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ORIGINAL RESEARCH

Novel Case-Based Reasoning System for Public Health Emergencies

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Purpose: Several threatening infectious diseases, including influenza, Ebola, SARS, and COVID-19, have affected human society over the past decades. These disease outbreaks naturally inspire a demand for sustained and advanced safety and suppression measures. To protect public health and safety, further research developments on emergency analysis methods and approaches for effective emergency treatment generation are urgently needed to mitigate the severity of the pandemic and save lives.
Methods: To address these issues, a novel case-based reasoning (CBR) system is proposed using three phases. In the first phase, the similarity between the current case and the historical cases is calculated under a variety of heterogeneous information. In the second phase, a filter approach based on grey clustering analysis is created to retrieve relevant cases. In the third phase, the cases retrieved are taken as initial host nests in a cuckoo search (CS) algorithm, and our system searches an optimal solution through iteration of this algorithm.
Results: The proposed model is compared with a CBR method improved by particle swarm optimization (PSO) and a CBR method improved by a differential evolution algorithm (DE), to confirm the efficiency of our CS algorithm in adapting solutions for public health emergencies. The results show that the proposed model is better than the existing algorithms.
Conclusion: The proposed model improves the speed of case retrieval using grey clustering and increases solution accuracy with CS algorithms. The present research can contribute to government, CDC, and infectious disease emergency management fields with regard to the implementation of fast and accurate public biohazard prevention and control measures based on a variety of heterogeneous information.
Keywords: case-based reasoning, grey clustering, cuckoo search algorithm, public health emergencies

Introduction

Since the outbreak of the novel coronavirus disease in 2019, it has posed a serious threat to public health and safety. COVID-19 is the most serious public health emergency in recent decades, spreading rapidly and widely and proving to be extremely difficult to control. So far, the latest epidemic data are shown in Table 1.[1] Furthermore, the frequency and serious consequences of public health emergencies in general have always warned governments of the importance of effective emergency planning. Scholars have also conducted in-depth research on intelligent decision-making in public health.[2,3]

When public health emergencies such as infectious diseases occur, it becomes vital to provide sufficiently rapid response measures. However, public health events take place in highly complex and changeable situations. The limited knowledge and

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Table 1 The Latest Report on COVID-19

Epidemic Area of COVID-19	Cumulative Number of Confirmed Cases	Cumulative Number of Deaths
China	95,998	4773
The whole world	78,194, 447	1717, 184

experience of decision-makers may well be insufficient. This poses a serious challenge to policymakers.[4] If effective emergency measures are not taken in time, or ineffective emergency measures are taken, irreparable losses are realistically possible.[5] Thus, it is crucial for decision-makers to take efficient and effective measures to control emergency situations, avoiding gradual escalation, to ensure the safety of human lives and the security of public property, as well as social stability.[6]

A primary task of public health emergency management is to take corresponding early warning measures according to relevant information and data. The core goal is create flexible solutions based on early warning measures to adapt rapidly to problem scenarios. For such applications, studies have put forward methods to simulate human thinking in emergency management systems. There are three main approaches to public health emergency decision-making assistance systems, focusing on using empirical knowledge, knowledge of systems of formal rules, and knowledge of a model or representation.[7]

Case-based reasoning (CBR) is an empirical knowledge reasoning method, where the current problem or situation is referred to as the target case, and recorded problems or situations that have occurred in the past are referred to as source cases or historical cases. CBR is a strategy to find the source case most relevant to the target case and use it to guide the solution of the target case.[8] While CBR represents tacit knowledge as cases, rule-based reasoning (RBR) represents explicit knowledge as rules. RBR focuses on mechanisms of reasoning and knowledge acquisition with less concern for information media and knowledge content. Model-based reasoning (MBR) relies on professional expert knowledge of problem background domains and makes associations along with generalized relationships between problem descriptors and conclusions. For example, an intelligent decision model might utilize a psychological model, incorporating prospect theory,[9,10] group decision-making theory,[11,12] rough set theory,[13] and root cause analysis.[14] Compared with MBR, CBR methods can generate a set of referential solutions quickly and based on significantly less detailed experience and knowledge, by extracting the key feature information on problems and solutions from the historical case base.[15,16] Moreover, CBR is an incremental learning model, that is, throughout successive learning processes, positive outputs can be gradually retained for later use.[17]

These three methods have various advantages and disadvantages in various application fields. In RBR, the more rules needed to match data patterns, the more complex the problem-solving process becomes. Furthermore, RBR has relatively less learning ability due to its difficulty in acquiring incremental knowledge through pattern matching.[18] RBR and MBR presently have the following defects: 1) It is difficult to obtain knowledge. On the one hand, it takes a significant investment of time to acquire knowledge from domain experts, which may delay corresponding decision-making systems; on the other hand, complex domains require an elaborate set of rules and parameters, a complete set of which is very difficult to construct, affecting the accuracy of the models' reasoning. 2) It is difficult to maintain the knowledge base. Various rules or parameters often depend on each other, making daily maintenance of the knowledge base more difficult. 3) The vulnerability of the reasoning methods themselves to corresponding failure conditions is a limitation. When the input data have missing values or data values do not meet the requirements, these two reasoning methods cannot conclude. 4) The knowledge base is not capable of self-renewal, that is, all changes and updates of the knowledge base need to be performed by human operators. The remarkable advantages of CBR are its relatively complete expression of information, incremental learning capabilities, ease of knowledge acquisition, and high efficiency.[19,20]

From the comparison of the above three types of intelligent reasoning technology, we can observe that CBR has advantages in solving domain problems where domain knowledge is lacking but rich experience is available.[21] The application of CBR to public health emergency decision-making has the following two advantages:

(1) CBR can solve the bottleneck problem of knowledge acquisition in emergency decision-making in the public health field. There are many types of public health emergencies, occurring for various reasons. This complexity makes it difficult to form a rule base for RBR for this application. Many types of bacteria or viruses causing infectious diseases exist, providing numerous examples of infectious disease outbreaks. In the same way, there

are many types of chemicals and pathogenic bacteria that have led to food poisoning events. If these factors are combined into decision-making rules, this inevitably leads to the combinatorial explosion. The 2019 novel coronavirus disease, H1N1, and SARS were caused by pathogens that are not fully understood. Human beings did not have knowledge of and experience with these diseases before their appearances. Therefore, when such diseases break out, it is almost impossible for human beings to develop accurate guidance rules describing the dangers in a short enough time frame. This is the so-called bottleneck of knowledge acquisition. However, CBR can solve these problems quite effectively. When a public health emergency is caused by an unknown pathogen, we typically can find similar cases of public health emergencies according to the location, symptoms, and impacts of the disease. Moreover, CBR has the advantage of incremental learning capability. With increase in the case base used by such systems, the knowledge fields that can be addressed also expand, and the emergency decision-making case analyses produced by the system progressively improve.

