Artif Intell Rev (2019) 52:2131–2168
https://doi.org/10.1007/s10462-017-9589-8

Application of computational intelligence technologies in emergency management: a literature review

Ning Chen[1] · Wenjing Liu[2] · Ruizhen Bai[3] · An Chen[3,4]

Published online: 9 November 2017

Abstract Due to the frequently occurring disasters in the world, emergency management is an attractive research area aiming to stabilize the disasters and reduce the potential damage to human, facility and environment. The timely and effective emergency management is highly relied on the utilization of observable information and the integration of available resources. Computational intelligence is one of the fastest growing areas in the field of computer technology. Nowadays, big data has brought ever-increasing impact and challenge to effective data processing and intelligent decision-making. Computation intelligence technologies play a vital role during the lifecycle of emergency management in the context of big data. This review provides a comprehensive survey of state-of-the-art computation intelligence technologies widely applied in the emergency management, and summarizes the present-day emergency management systems in diverse industries. Finally, some promising future research directions and challenges are indicated.

✉ Ning Chen
nchenyx@outlook.com

Wenjing Liu
liuwenjing6631@163.com

Ruizhen Bai
brzandrea@163.com

An Chen
change1970@163.com

1 College of Computer Science and Technology, Henan Polytechnic University, No. 2001, Century Avenue, Jiaozuo, Henan, People's Republic of China

2 School of Business, Jiangnan University, No. 1800, Lihu Avenue, Wuxi, Jiangsu, People's Republic of China

3 Institute of Policy and Management, University of the Chinese Academy of Sciences, Beijing, People's Republic of China

4 Safety and Emergency Management Research Center, Henan Polytechnic University, No. 2001, Century Avenue, Jiaozuo, Henan, People's Republic of China

Keywords Disaster · Emergency management · Computational intelligence · Big data · Intelligent decision-making

1 Introduction to emergency management

In the contemporary society, a variety of disasters take place more and more frequently. Inevitably, a considerable number of emergency events have posed a devastating threat to human life, environmental protection, social stability, and even political relationship of all countries around the world. The negative effects of disasters highlight the need to improve the emergency management capability and strengthen the security for all countries in the world.

Emergency management (EM) is served as a new discipline and there does not exist a unified definition (Ji et al. 2007). Some representative definitions in the literature are as follows:

- Defined by the Federal Emergency Management Agency (FEMA) of USA, emergency management is the process of preparing for, mitigating, responding to, and recovering from an emergency when a disaster happens (Federal Emergency Management Agency 1999).
- Emergency management disposes the disastrous events by implementing a serious of activities, including detection, preparation, planning, mitigation, response, and recovery (George et al. 2007).
- Modern emergency management is a process to apply modern technologies and management methods to effectively monitor, response to, control, and process the emergency events, by integrating various social resources and analyzing scientifically the cause, development process and negative impact of events (Chen et al. 2009).

In short, emergency management is a complex and multifaceted task that involves a variety of management activities from managers and stakeholders, so as to prevent the occurrence of unexpected events, to control the social damages, and to eliminate the impacts caused by emergency events.

The frequent occurrence of natural and man-made disasters prompted all countries to continuously improve the emergency management process and mechanism. In the USA (Department of Homeland Security of USA 2017), congress approved Emergency Banking Act in 1933, which marked the beginning of emergency management. In 1967, the nation promoted the construction of emergency system. In 1979, FEMA was established as a federal emergency management organization. Later, the 911 terrorist attack and hurricane Katrina urged the US to issue the notable National Incident Management System (NIMS) in 2008.

Japan is one of the countries with massive disasters, especially earthquake, in the world. It has been equipped with specialized emergency management mechanism based on the science and technology in hazard mitigation. In 1993, the International Emergency Management Society (IEMS) was published (Rego 2001). In 1990s, the government designed an assessment system to evaluate the emergency management capability of government and provincials. Nowadays, Japan has built a multi-angle, multi-domain and multi-level coordination system from prime minister's office to various levels of power.

Emergency management in China started lately compared with the developed countries (Chen et al. 2009). In the aftermath of the SARS in 2003, China initiated the development of emergency management to cope with all types of disasters, ranging from natural hazards, industrial accidents, epidemics, to terrorist attack. In 2007, China promulgated the Law of

Emergency Response, which is the first overall and standardized document of emergency management. Afterwards, more and more special emergency plans have been introduced to meet the practical requirements. In 2015, the Anti-Terrorism Law was issued as a milestone of emergency management for China.

Over the years, unconventional emergency management (Chen et al. 2009) has gradually evolved as a focus of research. Unconventional emergency management is aimed to deal with the unexpected, unconventional emergencies (disasters, incidents, hazards) that happened frequently in the world. Unconventional emergency management is characterized by (1) no established rules; (2) a variety of constraints on time, information, and decision; (3) intangible and conflicting criteria. These properties pose significant challenges to intelligent data analysis and decision-support in emergency response. The objective of unconventional emergency decision-making is to make fast and effective decisions with the partial and incomplete information during the emergency response.

The evolution of an incident is composed of three stages in general, namely pre-incident, during-incident, and post-incident. Accordingly, emergency management refers to the process of three phases: (1) detect the early warning signs and predict the occurrence of potential incidents; (2) response to, control, and process the emergency events for the purpose of reducing the negative impact; (3) evaluate the loss caused by incidents and the execution of response, and recover from an emergency. In Chen et al. (2009), emergency management is described as a '4R' process, namely reduction, readiness, response and recovery, where reduction is referred to pre-incident phase, readiness and response are referred to during-incident phase, and recovery is referred to post-incident phase. In each phase, the outcome of decision-making impacts significantly the evolution of incidents and the effectiveness of emergency management.

With the popularity of Internet, big data has become a challenging problem in the world and therefore brought ever-increasing impact with both benefits and negatives in a wide range of industries (Chen et al. 2012; McAfee and Brynjolfsson 2012). Big data is characterized by '4V's (i.e., volume, variety, velocity, and veracity) that have brought great difficulties and challenges to traditional data understanding and analysis. Within the present-day emergency management systems, the immediate and accurate decision-making more and more relies on the capability of data analysis and processing especially in the face of big data. Therefore, there is an urgent need to enhance the computational intelligence functionality of emergency management, such as, to develop scalable and real-time algorithms for time-sensitive decisions, to integrate structured, unstructured, and semi-structured data, to deal with the imprecise and uncertain information, to extract dynamic patterns and outline the evolution of these patterns, to work in distributed environment, and to present the multi-scale, multi-level and multi-dimensional patterns through various visualization approaches (Amaye et al. 2016).

With the overwhelming increase of data, computational intelligence is regarded as a vital decision-supporting technique in many popular emergency management systems. So far, although both computational intelligence and emergency management have attracted considerable attention in their research areas, little effort Chen and Chen (2009) was devoted to the systemic literature review of computational intelligence technology application in emergency management. There is an urgent necessity to review the development of current emergency management systems from the computational intelligence view and identify the gap between computational intelligence and emergency management. Our work is deemed for this task contributing to the literature in the following issues. (1) It provides an extensive review of existing computational intelligence technologies broadly applied in emergency management. (2) It demonstrates the roles and functionalities of decision-supporting components embedded in real-world emergency management systems with the consideration of industrial specificity. (3) It analyzes the challenges to computational intelligence in the big data era when establishing an effective and applicable emergency management system, and provides some caveats and guidelines for future research.

The rest of the paper is organized as follows. Section 2 reviews state-of-the-art computational intelligence and related technologies, including decision tree, artificial neural networks, support vector machines, evolutionary computation algorithms, approximate reasoning approaches, association rule mining, case-based reasoning, clustering and visualization. Section 3 discusses the major topics in emergency management with the emphasis on the contribution of computational intelligence. The potential of computational intelligence is extensively addressed in different tasks of emergency management, including risk assessment and early warning evaluation, emergency service facility location, emergency supply allocation and route programming, crowd evacuation in emergencies, emergency response planning, emergency data preprocessing and visualization. In Sect. 4, we propose a multi-level framework of intelligent emergency management system integrating a variety of sources and functionalities. Some real-world emergency management systems categorized by industries are introduced mainly focusing on the functionalities of computational intelligence technologies. Section 5 concludes the paper and highlights some interesting directions for future research.

2 Literature of computational intelligence technologies

Computational intelligence (CI) is a sub-discipline of artificial intelligence (AI), usually defined as a set of computational methodologies and approaches designed to solve a specific task. The concept of computational intelligence was proposed for the first time in Bezdek (1992) and later the 1st World Congress on Computational Intelligence (WCCI) was held in 1994. Nowadays, computational intelligence has become a hot and ongoing research subject of computer science and has a wide range of applications in real world. Computational intelligence has potential advantages over traditional modeling methods to address the difficult real-world problems which are characterized by complexity, uncertainty and stochastic process in nature. As an interdisciplinary subject, the methodologies and principles of computational intelligence come from multiple subjects including physics, chemistry, mathematics, biology, psychology, physiology, neuroscience, computer science, etc.

Conventional computing mostly involves the methods implemented manually by a set of programs and data structures, such as databases, word processors, and spreadsheet analysis. In contrast, computational intelligence involves the iterative learning from empirical data and eventually emulating an intelligent response to users. From the perspective of data, the learning can be categorized into supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning is the machine learning task which analyzes the labeled data with desired input and output, and infers a mapping function that can be used on new data. Typical examples of supervised learning include face recognition, medical diagnosis, fault detection, generally producing a prediction in response to a query. The widely studied supervised learning problems are binary classification, multi-class classification, multi-label classification, ranking problems, and real-valued prediction (Jordan and Mitchell 2015). Unsupervised learning intends to discover the hidden patterns under specific assumptions about the structural properties of unlabeled data. A diverse array of clustering methods have been developed to detect the structure of clusters embedded in data. In addition, semi-supervised learning that falls between supervised learning and unsupervised learning makes use of unlabeled data along with labeled data in the context of supervised learning.

From a general perspective, computational intelligence tools mainly comprise neural computing, fuzzy logic computing, evolutionary computation, and other related intelligent computing methods. Neural computing typically refers to artificial neural network algorithms which simulate the human intelligence by a network structure of artificial neurons. Fuzzy logic computing imitates the imprecise concepts of human language and thought. Evolutionary computation algorithms that simulate the wisdom of nature include genetic algorithm, swarm intelligence algorithms (ant colony optimization algorithm, particle swarm optimization algorithm, etc.), immune algorithm, simulated annealing algorithm, Tabu search algorithm, and so forth. In addition, some other intelligent computing methods (such as decision tree, association rule mining, clustering and visualization) also have extensive utilization in emergency management. In this article, our efforts are directed to the application of these technologies in different emergency management tasks that cover the lifecycle of emergency and the corresponding management.

2.1 Decision trees

Classification is one of the most important tasks in emergency management, dealing with the likelihood of an incident's occurrence, quantitative rating of the damage, assessment of emergency actions, and recognition of affected objects. Classification is typically a supervised learning process which learns the patterns that best fit the relation between independent features and target feature (i.e., class label) given a training data set, and then predicts the class of new data whose label is unknown. Among all different classification methods, decision tree (DT) is one of the fastest and easily interpreted algorithms. Decision tree infers a tree-shape structure in which the internal nodes define a test on the value of independent attributes, and the leaf nodes indicate the class of associated instances. It is constructed by recursively selecting the best feature and value that split the data into subsets (corresponding to the tree branches) until the stopping criterion is met. So far, different decision tree algorithms such as ID3, C4.5, CART, Random Forest, ADTree have been proposed differing in feature selection, tree pruning, and data structure to improve the generalization capability and scalability of decision trees. In a post-earthquake emergency building inspection system, an assessment model based on C4.5 decision tree was designed to evaluate the damage and usability of affected buildings (Gerbesioti et al. 2001). Decision trees have some advantages: (1) The learning process of decision trees is non-parametric without the requirement of other domain knowledge. (2) Decision trees can deal with both discrete and continuous data. (3) Decision trees have comparable accuracy with neural networks, but the computational cost is much lower. (4) The hierarchical tree model is simple and easily interpreted. Once the tree is constructed, the classification of new samples is operated by a series of test on the independent features. A set of classification rules can be easily derived by combining the tests along the path from the tree root to the leaf nodes. (5) Decision trees are able to discover the dominant variables that determine the target class. For example, Revillaromero et al. (2014) used random forest decision tree to recognize the potential factors that affected the remote sensing signal of Global Flood Detection System on the analysis of 322 river measurement locations in Africa, Asia, Europe, North America and South America.

2.2 Artificial neural networks

Artificial neural network (ANN) is an information processing paradigm inspired from the biological system to deal with nonlinear complex problems that are difficult for conventional computations. It is composed of a set of highly interconnected processing elements (i.e., artificial neurons) working in parallel for data computation through an adaptive learning approach. Artificial neural networks have different architectures accordingly used in various emergency management tasks. Generally, the ANN family consists of many variants including multi-layer perceptron (MLP), self-organizing map (SOM), learning vector quantization (LVQ) among others.

MLP where the connections between neurons do not form a direct circle is aimed to optimize the connection weights by back-propagation (BP) algorithm that minimizes the outcome error. MLP has remarkable ability to approximate any nonlinear relationship embedded in the real-world data. The prediction models based on ANNs usually demonstrate high accuracy and robustness to noise data. However, artificial neural networks suffer from some weaknesses, such as, explanation difficulty as a black-box algorithm, high computational cost, sensitivity to parameters, convergence to local minima, overfitting to the training data, handling only continuous data. MLP neural network has a wide range of applications in emergency management mostly focusing on prediction and evaluation tasks, such as the risk of incidents, vulnerability of facilities, and effectiveness of emergency response. It was ever used to evaluate the validity of electric power emergency management system (Zhang et al. 2010), city emergency management system (Jiang and Li 2012), and coal mine safety emergency management (Wen et al. 2013).

