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ORIGINAL RESEARCH

Crowd sensing aware disaster framework design with IoT technologies

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Abstract

When a disaster occurs, a huge amount of inconsistent victim or damage information data is received by many different sources. Disaster management systems achieve the completion of a significantly vital task, which is to reduce the number of victims or amount of damage caused by a disaster, with real-time information monitoring infrastructure. A fundamental role of these systems that could help rescue teams is to make a quick and accurate decision about the region that will be affected by the disaster and the possible effects of the tragedy. Employing IoT solutions in these systems provides the possibility of rapidly and precisely orienting rescue teams to be dispatched to the disaster area and also quickly receive specific information about the effects of the disaster. To achieve this purpose, we present a post-disaster framework using the IoT communication technologies for disaster management based on the proposed crowd sensing clustering algorithm in this paper. The proposed framework provides information about the damage status of buildings with crowd density data along with efficient real-time data collection, data aggregation, and the process of monitoring dissemination stages. This framework realizes clustering of resident density by using the cellular networks and Wi-Fi connections and calculating the damage status of buildings through the designed and specifically implemented IoT unit data. Furthermore, it employs a fuzzy logic-based decision support system to manage the resources. The proposed framework, on real base stations and access points dataset, has shown significant results for identifying crowd densities with the highlighting status of buildings in the disaster area.

Keywords Cellular and Wi-Fi networks · Fuzzy logic · Clustering · Crowd sensing · Disaster management · Internet of things (IoT) · Online monitoring

Abbreviations

API	Application programming interface
SAR	Search and rescue
IoT	Internet of things
IDE	Integrated development environment
MQTT	Message queue telemetry transport
RFID	Radio frequency identification
Wi-Fi	Wireless fidelity
BS	Base station
AP	Access point
GPRS	General packet radio
GSM	Global system for mobile communication
3G	Third generation
4G	Fourth generation
HDFS	Hadoop distributed file system
TCP/IP	Transmission control protocol/internet protocol
CSS	Cascading style sheets
HTML5	Hypertext markup language 5
SENDROM	Sensor networks for disaster relief operations management
JDK	Java development kit
QoS	Quality of service

List of symbols

a	Acceleration
v	Velocity

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s	Distance
SA	Static acceleration vector length
a_x	The latitude component of the static acceleration vector
a_y	The longitude component of the static acceleration vector
a_z	The altitude component of the static acceleration vector
DA	Dynamic acceleration vector length
b_x	The latitude component of the dynamic acceleration vector
b_y	The longitude component of the dynamic acceleration vector
b_z	The altitude component of the dynamic acceleration vector
G	Gravity
VA	Vertical acceleration vector length
Θ	Angle of rotation of the building
ϑ_y	The x-axis angle of rotation vector of the IoT-unit
ϑ_y	The y-axis angle of rotation vector of the IoT-unit
ϑ_z	The z-axis angle of rotation vector of the IoT-unit
D^{BS}	The base station data set
D^{WF}	The access point data set
PN	The subscriber's phone number
φ^{BS}	The base station's latitude
λ^{BS}	The base station's longitude
t^{BS}	The subscriber connection time to the BS
Δt^{BS}	The duration time of the subscriber
MAC	The user's MAC number
φ^{WF}	The access point's latitude
λ^{WF}	The access point's longitude
t^{WF}	The user connection time to the AP
Δt^{WF}	The duration time of the user
d^{BS}	The distance between the two BSs
d^{WF}	The distance between the two APs
R_e	The radius of the equator
R_p	The radius to the north pole
φ_c	The latitude of the cluster center
λ_c	The longitude of the cluster center
ΔT^{BS}	Time difference between two base station data
ΔT^{WF}	Time difference between two base station data
$user\_n_c$	The number of smart phone users attained to the BS
$T_{BS_{MAX}}$	The subscriber duration time threshold for the BS
$T_{WF_{MAX}}$	The user duration time threshold for the AP

1 Introduction

Natural or non-natural disasters can cause the loss of human life, as well as destruction and damage to the affected economy, infrastructure, and transportation systems. After a disaster, search and rescue (SAR) operations are carried out by public or private organizations. When a disaster occurs, SAR teams try to reach the disaster area as soon as possible. Moreover, the efficient use of limited resources during a disaster is very significant. Disaster management carries out the organization and management of resources, including SAR teams and equipment. In other words, disaster management systems conduct the SAR processes. Consequently, efficient disaster management systems reduce the number of victims and the damage from disasters (Sharma and Sharma 2016; Sakhardande et al. 2016; Fersini et al. 2017).

Internet of things (IoT) solutions—which have widespread usage areas, such as smart home applications, smart cities, healthcare, and remote monitoring—aim to increase the quality of life (Hsu and Lin 2018; Tokognon et al. 2017; Mahmud et al. 2017). Generally, IoT is a global network of smart devices and hardware that communicates using various protocols and has sensing capabilities. Nowadays, IoT-based technologies, including radio frequency identification (RFID), Wi-Fi, wireless sensor networks, and mobile phone systems are a source of a massive amount of data, and this data can be used for many problems (Inoue et al. 2014; Kim et al. 2015; Alphonsa and Ravi 2016; Zafar and Afzaal 2017; Durresi et al. 2019). In recent years, these technologies have been used in disaster management systems (Atzori et al. 2010; Zanella et al. 2014; Al-Fuqaha et al. 2015).

The impacts of disasters can be reduced by employing efficient disaster management systems equipped with IoT technologies (Kamruzzaman et al. 2017). In a disaster case, applying IoT technologies provides many advantages. First, IoT provides disaster management systems with fast, accurate knowledge about the effects of a disaster on a region. Second, this kind of system offers adequate management and scheduling of resources, such as rescue personnel, equipment, and vehicles. Another advantage is the realistic risk assessment (Spalazzi et al. 2014; Kamruzzaman et al. 2017). Therefore, employing IoT technologies facilitates the process of disaster management (Sakhardande et al. 2016). However, the application of IoT-based post-disaster management solutions is still an unknown subject area at this time (Ray et al. 2017). Accurate determination of the number of people in a disaster with position information is the most important problem for the disaster management systems. Therefore, the use of IoT technologies for crowd sensing can reduce system cost and provide timely delivery with the required resource (Liu et al. 2018; Sharma et al. 2018).

The most critical data for the disaster management systems is the crowd density, which is provided with the location information (Sharma et al. 2018). This density can be obtained with different sensors and technologies (Fersini et al. 2017). The connection information of the smart devices is one of the solutions that can provide a data flow for these systems. This connection information generates a huge amount of real-time data. In order to effectively extract and organize from the huge amount of data available in the data networks, we need to design and implement several efficient data stream, computational and monitoring techniques able to deal with unstructured nature of the user-generated mobility information. The main challenge is, therefore, to realize of the hardware that can provide real-time information for specific region, design the clustering algorithm that can effectively determine the specific disaster region and provide the decision support mechanisms that can quickly support the SAR teams. The alarm which is included the potentially critical region information for a disaster case should be communicated to the SAR teams with real-time crowd density related to the building status information in order to speed up the decision-making process. As a result of the effective determination of crowd density and building status information, it is ensured that SAR teams perform their complex tasks effectively.

The primary objective of this proposed study is to design and implement a disaster framework based on IoT technologies. Before a disaster occurs, the cellular network subscribers and Wi-Fi users enter the communication range of the base station and access points of a specific region, and the proposed framework captures the connection data from BSs and APs. It has two main components. On the other hand, the implemented IoT-unit broadcasts the buildings acceleration and gyroscope data using cellular or Wi-Fi communication technologies; then, the proposed framework records the status of the building in real-time. When a disaster occurs, the IoT units detect each building status using building damage procedure to inform the framework. Then, the proposed framework run resident density clustering mechanism to determine resident density in the specified region. So that SAR teams efficiently manage the disaster recovery progress. We present two main components in this paper to manage the disaster among the IoT unit, the cellular network, and the Wi-Fi network. First, a designed and implemented IoT unit consists of sensors, communication units, microcontrollers, etc., and is deployed on critical structures, such as hospitals, public buildings, dams, bridges, and viaducts. Its primary task is to collect data on the status of the structure on which it is deployed and send the collected data to the cloud. To connect to the cloud, the IoT unit employs a message queue telemetry transport (MQTT) protocol as an IoT connectivity protocol (Al-Fuqaha et al. 2015). MQTT is a commonly used lightweight publish/subscribe messaging transport protocol that has efficient features compared with other IoT connectivity protocols. Second, the IoT analysis platform enables to conduct of the disaster framework. This platform performs several functions, including aggregating data, analyzing and monitoring the data collected from the disaster area through the IoT technologies. To this end, the IoT analysis platform consists of four key components: (1) calculations of building damage status, using data received from IoT units; (2) a resident density clustering mechanism for the disaster region, developed through IoT technologies, such as mobile phone records and Wi-Fi connections; (3) a decision support system based on fuzzy logic, considering building damage status and resident density data in order to manage resources efficiently; and (4) a user interface. Therefore, the platform provides information about disaster areas for users. We implement a disaster management framework that collects data connection and building status and analyzes them using Apache Kafka and Apache Spark Streaming in conjunction with Hadoop in order to address the database limitations. Also, this framework monitors the resident densities with the status of building using ESRI geospatial cloud (ArcGIS Online 2019).

