

## *Retraction*

# **Retracted: Emergency Project Management Decision Support Algorithm for Network Public Opinion Emergencies Based on Time Series**

### **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] G. Guo, C. Yao, and M. Shoeibi, "Emergency Project Management Decision Support Algorithm for Network Public Opinion Emergencies Based on Time Series," *Complexity*, vol. 2022, Article ID 4732999, 9 pages, 2022.

## Research Article

# Emergency Project Management Decision Support Algorithm for Network Public Opinion Emergencies Based on Time Series

Gaohuizi Guo <sup>1</sup>, Cuiyou Yao,<sup>1</sup> and Mehrdad Shoeibi <sup>2</sup>

<sup>1</sup>School of Management and Engineering, Capital University of Economics and Business, Beijing 100070, China

<sup>2</sup>Industrial Engineering and Management Systems Department, Institute for Management and Planning Studies, Tehran, Iran

Correspondence should be addressed to Gaohuizi Guo; [huizi@cueb.edu.cn](mailto:huizi@cueb.edu.cn) and Mehrdad Shoeibi; [m.shoeibi@imps.ac.ir](mailto:m.shoeibi@imps.ac.ir)

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The present study aims at proposing a time series-based network public opinion emergency (NPOE) management decision support algorithm for the problems of low decision accuracy and long decision time in traditional similar algorithms. In this proposed algorithm, after the time series data are preprocessed, the association rules of the original indicator data of network public opinion emergencies (NPOEs) are mined, the original indicator data matrix of NPOEs will be constructed, and the improved local linear embedding approach will be employed to obtain the original indicator data of NPOEs. After carrying out the preprocessing according to the preprocessing results, the objective weight of the emergency decision index is calculated through the interval value fuzzy information entropy measurement of the emergency decision index, the emergency management decision support model is constructed, and the emergency management decision support of the NPOE is realized. The simulation experiment results show that the proposed algorithm has a better effect on the decision-making effect of the management of NPOEs, and a higher decision-making efficiency is achieved.

## 1. Introduction

The development and popularity of the Internet are strongly related to emergency management; the manner in which people acquire information has undergone dramatic changes. People can now use their mobile devices to access the Internet anywhere, anytime, and more conveniently, allowing them to share their opinions and attitudes more frequently. In this instance, the trend is the complication of the ethical issue and online public opinion crises. Emergency contact network public opinion occurs instantly via the network whose underlying topic is characteristic and refers to the sentiment and public attitude of public opinion on a specific event: communication interaction, the richness of content, and the network cascade [1].

The Internet has become an integral component of the majority of people's daily life. Such a platform enables the free expression of attitudes and opinions regarding a particular social phenomenon or issue, forming the network of

public opinion by mapping social public opinion in the Internet space, which is a direct mirror of social public opinion [2]. When certain emergencies occur in real society, the rapid spread of these events through the Internet will quickly become a hot topic on the Internet. It is this free and open public opinion platform that has led to changes in the way the public and the government communicate. Especially at present, the Internet lacks timely openness and transparency, and it is easier for netizens to participate in active discussions on Internet hotspot events [3].

The most significant characteristic of public view concerning public emergencies in an overall emergency system is the very fast contentions and distribution. Oppositely, the emergency is regarded as a public section. With the quick emergence of social media, the general public could make complete evaluations that are demanding and true and are also able to take an immediate answer. However, the Internet is a public platform and is described as an extensive interaction network. Thus, this question arises that can such an

efficient and interactive and swift online public view deal with emergencies? The intrusion noise of the system is the most significant exterior contextual element affecting the expansion of network public view in emergencies.

Public emergencies take advantage of their web, present soil for the noise of the system (e.g., precariousness, main crashes, amplification information, and cyber leakage), and monitor problems and propinquity.

The generic data release strategy had an effect on or led to the abandonment of the environmental factors approach. As a result of the complexity of information distribution, symbolic interpretations might be confused and ambiguous [4–8]. The spread of rumors, misinterpretations, and problems with external systems could culminate in a collapse of the transference structure and system. The Internet public perspective differs from campus management, which deals with emergency exception administration. The only thing that persisted was the emergency passively coping with Internet misinformation, but the leaders did not consider it. Education, scientific research investigations, and online poll management are also effective elements. Since universities began to modify their conceptions of development, they have prioritized developing university competitions while ignoring the structure of “soft power.” The network environment serves numerous purposes, including the formation and enhancement of values and ethical concepts. Network features and transference models impact the study and life of college learners, and the procedure could take time. The university is considered a significant human resources center, and the negligence of managers influences human resource improvement.

