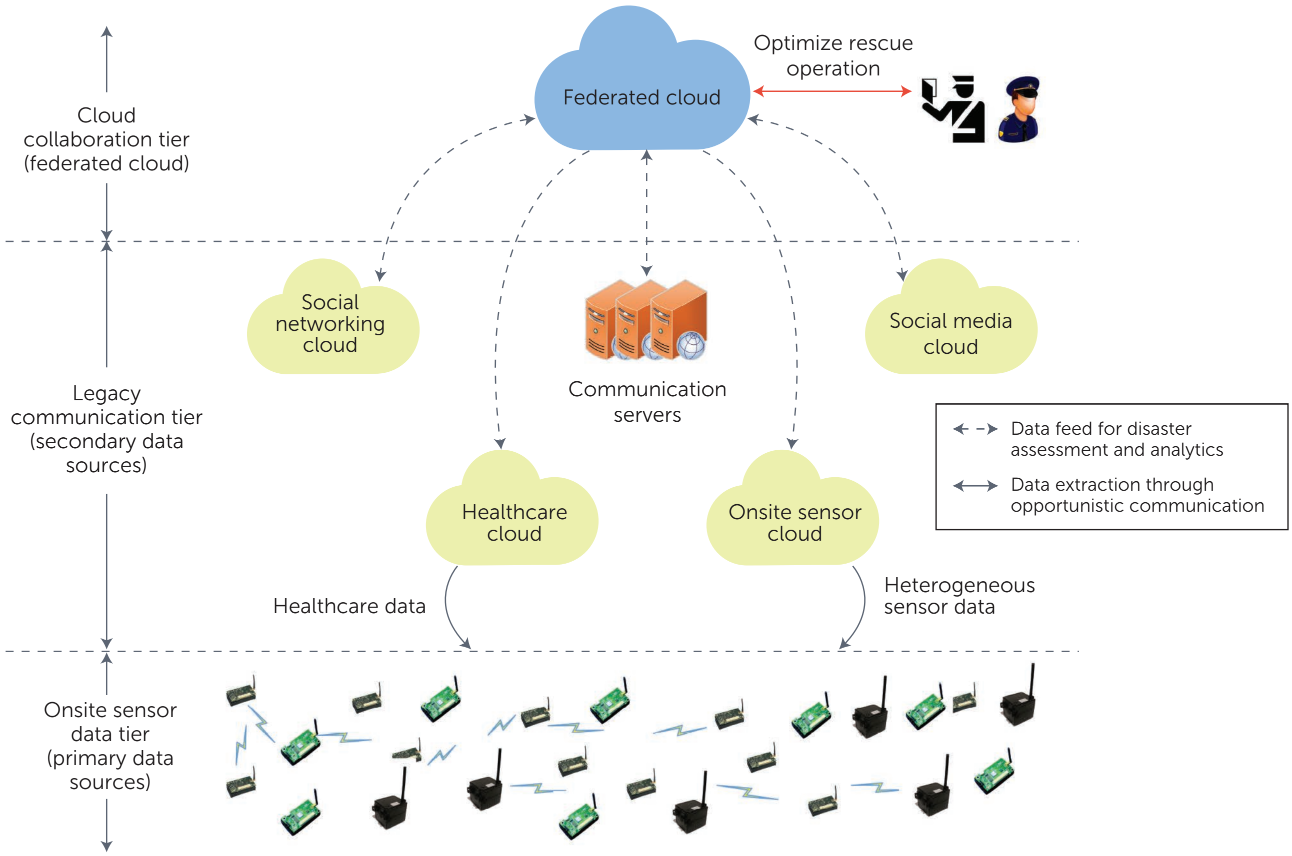

FIGURE 1. Federated cloud architecture for emergency management. The three tiers include heterogeneous sensor nodes, legacy systems, and a federated cloud.

emergency health monitoring.[8,9] Thus, we can assume that some subgroup of victims in a disaster area (patients or elderly people) will be pre-equipped with body sensor nodes.[10–12] The medical experts could analyze data from these nodes to obtain the physiological status of the live victims within the disaster-affected zones.

Secondary Data Sources: Clouds and Servers

The *legacy communication* tier comprises multiple public, private, and/or community clouds that serve as generic data repositories for various data types. These clouds provide aggregated information after processing the raw data obtained from their data sources.