1.1 Contributions

The contributions of this paper are as follows:

- Propose and implement a post-disaster management framework for disaster recovery when allocating tasks to SAR teams.
- Present an efficient hierarchical clustering technique based on IoT technologies which are the cellular and Wi-Fi networks so that SAR teams and their resources are efficiently managed to prevent resource overload, in accordance with the information obtained from the IoT unit, including building damage levels and number of residents.
- Define how disaster management systems can be used to exploit IoT based technologies for IoT based effective crowd sensing in location-specific areas and for supporting information exchange about structural damage.
- Implement the IoT unit for the proposed disaster framework.
- Use the fuzzy logic-based decision support system for the proposed disaster framework.
- Propose efficient disaster management framework design with environmental setup for IoT based crowd sensing.
- Demonstrate simulation-based experiments showing performance in terms of resident density population statistics.

Disaster management systems need different requirements, such as fast response, a lifetime network, interoperability, ease of use, equipment cost, and network coverage or infrastructure. The proposed framework focuses on the prediction and monitoring phases of post-disaster management systems. Therefore, setting up a communication infrastructure after the disaster is out of the scope of this manuscript.

The basic organization of the paper is as follows: Sect. 2 introduces some background and related works about disaster management with IoT technologies. The details of the proposed disaster management system are introduced in Sect. 3. And the example scenario case for evaluation of the proposed disaster framework is presented in Sect. 4. Finally, Sect. 5 is the conclusion of the realized study.

2 Related work

This section covers the relevant studies on disaster management based on IoT technologies. Many studies have been proposed on IoT-based disaster management in the literature to reduce disaster effect. These systems use different communication technologies including cellular, non-cellular, bluetooth, etc., focus on different disaster events such as an earthquake, flood, landslide, etc., and employ various sensors. Consequently, there is no general model or a benchmark for performance assessment due to the ranges of the disaster management system are so versatile. Therefore, we present a comparison of disaster management studies regarding IoT technology, feature, motivation, application area, classification, performance evaluation, and method in Table 1. According to this comparison, most of these studies have focused on building the communication infrastructure for disaster moment and post-disaster. Besides, post-disaster studies require the installation of an additional hardware unit to the building or structure. However, the proposed framework offers a flexible architecture that can be implemented for the post-disaster organization with the existing cellular and Wi-Fi network infrastructure without creating any additional hardware overhead.

Sakhardande et al. (2016) present a system of interworked smart modules to use IoT technologies in disaster management systems and smart city monitoring applications. Arduino based smart modules communicate with each other and with the central monitoring system through Wi-Fi. An IoT based early warning system for crisis management in case of natural disasters such as earthquakes, tsunami, and so on is introduced (Poslad et al. 2015). In another study, an overview of disaster management project using wireless sensor networks is presented (Benkhelifa et al. 2014). Notably, this study emphasizes the importance of collecting and sharing data about the disaster. Bhosle and Gavhane (2016) propose a disaster management system model using a wireless sensor network in the forest. When a sensor node deployed in the forest senses a blazing case, it sends to sink node this information via wireless links. They do not implement any physical application in their work (Bhosle and Gavhane 2016). Authors in Kamruzzaman et al. (2017) proposes an IoT-based communication framework as an alternative to the cellular network for post-disaster management. Authors in Vojtech et al. (2015) have used RFID technology and developed RFID localization system to the control of the disaster. Active RFID IoT units are included in triage tags that are fastened to all casualties during the first step of rescue teams with a mobile terminal in their maps. Resilient disaster information gathering and urban crowd mobility prediction mechanisms based on the edge computing paradigm are described for building safety and smart cities resistant to disasters in Higashino et al. (2017). In particular, the prediction of the probability of the flood in a river basin is achieved based on IoT technologies and machine learning methods (Ghumman et al. 2004). The prediction system compromises a network connection using ZigBee for the sensed information and a general packet radio service (GPRS) module to transmit this information. The artificial neural network model used this information to predict the flood probability. Authors in Cao et al. (2016) point out some complications such as the traffic management, security of the child, and energy management of existing implementations indicated that emerging IoT technologies could assist in overcoming these complications and proposed specific IoT services as solutions. Cayirci and Coplu (2007) presented a new architecture namely sensor networks for disaster relief operations management (SENDROM) based on sensor network to manage rescue operations in the case of a disaster such as an earthquake. SENDROM has two type sensor nodes including a sensor node and the central node. Sensor nodes are randomly deployed to the disaster region and provide information about living people in the disaster area. Primary nodes gather data from sensor nodes and deliver obtained data to disaster management system database.

Nevertheless, these studies aim to manage different type of disasters with some useful IoT techniques. Our proposed disaster management system has several significant advantages. One is that it obtains fast and accurate information from the disaster area due to employing IoT technologies. Another one is it includes multiple IoT-based technologies such as IoT-unit, mobile phone records, Wi-Fi connections. The third advantage is the decision support system that contributes to making the right and fast decisions for disaster management system users.

3 The proposed disaster management system

3.1 System overview

The illustration of the proposed system architecture is shown in Fig. 1. The proposed disaster framework using

Table 1 Comparison of various techniques for disaster mitigation system with the proposed framework

Article	IoT technology	Feature	Motivation	Application	Class	Performance evolution	Method
Inoue et al. 2014	Wi-Fi, Ethernet, FWA, Satellite	Bypass networks	To maintain communications after a disaster	Earthquake	Natural disaster management	No	Disaster mitigation
Kim et al. 2015	BLE, 3G/LTE	Monitoring gas facilities	To produce decision support and damage prediction rate	Volcanic	Natural disaster management	No	Prediction
Alphonsa and Ravi 2016	WSN	Zigbee	To measure and warn people	Earthquake	Natural disaster management	Yes	Prediction
Manaffam and Jabalameli 2016	RFID	Clustering	To communicate with nearby things	Localization	Natural disaster management	Yes	Prediction
Ahmed and Morita 2017	N/A	Statistic based	To identify correlations between the emergency response and population density	Earthquake	Post disaster management	Yes	Management
Wu et al. 2011	RFID	Management information system	To accomplish the management, scheduling, and tracking of resources	Earthquake	Natural disaster management	No	Management
Zafar and Afzaal 2017	WSN	Mathematical approach	To correspond store, process and transmit the information with the graph-based model	Earthquake	Post disaster management	No	Disaster mitigation/management
Kamruzzaman et al. 2017	Wi-Fi, Cellular networks, BLE	Framework	To provide an insight into the existing IoT-based work and maintain communications	Earthquake, Flood, Tsunami	Post disaster management	No	Management
Proposed Framework	Wi-Fi, Cellular networks	Crowdsensing and clustering	To realize the management of the rescue teams and tracing of resources	Earthquake	Post disaster management	Yes	Prediction

IoT technologies consists of two tiers: (1) IoT-unit and (2) IoT-analysis platform that processes the obtained data by using IoT technologies.

IoT is a network system that consists of things that have sensing, communication, addressing, and data processing capabilities. IoT-unit includes sensors, communication units, and microcontroller. They connect to the internet or cloud using an IoT communication protocol. Primarily, our study focuses on disasters including earthquake, building destruction, etc. Therefore, we assume that IoT-units are deployed on different structures including public building, dam, bridge, etc. IoT-units track status of the constructions in which they are placed and send sensed data to the IoT-analysis platform through an IoT communication protocol. We use the MQTT protocol that is a lightweight publish/subscribe messaging transport protocol for the communication between IoT-units and IoT-analysis platform.