(2) CBR method has advantages in emergency decision-making under conditions of strictly limited information availability. A common problem faced in emergencies is that it becomes difficult for decision-makers to collect all the relevant information in a short period. If all relevant decision-making information for an emergency is completely collected, even if ideal decision-making results were obtained, it would have little significance if the critical time frame had already elapsed. Thus, it is important that such decisions be made as quickly and effectively as possible with accurate but incomplete information, and then improve over time with further gradual collection of decision-making information. CBR can match part of the information collected from the target problem with cases in the case base.

From the above analysis, we can see that CBR is an appropriate and effective method to for use in public health emergency management. In order to best apply this method, two key problems need to be solved. First, public health emergencies should be prevented and controlled quickly, and case retrieval time needs to be shortened. Secondly, case retrieval and adaptation methods are critical in the field of public health emergency management. Appropriate case retrieval and adaptation methods can meet the requirements of low fault tolerance in emergency decision-making.

The emergency decision-making method based on CBR has been widely applied. In recent years, some studies have attempted and innovated CBR by combining it with other intelligent algorithms. These studies have contributed significant breakthroughs into certain areas such as emergency management of natural disasters,[22,23] public health.[24]

Recent CBR application studies largely focused on structural description[25,26] and matching[27–32] of the collected cases. Less attention is paid to the organization and optimization of cases in the retrieval and adaptation step. This study is based on cluster analysis to simplify the case database without neglecting or omitting key information. An intelligent optimization algorithm is used to optimize the set of similar cases to enhance the usability of available domain experience-based knowledge.

To address these problems, we propose a novel CBR method to respond public health emergencies as quickly and effectively as possible. In the retrieval stage of CBR, we propose a case clustering retrieval method. Through an aggregation analysis of the case database, our method finds the central point of each similar case class (cluster). The clustered cases are indexed according to the distance between them and the center point, to improve the retrieval strategy. We use the Cuckoo Search (CS) algorithm in the case adaptation stage to improve the accuracy and adaptability of emergency solutions.

Section 2 describes the use of a grey cluster to condense the case base. The proposed novel CBR improved by grey clustering analysis and a CS algorithm (GCCS-CBR) is described and discussed in Section 3. In Section 4, an example application is presented. Section 5 presents the main conclusions and suggests directions for possible future research.

Methods

The GCCS-CBR model consists of three stages. Firstly, grey relational method is used to calculate similarity between the current case and historical cases. Secondly, the similar case set is retrieved with grey clustering. Thirdly, the corresponding adaptation of solutions is optimized by the CS algorithm. The flow chart is shown in Figure 1.

Calculation of Similarity

The traditional grey relational degree of case characteristic attributes is used to represent local similarity, and then each local similarity is weighted and balanced.[33,34] Thus, the overall similarity is obtained. Considering the importance of feature attributes, when calculating local similarity, feature weights are included in the comparison.[35,36] In

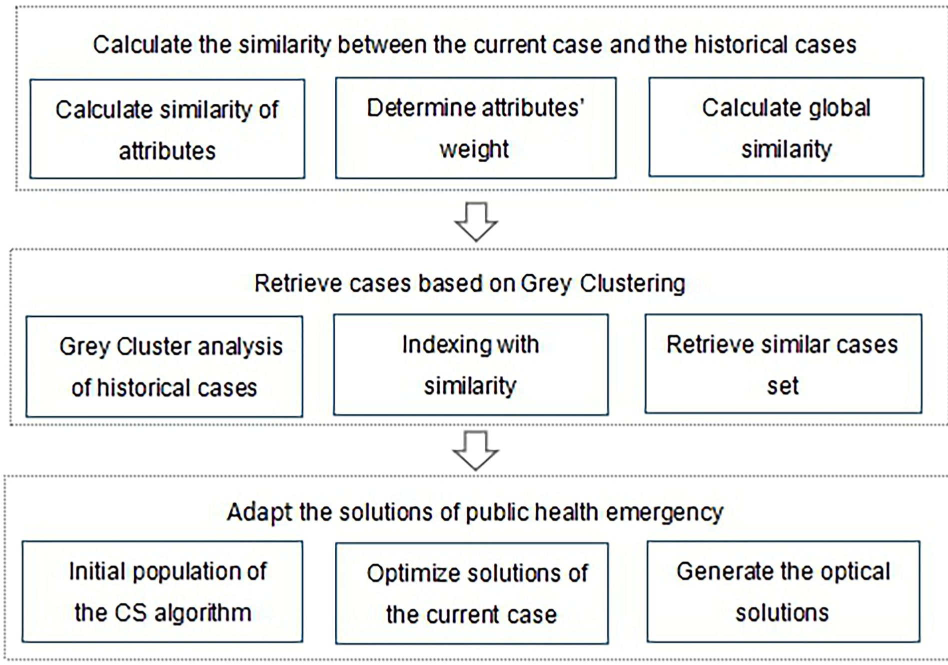

Figure 1 Flowchart of GCCS-CBR model.

this way, we obtain an improved local grey similarity calculation model.

Let the case base includes $m$cases, denoted as s_i, $1 \leq i \leq m$, with case problem features composed of $n$attributes, denoted as $s_i = (s_i(1), s_i(2), \ldots, s_i(n))$. Feature values of the current scenario are represented by $P = (s_0(1), s_0(2), \ldots, s_0(n))$. Building on this, we present the following definitions.

Definition 1

Local grey relational similarity on feature k between the current case and historical cases is defined as[37]

$$G_s(s_0(k), s_1(k)) = \frac{\min\limits_{i\in m}\min\limits_{k\in m}(w_i sim(s_0(k), s_j(k))}{w_i sim(s_0(k), s_j(k)) + \zeta \max\limits_{i\in m}\max\limits_{k\in n}(w_i sim(s_0(k), s_j(k)))} + \frac{\zeta \max\limits_{i\in m}\max\limits_{k\in n}(w_i sim(s_0(k), s_j(k)))}{w_i sim(s_0(k), s_j(k)) + \zeta \max\limits_{i\in m}\max\limits_{k\in n}(w_i sim(s_0(k), s_j(k)))} \quad (1)$$

Among these terms, $[0, 1]$, is the distinguishing coefficient. We generally let $= 0.5$; $sim(\cdot)$refers to the grey relational analysis similarity of features, w_k is the feature weights, which indicate the importance of the attribute to the decision-making process.

