A distance-based group decision-making methodology for multi-person multi-criteria emergency decision support

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ABSTRACT

In this paper, a distance-based group decision-making (GDM) methodology is proposed to solve unconventional multi-person multi-criteria emergency decision-making problems. In this model, some decision-makers are first identified to formulate a group decision-making framework. Then a standard multi-criteria decision-making (MCDM) process is performed on specific decision-making problems and different decision results are obtained from different decision-makers. Finally, these different decision results are aggregated into a group consensus to support the final decision-making. For illustration and verification purposes, a numerical example and a practical unconventional emergency decision case are presented. Experimental results obtained demonstrate that the proposed distance-based multi-criteria GDM methodology can improve decision-making objectivity and emergency management effectiveness.

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1. Introduction

Unconventional emergency events, such as earthquakes and hurricanes, often lead to unexpected catastrophic consequences [5]. When such devastating incidents occur, emergency planning and management play a crucial role in reduction and mitigation of their effects. In the emergency planning and management, there are a great many emergency decision-making problems that need to be solved, to handle effects of the destructive events. Usually, an emergency decision has the following two distinct features. First, an emergency decision must often be made in a short period of time using partial or incomplete information, especially in the early stages of the disaster occurrence. Accordingly, emergency group decision-making (GDM) is an intractable task, particularly when handling some unconventional high impact emergency events. Second, these decisions may have potentially serious outcomes. In many situations, a wrong decision could result in deadly consequences [13]. In view of the unique characteristics of emergency decisions, using group decision support systems (GDSS) [6,8,9] to handle emergency decision problems could be extremely valuable.

Some previous studies [13,15,27] also revealed that the GDSS has great potential applications in modern emergency planning and management. For example, Levy and Tajj [13] proposed a group analytic network process (GANP) to construct a GDSS to support hazard planning and emergency management under incomplete information. In their study, a typical unconventional emergency event, a chemical spill in the city of Brandon, Manitoba is simulated. With application in evacuation and shelter-in-place decisions, it is shown that the proposed GANP model improves emergency management effectiveness, decision transparency, and user satisfaction [13]. Zografos et al. [27] presented a methodological framework for developing a hazardous material emergency response (HMER) decision support system (DSS) to manage emergency response operations for large-scale industrial accidents in Western Attica, Greece. Similarly, Mendonca et al. [15] designed a gaming simulation to assess GDSS for emergency response in emergency management.

Although these existing studies have shown that GDSS can improve emergency management effectiveness and decision transparency due to the fact that it can integrate group wisdom of multiple decision-makers into one group wisdom, there are two key issues that are apparently not solved well by GDSS. On the one hand, in the process of multi-criteria decision-making (MCDM), determining a set of suitable weights for multiple evaluation criteria is often considered to be a very difficult task. In the existing literature, many researchers usually set some arbitrary weights for each criterion to solve specific decision-making problems in terms of subjective judgments of decision-makers. But such a processing method will add the subjectivity and thus reducing the decision accuracy, sometimes leading to wrong decision results. On the other hand, in the process of using GDM, evolving an effective group consensus out of different judgments from different decision-makers, is still an unsolved issue in the previous studies.

Inspired by the GDSS, this study attempts to propose a distance-based multi-criteria group decision-making (GDM) methodology to support multi-person emergency decision problems. As is known, GDM is one of the most active research fields within MCDM [3].
GDM, group members (i.e., decision-makers) first make their own judgments on the same decision problem independently, i.e. decision actions and alternatives, based on multiple evaluation criteria. These judgments from different decision-makers are then aggregated into a group consensus to support the final decision. Different from previous studies, this study tries to give an effective solution to the two unresolved issues, and to construct a distance-based multi-criteria GDM methodology for multi-person emergency decision support.

Generally, the proposed distance-based multi-criteria GDM methodology is comprised of three stages. In the first stage, some decision-makers (DMs) are first identified to formulate a GDM framework. Then a standard MCDM process is performed on the specific decision-making problems, and accordingly different decision results are obtained from different decision-makers in the second stage. In the third stage, these different decision results are aggregated into a group consensus to support the final decision. The main purpose of this study is to propose a new distance-based multi-criteria GDM model to support unconventional emergency decision-making problems. Using the proposed distance-based GDM model, many practical emergency decision-making problems can be solved effectively. For these real-world problems, decisions are made on the basis of a set of pre-defined criteria. Therefore, the proposed distance-based multi-criteria GDM methodology is suitable for solving these multi-person emergency decision-making problems.

