Establishing effective communications in disaster affected areas and artificial intelligence based detection using social media platform

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Abstract: Floods, earthquakes, storm surges and other natural disasters severely affect the communication infrastructure and thus compromise the effectiveness of communications dependent rescue and warning services. In this paper, a user centric approach is proposed to establish communications in disaster affected and communication outage areas. The proposed scheme forms ad-hoc clusters to facilitate emergency communications and connect end-users/ User Equipment (UE) to the core network. A novel cluster formation with single and multi-hop communication framework is proposed. The overall throughput in the formed clusters is maximized using convex optimization. In addition, an intelligent system is designed to label different clusters and their localities into affected and non-affected areas. As a proof of concept, the labeling is achieved on flooding dataset where region specific social media information is used in proposed machine learning techniques to classify the disaster-prone areas as flooded or unflooded. The suitable results of the proposed machine learning schemes suggest its use along with proposed clustering techniques to revive communications in disaster affected areas and to classify the impact of disaster for different locations in disaster-prone areas.

Keywords: Ad-hoc networks, heterogeneous networks (HetNets), social sensors, infrastructure less communications, machine learning. 5G, device to device (d2d), boosting classifiers

1. Introduction

Natural hazards and catastrophes can significantly interfere and effect people's life, property and socioeconomic cycle. Natural hazards can be categorized into three main classes [1]: meteorological hazards, hydrological hazards and geological hazards. These hazards are depicted in Figure 1. Meteorological events are composed of tornados, hurricanes, thunderstorms, winter storms (ice storms) and summer storms (wildfire). Hydrological events consist of all flood types (fluvial, pluvial, and coastal), storms surges and tsunamis. Geological hazards comprise of earthquakes, volcanic eruptions and mass movements (land sliding, mudflows, avalanches etc.).

In the event of such hazards, disaster management play a vital role. Disaster management requires preparedness and timely responses to mitigate and recover normal state of living along with increasing resilience of society. However, limited capacity of the governmental institutes, non-governmental organizations (NGOs), first responders and rescue workers to effectively execute help and rescue services for the affected regions in natural disasters pose several challenges. To effectively engage in the rescue services and better coordinate the activities, communication system plays an important role [2, 3]. However, in case of natural calamities, the communications infrastructure, whether it is wired or wireless, is severely incapacitated [4]. Communications failure not only makes the rescue activities harder but also makes the assets (social sensors, volunteers (recruited in pre-disaster phase)) useless. It also affects information authenticity and coordination activities harder with limited to no communication with the social sensors and volunteers in affected areas. The power failures in the affected regions result in inability of affected population to receive telecasts (one-way simplex communications for general instructions). The devastating impact of natural catastrophes on communication backbone networks disturb both wired and wireless links (duplex communications) alike. Lack of effective communications between the inhabitants of affected areas and the rescue workers/first responders, among various rescue teams and with the rescue operation coordinating agencies result in poor management of rescue activities [5, 6]. The poor flow of information also results in inaccurate analysis of situation thus, resulting in inaccurate distribution of resources.

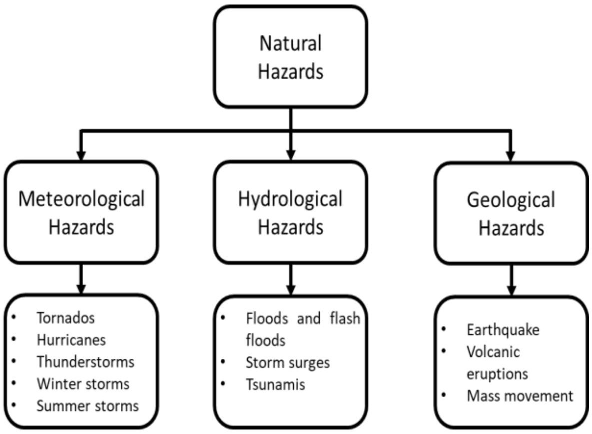

Figure 1 Classification of natural hazards

The importance of communications is evident in the event of a natural disasters [7, 8]. However, the low resilience of traditional cellular infrastructure and inability to operate in severe circumstances makes it more vulnerable and fault intolerant. Besides, natural disasters also cause failure in operations of Base Station System(s) (BSS) and affects the communications of all connected Mobile Stations (MS) in the region. For instance, the 2011 earthquake in Japan caused over 16 thousand deaths while thousands were injured and missing [9]. The communications infrastructure including major coastal transmission lines and utility poles were heavily damaged, causing a shutdown of approximately 29,000 base stations [10]. Consequently, 1.9 million subscribers were affected due to this major collapse in communication infrastructure. The catastrophic flash floods in India in 2013 significantly affected the northern regions and many areas of socioeconomic significance were isolated due to inefficient communication infrastructure [11]. The wired and wireless services including the cellular and internet were severely affected due to high congestion, which resulted in significant delays in rescue and evacuation activities. More recently in 2015, the earthquake of 7.8 magnitude hit all across Nepal causing thousands of deaths, injuries and major property damages [12]. Cellular stations, power stations and internet communications were also significantly disrupted. This largescale communications failure stopped information exchange between the rescue authorities and the residents of thousands of rural villages, thus, depriving survivors to receive lifesaving information even after weeks of this catastrophic event [13]. These events highlight the importance of communication infrastructure which can potentially reduce collateral damage and loss of life. Moreover, the World Health Organization (WHO) for Europe [14] highlighted the essence of telecommunication in emergencies, and considered resilient telecommunication infrastructure as one of the essential attributes of emergency crisis management system. Davis et al. [15] conducted a study which gathered information from 26 WHO communication officers who had experiences in dealing with a total of 18 natural disasters (tsunamis, earthquakes, floods etc.) that unfortunately resulted into 29 outbreaks of 13 diseases. The report highlighted that communication infrastructure in the form of text messages and social media (through internet) can augment and disseminate the lifesaving information and health messages to prevent panic during and after disastrous events [15].

The centralized hierarchy supported by the legacy cellular systems is especially affected in the areas in need of rescue services. Therefore, decentralized emergency communication frameworks are required to offer necessary feedback communication within the affected areas [37]. Most of the existing efforts in restoring disaster affected communications require deployment of remote BSS which restricts the suitability of such communication networks. Furthermore, the robustness and scalability in such systems is usually unattainable. Localization of the MS for accurate region-wise threat analysis and statistical feedback of trapped survivors is also a challenge. The bulk information generated in communication functional areas (where communication networks are restored or survived the disaster) is also hard to analyze using conventional techniques. Machine intelligence can be used to better read the situation in different disaster affected areas and characterize level of emergency in different regions based on the communications originating from that region.

This paper proposes a location-based ad-hoc network formation mechanism to restore necessary communications of UE/MS in case of failure in core communication infrastructure. The main contributions of the paper include

1) Single-hop and Multi-hop communications link establishment to the core network in the event of communication infrastructure collapse
2) Efficient cluster formation and optimized cluster-head (CH) selection
3) Throughput optimization within the clusters
4) Machine learning based data analysis for identification of disaster situation in different regions
5) Accurate localization of the disaster affected areas with high performance

The rest of the paper is organized as follows. Related work is presented in section 2. Section 3 describes the methodology of the proposed novel communication infrastructure to establish communications in disaster affected areas. Section 4 introduces the proposed AI-empowered disaster detection system which exploits social media platform for pre-disaster vulnerability prediction and localizing disastrous area until the communication infrastructure sustains. Results and discussion are presented in section 5, while section 6 concludes the findings of the study, highlights its limitations and give future directions.