Predicting and analyzing time series could be the main title that is implemented in the traffic finance, engineering, and complicated web fields. Analyzing time series could contribute to parsing the features of data and investigating possible information [9–14].

So far, to the best of our knowledge, no study has proposed an emergency project management decision support algorithm for NPOEs based on time series. Hence, the present study suggested a fuzzy time series (FTS) approach based on Markov Chains which provide a mathematical system that experiences transitions from one state to another according to certain probabilistic rules. All of these methods predict FTSs using the first-order FTS prediction model. Most FTS prediction approaches in the literature are based on the model of high-order FTS, bivariate FTS, and multivariate FTS [15–20].

In general, the methods of FTS rely on three phases, including (1) fuzzification, (2) fuzzy relation specification, and (3) defuzzification. In the relevant literature, the FTS methods are developed in the abovementioned three phases employing various artificial intelligence (AI) approaches. In the present study, time series are evaluated in order to tackle the aforementioned algorithmic issues, a time series-based network public view emergency response group decision support algorithm is recommended, and the algorithm efficiency is confirmed using simulation tests.

## 2. Literature Review

Chen suggested in 2010 a new FTS model, the high-order FTS model, to address forecasting issues and to design an algorithm for predicting enrollments at the University of Alabama. The accuracy of the proposed method was superior to that of previously utilized techniques [16].

In 2012, Xie and Wu created an emergency group decision-making method for use in unorthodox emergency situations. Important decision information is provided by their scenario analysis approach in the form of analysis results of present situations and future trends of emergency events. In addition, dynamic Bayesian networks theory is employed to develop a scenario-response model of emergency group decision-making. The results of their investigation indicate that the scenario-response paradigm promotes initiative and effectiveness in unorthodox emergency responses. In the emergency decision-making process, the results also imply that present events and possible patterns of atypical emergencies should be evaluated as decision support information [1].

Multiple decision makers participated in Zhang’s 2019 collaborative group decision model for online public opinion emergency with an interval-valued index. Using the emergency decision model proposed, the ideal weight of each individual and collaborative emergency index may be calculated. Last but not least, the global crisis of each emergency can be determined by combining the individual severity with the collaborative severity. According to crisis ranking, the emergency department can build an appropriate decision scheme to address all Internet public opinion emergencies [21].

Fu et al. suggested in 2019 a multiattribute group decision-making (MAGDM) method according to intuitionistic fuzzy preference data for the multiattribute intuitionistic fuzzy group decision-making problem (MAIFGDM) in which the decision-maker weight and attribute weight are not quite certain and the decision maker has preference information for the scheme. Their proposed technique helps decision makers to choose and execute the ideal emergency response plan in a timely and efficient manner, which enhances the emergency treatment efficiency of network public opinion crisis, helps emergency departments to better deal with the network public opinion crisis, improves the ability of public opinion guidance and control, and offers a novel way and approach for MAIFGDM [22].

## 3. Problem Statement

As mentioned above, the most significant characteristic of public view concerning public emergencies in an overall emergency system is the very fast contentions and distribution. Oppositely, the emergency is regarded as a public section. With the quick emergence of social media, the general public could make complete evaluations that are demanding and true and are also able to take an immediate answer. However, the Internet is a public platform and is

described as an extensive interaction network. Thus, this question arises that can such an efficient and interactive and swift online public view deal with emergencies? The intrusion noise of the system is the most significant exterior contextual element affecting the expansion of network public view in emergencies.

**3.1. Some Important Definitions of Time Series.** Based on TFS, the time-invariant and time-variant definitions are given as follows.

*Definition 1.* Suppose  $Y(t)$  ( $t = \dots, 0, 1, 2, \dots$ ), which is a real-number subcollection, to be considered as the universe of discourse where the definition of fuzzy sets  $f_j(t)$  is performed. If  $F(t)$  is a collection of  $f_1(t), f_2(t), \dots$ , then  $F(t)$  is named a FTS defined on  $Y(t)$ .