The main contribution of this study is that a new distance-based multi-criteria GDM methodology is proposed to support unconventional emergency decision-making problems. Using the proposed distance-based GDM model, many practical emergency decision-making problems can be solved effectively. For these real-world problems, decisions are made on the basis of a set of pre-defined criteria. Therefore, the proposed distance-based multi-criteria GDM methodology is suitable for solving these multi-person emergency decision-making problems.

2. Formulation of distance-based multi-criteria GDM methodology

In this section, a general framework for multi-criteria GDM methodology is first presented. Then some main procedures or steps involved in the proposed distance-based multi-criteria GDM methodology are described in detail. Finally a summary for distance-based multi-criteria GDM methodology is given.

2.1. General framework for multi-criteria GDM methodology

In this study, a general multi-criteria GDM methodology framework is proposed for complex and multi-faceted decision-making problems. In order to help readers understand multi-criteria GDM problems, a general form of multi-criteria GDM problem is shown in Table 1.

In Table 1, \( C_1, C_2, \ldots, C_m \) denotes a number of evaluation criteria or evaluation attributes, \( (A_1, A_2, \ldots, A_n) \) represents a set of alternatives or actions, \( (D_{M_1}, D_{M_2}, \ldots, D_{M_p}) \) is a group of decision-makers and \( U_i(C_j(A_l))(i=1,2,\ldots,n;j=1,2,\ldots,m;k=1,2,\ldots,p) \) denotes the utility value (evaluation value) of the \( i \)th alternative under the \( j \)th evaluation criterion in terms of the judgment of the \( k \)th decision-maker. The main feature of the multi-criteria GDM framework for solving decision-making problems is to formulate a comprehensive ordering/ranking mechanism for the given alternatives, based on a set of specified evaluation criteria and a group of decision-makers. To realize this, a general framework for multi-person multi-criteria GDM methodology is proposed, as shown in Fig. 1.

As can be seen from Fig. 1, we can find that the proposed multi-criteria GDM methodology consists of three main procedures: identification of group decision-makers, implementation of standard MCDM process for each decision-maker and formulation of group consensus, which are elaborated in the following subsections.

2.2. Identification of group decision-makers in GDM environment

In GDM environment, identification of members of the group decision-makers is an extremely important step as only competent decision-makers can effectively make eligible decisions based on a set of specified evaluation criteria; incompetent decision-makers can lead to some unexpected decision results. Usually, multiple domain experts and important leaders from different fields can form a decision group to solve specified decision-making problems. In particularly, when we try to solve some complex and important decision-making problems, the decisions are often made by a decision group not only because of the problem complexity but also because of wider implications of the decision in terms of responsibility. For example, in the process of solving some unconventional emergency event (e.g., earthquake) decision-making problems, some experts from seismology, geology, meteorology and catastrophology, as well as officers from government departments should be included in the decision group. In order to form an effective decision group, the GDM manager or moderator, in most situations, is required to have abundant knowledge of GDM and have the capability of identifying and selecting some suitable experts in specified areas. In this way, GDM environment can be constructed and GDM consensus can be formed effectively.

2.3. Implementation of standard MCDM process

For a specified decision problem or decision alternative, different decision-makers usually give different estimations or judgments over a set of evaluation criteria \( C = (C_1, C_2, \ldots, C_m) \). That is, a standard MCDM process is implemented for a specified decision alternative and a set of evaluation criteria after a suitable decision group is formed.

MCDM is a well-known branch of a general class of operations research (OR) models, which deal with a set of decision alternatives in terms of a number of evaluation criteria. In existing studies, there are a
great number of multi-criteria models and approaches [20]. However, the standard MCDM process can be summarized in the following four main steps.

(1) **Criteria selection.** For any given decision-making problem, a number of suitable evaluation criteria should be first determined. Very often different decision problems have different evaluation criteria. However, a MCDM process must have a number of evaluation criteria beforehand. If there are too many criteria for a decision-making problem, it is necessary to extract a subset of criteria from out of a vast number of criteria.

(2) **Alternative formulation.** In the process of MCDM, some feasible decision alternatives should be formulated so that a suitable number of decision alternatives can be used for evaluation, in terms of a set of decision criteria. Meantime, different utility values or evaluation scores (evaluation values) are assigned to each alternative in terms of different criteria.