2. Related work

The centralized architecture in cellular network make it vulnerable to large scale communications outage in the disaster affected areas. Under such circumstances, the device to device (d2d) and localized communications can play a vital role in restoring the necessary communications. Over the years, several schemes were proposed to offer sustainable communications in pre-disaster as well as post-disaster phases.

The inability of existing communication infrastructure to cope with extreme unprecedented events cause complete communication infrastructure breakdown. Gomes et al. [16] extensively reviewed the communication strategies in pre-disaster and post-disaster scenarios and highlighted the limitations of existing systems with possible improvement suggestions for robust communication infrastructure. It was suggested that the network solution requires added redundancy, content connectivity and traffic connection management to provide robust communication in pre-disaster scenarios. Added redundancy ensures accessibility of a UE to other UE within the network by introducing immunization strategies to provide extra protection to the network. Content connectivity allows content delivery to each node in disconnected network during a catastrophic event. Whereas, traffic congestion management distributes traffic to less congested UE or allocates extra capacity in disastrous situations [16]. The out of network robustness in pre-disaster situations can be achieved by ensuring the power supply to the network infrastructure through multiple power sources and by deploying the network software platform in a region less prone to natural disasters. The post disaster recommendations to ensure network recovery and robustness suggested prompt deployment of emergency networks based on transportable networks nodes (base stations and access points). Deployment of mesh and ad-hoc networks was also suggested for end user devices in addition to taking instantaneous measures to ensure the efficient and robust maintenance of the network [16]. A recent study [17] also highlighted several key aspects of communication infrastructure that are essential in providing efficient communications in natural catastrophes and emergency conditions. These include robustness, reliability, user and network mobility, interoperability of communication infrastructure, rapid deployment, scalability, quality of service, security, cost effectiveness, energy efficiency, localization, capacity and coverage [17, 18].

In [19], an approach to calculate the reliability index of user devices for peer selection in d2d networks using physical layer relation (such as mobility, spectrum, power, etc.) was introduced. A single cell scenario was considered in this study and therefore, raised the concern of scalability of the proposed approach. A time dependent local decision-making technique was introduced for service discovery. FINER, a multi-hop d2d communication with hybrid ant colony optimization-based routing algorithm to locate-and-reconnect the isolated mobile nodes in the disaster zone was presented in [21]. Social network information was used to improve the energy efficiency during data dissemination in d2d communication [22]. The study limited the d2d transmission to users with social ties and excluded user mobility. The authors in [40] investigated the convergence of social networks and d2d communication from resource allocation and optimization perspective. However, their study was generic and did not specifically consider disaster scenarios.

Authors in [23] demonstrated the benefits of using multi-hop communications over single-hop d2d communications in a laboratory testbed. Energy consumption, network delay, coverage and link quality were the key performance parameters which showed improved performance in a laboratory setup. While the results were promising, yet, in real-life scenarios where there will be thousands of devices, effectiveness of system model to handle such complexity was questionable. To establish long-range links for multi hop d2d communication networks, the authors in [24] exploited social network features and communication domain constraints. A greedy algorithm based on critical edge and coalition graph game using social community information was proposed to model long-range links creation. Further, a weighted social relationships approach was explored in [25] to enable data dissemination over d2d networks using direct or indirect links between any two users in a connected community. The authors proposed monetary auction-based mechanism which claimed to obtain the global optimal solution and achieves truthfulness, and a moneyless matching-based mechanism claimed to guarantee two-sided stability with a lightweight implementation.

A mechanism called 'survival on sharing' to prolong the battery life and device connectivity in disaster zones was proposed in [26]. The results from both experimental and simulation-based analysis showed significant performance gain when using d2d communications. An information diffusion-based approach, combining network metrics for different transmission modes (i.e., multicast, unicast, d2d) and social relationships was highlighted in [27] for data dissemination process. In addition, a metric called social network contact time was introduced to characterize the user behavior in identifying the frequency of interaction of an end-user with a social network platform.

Recent works have also proposed drone/UAV based systems to recover wireless network services in a post-disaster situation. Clustered deployment of drone-based small cells in stochastic geometric framework was investigated in [28] to optimize the energy efficiency and coverage probability of the ground users. It was identified that the key parameters influencing optimal deployment were transmission power ratio between drone base stations and traditional base stations, drone altitudes and the number of drones in a cluster. Authors in [29] proposed learning-based clustering algorithm and relaxed optimization algorithm for user association where the UAVs and d2d connections were jointly leveraged to recover the wireless service. The work has highlighted the advantage of using artificial intelligence methods to achieve high performance with low complexity. A multi-hop d2d and UAV combined approach to perform downlink transmission was studied in [30] and has presented the outage probability and precoding performance of the downlink from UAV to devices. Even though the study used clusters to evaluate their model, they did not use a specific clustering technique. Considering high mobility, low cost, and flexible deployment features of UAV, the authors in [41] explored the possibilities of employing UAVs to cope with the challenges of existing network technologies such as limited coverage and scarce resources. To tackle the problem of limited energy power of IoT nodes, the authors in [42] employed UAV for data collection and power supply. An IoT node harvests energy from a UAV through directional wireless energy transfer and sends data packets back to it. Some recent studies suggested the idea of employing mobile crowd sensing [43] for situation awareness in disaster affected areas.

Over the years, several ad-hoc schemes are proposed to facilitate communications in disaster affected and communication outage areas. While some of the schemes lack scalability, others require dedicated equipment and additional resources, not readily available in disaster affected areas. In addition, almost all of the techniques lack the ability to identify region-wise vulnerability of disaster affected area. In the proposed work, a machine learning based vulnerability analysis of disaster prone/affected areas is evaluated along with a suitable ad-hoc communication infrastructure to cope with the adverse effects of communication failure in such regions. The proposed communication infrastructure enables instantaneous clustered network establishment to facilitate the communications where the cellular and other means of communications have failed. In addition, as a proof of concept, a machine learning technique is proposed to evaluate social media to assess vulnerability of people in disaster areas with potential extension to region wise susceptibility. The details of the proposed communication infrastructure and machine learning technique are covered in the following sections.

3. Proposed communication infrastructure in disastrous situations

The communications are essential for both first responders and civilians trapped in the disaster-stricken areas. In critical circumstances, failure in communications can affect the rescue services and limit the effectiveness of first responders in the affected areas. The rescue activities of the first responders and rescue workers are very important in minimizing further loss of life and injuries and therefore, the necessity of resilient communication networks cannot be denied.

In the event of a natural disaster, the electrical power and the communications infrastructure can be seriously affected. The inability to communicate affects coordination among the trapped survivors, rescue workers and outside world. In the event of a failure in cellular infrastructure, adaptive d2d and multi-hop communications can offer an alternate communications setup. To restore necessary communications within the vulnerable areas, suitable infrastructural changes need to be introduced. In this paper, a clustering and communications scheme is proposed to facilitate communications within the disaster affected and communications outage areas. The system parameters are presented in Table 1, whereas a detailed description of proposed scheme is as follows.

