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# A Systematic Review of Prediction Methods for Emergency Management

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**Abstract**

With the trend of global warming and destructive human activities, the frequent occurrences of catastrophes have posed devastating threats to human life and social stability worldwide. The emergency management (EM) system plays a significant role in saving people's lives and reducing property damage. The prediction system for the occurrence of emergency events and resulting impacts is widely recognized as the first stage of the EM system, the accuracy of which has a significant impact on the efficiency of resource allocation, dispatching, and evacuation. In fact, the number and variety of contributions to prediction techniques, such as statistic analysis, artificial intelligence, and simulation method, are exploded in recent years, motivating the need for a systematic analysis of the current works on disaster prediction. To this end, this paper presents a systematic review of contributions on prediction methods for emergency occurrence and resource demand of both natural and man-made disasters. Through a detailed discussion on the features of each type of emergency event, this paper presents a comprehensive survey of state-of-the-art prediction technologies which have been widely applied in EM. After that, we summarize the challenges of current efforts and point out future directions.

*Keywords:* Emergency management system; Disaster; Prediction methods;

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Resource demand; Artificial intelligence; Review.

## 1. Introduction

The past decades have witnessed a dramatic increase in disaster events worldwide. As reported by the Emergency Events Database (EM-DAT, 2020), over the last twenty years, 7,348 disaster events were recorded, which has increased by 73% compared with that between 1980 and 1999. There is clear evidence that the earth is experiencing a gradual increase in the global average temperature, which is seen as the main reason for extreme natural events, including droughts, flooding, hurricanes, and wildfires (Ortuño et al., 2013). In addition, human-made or technological disasters, such as industrial accidents and transportation accidents, further increase the risk of human exposure to extreme urban hazards, and cause high casualties and financial losses as well.

The development of timely and effective emergency management (EM) system has become increasingly attractive, the primary aim of which is to help and enable emergency managers to prepare for disasters and respond to urgent events. The general framework of the EM system is composed of a series of decision-making problems belonging to three phases (Zhou et al., 2018): (i) pre-event forecasting and preparation; (ii) in-event response and evacuation; and (iii) post-event recovery. Many efforts have been devoted to giving overviews of state-of-the-art literature. Readers interested in detailed operation strategies of EM system should refer to the publications summarized in Table 1.

Table 1: Existing literature reviews on EM system

| **Stage** | **Subproblem** | **Publication** |
|---|---|---|
| Pre-event | Resource demand forecasting | Zhu et al. (2019) |
| | Resource prepositoning | Sabbaghtorkan et al. (2020) |
| | Emergency facility location | Li et al. (2011a) |
| In-event | Emergency vehicle routing | Humagain et al. (2020) |
| | Emergency evacuation | Abdelgawad & Abdulhai (2009) |
| | Relief resource distribution | Anaya-Arenas et al. (2014) |
| Post-event | Disaster recovery | Özdamar & Ertem (2015) |

The recent popularity of intelligence EM systems emphasizes the importance of learning from previous experience when a new emergency event occurs by analyzing historical data of similar events or scenarios (Chen et al., 2019). These facts confirm that a variety of advanced technologies have been applied in EM systems to collect, process, and update the spatial, temporal, and environmental information during emergency events, such as the 3S technologies: Remote Sensing (RS), Geography Information Systems (GIS), and Global Positioning Systems (GPS). The analysis of historical data is capable of reproducing the evolutionary process of emergency events and provide better forecasts such as affected areas, population and, in particular, the demand for relief resources.

The extraordinary progress of big data, Artificial Intelligence (AI), and Internet of Things (IoT) in recent years allows the development of the prediction system for emergency occurrence and demand (Aringhieri et al., 2017). Chen et al. (2019) give a timely survey of the latest computation intelligence technologies applied in EM. It reports that more than 170 papers have been published emphasizing this emerging topic. The capabilities of AI techniques to make full use of acquired data and deal with imprecise or uncertain information are widely recognized, especially in forecasting the occurrence of unexpected emergency events and evaluating their impacts on the economy and society.

The roles of big data analytics and IoT have also received growing attention in the last few years. For instance, Thibaud et al. (2018) focus on the applications of IoT and semantic web technologies for natural disaster detection. Heterogeneous data is collected by IoT sensors, based on which insightful knowledge could be investigated through semantic reasoners. Zafar et al. (2019) indicate that IoT is particularly effective for the preparedness phase of EM due to its capability of integrating a variety of knowledge and research domains. Shah et al. (2019) highlight the application of big data and IoT techniques in EM and point out the current opportunities and challenges in this area.

Though it is almost impossible to know the time of occurrence and intensity of any emergency event, the occurrence possibility can be estimated using data mining techniques through historical data set of similar events, real-time observed data, and expert knowledge (Qiu et al., 2014; Amezquita-Sanchez et al., 2017). Forecasting the resource demand is another critical task in the aftermath of an emergency event, which serves as the premise and basis of the emergency management of unconventional emergencies (Liu et al., 2012). Facing the overwhelming increase of data, Zhu et al. (2019) focus on the application of AI in the forecasting methods of emergency resources.

Owing to the wide variety of emergency events, including both natural and man-made, the forecasting model is event-dependent with the consideration of various social and environmental factors concerning different types of events, such as socio-economic conditions and geographical characteristics. The decision-making process during a disaster operations management also differs drastically with respect to the types of events, considering the severity, affected area, population density, surrounding landscape, among others. Though very few, some efforts have been devoted to discussing the current prediction and assessment methods of natural disasters, e.g., Amezquita-Sanchez et al. (2017). On the other hand, man-made catastrophes have also received increasing attention all over the world, such as severe accidents in highway and urban transportation systems, worldwide public health emergencies, among others. Therefore, in this paper, we aim to fill this gap by presenting a systematic review of efforts on the resource demand forecasting methods in response to different types of emergency events containing both natural and man-made disasters.

The following contributions are expected from this study. The first and major contribution of this study is to elaborate the unique features of different types of emergency events, which is of paramount importance in choosing proper forecasting models and decision variables. Second, we provide a systematization of the literature applying traditional statistical forecasting methods and state-of-the-art AI technologies. The third contribution is to identify several open research questions to be explored in the future.

The rest of this paper is organized as follows. Section 2 first defines the boundaries of this study. Section 3 elaborates the characteristics of different types of emergencies. Section 4 introduces the existing emergency demand forecasting models. Section 5 discusses the existing challenges and several future directions. Section 6 serves as a conclusion.

## 2. Boundaries of the study

### *2.1. Definitions of key concepts*

To highlight the boundaries of this study, the following questions must be answered: What is the *EM system*? And what is the task of *prediction models*? The first question does not have a unified answer because the definition of EM is broad and has diverse definitions in the literature. Some representative definitions are presented as follows:

- The National Governors' Association Emergency Preparedness Project defines that the EM as a process of mitigation, preparedness, response, and recovery when a disaster happens (Altay & Green III, 2006).
- Chen et al. (2019) state that EM is a complex task that involves multiple stakeholders to prevent the occurrence of unexpected events and to mitigate the impacts caused by emergency events.
- Bullock et al. (2017) give a simplified definition for EM, that is, "a discipline that deals with risk and risk avoidance."