(3) **Criteria weight determination.** In MCDM process, determination of the importance of various criteria is a critical step in formulation of the MCDM. In existing literature, there are many methods to determine criteria weights in the MCDM process. Typical approaches for criteria weight determination include expert method, Delphi method, AHP method, variation coefficient method and entropy-based method [18, 19]. In these approaches, the first three methods involve the subjective influence of the decision-maker, while the latter two are ascertained without direct participation of the decision-maker. The main advantage of the latter two methods over the former three methods is that they remove the subjectivity of the decision-maker in determining criteria weights, and are very useful in cases where decision-makers disagree on values of weights. Therefore, the latter two approaches are often considered as objective methods, which are more reliable than the former three subjective methods. Therefore, this paper applies the latter two objective methods to determine weights of criteria for comparison purpose. Meantime, another objective distance-based method is also proposed for criteria weight determination.

Usually, objective methods are based on the consideration that importance of a criterion is a direct function of the information conveyed by it, relative to a whole set of alternatives. In terms of the foregoing consideration, it concludes that a criterion is more important, if there is a greater dispersion in evaluations of alternatives [19]. This conclusion will be used as a generic rule to determine objective criteria weights in the subsequent task. Suppose there is a standard MCDM problem, and the matrix \( U(C_j(A_i)) \) \( (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m) \) is used for the evaluation process, where \( U(C_j(A_i)) \) denotes utility values or evaluation scores (evaluation values) of alternative \( A_i(i = 1, 2, \ldots, n) \), based on criterion \( C_j(j = 1, 2, \ldots, m) \), and \( n \) and \( m \) are the maximum numbers of criteria and alternatives, respectively.
2.3.1. Variation coefficient method for criteria weight determination

For the variation coefficient method [18], the working process for criteria weight determination is shown as follows:

(a) Normalization of evaluation value. For every criterion \( j (j = 1, 2, \cdots, m) \), all evaluation values are divided by \( \sum_{i=1}^{n} U(\mathcal{C}_j(A_i)) \), i.e.

\[
U'(\mathcal{C}_j(A_i)) = \frac{U(\mathcal{C}_j(A_i))}{\sum_{i=1}^{n} U(\mathcal{C}_j(A_i))}.
\]

In this way, all evaluation values are normalized into the interval \([0, 1]\). The main purpose of normalization is to remove the effect of magnitude of data.

(b) Mean computation of the normalized evaluation value. For the \( j \)-th evaluation criterion, the average evaluation value (i.e., mean value) can be calculated by

\[
\overline{U}(\mathcal{C}_j) = \frac{1}{n} \sum_{i=1}^{n} U'(\mathcal{C}_j(A_i)).
\]

(c) Standard deviation computation of the normalized evaluation value. Using the mean value and evaluation values, the value of standard deviation is computed by the following equation:

\[
\sigma(\overline{U}(\mathcal{C}_j)) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( U'(\mathcal{C}_j(A_i)) - \overline{U}(\mathcal{C}_j) \right)^2}.
\]

(d) Variation coefficient computation for dispersion measurement. Using the mean value and standard deviation, the variation coefficient of the \( j \)-th criterion for dispersion measurement can be expressed by

\[
\delta_j = \frac{\sigma(\overline{U}(\mathcal{C}_j))}{\overline{U}(\mathcal{C}_j)}.
\]

In this dispersion measurement, the larger the variation coefficient, the higher is the dispersion degree, which is consistent with the previous generic rule.

(e) Determination of criteria weights. For each criterion \( \mathcal{C}_j \), the weight can be determined by the following form

\[
w_j = \frac{\delta_j}{\sum_{j=1}^{n} \delta_j}.
\]

2.3.2. Entropy-based method for criteria weight determination

For the entropy-based method [19], the process of criteria weight determination consists of the following four steps:

(a) Normalization of evaluation values. Similar to the variation coefficient method, the entropy method uses the same normalization method. Accordingly, the normalized evaluation values \( U'(\mathcal{C}_j(A_i)) \) can be obtained from Eq. (1).

(b) Entropy computation for the \( j \)-th evaluation criterion. For each criterion \( \mathcal{C}_j \), the entropy value can be represented as

\[
\mathcal{E}_j = -k \sum_{i=1}^{n} U'(\mathcal{C}_j(A_i)) \log \left( U'(\mathcal{C}_j(A_i)) \right)
\]

where \( k \) is a constant and is determined through relation \( k = 1/\log(m) \) [19] and \( m \) is the number of criteria.