SOM where the neurons are set along a grid and connected through a neighborhood function is learned in an unsupervised manner. SOM is able to reduce the amount of data and simultaneously project the data onto a lower dimensional array, so that it is usually used for data clustering and visualization while dealing with big data. SOM was used to discover and visualize the spatial and temporal anomalies from the large amount of emergency calls in the Czech Republic (Klement and Snase 2010).

LVQ is a supervised variant of SOM designed for data classification. In Abpeykar and Ghatee (2014), a decision support system was implemented based on both unsupervised learning (including SOM, K-means, and hierarchical clustering) and supervised learning (including LVQ, SVM, and CART decision tree) for intelligent incident management in Tehran Niayesh tunnel.

2.3 Support vector machines

Support vector machines (SVMs) are supervised learning models that define a kernel function able to transform the data to a high-dimensional feature space where the data can be separated by linear models. SVMs search for an optimal hyper-plane that separates the different class samples with the maximal margin. The points closest to the hyper-plane (decision boundary) are called support vectors which in fact are the most difficultly classified samples. SVMs are typically categorized as a type of ANN in the sense they share the same form of model, whilst they differ in the selection of activation function and regularization. SVMs have demonstrated significant generalization performance when the underlying data is nonlinear and non-stationary, and therefore gained wide popularity in solving both regression and classification tasks. SVMs are designed for binary classification in nature, but they can also solve the multi-class classification problems through one-against-one or one-against-all strategy. SVMs were found effective in Emergency Rescue Evacuation Support System (ERESS) to detect the occurrence of a sudden incidence and generate an appropriate evacuation route so as to decrease the human damage in panic-type disasters (Higuchi et al. 2014; Mori et al. 2012).

2.4 Evolutionary computation algorithms

It is well known that many decision-making problems, such as the allocation optimization and route scheduling of emergency supplies, emergency facility location, and crowd evacuation, can be defined as an optimization solving problem. Evolutionary computation algorithms and recently emerged swarm intelligence methods are the widely employed strategies to solve optimization problems. The most commonly used evolutionary computation algorithms consist of genetic algorithm, Tabu search, simulated annealing, swarm intelligence.

The genetic algorithm (GA), proposed by Holland in the 1970, simulates the evolutionary process of natural selection to find the global solution to an optimization problem. It represents the solution in the form of chromosome string coded in a proper way. The evolutionary process starts from an initial population of solutions, and iteratively improves the solutions to achieve better fitness by selection, crossover and mutation operators. GA has promising advantages of self-organization, self-adaption, self-learning, fault tolerance, and implicit parallelization. It was proved an effective approach to solve the location and allocation optimization problems of emergency facilities (Chuan-Feng and Chao 2009; Donmez 2015).

Tabu search is a meta-heuristic random search method for mathematical optimization problems. It starts from an initial solution, and searches the neighbors for an improved solution (local search) with some relaxed rules. During the search process, a Tabu table which records the previously visited solutions is employed to avoid the convergence of local optimal solution. In Ren et al. (2012), a Tabu search heuristic algorithm was developed to solve the dynamic scheduling optimization problem for emergency rescue. In a similar way, simulated annealing (SA) is an improved local search algorithm based on the principle that a bad solution can be accepted with a certain probability so that the search has the opportunity to jump out the local optimal solutions and finally reach the global optimal solution. SA was used in a dynamic optimization model to calculate the optimal allocation of available resources to different operational areas (Fiedrich et al. 2000).

Swarm intelligence algorithms inspired by the swarm behavior of insects, birds, and other animals, attempt to find the optimal solution through the collective intelligence of the swarm. Swarm intelligence algorithms are remarkable in robustness, self-organization, distribution, simplicity, scalability, and especially appropriate for solving complex optimization problems in large data environment. In the implementation of multi-agent systems, swarm intelligence algorithms have shown the notable potential in improving the robustness, flexibility and adaptability of systems (Duan 2012). At present, the commonly applied swarm intelligence algorithms are ant colony algorithm (ACO), particle swarm optimization (PSO), bacterial foraging optimization (BFO), frog leading algorithm (FLA), artificial bee colony algorithm (ABC). The swarm intelligence algorithms are usually applied in stand-alone manner to optimization problems or combined with the prediction models to improve the prediction accuracy. In many studies, swarm intelligence algorithms are proved particularly practical to solve the multi-objective optimization problems involved in various emergency tasks. Ibri et al. (2010) combined ACO with Tabu search heuristic algorithm in the hope of improving the dispatching and covering optimization for emergency vehicle fleet management system. Wen et al. (2013) proposed an ACO algorithm to solve the resource location-allocation problem and route planning problem. Zhang et al. (2015) used PSO to simulate the individual and crowd movement in a fire and designed the best evacuation mechanism.

2.5 Approximate reasoning approaches

Unconventional emergency management decision making problems are usually characterized by insufficient risk identification, incomplete and inaccurate information, and uncertain decision-making environment to which the classic determinate decision models are no longer feasible (Sun et al. 2013). Fuzzy logic, rough set, and Bayesian theory belong to the soft computing and approximate reasoning approaches capable to address the imprecise, inconsistent, incomplete information and knowledge.

Fuzzy sets were introduced by Zadeh in 1965 as an extension of crisp sets. Different from crisp sets where an element belongs to a set definitely, fuzzy sets define an indefinite boundary that elements have a membership degree to the set by a real number between 0 and 1. Application of fuzzy logic can be found in many disciplines, such as computer science, control engineering, decision theory, expert systems. Fuzzy logic is of extreme interest in dealing with the uncertain problems, in particular the intricate process of inter-organizational problem solving. In emergency management, Fuzzy logic can assist decision makers to handle the complex decision making problems in uncertain environments in the form of linguistic concepts and rules (Guo et al. 2014). Dellorco has embedded the fuzzy perception and anxiety reasoning in a microscopic model of crowd evacuation able to depict the collective behavior of the crowd (Dellorco 2007). To evaluate the physical effects of non-lethal weapons, a fuzzy logic-based crowd injury model was proposed by using linguistic rules properly designed by the problem domain experts (Kugu et al. 2014).

Rough set approximates the imprecise concepts with a number of precise concepts. Given an imprecise concept A, the rough set is based on two approximation operators: lower approximation operator indicates the precise concepts contained in A, and upper approximation operator indicates the precise concepts whose intersection with A is non-empty. Rough set has potential in dealing with uncertain concepts, without the necessity to define the membership function as it was in fuzzy logic. The research on rough set theory is mainly focused on feature reduction, rule acquisition, and hybrid prediction model. Sun et al. (2013) developed a fuzzy rough set model (Dai and Tian 2013) to predict the emergency material demand and applied with success in earthquake emergency material demand forecasting. Xi and Sun implemented an urban emergency early warning system by the use of rough set theory to improve the prediction accuracy (Xi and Sun 2013). Fuzzy logic and rough set are usually combined with some modeling approaches (for example, a soft CBR model that combined fuzzy logic with case-based reasoning Krupka et al. 2009) to handle the vagueness and uncertainty during the knowledge description in emergency management.

Bayesian decision theory is a probability decision paradigm under incomplete information, by estimating the unknown state with subjective probability, modifying the probability by Bayesian rules, and making optimal decisions with respect to the expected value and corrected probability. A Bayesian decision framework for hurricane forecast is intended to address the complex decision making problems (mandatory evacuation, evacuation supplies location, etc.) with respect to an observed tropical cyclone with a tradeoff between the efficiency and accuracy (Taskin and Lodree 2011). Bayesian theory has notable benefit to describe the uncertainty of the relationship among decision makers, decision and decision alternatives. It was recently used to derive decision rules with the consideration of dynamic changes of the relation among the three factors. The effectiveness of the decision model was verified in a flood disaster emergency case (Wang and Luo 2015).

2.6 Association rule mining

Association rule (AR) mining is intended to discover the interesting correlation among variables in large databases. It was initially introduced to discover the relation among products (items) from the purchase data (transactions) of supermarkets and has extended to various types of databases and application areas. The present-day AR mining algorithms are able to discover binary association rules, quantitative association rules, multi-level association rules, and sequence rules. The strength of an association rule is measured in terms of support and confidence. The former indicates the possibility of the items (item sets) occurring in the transaction. The latter indicates the conditional possibility of some items (referred to the right part of rule) occurring in the transaction in the presence of other items (referred to the left part of rule) in the same transaction. In generally, AR mining consists of two steps: it firstly finds all large item sets which satisfy the support threshold, and then generates the association rules meeting the confidence threshold. In emergency management, AR mining is usually used in risk assessment of a particular incident or exploring the implicit relationship in emergency event analysis (Harms et al. 2004). It was applied to explore the spatial relationship between emergency locations and surrounding objects that contribute to emergency resource planning (Fan and Luo 2013), as well as the inner relationship of related parameters about drilling accidents (Yue and Xiao 2013).

2.7 Case-based reasoning

Case-based reasoning (CBR) is a popular and well researched method based on the concept that previous experience is able to provide suggestions to new problems by recalling the similar historical events and scenarios. The kernel of CBR is K-nearest neighbors (KNN) principle which measures the similarity of a new instance with the past samples using a properly-defined kernel function. CBR system is a '4R' process: (1) Retrieval step searches the case base for the similar past samples; (2) Reuse step adapts the similar samples to the new situation and generates the solution; (3) Revise step validates the effectiveness of new solution in terms of some criteria; (4) Retain step adds the new sample and its solution to the case base if the validation is accepted. Despite the disadvantages (e.g., sensitivity to kernel function, high computational cost, and maintenance overhead of the case base) compared with the rule-based learning paradigm, CBR avoids the complicated model training phase and is applicable to a variety of data types. In emergency management, CBR is the most commonly used approach to generate the emergency response plan under the support of a well-managed plan database. An emergency response plan starts from the risk assessment that identifies the potential emergency scenario, then understands the resource requirements, and finally creates a response plan for all the facilities involved with the full use of available resources. A CBR-based model was realized to offer the rescue recommendations to the commander of a fire protection unit (Krupka et al. 2009). The decision is made based on previous cases, namely the guidelines in the fire protection manual, and modified with respect to the real situation and constraints. Later, Huang et al. (2012) applied natural language process technique that generates imperfect cases from raw information to a practical CBR system for incident reaction and treatment of emergency engineering. In Ma et al. (2014), CBR was introduced to automatically generate the traffic incident response plan. In this approach, Bayesian theory was adopted to predict the unknown values in order to enhance the accuracy of case retrieval. CBR was also embedded in a decision support system to generate the response and recovery measures to nuclear emergencies (Moehrle and Raskob 2015). However, the application of

CBR in emergency management is mostly limited to specific disaster types like fire, hurricane, flood, where the domain knowledge could be easily obtained and structured.

2.8 Clustering and visualization

Clustering analysis is an unsupervised process to group the data into a number of homogeneous clusters that have maximal intra-class similarity and minimal inter-class similarity. The intrinsic similarity or distance measure is defined with respect to the data type and investigated problem. Clustering is a very useful approach when there is no pre-classified data. It is usually carried out in the pre-processing phase to generate compressed representatives of raw data so that the deep data analysis becomes easier especially for large, complex data set with many variables and a lot of internal structures. The use of clustering in emergency management mainly focuses on the high quality information acquisition from a mass of raw data with redundancy and noise. There are multiple approaches to clustering, including partitional clustering, hierarchical clustering, density-based clustering, grid clustering, concept clustering, self-organizing map and so on. In additional to the traditional data, social media (such as Twitter, Flickr and YouTube) has become a vital part with increasing popularity in emergency management. Sakai and Tamura (2014) utilized geotagged tweets to identify the bursty areas of emergency topics using a density-based spatiotemporal clustering algorithm. Clustering was used to generate the situational summaries by making use of the image and video streams from social media and recognize the sub-events that are valuable to emergency management response (Pohl et al. 2016).

Visualization offers a visual and interactive representation for users to understand the data. Visualization plays an important role in emergency management, such as to detect the distribution and property of the incident, facility and environment, to monitor the evolution of incidents and the process of emergency response, and to provide a user-friendly interface to emergency experts (Lu et al. 2013; Wu et al. 2013). When the data is in low dimension (< 3), the commonly used visualization techniques include histogram, box plot, scatter plot, dendrogram, heatmap, plot matrix, hyperbolic tree, parallel coordinates, tree mapping, cobweb, etc. For high dimensional data that are unable to be visualized in a straightforward way, dimensional reduction is an indispensable technique not only for data visualization but also for the subsequent classification or clustering. From the perspective of reduction strategy, dimension reduction can be divided into feature selection and feature construction. The former selects an optimal sub-set from original features by the use of embedding, packaging, or filtering approaches. The latter transforms the high-dimensional original data through a linear or nonlinear projection to a low-dimensional space where the new features are the composition of original ones. The well-known linear data projection methods include principal component analysis (PCA), linear discriminant analysis (LDA), independent component analysis (ICA), singular value decomposition (SVD). Linear methods are able to preserve the linear relation embedded in the data through a simple, fast transformation, but inapplicable to data with complicated and nonlinear structures. Nonlinear methods overcome the linear assumption of data structures and hence effectively explore the real embedded structures and reduce the generalization error of classification. The commonly used nonlinear methods include multidimensional scaling analysis (MDS), kernel mapping, non-negative matrix factorization, manifold learning. Wang et al. (2016) adopted a kernel mapping dimension reduction method in the pre-processing of big data for emergency management of power system.