In sum, the EM system is an integrated decision support system composed of a variety of tasks that covers the lifecycle of an emergency event. It can be seen that the effective prevention or avoidance of emergency events plays a critical role in the EM system that aims at minimizing or eliminating the loss before the disaster. Hence, the first task of prediction methods discussed in this survey is to predict the occurrence of emergency events by identifying their unique causes and features.

It is evident that critical factors that influence the evolution of emergencies are dissimilar among different types of events. For instance, the prediction of earthquake occurrence is difficult by the damage of affected area can be estimated roughly according to the magnitude of the earthquake which can be monitored and assessed dynamically (Kossobokov, 2013); while the occurrence of a hurricane can be observed and predicted using sea surface temperature (Vecchi et al., 2011). In this study, we define the *features of disasters* as the essential nature of this type of disaster which should be analyzed in the prediction models.

In this survey, the *urgent relief demand* or *emergency demand* refers to the requirement of relief commodities that could alleviate the casualties and injuries of vulnerable people. Zhu et al. (2019) classify emergency resources into four categories: (i) relief materials (including food, purified water, tent, etc.); (ii) equipment and facilities (including communication equipment, means of transport, first-aid medicine, etc.); (iii) technological resources (including satellite telemetering technology, communication technology, computer networking technology, etc.); and (iv) manpower resources. The effectiveness and efficiency of the allocation and distribution of the above emergency resources are highly dependent on the accurate prediction and assessment of the disaster damage from both spatial and temporal dimensions. To this end, the second task of prediction methods covered in this survey is to predict the relief resource demand with respect to the disaster's features. It is noteworthy that the discussion of the optimization models for resource logistics problems is beyond the scope of this survey. Interested readers could refer to Ortuño et al. (2013), Anaya-Arenas et al. (2014), and Özdamar & Ertem (2015) for more details.

### 2.2. *The search process*

A multi-stage search and screening methodology proposed by Farahani et al. (2020) are applied in this study (see Fig. 1). Several academic search engines such as Google Scholar, Scopus, and Web of Science (WOS) are used for initial metasearch. Keywords "emergency management", "disaster", "catastrophe" and "forecasting model" are searched in the title, abstract, and full text of journal articles and conference proceedings published in English between 2000 and 2021.

Because the research of EM is significantly cross-functional, journals belonging to a wide variety of research fields are considered, including "Geoscience", "Environmental Science", "Operation Research and Management Science", "Computer Science", among many others. By screening titles, abstracts, and full texts in the last three steps, we further omit the papers that beyond the scope of this paper. In the end, a total of 137 papers are comprehensively considered in this review.

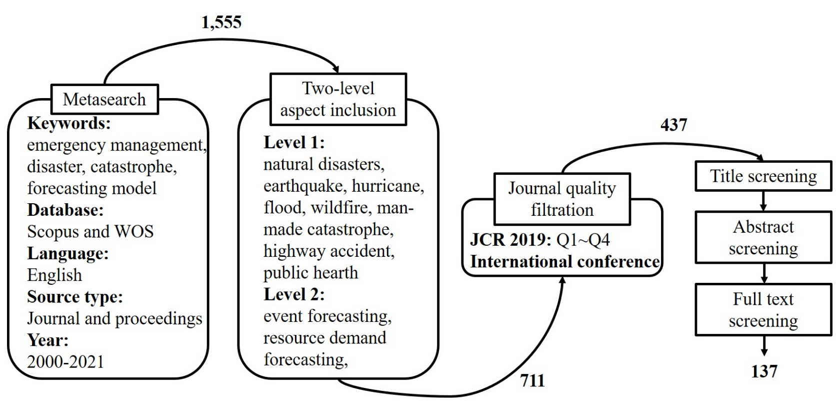


Figure 1: Search and screening methodology.

## 3. Emergency event

### 3.1. *Natural disaster*

In the face of climate change, the recent increase in the frequency and intensity of extreme weather and associated natural disasters has caused substantial economic, social, and environmental impacts all over the world. China's 2008 Wenchuan earthquake caused a great loss of life and property, the total damage of which is estimated to exceed 100 billion dollars (Wang, 2008). Japan's 2011 Earthquake and Tsunami, which is considered as the severest disaster since 1965, caused an estimated economic loss of 240 billion dollars, accounting for 4.1% of the country's GDP of that year (Guha-Sapir et al., 2012). The performance of search-and-rescue after disasters is of great importance in decreasing the total number of fatalities. Hence, the prediction of victims and the minimum guaranteed requirements is the key to effective and quick responses to the disaster.

#### *3.1.1. Earthquake*

Earthquake refers to the sharp shaking of the earth's crust in seconds, which is the result of the tremendous loss of lives and a series of high degree damages to infrastructure (such as buildings, highways, and bridges), electric power distribution systems, communication systems, etc. Many efforts have been devoted to making retrospective predictions or computing the probability of the earthquake occurrence, among which three parameters are widely received considerable attention: time of occurrence, epicentral location, and the magnitude of upcoming earthquakes (Panakkat & Adeli, 2008). As a result of the earth's geophysical process, a variety of precursors can be observed and analyzed, including animal behavior (Fidani, 2013), water composition (Tsunomori & Tanaka, 2014), anomalous electromagnetic field (Chavez et al., 2016), foreshocks (Brodsky & Lay, 2014), etc. Besides, the historical data of earthquake occurrence in a region can also be applied for retrospective analysis by using machine learning methods (Dai & Cao, 2017).

Though difficult to solve, many efforts have been devoted to the prediction problem of damage, casualties, and resulting resource demand when earthquakes accidentally occur. Xing et al. (2015) propose a casualty prediction model based on the support vector machine. A robust model is developed by applying several loss functions to handle different data of casualty predictors. Zeng et al.

(2016) present a regional earthquake loss prediction model based on the multi-story concentrated-mass shear models, which can effectively quantify the loss, especially buildings, of a major city center. A critical issue of vulnerability assessment is that how to analyze the varying temporal and spatial distributions of damage in the affected area (Li et al., 2011b), which leads to the equity and efficiency issue of relief demand forecasting and allocation. For instance, Huang et al. (2012) are among the first to highlight this issue by proposing a set of performance metrics in relief distribution.

Given the increasing importance placed on IoT, it becomes salient to utilizing heterogeneous data in the early warning system of earthquakes. Zambrano et al. (2017) use smartphones as sensors and build an accelerograph to detect seismic-peak through a data fusion process. Greco et al. (2018) design an abnormal event detection system, especially for earthquakes, which retrieve data from IoT sensors and semantically annotate them. Mei et al. (2019) provide a detailed survey of the application of IoT in geologic hazard prevention. It indicates that it is still challenging to guarantee the reliability of the IoT-based EM system in a complex environment.