Social networking clouds. Social networking clouds collect information from different social networking sites and publicly available portals. By analyzing the origin of status posts, tweets, and other feeds, rescue teams can identify zones in which clusters of victims are trapped.

Social media clouds. These cloud platforms gather data from different social media sites and aggregate it to provide information about the emergency's severity across the affected regions. Through interviews and surveys, media personnel obtain data directly from the victims or the victimized spots and feed it to the cloud, thereby providing a thorough analysis of the state of the disaster areas.

Healthcare clouds. Healthcare clouds collect physiological data from various body sensor nodes from the onsite sensor data tier, and process it for real-time and remote monitoring and analytics.

Onsite sensor clouds. These clouds gather real-time sensor data in situ. They collect heterogeneous data from varied sensor nodes and aggregate it meaningfully.

Communication servers. These servers primarily manage information originating from telephonic communication. During an emergency, when people in the affected areas engage in frequent communication with their families and relatives through phone calls, short message service (SMS), or multimedia message service (MMS), data about the origin and destination of these communications can lead rescue workers to victims. They can also use the information stored in these servers to assess the disaster's spread and evaluate its severity.

Clouds in Collaboration: Federated Clouds

Using a federated cloud for emergency management enables us to arrive at a reliable and plausible assessment, and evaluate the different aspects of a disaster. In a disaster scenario, a singular data source, such as onsite sensors, might be temporarily nonfunctioning, leading to inaccurate or inadequate information for analysis. Or, one of the cloud servers might be down because of overwhelming traffic congestion, causing interruption and cessation of computation. In such conditions, multiple data sources are likely to provide more stable and decisive information. Therefore, federation aims to unify heterogeneous primary and secondary data sources, and eventually concludes with an acceptable decision.

The proposed federated cloud considers the management and coordination of multiple organizational and nonorganizational clouds following diverse models. In addition, it synchronizes and analyzes the data from the component clouds to perform real-time analysis of the damage's severity. Finally, to ensure real-time event-driven decision making, federation takes into account advanced big data management techniques and principles. Our system structures, processes, and stores the vast and copious heterogeneous data arriving at the federated cloud server using advanced big data classification algorithms.

Network Communication and Data Management

It's important to analyze the data obtained into consolidated information, and thereby make efficient decisions concerning the rescue and evacuation operation. We segregate the data management policies into two categories: within network and within cloud servers.

Within Network: Opportunistic Communications

Network congestion, channel blocking, and heavy packet drops due to collisions are common problems in disaster scenarios. Moreover, because victims typically move randomly and frequently, mobile communication challenges are prominent. Thus, emergency management also involves resolving the communication difficulties that generally arise in disaster zones. To avoid the collapse and disintegration of the communication network, a disaster management system should identify victims' spatial distribution.

The network communication server analyzes packet drops and failures to identify regions of handoff failure. In addition, the communication server gathers mobile communications data to enable opportunistic connections in these regions, and network resources are dynamically shared using conventional network allocation algorithms. Rescue teams are mobilized using vehicles equipped with smart mobile communication devices. The devices trap communication signals and analyze them to obtain the spread and intensity of the disaster and determine the optimal routes for rescue operations. This enhances the opportunity for rescue teams and officials to contact and connect with victims. The mobility model also supports efficient and reliable packet delivery. Thus, opportunistic communication in an emergency scenario can reduce the number of communication failures.

Within Cloud Servers: Big Data Analytics

Once the cloud server gathers data from primary and secondary sources, a major challenge is managing this high-velocity, voluminous data. The data's heterogeneity adds to the complexity of inferring and interpreting the data. For example, in March 2011, Japan experienced an 8.9 magnitude earthquake and subsequent tsunami on its coasts. This event triggered a record number of tweets across the country. An overwhelming rate of 5,530 tweets per second collapsed the entire communication system within minutes. Given that the typical average was 600 tweets per second, the servers were prostrated by the high number of requests. Such a scenario demands an infrastructure capable of managing a high velocity and volume of data—in other words, a big data management system.

With approximately 1.2 billion smartphone users worldwide, recent calamities have led to peak request-handling rates for social networking sites. Voice communication over mobile phones also peaks following any calamity. We envision using all these data, generated from the disaster-affected areas, to analyze the severity of the damage and coordinate rescue troops accordingly. The big data dealt with in this context is representative of the collective datasets acquired from social networking sites, social media, and onsite sensors. We analyze these digital data alongside the analog communications data that's generated from voice calls made over telephones. We classify the analysis run on the federated cloud platform into five broad categories.