3 Emergency management tasks

As a branch of artificial intelligence, computational intelligence technologies have the outstanding advantages of self-learning, self-organization, and self-adaptation, along with simpleness, generality and robustness. These technologies can greatly improve the ability and effectiveness of emergency management. Successful emergency management requires comprehensive emergency planning, preparedness, effective response and recovery. A variety of tasks are involved during the lifecycle of emergency management.

- Risk analysis and warning helps the possibly-influenced area and people to defend, evacuate, and eliminate the disaster.
- Resource management provides the shelter, food, water, relief, and other technical equipment.
- Emergency training and exercising refers to the basic skill of people when they are facing the disaster, incident, hurt, and other mishap suddenness.
- Debris removal focuses on the polluted residues that are harmful to the environment and resident.
- Temporary housing provides the temporary houses and ancillary facilities for the victims of the hazard.
- Emergency service facility location aims to set up a reliable and responsive emergency service network able to satisfy the service demand of the victims.
- Supply distribution and route programming concern on the distribution planning and vehicle route programming of diverse emergency materials to the disaster area.
- Evacuation planning studies the human behavior and logical patterns, crowd evacuation animation model and decision making after the occurrence of hazard.
- Emergency planning management is responsible for implementing the effective planning of emergency response.
- Life-support system restoration refers to the recovery and restoration throughout the lifecycle of the disaster.

In this section, we will illustrate some emergency management tasks that are studied extensively in modern emergency management and closely related to intelligent computing and decision making, with the emphasis on the computational intelligence technologies commonly used in each task.

3.1 Risk assessment and early warning evaluation

In emergency management, evaluation is one of critical and complex tasks. From the time dimension of view, emergency evaluation can be categorized into three types (Chen and Chen 2012): pre-disaster assessment, in-disaster assessment, and post-disaster assessment as shown in Fig. 1. Particularly the pre-disaster assessment serves as the basis of disaster prevention and mitigation, mainly to predict the occurrence and severity of potential disasters, dispatch the early warning signs, evaluate the vulnerability of affected facilities, and assess the capacity of emergency management. Among them, risk assessment is an independent and scientific process, generally consisting of three typical steps: (1) hazard identification to recognize what can be likely to go wrong and result in casualties and damage; (2) exposure assessment to describe the likelihood that hazards occur in a qualitative and / or quantitative way; (3) consequence estimation to predict what might be the consequence caused by the hazards and their severity (Jacxsens et al. 2016).

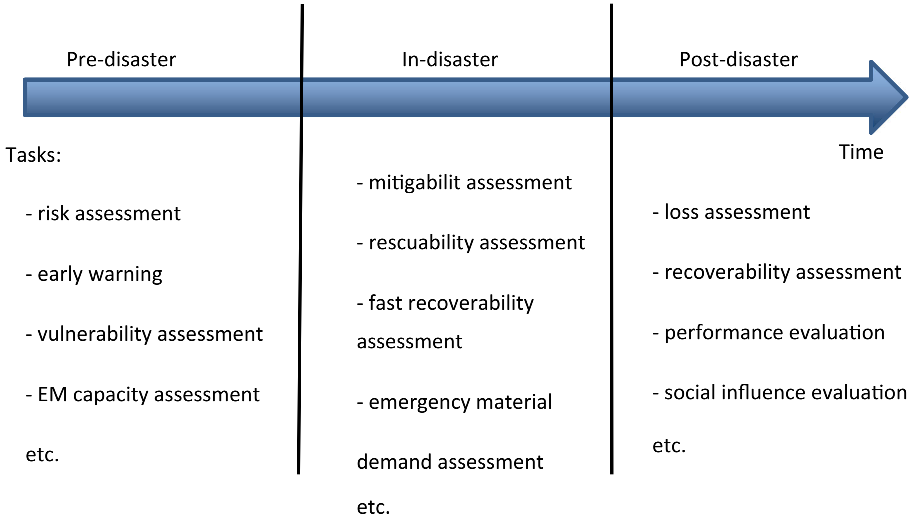

Fig. 1 Evaluation tasks during the lifecycle of emergency management

Emergency risk refers to the likelihood that an event could occur to a particular community or a society within a given time and inflict the loss of life and property (Chiou and Chen 2015). Reasonable assessment of risk and response is critical to suppress the deterioration of emergency. Huang (2013) provided some measurements of risk analysis and crisis response based on the information collected from Internet. According to different criteria, risks can be divided into various categories as showed in Table 1.

According to risk severity, risks can be divided into five levels: extremely high, high, moderate, low and very low risks (Gao 2016). The category is based on the risk value but varies with the applied domains and the assessment methods. Take Chiou's approach (Chiou and Chen 2015) as an example, the risk value depends on four parameters, namely mitigation, hazard, exposure, and resistance (MHER): Risk $= (1 - M) \times H \times E \times (1 - R)$, where the values of all parameters are normalized to [0, 1]. The risk severity is then defined as: "Extremely high" (Risk ≥ 0.7), "High" ($0.7 >$ Risk ≥ 0.5), "Moderate" ($0.5 >$ Risk ≥ 0.3), "Low" ($0.3 >$ Risk ≥ 0.2), and "Very low" (Risk < 0.2). The assessment results lay foundations for further risk early warning. In other approaches, the warning degree was divided into red, yellow and blue warning (Liu et al. 2017) (or red, orange and yellow warning Zhang et al. 2014), representing the severity of risk from the high to low level.

The process of emergency assessment methods can be performed in a qualitative or quantitative way depending on the data available and the application. The qualitative assessment methods include Checklist, Delphi, Brain storm, Fault tree, Risk-matrix and so forth. This review focuses on the computational intelligence related assessment methods that typically belong to the quantitative scope. The broadly used assessment methods include decision tree, neural network, support vector machines, Bayesian theory, association rule mining, and so forth.

3.2 Emergency service facility location

Generally, a city is split up into several administrative districts, where a number of emergency service facilities (e.g., ambulances, fire engines, police patrol vehicles) are constructed in

Table 1 Categories of emergency risks (Chiou and Chen 2015)

Classification criteria	Risk categories	Characteristics
Nature of risk	Pure risks	Cause loss only
	Speculative risks	Be likely to cause loss, but meanwhile possible to bring benefit
Impact scope of risk	Fundamental risks	Affect the whole society or most people;
		Universality;
		Large influence scope;
		Examples: wars, natural disasters, etc.
	Particular risks	Affect only some specific units (e.g., individual or a company);
		No universality;
		Small influence scope;
		Examples: Bank robbing, house firing
Emergency type	Natural disaster risks	Earthquake, tsunami, hurricane, flood, etc.
	Accidental disaster risks	Terrorist attack, transportation accident, fire, etc.
	Public health risks	Infectious disease, etc.
	Social security risks	Chemical leak, even exposure, etc.
Risk severity	Extremely high risks	Risk value depended on specific risk assessment method
	High risks	
	Moderate risks	
	Low risks	
	Very low risks	

order to provide rescue materials to event scene. It should be noted that the emergency service facilities would be taken into operation for a long term once they were built, and the operation cost is highly relevant to the facility location. For the sake of utility maximization, it is of great value to design and optimize the distribution of emergency service facilities, which will directly affect whether the supply of emergency resources may achieve the maximum and optimal effect. Emergency service facility location can be identified as an optimization problem (Mahmud and Indriasari 2009) under the consideration of some requirements.

- Time urgency: arrive at the affected spot within a given time;
- Space full coverage: cover the entire area without rescue blind-spot;
- Cost minimization: avoid the redundant sites and reduce the construction investment and operation cost;
- Service difference: set up different emergency service sites concerning the diversity in disaster type and intensity;
- Coordination efficiency: enhance the coordination among sites and undertake the rescue mission reasonably.

However, these requirements (normally called objectives) are hardly met simultaneously and even conflict with each other in reality. Therefore, only some objectives will be considered in real-world optimization problems. Among them, two optimization problems are commonly investigated: single-objective location-related decision-making problem and multi-objective

Table 2 Four emergency service facility location models

Models	Objective	Advantages	Disadvantages
PMP	Minimize the total (or average) distance	Take the cost into account	Rescue point can acquire emergency services on the condition that the distance between facility site and demand place is less than a certain value
PCP	Minimize the furthest distance	The furthest rescue point can acquire emergency services in the shortest time	Be likely to cause resource waste
LSCP	Optimize the number of facilities with the constraint of the response time less than a given value	Cover all rescue points	Be likely to make the cost too high without the consideration of requirement scale and weight
MCLP	Maximize the services for demand with limited resources	Make the full use of resources	No consideration of requirement scale and no explicit explanation on uncovered demand places

location-related decision-making problem. In last decades, a lot of efforts have been devoted to constructing optimization models of emergency service facility location. There are four classical location models, namely P-median problem (PMP), P-center problem (PCP), location set covering problem (LSCP), and maximal covering location problem (MCLP). Table 2 compares the four problems in the terms of objective, advantages and disadvantages.

Emergency service facility location is characterized by an optimization problem in nature regardless of the format of models. At present, there are various types of optimization algorithms including linear programming and dynamic programming, local search algorithm, and computational intelligence techniques. Given a location problem, the optimization algorithm is determined concerning the complexity of problem, expected solution effectiveness, processing time limitation, data size and other considerations (Mahmud and Indriasari 2009).

Genetic algorithm (GA) is an optimal heuristic method which simulates the biological evolution process in nature. In Guan et al. (2013), GA algorithm was designed to solve the location-allocation models which satisfy the large-scale emergency requirement. Other applications of GA include subway emergency service facility location problem (Li et al. 2011) and risk-based optimization of emergency rescue facility locations (Zhao and Chen 2015). Genetic-simulated annealing algorithm (GA-SA) enriches the searching behavior in optimization process, and has strong capability of exploration in large search space (Ma et al. 2012). In this algorithm, GA algorithm controls the search direction, while SA algorithm makes contribution to local optimum convergence. Case study showed that the algorithm had strong practicability not only calculating the optimal location results, but also getting the possible affected points that are covered by the selected facilities (Li and Yeh 2005; Murray and Church 2004).

Swarm intelligence algorithms referring to a collective behavior of decentralized, self-organized systems, consist of a population of simple agents. There exist interactive activities between agent and agent, and between agents and their environments (Hinchey et al. 2007; Rubio-Largo et al. 2012). Different swarm intelligence algorithms, such as ant colony optimization, particle swarm optimization, artificial bee colony algorithm, bacterial foraging optimization algorithm, glowworm swarm optimization, have been extensively applied to emergency service facility location problem (Aydin and Murat 2013; Xu and Xu 2014).

3.3 Emergency supply allocation and route programming

In the process of emergency management, appropriate emergency supply allocation (or distribution) is an important and challenging task due to the dispersity of supply sources, limitation of transportation capacity, and uncertainty of supply-and-demand. To decrease the disasters' related casualties and financial losses, a mass of emergency supplies and timely delivery are needed. However, in reality although all kinds of official and unofficial organizations have reserved an amount of relief materials, emergency supplies are usually insufficient. The study of emergency logistics, particularly the supply distribution and route programming, is always one of the most popular research fields in emergency management (Anaya-Arenas et al. 2014). Likewise, Holguín-Veras et al. (2012) focused on designing the relief distribution network such as the knowledge of demand, the periodicity of logistic activities and supporting system. Some studies from more concreted perspectives analyzed available supplies after disasters (Davis et al. 2013) or solved a practical transportation problem encountered by crisis managers in dealing with emergency situations (Berkoune et al. 2012). Vitoriano et al. (2015) proposed two intelligent decision aid models for humanitarian logistics to provide emergency relief.

Emergency supply distribution is intended to allocate all kinds of emergency supplies including food, clothes, tents, medical materials and specialized rescue equipment, to distribution centers in disaster-affected areas (Ozdamar et al. 2004; Yi and Ozdamar 2007). In emergency logistics, emergency supply distribution and routing programming are two continuous or inter-sectional activities. When the emergency alert is given, the authorities need to allocate all available resources, determine specific vehicles, and program the vehicle route to the destination. The objectives of emergency supply distribution and routing programming always concern the following restrictions: (1) cost minimization; (2) covering maximization; (3) minimization of transportation time between the supply centers and demand centers. Qiang proposed a vehicle scheduling model along with hill climbing method for better route selection and shorter allocation time in emergency logistics (Qiang 2012). A hybrid simulated annealing (HSA) with a Tabu list that converges fast to reasonable solutions was developed to solve the HP-hard location and routing scheduling problems (Mousavi and Tavakkoli-Moghaddam 2013). Particle swarm optimization and ant colony optimization algorithm have demonstrated the remarkable capacity in emergency supply distribution and route programming (Tian et al. 2011; Zhang et al. 2014).

3.4 Crowd evacuation in emergencies

When disasters occur, one of the urgent tasks is to organize the evacuation of a large number of population in the affected areas. Without a doubt, it is of practical significance to research on crowd evacuation under emergency conditions. A large quantity of researchers from various fields have investigated crowd evacuation in emergencies and recognized the factors hindering the evacuation (Gu et al. 2016; Jafer and Lawler 2016). These studies can be categorized into three types: crowd emergency evacuation theory, evacuation risk assessment and evacuation modeling, evacuation decision-making and simulation.