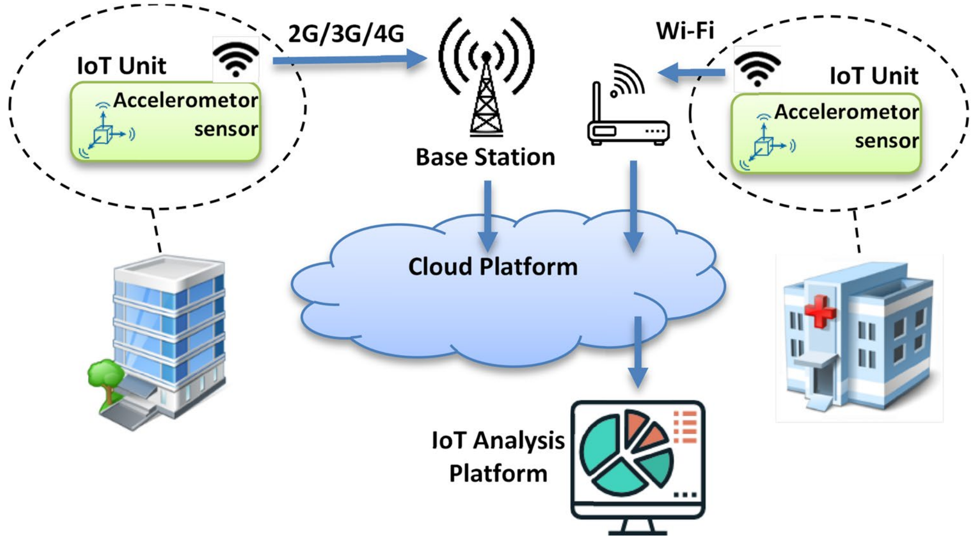


Fig. 1 The proposed framework architecture based on IoT technologies

IoT-analysis platform is the most crucial part of the proposed disaster management system. The platform aims effective disaster management. To this end, it has a decision support mechanism based on fuzzy logic. The platform performs many tasks. Firstly, it records, monitors, and analyzes the received data from IoT-units and other IoT technologies on disaster area. Also, we assume that the IoT-analysis platform uses data from many different IoT-based systems including mobile phone records, Wi-Fi connections, etc. By considering the collected data from IoT-based systems, the IoT-analysis platform performs clustering, determining damage status via IoT-unit data, organization, and management of resource including SAR team's, equipment, etc., in case of disaster. The simplified state machines of the proposed disaster framework are distinctly given in Fig. 2. The proposed framework is divided into two parts in the state machine diagram. According to this; IoT-unit can be found in four different states such as idle, read IoT-unit status data, read accelerometer data, and send data. While idle is unforced state, the others are forced state. IoT-analysis platform consists of five different states which are idle, collect and store user density, perform preprocessing, clustering engine for disaster area, run decision support system, and monitor the population and the IoT-unit. Here idle and perform preprocessing are unforced state, the others are forced state. These two separated parts of the state machine diagram are connected with send data and clustering engine for disaster area states. To decrease the energy consumption of IoT-unit, sensed data is sent to IoT-analysis platform when data change has been detected.

3.2 IoT unit

Figure 3 shows the block diagram of the designed IoT-unit. IoT-unit consists of an embedded system having a microcontroller (e.g., Arduino, Raspberry Pi), a wireless communication unit (optionally Wi-Fi, ESP8266, GSM/GPRS, 3G, 4G etc.), a sensor unit including an accelerometer, barometer, gyro, etc. (e.g., ADXL 345, BMP180), and battery. Sensor unit senses the status of the deployment building such as direction and distance destruction of constructions etc., and transmits the sensed data to IoT-analysis platform through IoT connectivity protocol. The wireless unit enables communication between IoT-unit and IoT-analysis platform.

MQTT, one of the most popular IoT connectivity protocols is used. MQTT is an extremely lightweight messaging protocol for IoT devices that can operate with a constrained resource such as low bandwidth links, memory, processing capability, etc. MQTT has been employed in various fields including smart city, energy monitoring, healthcare, and so on. In 1999, MQTT was developed by Dr. Andy Standford-Clark of IBM and Arlen Nipper of Arcom (Al-Fuqaha et al. 2015). It was standardized in 2013 at OASIS-MQTT protocol has two significant specifications including MQTT v.3.1 and MQTT-SN (Bhosle and Gavhane 2016; MQTT 2019; ISO/IEC20922:2016 2016).

MQTT protocol is built on TCP/IP protocol, and it enables IoT devices to connect to the internet (cloud). MQTT is a Client–Server publish/subscribe messaging protocol. MQTT is comprised of three components: (1) publisher, (2) subscriber and (3) a broker as seen in Fig. 4. The publisher is a data generator and the source of data. The purpose of an IoT device as a publisher is to send sensed/generated data to subscribers. The data consist of two components named message and topic. Subscribers that are the consumer of the data receive published data to process and analyze. MQTT broker carries out the distribution of the data according to the topic between publisher and subscribers. In other words, MQTT broker/server stores, filters and forwards the data

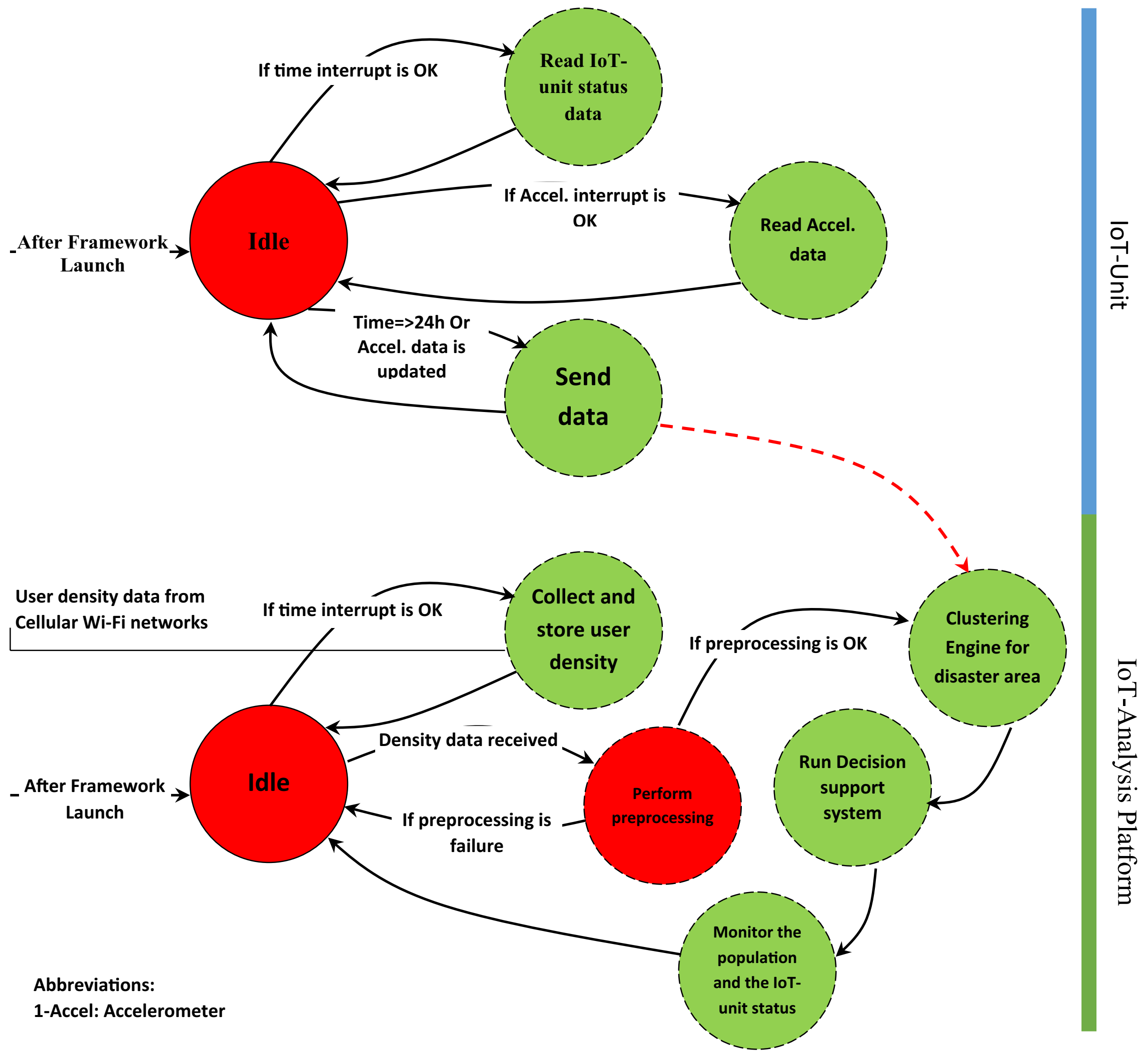
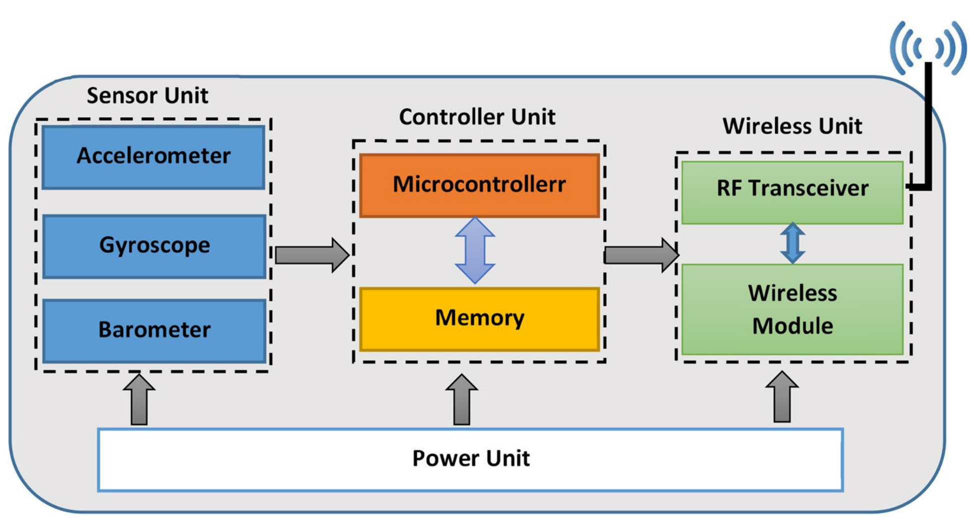