*Definition 2.* Let  $F(t)$  be merely implied by  $F(t-1)$ , that is,  $F(t-1) \rightarrow F(t)$ . Next, such a correlation may be demonstrated as  $F(t) = F(t-1) \circ R(t, t-1)$ , in which  $R(t, t-1)$  indicates a fuzzy relation between  $F(t)$  and  $F(t-1)$ , and  $F(t) = F(t-1) \circ R(t, t-1)$  is named the 1<sup>st</sup> order model of  $F(t)$ .

*Definition 3.* Let  $R(t, t-1)$  be the 1<sup>st</sup> order model of  $F(t)$ . In the case where  $R(t, t-1)$  is independent of  $t$  for any  $t$ , that is,  $R(t, t-1) = R(t-1, t-2)$  for any  $t$ , it can be concluded that  $F(t)$  is named a time-invariant FTS; otherwise, it will be named a time-variant FTS.

*Definition 4.* Let  $R(t, t-1)$  be the 1<sup>st</sup> order model of  $F(t)$ . In cases where  $R(t, t-1)$  is independent of  $t$ , that is,  $R(t, t-1) = R(t-1, t-2)$ , then  $F(t)$  is named a time-invariant FTS; otherwise, it is named a time-variant FTS. The symbol “ $\circ$ ” represents max-min composition of fuzzy sets. Song and Chisom [3] firstly introduced an algorithm according to the 1<sup>st</sup> order model to predict time-invariant  $F(t)$ . In Song and Chisom [23, 24], the matrix of fuzzy relationship  $R(t, t-1) = R$  is calculated through plenty of matricial operations. The fuzzy prediction is made according to max-min composition as follows:

$$F(t) = F(t-1) \circ R. \quad (1)$$

The dimension of  $R$  is depending on the quantity of fuzzy sets, namely, the partition number of discourse and universe.

**3.2. Applying Time Series to the Mining of NPOEs.** To apply time series to the mining of association rules among the original indicators of NPOEs, the corresponding time series must be initially constructed. However, since in any network, public opinion emergency data packet contains a large amount of network data, it will be hard to process directly even if the time series speed is fast. Therefore, it is necessary to preprocess the original index data of NPOEs [25]. Information entropy is a better method of preprocessing. The detected data are packaged and the information is selected as a set of random events, as follows:

$$X = n_i (i = 1, 2, \dots, N). \quad (2)$$

(1) can express the number of times the address in the information packet occurs when different events occur, and the information entropy  $H(X)$  can be calculated as

$$H(X) = - \sum_{i=1}^N \left( \frac{n_i}{S} \right) \lg_2 \left( \frac{n_i}{S} \right). \quad (3)$$

The formula  $S$  represents the total quantity of occurrences of a certain address, which can be expressed as

$$S = \sum_{i=1}^N n_i. \quad (4)$$

In (3),  $N$  represents the total quantity of random events, and  $n_i$  is a single event in the event set. Preprocessing is carried out using information entropy, and the original indicators of NPOEs can be expressed by altering the entropy value of IP source address, a destination address, and port number. In emergencies of online public opinion, the more concentrated the data, the smaller the information entropy, otherwise the larger the information entropy. The preprocessed data information is stored in the database. When index mining is performed, the database is scanned once to obtain the set of frequency sets and the corresponding minimum degree of support, and the frequency sets are arranged in descending order to obtain the set  $L$ .

After completing the time series preprocessing, the time series data are symbolized and converted into a transaction set. Since the time series is flowing, the particle swarm method is used to restrict the data flow. In the particle swarm method, new data will continue to enter, and old data will slide out [26]. Therefore, when mining rules of the association are applied, we must be able to support incremental mining of data increase and support the removal of old data concurrently. The data set is dynamically changing, and the mining association rules are also dynamically changing, and the mining in this article is the association rule of multivariate time series data, and the volume of data is relatively high, so we must perform recursive calculations on the movement of ions:

$$\bar{V}_i^{k+1} = \bar{V}_i^k + c_1 * r_1 \left( \bar{P}_i^k - \bar{X}_i^k \right). \quad (5)$$