Definition 2

Local grey relational distance (GD) between the k feature of the current case and historical cases is defined as

$$G_d(s_0(k), s_1(k)) = \frac{1}{G_s(s_0(k), s_1(k))} - 1 \quad (2)$$

Definition 3

Based on the Euclidean distance, we define the distance on n features between current case s_0 and the historical cases s_i as

$$G_d(s_0, s_1) = \sqrt{\sum_{k=1}^{n} G_d^2(s_0(k), s_1(k))} \quad (3)$$

Definition 4

Based on the relationship between similarity and distance, the grey relational similarity on features of the current case and the historical cases is defined as

$$G_s(s_0, s_i) = \frac{1}{1 + G_d(s_0, s_i)} \quad (4)$$

Grey Clustering in CBR

In the CBR case database, each case is independent. The relative divergence between feature attribute values from one case to another varies significantly. Thus, using grey clustering to filter the case database, we obtain several clusters and establish a new index, allowing the method to reduce retrieval time for similar cases and improve retrieval speed.

Grey Clustering Algorithm

We use a grey clustering method to aggregate some observation indexes or observation objects into several definable categories according to a grey incidence matrix or whiteness weight function. The number of classes is specified by the user in advance. Grey clustering is an improvement on the traditional K-means clustering algorithm, which uses grey similarity to replace the traditional Euclidean distance similarity. Let the case base DB m cases, denoted by X_i, $1 \le i \le m$, and the description of the problem of the case contains n features, denoted by $X_i(j)$, $1 \le j \le n$, $\{C_1, C_2, \ldots, C_k\}$ denotes the k classes obtained from the case base clustering analysis, and the center point of each class is M_t, $1 \le t \le k$. The principles of grey clustering and K-means clustering algorithm are the same, both aiming to minimize the sum of distances between all cases and their centers. The objective function is defined as follows:

$$Min \sum_{i=1}^{m} \sum_{t=1}^{k} u_{i,t} \times G_d(X_i, M_t) = Min \sum_{i=1}^{m} \sum_{t=1}^{k} \sum_{j=1}^{n} u_{i,t} \times w_j \times G_d(X_i(j), M_t(j)) \tag{5}$$

The constraint being

$$\begin{cases} u_{i,t}(0,1), and \sum_{t=1}^{k} u_{i,t} = 1 \\ w_j \ge 0, and \sum_{j=1}^{n} w_j = 1 \end{cases} \tag{6}$$

where the matrix $U = u_{i,tm\times k}$ represents the class to which the case belongs. If $u_{i,t} = 1$, this indicates that case X_i belongs to class t; otherwise, X_i does not belong to class t; w_j represents the weight of feature $X_i(j)$, and $G_d(\cdot,\cdot)$ represents the grey distance between two cases or features.

The steps to solve the above minimization problem are as follows:

(1) Computing matrix U

The matrix U indicates that a case belongs to the nearest class. The element $u_{i,t}$ in the matrix can be calculated by the following formula:

$$u_{i,t} = \begin{cases} 1, if \sum_{j=1}^{n} w_j \times G_d(X_i(j), M_t(j)) \le \sum_{j=1}^{n} w_j \\ \times G_d\big(X_i(j), M_p(j)\big), p \in (1, 2, \ldots .k) \\ and\ p \ne t\ 0, otherwise \end{cases} \tag{7}$$

(2) Computing cluster centers M_i

This calculation is the same as the traditional K-means algorithm. Through repeated iterations, the mean value of all cases in this class is used as the clustering center.

$$M_t = \sum_{i=1}^{m} u_{i,t} \times \frac{X_{i,}}{\sum_{i=1}^{m} u_{i,t}}, 1 \le t \le k \tag{8}$$

(3) Calculate the feature weight w_j

We measure weights of case features according to their impact on the clustering effect and express clustering quality through the minimum separation degree $G_{classin}$ and the maximum separation degree $G_{classout}$ between the cases within the class.

$$w = \frac{\sum_{t=1}^{k}(||C_t|| \sum_{j}^{n}(w_j \times G_d(g(j), M_i(j)))}{\sum_{i=1}^{m} \sum_{t=1}^{k} \sum_{j=1}^{n} u_{i,t} \times w_j \times G_d((X_i(j), M_t(j)))} = \frac{\sum_{j=1}^{n}(w_j \times G_{classin}(j))}{\sum_{j=1}^{n}(w_j \times G_{classout}(j))} \tag{9}$$

where g is the initial global center of the case base, and the j^{th} feature value $g_j = \frac{\sum_{i=1}^{m} X_i(j)}{m}$, $\|\cdot\|$ denotes the radix of the set.

According to the common result optimization method in linear programming theory, the updating quantity Δw_j of weight w_j is established by formula (10).

$$\Delta w_j = \frac{G_{classin}(j) / G_{classout}(j)}{\sum_{j=1}^{n}\left(G_{classin}(j) / G_{classout}(j)\right)} \tag{10}$$

Therefore, in the iteration process, the j^{th} feature weight w'_j of the case X_i is updated as follows.

$$w'_j = w_j + \Delta w_j \tag{11}$$

Case Retrieval

Several clusters are obtained through the above grey clustering methods. Each cluster is equivalent to a small independent case base. Let $DB = \{X_1, X_2, \ldots, X_m\}, \{C_1, C_2, \ldots, C_k\}$ denote the k classes obtained by clustering analysis; the center point is M_t and radius of each class is R_t, $1 \le t \le k$; SCS is a similar case set matching the current case, and before the retrieval starts, $SCS = \varphi$; R is the similarity threshold. The steps of case retrieval are as follows:

Step 1: Establishing indexes in clustering

The index is established from the center point of each class. The index number of the cases in the class is determined according to the distance between the center point and the cases in the class. Thus, the proposed method avoids the excessive time consumption of an exhaustive search, and improves retrieval efficiency while maintaining accuracy.

The grey relational distance $G_d(X_{ti}, M_t)$ between each case in C_t and the cluster center M_t is calculated; then the cases in the class are numbered according to the distance from the cluster center point; finally, C_t, the maximum grey correlation distance between the case in C_t and the cluster center M_t is selected as the radius of $C_t, R_t = max\{G_d(X_{ti}, M_t)\}|X_{ti}C_t\}$.

Step 2: The grey relational distance $G_d(X_0, M_t)$ between the current case X_0 and the cluster center point M_t is calculated.

Step 3: Classes with possible similar cases are screened. If $G_d(X_0, M_t) \geq R_t + R$, the intersection of SCS and C_t is empty, and there is no case similar to the current case X_0 in C_t, that is, $SCS = \varphi$. Therefore, the retrieval of this class can be terminated directly.

Step 4: Similar candidate cases are determined. For case class C_t, if $G(X_0, M_t) < R_t + R$, then the intersection of SCS and C_t is not empty. Further, based on the distance between the cases in C_t and the center point, candidates for similar cases are selected, and the candidates meet the following conditions.

$$\begin{aligned} SCS_t^c = \{X_i | G_d(X_0, M_t) - R \leq G_d(X_i, M_t) \\ \leq G_d(X_0, M_t) + R, X_i C_t\} \end{aligned}$$

Step 5: From the candidate's similar case set SCS_t^c, the best similar case matching the current case $SCS_t^* = \left\{X_i | G_d(X_0, X_i) \leq R, X_i SCS_t^c\right\}$ is found.