Crowd emergency evacuation theory basically concerns on the parameters associated with pedestrians' movement, crowd behaviors and pedestrians' behavior rules in evacuation.

Compared with the pedestrians' behaviors under normal conditions, their behaviors under emergency circumstances are much more chaotic and disordered (Haghani and Sarvi 2016).

Evacuation risks are mainly originated from the crowd risk and traffic evacuation risk. When a large crowd is gathered, stampedes are easily caused which bring high risk for crowd safety evacuation. Crowd-gathering risk aims to identify the reason that incidents occur in crowd by analyzing the crowd movement behaviors and individual psychological characters (Haghani and Sarvi 2016). Meantime, the road capacity and the number of pedestrians two are critical factors that influence the evacuation effect. For this problem, a cluster model was applied to evacuation risk assessment within the evacuation areas (Chen et al. 2009). In Chen et al. (2012), the researchers developed a critical cluster model (CCM) that integrated both pre-disaster factors (e.g., the vulnerability and accessibility of the road network) and post-disaster factors (e.g. the impact of disaster and evacuees' behaviors) for evacuation risk assessment and visualization . A large quantity of literature focused on egress and evacuation modeling. Jafer and Lawler divided the evacuation models into five categories, namely random movement models, optimal movement models, directional movement models, patrol movement models, and herd movement models from the perspective of the movement and behavior property of crowd (Jafer and Lawler 2016). In another way, evacuation models was partitioned into mathematics models, human behavior and decision making models, software simulation models, integrated virtual crowd simulation models, and human-centered sensing models (Gonzalez et al. 2014). The mathematics-based models aim to derive quantitative crowd evacuation rules in emergencies so as to predict the crowd movement state and improve the evacuation strategies. These models can be categorized into micro-models (e.g., social force model, cellular automate) and macro-models (e.g., queue network model, fluid dynamic model). The commonly used optimization algorithms have shown the superiority in constructing optimal micro- and macro- evacuation models. The swarm intelligence algorithms were applied to improve the quality of emergency crowd evacuation (Chen and Lin 2009; Forcael et al. 2014). Also, simulated annealing algorithm was used as an optimal solution in crowd evacuation especially for predictable crisis (Afandizadeh et al. 2013; Sutliff et al. 2011).

Emergency crowd evacuation is typically a process that performs the movement of crowd from affected area to safe places. Accordingly, evacuation decision-making includes evacuation path choice, evacuation number allocation and resource allocation. Evacuation path choice is somewhat similar to routing programming that selects the optimal path which usually takes as objective the shortest distance, the shortest time or the most number of evacuation individuals. Once the evacuation paths have been decided, how many individuals should be allocated in every path is the next problem. What's more, resources (relief staff, emergency evacuation vehicles, etc.) are important guarantee for smooth evacuation. A dynamic model was built by coordinating the logistics and evacuation operations for commodity dispatch and crowd evacuation in disaster response activities (Yi and Ozdamar 2007).

3.5 Emergency planning management

Although the disasters cannot be absolutely avoided no matter how advanced risk prediction models are used, there are many approaches to mitigate the consequence of disasters. Among them, emergency planning is of practical significance to avoid the blind and disorder response when the disasters actually occur. Emergency plan is an important preparation that helps government officials to make prompt and efficient emergency response (Wang et al. 2010). Emergency planning management is responsible for implementing the planning effectively in terms of clear objectives, comprehensive content, multi-level balance, coordination among various departments, unified and standardized lead tools (Zhou et al. 2010). A complete emergency planning consists of four elements: risk scenarios, emergency host organization, emergency resource, and emergency activity (Pilone et al. 2016). In China, since General Emergency Plan for National Public Emergency was generated in 2006, a number of emergency plans have been applied in different incidents. In this perspective, emergency plans can be partitioned into general emergency plans and specific plans. General emergency plans provide general procedures, principles and foundation for government in dealing with emergencies, determine the departments or individuals responsible for emergency disposal and define their responsibilities, and ensure the emergency resources. Specific emergency plans further determine the departments and individuals that participant in emergency disposal, as well as the resources required under the framework of general emergency plan. However, it's worth to notice that emergency plan doesn't provide the concrete action tasks for real operations because emergency circumstance is usually uncertain (Tian and Li 2012). There exists a gap between the generation and operation of an emergency plan so that applying an emergency plan would be more challenging than formulating it (Sun et al. 2014).

During the process of developing emergency plans, the typical and major events in history are helpful to generate a more comprehensive emergency plan. Nowadays, CBR is the mostly used approach for generating emergency planning. CBR is a reasoning approach to present solution based on the experience of solving similar problems in the past. Solution of a new problem can be generated by duplicating and modifying similar and successful case solutions existing in the case base. CBR is usually integrated with other modeling methods to achieve a better solution. For example, Li et al. (2013) utilized a rule-based reasoning (RBR) to boost the nearest neighborhood matching of CBR when generating a new emergency plan.

3.6 Emergency data preprocessing and visualization

In the emergency context, the preprocessing and visualization of data have an important effect on emergency management by well understanding the patterns of emergencies and related data (Amaye et al. 2016). Emergency data has various sources from social media, remote sensing, and geographical systems. Generally, they can be divided into six types:

- Basic data: all kinds of social, economic and population data related to emergency management, regional dangerous sources, emergency refuge, emergency organizations, distribution of emergency supplies, emergency rescue force, etc.
- Spatial information data: physical geographic data (e.g., landforms, rivers, vegetation, mountains lakes), basic geographic units (e.g., residential areas, traffic network, boundary, landmark buildings, airports, docks, stations), etc.
- Reported data: monitoring and warning data, loss evaluation data, etc.
- Models: risk prediction models, early alerting models, facility location models, route programming models, supply allocation models, crowd evacuation models, etc.
- Emergency management knowledge: relevant concepts, theories and experience, etc.
- Cases: emergency plans, etc.

The quality of real emergency data is usually not high with an amount of dirty data originating from multiple and disparate data sources (Jia et al. 2016). Moreover, there are inevitably redundant, missing, noisy, inconsistent and uncertain data. In order to avoid decision-making faults caused possibly by these data, it's extremely necessary to preprocess the data before decision-making, including data cleaning, data transformation, data integration to disposal the missing value, delete the mutation data and combine the multi-source data.

Data visualization aims to present data in a graphical present pictorial way so as to depict the relationship embedded in the data intuitively and visually (Brigham 2016). The aforementioned data clustering and visualization techniques introduced in Sect. 2.8 are commonly used approaches to obtain more compact and accurate information from the raw data that contribute to the subsequent in-depth data analysis. Image recognition is another well-known technique to discover the potential disasters (e.g., the landslide disasters along railway by using SVM Wei 2013), or affected individuals (e.g., face-image classification by using FNN Dai et al. 2015) from the images not only saving a lot of human efforts but also improving the recognition accuracy.

In conclusion, computational intelligence has become one of the crucial decision-making techniques in emergency management. In Table 3, the advanced computational intelligence technologies adopted in different emergency management tasks are summarized from the aspect of principle, advantages, and limitations.

4 Intelligence emergency management systems

Emergency management aims at maintaining the social stability, strengthening the national security and resilience for the threats that pose risk to life and property. Accordingly, the evolution of the emergency management system (EMS) determines the national emergency response capacity and efficiency. Emergency management systems with different functions have been proposed and applied with success in coping with devastating incidents. Emergency management relates to the whole spectrum of incidents, also known as a kind of system engineering. Hence, a complete emergency management system plays a vital role in improving efficiency and effectiveness of emergency management (Lee et al. 2012). The modern emergency management system is an intelligent decision support system, able to assist managers in making timely and effective response to emergencies.

Emergency management develops earlier and more mature in America compared with other countries. Department of Homeland Security (DHS) released the National Incident Management System to implement all-hazard emergency management which is applicable at all jurisdictional levels, including preparedness, communication and information system, resource management, command and management, ongoing management and maintenance (Department of Homeland Security of USA 2017). All the time, emergency management system has attracted the researches' attention due to its robustness to cope with complex emergencies. Over the several decades, emergency management systems have become more and more mature in various aspects as shown in Table 4. In this table, 'Early' refers to 'before the big data era' where the level of technologies and productivity was still underdeveloped. 'Modern' refers to 'in the big data Era', where cloud computing, big data and mobile Internet are three major themes with the development of Internet and computational intelligence technologies in the recent decades.

A variety of advanced techniques have been implemented within the emergency management systems. The 3S technologies, namely Remote sensing (RS), Geography information systems (GIS), and Global positioning systems (GPS), possess the function of collecting, processing and updating the spatial information and environmental information rapidly, accurately and reliably. They have been applied in the emergency management, such as disaster rescue management system (Yotsukura and Takahashi 2009), forest fire protection (Kalabokidis et al. 2012), environmental risk source management (Ma et al. 2013), and recovery analysis of damaged highway in earthquake (Liu et al. 2015). Some other soft technologies

Table 3 Computation intelligence technologies in emergency management

CI technologies	Principle	Advantages	Disadvantages/difficulties	Emergency management task examples
Decision trees	Construct a tree by risk factors as nodes and compute the possibility of each node and path	Non-parametric learning process;	Objective should not be complex;	Risk assessment and early warning (Revillaromero et al. 2014; Yan et al. 2016)
		Handle both discrete and continuous data;	Complex calculation if many values are uncertain	Loss evaluation (Gerbesioti et al. 2001)
		High accuracy and low computational cost;		
		Easily interpreted;		
Artificial neural networks	Inspired from the biological system to deal with nonlinear complex problems	Distributed information storage;	Choose appropriate neural network structure;	Risk assessment and early warning (Jiang and Li 2012; Li and Li 2012; Wen et al. 2013; Zhang et al. 2010)
		Parallel processing;	Convergence to local optimum; Overfitting to the training data; Handling only continuous data	Clustering and visualization (Lee 2010)
		Self-learning;		
Support vector machines	Search for an optimal hyper-plane that separates the different class samples with the maximal margin	Avoid overfitting;	Choose optimal kernel and parameters;	Risk assessment and early warning (Gu et al. 2010; Wei 2013)
		Approximation to a bound on the test error rate; Applicable to small scale of samples	Time-consuming	Evacuation route programming (Higuchi et al. 2014; Mori et al. 2012)
Bayesian theory	Handle uncertainty through subjective probability	Incomplete information; Risk probability estimation	Complex calculation process	Risk assessment and early warning (Simon et al. 2016; Villa et al. 2016; Wang and Luo 2015)

Table 3 continued

CI technologies	Principle	Advantages	Disadvantages/difficulties	Emergency management task examples
Fuzzy set theory	Define an indefinite boundary that elements have a membership degree	Handle the complex decision making problems in uncertain environments in the form of linguistic concepts and rules	Define the proper membership function by experts	Risk assessment and early warning (Guo et al. 2014)
			Discretization of continuous data	Crowd behavior prediction (Dellorco 2007; Kugu et al. 2014)
Rough set theory	Approximate the imprecise concepts in terms of precise concepts	Deal with indiscernibility, ambiguity and imprecision in data;	Discretization of continuous data	Risk assessment and early warning (Xi and Sun 2013)
		No definition of the membership function		Emergency material demand forecasting (Sun et al. 2013)
Association rule mining	Discover implicit correlation among variables	Discover various types of rules;	Specify support and confidence thresholds manually	Risk assessment and early warning (Harms et al. 2004; Yue and Xiao 2013)
		Handle both continuous and discrete data		Emergency supply allocation (Fan and Luo 2013)
Genetic algorithm	Simulate the process of biological evolution to find the global solution to an optimization problem	Easy accomplishment;	No guarantee of finding global optimum;	Emergency facility location (Donmez 2015; Feng 2006; Li and Yeh 2005; Murray and Church 2004; Zheng et al. 2014)
		Robustness;	Long optimization time;	Emergency supply allocation (Lu and Zhang 2014)
		High universality;	Unguided mutation;	Crowd evacuation (Yasufuku et al. 2014)
		Wide application scope	Choice of fitness function and genetic encoding	

Table 3 continued

CI technologies	Principle	Advantages	Disadvantages/difficulties	Emergency management task examples
Simulated annealing algorithm	Local search by accepting a worse solution with a certain probability	Insensitive to initial value;	Designed with high initial temperature;	Emergency facility location (Ma et al. 2012)
		Easy coding	No guarantee of finding global optimum	Emergency supply allocation (Fiedrich et al. 2000)
				Crowd evacuation (Afandizadeh et al. 2013; Sutliff et al. 2011)
Tabu search	Search the immediate neighbors for an improved solution with some relaxed rules	Avoid the convergence of a local optimal solution	Determine the length of Tabu table;	Emergency facility location (Basu et al. 2015)
			No guarantee of finding global optimum	Vehicle route scheduling (Ibri et al. 2010)
				Evacuation route optimization (Jiang et al. 2013)
Swarm Intelligence Algorithms	Imitating individual behavior by special information communication	Avoid binary code;	Randomness of initial process makes particle's quality uncertain;	Emergency facility location (Aydin and Murat 2013; Xu and Xu 2014)
		Distributed computing;	Easy to fall into local optimum	Emergency supply allocation (Tian et al. 2011; Wen et al. 2013; Zhang et al. 2014)
		Robustness; Easy hybridization with other algorithms		Crowd evacuation (Chen et al. 2009; Forcael et al. 2014)
Case-based Reasoning	Generate solution to a new problem by duplicating and modifying the similar cases	Easy to set up a knowledge base; Applicable to problem domains that are not well understood;	Bottleneck of case matching; Sensitivity to similarity measure;	Emergency planning (Huang et al. 2012; Krupka et al. 2009; Moehrle and Raskob 2015)
		Easily be expanded	High computational cost;	
			Maintenance overhead of case base	