Fig. 2 Simplified state machines of the proposed framework

Fig. 3 Block diagram of the designed IoT-unit components



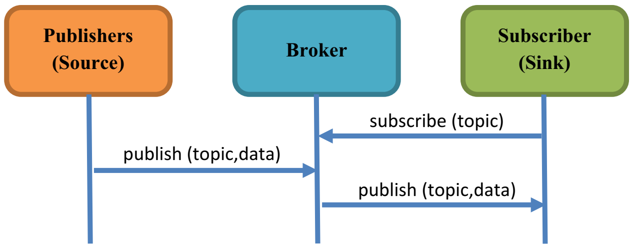


Fig. 4 The communication between the MQTT components

from the publisher client to the subscriber clients. Also, MQTT supports three levels of quality of service (QoS) to deliver a message (Al-Fuqaha et al. 2015; Bhosle and Gavhane 2016; Tantitharanukul et al. 2016; MQTT 2019). In this study, the publisher is the implemented IoT Unit. The subscriber is IoT-analysis platform. The Mosquito that is an open source message broker is used as MQTT broker.

3.3 IoT analysis platform

IoT-analysis platform carries out analysis, visualization, and monitoring of the received data from IoT-units. In other words, this platform is the user interface of the disaster management system.

In the development process of the IoT-analysis platform, HTML5, Javascript, CSS, Google Map, and Firebase technologies have been utilized. Google Map can be easily added to the project using the API-KEY. Also, this map enables many features including a specific area selection, coloring, etc. Firebase is a popular cloud-based platform developed by Google for mobile and web-based applications. Firebase stores and synchronizes data in real-time between users and devices using a NoSQL database.

The whole IoT-analysis platform is composed of the building damage procedure block, the resident density clustering block, the decision support system block, and user interface. The first block of the platform determines the building damage level. All of the designed IoT units can be users of the damage procedure block. As a bridge between other IoT technologies (cellular networks and Wi-Fi) and the decision support system, the resident density clustering block plays two critical roles in the platform. One is to act as a database to provide IoT based disaster management for enabling sufficient interactivity. Another function of this block is to serve as a computer to implement clustering on this database using mobile phone records and Wi-Fi connections. The third block, decision support system, is based on a fuzzy logic mechanism to manage resources efficiently. This block uses building damage status and resident density clustering outputs as the inputs. The last block of the platform is the user interface to see the desired map with the damage situation in the disaster area. When a disaster occurs, firstly, the disaster area is displayed roughly and colored on the map. Then, detailed damage information can be reached by zooming the colored region. Figure 5 shows localization of damaged buildings and its damage information without resident density.

3.3.1 Building damage procedure

Sensor tier of the IoT-unit obtains structural measure in deployment building. Sensor unit senses status of the deployment building such as direction and distance destruction of building etc. This measure is utilized to calculate building damage procedure (Bayilmis et al. 2015; Sevin et al. 2016). For example, the acceleration data figure out the variation of the velocity. In other words, the data is the displacement of acceleration in concerning time. Thus, the position of a building can be estimated because of the initial status of the structure is known. If distance as a function of time is assumed ($s(t)$), velocity and acceleration can be formulated as follows;

$$a(t) = v'(t) = s''(t) \tag{1}$$

where $a(t)$ and $v(t)$ are acceleration and velocity as a function of time, respectively. We have used $'$ for the derivative with respect to time.

ADXL345 used in IoT-unit has three-axis accelerometer with high resolution. The accelerometer measures the static and dynamic acceleration of gravity. We utilized both acceleration data to calculate the building damage status. Because static acceleration is used in tilt-sensing applications and dynamic acceleration is utilized in motion-sensing applications. Total static acceleration vector length (SA) is computed by IoT-unit as follows:

$$SA = \sqrt{\left(a_x\right)^2 + \left(a_y\right)^2 + \left(a_z\right)^2} \tag{2}$$

where a_x, a_y, and a_z are the three components of the static acceleration vector of gravity ($\vec{a}$).

Similarly, total dynamic acceleration vector length (DA) is calculated as follows:

$$DA = \sqrt{\left(b_x\right)^2 + \left(b_y\right)^2 + \left(b_z\right)^2} \tag{3}$$

where $\vec{b} = \left(b_x b_y b_z\right)$ is the dynamic acceleration vector of gravity of the three axes.

To calculate the destruction distance of the building, we obtain vertical acceleration by total static and dynamic acceleration vectors as follows:

$$VA = \sqrt{(SA)^2 - (DA)^2 - (G)^2 / 2G} \tag{4}$$

where $\mathcal{G}$ represents the gravity.

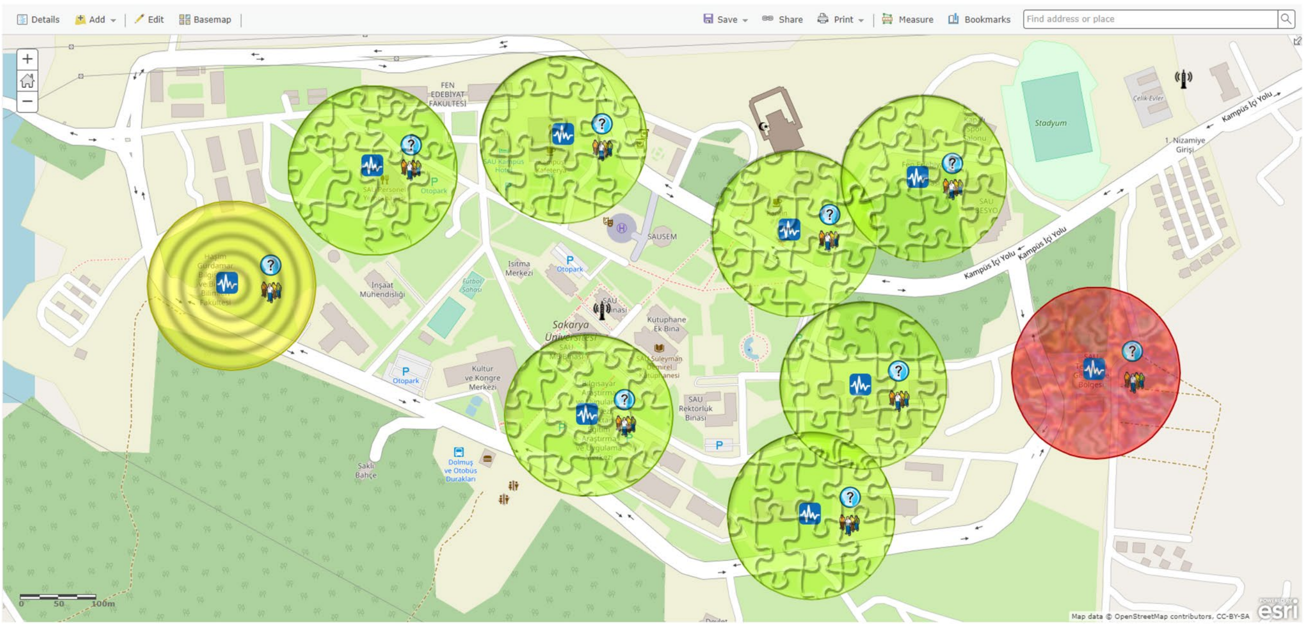


Fig. 5 The position of the buildings in a disaster area and its damage information

In addition, we obtain the angle of rotation of the building using gyroscope data as follows:

$$\Theta = \sqrt{\left(\vartheta_x\right)^2 + \left(\vartheta_y\right)^2 + \left(\vartheta_z\right)^2} \tag{5}$$

where $\vec{\vartheta} = \left(\vartheta_x \vartheta_y \vartheta_z\right)$ is the angle of rotation vector of the IoT-unit.