Table 1 System Parameters

Parameters	Variable(s)	Value(s)
Control channel Superframe duration	T_{sf}	4.83ms
Transmission slots	m	8
Receiver sensitivity	δ_r	-95 dBm
Desired SNR margin	SNR_m	10 dB
Received Power	P_r	-
Transmitted power	P_t	-
Transmitter gain	G_T	3dB
Receiver gain	G_R	3dB
Transmission power multiplying factor	g	1-3
Extended range of control channel	d_e	-
control channel band	f	900/1800/2100 MHz
Path-loss exponent	n	2-4
Average Smart Phone (SP) penetration	μ_1	
Expected deviation in average SP	σ_1	
Transmitted power of the satellite	P_s	
Noise Power	${\sigma_n}^2$	
GPS coordinates: x-y plane mean location and expected deviation	$\mu_x, \sigma_x, \mu_y, \sigma_y$	
Bivariate gaussian distribution symmetry	ρ	0
Distance vector between j and k	d_{jk}	
Hop-count to the core network at time t	$H_{count}(t)$	

3.1 Extended coverage establishment

In the event of a failure in one or more cellular BSS, the active BSS, near the communications outage area will initiate a high-power clustering request using the prespecified control channel. The proposed scheme uses synchronized communications from active BSS situated next to the disaster affected areas, allowing to extend its coverage to the communications dead zone. The extended coverage area for the control channel is presented in Figure 2.

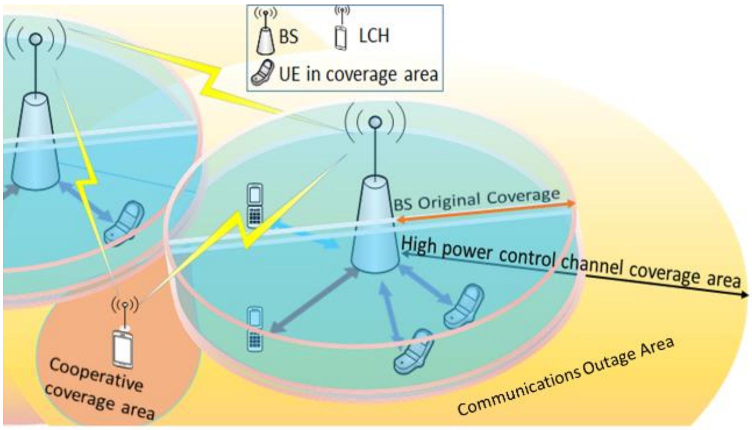

Figure 2 High power control channel coverage and cluster-head (CH) selection

The extended coverage range of the BSS is trigged in the event of a disaster. The extended coverage range is achieved by introducing two changes in control channel communications: 1) use of relatively low frequency and 2) high transmission power. The justification for the extended range can be validated from Friis' Equation which suggests the received power can be expressed as [38, 39]

$$\mathrm{P_r} = \left(\frac{P_t G_T G_R \lambda^2}{(4\pi d_e)^2}\right) \tag{1}$$

here d_e is extended coverage range, P_t is original transmission power, G_t and G_r are the transmitter and receiver gain. λ is wavelength (where $\lambda = c/f$),

The extended coverage range is directly related to the pathloss. Since time and frequency division is used to eliminate the interference from neighboring BSS, therefore, with an increase in the transmission power by a factor g will result in additional coverage area represented in Eq. 2. Based on this equation, since maximum range is considered, therefore received power can be replaced with receiver sensitivity, δ_r, which can give us maximum communication range of the base station. Note that relatively low frequency control channels are used to extend the coverage range and to convey the beacon signals farther.

$$d_e = \sqrt[n]{\left(\frac{gP_tG_TG_R\lambda^2}{(4\pi)^2\delta_r}\right)} \tag{2}$$

here $n = 2$, and gP_t is g times original transmission power for extended coverage area.

3.2 Control communications and scheduling

Figure 2 highlights the cooperative coverage area (covered by more than one BSS). To avoid interference, time division multiple access (TDMA) is used to establish control channel communications, where the communications from different BSS are adaptively scheduled. An example scenario is presented in Figure 3, where BS1, BS2 and BS3 are the active BSS in the neighboring region of communications outage area. The hexagonal cells in Figure 3 represent original coverage area where extended coverage area is represented with circular coverage areas. The control channel communications schedule of these BSS is also presented in Figure 3 where these base stations cover the areas CA_1 (Coverage area of BS_1), CA_2 (Coverage area of BS_2), CA_3 (Coverage area of BS_3), CC_{12} (Cooperative coverage area of BS_1 and BS_2) and CC_{23} (Cooperative coverage area of BS_2 and BS_3). The slotted broadcast of the BSS uses a control channel frame of duration T_{sf} with m transmission slots, which can cover all possible aspects of collision and failure scenarios in hexagonal cellular structure.

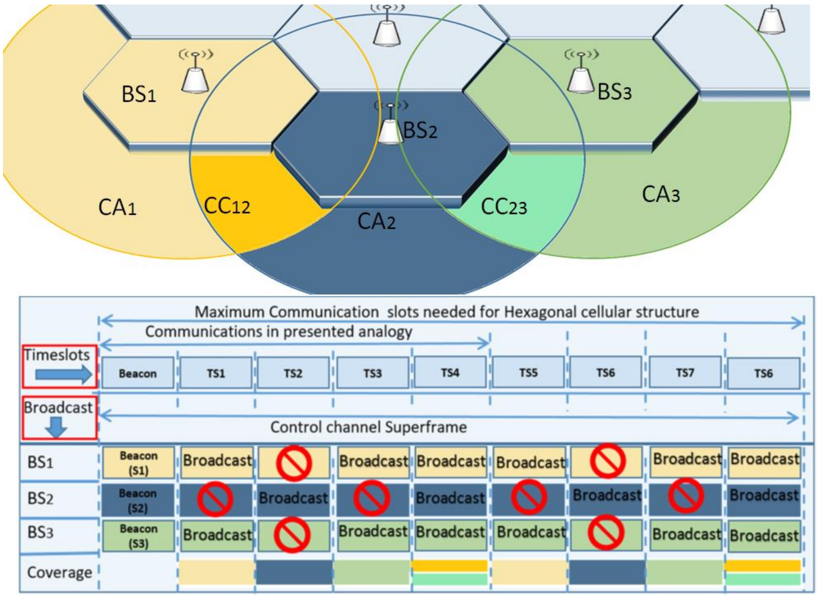

Figure 3 Control channel communication synchronization

3.3 Localization of MS in Disaster Areas

MS/UE are assumed to have certain penetration of Smart Phone(s) (SPs) allowing global positioning system (GPS) based localization. The SP penetration of selected countries is listed in Table 2, whereas the extended list can be found in [31]. In a particular vicinity, the existence of SP is modelled as follows:

$$f(x \mid \mu_1, \sigma_1) = \frac{\left(\frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1{}^2}}\right)}{\int_0^1 \left(\frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1{}^2}}\right) dx} \qquad x \in \mathbb{R}(\{0,1\}) \tag{3}$$

here μ_1 is the average SP percentage in the selected region, whereas σ_1 is the expected deviation from the average penetration of smart phones.