(c) Dispersion measurement for each criterion \( \mathcal{C}_j \). In the entropy method, the measure of dispersion for the \( j \)-th evaluation criterion [19] is expressed as

\[
\mathcal{E}_j = 1 - \mathcal{E}_j
\]

(d) Determination of criteria weights. For each criterion \( \mathcal{C}_j \), the weight can be determined by

\[
w_j = \frac{\mathcal{E}_j}{\sum_{j=1}^{n} \mathcal{E}_j}.
\]

2.3.3. Distance-based method for criteria weight determination

Motivated by the previous two objective methods, a distance-based objective weight determination method is proposed in terms of optimistic and pessimistic utility values. The distance-based method works as follows:

(a) Normalization of evaluation values. Similar to the variation coefficient method and entropy-based method, the distance-based method applies the same normalization method to normalize initial evaluation values. Accordingly, the normalized evaluation values \( U'(\mathcal{C}_j(A_i)) \) can be obtained from Eq. (1).

(b) Determination of optimistic and pessimistic evaluation values for the \( j \)-th evaluation criterion. For each criterion \( \mathcal{C}_j \), optimistic and pessimistic values are defined as

Optimistic values : \( U^+ = \left( U_1^+, U_2^+, \cdots, U_m^+ \right) \)

Pessimistic values : \( U^- = \left( U_1^-, U_2^-, \cdots, U_m^- \right) \)

where

\[
U_j^+ = \left\{ \begin{array}{ll}
\max & \left( U'(\mathcal{C}_j(A_i)) \right), j \in J_1, \\
\min & \left( U'(\mathcal{C}_j(A_i)) \right), j \in J_2.
\end{array} \right.
\]

\[
U_j^- = \left\{ \begin{array}{ll}
\min & \left( U'(\mathcal{C}_j(A_i)) \right), j \in J_1, \\
\max & \left( U'(\mathcal{C}_j(A_i)) \right), j \in J_2.
\end{array} \right.
\]

where \( J_1 \) represents the positive criteria (e.g., profit) and \( J_2 \) is the negative criteria (e.g., cost).

(c) Distance computation between criteria values and optimistic/pessimistic values. Using optimistic and pessimistic values, the distance between utility values of the \( j \)-th \((j = 1, 2, \cdots, m)\) criteria and optimistic/pessimistic values of the criteria can be calculated by

\[
d_j^+ = \sqrt{\sum_{i=1}^{n} \left( U'(\mathcal{C}_j(A_i)) - U_j^+ \right)^2},
\]

\[
d_j^- = \sqrt{\sum_{i=1}^{n} \left( U'(\mathcal{C}_j(A_i)) - U_j^- \right)^2}.
\]

(d) Dispersion measurement for each criterion \( \mathcal{C}_j \). In the distance-based method, the measure of dispersion for the \( j \)-th criterion is expressed as

\[
\gamma_j = \frac{d_j^+}{d_j^+ + d_j^-}.
\]
According to Eq. (13), the larger the value of \( \xi_k \), the larger is the dispersion measure and accordingly the more important is the \( j \)th criterion, which is also consistent with the generic rule of criteria weight determination.

(e) Determination of criteria weights. For each criterion \( C_j \), the weight can be determined based on the dispersion measurement, as shown in the following equation:

\[
\omega_j = \frac{\xi_j}{\sum_{j=1}^{p} \xi_j} \tag{16}
\]

Using criteria weights and utility values of every alternative, the alternative evaluation can be easily conducted in the next step.

(4) Alternative evaluation. After determining the criteria weights, the decision score of the \( i \)th alternative evaluation can be computed in the following additive form:

\[
z_i = \sum_{j=1}^{p} \omega_j \cdot U(C_j(A_i)), i = 1, \ldots, n. \tag{17}
\]

Using the aforementioned four steps, a standard MCDM process can be easily performed.