3.3.2 Resident density clustering

Resident density information is the crucial data to route the rescue teams. We use the clustering algorithm to analyze this density information (Guo et al. 2016). Different from Guo et al. (2016), smartphones can be connected to the base stations (BS) built in the cities and Wi-Fi access points (AP) placed in the buildings. We consider both BS and AP connection data set for clustering. This connection data set is used as the input of our disaster management platform. These data are described as:

$$D_i^{BS} = \left\{PN_i, \varphi_i^{BS}, \lambda_i^{BS}, t_i^{BS}, \Delta t_i^{BS}\right\}$$

$$D_j^{WF} = \left\{MAC_j, \varphi_j^{WF}, \lambda_j^{WF}, t_j^{WF}, \Delta t_j^{WF}\right\} \tag{6}$$

where PN_i is the i-th subscriber's phone number, φ_i^{BS} and λ_i^{BS} are the BS's latitude and longitude, t_i^{BS} is the subscriber connection time to the BS, Δt_i^{BS}: the duration time of the PN_i for the connection information of the BS. MAC_j is the j-th user's MAC number, φ_j^{WF} and λ_j^{WF} are the AP's latitude and longitude, t_j^{WF} is the user connection time to the access point, and Δt_j^{WF} is the duration time of the MAC_j.

Connection dataset handled by BS and AP connection is irregular and formless, and the connection period data of a smartphone attained to a BS or AP is not contained. So it is necessary to implement some preliminary processing on this data set. Initial processing consists of discarding of irrelevant data, deleting of Handover effect, detecting or correction of connection time of users with BS or AP, etc. Handover is eliminated by considering two data sets D_i^{BS} and D_{i+1}^{BS} or D_j^{WF} and D_{j+1}^{WF} for a smart phone's attained to the BS or the AP, respectively. The first step in eliminating Handover is to find the gap between the BSs to which the user is communicating. The distance between the BSs is calculated as follows (Ranacher et al. 2015):

$$d^{BS} = \sqrt{R_e^2\left(\varphi_i^{BS} - \varphi_{i+1}^{BS}\right)^2 + R_p^2\left(\lambda_i^{BS} - \lambda_{i+1}^{BS}\right)^2 \cos\left(\frac{\varphi_i^{BS} - \varphi_{i+1}^{BS}}{2}\right)^2} \tag{7}$$

where R_e is the radius of the equator, R_p: the radius to the north pole. Similarly, the distance between the two access points is computed as follows:

$$d^{WF} = \sqrt{R_e^2\left(\varphi_j^{WF} - \varphi_{j+1}^{WF}\right)^2 + R_p^2\left(\lambda_j^{WF} - \lambda_{j+1}^{WF}\right)^2 \cos\left(\frac{\varphi_j^{WF} - \varphi_{j+1}^{WF}}{2}\right)^2} \tag{8}$$

Afterward the investigation of the BS and AP connection data and the communication range of them, it is found that when the tuning parameters of $T_{BS_{MAX}}$ and $T_{WF_{MAX}}$ are half an hour and 5 min produce the best result, respectively. We have two rules to eliminate Handover effect for BS or AP as follows:

$$d^{BS} \leq 5\text{km or } d^{WF} \leq 100\text{ m} \tag{9}$$

$$\Delta T^{BS} < T_{BS_{MAX}} \text{ or } \Delta T^{WF} < T_{WF_{MAX}} \tag{10}$$

where ΔT^{BS} is a time difference between two BS data, ΔT^{WF} is a time difference between two AP data.

Another important parameter is the duration of connection time. The time difference can be determined two folds: (1) a smartphone user is not mobile and re-connecting to the same BS within 30 min, (2) a smartphone user is not mobile re-connecting to the same AP within 5 min. So this preprocessing step corrected by (9) and (10) with a user data from BS or AP, then we set D_i^{BS} or D_j^{WF} as ith or jth latitude, longitude, Δt is computed with $t_2 - t_1 + \Delta t_2$ and all the data including D_{i+1}^{BS} or D_{j+1}^{WF} between D_i^{BS} or D_j^{WF} and D_{i+1}^{BS} or D_{j+1}^{WF} is erased. As a result of the above operations, the Handover effect ceases to exist.

High-density population areas of the city or building are discovered by the hierarchical clustering technique (Guo et al. 2016). The decision criterion of the population density is made by the number of connections to the BSs or APs of the users in the given area. The higher number of connections generally points to a much denser population. In this framework, the high-density population regions are explored by clustering to manage a disaster. Clustering process includes both the number of BSs and APs and the number of smartphones attained to the BSs and APs. Ideally, the BS and AP are connected to phones that have greater weight during clustering. For each known BS and AP, the number of users on a daily basis is determined.

The number of connected users is taken into account as a weight for the clustering process. Before this process begins, a weighted center point is adjusted for each cluster. Both clusters at the shortest gap are combined into a cluster at each process. The distance between the centers of the two cluster is used to denote the distance between the two clusters as the following equations:

$$\varphi_c = \frac{(user\_n_1)(\varphi_c^1) + (user\_n_2)(\varphi_c^2)}{user\_n_1 + user\_n_2} \tag{11}$$

$$\lambda_c = \frac{(user\_n_1)(\lambda_c^1) + (user\_n_2)(\lambda_c^2)}{user\_n_1 + user\_n_2} \tag{12}$$

$$user\_n_c = user\_n_1 + user\_n_2 \tag{13}$$

where $user\_n_c$: the number of smart phone users attained to the BS, φ_c and λ_c represent the latitude and longitude of the cluster center, respectively,

First, each BS or AP is set as a cluster. For this reason, the center point of each cluster is the coordinates of a BS or an AP and the weight value is taken as 1. Two clusters are then combined with the shortest distance. This process continues until the threshold distance has been met and then the aggregation has been completed.

The processing and data storage is made in parallel with a set of computers because every smartphone or Wi-Fi user is evaluated separately. Therefore, Apache Spark and Hadoop Distributed File System (HDFS) is assessed in the proposed disaster management system. Apache Spark is a quick and common engine for large-scale data processing (Ivannikova 2017). Spark runs on top of existing HDFS infrastructure to supply advanced and additional properties. HDFS is employed to store all the BS and AP connection data. These data are examined and processed by Apache Spark (Apache 2019). We also used analytic Python packages Anaconda included several open source development environments. Also, JDK 8 development environment is used with HDFS and Apache Spark.

3.3.3 Fuzzy logic based decision support system

The main aim of the disaster management system is to manage rescue sources fairly and more efficiently. We used fuzzy logic as a decision support system since it is one of the commonly used methods in disaster management systems in the literature (Chen et al. 2011; Zlateva et al. 2011; Zlateva and Velev 2013). For this purpose, the proposed disaster framework has a fuzzy based decision support system shown in Fig. 6. This system decides the usage of rescue sources according to structural measures including direction and distance destruction of a building and the resident density information in the disaster area.

Fuzzy logic based decision system consists of three main parts: Fuzzifier, Fuzzy Inference, and Defuzzifier. Fuzzifier converts structural measures belong to status data of building and resident density information into the fuzzy set. The fuzzy set comprises linguistic variables with appropriate membership functions (Çalhan and Çeken 2010). Also, fuzzy rules consist of these linguistic variables.