Communications origin. In a postdisaster scenario, a victim's main concern is ensuring that his or her family members and close friends are safe and secure. Thus, many phone calls originate from disaster-affected areas. It's easy to track the origin and destination of analog voice communications. In addition, most smartphones being sold today are GPS-enabled, making it easier to track users' locations. To determine the origins of data communications, such as status messages, tweets, and social networking site posts, we'll run analytics on the datasets. For onsite sensor nodes, we can trace data packets' origins by their content. After ascertaining the origins of all the communications taking place in the vicinity of the disaster, we construct separate cluster diagrams for each mode of communication. These diagrams act as frequency maps (similar to heat maps), and provide significant information about the damage severity by area.

Data severity. The onsite sensor nodes also provide important environmental data from the affected regions. A heterogeneous deployment of these sensor nodes provides a wider variety of data. The significance of the different data types acquired from the sensor devices is often disaster specific. For example, for an earthquake-affected region, vibration and temperature sensor data is instrumental, whereas fluid-velocity and pressure sensor data is highly valued in a flood or tsunami scenario.

Clusters of living victims. The significance of the data acquired from the body sensor nodes, however, is pivotal, irrespective of the disaster type. These body sensor nodes give the locations and current health conditions of living victims. Rescue workers can use this data to identify regions in which clusters of living people are trapped, and helps us distribute and channel rescue and medical support teams accordingly.

Infrared images generated by thermographic camera sensors are useful in identifying zones in which victims are trapped. These images help distinguish the zones in which people are trapped alive from those in which there are no living victims. Further sequential analysis of the frames gives us some idea about victims' mobility patterns and clustering, which becomes crucial in dynamic route determination for rescuing and safeguarding victims.

Keyword identification. Keyword identification involves data mining and natural language processing. In the first step, we identify the keywords and assign weights to rank them according to their impact, in the context of a disaster-hit environment. Based on these weighted ranks, we conduct a region-specific, real-time analysis of the tweets, posts, and statuses posted through social media. Through this keyword analysis, we can estimate the zonal severity of the disaster, which supports optimal distribution and coordination of relief workers and medical troops.

Disaster spread pattern. Real-time geospatial analysis of the data acquired by the different sensor devices shows the dynamic spread pattern for the disaster. Most disasters, such as flood, storms, and tsunamis, spread along collocated regions with time. In addition to real-time analysis of sensor data, feeds acquired from social media assist in determining the disaster spread pattern. Based on this information, official can issue alerts, evacuate citizens in advance, and plan dynamic relief operations.

Rescue and Evacuation Strategy

Motivated by the limitations of contemporary rescue strategies, we illustrate our proposed techniques for evaluating rescue teams. In addition to managing data, an evacuation system must assess details about the rescue troops to be deployed, including their size, equipment, routes, and coordination.

The system must determine rescue routes and evacuation strategies based on the severity of damage in the affected regions. Figure 2 illustrates the control and data flow within the system's functional components. After acquiring data from the primary and secondary data sources, the cloud servers feed the data into the federated cloud environment. It obtains surface plots corresponding to each secondary data source, which it superimposes to generate a single, aggregated 2D projection. From the resultant 2D plot, we obtain a composite utility metric for the constituent zones of the entire disaster area. We divide the entire victimized terrain into equal-sized zones for region-specific examination and interpretation, and perform subsequent zonal analysis to quantify the zonal severity. Additionally, we formulate the distribution of clusters of live victims and the disaster spread pattern. By combining the zonal utility and the distance between each pair of zones, we evaluate the zonal costs. Eventually, we obtain a zonal ranking by executing the cost-based traveling salesman algorithm. The system analysis also facilitates proactive predeployment of rescue workers in zones where the disaster and its consequent effects are predicted to spread, creating the opportunity for evacuating people from the suspected regions.