Step 6: Repeat (2) ~ (5) until a similar case set in all classes with the current cases $SCS^* = \overset{t=1}{\overset{k}{\cup}} SCS_t^*$ is found.

CBR Adaptation Based on Cuckoo Search (CS) Algorithm

Cuckoo Search (CS) Algorithm

CS, algorithm developed by Yang and Deb (2009),[38] is a meta-heuristic optimization method based on obligate brood parasitic behavior in cuckoos. The following three idealized rules are used in the CS algorithm:[39] (i) each cuckoo lays one egg at a time and dumps them in a random nest to be hidden, (ii) the best nest with high-quality eggs survives and is carried to the next generations, and (iii) the number of host nests is fixed and p_α is the probability of the host bird identifying an alien egg.

Compared with other intelligent search algorithms, the cuckoo search algorithm has the following advantages:

1. There are a few parameters in the CS algorithm: in addition to population size, the CS algorithm has only one parameter p_a that needs to be adjusted. The convergence speed of the algorithm is not sensitive to the parameter p_a, which means that the CS algorithm has good versatility and strong robustness.
2. CS can meet the requirements of global convergence: theoretical research by He et al[40] proved that the CS algorithm has global convergence.

CS algorithm is capable of local search and global search: local search can improve the optimal solution through a directed random walk, and global search can maintain the diversity of population through Levy flight. The balance between the two components of random search is controlled by the switching probability p_a, which enables a CS to explore the search space more effectively in the global scope, thus effectively maintaining the population diversity. Therefore, our study presents a novel solution adaption model using the CS algorithm. In the adaption step, a new problem scenario $x_i(t+1)$ is given by formula (12).

$$x_i(t+1) = x_i(t) + a \oplus \text{levy}(1) \tag{12}$$

In formula 12, α is the parameter of step size.[41,42] The CS algorithm does a random walk in a biased way with random step sizes. The current nest and transition probability p_a determine the next nest. The symbol $\oplus$ denotes entry-wise multiplications. The search space is explored by using Lévy flight, as its step length is ultimately much longer.

CBR Adaption Approach

In the proposed model, the CS algorithm is used to further optimize the solutions. The cuckoo search algorithm requires a random initialization of the population. In the CBR adaption step, we use the similar case set SCS^* from the grey cluster to initialize the population for the CS algorithm.

In the CBR system, adaptation is a vital step for complicated scenarios. We can regard scenarios and solutions as a kind of mapping relationship. All cases in the case library are represented by the structured data, so we can express the mapping as case=<problem (X_i), solution (S_i) >. From the grey cluster method, a similar case set SCS^* based on all classes for the current case is found. Then, this similar case set SCS^* is taken as the initial population for the CS algorithm. Problem scenarios X_i have various attributes. For example, the rank risk of each incident, transmission routes, symptoms, pathological characteristics, average quarantine period, infection ratio, number of infected, fatality ratio, and number of deaths should be considered in infectious disease breakouts. We use a CS algorithm to optimize the solutions as follows.

Step 1: Set the similar case set SCS^* as the initial nest.

There are two variables: problem scenario X_i and solutionsS_i.

Step 2: Establish a fitness function.

In this study, the fitness function is set with the similarity between the historical problem X_i and the current case X_0. We use grey relational similarity to replace the traditional Euclidean distance similarity according to Definition 1 to Definition 4.

Step 3: Generate a new nest according to.

Step 4: Calculate the fitness function. The fitness value is the similarity between the generated scenario X_i' and the current caseX_0.

Step 5: Replace the previous solutions with better new solutions and replace the fraction (p_a) of suboptimal solutions with random new solutions. The fitness value $Sim(X_i, X_0)$ is compared with the $Sim\left(X_i', X_0\right)$, and the choice with better similarity is kept and the corresponding solution gradually optimized.

Step 6: Stop iteration if the condition is met, and output the calculated optimal solutions.

The flow-process of our novel CBR method improved by grey clustering analysis and a CS algorithm is presented in Figure 2.

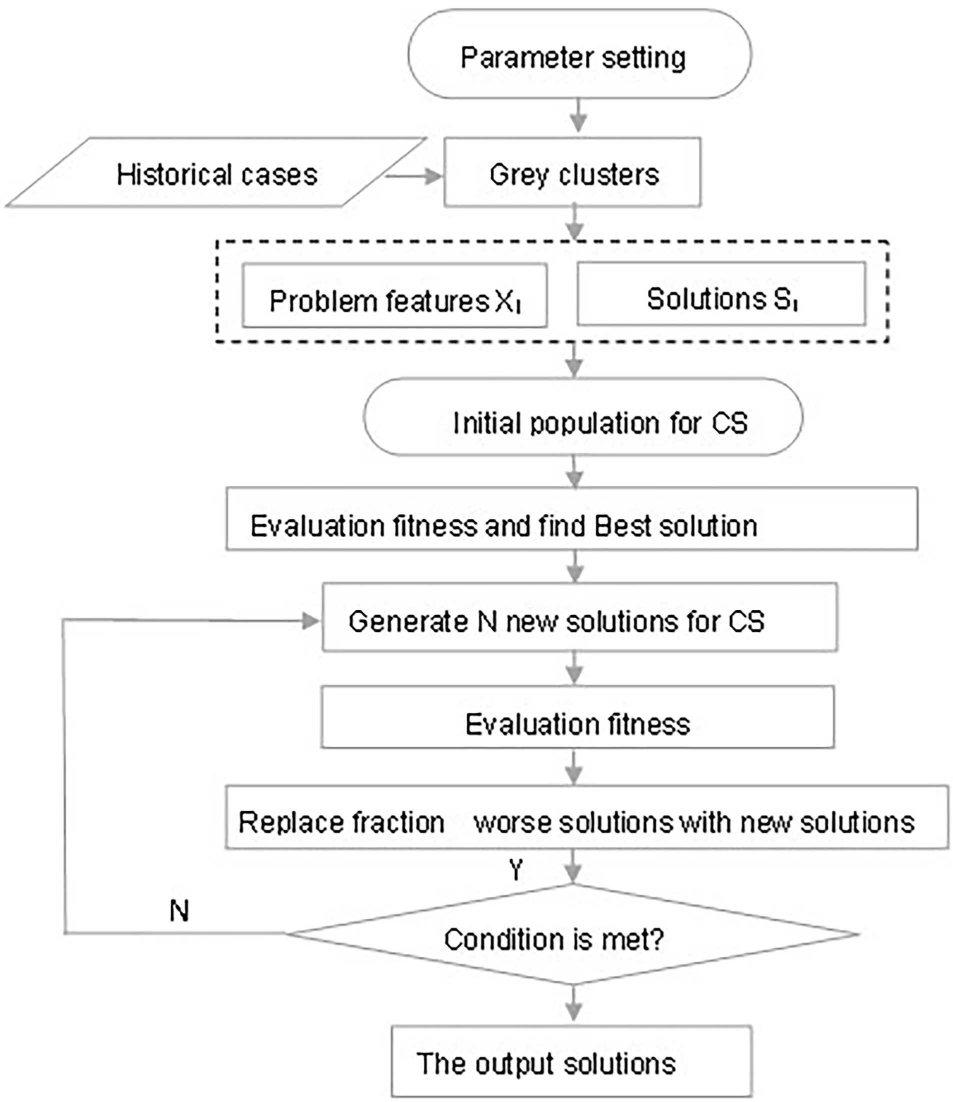

Figure 2 Flow of the proposed adaptation.