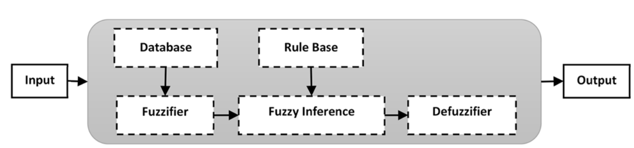


Fig. 6 Block diagram of the proposed fuzzy logic based decision part of the disaster framework

Figure 7 shows fuzzy membership functions, respectively. Types of membership functions have been selected as Trimf and Trapmf. These types are appropriate for input and output value in this study. In addition, Trimf and Trapmf have better performance for real-time applications. There are two input and one output in this system. Input values are resident density information and structural measure including direction and distance destruction of the building. Resident density information in the disaster area has three membership functions: few, medium, and much. Similarly, other input structural measure has three membership functions: low, medium, and high. Also, output has three membership functions including insignificant, medium, and significant. The environmental diagram is shown in Fig. 8 for the proposed disaster framework. This environment diagram aims to show the real-time data analyzes the process to post disaster management system briefly. Data of the proposed disaster framework is stored on Hadoop. Apache Kafka is used message distributor between the employed IoT technologies including IoT units, cellular and Wi-Fi connection data, and IoT analysis platform. Apache Spark Streaming provides big data analysis tools on streaming data. Fuzzy logic based decision mechanism works on Spark. The framework visualizes the results using the ESRI APIs.

4 The performance utilizing of the designed framework

In this section, we report our evaluation results using large-scale, real-world residential densities to verify the effectiveness of our proposed framework, which was designed for managing resources in disasters and for search-and-rescue teams. We have realized the application of the developed disaster framework in an example scenario. In general, it is inconvenient and costly to determine the proposed system's attitude because of the additional IoT-units and substantial gaps in a real system. Therefore, an example scenario reduced to a university campus scale, with some assumptions and conditions, is examined for the performance evaluation and verification of the framework.

We used the Sakarya University Campus as the disaster region in this scenario. We have the following assumptions and conditions in this experimental scenario. (1) There are seven BS towers within 5 km of the campus, as shown in Table 2, from the real BS deployment (Open Database of Cell Towers & Geolocation (OpenCellID) 2019). These BS towers were utilized for resident density clustering. (2) We used 50 Wi-Fi access points around the university campus. These APs were used for the proposed framework

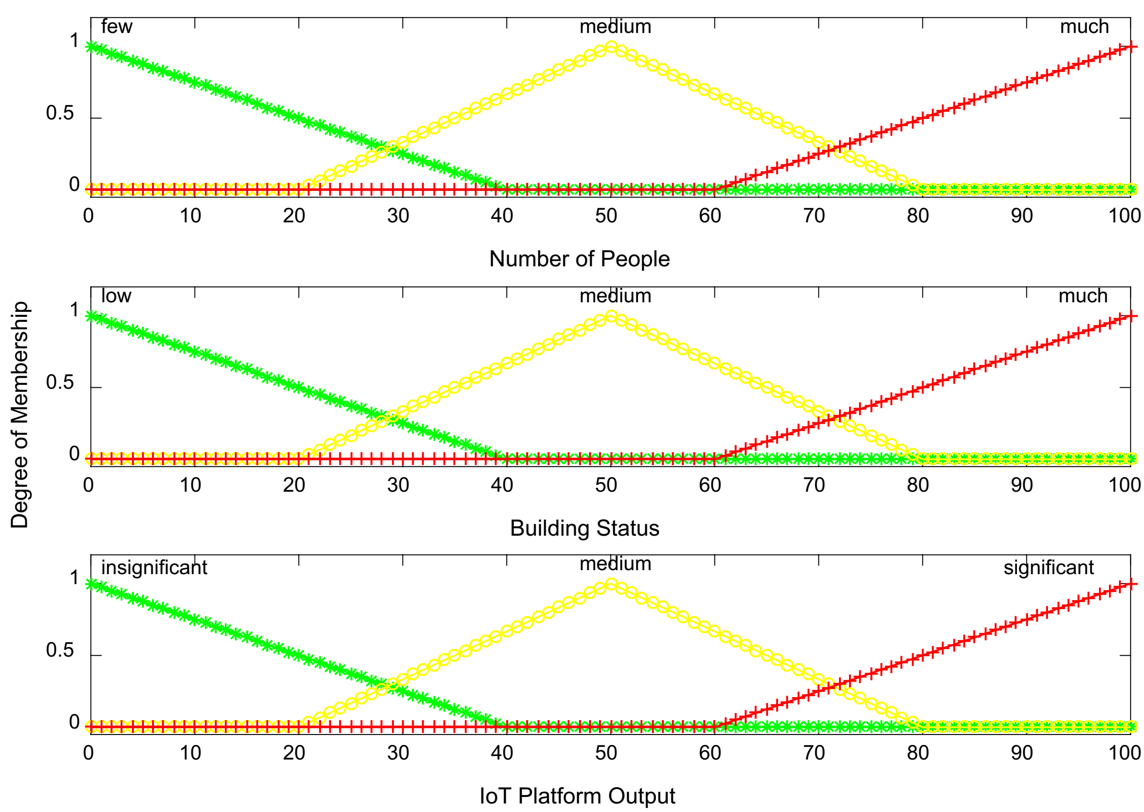


Fig. 7 Fuzzy membership functions for the number of people, the status of the building, and IoT platform output

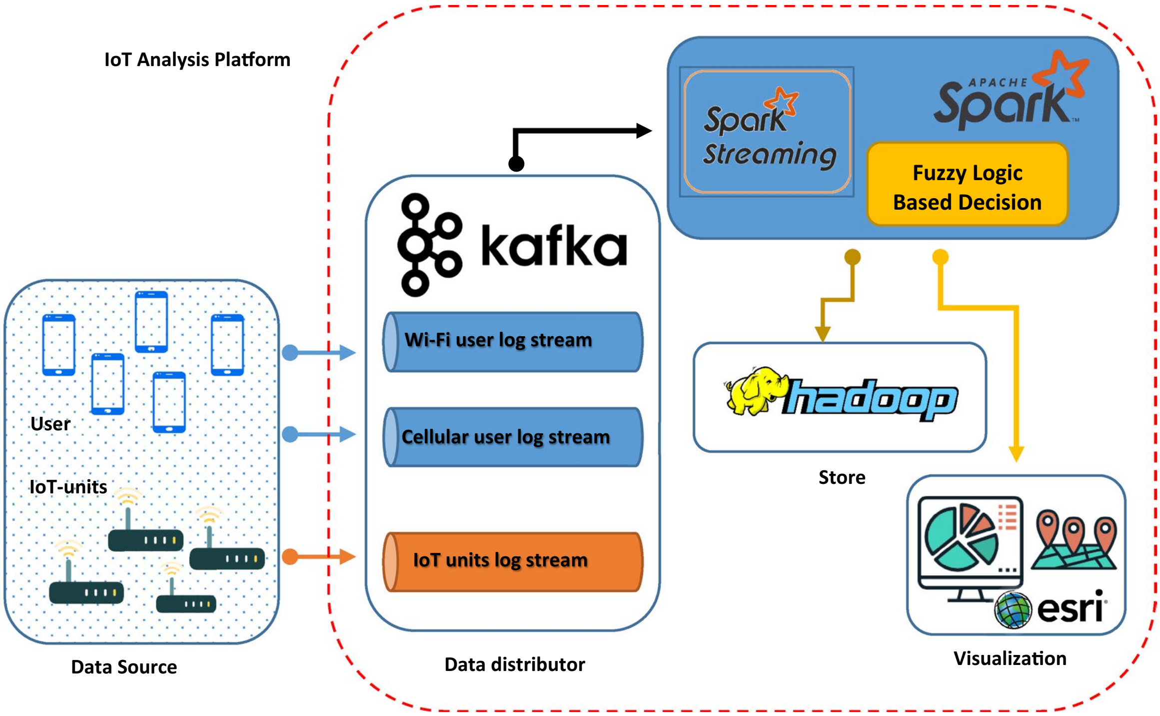


Fig. 8 Environmental setup of a disaster framework for IoT based crowd sensing

Table 2 The base station location information and range estimations from OpencellID

Radio	MCC	MNC	Area	Cell ID	Longitude	Latitude	Range
UMTS	286	2	55,407	2,987,665	30.343551635742	40.733871459961	1000
UMTS	286	2	55,407	58,742	30.351907	40.729752	3454
UMTS	286	1	20,654	56,172	30.34259	40.733734	1591
GSM	286	2	55,407	59,147	30.340347	40.744858	1000
UMTS	286	2	55,407	58,412	30.31944	40.711366	3756
GSM	286	2	55,407	59,148	30.331192016602	40.742111206055	1000
UMTS	286	1	60,154	157,386,004	30.33805847168	40.736618041992	1000

experimental setup. (3) The designed four IoT-units are deployed, and six virtual IoT-units are assumed to implement different buildings. This means that a software was used for six virtual IoT-units. This software virtualizes the IoT-units to behave as if there was a disaster. (4) The IoT-units send accelerometer data in each 24-h cycle if there is a difference between the data positions. Therefore, the proposed framework was fed in real time with IoT-units nodes. (5) The IoT-units can connect to the system using Wi-Fi or GSM technologies. (6) The data constituted by Sakarya University Campus' smartphone connections to BSs and Wi-Fi APs during a week were used for the dataset. This dataset was transmitted to the proposed framework in real time by the system administrators of both the cellular and the Wi-Fi network. (7) The system is triggered every day of the week, as if a disaster has occurred. Thus, the performance of the proposed framework has been tested as a disaster.