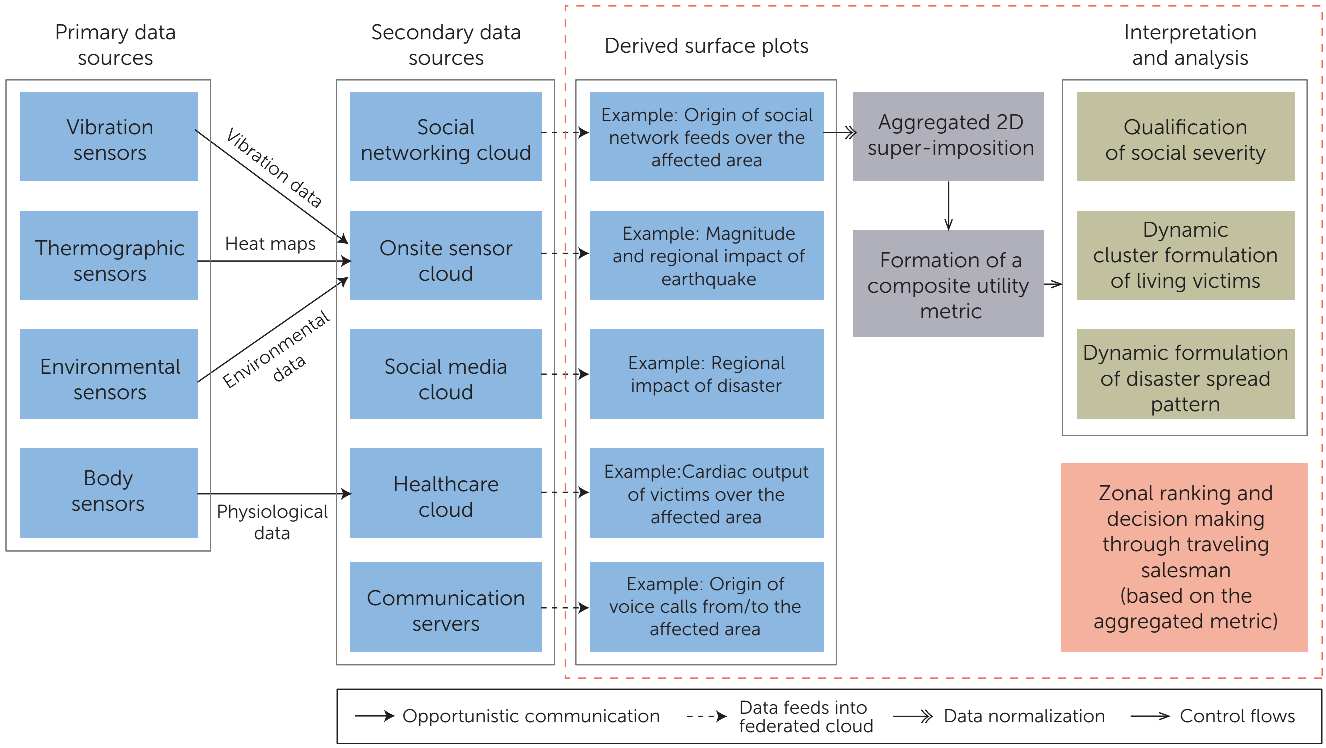

FIGURE 2. Diagrammatic representation of the federated cloud system's control and data flow. The figure illustrates the flow of the internal processes and the coherence of the various functional modules within the system.

Example Case Study: Earthquake

We assume a postdisaster situation following an earthquake spread over an 800 × 240 meter terrain. The epicenter is located at [500, 150], and the quake's magnitude is taken as 9.6 on the Richter scale. The population within the zone at the time of the earthquake is 50,000. We assume a predeployment of 120 vibration sensors over the affected area. The processes of social media feeds and mobile communications are generally stochastic in nature,[13] although they follow a Poisson distribution under normalcy. The terrain is divided into 16 nonoverlapping, exhaustive, equal-sized zones.

Geospatial Analysis

Initially, we observe the data reported by the predeployed onsite vibration sensors (Figure 3). The surface plot in Figure 3a illustrates the data as reported by the vibration sensors.[14] The x- and y-axes denote the length and breadth of the affected zone, respectively. The z-axis indicates the data from the vibration sensors, aggregated into interpretable Richter scale magnitudes. Having obtained the surface plot of the data from the vibration sensors, the data is projected over a 2D plane, as Figure 3b shows. The heat map, thus obtained, illustrates the earthquake's spread over the terrain. As the color bar indicates, regions experiencing the quake at a higher magnitude are darker whereas those experiencing the earthquake at a lesser magnitude are lighter.

Figure 4 demonstrates the attempts at mobile communication to and from the affected regions. Figure 4a shows the 3D plot depicting the number of telephone calls attempted per second after the earthquake. The darker crests indicate a higher number of attempts, and the lighter troughs represent fewer call attempts over the terrain. The 2D projection in Figure 4b provides a clear manifestation of the regional density of voice communication attempts per second.