Table 2 Smart Phone Penetration 2017

Countries	Smart Phone Users	Smart phone penetration
United Kingdom	44,953,000	68.6%
United States	226,289,000	69.3%
Indonesia	54,494,000	20.7%
Turkey	40,010,000	49.8
Vietnam	25,162,000	26.4%
Sweden	7,167,000	72.2%

Given the communications outage and BSS failure in the region under consideration, the accurate localization of other MS and SPs is achieved using Received Signal Strength (RSS) and GPS information from selected SPs with GPS access. The SPs are assumed to have GPS. The GPS is assumed to be evaluated using Fault Detection and Isolation (FDI) algorithm [32] where instantaneous pseudo range, R, of a receiver j from satellite k is expressed as

$$R_{jk}(t) = \upsilon_{jk}(t) + \delta_{jk}(t) \tag{4}$$

here $\upsilon_{jk}(t)$ represents geometric distance between the satellite k and the receiver j and $\delta_{jk}(t)$ represents clock bias. The received SNR of the GPS receiver is given by

$$SNR_{dB} = 10 \log_{10}\left(\frac{P_s}{{\sigma_n}^2}\right) \tag{5}$$

where P_s is the transmitted power of the satellite and ${\sigma_n}^2$ is the noise power. The positioning accuracy is modelled with statistical attributes for realistic analysis. Whereas, the circular error probable (CEP) is defined to be 1m with 50% accuracy assigned and twice the Distance Root Mean Square (2DRMS) is considered to be 5m with 98% accuracy of GPS analysis within 2DRMS range [33].

The estimated location of GPS is modelled in 2-d space using bivariate gaussian distribution where the density function is expressed as follows

$$f(x, y \mid \mu_x, \sigma_x, \mu_y, \sigma_y, \rho) = \frac{exp\left[-\frac{\left(\frac{x-\mu_x}{\sigma_x}\right) - \frac{2\rho(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y} + \left(\frac{y-\mu_y}{\sigma_y}\right)}{2(1-\rho^2)}\right]}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \tag{6}$$

here x and y represent x and y position on the ground plane, $\mu_x$and μ_y represent the original position of the SP, σ_x and σ_y represent deviation from mean position in x and y direction on ground plane, evaluated using the CEP and 2DRMS ranges and ρ defines the symmetry where $-1 \leq \rho \leq 1$. Here $\rho = 0$, as the deviation is expected to be symmetrical in both x, y direction of the original position of the SP.

The initial transmission from the BSS, as represented in superframe in Figure 3, will initiate a chain of beacon signal transmissions from the selected SPs in extended coverage area. The beacons transmitted from the BSS and SPs allow other MS and indoor SPs (deprived from positioning information) to evaluate their position using RSS. Based on the beacon information emitted from BSS and SPs, the remaining phones will localize themselves.

The distance vector between j and k (BSS and MS pair or SP and non-SP MS pair) is evaluated as follows

$$d_{jk} = \left\{ \left(\sum_{i=1}^{I}(a_{ji} - a_{ki})^b\right)^{1/b} \,\middle|\, \begin{cases} I = 2, & 2 - dimensional\ plane \\ I = 3, & 3 - dimensional\ plane \\ \quad b = 2,\ d_{ij} \rightarrow & Euclidean\ Distance \end{cases} \right\} \tag{7}$$

The positioning information of MS is evaluated at relevant MS and transmitted to the core network via suitable transmission link to BSS. The MS connected to the BSS will pass their location and other relevant information to BSS directly, or via the most suited SP to the relevant BSS. At BSS, Eq. 8. is used to evaluate the extended distance matrix of the MS and SPs in the network. The BSS forms a centralized location-based map of each active MS/SP/BSS in the area. Location information of all active MS, SP and BSS in communications outage and neighboring areas is represented as $n \times n$ matrix, U. Where U can be expressed as

$$U = \begin{bmatrix} u_{11} & \cdots & u_{n1} \\ \vdots & \ddots & \vdots \\ u_{1n} & \cdots & u_{nn} \end{bmatrix} \tag{8}$$

here u_{jk} is the distance between the two devices j and k, where $(j,k) \in \{BSS, MS, SP\}$. In U, diagonal is all zeros.

In initial communications, apart from the location information, the MS/SPs also send the energy information, beacon sources used for position estimation and other relevant details to the BSS. It allows the BSS to decide which MS/SPs are more suitable to serve as temporary BSS in communications outage area. It is worth noticing that the smart phones share two location values: one from GPS and other from RSS. Furthermore, the position estimation is improved by using the GPS based localization of SP in comparison to RSS to introduce the correction factor. Given the accuracy of GPS, adaptive weighted correction is assumed to improve the localization accuracy of MS. The location information of each MS/UE is used in the machine learning phase which proposes region wise disaster criticality level evaluation based on originated communications from MS/UE, thus also giving an accurate disaster emergency level of different regions in disaster affected area.

Note that at least three beacons are required for position estimation of a MS in normal circumstances. In case the BSS failure is not random, rather uniformly distributed as represented in Figure 3, where a certain boundary can be established between functional and non-functional BSS, then only two beacons are required.

3.4 Cluster-Head Selection and MS distribution

The overall disaster area can be presented as shown in Figure 4. As represented in the figure, only the smart phones can serve as a CH for obvious reasons of having extended features. Note that the initial criteria for being a local cluster-head (LCH) is to be in the extended transmission range of an active BSS in first instance. The potential CHs in suitable extended coverage location are then evaluated based on four parameters: 1) Hop count, 2) delay, 3) remaining battery and 4) received signal strength. A weighted voting of all these components is used to decide which CH is more suitable. In this study, equal voting is used to evaluate smart phone's suitability to become CH. Finally, the potential CHs are compared and most suitable of all is selected as LCH.

In the extended coverage areas (CA_1, CC_{12}, CA_2, CC_{23}, CA_3) and communications outage area, the BSS will designate suitable LCHs. Any LCHs unable to connect with any BSS directly will relay information to the BS using relay MS in communication functional area. BSS will evaluate link quality, battery level, hop-count to core network, communication delay and location to identify and nominate suitable CHs. Note that the geographical location is used to create clusters, therefore, CHs are selected within each cluster space. The mathematical notation for selection of CHs is listed as follows:

$$C_{head}(j) = \left(\alpha \times H_{count}(t) + \beta \times d_{mh}(t) + \gamma \times \mathcal{E}n_j(t) + \omega \times LQ(t)\right) \tag{9}$$

i. $C_{head}(j)$ is the suitability of MS j to become a CH. $C_{head}(j)$ is compared to $\psi(i)$ where $\psi(i)$ is the threshold for deciding if a MS is suitable to work as a CH.
ii. $H_{count}(t)$ is the number of hops to the core network/BSS from the CH j.
iii. $d_{mh}(t)$ is the delay from CH j to the core network and can be modelled as a recursive function.
iv. $\mathcal{E}n(t)$ is the depleted battery level of CH j at time t.
v. $LQ(t)$ is the Radio Signal Strength (RSS) based link quality between MS j and the core network. It is evaluated in reference to the receiver sensitivity (δ_r). It is also assumed that the communication channel is symmetric. The evaluated RSSI in normalized between 0 to 1, where $LQ(t) = 1 - RSSI(t)$.
vi. Furthermore, the cost coefficients defined as α, β, γ and ω can be customized to specify contribution from each performance metric to tailor the suitability of various performance metrics in accordance with the requirements at hand.