Under these conditions, approximately 2 M cellular network data usage and over 10 M Wi-Fi connection data simulations were performed. The system enumerated the density of people in the campus region every hour. Each day's residential density on campus was examined, and it was found that the density of residents was similar on weekdays. When we assumed that an earthquake was happening, we conducted a different manual effect on the deployed IoT-units, sequentially, and we generated different damage levels for the virtual IoT-units to feed the disaster management system. Afterward, we examined the proposed system, which is implemented by the given environmental diagram.

Figure 9 shows the residential density in crowd sensing from the cellular and Wi-Fi connection data on Thursday. The error bars navigate the statistics of the resident frequency on campus for the whole week. These densities were distributed among all campus area geofences. By

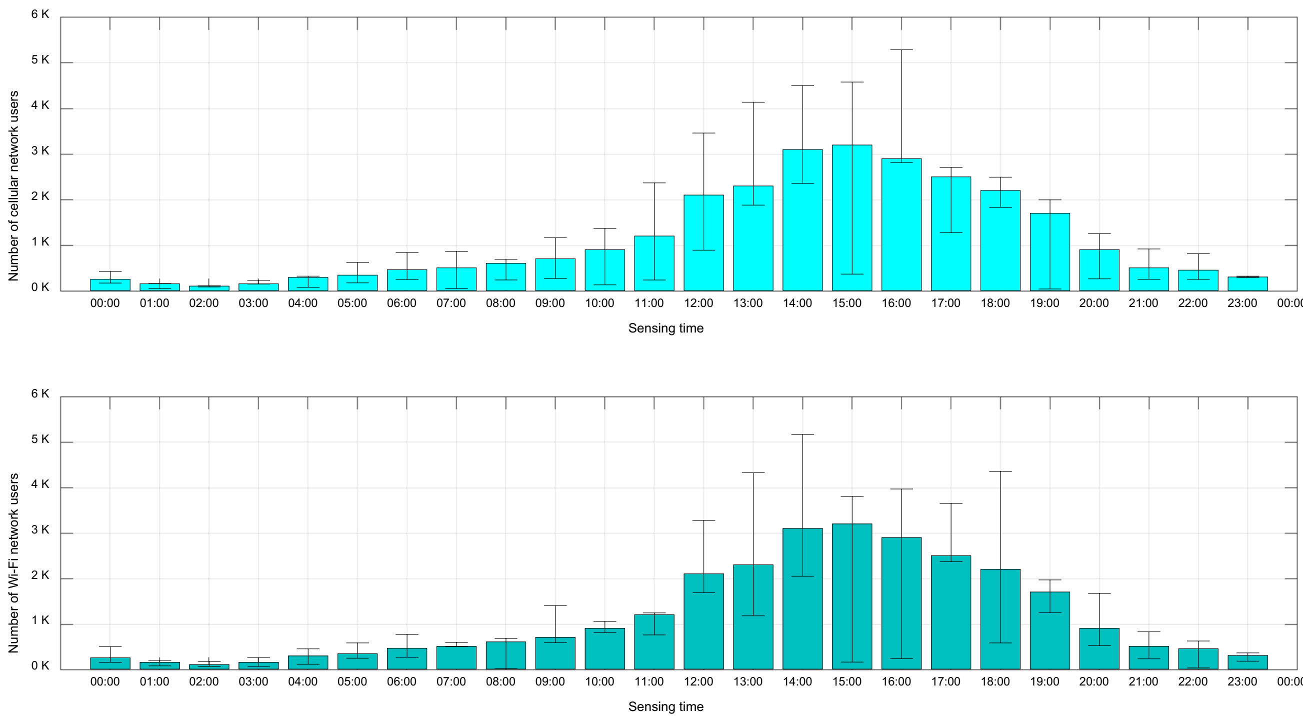


Fig. 9 Statistics of cellular and Wi-Fi networks traces during a typical Thursday and the week at the Sakarya university campus

analyzing Fig. 9, some considerations can be drawn for the crowd densities for weekdays. These densities for both IoT technologies reached the highest ratio from 12:00 to 19:00, which means that the residential density grew during these hours. These results show that the residential density can be determined by the BS and AP connection information in a specific region.

A user interface is a powerful tool to aid quick and efficient decision making in disaster management while considering different information. In our proposed system, we have categorized map visualizations into zoom levels that populate the map screen with either cellular network data or with mobile network and Wi-Fi connection data. Here, the Open Street Maps mapping service evaluates displays through Esri APIs (ArcGIS Online 2019). Figure 10 presents part of the analysis platform of the user interface with cellular network data displayed over the Sakarya University map; these data represent the detected damage level in the disaster area. In this particular scenario, the various damage levels and residential densities detected are represented by different colors. The proposed disaster management system can recognize three types of damage level: no damage in the area (green); damage to some structures in the area (yellow); and damage to all structures in the area (red). The coverage of these colored circles approximately represents the residential density for a population. As can be seen, data from two base stations have intended and concluded the resident frequency. Figure 10 represents crowd densities utilized by the proposed framework that vary with the different number of damage levels. The framework achieves no damage area in the real-time when numbers of resident reach 17,426 because the eight IoT units are covered without any change of the accelerometer data. Similarly, the resident density of the proposed framework for determining damage to some structures is also shown in the yellow region with 5852 resident. The red region shows the damage to all structures in the area for 3173 resident. The proposed framework takes a low resolution for resident density using the cellular networks as there are fewer BS data connection records available in the system to perform SAR operation.

Additionally, Fig. 11 illustrates an example of heat maps of the proposed framework. The accurate categorization of the damage level is one of the steps in our proposed framework. There are two-type circles that represent clustering using cellular network or Wi-Fi connection data detecting the damage level associated with a given area. The framed circles describe the clustering with Wi-Fi connection data. Using the cellular and Wi-Fi networks connection data for the clustering in the proposed framework, the resident densities are taken with high resolution according to use only the cellular network connection data. When analyzing Fig. 11, framed circles in the no damage area when numbers of resident reach 813, 2451, 628, etc. It is indicated by coverage areas according to the number of resident density. An important result of the study is revealed in the yellow region for this scenario. With higher resolution, the location