2.4. Formulation of group consensus

In the multi-person multi-criteria GDM framework, every decision-maker can perform the standard MCDM process for a specified decision problem and obtain a decision result based on his/her own evaluations. A subsequent task is to aggregate different decision results to an integrated group consensus. Suppose that there are \( p \) decision-makers (DMs), the \( p \) DMs produce \( p \) different decision results, i.e.

\[Z_k = z_{ki} = (z_{k1}, z_{k2}, \ldots, z_{kn}), k = 1, \ldots, p.\]  

In order to fuse the different decision results, let \( Z = \psi(Z_1, Z_2, \ldots, Z_p) \) be the aggregation of the \( p \) decision results, where \( \psi(\cdot) \) is an aggregation function. Now how to determine the aggregation function or how to aggregate these different decision results into a group consensus is an important and critical problem under the multi-person multi-criteria GDM environment. Generally speaking, there are many aggregation techniques and rules that can be used to aggregate different decision results. Some of them are linear, while others are non-linear. Interested readers may kindly refer to Alfaris and Duffuaa [1], Yager [24,25], Belgeno et al. [7], Cabreroiz et al. [4] Lee [12], Xu [21,22], Zhang and Lu [26], and Xu [23] for more details. Usually, decision results of the group members will be aggregated by using a commonly used linear additive procedure, i.e.

\[
Z = \sum_{k=1}^{p} \omega_{k} Z_k = \left( \sum_{k=1}^{p} \omega_{k}^{DM} z_{1k}, \sum_{k=1}^{p} \omega_{k}^{DM} z_{2k}, \ldots, \sum_{k=1}^{p} \omega_{k}^{DM} z_{nk} \right) \tag{19}
\]

where \( \omega_{k}^{DM} \) is the weight of the \( k \)th decision-maker, \( k = 1, 2, \ldots, p \). The weights usually satisfy the following normalization condition:

\[
\sum_{k=1}^{p} \omega_{k}^{DM} = 1 \tag{20}
\]

Now our problem is how to determine the optimal weight \( \omega_{k}^{DM} \) of the \( k \)th decision-maker under the multi-person multi-criteria GDM environment. Often, different decision results from different DMs are largely dispersed and separated. In order to achieve the maximum similarity, decision results should move towards one another. This is the principle on the basis of which an aggregated decision result is generated. Based upon this principle, a distance-based least-square aggregation optimization approach is proposed to integrate different decision results produced by different DMs.

The generic idea of this proposed distance-based aggregation optimization approach is to minimize the sum of the squared distance from one decision result to another and thus make them achieve maximum agreement. Specifically, the squared distance between \( Z_k \) and \( Z_l \) can be defined as

\[
d_{kl}^2 = \left( \sqrt{(w_{k}^{DM} z_{ki} - w_{l}^{DM} z_{li})^2} \right)^2 = \sum_{i=1}^{n} \left( w_{k}^{DM} z_{ki} - w_{l}^{DM} z_{li} \right)^2 \tag{21}
\]

where \( k, l \) represent the \( k \)th and \( l \)th decision-makers, i.e. \( k = 1, 2, \ldots, p, l = 1, 2, \ldots, p \) and \( i \) denotes the \( i \)th alternative, \( i = 1, 2, \ldots, n \).

Using this squared distance, we can construct the following optimization model, which minimizes the sum of the squared distances between all pairs of decision results with weights:

\[
\text{Min } D = \sum_{k=1}^{p} \sum_{i=1, i \neq k}^{p} d_{kl}^2 = \sum_{k=1}^{p} \left( \sum_{i=1, i \neq k}^{p} \sum_{l=1, l \neq k}^{p} \left( w_{k}^{DM} z_{ki} - w_{l}^{DM} z_{li} \right)^2 \right) \tag{22}
\]

Subject to \( \sum_{k=1}^{p} w_{k}^{DM} = 1 \) \tag{23}

\[
w_{k}^{DM} \geq 0, \ k = 1, 2, \ldots, p \tag{24}
\]

In order to obtain the aforementioned optimal weights of the decision-makers, constraint (Eq. (24)) is not considered, for convenience of computation. If the solution turns out to be non-negative, then constraint (Eq. (24)) is satisfied automatically. Using the Lagrange multiplier theorem, Eqs. (22) and (23) in the foregoing optimization problem are combined to be the following Lagrangian function:

\[
L(w^{DM}, \lambda) = \sum_{k=1}^{p} \sum_{i=1, i \neq k}^{p} \left[ \sum_{i=1}^{n} \left( w_{k}^{DM} z_{ki} - w_{l}^{DM} z_{li} \right)^2 \right] - 2\lambda \left( \sum_{k=1}^{p} w_{k}^{DM} - 1 \right) \tag{25}
\]

Differentiating Eq. (25) with \( w_{k}^{DM} \), we can obtain

\[
\frac{\partial L}{\partial w_{k}^{DM}} = 2 \sum_{i=1, i \neq k}^{p} \sum_{l=1, l \neq k}^{p} \left( w_{k}^{DM} z_{ki} - w_{l}^{DM} z_{li} \right) - 2\lambda = 0 \tag{26}
\]

for each \( k = 1, 2, \ldots, p \).