Finally, Figure 5 shows the average number of social network feeds per second. The darker crests indicate a large number of social network feeds being generated, and the lighter troughs indicate fewer feeds. The projection of Figure 5a is shown in Figure 5b. The figure shows the variation in number of social network feeds over the 16 zones.

Rescue and Evaluation Policies

In the first step, for the set of all 16 zones $Z = \{Z_1, Z_2, \ldots, Z_{16}\}$, we normalize data from the three heat

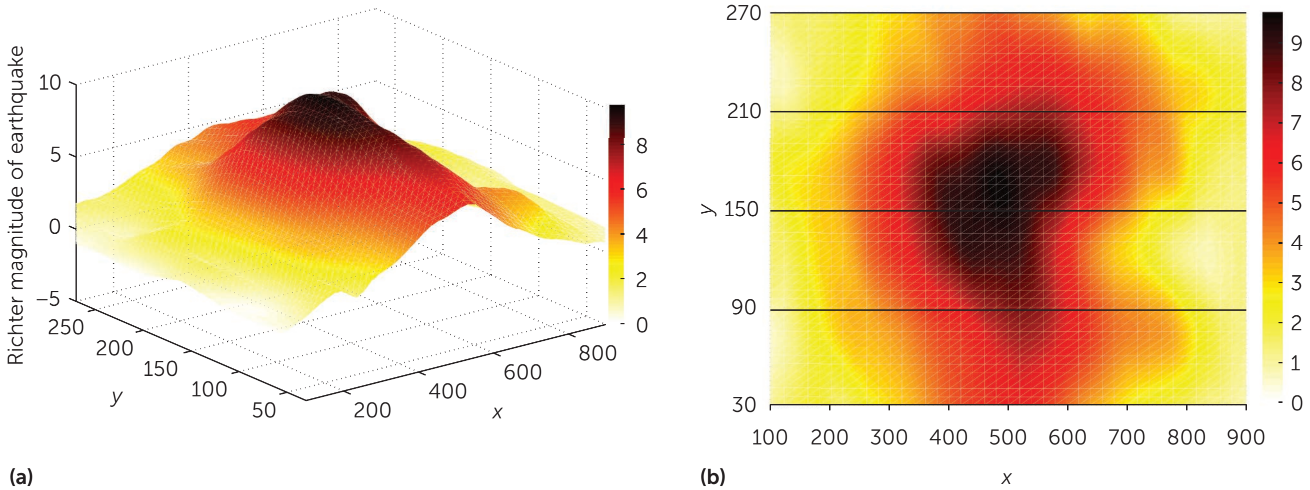

FIGURE 3. Geospatial analysis of data from vibration sensors: (a) 3D surface plot and (b) projection over a 2D plane.