In the above formula, the particle label is  $i = 1, 2, \dots, m$ ,  $k$  represents iterations quantity,  $\bar{V}_i^{k+1}$  indicates the particle velocity,  $\bar{V}_i^k$  is the particle velocity in the former moment,  $c_1$  and  $r_1$  are both learning factors, and  $\bar{P}_i^k \bar{X}_i^k$  is the motion vectors. Among them,

$$\bar{X}_i^{k+1} = \bar{X}_i^k + \bar{V}_i^{k+1}. \quad (6)$$

**3.3. Mining Association Rules of Original Index Data of NPOEs Based on Time Series.** Association rule mining is considered a crucial research topic in data mining. It digs out some interesting rules from a large amount of data. From these association rules, we can understand the relationship

between events, which can guide people to make some practical and meaningful behaviors [27]. This article is based on time series to mine the association rules of the original index data of NPOEs. The relevant mining flowchart is depicted in Figure 1.

In Figure 1, the time series algorithm provides a depth-first search. It uses the recursive search for short patterns instead of long frequent pattern mining. It only requires two database scans: a scan of the database which generates frequent itemsets and the scan of the database which establishes a global time series. The analysis of the mining process is divided into three steps: compressing the frequent sets in the database, retaining the associated information between the data, and storing them in the set of time series. Since the set of time series contains all frequency sets, the work of data mining only needs to be in the time. It is performed on the sequence set and then is separated into a conditional pattern library. Thus, a conditional time sequence set is established, respectively, and finally, recursive mining is performed [28].

The above two formulas will work together on the moving position of the particles in the next step. Considering a 2D space as an instance, the process from the initial position to the new position is shown in Figure 2.

The particle traversal approach is employed to calculate the support degree of the item set which has been introduced by the particle [29]. Combining the properties of the data source and the characteristics of the basic algorithm, the connected list data structure is applied to the dynamic storage structure. A linked/connected list header is built for each of the items in the full database, the set of itemsets, in turn, is scanned, and the items included in each item set are appended to the end of the relevant linked list. The sparse linked list construction process is shown in Figure 3.

We consider the  $n^{\text{th}}$  item set (50, 180, 17) and 200 linked list heads in the linked list as an example, start the search from the linked list 50, assuming that the  $64^{\text{th}}$  item set found contains the item 50. Accordingly, the linked lists 108 and 17 are respectively corresponding to 88 and 24. In other words, none of the itemsets before the  $88^{\text{th}}$  item set contains the item relevant to the particle, directly search for the  $88^{\text{th}}$  item set. If it contains (50, 108, 17), the particle support will increase by 1; otherwise, it will keep up searching, and the linked list (50, 108, 17) will discover the proceeding data, respectively, assuming that they correspond to 121, 90, and 65 and directly search for the  $121^{\text{st}}$  item set. If it contains (50, 108, 17), the particle support will increase by 1, otherwise it will keep up searching, the linked list (50, 108, 17), respectively, will find the next data, assuming that they relate to 121, 184, and 121 and directly look for the  $184^{\text{th}}$  item set. If it contains (50, 108, 17), the particle support will increase by 1. So far, the association rule mining has been completed based on the original index data of NPOEs in accordance with the time series [21].

**3.4. The Construction of the Original Index Data Matrix of NPOEs.** The original indicator data matrix of NPOEs is built using the original index data of NPOEs that were previously

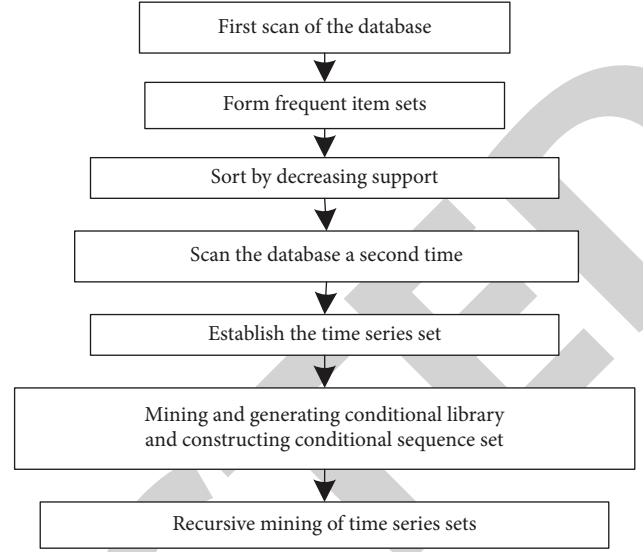


FIGURE 1: Flowchart of time series association rule mining.