Note that the potential CH with lowest $C_{head}(j)$ value is nominated as LCH. It is worth noticing that the threshold, $\psi(i)$, of i^{th} iteration of setup mode is given by

$$\psi(i) = \sum_{j=1}^{c_i} C_{head}(j) \Big/ c_i \tag{10}$$

here i is the number of times the setup mode is re-run. c_i is the total number of MS in the network. Each MS designated as LCH serves as a BSS to penetrate further in the communications outage area and broadcast clustering beacon using designated control channel to allow further clustering as represented in Figure 5.

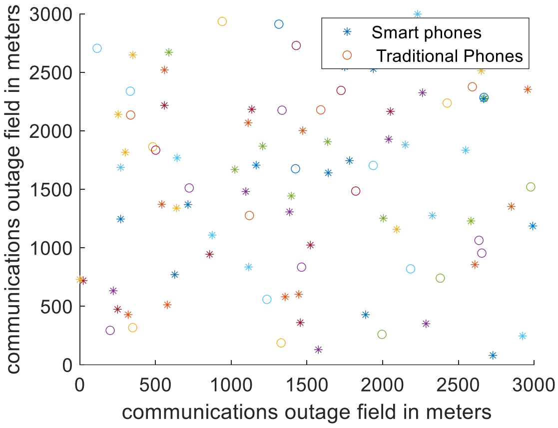

Figure 4 Field view of smart phones vs traditional phones distribution

The BSS is directly connected to the backhaul network. It distributes the assigned bandwidth among the LCHs it is serving. The proposed scenario assumes that the disaster management system (DMS) holds an approximate risk map of the region. Thus, based on this information the bandwidth allocation is tailored. An example scenario is presented in Figure 5. In this figure, based on failure statistics in the core network, the communication outage area is highlighted (see Figure 5 green region). In this region, MS, unable to connect with the BSS will tune to the control frequency for further instructions. Once the clustering instructions are received the MS in this area will either use GPS or triangulation to identify its location and submits its other attributes (battery level, range, hop-count) to BSS. MS, depending on its attributes will be elected as LCH. Once the LCH broadcasts clustering message, the MS in the vicinity will join the LCH and become cluster-member (CM). Each elected LCH will be responsible for three tasks: 1) periodically broadcasting clustering message on control channel, 2) downloading emergency content from the BSS to disseminate up to date disaster related information to the CM, 3) It will coordinate communications from CM to backhaul.

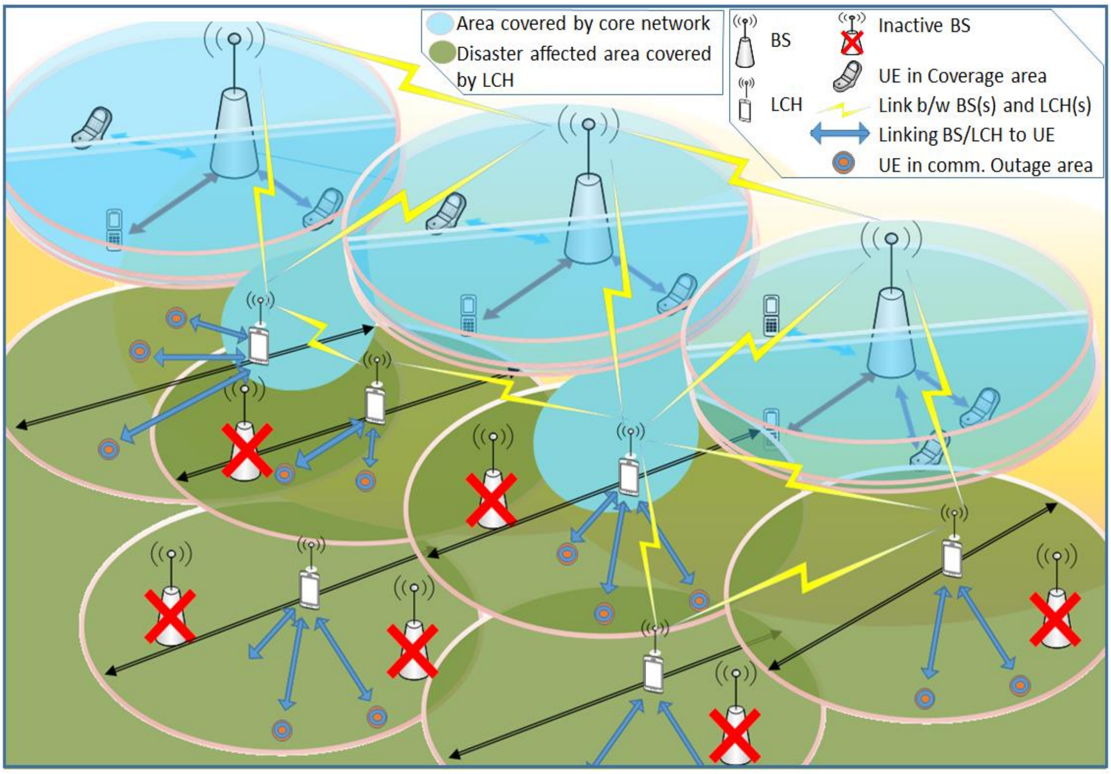

Figure 5 Network Diagram

Each LCH will behave as a BSS for next-hop LCH and will provide basic services. In addition, a log will be maintained to designate each MS either into Cat-1 or Cat-2 devices. In Cat-1, high end capability MS with potential to become LCH will be included, which can take over some of the radio access network (RAN) functionalities when one or more BSS/LCH becomes dysfunctional. Such functionalities may include providing synchronization signals, directing d2d links and managing the resource usage among a group of d2d devices (UEs) associated with it. In Cat-2, MS which can only act as CM are considered, where these MS are controlled by appropriate Cat-1 LCH. The Flowchart for LCH-identification and Cat-1/Cat-2 distribution of MS is presented in Figure 6.