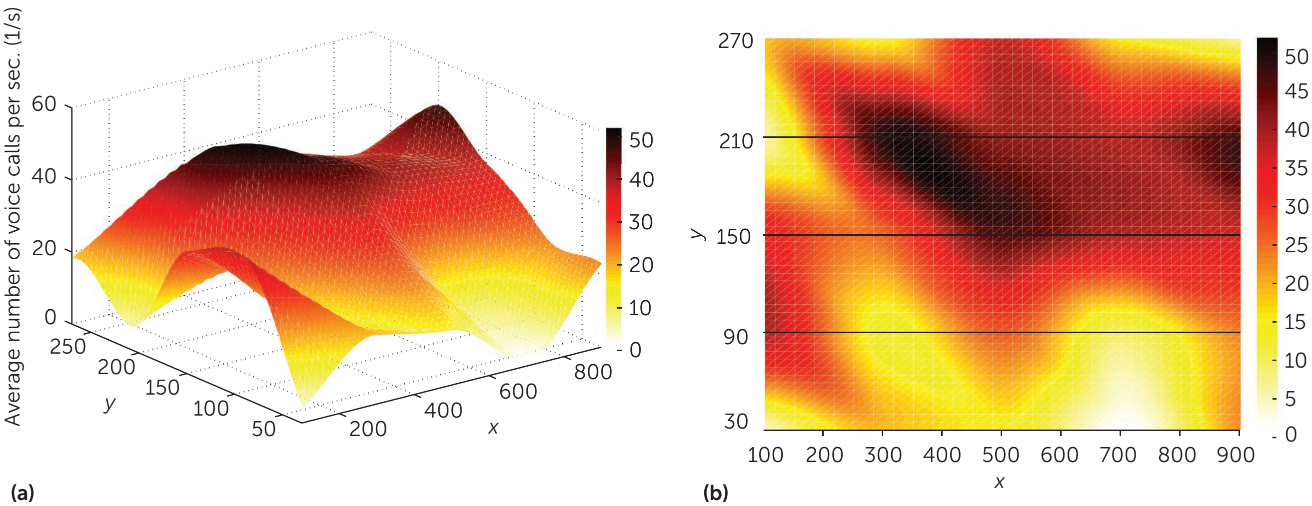

FIGURE 4. Geospatial analysis of voice communication: (a) 3D surface plot and (b) projection over a 2D plane.

maps, as shown in Figures 3b, 4b, and 5b. Next, we compute a composite utility value $\zeta_{x,y}$, $\forall_x \in X$, $y \in Y$, at every coordinate of the disaster-affected area. For each zone Z_i, we derive the mean zonal utility ζ_{Z_i} as

$$\zeta_{z_i} = \frac{\sum_{x \in X \cap Z_i^x, y \in Y \cap Z_i^y} \zeta_{x,y}}{\left|Z_i^x\right| \times \left|Z_i^y\right|}, \tag{1}$$

where X and Y are the sets of integral abscissas and ordinates of the entire victimized area, respectively, and Z_i^x and Z_i^y are the sets of abscissas and ordinates within zone Z_i, respectively. Having obtained $\zeta_z = \{\zeta_{z_1}, \zeta_{z_2}, \ldots, \zeta_{z_{16}}\}$, as Figure 6a indicates, we want to determine the final zonal ordering $\hat{Z} = \left\{\hat{Z}_1, \hat{Z}_2, \ldots, \hat{Z}_{16}\right\}$ that depicts the order in which rescue teams should visit the victimized zones. For traversing from zone Z_i to Z_j, we compute the cost as

$$\Psi_{Z_i,Z_j} = \frac{\zeta_{Z_j}}{d_{Z_i,Z_j}},$$

where d_{Z_i,Z_j} is the distance between the respective zones. Thus, in our case, the traveling salesman problem (TSP) considers Ψ as the computational cost. We express the TSP as, given a zone Z_i, we must determine Z_j, $j \neq i$, $1 \leq j \leq 16$, such that

$$\text{maximize}\left(\sum_{i=1}^{15} \Psi_{\hat{z}_i, \hat{z}_{i+1}}\right), \hat{z}_{i+1} = z_j\,. \tag{2}$$