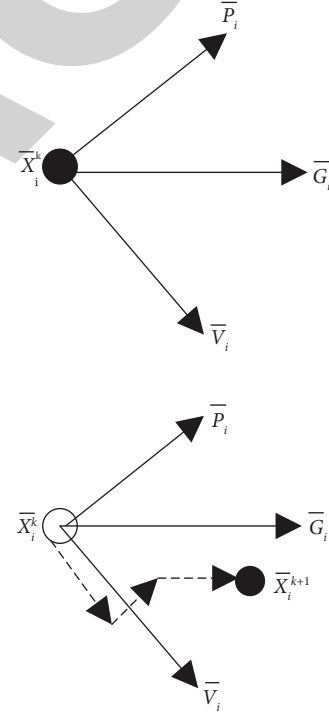


FIGURE 2: Process diagram of particle movement.

mined. Assume that, due to a shortage of emergency people and emergency resources in a particular region, the government must address the most severe online public opinion crisis first, followed by the relatively little number of crisis incidents [30]. When  $n$  NPOEs  $\{X_1, X_2, \dots, X_n\}$  broke out at the same time in the area, the emergency department needs to construct the corresponding model for decision-making of emergency management in accordance with the original index data of the current  $n$  NPOEs that are broken out concurrently. To ensure the scientificity and rationality of the final decision-making results of NPOEs, firstly,

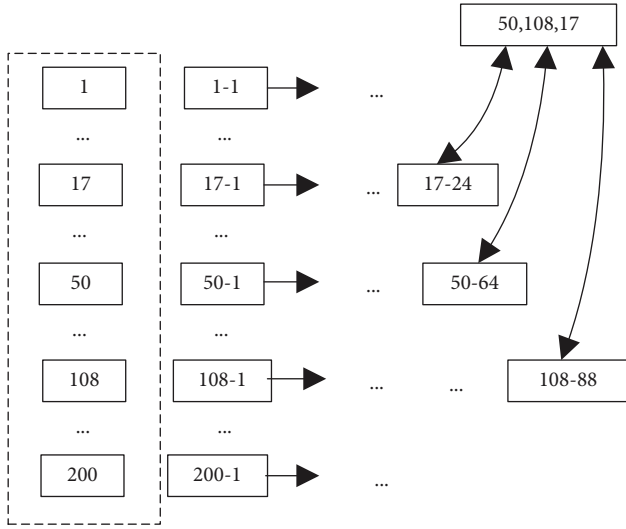


FIGURE 3: Construction process of sparse linked list.

emergency decision-making experts (assuming that the experts are of equal status) can conduct online questionnaire surveys on the emergency decision-making indicators of NPOEs and select  $m$  key emergency decision-making indexes  $\{C_1, C_2, \dots, C_m\}$ . Then, they will select emergency decision-making expert groups from different fields to conduct a preliminary evaluation of all emergency decision-making indicators for all emergencies of online public opinion based on their knowledge, experience, and network public opinion crisis monitoring data in the region. Finally, they will finally obtain the NPOE data matrix  $R = [X_{ij}]_{nm}$  of the original NPOEs regarding all emergency decision-making indicators of the incident:

$$R = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{nm} \end{bmatrix}. \quad (7)$$

**3.5. Data Preprocessing.** The generated NPOEs have distinct meanings reflected by the emergency decision-making indicators after being derived from the original index data matrix of NPOEs, leading to high index data dimensions and complicated computations and lowering NPOEs. As a result, in order to lower the dimensionality of the NPOEs emergency management decision-making index data, decision-making efficiency must be improved. The following actions are detailed:

*Step 1.* Locating  $k$  neighboring points of the data sample for the emergency management decision-making index of the NPOE;

*Step 2.* Computing the above-located neighboring points and then build a weight matrix based on the results of the computation;

*Step 3.* Using the calculation results from Step 2, we determine the low-dimensional embedding output value for the sample points of the NPOE management decision index data [31].