Infectious Disease Outbreaks Application

An example of an application is proposed to demonstrate the effectiveness and efficiency of the GCCS-CBR model. Infectious disease outbreaks are a major type of public health emergency with serious consequences. Problem scenarios and solutions include the features in Table 2. We represent the current case as $X_0 = \{2 \quad 1 \quad 1 \quad 4 \quad 7 \quad 1 \quad 625 \quad 1 \quad 6\}$. We use nine problem scenario features, including the rank risk of incident (RRI), transmission routes (TR), symptoms (SP), pathological characteristics (PC), average quarantine period (AQP), infection ratio (IR), number of infected (NI), fatality ratio (FR), and number of deaths (ND).[43–47] Every solution consists of a medical rescue team (MST), public health workers (PHW), psychological experts (PE), a supply of beds in infectious disease facilities (SB), and medical protection materials (MPM). According to the characteristics and history of infectious diseases in China, let $m = 18, \quad n = 9, \quad s = 5$.

Establishment of Case Index

The historical cases of infectious disease outbreaks are collected into a space distribution of case sets as shown in Figure 3A. First, the grey clustering analysis of the case dataset is carried out, and four grey classes are generated as shown in Figure 3B. The corresponding center points M_1, M_2, M_3, and M_4 are obtained. The indexing structure is designed according to grey relational distance from the case and the center point of the grey class as shown in Figure 3C. The distance between the center point and the case farthest from the center point is selected as the radius R_1, R_2, R_3, and R_4 of the classes, as shown in Figure 3D.

Matching Process

Assuming that the current case X_0 is located as shown in Figure 3C, and the similarity threshold is R, the process of calculating the similar case to X_0 is as follows:

① The grey classes with possible similar cases are screened.

$$G_d(M_1, X_0) < R_1 + R, \; G_d(M_2, X_0) > R_2 + R, G_d(M_3, X_0) > R_3 + R, \; G_d(M_4, X_0) < R_4 + R$$

Thus, there are similar cases to X_0, and the possible classes are grey class 1, and class 3.

② Candidate similar cases are determined.

$$G_d(X_O, M_1) - R < G_d(X_2, M_1) < G_d(X_0, M_1) + R,$$
$$G_d(X_O, M_1) - R \leq G_d(X_{12}, M_1) \leq G_d(X_O, M_1) + R,$$
$$G_d(X_O, M_1) - R \leq G_d(X_3, M_1) \leq G_d(X_0, M_1) + R, G_d(X_O, M_3) - R \leq G_d(X_{16}, M_3) \leq G_d(X_0, M_3) + R,$$
$$G_d(X_O, M_3) - R \leq G_d(X_{11}, M_3) \leq G_d(X_0, M_3) + R,$$
$$G_d(X_0, M_3) - R \leq G_d(X_1, M_3) \leq G_d(X_0, M_3) + R.$$

Table 2 Historical Cases of Infectious Disease Outbreaks

Case	Problem Scenario Feature									Solutions				
	RRI	TR	SP	PC	AQP	IR	NI	FR	ND	MRT	PHW	PE	SB	MPM
1	2	3	3	1	7	1	545	1	5	47	7	2	750	165
2	2	1	2	3	7	1	364	1.5	5	52	6	3	500	108
3	2	3	2	4	14	1.5	500	1	5	45	8	4	1000	152
4	4	5	3	4	14	2	600	0.5	3	36	9	4	1000	134
5	3	2	4	4	7	2	450	1	5	50	6	3	650	143
6	2	2	3	3	7	1	860	1	9	87	9	5	1200	210
7	2	2	6	2	30	3	700	1.5	11	90	11	6	1500	230
8	3	3	3	1	30	3	650	2	13	63	15	8	1250	244
9	1	3	3	1	7	3	200	1	2	32	6	3	500	65
10	1	5	1	2	60	2	5327	6.5	349	350	58	32	8000	5500
11	3	2	1	3	7	1	1350	1.5	20	123	20	11	1600	2300
12	4	2	1	4	14	1	2600	1	26	157	29	15	5000	1500
13	4	4	2	5	30	1	3200	0.5	16	127	31	17	5000	3200
14	1	3	1	3	14	1.5	1050	1.5	16	169	17	9	1500	2430
15	3	3	1	4	7	1	330	2	7	48	6	3	500	98
16	2	1	1	3	7	2	570	2	11	62	12	6	950	163
17	4	1	2	3	14	3	1460	0.5	7	104	15	7	2100	1230
18	2	5	4	2	14	1	750	1	8	73	9	5	1100	175