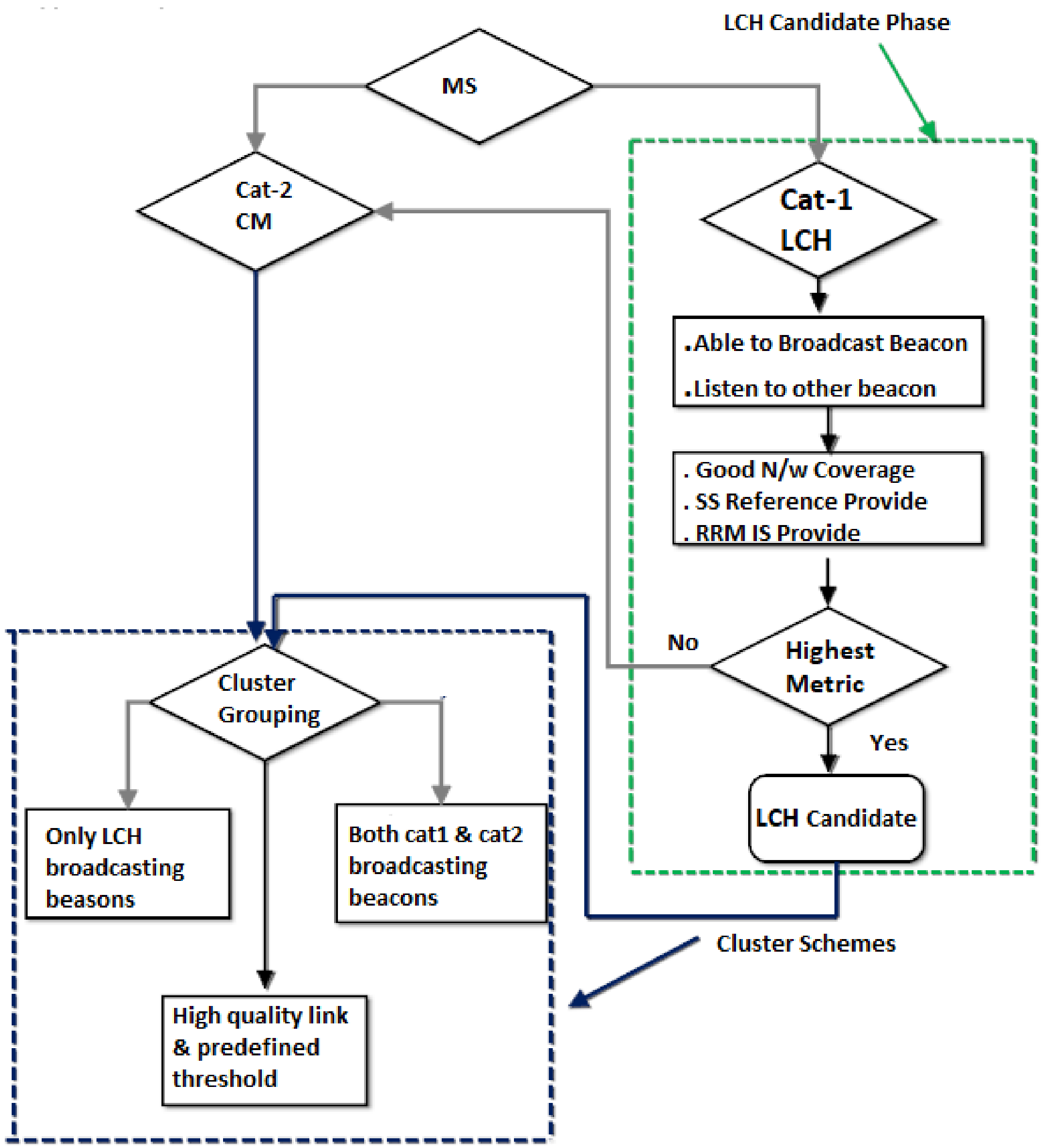

Figure 6 Mobile station labeling and local cluster-head (LCH) selection

The allocated bandwidth for each nominated LCH is distributed in frequency division multiple access (FDMA) and TDMA where multiple communication streams can be established from affiliated CMs. The communications from CMs to LCH is established in star topology. Whereas the communications between the LCH and BSS is established in single-hop ($|\ H_{count} = 1$), or multi-hop ($|H_{count} > 1$) communications.

To manage the proposed scenario more effectively, a coalition formation algorithm is proposed to form the clusters in the most energy-efficient way. The proposed algorithm forms clusters among all LCHs in a way to reduce the average energy consumption. As soon as a MS decides to enter/form a cluster, it enters a binding agreement with the other UE within the coalition, and then considers the benefit of the coalition above its individual benefit.

In addition, the proposed approach is considered to maximize the overall throughput for the public safety network (PSN). To maximize the throughput of all MS/UE, optimization problem is formulated which is presented as follows:

$$\max(R_{total}) \tag{11}$$

$subject\ to$:

$$r_{kn} \leq C_o,\ \forall\ ch \in CH \tag{12}$$

$$\sum_{n \in N} \eta_{kch} \leq 1\ , \forall\ k \in K \tag{13}$$

$$\sum_{k \in K} \eta_{kch} \leq q_n\ , \forall\ ch \in CH \tag{14}$$

$$\eta_{kch} \in \{0, 1\}, \forall\ k \in K\ \&\ \forall\ ch \in CH \tag{15}$$

Here, the objective function in Eq. 11 represents the overall throughput of all present MS/UE in the disaster area.

- The constraint in Eq. 12 implies that the rate for each user should not exceed the Shannon capacity limit, C_o, of the channel.
- The constraint in Eq. 13 implies that each MS_k may be allocated to maximum one LCH or not allocated to any LCH at all.
- The constraint in Eq. 14 suggests that the maximum number of allocated CM to LCH cannot exceed its capacity (i.e. the maximum number of servable CMs).
- The constraint in Eq. 15 defines the binary nature of η_{kch} variable.

Whereas, K is the set of MS, C is the set of clusters**,** R_{total} is accumulative throughput of all MS/UE, η_{kch} is a binary variable with value 1 if MS_k is allocated to CH, and 0 otherwise.

The total number of available resource allocations to the MS/UE by LCH is given by

$$q_n = C_n / R_B \tag{16}$$

where C_n is the Shannon capacity of LCH and R_B is the allocated capacity of individual UE.

It is worth mentioning that the analyses depict throughput gains obtained by appropriate cluster selection. Each LCH is considered to have several MS connected to it as shown in Figure 5. The expected MS/UE affiliation with a suitable LCH is usually governed by distance-based schemes. However, in the proposed work, the affiliation is achieved using the above throughput optimization function. It enhances the throughput and allows the affiliation of MS to suitable LCH which results in enhanced throughput. Thus, in this work, the proposed optimization technique provides better throughput in contrast to distance based affiliation of CMs. The work showed that the throughput of the network can be improved significantly by optimally affiliating the CMs to appropriate LCHs. The affiliation of MS/UE with LCHs is presented in Figure 7.

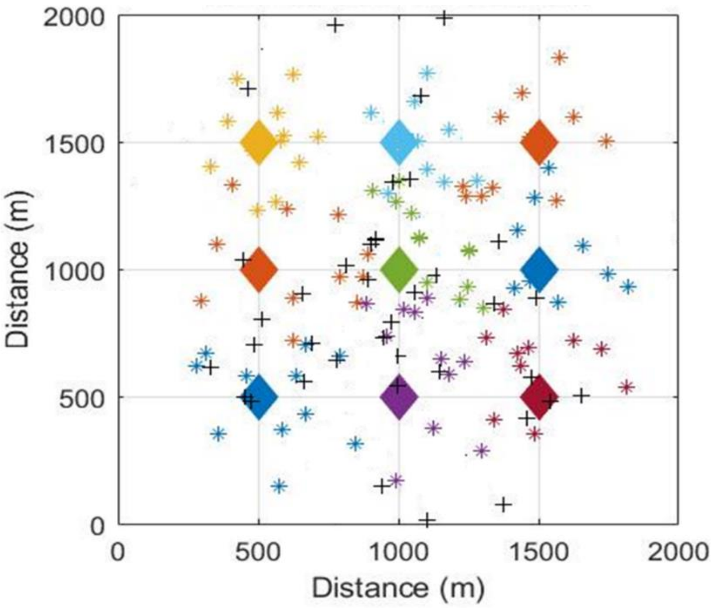

Figure 7 Optimal affiliation of cluster-members (CMs) with local cluster-heads (LCHs) in disaster area

In Figure 7, the affiliated UE is represented by a star of the same color of the diamond, which is representing an LCH. The black plus signs signify the UE that are not affiliated with any LCH. Further details on the performance of proposed scheme is presented in Section 5.