Although the disaster caused by data dimensionality can be solved using the locally linear embedding method, the dimensionality reduction impact is not good. In order to enhance the locally linear embedding method, the estimated reconstruction coefficient is employed to constrain the reconstruction error. The improved local linear embedding method's steps for dimensionality reduction are as follows:

- (1) Using the Euclidean distance formula to determine  $k$  ( $k < N$ ) as the closest neighbors of the sample point in the emergency management decision index data of the NPOE:

$$d_{ij} = \left[ \sum_{k=1}^D \|x_{ik} - x_{jk}\|^2 \right]^{1/2}, \quad (8)$$

where  $D$  represents the number of dimensions.

- (2) We create a weight matrix of the neighboring points  $X_{ij}$  ( $w_{ij}$ ) based on the outcome of the aforementioned formula, setting the weight between the sample point  $x_i$  of the emergency management decision-making index data of the NPOE and its neighbor points  $k$ :

$$\begin{cases} \min e(W) = d_{ij} \sum_{i=1}^N \left\| x_i - \sum_{j=1}^N w_{ij} x_j \right\|_2^2, \\ \text{S. t. } \sum_{j=1}^k w_{ij} = 1. \end{cases} \quad (9)$$

Formula (7) can be reformulated as follows when combined with the limitation conditions:

$$\begin{aligned} \min e(W) &= \sum_{i=1}^N \left\| \sum_{j=1}^N w_{ij} (x_i - x_{ij}) \right\|_2^2, \\ &= \sum_{i=1}^N \|(x_i - x_{ij}) w_i\|_2^2, \\ &= \sum_{i=1}^N (w_i)^T Z_i w_i. \end{aligned} \quad (10)$$

Here, the local covariance matrix  $Z_i$  must be constructed, then

$$\begin{aligned} Z_i &= (x_i - x_{ij})^T (x_i - x_{ij}), \\ w_i &= [w_{i1}, w_{i2}, \dots, w_{ik}]^T, \end{aligned} \quad (11)$$

where  $w_i$  represents the local reconstruction weight, and  $i$  represents the number of sample points.

We introduce Lagrange multiplier to solve, then

$$L(W) = \sum_{i=1}^N (w_i)^T Z_i w_i + \left( \sum_{j=1}^N w_{ij} - 1 \right). \quad (12)$$

Usually, a simple solution method is used, let  $Z_i w_i = 1$ , to find  $w_i$ .

- (3) We set the mean distance of intra-class for the sample points of the emergency management decision-making index data of the  $j$ -type NPOEs  $d_w^j$ , and the rough reconstruction coefficient  $s_i^j$  of the reconstruction error according to the abovementioned NPOE management decision-making index data sample point  $x_i$ :

$$s_i^j = \frac{d_w^j L(W)}{d_b^j \min e(W)}, \quad (13)$$

where  $d_w^j$  represents the distance between the data sample of the emergency management decision-making index data sample of the  $j$ -type NPOE incident and the overall NPOE management decision-making index data sample center.

Through the Lagrange multiplier approach, we create the  $N$ -dimensional unit matrix  $I$  and the diagonal matrix  $W$  to obtain

$$S = (I - W)^T (I - W) s_i^j. \quad (14)$$

- (4) Results of the above calculation are used as low-dimensional coordinates to supplement the dimensionality reduction processing of emergency management decision-making index data for NPOEs.

### 3.6. Emergency Decision-Making Index Weight Calculation.

According to the preprocessing results of the original index data of the aforementioned NPOEs, the emergency decision-making index weights are calculated. The measure of information entropy reflects the degree of disorder of system information. If the measure of information entropy of a certain decision index in the emergency decision-making system of NPOEs is larger, it means that the decision index carries less useful information, indicating that the decision is made. The lower the importance of the index, the less the decision index should be given a smaller weight. The traditional method of determining the weights of emergency decision-making indicators is mainly obtained through methods such as the emergency expert scoring method or fuzzy analytic hierarchy process, and thus subjective human factors have a strong influence. Therefore, to assure the objectivity and logic of the NPOE's final decision-making outcome, this study will determine the objective weight of each emergency evaluation index based on the NPOE's emergency decision-making index's interval value fuzzy information entropy.