#### *3.1.2. Tsunami*

Tsunami consists of a series of waves that arose from the ocean resulting from submarine earthquakes or other underwater explosions such as volcanic eruptions and landslides. Although the affected area of tsunami is limited to coastal areas, it has destructive power and may cause enormous human and economical losses. For instance, the Indian Ocean tsunami that happened in 2004 results in more than 225,000 deaths (Altay & Green III, 2006). Two parameters, which are used to provide early warning are evacuation decisions, need to be predicted in tsunami prediction models, namely, arrival time and wave height. Existing prediction methods apply a variety of data sources. For instance, Wei et al. (2008) utilize the real-time tsunami data collected by the deep-ocean detection buoy to predict the tsunami within two hours before its occurrence. Wei et al. (2014) then predict the arrival time of tsunami using three models with different data sources, i.e., tsunameter measurements, GPS, and seismic waveforms. The result shows that the model with deep-ocean tsunameter measurements provides high-quality forecasting by presenting a comprehensive understanding of tsunami generation.

Since the arrival time and wave height can be forecasted by real-time methods, there is a chance that the residents evacuate from the coast immediately. There is a large body of research on using simulation tools to provide information for evacuation risk assessment and effective evacuation planning decisions. Takabatake et al. (2017) develop an agent-based evacuation model considering the different behavior of residents and visitors, through which the following parameters are estimated, including evacuation time, the number of individuals evacuated, bottleneck location, and the number of casualties. Wang & Jia (2021) propose a novel multi-modal evacuation simulation model considering the interactive effects between walking and vehicles.

#### *3.1.3. Hurricane*

Hurricane is a kind of strong tropical storm that usually occurs during the summer. The storms and heavy rains caused by hurricane landfall would result in different types of damages with respect to the topographical features of the affected area, such as flash floods and landslides in the mountain area, and infrastructure destruction in the plain area. Wind field modeling, which is the basis of hurricane prediction methods, is a process of estimating wind speed and adjusting it to different parameters for further analysis, such as hurricane boundary layer (Vickery et al., 2009), trajectory (Cox et al., 2018), and damage (Chung Yau et al., 2011).

Similar to tsunami, the arrival time and possible magnitude of damage can be forecasted with respect to the real-time observation of related indicators. Hence, pre-disaster preparation for emergency items. Rawls & Turnquist (2010) develop an emergency response planning tool for hurricanes, which determines the optimal location and quantities of a variety of emergency supplies before the occurrence of hurricanes or other disaster threats. Galindo & Batta (2013) propose an integer programming model which jointly optimizes the location and level of storage for supplies. Xu et al. (2016) focus on the prediction of the evacuation rate of the hurricane by using statistical models of evacuation behavior, which could provide valuable information for evacuation planning decisions.

#### *3.1.4. Flood*

The occurrence of flood can be attributed to the intense and frequent extreme precipitation caused by global climate warming (Wu et al., 2015). Maier et al. (2010) and Mosavi et al. (2018) have conducted detailed reviews for the prediction model for flood and conduct that rainfall and the spatial examination of hydrologic cycle are two critical indicators in flood modeling among other water resource variables, such as water level, soil moisture, river inflow. Moreover, considering the seasonal feature of floods, historical records of floods have been widely applied and analyzed with real-time monitoring technologies, such as remote sensing and GIS. Yu et al. (2017) evaluate the performance of two machine learning techniques, namely, random forest and support vector machine, in the forecasting model of rainfall based on radar-derived rainfall data. Avand et al. (2021) propose an integrated model which contains machine learning, remote sensing, and GIS technologies to analyze the impacts of climate change and land use on flood probability. The result shows that the most significant impact factors are elevation, Land use and land cover, slope, and rainfall. Sood et al. (2018) propose an IoT-based flood monitoring and forecasting system, in which all flood causing and preventing attributes are sensed by IoT devices and processed by a multi-layered system, including dimension reduction, cluster analysis, and flood forecasting.

Another critical task of flood management is to forecast and assess its impact, based on which the mitigation and evacuation strategies can be derived. Jonkman et al. (2008) develop a method to estimate the loss of life caused by a large-scale flood. Balica et al. (2013) adopt two methods to conduct the flood risk and vulnerability assessment, namely, physically-based modelling and parametric approaches. It indicates that the parametric approach is suitable for larger-scale vulnerability assessment; while physically-based has a better science base but is better for a specific case.

#### *3.1.5. Wildfire*

Wildfire has received increasing attention in the past three years because of its frequent occurrence and significant damage. According to the report published by the Emergency Events Database (EM-DAT, 2019), at least 14 wildfires occurred in 2019 around the world, of which the severest were in the US, Australia, and Brazil, with total damage and economic cost of over 30 billion US dollars. Though the primary cause of wildfire can also be attributed to global warming and climate change, other influencing factors, such as vegetation (Adab et al., 2015), topographic variables (Parisien et al., 2012), and human activities (Parisien et al., 2016), have also received considerable attention in the literature.

The objectives of wildfire prediction fall into two categories: wildfire probability and its corresponding scale. Parisien et al. (2016) use statistical models to evaluate the joint impact of climate, topography features, lightning, and human activities on wildfire probability. The result shows that fire probability has a negative relationship with human influences. Nami et al. (2018) propose a data-driven evidential belief function model integrated with GIS technologies to predict the spatial pattern of wildfire probability. Jaafari et al. (2019) conduct a comparative analysis of four artificial intelligence methods for the prediction of wildfire probability in spatial scope. It shows that the hybrid model of the adaptive neuro-fuzzy inference system and the imperialist competitive algorithm has a superior performance. Liang et al. (2019) focus on predicting the wildfire scale which is determined by the fire's duration and size of the burning area. Three prediction models are applied, namely, backpropagation neural network (BPNN), recurrent neural network (RNN), and long short-term memory (LSTM), among which the LSTM reaches the highest accuracy of 90.9%.

### 3.2. Urban emergency

#### 3.2.1. General urban incident

The emergencies occurring in the urban area are often caused by two kinds of events: natural disasters and social incidents (e.g., fire, explosion, terrorist attack, crime, and traffic accident). The affected people require immediate assistance and have to be evacuated out of the hazard area. Hence, the major objective of the urban emergency demand forecasting problem is to determine the number of victims or affected people due to disasters, providing input for evacuation planning and resource management optimization, including shelter location and capacity, evacuation path, resource allocation, among others.

In general, the required shelter capacity can be approximated by the product of the number of victims and effective area per capita ($\leq 6m^2$) (Chu & Su, 2012). For a temporary shelter, which provides temporary living spaces for people who would be evacuated and transferred in a short time, the number of victims is equal to the usually resident population. In contrast, the purpose of a permanent shelter is to provide a sustainable habitat for the people whose houses are destroyed. Hence, it is necessary to estimate the number of victims assigned to each shelter located scattered in the affected area considering major impact factors including event type, population distribution, geographical position, and land use.