Table 3 continued

CI technologies	Principle	Advantages	Disadvantages/difficulties	Emergency management task examples
Soft case-based reasoning	Conjunct case-based reasoning with soft computing methods	Handle the imprecise, incomplete, and uncertain information in case matching	Define the fuzzy membership by experts	Emergency planning (Ma et al. 2014)
		Tractability, robustness, closer resemblance to human decision making		
Clustering and visualization	Partition the data into homogeneous clusters based on the intrinsic similarity and provide a visual and interactive representation	Unsupervised learning process; Generate compressed representatives of raw data;	High computational cost;	Identify bursty areas (Sakai and Tamura 2014)
		Acquire high quality information;	Difficult to recognize complex structures;	Clustering emergency rescue route (Li 2011)
		Identify redundant and noise data	Different variants applicable to different data	

Table 4 Development of emergency management systems

	Early emergency management systems	Modern emergency management systems
Country	Several developed countries, such as US, Switzerland, Canada, Europe, Japan, Korea	Both developed and developing countries, such as Greece, China, India, Mexico, Italian, Turkey, etc.
Industry	Limited industries including environment, transportation, earthquake, nuclear	A variety of industries including environmental, transportation, earthquake, nuclear, flood, fire, hurricane, food, electric power, construction, medicine and health, etc.
Complexity	Single industry, department and region;	Cross-industry, inter-department and cross-region;
	Limited functionality;	Multi-functionality;
	Provide simple patterns	Provide multi-scale, multi-level, and multi-dimensional patterns
Platform	Access, Foxpro	MySQL, Berkeley, Solid, SQLite, Hadoop, Spark, Java, etc.
Data source (volume and data type)	Small amount of data;	Big data in data warehouse;
	Numeric, discrete, spatial and relational data	Structured, semi-structured, unstructured, spatial, and relational data
Decision-support functions	Collect information in small database;	Collect and organize information continuously;
	Single region response;	Real-time track temporal development;
	Response simulation	Humanized interactive interface
Decision-making technologies	Neural network, Data assimilation, vision-based incident detection, Decision tree, Genetic algorithm	CBR, GA, ANN, PSO, Fuzzy logic, Bayesian theory, GA-SA, SVM, Decision tree, Clustering, Visualization, Petri net, 3S, RFID, Wireless sensor, Cloud Computing, Web-GIS, Internet of Things, etc.

have been used in specific industries. Radio Frequency Identification (RFID) technology is used in intelligent inventory management system to real-time trace (Ozguven and Ozbay 2015). It can utilize management techniques to keep track of real-time commodities in the aftermath of a disaster. Furthermore, sensor network attracts the interest of both academic research and government, such as information communication technology, wireless sensor network, and internet of things (Quan and Zhu 2012; Zambrano et al. 2016).

In the era of big data, computational intelligence technologies are more and more considered vital in a wide range of domains. Inevitably, there is massive unstructured information during the process of emergency handling. Lee et al. (2012) presented an unstructured information management system (UIMS) to organize useful knowledge quickly and accurately. The UIMS can be implemented as a city emergency management system (CEMS), in which dynamic clustering was used to process the unstructured information. In recent years, cloud computing is provided as a service over the Internet. Palmieri presented a hybrid cloud architecture to compute and storage resources (Palmieria et al. 2016). Balis proposed modern environmental monitoring and decision support systems incorporating IT and cloud computing (Balis et al. 2016). How to introduce the newly-emerging technologies into the lifecycle of emergency management and realize emergency management system intelligent, real-time and interactive is still an urgent and on-going issue to both academic researchers and industrial practitioners.

4.1 A general framework of emergency management systems

Various emergency management systems and tools have been developed in different industries. Despite the specificity due to the industrial characteristics, they have some generalities. According to the requirement analysis of emergency management and core components of specific emergency management systems, we propose a general framework of intelligent emergency management system in Fig. 2. It should be noted the real-world emergency management systems may be designed with some components and limited capabilities. The framework consists of data layer, network middleware, application layer and interaction layer. Semantic Web technologies are adopted to harmonize heterogeneous data from databases in data layer via data access and network middleware. Then, the heterogeneous data are processed in application layer. And finally, emergency management decision results are presented through interaction platform. In brief, the framework outlines the procedure of emergency management: data collection (data-layer), data analysis (network middleware and application-layer), and data dissemination (interaction-layer).

- The data-layer is in charge of collecting and installing information from sensor devices located in various regions. During the disposing emergency events, information acquisition can determine the effectiveness of intelligent decision-making. For this purpose, the framework has the function of static information storage and dynamic information searching (Chen and Chen 2016; Sedighi 2008).
- The network middleware is a channel of achieving application-layer communication usually composed of wireless sensor networks and local area networks.
- The application-layer comprises eight sub-systems, which is the platform for decision support system to analyze, dispose emergency information and make decisions. Among them, prevention and preparation system is responsible for training commanders, making plans, public education and emergency drilling in day-to-day operations. Recover and reconstruction system is in charge of constructing lifeline engineering and providing psychological assistance for affected people after disasters. Legal guarantee system manages the laws, regulations and standards. Decision support system as the heart of an EMS, processes the emergency information to generate decisions for emergency commanders. Incident command system contains multi-agent coordination and resource management system.
- The interaction-layer presents a variety of information under the help of visualization technologies. The social media and Web-based platform can communicate the real-time information to the public, and provide decision-making alternatives to the emergency commanders.

4.2 Fire emergency management systems

Among all kinds of natural disasters, fire is one of the most frequent and widespread hazards that threaten major ecosystem and social development. Effective and ideal fire warning is an important task which can discover the potential risks and avoid the occurrence of some events.

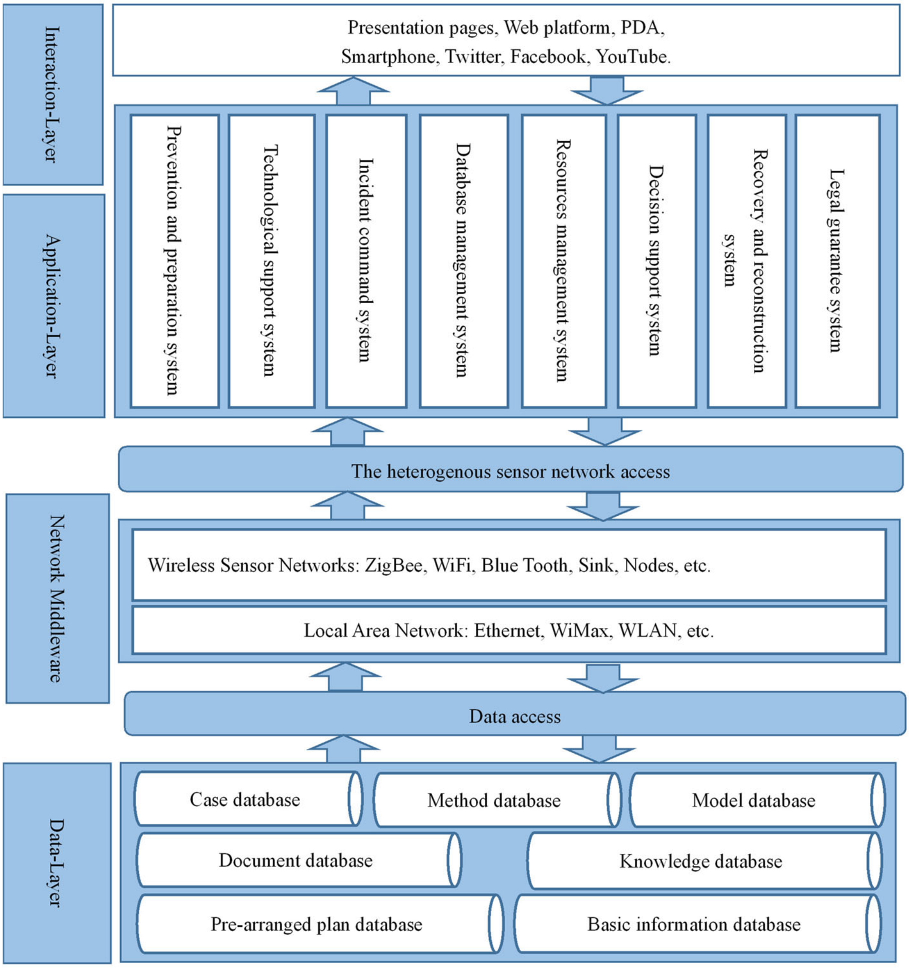

Fig. 2 The general framework of intelligent emergency management system

In the past, most countries focused on fire suppression, such as Spain in the 1980s and 1990s of the last century (Munoz 2007). For example, CBR was applied widely in fire rescue service (Krupka et al. 2009) and knowledge management of fire response (Baisakhi et al. 2010). Kostas et al. (2012) developed a decision support system (DSS) using 3S technologies. Zheng et al. (2014) applied particle swarm optimization algorithm to classify population in fire evacuation. Zia et al. (2014) proposed a fire emergency management system in the Web-of-Objects (WoO) infrastructure through sensors and actuators. Generally, the existing fire management systems have ability of reviewing fuel behavior and weather conditions. Involving economic analysis in fire management will be a future research direction with practical significance (Robert et al. 2013).

4.3 Earthquake emergency management systems

Earthquake is sharp shocking of the earth's crust within several seconds, which can lead to tremendous losses to lives and property. This disaster has abruptness characteristic and usually results in a chain of evolutional disasters, such as quake aftershocks and tsunami threats (Li and Li 2012). The formulation and implementation of emergency plan is indubitably an effective way to deal with the earthquake (Hou and Li 2008).

In some developed countries, earthquake early warning systems are applied in view of the time difference between receiving S and P waves (Zollo and Lancieri 2007). Tomohiro et al. (2011) designed an earthquake early warning system (EEWS) and real-time strong motion monitoring system (PSMS) for high-rise buildings. Kangi (2015) applied clustering technique to prepare the rescue and relief operations in earthquake damage system. A multi-objective stochastic programming model was constructed using particle swarm optimization algorithm for developing earthquake response plan (Mohammadi et al. 2016). Munib et al. (2016) designed prediction and warning systems using Wireless Sensor Networks and Information Communication Technologies (ICT). However, the effectiveness of warnings highly depends on the location of person and whether he (or she) can escape to a safe area. Despite the supporting systems, improving the emergency awareness and response capacity of the public is still an important prerequisite for successful earthquake rescue.

4.4 Environment emergency management systems

Environmental emergency refers to natural or man-made accidents that suddenly take place and cause serious environmental damage, such as water pollution, heavy metal pollution, ecological damage and species crisis. Such events usually occur suddenly and release a considerable number of contaminants within a short period of time.

It has been demonstrated that computational intelligence technologies have a great potential in environmental EMS. The application of CBR is mature in environment management (Chen et al. 2008). However, CBR-based systems suffered from the deficiency of cases and difficulty of case adaptation, therefore they were usually integrated with GA (Kerstin et al. 2013) and BP-ANN (Kostas and Stamoulis 2007; Liao et al. 2012) to achieve a better performance. Ma et al. (2013) developed an environmental risk source management system on GIS platform. Later, Chen et al. (2014) developed an environmental risk analysis system for petrochemical industry based on a browser/server model and Web-GIS technology. More recently, a two-stage optimization model was presented to identify the material warehouse locations and emergency material reserve schemes in pre-incident stage (Liu et al. 2016).

4.5 Transportation emergency management systems

Nowadays, the increasing number of vehicles poses great threats on traffic safety, such as the traffic congestion and illegal driving. Some developed countries have established stable traffic emergency management system and mechanism, such as, Freeway Incident Management System by US (Deng 2000), Vehicle Information and Communication System (VICS) by Japan (Rego 2001), and Traffic Incident Assistance System (TIAS) by Germany (Feng 2006). These systems greatly enhance the traffic safety and achieve abundant experience in transportation emergency management.

Some computational intelligence algorithms, including neural networks (Srinivasan et al. 2004), fuzzy logic (Kong and Xue 2006), wavelet analysis (Samant and Adeli 2000), Bayesian network (Zhang and Taylor 2006), hybridization algorithms of ANN and GA (Lee 2010), have shown their advantages on high detection accuracy and computational efficiency in transportation emergency management. Regarding the problem of heterogeneous information processing and environmental interaction in traffic accidents, Wang et al. (2012) developed a Cyber-Physical System (CPS) based on perceptual control theory. Alvear et al. (2013) applied decision tree to estimate the rescue and evacuation time of the traffic accidents occurred in road tunnels.

4.6 Flood emergency management systems

Flood is a common natural disaster with increasing frequency in the world and usually accompanied by destructive damage. It is of critical importance to establish an efficient flood emergency management system which is scientifically sound and technologically rigorous.

A Web heterogeneous node meta-mode (Chen et al. 2014) called Petrochemical Industry Environmental Risk Source Management System (PIERSMS) was developed to evaluate the environmental risk of the petrochemical industry in China. A Web-based decision support system (www.flire-dss.eu) Giorgos et al. (2016) was developed by Greece researchers for dynamic flood monitoring and warning. A chaotic PSO algorithm was designed to flood control operation (He et al. 2014). In order to protect against flood in built-up areas, Magdalena et al. (2015) developed a decision support system for emergency flood embankment stability. A flood controlling system was developed in combination of various algorithms including PSO, fuzzy logic, and GA (Hamed et al. 2016). In addition to flood controlling, the study of flood emergency has mostly focused on computer simulation (Liu et al. 2012), decision support (Horita et al. 2015) and flood vulnerability evaluation (Louis et al. 2016).