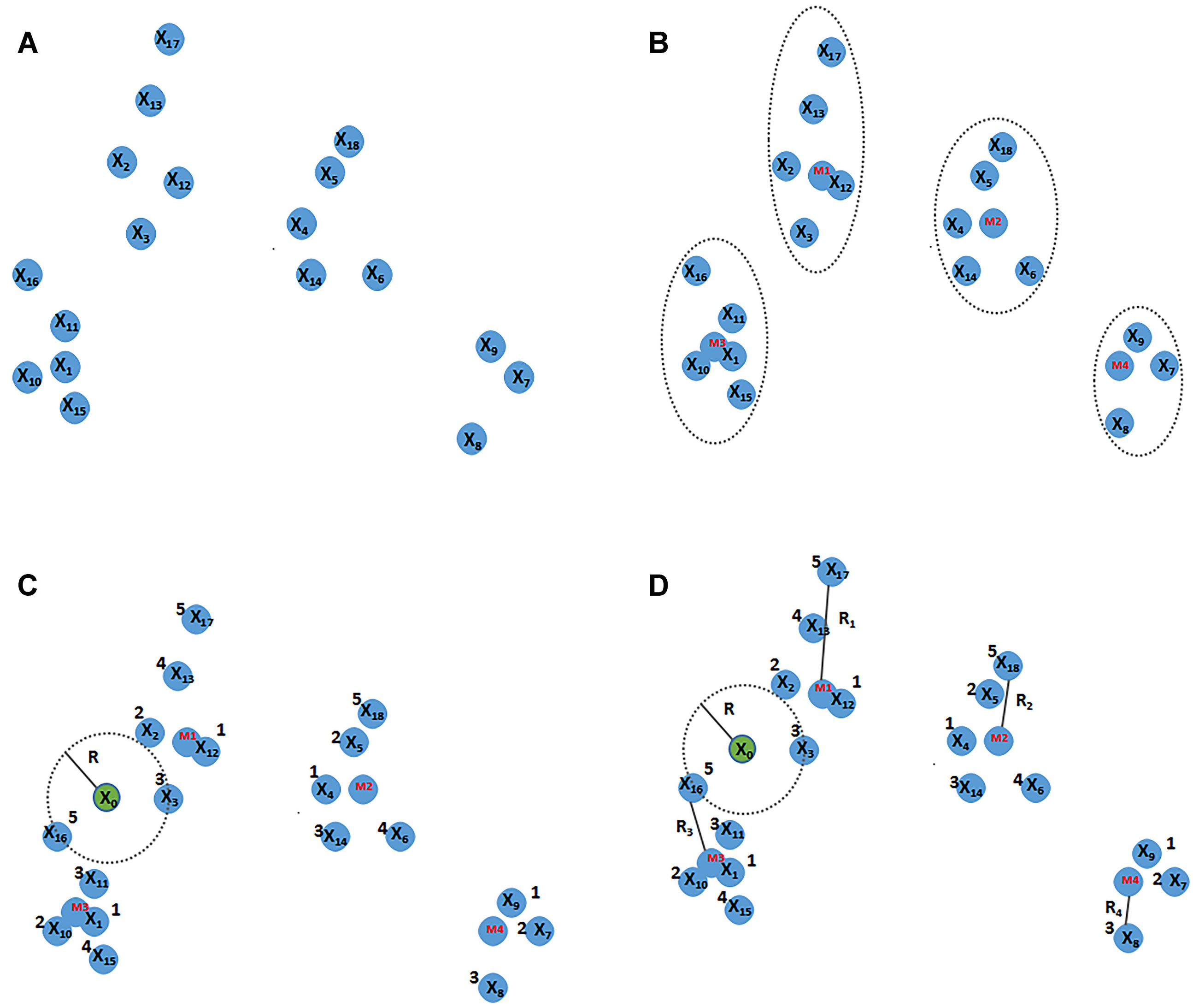

Figure 3 (**A**) Space distribution of case sets. (**B**) Aggregation results. (**C**) Index of cases. (**D**) Radius of each class.

Therefore, the cases that may be similar to X_0 in class 1 are X_2, X_{12}, and X_3. There are X_{16}, X_{11}, and X_1 that may be similar to X_0 in class 3.

③ From the candidate similar cases, we find the similar cases that match the current case.

$$G_d(X_O, X_3) - R, G_d(X_O, X_{16}) < R$$

Therefore, the similar case set of X_0 is $SCS^* = \{X_3, X_{16}\}$.

Adaptation Case

The adaptation process is vital for public health emergencies. Public health emergencies tend to be highly accidental, and such situations develop rapidly. Through the formulation of effective emergency response plans, selection of a course of action based on scientific methods, reasonable allocation of resources, and careful organization of the use of emergency response forces, the effectiveness of emergency response actions can be maximized. Therefore, the question of how to plan and adjust public health emergency response plans is the primary problem addressed by the present research. Using grey clustering for case retrieval, we find a similar case set SCS^*. Then the retrieved cases are taken as the cuckoo search (CS) algorithm's initial host nests. Let the parameter of the CS algorithm $p_a = 0.25$, step scaling factor$\alpha = 0.01$, and time of iteration $T = 250$. Moreover, the similarities of the initial nests and corresponding solutions are obtained from SCS^*:

$$Sim = \begin{Bmatrix} 0.625 \\ 0.593 \end{Bmatrix},$$

$$Intialsolutions = \begin{Bmatrix} 45 & 8 & 4 & 1000 & 152 \\ 62 & 12 & 6 & 950 & 163 \end{Bmatrix}.$$

We assume that there is a mapping between the problem and the solution. The CS algorithm is adopted to generate a new problem scenario X_i' and corresponding solutions S_i' according to $x_i(t+1) = x_i(t) + a \oplus \text{levy}(1)$. The new features value of the CS algorithm is generated as $X' = \{2 \quad 1 \quad 1 \quad 3 \quad 7 \quad 1 \quad 650 \quad 1 \quad 6\}$, and $S' = \{56 \quad 10 \quad 5 \quad 900 \quad 158\}$.

Table 3 Parameter Settings for the Three Methods

Parameters	PSO	DE	CS
Probability(pa)			0.25
Step scaling factor(α)			0.01
Times of iteration	250	250	250
Cognitive constant(c1)	2		
Social constant(c2)	2		
Inertia weight	0.8		
Crossover rate		0.5	
Mutation rate		0.8	

Results

In existent studies, differential evolution (DE) and Particle Swarm Optimization (PSO) have been used to improve CBR on responding emergencies towards gas explosion and natural disasters. Therefore, this paper applies three intelligent optimization algorithms, including the CS algorithm, differential evolution (DE),[22] and Particle Swarm Optimization (PSO)[25] to optimize solutions of CBR for servicing public health emergencies. We show the parameter settings for the three algorithms in Table 3. 250 iterations are used. The output with the highest similarity is the optimal solution.

Figure 4 shows the iterative process of the three algorithms. The results of our novel method based on a CS algorithm are optimal and have the fastest convergence speed. The fitness function value of the proposed method is higher than that of the other two algorithms. The calculated solutions including MST, PHW, PE, SB, MPM, can be used to deal with the current infectious disease emergency.

We consider computation time and fitness function value to show the performance of the GCCS-CBR model. The comparative results of the CS algorithm and the other two algorithms are shown in Table 4. To reduce the impact of random chance, the three models were repeated 30 times We can see that the CS method benefits from better computational efficiency than the other two algorithms. Further, the CS method also outperforms the mean similarity.