#### 3.2.2. Crime

Predicting the temporal and spatial distributions of crimes in the urban area is a longstanding issue in the urban management system (Zhao & Tang, 2017). In literature, it is usually assumed that the number of crimes is dependent on explicative variables such as unemployment and income (Phillips & Land, 2012), based on which linear regression models are carried out to analyze their interrelationships (Alves et al., 2015). However, Alves et al. (2018) indicate that the relationship between crime occurrence and urban indicators is usually nonlinear. This study then uses the random forest algorithm to quantify the importance of indicators and predict the number of homicides, which reaches an accuracy of 97%. Zhang et al. (2015) have pointed out that most crimes are opportunistic, but the location and time of crimes are dependent on police deployment. Hence, this study develops a patrol scheduler to predict the occurrence of crime by learning criminals' behavior, which is analyzed through a multi-source database. Seo et al. (2018) propose an automatic system for crime classification. A novel Partially Generative Neural Networks is introduced which is capable of classifying crimes with both full or partial information. Gholami et al. (2018) focus on the prediction method of crimes that occurred in the wildlife protection domain. To overcome the shortcoming of lacking observed data, a new ensemble technique is designed to predict poachers' behavior, the results of which are further utilized in the patrol planning problem. Liao et al. (2020) elaborate the necessity of applying IoT techniques in urban security analysis. However, it also points out that IoT system suffers from vulnerabilities and threats as well, which needs a strong security mechanism.

There also have been some studies modelling crime prevention from the scope of game theory. For instance, Tambe et al. (2012) and Tambe et al. (2014) define this problem as a "security game" model, where the defender is the leader and the attacker the follower. Yin et al. (2012) utilize this approach in the fare inspection problem in transit systems.

#### *3.2.3. Traffic accident*

Another important application of prediction models in urban emergencies is to predict traffic accidents. A large body of research applies statistical and artificial intelligence approaches to analyze the influencing factors for traffic accidents and to predict the occurrence of accidents. With the help of advanced data collection techniques, a large amount of data obtained from a variety of sources is available for traffic flow analysis. To select the most significant explanatory variables or features, Lin et al. (2015) propose a novel variable selection method based on the Frequent Pattern (FP) tree. The result shows that the proposed FP tree method performs better than the random forest-based model with respect to the type of prediction models. Lu et al. (2015) focus on the prediction of accident hotspots in urban areas. A Logistic regression analysis is conducted to investigate the relationships between traffic accidents and road type, vehicle type, driver state, etc. Recently, many efforts have been devoted to neural network approaches. For instance, Alkheder et al. (2017) use the artificial neural network (ANN) to predict the injury severity of traffic accidents based on nearly 6,000 traffic accident records. Consider the case with limited data, Yuan et al. (2018) develop a deep learning approach, namely, the Convolutional Long Short-Term Memory neural network model, for traffic accident prediction. Mukhopadhyay & Vorobeychik (2017) indicate most studies ignore the incident properties which are related to the further emergency dispatch problem. To this end, a novel incident prediction method is proposed by jointly analyzing both incident arrival time and severity. Mukhopadhyay et al. (2020) have done a comprehensive survey on the incident prediction, resource allocation, and dispatch models, which is among the first to cover the entire urban emergency response management system.

### *3.3. Highway and logistics*

The increasing number of vehicles has imposed overwhelming pressure on highway traffic. Traffic incidents caused by accident, breakdown, adverse weather, and natural disaster pose serious threats to the safety and efficiency of transport and logistics systems. In literature, the critical issues related to highway emergency management include improving emergency response and reducing rescue time. Increasing awareness of these issues has led to a growing body of literature, which can be divided into three categories: emergency resource demand forecasting problem, facility location (or pre-positioning) problem, resource allocation problem, and relief distribution problem. The first three problems are addressed in the pre-event phase, while the last one in the post-event phase (Tufekci & Wallace, 1998). In this subsection, we mainly discuss the influencing factors on highway emergencies, which are critical to emergency resource predictions in the scenario of highway and logistics. Issues related to emergency resource planning and management will be discussed in the following sections.

Many efforts have been devoted to investigating the causes of highway emergencies especially traffic accidents (Ayati & Abbasi, 2011; Anastasopoulos et al., 2012; Mannering et al., 2016; Chang, 2017; Mannering, 2018). Generally, two types of influencing factors are identified in highway emergencies: internal and external factors. The first type of factors is related to the driver's physical characteristics, including age, gender, reaction time, risk-taking behavior, among others. The external factors are dependent on roadway characters, time-varying traffic, and weather conditions. Though an increased interest in investigating the contributing factors to traffic safety can be observed in recent decades, forecasting and precaution problems in highway emergencies are still difficult to address (Mannering, 2018).

Data-driven approaches bring new opportunities to investigate the uncovering correlations between influencing factors and develop accurate predictive models. Two datasets are analyzed in recent studies, i.e., traffic flow data (speed, lane occupancy ratio, flow, density, among others) and accident data (time and location). The aim of highway crash risk prediction is to identify explanatory variables from a high-dimensional variable set using traditional statistical models or machine learning techniques. However, because of the lack of time-series historical data in disaster cases, it is still a challenging issue to predict pre-event, or real-time relief demands (Sheu, 2007a).

### *3.4. Public health emergency*

Outbreaks of epidemics account for a great number of death and damages through financial and economic losses across the globe. For instance, COVID-19, which started in December 2019, has played havoc in the world. According to the World Health Organization (WHO) report dated October 16, 2020, more than 38 million people in more than 100 countries are infected. It is widely recognized that COVID-19 has posed the most serious threat to the global economy since World War II (Sarkar et al., 2020). To understand and mitigate the implications of COVID-19, Elsevier launched the open Special Issue on Modeling and Forecasting of Epidemic Spreading, where a hundred papers are collected. This special issue presents a systematic collection of novel methods, strategies forecasting techniques, and models that reveal a deeper understanding of the spread process of the current pandemic, which also provides guidance for future pandemics. Interested readers can refer to Boccaletti et al. (2020) for details.

Quick responding to large-scale public health emergencies requires accurate prediction of the trend and assessment of resource demand under changing circumstances. The main task in the prediction of the future trend in terms of the total amount of infected people is to derive the epidemic curve. Wang et al. (2020c) indicate that three critical points have to be identified in the prediction model: i) the epidemic peak point, ii) the point with the highest slope, and iii) the point when the number of cumulative cured cases exceeds the number of active confirmed cases, which indicate the initial control of the epidemic. Bouchnita & Jebrane (2020) develop an agent-based model to simulate the transmission dynamics of COVID-19. The results show that restricted movement policies could curb coronavirus contagion. However, due to the difference of prevention measures between countries, the prediction model is location-dependent by comprehensively considering social, political, and economic features (Firmino et al., 2020).

## 4. Resource demand forecasting method

As discussed in the above section, the influencing factors on resource demand and data basis vary with respect to the type of emergency event. For instance, it is difficult to forecast the timing, location, and density of any natural disaster due to the lack of referable time-series historical data. In contrast, in the highway transportation system, a vast amount of data can be applied to predict and analyze potential dangers and to develop an optimal allocation strategy of emergency resources. Admittedly, it is always challenging to accurately forecast the number of survivors in affected areas considering the real-world complexities and uncertainties (Sheu, 2007a,b). With the help of available disaster databases, such as EM-DAT, which stores massive amounts of data collected from more than 18,000 disasters worldwide since 1900, it is sufficient to predict the potential post-disaster impacts, especially the number of victims, impact area, and severity, which serve as the reference to further management of emergency resources.

Over the last few years, the growing body of literature paid much attention to the application of artificial intelligence methods in emergency demand forecasting models. In this subsection, the existing emergency resources demand prediction approaches are summarized. In general, demand forecasting can be roughly classified into two categories (see Tables 2 and 3): traditional methods, artificial intelligence methods, and simulation methods. The methodology and application of each category will be discussed considering the features of the studied problems.