4.7 Nuclear emergency management systems

Nuclear accidents are caused by large nuclear facilities, which may result in radiation damage and radioactive contamination, even pollute the surrounding environment over a long period of time. For instance, the Chernobyl disaster in 1986 has been lingering until today. Radiological accidents are considered a major threat that requires effective prevention and rapid reaction (Benamrane and Boustras 2015).

An interactive computer support in decision conferencing was an early attempt for quick response to offsite emergency (Jyri et al. 2007). Later, a nuclear radiation release prediction system was implemented in nuclear emergency management (Benamrane et al. 2013). CBR was extensively applied in nuclear emergency management for creating response plan (Farah et al. 2011; Stella and Wolfgang 2015). Zhang et al. (2014) applied GA-SA algorithm to source term inversion of nuclear accident. Zhao et al. (2014) analyzed the accident scenarios by accident diagnosis model based on BP-ANN. Recently, Xie et al. (2016) developed a framework of the cross-domain integration processes using Space Mapping and Semantic Web. For Fukushima accident shocking nuclear management, Mahdi and Mohammad (2016) proposed a modern Accident Management Support Tool (AMST) that adopted ANN, fuzzy logic, heuristic methods and expert system.

4.8 Hurricane emergency management systems

Hurricanes are deep tropical cyclones, generally accompanied by strong wind and heavy rain. Timely forecast and evacuations before hurricane are fundamental to reduce the damage. Some representative hurricane emergency management systems have emerged in the past. Selda and Emmett (2010) presented inventory decisions for emergency supplies based on hurricane prediction. Yin et al. (2014) developed an agent-based modeling system for travel demand simulation. Taramelli et al. (2015) proposed a GIS-based approach for hurricane hazard and vulnerability assessment, able to judge the hazard (type, magnitude), identify the risk elements (type, location, data features), and assess the vulnerability. Gu et al. (2010) forecasted the tropical cyclone intensity based on PSO in conjunction with SVM. Dong and Pi (2014) established hurricane trajectory prediction model by association rules.

4.9 Integrated emergency management systems

The integrated emergency management systems are characterized by multi-agency, multi-objective, multi-layer and comprehensive aspects. They are usually designed as inter-departmental, cross-regional and cross-industrial taking into consideration the connection among disasters and coordination among departments. The most typical system is National Integrated Management System of USA, which can take response to both natural and man-made disasters coordinating individuals and federal government. The city emergency response systems aim to integrate the public security, transportation, communications, electric power, water conservancy, earthquake, civil air defense, municipal administration and other governmental departments into a unified operation system in order to achieve cross-regional, inter-departmental, and cross-industrial management to disasters. In China, a number of cities (e.g., Beijing, Shanghai, Nanning, Chongqing, Weihai, Liuzhou) have established the city emergency response systems which provide the guarantee for the public safety of the city (Pei et al. 2010; Wan and Song 2012). In Australia, some scholars have put forward a mobile-based emergency response system for intelligent m-government services with the attempt to enhance the interaction between multiple agencies in emergency situations (Amailef and Lu 2011). In United States, many cities such as San Francisco, Portland and Seattle have built comprehensive public security geographic information systems and emergency resource systems to achieve scientific allocation of personnel, equipment, supplies (Zhong 2011). In Japan, a cross-department and comprehensive urban crisis management institution has been established under the leadership of the mayor. For example, Tokyo set up a comprehensive disaster prevention department against various types of crisis in 2003 (Jin 2015). In England, a city risk management system based on the comprehensive risk registration was established in London, and a syndromic surveillance system was used to detect a bioterrorism attack in Scotland (Meyer et al. 2008).

In conclusion, computational intelligence technologies can discover the potential value of data by realizing the intelligent disposal of unexpected events. It is commonly believed that the CI-based emergency management can systematically help the commanders to identify the risk sources and provide response measures, especially under the circumstance of limited time, enormous pressure and information asymmetry. Table 5 summarizes the representative emergency management systems in specific industries with the focus on the adopted computational intelligence technologies and primary functions.

Table 5 Summary of emergency management systems

Industries	Primary functions	Representative systems	CI technologies
Fire	Provide fire rescue services	Fire emergency handling system (Baisakhi et al. 2010; Krupka et al. 2009)	CBR
	Satisfy interaction services	Fire emergency management system (Zia et al. 2014)	CBR; Visualization
	Classify evacuee population	Fire evacuation system (Zheng et al. 2014)	PSO
	Divide people's actions	Rescue evacuation support system (Higuchi et al. 2014)	SVM
Earthquake	Pre-deploy emergency supplies	Stochastic programming model (Mohammadi et al. 2016)	PSO
	Transmit precautionary measures	Warning and prediction system (Munib et al. 2016)	Visualization
	Prepare rescue and relief operations	Earthquake damage system (Kangi 2015)	Clustering
	Optimize resource allocation	Emergency response model (Fiedrich et al. 2000)	SA
	Assess usability of buildings	Post-earthquake management system (Gerbesioti et al. 2001)	Decision tree
Environment	Retrieve knowledge	Environmental emergency model (Kerstin et al. 2013)	CBR; GA
	Simulate air pollutant concentration	Air pollution model (Kostas and Stamoulis 2007)	ANN
	Support emergency rescue	Two-stage optimization framework (Liu et al. 2016)	Hierarchical clustering
	Achieve case adaption	Environmental emergency preparedness system (Liao et al. 2012)	CBR; GA
	Generate decision models	Environmental emergency DSS (Liao et al. 2012)	CBR; GA; ANN; BP-ANN
Transportation	Deploy emergency services	Emergency decision support system (Alvear et al. 2013)	Decision tree
	Monitor abnormal circumstances	Traffic cyber-physical system (Wang et al. 2012)	Visualization
	Detect incident automatically	Freeway monitoring system (Srinivasan et al. 2004)	ANN
	Reduce traffic congestion	Incident detection system (Kong and Xue 2006; Samant and Adeli 2000; Zhang and Taylor 2006)	Fuzzy logic, Bayesian network, Wavelet transform
	Update incident probability		
	Extract incident-related features		
	Forecast accident duration	Accident duration model (Lee 2010)	GA; ANN

Table 5 continued

Industries	Primary functions	Representative systems	CI technologies
Flood	Migrate to a mobile platform	Web-based decision support system (Giorgos et al. 2016)	Visualization
	Monitor flood control gate	Flood controlling system (Hamed et al. 2016)	GA; PSO; Fuzzy logic
	Control parameters	Flood control operation model (He et al. 2014)	PSO
	Simulate indoor pedestrian evacuation	Evacuation simulation (Zhang et al. 2015)	PSO
	Analyze relationship of multi-agent	Decision-making model (Wang and Luo 2015)	Bayesian network
Nuclear	Structure and reuse knowledge	Emergency and remediation management system (Stella and Wolfgang 2015)	CBR
	Identify accident initiators	Management support system (Mahdi and Mohammad 2016)	ANN; Fuzzy logic
	Determine fault location		
	Estimate break size		
	Evaluate source term	Source term inversion model (Zhang et al. 2014)	GA-SA
	Analyze accident scenarios	Accident diagnosis model (Zhao et al. 2014)	BP-ANN
Hurricane	Identify inventory location	Supply inventory planning (Selda and Emmett 2010)	Bayesian theory
	Mine trajectory database	Hurricane trajectory prediction model (Dong and Pi 2014)	Association rules
	Forecast hurricane intensity	Intensity forecast model (Gu et al. 2010)	PSO; SVM

CBR cased-based reasoning, *PSO* particle swarm optimization, *SVM* support vector machine, *GA* genetic algorithm, *ANN* artificial neural network, *SA* simulated annealing, *BP* back propagation

5 Conclusions and future remarks

Emergency management has become a major and growing discipline in the world. As an important innovation and development element in the global society, big data has a significant influence on emergency management (Wu et al. 2016). Under the background of big data era, the acquired data should be well utilized to meet the requirement of the timely and effective emergency management. Computational intelligence technologies able to deal with big data are intended to make the full use of all acquired data, construct more accurate models, so as to take the timely and effective emergency response, and eventually decrease the damage and stabilize the incidents. Over the recent years, it has been observed an increasing interest of integrating a diversity of computational intelligence technologies in emergency management for diverse tasks and industries. However, effective decision support still requires the in-depth integration of newly-emerging computational intelligence techniques. This paper presents a comprehensive survey of the state-of-the-art computational intelligence techniques commonly applied in the literature of emergency management considering the challenges of big data. In this research survey, we reviewed more than 170 papers published in scientific referred journals and related international conferences putting the emphasis on the computation intelligence technologies integrated in emergency management theory and systems. The computational intelligence techniques are discussed from the perspective of emergency management tasks and industries. It can be revealed that computational intelligence has become one of the critical aspects to develop an intelligent emergency management system especially in big data era.

There are some critical open issues necessary to be addressed. (1) The growth of unconventional incidents today highlights the ability to handle incomplete information, incompatible criteria under pressures and uncertainties. Although the importance of emergency management has been broadly recognized, applicable methods in the emergency management process still cannot fill the requirements. The research of unconventional emergency decision-making is ongoing to bring computational intelligence technologies and other related disciplines together. (2) The explosive growth of acquirable information provides a rich repository for evidence-based decision-making, whilst at the same time makes the decision-making more difficult and complicated. The traditional methods usually become infeasible when dealing with large-scale, high-dimensional, sparse, and incomplete data. The applicable techniques able to process the big data are of strong and urgent necessity for providing critical decision support in emergency management. For example, the scalability of decision-making algorithms is in particular important when the real-time response is of great value. The recently emerged research techniques designed for big data analysis (such as deep learning algorithms characterized by semi-supervised feature learning, and transfer of learning algorithms that utilize the knowledge learned in one context to another similar context) and the adaptation of these techniques specifically for emergency management are considered crucial issues in future research. One major concern of this research review is to promote the theoretical results of computational intelligence being applied to practical emergency management. On the other hand, computational intelligence is still a young and rapidly expanding field with new invented methods over the past two decades. Emergency management undoubtedly has a substantial impact on the development of computational intelligence driven by some practical problems across a range of emergency industries. (3) Emergency management is an active and developing research area due to the fact that it has broad applications closely related to the human safety. Although a variety of industry-oriented emergency management systems have been developed continuously, they share some general characteristics, such as the mechanism of incidents. A framework to describe the inherent mechanisms of different harmful incidents and clarify the universality and particularity of the evolving logic is required for successful approaches to emergency management. (4) It was found that a disaster may derive other types of disaster making the response more complicated and difficult. It is necessary to investigate the relation among disasters, and integrate all emergency sources in disaster responding. In this sense, the integrated emergency management system is a research direction of practical value for both academic and industry.

Acknowledgements This work was supported by the National Social Science Foundation of China (Contact No. 16FGL001) and Scientific Research Foundation of Henan Polytechnic University (No. Y2017-1).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Abpeykar S, Ghatee M (2014) Supervised and unsupervised learning DSS for incident management in intelligent tunnel: a case study in Tehran Niayesh tunnel. Tunn Undergr Space Technol 42(11):293–306

Afandizadeh S, Jahangiri A, Kalantari N (2013) Identifying the optimal configuration of one-way and two-way streets for contraflow operation during an emergency evacuation. Nat Hazards 69(3):1315–1133

Alvear D, Abreu O, Cuesta A et al (2013) Decision support system for emergency management: road tunnels. Tunnel Undergr Space Technol 34:13–21

Amailef K, Lu J (2011) A mobile-based emergency response system for intelligent M-government services. J Enterpr Inf Manag 24(4):338–358

Amaye A, Neville K, Pope A (2016) BigPromises: using organisational mindfulness to integrate big data in emergency management decision making. J Decis Syst 25(Suppl 1):76–84

Anaya-Arenas AM, Renaud J, Ruiz A (2014) Relief distribution networks: a systematic review. Ann Oper Res 223(1):53–79

Aydin N, Murat A (2013) A swarm intelligence based sample average approximation algorithm for the capacitated reliable facility location problem. Int J Prod Econ 145(1):173–183

Baisakhi C, Ghosh D, Maji RK et al (2010) Knowledge management with case-based reasoning applied on fire emergency handling. IEEE international conference on industrial informatics. IEEE Press, pp 708–713

Balis B, Brzoza R, Bubak M et al (2016) Holistic approach to management of IT infrastructure for environmental monitoring and decision support systems with urgent computing capabilities. Future Gener Comput Syst. https://doi.org/10.1016/j.future.2016.08.007

Basu S, Sharma M, Ghosh PS (2015) Metaheuristic applications on discrete facility location problems: a survey. Opsearch 52(3):530–561

Benamrane Y, Boustras G (2015) Atmospheric dispersion and impact modeling systems: how are they perceived as support tools for nuclear crises management? Saf Sci 71:48–55

Benamrane Y, Wybo JL, Armand P (2013) Chernobyl and Fukushima nuclear accidents: what has changed in the use of atmospheric dispersion modeling? J Environ Radioact 126:239–252

Berkoune D, Renaud J, Rekik M, Ruiz A (2012) Transportation in disaster response operations. Socio-Econ Plan Sci 46(1):23–32

Bezdek JC (1992) On the relationship between neural networks, pattern recognition and intelligence. Int J Approx Reason 6(2):85–107