After obtaining the standard emergency decision matrix  $R = [X_{ij}]_{nm}$  of NPOEs, then the interval value set of all NPOEs regarding the  $j$ -th emergency decision index can be thought of as an interval value fuzzy set, and it can be determined using the formula as follows. The index's fuzzy information entropy metric, interval value:

$$e(A) = S_j [X_{ij}]_{nm}. \quad (15)$$

Then, using the entropy weight method, we determine the objective weight of the decision-making index according to the interval value fuzzy information entropy measure of the NPOE event's  $j$ -th emergency decision-making index:

$$q_j = \frac{1 - e(A)}{\sum_{j=1}^m (1 - e(A))}. \quad (16)$$

**3.7. Emergency Management Decision Support Model for Internet Public Opinion Emergencies.** Using the reasonable weights of the emergency decision-making indicators obtained by the above calculation, the weighted arithmetic average of all the interval evaluation index values of the NPOEs is carried out to obtain the comprehensive damage interval evaluation value of each NPOE for all the emergency decision-making indicators. Then, we calculate the integrated interval evaluation value of all emergency decision-making indicators for the  $i$ -th NPOE event according to the following formula:

$$S_j = \sum_{j=1}^m q_j [r_{ij}^-, r_{ij}^+]. \quad (17)$$

The formula  $[r_{ij}^-, r_{ij}^+]$  represents the interval evaluation value of the original evaluation value  $X_{ij}$  of the  $i$ -th NPOE in accordance with the  $j$ -th interval index.

The evaluation values of the comprehensive hazard interval of all online public opinion emergency events are compared in pairs, and the corresponding probability is calculated, after the aforementioned calculations have produced the weighted aggregate comprehensive hazard interval evaluation value of all emergency decision-making indicators for each NPOE. We create the corresponding possibility matrix after that

$$P = \sum_{j=1}^m (S_j)_{n \times m}. \quad (18)$$

According to the abovementioned possibility matrix, we construct the emergency management decision support model of NPOEs:

$$U_i = \frac{\sum_{k=1}^n P + n/2}{n(n-1)}. \quad (19)$$

The larger the value  $U_i$ , the higher the seriousness of the severity of the relevant online emergencies. Under the conditions of limited resources and personnel, the local government should first respond to online public opinion emergencies.

## 4. Results

**4.1. Analysis of Simulation Experiment.** To verify the effectiveness of the NPOE management decision support algorithm based on time series in a practical application, an



TABLE 1: Simulation experiment environment.

Name	Parameter
Computer hardware	CPU Intel Duo Core (TM) i5-3230M 2.6 UGHz, memory size 4GB, hard disk size 1TB
Development language	Java (version number: 1.8.0 111)
Development tools	Eclipse (version number: Neon.2 release 4.6.2)
Third-party library	Weka (version number: 3.8.1), Mulan (version number: 1.5.0), IK-Analyzer (version number: 5.0.1)
Operating system	Windows 10 Ultimate Edition
Other tools	UitraF.dit (version number: 24.00.0.72), StarUML (version number: 5.0.2.1570)

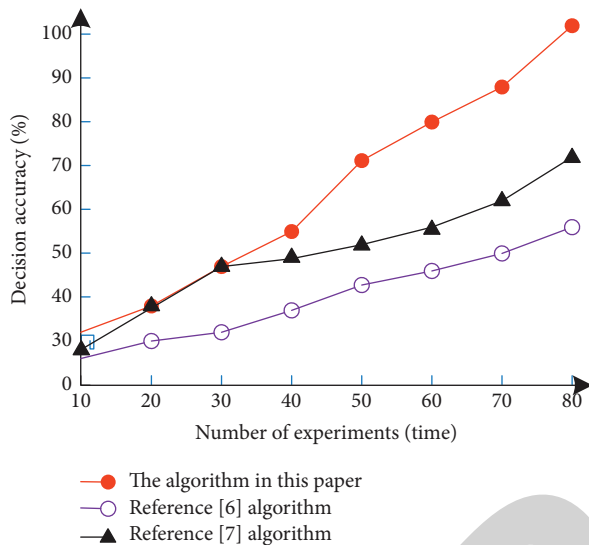


FIGURE 4: Comparison of results of the decision accuracy of the three algorithms.

analysis on simulation experiment is conducted and the results are presented in Table 1.