Conclusion

We conclude that CBR is an effective and efficient method to assist decision-makers in providing public health emergency response measures. The key steps to providing effective and appropriate emergency response measures are case retrieval and adaptation

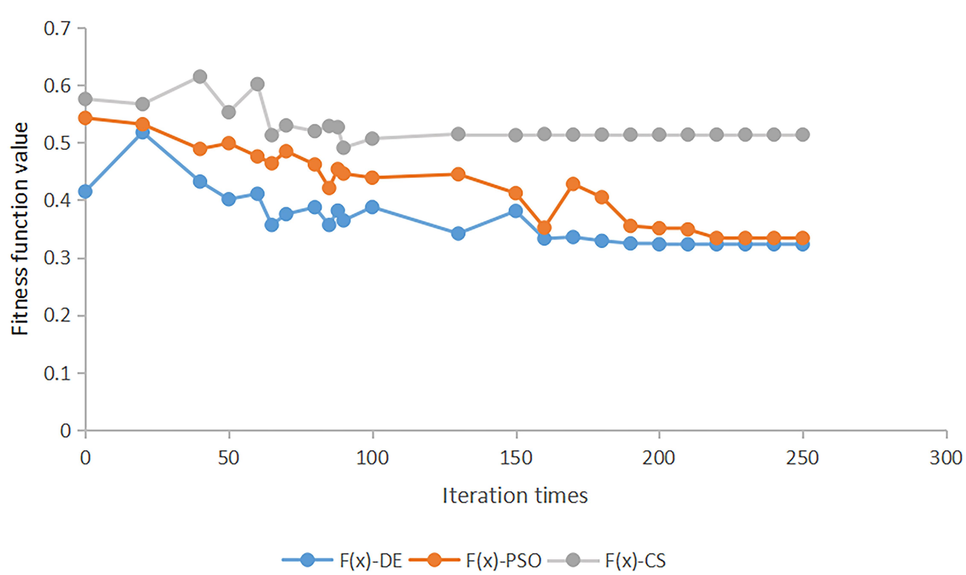

Figure 4 Iterative process.

Table 4 Comparison of the Three Methods

Methods	Mean Computation Time (Second)	Mean Fitness Function Value
DE	510	0.415
PSO	850	0.543
CS	450	0.576

processes. During infectious disease outbreaks, decision-makers have limited time to assess emergency decisions. Additionally, available human experience and knowledge may well be insufficient to meet the requirements of emergency planning, so computer-assisted methods are critical. However, knowledge-based rules for dealing with public health emergencies are difficult to extract accurately. To address these problems, a novel CBR system, improved by grey clustering and the CS algorithm, is presented here to retrieve and adapt cases. Grey clustering analysis is used to condense the case base DB. The CS algorithm is then used to optimize the obtained solutions from the grey clustering model in adaptation cases. The method has been applied to simulated infectious disease emergencies. Further, the method has also been compared with other methods, PSO and DE. The results clearly show the efficiency and effectiveness of our proposed method.

With the help of the CS algorithm, CBR experiments have demonstrated that GCCS-CBR can generate appropriate solutions by exploring knowledge of responding crises in historical cases. GCCS-CBR can be applied in more fields with contributing sensible solutions for prospective public health emergency, such as infectious diseases outbreak, natural disasters, mass food poisoning, and other crises which may have a serious impact on public health and safety.

In the early stage of epidemics, the GCCS-CBR can provide supports on decision-makings for public services include government departments, centers for disease control (CDC), medical emergency service, etc. This method not only benefits them with a punctual prevention and control on crises, but also mitigates the happening of failure caused by unprofessional knowledge and insufficient experience. During a pandemic, emergency management departments can achieve relevant measures by applying required data of current epidemic into the GCCS-CBR method, which provides suggestions on allocating numbers of medics include emergency services, public health workers and psychological experts; preparing for hospital beds and medical supplies, etc.

Public health emergency situations often demonstrate periodic changes. Therefore, the proposed method can further use a dynamic stochastic process such as a Markov Chain to simulate real-time changes in problem scenarios and formulate dynamic emergency measures. Finally, the question of whether the similarity of a problem scenario and of possible resolution measures is homogeneous also needs to be considered, to quickly generate more effective measures.

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Disclosure

The authors report no conflicts of interest in this work.

References

1. Danielle NP, Daniel JE, Lawrence OG, Elizabeth DL, Talbot EA. Responding to the COVID-19 pandemic in complex humanitarian crises. *Int J Equity Health*. 2020;19(1):41–55. doi:10.1186/s12939-020-01162-y
2. Qu TJ, Gu SY, Li MZ, Zhang XL, Sun MJ, He ZS. Status and challenges of public health emergency management in china. *Chin J Public Health Manag*. 2019;35:433–435.
3. Wang W, Tang JM, Wei FQ. Updated understanding of the outbreak of 2019 novel coronavirus (2019-nCoV) in Wuhan, China. *J Med Virol*. 2020;92(4):441–447. doi:10.1002/jmv.25689
4. Liao Z, Mao X, Hannam PM, Zhao T. Adaptation methodology of CBR for environmental emergency preparedness system based on an Improved Genetic Algorithm. *Expert Syst Appl Int J*. 2012;39 (8):7029–7040. doi:10.1016/j.eswa.2012.01.044
5. Lurie N, Manolio T, Patterson AP, Collins F, Frieden T. Research as a Part of Public Health Emergency Response. *N Engl J Med*. 2013;368(13):1251–1255. doi:10.1056/NEJMsb1209510
6. Araz OM, Technological Forecasting JM. Social Change Improving public health emergency preparedness through enhanced decision-making environments: a simulation and survey based evaluation. *Technol Forecast Soc Change*. 2013;80(9):1775–1781. doi:10.1016/j.techfore.2012.09.018
7. Zhu N, Zhang D, Wang W, et al. A Novel Coronavirus from Patients with Pneumonia in China. *N Engl J Med*. 2020;382(8):727–733. doi:10.1056/NEJMoa2001017
8. Yan A, Yu H, Wang D. Case-based reasoning classifier based on learning pseudo metric retrieval. *Expert Syst Appl*. 2017;89:91–98. doi:10.1016/j.eswa.2017.07.022
9. Liang H, Xiong W, Computers DY. Industrial Engineering A prospect theory-based method for fusing the individual preference- approval structures in group decision making. *Comput Ind Eng*. 2018;117:237–248. doi:10.1016/j.cie.2018.01.001
10. Wang L, Wang Y, Martínez L. A group decision method based on prospect theory for emergency situations. *Int J Syst*. 2017;419:119–135.
11. Yu L, Lai KK. A distance-based group decision-making methodology for multiperson multi-criteria emergency decision support. *Decis Support Syst*. 2011;51(2):307–315. doi:10.1016/j.dss.201011.024