Brigham TJ (2016) Feast for the eyes: an introduction to data visualization. Alexis Med Ref Serv Q 35(2):215–223

Chen N, Chen A (2012) Emergency evaluation model and method: a perspective overview. J Saf Crisis Manag 2(1):11–23

Chen L, Chen A (2016) Improve the efficiency of improvisation decision of emergency management-analysis on the explosion event of hazardous chemical products in Tianjin. Theor Explor 1:80–84

Chen Y, Lin Y (2009) Controlling the movement of crowds in computer graphics by using the mechanism of particle swarm optimization. Appl Soft Comput 9:1170–1176

Chen SH, Jakeman AJ, Norton JP (2008) Artificial intelligence techniques: an introduction to their use for modelling environmental systems. Math Comput Simul 78:379–400

Chen A, Chen N, Ni H (2009) Modern emergency management theory and method. Science Press, Beijing, pp 1–6
Chen Q, Chen X, Tang Q et al (2009) An evacuation risk assessment model for emergency traffic with consideration of urban hazard installations. Chin Sci Bull 54:1000–1006
Chen H, Chiang R, Storey VC (2012) Business intelligence and analytics: from big data to big impact. MIS Q 36(4):1165–1188
Chen X, Kwan MP, Li Q (2012) A model for evacuation risk assessment with consideration of pre- and post-disaster factors. Comput Environ Urban Syst 36(3):207–217
Chen NC, Wang K, Xiao CJ et al (2014) A heterogeneous sensor Web node meta-model for the management of a flood monitoring system. Environ Model Softw 54:222–237
Chen Q, Jia Q, Yuan ZW et al (2014) Environmental risk source management system for the petrochemical industry. Process Saf Environ Prot 92:251–260
Chen N, Chen A (2009) The role of data mining techniques in emergency management. In: Proceedings of 11th international conference on enterprise information systems (ICEIS09), 6–10 May 2009, Milan, Italy, pp 118–123
Chiou I, Chen C et al (2015) Methodology of disaster risk assessment for debris flows in a river basin. Stoch Env Res Risk Assess 29:775–792
Chuan-Feng H, Chao Z (2009) Genetic algorithm for solving problems in emergency management. In: International conference on natural computation, pp 259–264
Dai J, Tian H (2013) Fuzzy rough set model for set-valued data. Fuzzy Sets Syst 229:54–68
Dai K, Zhao J, Cao F (2015) A novel algorithm of extended neural networks for image recognition. Eng Appl Artif Intell 42:57–66
Davis LB, Samanlioglu F, Qu X, Root S (2013) Inventory planning and coordination in disaster relief efforts. Int J Prod Econ 141:561–573
Dellorco M (2007) Competitive egress behaviour: a fuzzy logic-inspired microscopic model. Int J Crit Infrastruct 3:408–429
Deng ZY (2000) The new trend of American highway traffic safety. J Foreign Highw 1:9–13
Department of Homeland Security of USA (2017) National Incident Management System, Federal Emergency Management System. https://www.dhs.gov/. Accessed 17 Oct 2017
Dong X, Pi D (2014) Hurricane trajectory prediction method with pattern matching. J Chin Comput Syst 35(5):983–988
Donmez S (2015) A genetic algorithm based approach to provide solutions for emergency aid stations location problem and a case study for Pendik/İstanbul. J Homel Secur Emerg Manag 130(4):915–940
Duan JH (2012) Recent development of application of swarm intelligence in multi-agent system. Comput Sci 39(6):6–9
Fan B, Luo J (2013) Spatially enabled emergency event analysis using a multi-level association rule mining method. Nat Hazards 67(2):239–260
Farah J, Henriet J, Broggio D et al (2011) Development of a new CBR-based platform for human contamination emergency situations. Radiat Prot Dosimetry 144:564–570
Federal Emergency Management Agency (1999) Federal Response Plan (FRP)
Feng Q (2006) Enlightenment from management system of emergency response in Germany. City Disaster Reduct 2:17–19
Fiedrich F, Gehbauer F, Rickers U (2000) Optimized resource allocation for emergency response after earthquake disasters. Saf Sci 35(1–3):41–57
Forcael E, Gonzalez V, Orozco F et al (2014) Ant colony optimization model for Tsunamis evacuation routes. Comput-Aided Civil Infrastruct Eng 29(10):723–737
Gao J (2016) Analysis and assessment of the risk of snow and freezing disaster in China. Int J Disaster Risk Reduct 19:334–340
George H, Coppola DP, Bullock J (2007) Introduction to emergency management. Butterworth-Heinemann, Oxford, pp 2–5
Gerbesioti A, Delis V, Theodoridis Y (2001) Developing decision support tools for confronting seismic hazards. In: Proceeding of the 8th Panhellenic conference on informatics, 8–10 Nov 2001, Nicosia, Cyprus, pp 247–253
Giorgos K, Dimitris P, Nektarios C et al (2016) A web-based DSS for the management of floods and wildfires (FLIRE) in urban and periurban areas. Environ Model Softw 86:111–115
Gonzalez JJ, Radianti J, Granmo OC, Bouhmala N, Sarshar P (2014) Comparing different crowd emergency evacuation models based on human centered sensing criteria. Int J Inf Syst Crisis Response Manag 6(3):53–70
Gu J, Liu H, Sun Y (2010) Tropical cyclone intensity forecast experiment based on combination of particle swarm optimization and support vector machine. Meteorol Disaster Reduct Res 33(3):22–26

Gu Z, Liu Z, Shiwakoti N, Yang M (2016) Video-based analysis of school students' emergency evacuation behavior in earthquakes. Int J Disaster Risk Reduct 18:1–11
Guan X, Ge C, Wang X et al (2013) Models and algorithms for hub and spoke locations for emergency service facilities in response to serious emergency incidents. Hum Ecol Risk Asses 19:553–565
Guo E, Zhang J, Ren X et al (2014) Integrated risk assessment of flood disaster based on improved set pair analysis and the variable fuzzy set theory in central Liaoning Province. China. Nat Hazards 74(2):947–965
Haghani M, Sarvi M (2016) Human exit choice in crowded built environments: investigating underlying behavioural differences between normal egress and emergency evacuations. Fire Saf J 85:1–9
Hamed ZS, Delbert H, Shalamu A et al (2016) Optimization of adaptive fuzzy logic controller using novel combined evolutionary algorithms, and its application in Diez Lagos flood controlling system, Southern New Mexico. Expert Syst Appl 43:154–164
Harms SK, Goddard S, Tadesse T, Goddard S, Waltman WJ (2004) Data mining in a geospatial decision support system for drought risk management. In: Proceedings of national conference on digital government research, pp 9–16
He Y, Xu Q, Yang S et al (2014) Reservoir flood control operation based on chaotic particle swarm optimization algorithm. Appl Math Model 38:4480–4492
Higuchi H, Fujimura J, Nakamura T et al (2014) Disaster detection by statistics and SVM for emergency rescue evacuation support system. In: 43rd international conference on parallel processing workshops (ICCPW), 9–12 September 2014, pp 349–354
Hinchey MG, Sterritt R, Rouff C (2007) Swarms and swarm intelligence. Computer 40(4):111–113
Holguín-Veras J, Jaller M, Wassenhove L et al (2012) On the unique features of post-disaster humanitarian logistics. J Oper Manag 30(7–8):494–506
Horita F, Albuquerque J, Degrossi LC et al (2015) Development of a spatial decision system for flood risk management Brazil that combines volunteered geographic information with wireless sensor networks. Comput Geosci 80:84–94
Hou JS, Li M (2008) The process of earthquake disaster emergency management in China. Recent Dev World Seismol 1:14–20
Huang C (2013) The measurement of effective knowledge in multiple Internet of intelligences and application in risk assessment. In: 4th international conference on risk analysis and crisis response, Istanbul, Turkey, 27–29 August 2013, Huang C, Kahraman C (eds) Intelligent systems and decision making for risk analysis and crisis response, 1832(10). CRC Press, pp 1–8
Huang C, Shen S, Huang Q (2012) An Approach of information processing for CBR in emergency management engineering. Syst Eng Proc 5:185–190
Ibri S, Drias H, Nourelfath M (2010) A parallel hybrid Ant-Tabu algorithm for integrated emergency vehicle dispatching and covering problem. Int J Innov Comput Appl 2(4):226–236
Jacxsens L, Uyttendaele M, Meulenaer BD (2016) Challenges in risk assessment: quantitative risk assessment. Proc Food Sci 6:23–30
Jafer S, Lawler R (2016) Emergency crowd evacuation modeling and simulation framework with cellular discrete event systems. Simulation 92(8):795–817
Ji L, Chi H, Chen A et al (2007) Emergency management. Higher Education Press, Beijing, pp 8–12
Jia C, Wang H, Wei L (2016) Research on visualization of multi-dimensional real-time traffic data stream based on cloud computing. Proc Eng 137:709–718
Jiang DM, Li ZB (2012) The evaluation of city emergency management system results based on BP neural network. Appl Mech Mater 263–266:3288–3291
Jiang T, Ren G, Zhao X (2013) Evacuation route optimization based on Tabu search algorithm and hill-climbing algorithm. Proc Soc Behav Sci 96(1):865–872
Jin LT (2015) Comparison of emergency management of public security incidents in mega cities abroad. J Shenyang Off 17(4):51–53
Jordan MI, Mitchell TM (2015) Machine learning: trends, perspectives, and prospects. Science 349(6245):255–260
Jun Tian, Zhi Li (2012) Emergency tasks planning based on formal modeling of emergency plan and HTN planning system SHOP2. Intell Inf Manag 4:357–363
Jyri M, Raimo PH, Kari S (2007) Interactive computer support in decision conferencing: two cases on off-site nuclear emergency management. Decis Support Syst 42:2247–2260
Kalabokidis K, Xanthopoulos G, Moor P et al (2012) Decision support system for forest fire protection in the Euro-Mediterranean region. Eur J Forest Res 13(131):597–608
Kangi A (2015) Application of warning and rapid estimation of earthquake damage (WARED) system in unprepared cities cases study: Mashhad, north east of Iran. Int J Disaster Risk Reduct 13:139–144
Kerstin W, Ana C, Tomas M (2013) Parameter calibration framework for environmental emergency models. Simul Model Pract Theory 31:10–21

Klement P, Snase V (2010) SOM neural network—a piece of intelligence in disaster management. In: World congress on nature and biologically inspired computing, pp 872–877

Kong Y, Xue Anke (2006) Urban traffic incident detection based on fuzzy logic. In: IEEE conference on industrial electronics (IECON), IEEE, pp 772–775

Kostas DK, Stamoulis K (2007) Air pollution modelling with the aid of computational intelligence methods in Thessaloniki, Greece. Simul Model Pract Theory 15:1310–1319

Kostas K, Gavriil X, Peter M et al (2012) Decision support system for forest fire protection in the Euro-Mediterranean region. Eur J Forest Res 131(3):597–608

Krupka J, Kasparova M, Jirava P (2009) Case-based reasoning model in process of emergency management. Man-machine interactions. Springer, Berlin, Heidelberg, pp 77–84

Kugu E, Li J, Mckenzie FD et al (2014) Fuzzy logic approach and sensitivity analysis for agent-based crowd injury modeling. Simul Trans Soc Model Simul Int 1(1):1–18

Lee Y (2010) A computerized feature selection method using genetic algorithms to forecast freeway accident duration times. Comput-Aided Civil Infrastruct Eng 25:132–148

Lee WB, Wang Y, Wang WM et al (2012) An unstructured information management system (UIMS) for emergency management. Expert Syst Appl 39:12743–12758

Li Z (2011) Fuzzy clustering analysis of emergency rescue route. In: 2nd international conference on artificial intelligence, management science and electronic commerce (AIMSEC), pp 1148–1151

Li YJ, Li Z (2012) Great East Japan earthquake emergency evolution and contingency decision based on system engineering approach. Syst Eng Proc 5:254–259

Li X, Yeh AG (2005) Integration of genetic algorithms and GIS for optimal location search. Int J Geogr Inf Sci 19(5):581–601

Li Y, Li X, Wu Q, Chen L (2013) Emergency plan generating method based on CBR and RBR. Ordnance Ind Autom 32(5):31–35

Liao ZL, Mao XW, Phillip MH et al (2012) Adaptation methodology of CBR for environmental emergency preparedness system based on an Improved Genetic Algorithm. Expert Syst Appl 39:7029–7040

Liao ZL, Wang B, Xia XW et al (2012) Environmental emergency decision support system based on artificial neural network. Saf Sci 50:150–163

Liu YZ, Zhang WT, Cui XM (2012) Flood emergency management using hydrodynamic modelling. Proc Eng 28:750–753

Liu J, Liang G, Jiang JP et al (2016) A two-stage optimization model for emergency material reserve layout planning under uncertainty in response to environmental accidents. J Hazard Mater 310:30–39

Liu M, Wei J, Wang G, Wang F (2017) Water resources stress assessment and risk early warning–a case of Hebei Province China. Ecol Ind 73:358–368

Liu X, Chen A, Chi F et al (2015) Recoverability of broken highways in earthquake based-on remote sensing technology. In: Focus on China, pp 30–37

Li M, Wang Y, Sun C (2011) Research on the location allocation model for subway emergency service facilities under network operating conditions. In: Third Pacific-Asia conference on circuits, communications and system (PACCS). IEEE, pp 1–6

Louis GZ, Charles TS, Mustafa SA et al (2016) Flood vulnerability indices and emergency management planning in the Yazoo Basin, Mississippi. Int J Disaster Risk Reduct 18:89–99