4. Machine learning based region wise disaster severity detection using social media platform

A machine learning based disaster severity evaluation in different regions using social media platform is proposed along with the communication model for disaster affected areas. The fundamental objective of analyzing social media based platform in this study is to perform pre-disaster vulnerability prediction and localize disastrous areas until the communication infrastructure sustains. The role of proposed AI-empowered disaster detection system using social media is to assist government officials and emergency services to identify threats and overall vulnerability. The proposed machine learning scheme evaluates impact in different disaster affected areas where severity of underlying conditions is analyzed based on messages/pics/sentiments from the social media users within a certain geographical boundary. It is assumed that users' approximate location is known. Further details of the proposed machine learning technique and implemented system are presented in following subsections.

4.1 Dataset

The dataset used in this study in obtained from CrisisLex [34]. It is a data repository that uses social media platform (i.e. twitter) to understand the presence of disaster within a geographical boundary. CrisisLex contains the dataset of natural disasters (floods, hurricanes, tornados) as well as manmade disasters (explosions, bombings). This study utilizes only dataset of natural disasters and flooding in particular. The flooding dataset refers to 2013 flooding occurred in Alberta, Canada. The dataset was labeled using the crowd flower data annotation platform where each data sample (tweet) was labelled to either non-flood (irrelevant to Alberta flooding) or flood (relevant to Alberta flooding).

4.2 Pre-processing and feature-extraction of the dataset

The flood related social media messages obtained through twitter require extensive pre-processing before any feature extraction. It is essential in most of the natural language processing tasks to omit the unrelated information and to reduce the redundant information. For this purpose, regular expression (RE) operations and natural language toolkit (NLTK) [35] libraries have been used in python to remove the special characters, hashtags, URLs, punctuations, stop words. The resulted dataset is processed further through stemming and lemmatization operations, which helps to derive the root or basic form of words that can eventually ease the feature-extraction and further processing. Stemming is followed by feature extraction which is obtained through bag of words. This is a process to compute features from the text in such a way that the machine learning algorithm can be implemented to extract the meaningful patterns from the dataset. Bag on words consist of two steps: 1) build a vocabulary of the words within the dataset at hand, 2) compute the occurrences of each word in each data instance or data sample (a single tweet in our scenario). After building the vocabulary, vectorization was used as a measure of the occurrences of each word within a tweet or data sample. Vectorization converts the text into sparse matrix and each entry of this sparse matrix corresponds to the occurrences of a certain word within a tweet. The overall data processing pipeline of the proposed system in presented in Figure 8.

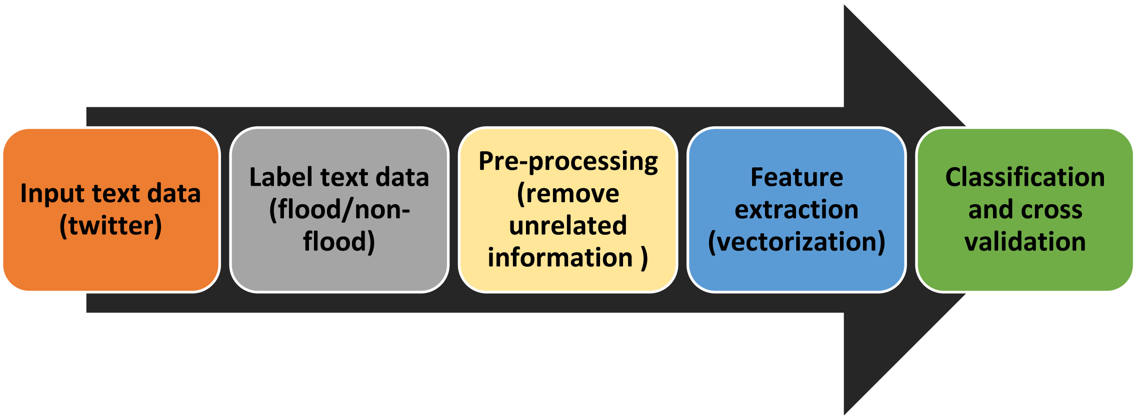

Figure 8 Data processing pipeline of disaster related information detection through machine learning

4.3 Classification and cross-validation

The proposed machine learning based disaster prediction model uses Multinomial Naïve base (MNB) classifier and XGB [36] implementation of gradient boosting classifier. The performance of the proposed classification models is evaluated on social media platform (Twitter) for detecting the flooding within a geographical boundary. The simulation parameters of XGB classifier are as follows: number of estimators=10, minimum child weight=7, learning rate=0.01, gamma=0.5, maximum depth=9. The pre-processing and feature extraction state resulted into 9865 data samples. The processed dataset is divided into 70/30 cross validation strategy in which 70% of the dataset is used to train the classifier and 30% is used for performance validation of the trained model. In this way, training and validation dataset comprised of 6905 and 2960 data samples respectively. Accuracy is used as evaluation metric to compute the performance of the proposed method and to compare the performance of the classifiers.

5. Results and Discussion

5.1 Performance evaluation of proposed communication infrastructure

The performance of the proposed clustering scheme is evaluated based on number of MS/UEs affiliated with the LCH, system throughput and energy efficiency. In the proposed scheme, the affiliation of UE is conditional to the throughput optimization, where if two UE can be affiliated to two LCHs, the selection will be made based on which UE's affiliation to which cluster maximizes the throughput. The results of the proposed throughput optimization scheme are also compared with the state-of-the-art distance-based affiliation scheme (D-Allocation) where affiliation to a cluster is dependent on the Euclidean distance.

In Figure 9, the results for both, distance-based scheme and the proposed scheme are presented. In the figure, the number of requesting MS/UEs are presented on x-axis, whereas the number of affiliated MS/UE are presented on y-axis. Although the performances are relatively similar, yet the proposed approach still offers slight improvements out of the two by examining it more closely. In case of increasing bandwidth from 10 MHz to 15 MHz and 20 MHz, a linear increase in allocations of UE is observed. In case of higher bandwidths (20MHz), the proposed scheme allows up to 8 additional MS/UE to be serviced by LCH.

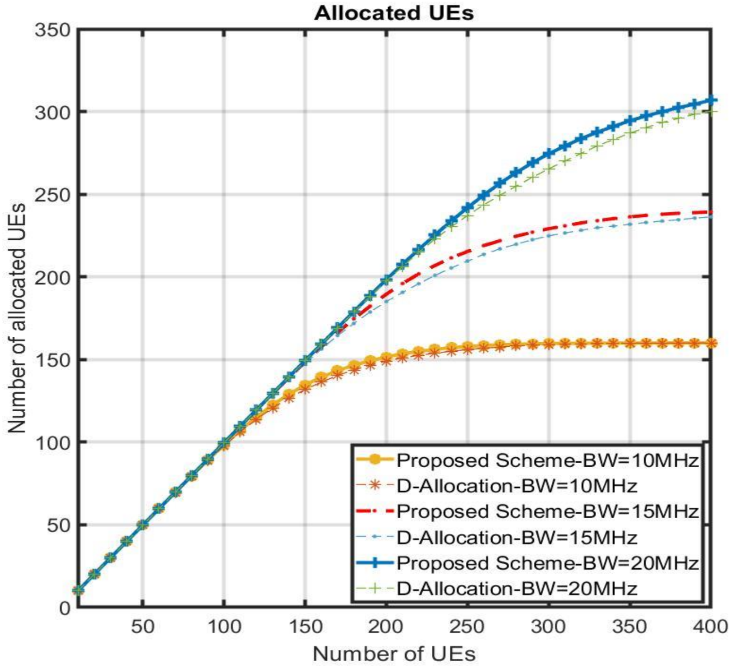

Figure 9 Allocation requests and allocated UE

In Figure 10, the system throughput for both D-Allocation and proposed scheme is presented. It can be observed that the system throughput increases as the number of MS/UEs increases where saturation is reached sooner for lower bandwidths and later for higher bandwidth systems. This is due to the resource limitations dictated by the system bandwidth. In the presented results in Figure 10, the proposed scheme performs much better than D-Allocation, where notable improvement in throughput can be observed.