The NPOE management decision-making approach is based on the hesitant fuzzy set proposed in [9] and the three-branch decision-making method proposed in the literature [15] and uses the time series-based NPOE management decision support algorithm proposed in this paper. Figure 4 displays the comparison result. It compares and analyzes the decision-making accuracy of prospect theory's NPOEs emergency management decision-making algorithm with that of NPOEs emergency management decision-making algorithm.

Figure 4 shows that the NPOE management decision-making accuracy of the network based on the hesitant fuzzy set proposed in [9] and the NPOE management decision support algorithm based on the time series provided in this paper can both reach up to 100%. The accuracy of the NPOE management decision-making algorithm is only between 55 and 70 percent according to the public opinion emergency management decision-making technique and [15] based on the three decision-making and prospect theories. The NPOE management decision support algorithm based on the time series developed in this paper has a greater decision-making accuracy than the method from the literature.

Using the time series-based NPOE management decision support algorithm proposed in this paper, the NPOE management decision-making method is based on the

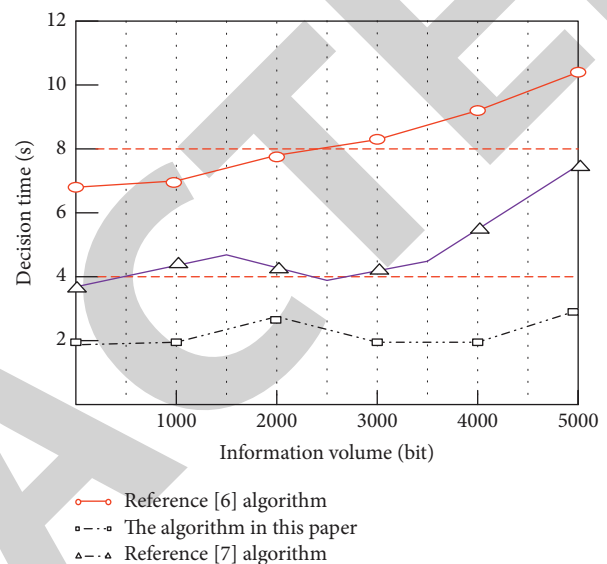


FIGURE 5: Comparison of results of the decision time of the three algorithms.

hesitant fuzzy set proposed in [9] and the three-branch decision-making method proposed in [15]. Compared with the NPOE management decision-making algorithm of prospect theory, the time of the NPOE management decision-making is compared and analyzed (Figure 5).

According to Figure 5, the NPOE management decision-making time based on the time series is within 3 s, which is better than the network public opinion based on the hesitating fuzzy set which was suggested in [9]. The emergency management decision-making method is for emergencies and Egrioglu et al. [15] proposed a short time for the NPOE management decision-making algorithm in accordance with the three decision-making and prospect theories.

## 5. Conclusions and Outlook

Internet public opinion is a double-edged sword. On one hand, it can guide and promote social development and progress. On the other side, it can also impede social advancement and disturb the regular flow of social life. As of June 2018, there were 802 million Chinese Internet users, and 40.9 percent of those users were using the social media platform Weibo, according to CNNIC data. They include the 376 million monthly active users of Sina Weibo, who receive updates every ten minutes. A hot topic has a significant effect on the Internet public opinion hotspot. The massive number



of online users in China has also sped up online public opinion's fermentation, dissemination, and diffusion. Government agencies have elevated the regulation and management of online public opinion above their regular duties. Internet public opinion emergencies are brought on by how Internet public opinion has changed to generate unexpected emergencies in reality. For example, if an emergency occurs in a certain area and the subsequent online public opinion is relatively positive and healthy, then positive guidance will help eliminate public doubts and help resolve public opinion crisis events as soon as possible, while negative loss of control may expand the situation of the event or even trigger a new crisis, causing serious harm to society. Therefore, the government can cope with network public opinion emergencies in a scientifically and logically sound manner with the use of research on the topic of emergency decision-making for NPOEs. Fast response to emergencies is also a core part of the government's emergency capacity building, which is an urgent need at present. The outstanding problems and challenges to be solved have quite critical, theoretical, and practical significance [32].

## Data Availability

No data were used in this study.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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