Lu L, Zhang H (2014) A route planning method for micro UAV based on improved genetic algorithm. Appl Mech Mater 602–605:1348–1351

Lu J, Yang M, Zhang HX et al (2013) Power grid ice melting decision method based on rough set theory and principal component analysis. J Electr Power Sci Technol 28(3):90–95

Ma C, Li Y, He R, Qi B, Diao A (2012) Research on location problem of emergency service facilities based on genetic-simulated annealing algorithm. Int J Wirel Mobile Comput 5:206–211

Ma S, Zhang S, Chen Y et al (2013) Design and realization of a major environmental risk source management system. Proc Environ Sci 18:372–376

Ma Y, Zhang W, Lu J et al (2014) Automated generation of traffic incident response plan based on case-based reasoning and Bayesian theory. Discrete Dyn Nat Soc 6:1–7

Magdalena H, Michal L, Monika C et al (2015) A decision support system for emergency flood embankment stability. Proc Comput Sci 51:2957–2961

Mahdi S, Mohammad BG (2016) Accident management support tools in nuclear power plants: a post-Fukushima review. Prog Nucl Energy 92:1–14

Mahmud AR, Indriasari V (2009) Facility location models development to maximize total service area. Theor Empir Res Urban Manag 4(1):87–100

McAfee A, Brynjolfsson E (2012) Big data: the management revolution. Harvard Bus Rev 90(10):60–68

Meyer N, McMenamin J, Robertson C, Donaghy M, Allardice G, Cooper D (2008) A multi-data source surveillance system to detect a bioterrorism attack during the G8 summit in Scotland. Epidem Infect 136(7):876–885
Moehrle S, Raskob W (2015) Structuring and reusing knowledge from historical events for supporting nuclear emergency and remediation management. Eng Appl Artif Intell 46(PB):303–311
Mohammadi R, Ghomi S, Jolai F (2016) Prepositioning emergency earthquake response supplies: a new multi-objective particle swarm optimization algorithm. Appl Math Model 40:5183–5199
Mori K, Tsudaka K, Wada T et al (2012) Development of emergency rescue evacuation support system (ERESS) in Panic-type disasters: disaster detection algorithm by Buffering-SVM. Ieice technical report information networks 111:65–70
Mousavi SM, Tavakkoli-Moghaddam R (2013) A hybrid simulated annealing algorithm for location and routing scheduling problems with cross-docking in the supply chain. J Manuf Syst 32(2):335–347
Munib R, Soliha R, Seema M et al (2016) Implementation of ICT and wireless sensor networks for earthquake alert and disaster management in earthquake prone areas. Proc Comput Sci 85:92–99
Munoz RV (2007) Experiences in Spain of community based fire management. In: 4th international wildland fire conference, Sevilla
Murray AT, Church RL (2004) Applying simulated annealing to location-planning models. J Heurist 2(1):31–53
Ozdamar L, Ekinci E, Kucukyazici B (2004) Emergency logistics planning in natural disasters. Ann Oper Res 129(1):217–245
Ozguven EE, Ozbay K (2015) An RFID-based inventory management framework for emergency relief operations. Transp Res Part C 57:166–187
Palmieria F, Ficcob M, Pardi S et al (2016) A cloud-based architecture for emergency management and first responders localization in smart city environments. Comput Electr Eng 56:810–830
Pei YS, Zhang KJ, Liu XG (2010) Environmental risk management with the aid of city emergency response system in Nanning City. Proc Environ Sci 2(6):2012–2019
Pilone E, Mussini P, Demichela M, Camuncoli G (2016) Municipal emergency plans in Italy: requirements and drawbacks. Saf Sci 85:163–170
Pohl D, Bouchachia A, Hellwagner H (2016) Online indexing and clustering of social media data for emergency management. Neurocomputing 172(C):168–179
Qiang X (2012) Vehicle scheduling model for emergency logistics distribution with improved genetic algorithm. Int J Adv Comput Technol 4(18):315–323
Quan DU, Zhu SB (2012) Research on urban public safety emergency management early warning system based on technologies for the internet of things. Proc Eng 45:748–754
Rego AJ (2001) National disaster management information systems and networks: an Asian overview. In: Global disaster information network conference (GDIN)
Ren SK, Yuan ZP, Yu XU (2012) Dynamic scheduling optimization for emergency rescue: taking KX blowout accident as an example. Oper Res Manag Sci 21(3):1–7
Revillaromero B, Thielen J, Salamon P (2014) Evaluation of the satellite-based global flood detection system for measuring river discharge: influence of local factors. Hydrol Earth Syst Sci 18(11):4467–4484
Robert M, Armando GC, Elsa V (2013) The state of development of fire management decision support systems in America and Europe. For Policy Econ 29:45–55
Rubio-Largo A, Vega-Rodriguez MA, Gomez-Pulido JA et al (2012) A comparative study on multi-objective swarm intelligence for the routing and wavelength assignment problem. IEEE Trans Syst Man Cybern-Part C Appl Rev 42(6):1644–1655
Sakai T, Tamura K (2014) Identifying bursty areas of emergency topics in geotagged tweets using density-based spatio-temporal clustering algorithm. In: IEEE international workshop on computational intelligence and applications, pp 95–100
Samant A, Adeli H (2000) Feature extraction for traffic incident detection using wavelet transform and linear discriminant analysis. Comput-Aided Civil Infrastruct Eng 15:241–250
Sedighi M (2008) Use of geographical information system (GIS) in the cataloging of documents–a case study of earthquake documents collections. Emerald Insight 26:454–465
Selda T, Emmett JL (2010) Inventory decisions for emergency supplies based on hurricane count predictions. Int J Prod Econ 126:66–75
Simon TW, Zhu Y, Dourson ML, Beck NB (2016) Bayesian methods for uncertainty factor application for derivation of reference values. Regul Toxicol Pharmacol 80:9–24
Srinivasan D, Jin X, Cheu RL (2004) Evaluation of adaptive neural network models for freeway incident detection. IEEE Trans Intell Transp Syst 5(1):1–11
Stella M, Wolfgang R (2015) Structuring and reusing knowledge from historical events for supporting nuclear emergency and remediation management. Eng Appl Artif Intell 46:303–311

Sun B, Ma W, Zhao H (2013) A fuzzy rough set approach to emergency material demand prediction over two universes. Appl Math Model 37(10–11):7062–7070

Sun HY, Rao LL, Zhou K, Li S (2014) Formulating an emergency plan based on expectation-maximization is one thing, but applying it to a single case is another. J Risk Res 17(7):785–814

Sutliff WD, Dulaney AD, Davis WL (2011) The optimization of traffic signal timing for emergency evacuation using the simulated annealing algorithm. Transport 26(2):133–140

Taramelli A, Valentini E, Sterlacchini S (2015) A GIS-based approach for hurricane hazard and vulnerability assessment in the Cayman Islands. Ocean Coast Manag 108:116–130

Taskin S, Lodree EJ (2011) A Bayesian decision model with hurricane forecast updates for emergency supplies inventory management. J Oper Res Soc 62(6):1098–1108

Tian J, Ma WZ, Wang YL, Wang KL (2011) Emergency supplies distributing and vehicle routes programming based on particle swarm optimization. Syst Eng Theory Pract 31(5):898–906

Tomohiro K, Yoshiaki H, Masahiro M et al (2011) Application of an earthquake early warning system and a real-time strong motion monitoring system in emergency response in a high-rise building. Soil Dyn Earthq Eng 31:231–239

Villa V, Paltrinieri N, Khan F, Cozzani V (2016) Towards dynamic risk analysis: a review of the risk assessment approach and its limitations in the chemical process industry. Saf Sci 89:77–93

Vitoriano B, Rodríguez JT, Tirado G, Martíncampo FJ, Ortuño MT, Montero J (2015) Intelligent decision-making models for disaster management. Hum Ecol Risk Assess 21(5):1341–1360

Wan JJ, Song YH (2012) Evaluation of the city integrated emergency response system based on the analytic hierarchy process. Adv Mater Res 461:830–834

Wang XZ, Zhou J, Huang ZL et al (2016) A multilevel deep learning method for big data analysis and emergency management of power system. In: IEEE international conference on big data analysis. IEEE Press, pp 1–5

Wang J, Luo D (2015) Research on emergency decision-making model based on Bayesian decision network. Chin J Manag Sci 1:316–324

Wang YD, Tan GZ, Wang Y et al (2012) Perceptual control architecture for cyber-physical systems in traffic incident management. J Syst Architect 58:398–411

Wang H, Andrews SP, Ni D, Collura J (2010) Scenario-based analysis of transportation impacts in case of dam failure flood evacuation in Franklin County, Massachusetts. In: 89th annual meeting of the transportation research board, Washington, DC, pp 10–14

Wei X (2013) Landslide disaster image recognition algorithm based on SVM. Electr Meas Technol 36(8):65–70

Wen L, Wang HB, Cai WF (2013) Coal mine emergency management safety early warning research based on factor analysis and BP network. Sci Technol Ind 13(10):145–148

Wen R, Zhong S, Zhang B (2013) Multi-Objective Optimization of post-disaster emergency resources scheduling using multiple ant colony systems optimization algorithm. In: Proceedings of 8th international conference on bio-inspired computing: theories and applications (BIC-TA). Springer, Berlin, Heidelberg, pp 1047–1054

Wu A, Convertino G, Ganoe C et al (2013) Supporting collaborative sense-making in emergency management through geo-visualization. Int J Hum Comput Stud 71(71):4–23

Wu X, Ji D, Chen A (2016) Opportunities and challenges of the reform of China's emergency management system in the age of big data. J Henan Polytech Univ 17(66):182–186

Xie T, Li CD, Wei YY et al (2016) Cross-domain integrating and reasoning spaces for offsite nuclear emergency response. Saf Sci 85:99–116

Xi Y, Sun F (2013) Intelligent urban emergency early warning system based on dynamic rough set and cloud computing. In: IEEE international conference on software engineering and service science, pp 701–704

Xu J, Xu X (2014) A fusion algorithm of swarm intelligence and its application in emergency services facility location. Comput Eng Sci 36(4):667–673

Yan R, Ma Z, Zhao Y, Kokogiannakis G (2016) A decision tree based data-driven diagnostic strategy for air handling units. Energy Build 133:37–45

Yasufuku K, Kashiwagi T, Abe H (2014) Development of arrangement system of evacuation facilities using genetic algorithm and evaluation the safety based on crowd movement. J Archit Plan 79(697):635–642

Yi W, Ozdamar L (2007) A dynamic logistics coordination model for evacuation and support in disaster response activities. Eur J Oper Res 179(3):177–1193

Yin WH, Pamela MT, Satish VU et al (2014) An agent-based modeling system for travel demand simulation for hurricane evacuation. Transp Res Part C 42:44–59

Yotsukura S, Takahashi T (2009) Framework of an emergency management system using different rescue simulators. Adv Robot 23:1233–1246

Yue J, Xiao Y (2013) Application of association rules mining in emergency management system. Netw Secur Technol Appl 1:56–58

Zambrano AM, Perez I, Palau C, Esteve M (2016) Technologies of internet of things applied to an earthquake early warning system. Future Gener Comput Syst 75:206–215
Zhang K, Taylor MAP (2006) Effective arterial road incident detection: a Bayesian network based algorithm. Transp Res Part C 14:403–417
Zhang Q, Zhang J, Wang C, Cui L, Yan D (2014) Risk early warning of maize drought disaster in Northwestern Liaoning Province. China. Nat Hazards 72(2):701–710
Zhang Y, Liang M, Li K et al (2014) Research of source term inversion based on genetic simulated annealing algorithms. Nucl Electron Detect Technol 34(4):451–473
Zhang Y, Dongxiao N, Liu J (2010) The evaluation of electric power emergency management mechanism based on BP neural network. In: IEEE international conference on computer science and information technology, pp 413–416
Zhang L, Li Y, Fei T et al (2014) Research of emergency logistics routing optimization based on particle swarm optimization. In: Proceedings of international conference on computer science and information technology. Springer, India, pp 4027–4030
Zhang W, Zhou Y, Tian W et al (2015) GIS-based indoor pedestrian evacuation simulation combining the particle swarm optimization and the floor field model, pp 1–4
Zhao M, Chen Q (2015) Risk-based optimization of emergency rescue facilities locations for large-scale environmental accidents to improve urban public safety. Nat Hazards 75(1):163–189
Zhao Y, Zhang L, Jie J (2014) Preliminary study on application of BP-neural network in AP1000 nuclear power plant accident diagnosis. Atomic Energy Sci Technol 48:480–484
Zheng Y, Ling H, Xue J et al (2014) Population classification in fire evacuation: a multi-objective particle swarm optimization approach. IEEE Trans Evol Comput 18(1):70–81
Zhong KB (2011) Progress and trend of urban emergency management information technology in the United States. Study Times, 17 Oct 2011
Zhou H, Jia L, YQin (2010) Railway emergency planning system and its implementation. In: Fourth international conference on information systems for crisis response and management, pp 368–374
Zia US, Safina SA, Chong I et al (2014) Web-of-objects (WoO)-based context aware emergency fire management systems for the internet of things. Sensors 14:2944–2966
Zollo A, Lancieri M (2007) Real-time estimation of earthquake magnitude for seismic early warning. In: Gasparini P, Manfredi G, Zschau J (eds) Earthquake early warning systems. Springer, Berlin, Heidelberg, pp 45–63