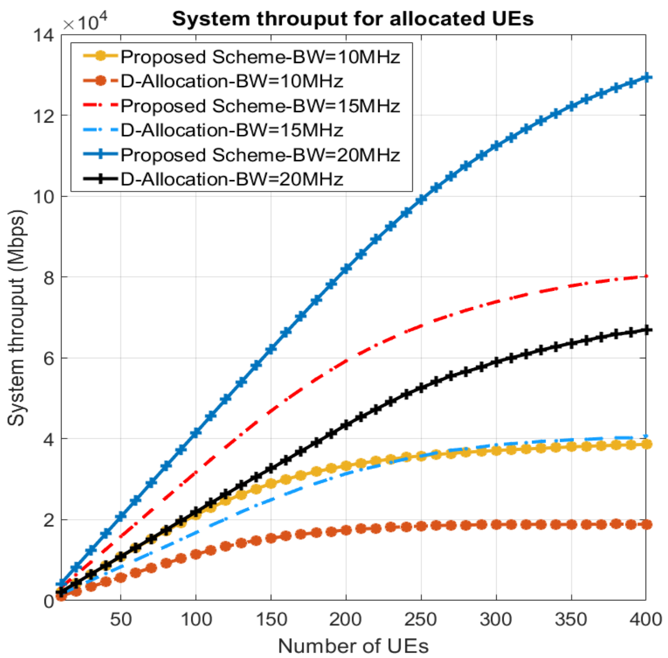

Figure 10 System throughput

The limited access to electricity in disaster affected area makes energy efficiency an important attribute of any ad-hoc clustering and communication scheme. In Figure 11, the energy efficiency of the proposed scheme is presented as a function of average distance between the affiliated UE and LCH. With the increase in distance, the energy efficiency of the system suffers. Increase in distance also leads to lower SNR and thus leading to poor throughput at the expense of same energy consumption. In Figure 11, steady curves can be seen, where energy efficiency decreases with the increase in average distance. Overall, the proposed work offers improved throughput and increased number of UEs which can be serviced by a cluster, however, it consumes relatively high energy. Nonetheless, scheme offers a suitable mechanism to restore communications in disaster affected and communications outage area.

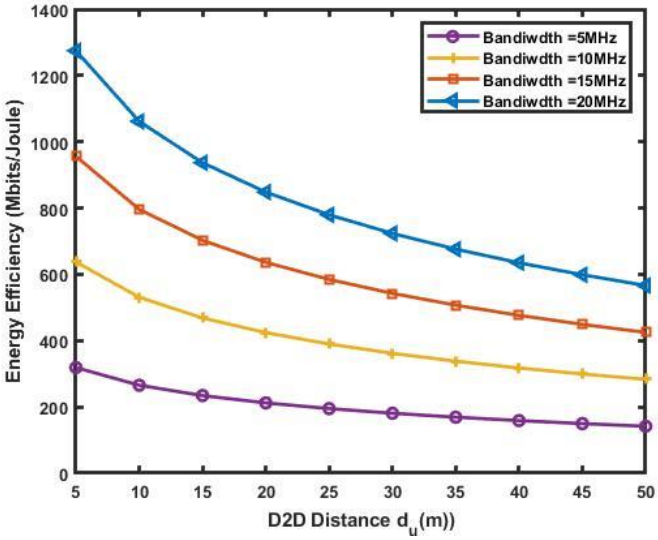

Figure 11 Energy Efficiency as a function of average distance of CMs

In addition to the ad-hoc communications framework, this work also extends its contribution with effective evaluation of the localized disaster situation in relatively larger disaster affected area. Machine learning based intelligent systems are proposed where accurate analysis of communications (messages/pics/videos/sentiments) originating from specific region is performed to identify disaster situation in the area. As a proof of concept an existing database is used to evaluate the accuracy of proposed machine learning scheme. Further details are as follows.

5.2 Performance evaluation of machine learning based disaster detection system

The performance of proposed MNB and XGB is evaluated to check suitability of proposed methods in classifying flood relevant and flood irrelevant tweets. Both classifiers i.e. MNB and XGB performed well in classifying the non-flood and flood related messages with an accuracy of above 90%. The achieved accuracy to differentiate flooding vs non-flooding events shows the strength of proposed system in localizing the flood within a geographical boundary. The XGB classifier performed better than MNB classifier with performance of 95.80%, while the MNB classifier achieved an accuracy of 91.22%. The confusion matrices obtained for MNB and XGB classifiers are presented in Table 3 and Table 4 respectively.

Table 3. Confusion matrix of MNB classifier

Accuracy 91.22%	**Predicted class**		
Actual class	**Classified as →**	**non-flood**	**flood**
	non-flood	1224	205
	flood	55	1476

Table 4. Confusion matrix of XGB classifier

Accuracy	**Predicted class**

95.80%			
Actual class	**Classified as →**	**non-flood**	**flood**
	non-flood	1365	64
	flood	60	1471

These findings show the strength of machine learning algorithm in detecting regional floods through social media platform. Although, this work only uses the twitter platform as a data source due to the unavailability of other means of data gathering mediums such as short messaging services (SMS), audio and video messages, yet the proposed method can easily be extended to mobile platforms using cellular networks, where flood affected inhabitants can inform the regional authorities and rescue services through SMS and other means.

The SMS data source is much more realistic and effective than twitter in instances where communication infrastructure is already collapsed. In such conditions, proposed machine intelligence based data processing pipeline can also help in localizing the emergency cases in severely affected area. Nevertheless, twitter-based pre-disaster vulnerability detection and finding the epicenter of the disaster for emergency aid are key contributions of such systems, Moreover, the proposed data processing paradigm can easily be translated to other natural disasters such as earthquake, hurricanes, tornados, wildfire etc.

6. Conclusion

Natural disasters significantly impact natural habitat and socioeconomic system. The significance of communications in effective post-disaster support and rescue, is undeniable, therefore, in this work, an ad-hoc cluster formation framework was proposed to establish communications in disaster affected and communications outage areas. The work also incorporated convex optimization for throughput enhancement and localization of UE for novel machine learning based identification of disaster struck areas. The proposed work effectively establishes communication infrastructure to facilitate communications in the affected areas. In addition, the proposed machine learning scheme assists in identifying critical regions in the affected areas by analyzing bulk information through social messaging platform. The results have been very favorable and offered improvement in throughput and serviceable users in newly formed clusters in comparison to state-of-the-art. A relatively high accuracy of above 95% was also achieved on CrisisLex flooding dataset while using the proposed machine learning based approach. However, there are certain limitations of the work. The proposed cluster formation scheme suffers from low energy efficiency and in future can be further improved with the help of suitable transmission power control and energy optimization scheme. In addition, analysis of the anonymized disaster region data can be used to generate risk maps and vulnerable regions in post-disaster phases.

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