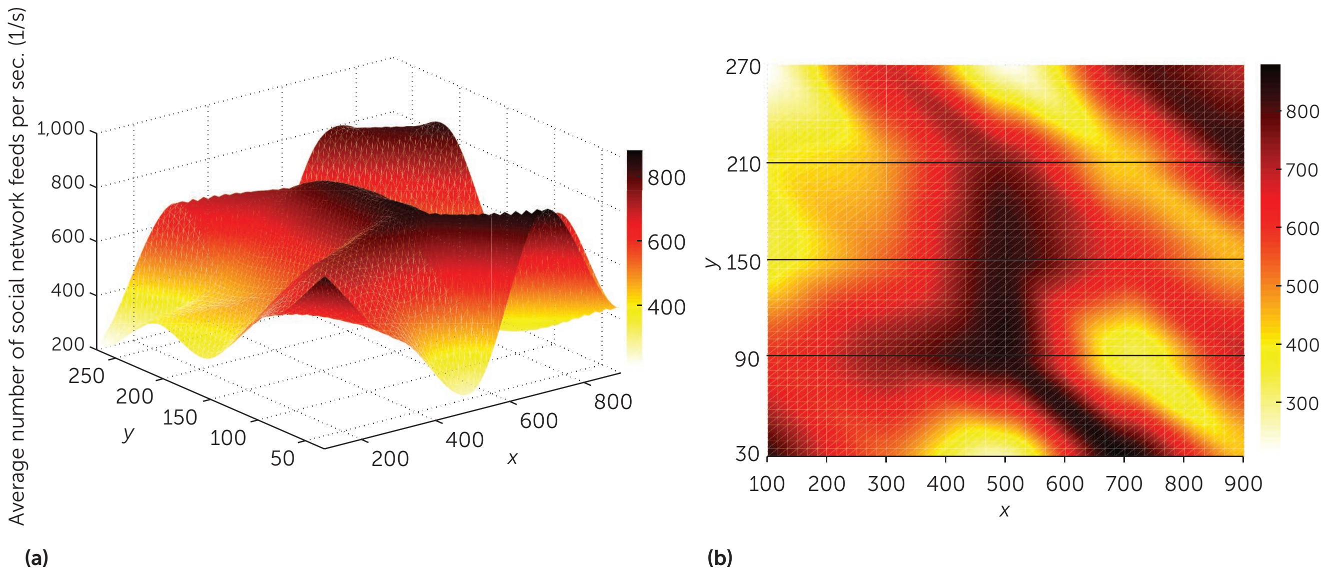

FIGURE 5. Geospatial analysis of the social network feeds: (a) 3D surface plot and (b) projection over a 2D plane.

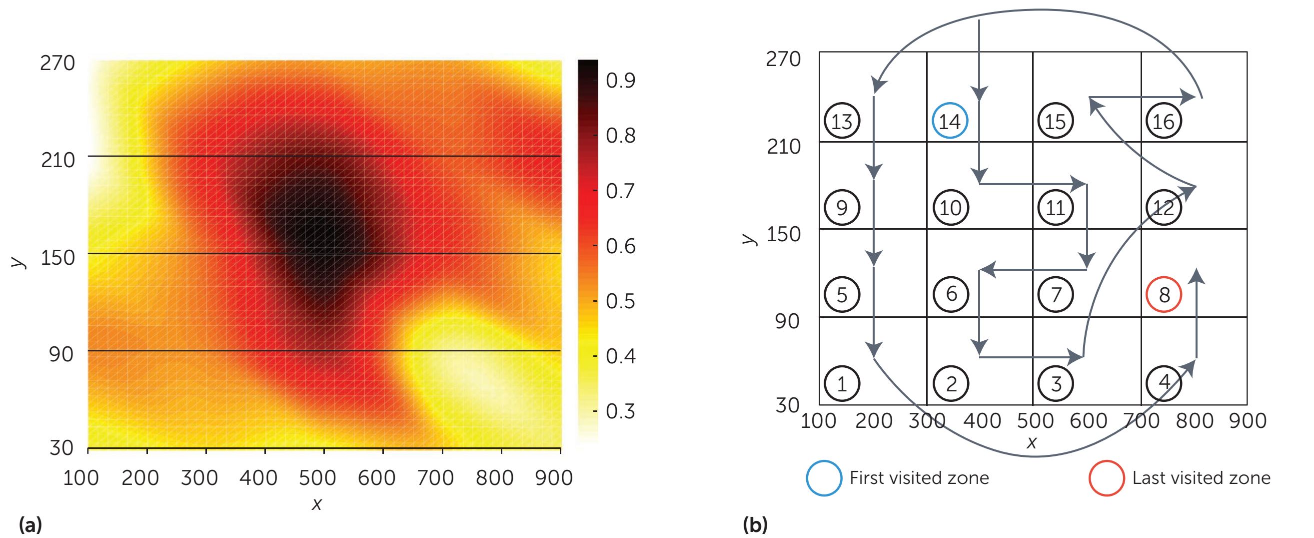

FIGURE 6. Determination of evacuation route based on the resultant heat map: (a) resultant heat map obtained after superposition, and (b) diagrammatic representation of traveling salesman algorithm.

As per our case study, we obtain a final zonal ordering of {Z_{14}, Z_{10}, Z_{11}, Z_7, Z_6, Z_2, Z_3, Z_{12}, Z_{15}, Z_{16}, Z_{13}, Z_9, Z_5, Z_1, Z_4, Z_8}, as Figure 6b shows. From the given values, we derive the zonal severity and formulate the dynamic cluster formation of living victims and the disaster spread pattern.

With current emergency management technologies, rescue teams would have visited the affected regions randomly or on a first-come, first-served manner, either of which would be sloppy and inefficient, thereby leading to disorganized and ineffective emergency management.

Future work will extend this research by developing a generic mathematical model for different types of disasters and designing the analytics for individual disaster types. We'll also explore the characterization of the disaster spread pattern and its correlation with the human mobility model. Another research area of interest is the optimization of rescue routes based on the disaster spread patterns.

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