12. Cai C, Xu X, Wang P, Chen X. A multi-stage conflict style large group emergency decision-making method. *Soft Comp*. 2017;21 (19):5765–5778. doi:10.1007/s00500-016-2155-5
13. Sun B, Ma W, Zhao H. An approach to emergency decision making based on decision-theoretic rough set over two universes. *Soft Computing*. 2016;20(9):3617–3628. doi:10.1007/s00500-015-1721-6
14. Kececi T, Arslan O. Share technique: a novel approach to root cause analysis of ship accidents. *Saf Sci*. 2017;96:1–21. doi:10.1016/j.ssci.2017.03.002
15. Lee GH. Rule-based and case-based reasoning approach for internal audit of bank. *Knowl Base Syst*. 2018;21(2):140–147. doi:10.1016/j.knosys.2007.04.001
16. Qin Y, Lu W, Qi Q, Liu X, Huang M, Scott PJ. Knowledge-Based Systems towards an ontology-supported case-based reasoning approach for computer-aided toleengjin Du; rance specification. *Knowl Base Syst*. 2018;141:129–147. doi:10.1016/j.knosys.2017.11.013
17. Nihad EG, Mohamed K, Mokhtar ENE. Designing and modeling of a multi-agent adaptive learning system (MAALS) using incremental hybrid case-based reasoning (IHCBR). *Int J Elect Computer Eng*. 2020;10:1980–1995.
18. Lim J, Chae M, Yang Y, et al. Fast Scheduling of Semiconductor Manufacturing Facilities Using Case-Based Reasoning. *IEEE Trans Semicond Manuf*. 2016;29(1):22–32. doi:10.1109/TSM.2015.2511798
19. Luo J. A Quick Emergency Response Plan Generation System Combining CBR and RBR. *J Computer Res Dev*. 2007;44 (4):660–666. doi:10.1360/crad20070416
20. Sharaf DA, Moawad IF, Khalifa ME, Choi W. A New Hybrid Case-Based Reasoning Approach for Medical Diagnosis Systems. *J Med Syst*. 2014;38(1):1–9. doi:10.1007/s10916-013-0001-1
21. Yang SY, Hsu CL. An ontological Proxy Agent with prediction, CBR, and RBR techniques for fast query processing. *Expert Syst Appl*. 2009;36(5):9358–9370. doi:10.1016/j.eswa.2009.01.011
22. Yu X, Zhao WX, Chen H, Chen H. A novel case adaptation method based on differential evolution algorithm for disaster emergency. *Appl Soft Comput*. 2020;92:1036–1048. doi:10.1016/j.asoc.2020.106306
23. Fan Z, Li YH, Wang X, et al. Hybrid similarity measure for case retrieval in CBR and its application to emergency response towards gas explosion. *Expert Syst Appl*. 2014;41(5):2526–2534. doi:10.1016/j.eswa.2013.09.051
24. Xiang YX, Jun LG, Xiao LN. Sudden Public Health Incident Emergency Plan Research Based on Case-Based Reasoning. *Int Symp Behav Based Safety Safety Manage BSM China*. 2011;613.
25. Qiang L, M J C, Wei X, et al. Multi-Robot Learning Using PSO Combined with CBR Algorithm. *J Univ Elect Sci Techn China*. 2014;43:23–28.
26. Jiang Z, Jiang Y, Wang Y, Zhang H, Cao H, Tian G. A hybrid approach of rough set and case-based reasoning to remanufacturing process planning. *J Intell Manuf*. 2019;30(1):19–32. doi:10.1007/s10845-016-1231-0
27. Duan W, Cao ZD, Wang YZ, et al. An ACP Approach to Public Health Emergency Management: using a Campus Outbreak of H1N1 Influenza as a Case Study. *IEEE Trans Syst Man Cybern Syst*. 2013;43(5):1028–1041. doi:10.1109/TSMC.2013.2256855
28. Schnall A, Nakata N, Talbert T, Bayleyegn T, Martinez D, Wolkin A. Community Assessment for Public Health Emergency Response (CASPER): an Innovative Emergency Management Tool in the United States. *Am J Public Health*. 2017;107(S2):186–192. doi:10.2105/AJPH.2017.303948
29. Chan EYY, Huang Z, Hung KKC, et al. Health Emergency Disaster Risk Management of Public Transport Systems: A Population-Based Study after the 2017 Subway Fire in Hong Kong, China. *Int J Environ Res Public Health*. 2019;16(2):228–242. doi:10.3390/ijerph16020228
30. Xu J, Zhou HY, Ye GH. Research on Construction of Public Health Emergency Knowledge. *Base Res Libr Sci*. 2018;11:26–39.
31. Chen YR, Ni PN, Tsai KJ. Construction of a sediment disaster risk assessment model. *Environ Earth Sci*. 2013;70(1):115–129. doi:10.1007/s12665-012-2108-y
32. Rauch J. Expert deduction rules in data mining with association rules: a case study. *Knowl Inf Syst*. 2018;1(4):1–29.
33. Deng JL. Control problems of grey systems. *Syst Control Lett*. 1982;1 (5):288–294. doi:10.1016/S0167-6911(82)80025-X
34. Liu SF, Lin Y. Introduction to Grey Systems Theory. *Understanding Complex Syst*. 2010;68(2):1–18.
35. Chang W, Zhao B, Li J Application of grey relational theory in transformer fault diagnosis. IEEE Power and Energy Engineering Conf., Wuhan, China, 2011.
36. Hu YC. Tolerance rough sets for pattern classification using multiple grey single-layer perceptrons. *Neurocomputing*. 2016;179:144–151. doi:10.1016/j.neucom.2015.11.066
37. Liu Y, Ben K. Research on Aggregation Retrieval and Correlation Evaluation Strategy for Fault Cases. *J Front Computer Sci Tech*. 2012;6:545–556.
38. Yang XS, Suash D. *Cuckoo Search via Levy Flights. World Congress on Nature & Biologically Inspired Computing Coimbatore 17th Annual Conf*. India; 2009:351.
39. Yang XS, Suash D. Cuckoo search: recent advances and applications. *Neural Comput Appl*. 2014;24(1):169–174. doi:10.1007/s00521-013-1367-1
40. He XS. Global Convergence Analysis of Cuckoo Search Using Markov Theory. *Nat Inspired Alg App Optimiz*. 2017;744:53–67.
41. Brown CT, Liebovitch LS, Glendon R. Lévy flights in dobe ju/hoansi foraging patterns. *Hum Ecol*. 2007;35:129–138. doi:10.1007/s10745-006-9083-4
42. Pavlyukevich I. Lévy flights non-local search and simulated annealing. *J Comput Phys*. 2007;226(2):1830–1844. doi:10.1016/j.jcp.2007.06.008
43. Ebrahimian A, Hashemiamrei SH, Monesan M. Exploring factors affecting the emergency specialists decision-making in case of emergencies in patients. *Crit Care Res Pract*. 2018;12:1–7. doi:10.1155/2018/9579807
44. Rui Y, Du G, Duan Z, Du M, Miao X, Tang Y. Knowledge System Analysis on Emergency Management of Public Health Emergencies. *Sustainability*. 2020;12(11):4410. doi:10.3390/su12114410
45. Humensky JL, Abedin Z, Muhammad K, et al. Promoting interdisciplinary research to respond to public health crises: the response of the Columbia University CTSA to the opioid crisis. *J Clin Trans Endocri*. 2020;4(1):22–27. doi:10.1017/cts.2019.426
46. Choi H, Cho W, Kim MH, et al. Public Health Emergency, and Crisis Management: case Study of SARS-CoV-2 Outbreak. *Int J Environ Res Public Health*. 2020;17(11):186–201.
47. Exum NG, Betanzo E, Schwab KJ. Extreme precipitation, public health emergencies, and safe drinking water in the USA. *Curr Environ Health Rep*. 2018;5(1):1–11. doi:10.1007/s40572-018-0173-4