### *4.1. Traditional method*

#### *4.1.1. Experience-based analysis*

Though the timing and location of emergencies, especially those caused by natural disasters, are unpredictable, impacts of disaster can be evaluated based on previous experience with similar types of emergency, density, and other features. Case-based reasoning (CBR) is proposed to solve new problems by referring to successful solutions to similar problems (Zhu et al., 2019). CBR formulates a comprehensive analogy reasoning from one case (new problem) to another (old problem). The process of CBR contains the following four steps (also known as 4R): i) retrieve similar historical cases; ii) reuse the past knowledge to solve the new problem; iii) revise the proposed solution according to new conditions; and iv) retain the new experience which is useful for solving future problems (Liu et al., 2012).

Table 2: Publications classified according to forecasting methods (Traditional methods)

| **Forecasting method** | **Publication** | **Emergency event category** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Earth-quake | Hurr-icane | Flood | Urban incidents | High-way | Public health | Others | General |
| *Experience-based analysis* | | | | | | | | | |
| Case-based reasoning | Guo et al. (2009) | | | • | | | | | |
| | Liu et al. (2012) | | | | | | | | • |
| | Zhu et al. (2016) | • | | | | | | | |
| | Feng & Li (2018) | | | | | | | | • |
| | Wang et al. (2020a) | | | | | | | | • |
| | Shao et al. (2020) | | | | | | | | • |
| Rule-based reasoning | Da et al. (2007) | | | | | | | | • |
| | Guo et al. (2009) | | | | | | | • | |
| *Time series analysis* | | | | | | | | | |
| ARIMA | Díaz-Robles et al. (2008) | | | | • | | | | |
| | Xu et al. (2010) | | | | | | | • | |
| | Holguín-Veras & Jaller (2012) | | • | | | | | | |
| | Juang et al. (2017) | | | | • | | | | |
| | Kırbaş et al. (2020) | | | | | | • | | |
| *Fuzzy theory-based method* | | | | | | | | | |
| Fuzzy set | Song et al. (1996) | • | | | | | | | |
| | Sun et al. (2013) | | | | | | | | • |
| | Shao et al. (2020) | • | | | | | | | |
| *Bayesian decision theory* | | | | | | | | | |
| Bayesian network | Molina et al. (2005) | | | • | | | | | |
| | Rohde et al. (2010) | | | | • | | | | |
| | Qiu et al. (2014) | | | | | | | | • |
| | Taskin & Lodree (2016) | | • | | | | | | |

Table 3: Publications classified according to forecasting methods (AI methods)

| **Forecasting method** | **Publication** | **Emergency event category** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Earthquake | Hurricane | Flood | Urban incidents | Highway | Public health | Others | General |
| *Supervised machine learning* | | | | | | | | | |
| Classification and regression | Revilla-Romero et al. (2014) | | | • | | | | | |
| | Asim et al. (2017) | • | | | | | | | |
| | Lee et al. (2017) | | | | | • | | | |
| | Chang (2017) | | | • | | | | | |
| | Chen et al. (2020) | | | • | | | | | |
| Support vector machine | Mori et al. (2013) | | | | • | | | | |
| | Higuchi et al. (2014) | | | | • | | | | |
| | Singh et al. (2020) | | | | | | • | | |
| *Unsupervised machine learning* | | | | | | | | | |
| Clustering | Sakai & Tamura (2014) | | | | • | | | | |
| | Pohl et al. (2016) | | | | • | | | | |
| *Neutral network* | | | | | | | | | |
| Artificial neutral network (ANN) | Díaz-Robles et al. (2008) | | | | • | | | | |
| | Moustra et al. (2011) | • | | | | | | | • |
| | Mohammadi et al. (2014) | | | | | | | | • |
| | Wang et al. (2020b) | | | | | | • | | |
| | Shastri et al. (2020) | | | | | | • | | |
| | Kamdem et al. (2020) | | | | | | • | | |
| Long short-term memory (LSTM) | Rahman & Hasan (2018) | | • | | | | | | |
| | Yousefi et al. (2019) | | | | • | | | | |
| | Nguyen et al. (2019) | | • | | | | | | |
| | Bao et al. (2019) | | | | | • | | | |
| | Hu et al. (2019) | | | • | | | | | |
| | Kim & Kim (2020) | | | • | | | | | |

However, the reasoning process of an emergency event is usually based on incomplete information: i) missing data in the case base, and ii) inaccurate post-disaster information due to the suddenness and urgencies. Hence, how to extract major features from the current case and to eliminate the disturbance of incomplete information is one of the critical issues of using CBR. Moreover, in order to obtain a feasible and effective relief plan in the immediate aftermath of a disaster, improving search efficiency by reducing the search space is another research focus on CBR.

When history cases are incorrect or not always fitting to the current decision problem, CBR can hardly search or match available cases based on similarities using the hidden domain knowledge. Role-Based Reasoning (RBR) is proposed to make up for this deficiency by considering the decision maker's specific requests. Da et al. (2007) propose an emergency decision-making method combining CBR and RBR. An iterative process is designed, where "if then" rules are added after obtaining similar cases through CBR, aiming to help the decision-maker to adjust his/her solutions. Guo et al. (2009) extend this hybrid reasoning process by integrating the Analytic Hierarchy Process (AHP). An index system is developed to identify distinctive attributes and to speed up the reasoning process.

Many efforts have been devoted to combining CBR and other techniques to increase search efficiency. Liu et al. (2012) conduct a risk analysis CBR on the target area to obtain significant features, such as incident type, occurrence probability, among others. To tackle the uncertainty of information, the fuzzy theory is adopted to CBR by constructing intuitionistic fuzzy sets, which quantitatively describes characteristic factors of emergency cases (Shao et al., 2020).

As mentioned in Section 3.1, secondary disasters also cause serious damage continuously. To describe the hidden relationship of the cascading disaster, the causal event sequence of the trigger disaster and secondary disasters is usually represented by a tree structure (May, 2007) or a "disaster chain" (Zhou et al., 2015). Feng & Li (2018) describe this kind of complex emergency cases as a genetic structure, that is, the retrieval and reuse of similar solutions in the case base are in analogy to the genetic translation and expression processes. Similarly, Wang et al. (2020a) analyze the emergency evolution mechanism with a multi-dimensional scenario space method, through which four types of critical features are identified: inducing factors, bearing factors, pregnant environments, and emergency actions. A decision model based on CBR is then constructed, where tailored matching algorithms are used for different types of data (i.e., accurate numerical data, fuzzy semantic data, and symbolic data).

#### *4.1.2. Time series analysis*

The time series analysis is developed to extract meaningful statistics and other characteristics of time series data (Box et al., 2011). It aims to obtain the characteristics of an emergency's temporal evolution from past observations and then to predict future values. However, time series data collected in an emergency event is usually nonlinear and irregular. The autoregressive integrated moving average (ARIMA) model is one of the most widely used time series methods that could process this kind of data properly. Three critical model parameters should be determined based on problem features and available data: i) the order of autoregressive model, $p$; ii) the degree of differencing, $d$; and iii) the order of moving-average model, $q$. Holguín-Veras & Jaller (2012) use ARIMA to predict the temporal patterns of resource requirements after the hurricane Katrina, such as the temporal evolution of demand and types of required commodities, as well as their corresponding importances. Juang et al. (2017) focus on the forecasting of visitors to the emergency department (e.g., medical center). Six different combinations of parameters are tested, and the results reveal that ARIMA(0,0,1) is appropriate for forecasting emergency department visits.