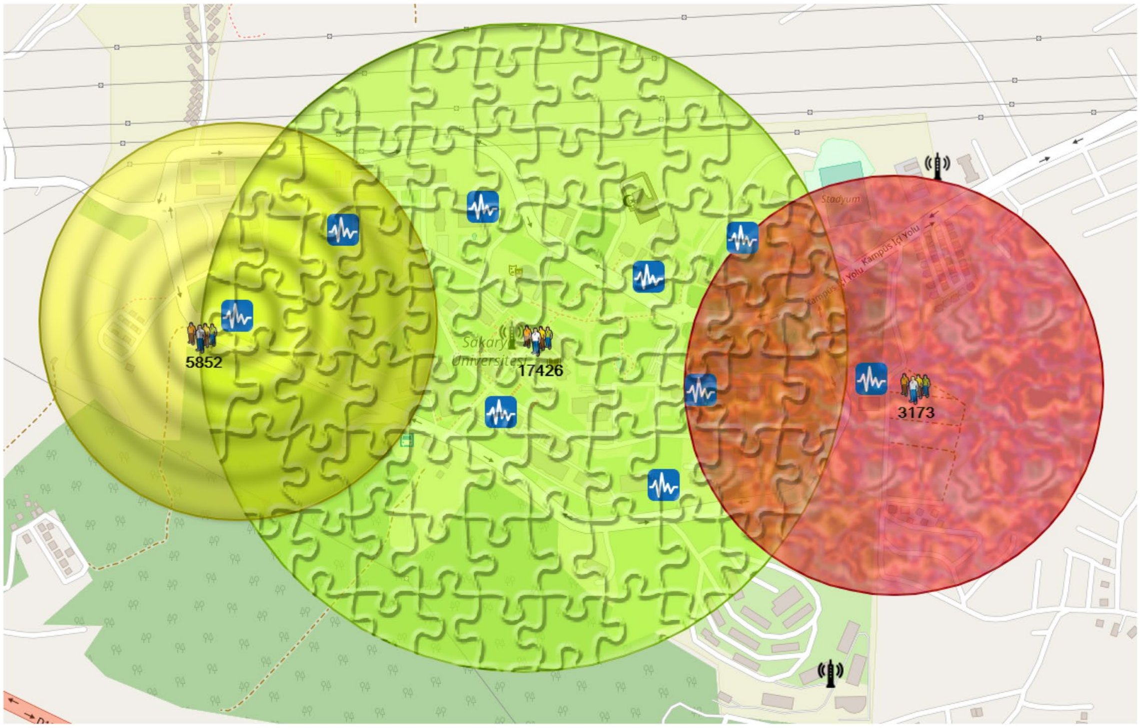


Fig. 10 Clustering map that shows the disaster area using the cellular network data represented as colors

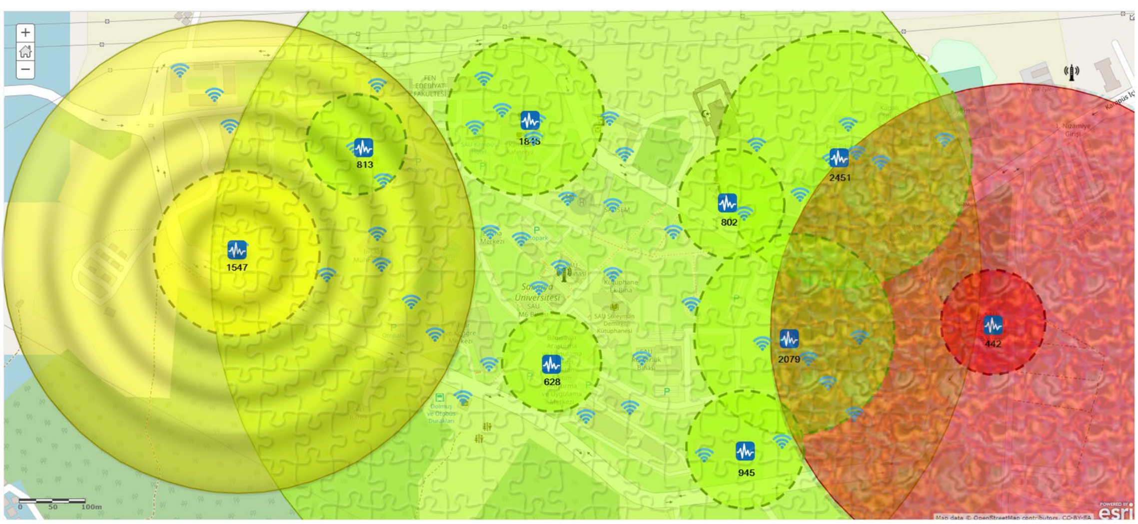


Fig. 11 Clustering-map that shows the disaster area using the cellular network data and Wi-Fi connections data represented as colors

of the damage placed IoT unit can be shown together with the resident density. The red region shows the damage to all structures in the area for 442 resident. In this disaster scenario context, it is crucial that fast and accurate decisions are performed in real time. Therefore, rescue teams may decide to operate in a red-circle area because they can immediately see that the damage level of this area is significant. The obtained density information could be determined using the Sakarya University database, with an error rate of 9%, approximately. Experimental results show that the proposed disaster management framework is a very useful and effective tool to analyze the disaster region using the implemented IoT-unit.

Clustering of cellular and Wi-Fi network data is aggregated using the fuzzy logic based decision system described in the previous section. In Fig. 12, we present the Avg./Min./

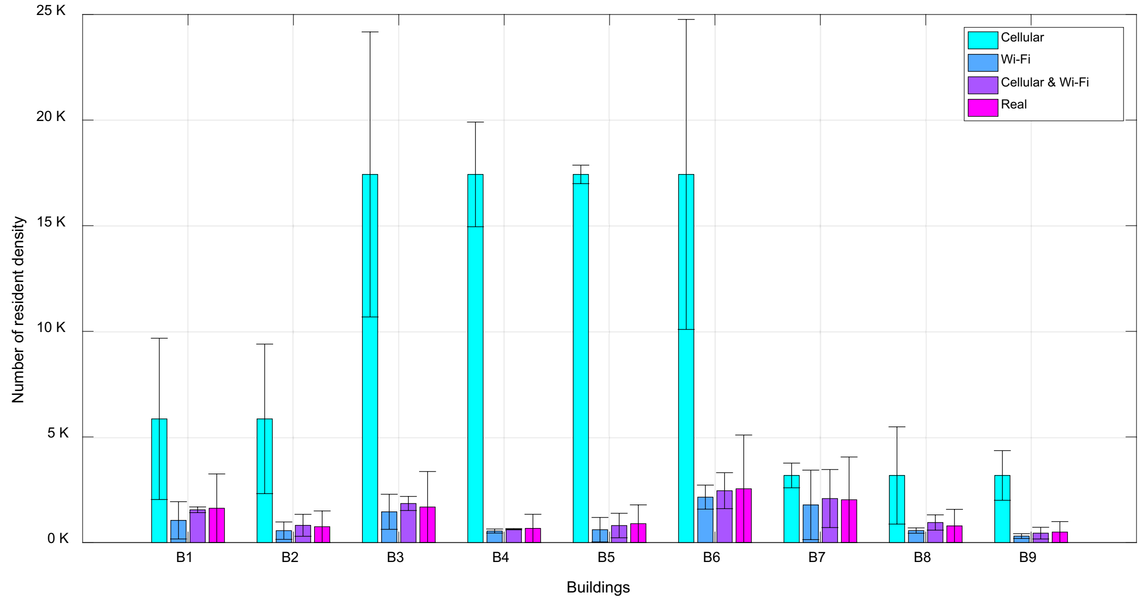


Fig. 12 Performance comparison of various clustering data feeds at the Sakarya university campus: cellular vs. Wi-Fi vs. cellular and Wi-Fi vs. real data

Max. values of residential density for cellular networks only, Wi-Fi networks only, and both cellular and Wi-Fi network connection data under the same conditions. For the disaster region, we show the statistics of the residential densities of all buildings that deployed the IoT-units per sensing time. On the one hand, it can be seen that observing residential density from the clustering of cellular network data does not provide realistic results. However, the results of clustering with Wi-Fi network data showed better performance than those using cellular network data only. The observations of residential density from using the proposed method are quite similar to those from using an existing method in which real density information is obtained from tourniquets placed at the entrances of the buildings where the designed IoT-units are installed. From the evaluation results, we can see that the proposed framework performs consistently better than the two different clustering approaches in terms of residential density and monitoring, while all the clustering data feed methods can achieve the goal of full coverage and collecting the sensed results when the disaster region and number of users are the same.

5 Conclusion

Receiving quick and accurate information pertaining to a disaster area is a vital necessity after a disaster occurs. Such situations are among the most significant problems of the disaster management systems. Disaster management systems can be equipped with the Internet of Things technologies in order to overcome such issues. Thereby, the number of affected individuals and the extent of damage from the disaster can be minimized. A disaster management system designed and implemented on IoT technologies is presented in this paper. The developed system utilizes several different IoT technologies, such as embedded systems, cellular networks, and Wi-Fi connections. The implemented disaster management system comprises IoT-unit and IoT-analysis platforms. Moreover, this system enables the transmission of two important types of information. The first is the damage status of buildings. In order to measure the state of a building, an IoT unit that comprises a microprocessor, sensor unit, communication unit, and a power unit is designed and implemented. The second type of information is the resident density of the region affected by the disaster. Clustering resident density is achieved by the IoT-analysis platform, utilizing cellular networks and Wi-Fi connections. Furthermore, this platform includes fuzzy logic-based decision systems to make an appropriate and quick decision for disaster management users. An exemplary application scenario of the proposed disaster management system is presented, which assumes that an earthquake has occurred. The system performance successfully represents the disaster area and the damage level, marked with different colors, circles, and density information, which can all aid in the management of the disaster.

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