However, the performance of ARIMA is unstable if time series data is highly nonlinear (Box et al., 2011). A considerable number of studies have been devoted to developing hybrid models that integrate ARIMA with emerging techniques to address nonlinearity. Díaz-Robles et al. (2008) combine ARIMA and ANN to forecast air quality in urban areas. The hybrid model takes the advantages of ARIMA and ANN in linear and nonlinear modeling, respectively, and achieves strong performance on forecasting air quality for a whole year. Xu et al. (2010) design a hybrid methodology combining ARIMA and the empirical mode decomposition (EMD) method. The proposed model extracts the intrinsic modes of the original time series through EMD and uses the ARIMA process for each mode.

#### *4.1.3. Fuzzy theory-based method*

The fuzzy theory has been widely used in emergency decision-making to treat uncertainties in the form of ambiguity and vagueness (Dubois, 1980), both of which widely exist in emergency management problems. For instance, ambiguity refers to the uncertain attributes with multiple options among a set of feasible alternatives from which the decision-maker can choose, while vagueness indicates unclear or imprecise data due to insufficient and incomplete information. The objective of the fuzzy theory is to describe these intrinsic uncertainties in the form of mathematics. Song et al. (1996) develop an earthquake damage evaluation method using the fuzzy sets theory to define the unclear boundary on the classification of earthquake damage grades. Sun et al. (2013) consider a fuzzy rough set over two universes aiming to deal with incomplete information smoothly. Shao et al. (2020) study the relief demand forecasting using the fuzzy CBR. Fuzzy logic is embedded in CBR to handle incomplete and complex historical data.

#### *4.1.4. Bayesian network*

To clearly track the real-time evolution of the disaster's impact, the Bayesian approach applies the probabilistic graphical model to present the conditional dependencies of influencing factors and forecast the occurrence and development of an emergency event. Molina et al. (2005) propose a spatio-temporal Bayesian network to predict the occurrence of river floods. Considering the uncertainty and real-time constraints, a dynamic Bayesian network is built based on the causal relations among different hydrologic processes. With the help of GIS-based analysis, Rohde et al. (2010) use the Bayesian approach to forecast domestic fires in an urban area. Three different datasets collected from past fire incidents, one aggregate dataset (census) and two disaggregate datasets (location and time), are combined using subjective Bayesian data analysis. Qiu et al. (2014) develop a novel Bayesian network-based method focusing on the evolutionary mechanisms of crisis events from both micro (crisis event) and macro (crisis chain reaction) points of view simultaneously. This method is capable of providing a comprehensive pre-warning and predicting the potential losses caused by the crisis event. Taskin & Lodree (2016) apply the sequential Bayesian decision model in the wind speed probability forecasting. A 5-day forecasting horizon is adopted, which is helpful for the proactive preparation of relief resources for potential hurricanes.

### *4.2. Machine learning method*

In the recent decade, big data has brought significant impacts and challenges to efficient data mining and processing in decision-making (Chen et al., 2019). Compared with traditional statistical tools, the machine learning method provides a more accurate and comprehensive description of the system in the context of big data by an iterative learning mechanism from historical information. Increasing awareness of these issues has led to a growing body of literature on the subject of applications of machine learning for emergency management.

#### *4.2.1. Supervised machine learning*

Classification and regression are two basic methods of supervised machine learning for the labeled dataset. The objective of classification is to construct a model with respect to the features of a dataset and to place each object into a known object class, e.g., classifying critical features of an emergency event and finding similar cases in the case base. Regression-based forecasting models use statistical methods to determine the relationship between dependent variables (e,g., resource demand and occurrence of disasters) and a series of independent variables (Yi et al., 2010; Gul & Celik, 2018). Generally, classification and regression methods provide a straightforward framework for identifying the relationship between dependent variables and predictor variables. Support vector machine (SVM) is another supervised learning method aiming to obtain an optimal hyper-plane that classifies the sample data with the maximal margin. Due to its high discriminability for pattern recognition, SVM has been widely used in recognition of disaster outbreaks from sensor data of smartphones (Mori et al., 2013; Higuchi et al., 2014).

Classification of an event's features can be explicitly described by a tree-structure, namely, the decision tree. Thus, the aim of a learning task is to find optimal classification rules which best explain values of dependent variables by classifying explanatory variables. Ensemble learning methods, e.g., Random Forest (RF) and boosted tree, are proposed based on multiple decision trees to deal with high-dimensional features, reduce over-fitting, and improve generalization (Breiman, 2001). Lee et al. (2017) employ RF and boosted-tree models to achieve the spatial prediction of flood susceptibility in Seoul, Korea. The results show that RF performs better than boosted-tree in the capture of a flood. Yu et al. (2017) construct two kinds of forecasting models to forecast real-time radar-derived rainfall based on RF and SVM, i.e., single-mode and multiple-mode models. It shows that the multiple-mode model provides better performance in 1-hour ahead forecasting, while the SVM-based model performs better in 2- and 3-hours forecasting. Chen et al. (2020) predict the flood occurrence using three tree-based methods, i.e., naïve Bayes tree (using naïve Bayes classifiers to replace leaf nodes of the decision tree), alternating decision tree (consisting of decision and prediction nodes), and RF. The spatial flood database is constructed using thirteen explanatory factors. The results demonstrate that the RF is an efficient and reliable model that has a higher prediction accuracy among different types of tree-based forecasting models.

### 4.2.2. Unsupervised machine learning

In contrast to classification, clustering is an unsupervised learning method that aims to divide a group of unlabeled examples into an unknown number of categories with similarities. For instance, Hadid et al. (2020) develop a data-driven modeling approach for flood forecasting, where a clustering-based procedure is embedded in a linear regression because the class labels of regression data are not known in advance. Sood et al. (2017) employ the K-mean clustering algorithm to classify the flood state in five disparate levels. Available data is collected by using collaborative Internet of Things devices installed in a web of hexagonal.

With the widespread adoption of social media, clustering is usually used to identify the occurrence of emergency events in real-time through online media data. Sakai & Tamura (2014) develop a new framework to identify the affected area of emergency in geotagged tweets using a spatiotemporal clustering technique. The proposed method has been validated to be effective in a real-world emergency topic in Japan through crawling geotagged tweets posted on the Twitter site. Pohl et al. (2016) propose an online indexing and clustering procedure of social media data for real-time emergency identification, where indexing aims to track the related vocabulary over time, and clustering is then applied to detect the set of events recognized through indexing.

## 4.3. Neural network

Artificial neural network (ANN) has become increasingly popular in the last decade due to its distinct advantages to exploit the available big datasets and provide higher forecasting accuracy compared with other machine learning methods (Hatcher & Yu, 2018). Wu et al. (2008) propose a risk evaluation model of heavy snow disasters using the ANN considering natural, social, economic, and environmental factors. Aghamohammadi et al. (2013) also use ANN to estimate the severity and distribution of loss in the earthquake. Two key factors are identified in the human loss estimation problem in disaster management: i) estimating the number of casualties caused by a disaster, and ii) determining the spatial spread of casualties. To achieve the goal of estimating the relief demand dynamically in a disaster, Lin et al. (2020) propose a multiplayer perceptron ANN considering the dynamic population distribution utilizing big data originating from web mapping service, social media, crowdsourcing system, among others. Compared with general ANN, radial basis function neural network (RBF-NN) has been proved to have a simpler design process and higher generalization ability (Yu et al., 2011). Mohammadi et al. (2014) use RBF-NN to predict the demand for emergency supplies. The network size and parameters of RBF-NN are optimized simultaneously by a novel hybrid evolutionary algorithm.

In the traditional ANN, all inputs are independent of each other, while the sequential information is not considered (Yousefi et al., 2019). To overcome this limitation, different architectures, i.e., recurrent neural networks (RNN) and convolution neural networks (CNN), are proposed, which have been proved to have better performance. Specifically, RNN is derived from ANN by adding a recurrent connection on the hidden layer, where the looping constraint ensures that the sequential information is captured in the input data. Chen et al. (2013) propose a multi-step-ahead real-time flood forecasting model based on RNN. Model parameters are adjusted repeatedly according to the current observed information to enhance the reliability and forecast accuracy of the proposed method.

CNN is a deep learning method including three types of hidden layers, namely, convolution layer, pooling layer, and fully-connected layer. It is designed to deal with grid-structured inputs, which indicate the data which has strong spatial dependencies in local regions of the grid, e.g., 2-dimensional image (Aggarwal, 2018). CNN is getting increasing attention due to its outstanding performance in the area of image processing. Hence, there have been some works in developing disaster detecting and forecasting models using satellite imagery (Amit & Aoki, 2017; Zhao et al., 2020). Additionally, Nguyen et al. (2017) propose a real-time emergency event detection system based on CNN by using social media data, such as tweets. Considering the huge amount of data for the learning phase, Aqib et al. (2017) are among the first to use Graphics Processing Unit (GPU) to expedite the training process of CNN in the urban traffic prediction problem. Lohumi & Roy (2018) develop a deep learning method to predict the severity level of flood based on videos, the performance of which is shown to be better than the traditional CNN model. Tian et al. (2019) propose a deep learning framework based on CNN to investigate disaster-related information from different modalities, including image, video, audio, text, etc. Qiao et al. (2020) propose an automatic change detection framework for natural disaster detection. The optical flow is estimated based on deep learning to detect pixel-based motion tracking.

One inherent limitation of NN is that the successive multiplication with the recurrent weight matrix is usually unstable because of various time-stamps, resulting in a good short-term memory but poor long-term memory (Aggarwal, 2018). LSTM is designed to address this problem (Hochreiter & Schmidhuber, 1997). Yousefi et al. (2019) forecast the patient visit in emergency departments using LSTM and other statistical approaches, including multiple linear regression (MLR), autoregressive integrated moving average, support vector regression, and ARIMA. The comparison results show that LSTM generally gives a better performance with the lowest MAPE and largest $R^2$ on average in experiments of 1-day to 7-days ahead forecasting. While, ARIMA performs better in short-term (one or two days ahead) forecasting horizons, and MLR shows better results in forecasting horizons of 3-7 days. Rahman & Hasan (2018) use LSTM to predict traffic speed on highways in an emergency event of the hurricane evacuation. The effectiveness of LSTM in capturing nonlinear relationships between traffic-related variables is verified by the result comparison between LSTM and traditional methods, including ARIMA, ANN, and k-nearest NN. Due to its capability of learning nonlinear functions of inputs and capturing long-term temporal dependencies, LSTM has been widely applied in forecasting the demand for relief resources during disasters, such as hurricane (Nguyen et al., 2019), flood (Hu et al., 2019; Kim & Kim, 2020), and public health emergency (Chimmula & Zhang, 2020; Shahid et al., 2020).

### 4.4. Simulation method

Simulation method for EM has raised widespread concerns since the 1980s (Amezquita-Sanchez et al., 2017), which is a powerful tool to study the complex system of emergency events. As one of the most widely applied disaster simulation tools, HAZUS, which began in the early 1990s, has the capability of estimating the intensity of hazards (including earthquake, flood, hurricane, tsunami, etc.) in the exposed area and corresponding potential losses (Schneider & Schauer, 2006). The construction of a simulation system is a typical interdisciplinary problem that contains many disciplines, such as geography, human behavior, information science, economics, urban planning, and transportation. This section will provide a detailed review of two types of simulation methods, namely, physics- and agent-based methods.

#### 4.4.1. Physics-based simulation

Compared with traditional statistics-based prediction models, the physics-based simulation model usually uses in-depth knowledge and expertise regarding disaster parameters to investigate the trigging mechanism of induced hazards (Homma et al., 2014). For instance, two statistical models are usually applied in earthquake prediction, namely, the rupture forecasting model and the ground-motion model, both of which are based on historical observation data. The physics-based waveform simulation could estimate the seismic hazard by simulating the ground motion (Graves et al., 2011).

Another important application of physics-based simulation is in floods, hydrological events, and resulting geological disasters, such as landslides (Zhang et al., 2018). Looper & Vieux (2012) develop physics-based hydrologic models for the flash flood forecasting system. The model using radar rainfall data achieves higher accuracy than that using rain gauge data alone. Though some works suggest that the physics-based method sometimes fails to predict floods due to high uncertainties, e.g., Shrestha et al. (2013), remarkable improvements have been made by using other knowledge. For instance, Bellos & Tsakiris

(2016) propose a hybrid model using both hydrodynamic and hydrological theories.

#### *4.4.2. Agent-based simulation*

Agent-based simulation (ABS) is a powerful tool to represent the complicated decision-making process by employing autonomous agents that can interact with the surrounding virtual environment (Yin et al., 2014). Hawe et al. (2012) indicate that ABS plays an important role in the EM system by achieving the following two goals: 1) reproducing the occurred emergency event and making preparedness for future similar events; and 2) simulating the real-time emergency and acting as a decision-support tool.

Considering the fact that the ABS is capable of simulating individuals' interaction in a dynamic system, it has been widely used in modeling the evacuation process and therefore predicting the evacuation demand, including whether to evacuate, time, path, mode, and other decisions (Wang et al., 2021). Yin et al. (2014) propose an agent-based travel demand model system for hurricane evacuation, through which six evacuation decisions are predicted, namely, evacuate or stay, accommodation type, destination, mode, vehicle usage, and departure time. Koc & Işık (2020) develop a multi-agent system (MAS) for flood risk assessment, which employs heterogeneous agents and simulates their negotiation, coordination, and cooperation. Three agents are considered in this work, namely, social, economical, and environmental agents.

## 5. Discussions

This section first presents our analysis of the reviewed paper by identifying the most challenging problems in the forecasting methods in the EM system. It then provides promising future directions to improve the accuracy and efficiency of forecasting methods.

### 5.1. Current challenges

#### 5.1.1. Natural disaster

Admittedly, accurate prediction of natural disasters is still intractable because of their abrupt occurrence, and limited actions can be made before their occurrence. There have been some works in investigating natural phenomena before a disaster. For instance, the generation of earthquakes may cause abnormal changes in animal behavior (Grant & Halliday, 2010), water composition and level (Grant et al., 2011), electrical and magnetic field signals (Masci & Thomas, 2015). However, very few works have considered the construction of a generalized assessment framework that can be easily implemented in different areas with heterogeneous social and environmental characteristics. One of the challenges in constructing such a framework is how to validate the accuracy of various methods utilizing different types of information and assumptions through cross-validation.

Though the location, time, and damage magnitude of disasters are challenging to predict, quick response to evaluate the scale of damage and estimate the urgent relief demand in the aftermath of a disaster is also of paramount importance. However, in such a complex disaster situation, a large amount of noise information (e.g., incorrect, incomplete, and inconsistent data) are collected, which further increases the difficulty of decision making (Huang et al., 2018). Developing efficient data mining techniques, including data cleaning, integration, and reduction, is a vital and challenging task due to the overwhelming increase of data in a disaster.

#### 5.1.2. Urban emergency

The urban area is the most vulnerable place for both natural disasters and man-made emergency events, which has a higher density of population and infrastructure. Additionally, the effectiveness and efficiency of in-event and post-event emergency management strategies are highly dependent on the accessibility of urban transportation system (Chang, 2003). Unlike the unpredictable natural disasters, the vulnerability of an urban transportation system can be detected beforehand, such as the preposition of assets and supplies (Sabbaghtorkan et al., 2020). With the development of cities, the environmental and social features are changing dynamically, such as population density, road network, among others. There is a lack in consideration of robustness, flexibility, and adaptability of forecasting methods accommodating the dynamic change of influencing factors.

It is true that recent advances have been made by the literature using data mining techniques to explore emergency-related information through social media (Sakai & Tamura, 2014; Pohl et al., 2016; Sabbaghtorkan et al., 2020), but most current efforts are post-hoc analysis. The construction of an EM system integrating real-time forecasting, monitoring, and early warning is still an open question in the literature.

#### *5.1.3. Highway and logistics*

Highway system is another critical component of the transportation infrastructure system that supports the mobility of relief goods and the evacuation of affected people before and after an emergency event. The accessibility of the highway system is of great importance, especially in the case that evacuees try to leave the affected area as fast as possible, such as hurricane and flood (Li et al., 2012). Faturechi & Miller-Hooks (2015) have given seven performance metrics for the highway system to measure its ability to resist emergencies: risk, vulnerability, reliability, robustness, flexibility, survivability, and resilience. Gu et al. (2020) review recent studies on the transportation network's vulnerability, reliability, and resilience under perturbations. It is stated that it is difficult to predict the likelihood of rare and extreme disturbances, i.e., natural disasters. However, recurrent perturbations, such as traffic jams, are predictable with respect to travel times. Though many efforts have been devoted to estimating travel times on highways, the data-driven methods depending on historical data are challenged by novel data fusion methodologies multi-source data collected from loop detectors, probe vehicle data, Global Positioning System (GPS), among others. To increase the accuracy and efficiency of the prediction models, data assimilation methodology with high-quality data and sophisticated prediction algorithms with experimental settings (e.g., the structure of feature structure, the trade-off between accuracy and efficiency) are two major challenging tasks for travel time prediction studies (Oh et al., 2015).

Additionally, cutting-edge traffic management strategies, such as customized service (Huang et al., 2020), traffic signal priority (Humagain et al., 2020), lane reservation (Huang et al., 2021), and lane pre-clearing (Wu et al., 2020), can also be combined with travel time prediction to improve the transportation efficiency for evacuees and relief goods.

#### *5.1.4. Public health emergency*

The prevention of the COVID-19 pandemic has become the first and foremost political policy for most nations in the world. Meanwhile, the coronavirus has mutated in a way that helps the pathogen spread more easily, which further increases the difficulty of the modeling and forecasting of epidemic spreading. Another challenge for epidemic models is how to take nationwide and local preventive measures, such as lockdown, compulsory quarantine, social distancing, travel restriction, into consideration to accommodate the overwhelming demand for healthcare resources and daily relief items. For instance, in current literature, it is assumed that the infection rate is a decreasing function of time of implementing lockdown (Sahoo & Sapra, 2020). Obviously, the epidemic model of infectious diseases is highly nonlinear and dynamic with respect to independent variables, such as time, population, among others, and it always falls behind the actual situation, which is changing over time. The underestimation of the spread of the disease would result in the resource shortage and the loss of life.

### *5.2. Future directions*

In view of the current challenges existing in literature, we then predict some possible directions of forecasting models for EM systems as well as possible opportunities in the coming year of the big data era.

### 5.2.1. *Fusion of multi-source big data*

With the wide equipment of smart devices, such as sensors, GPS, smartphones, and many other IoT-enabled devices, huge volumes and different types of data are available in an emergency event. An effective fusion of multi-source data could provide a consistent and reliable information environment by omitting incorrect and incomplete data sources. At present, though very few, some efforts have been devoted to building the platform for information sharing between different organizations during emergencies (Lee & Kang, 2015; Chen et al., 2019). Efficient data fusion methods involving data cleaning and mapping, critical feature extraction, and incomplete data interpolation would be beneficial for forecasting methods in the EM system and following decision-making problems.

### 5.2.2. *High-performance processing/computing technologies*

The quick response to urgent events relies on powerful computing technologies that enable emergency managers to capture, store, process, and analyze huge amounts of data. Huang et al. (2018) have proposed a conceptual framework of the big-data-driven safety decision-making system. Distributed data management systems and parallel processing techniques are two promising directions to accelerate data processing and decrease the training time in AI-based forecasting models. For instance, the Hadoop Distributed File System (HDFS) has been applied in the training phase of the CNN-based flood prediction model (Anbarasan et al., 2020). The actual need integrated EM system also provides a promising opportunity for the application of computational intelligence technologies.

## 6. Conclusions

During the last four decades, the forecasting method for emergency events has played a vital role in both society and scientific community because it is highly related to human life, property, society, and envionment. In this paper, we review a rich literature that works on forecasting models in the EM system. We categorize the surveyed papers in different ways to show the characteristics of various types of emergency events (see Section 3) and forecasting models including traditional statistical methods (see Section 4.1), machine learning methods (see Section 4.2), NN-based methods (see Section 4.3), and simulation methods (see Section 4.4). Despite the fact that significant advances have been made in recent years, we further highlight and discuss the gaps found through reviewing these papers (see Section 5.1) and provide potential future research directions (see Section 5.2).

The main limitation of this review is that though it summarizes the features of a variety of emergency events and gives an overview of corresponding prediction methods, the advantage of each prediction methods with respect to a certain emergency event is not well discussed, which may provide more insightful remarks and act as a guide for future studies and applications. Another limitation of this paper is that it only focuses on prediction models for relief resource demand and ignores the properties of allocation problems which take the results of resource demand as inputs. Prediction methods that integrate the prediction and allocation models are not included in this survey, which needs more attention in future research.


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