Eq. (26) can be simplified as

\[
(p-1) \left( \sum_{i=1}^{n} z_{ki}^2 \right) w_{k}^{DM} - \sum_{l=1, l \neq k}^{p} \left( \sum_{i=1}^{n} z_{ki} z_{li} \right) w_{l}^{DM} - \lambda = 0 \tag{27}
\]

for each \( k = 1, 2, \ldots, p \).

In Eq. (27), for convenience of representation, let \( b_{kl} = (p-1) \left( \sum_{i=1}^{n} z_{ki}^2 \right), (k = 1, 2, \ldots, p, b_{kl} = -\sum_{l=1}^{n} z_{ki} z_{li}, (k \neq l), k = 1, 2, \ldots, p, l = 1, 2, \ldots, p, \) then we have

\[
B = [b_{kl}]_{p \times p} = \begin{bmatrix}
(p-1) \left( \sum_{i=1}^{n} z_{ki}^2 \right) & \cdots & -\sum_{l=1}^{n} z_{ki} z_{pl} \\
-\sum_{l=1}^{n} z_{ki} z_{pl} & \cdots & \sum_{i=1}^{n} z_{ki}^2 \\
\cdots & \cdots & \cdots
\end{bmatrix} \tag{28}
\]
3.1. An illustrative numerical example

In order to illustrate the implementation process of the proposed distance-based multi-criteria GDM model, a simple numerical example is given. Suppose there are three evaluation criteria and five alternatives for a specified decision problem, three decision-makers give different utility values to different decision alternatives in terms of different evaluation criteria. Table 2 shows the different utility values for three evaluation criteria and five decision alternatives. Note that in the three criteria, $C_1$ and $C_3$ are positive criteria, while $C_2$ is a negative criterion.

According to the steps described in Section 2, the individual decision-maker can evaluate decision alternatives in terms of the criteria when the criteria weights are determined. In the process of criteria weight determination, three objective approaches are introduced. For comparison purpose, three criteria weight determination methods are performed. Table 3 presents the criteria weights using different approaches of different decision-makers.

Using the aforementioned criteria weights, it is not hard to obtain alternative evaluation results in terms of Eq. (19) for a certain decision-maker. In this example, we can easily obtain the following five alternative evaluation results for different decision-makers and different criteria weight determination methods, as given in Table 4.

As can be seen from Table 4, different decision-makers can obtain different evaluation results for specific alternatives when a certain criteria weight determination method is fixed. However, even for the same decision-makers, evaluation results are different when different criteria weight determination methods are used. Thus in the decision fusion stage there are two aggregations at different levels. On the one hand, aggregation of decision of different decision-makers is often used to capture from the decision-makers’ perspectives. Since every decision maker has different knowledge and expectations, different decision results are obtained from them. Naturally, aggregation of the decision of different decision-makers is, therefore, often used. On the other hand, for the same decision-makers, if they applied different method to obtain different decision results, aggregation of these different decision results obtained from different methods should be conducted to avoid confusion in decision-making. By changing the presentation form of Table 4, it is easy to obtain such a decision fusion scenario, as shown in Table 5.

In order to avoid ambiguous situations during the group decision-making process, methodology fusion is first performed. That is, each decision-maker must obtain a consistent decision result before group consensus is arrived. Based on the data of Table 5, aggregation of different decision results from the perspective of different criteria weight determination methodologies is conducted. Similarly, the key issue is how to determine method weights in the process of aggregation. Using the distance-based maximum similarity principle described in Section 2.4, weights for different methods are determined in terms of Eq. (32). Accordingly, aggregation of different methods is shown in Table 6.

As can be seen from Table 6, we can find that three different evaluation results from three different criteria weight determination methods for a certain decision-maker are aggregated into an integrated decision result. The subsequent task is to fuse three evaluation results obtained from three different decision-makers to obtain the final
A methodology is applied to the Brandon Emergency Support Team and Taji. That is, the proposed distance-based multi-criteria GDM is presented. For comparison purpose, all data are obtained from Levy model, a practical chemical spill emergency decision example is used. In order to verify effectiveness of the proposed multi-criteria GDM model, a practical chemical spill emergency decision example is presented. For comparison purpose, all data are obtained from Levy and Taji. That is, the proposed distance-based multi-criteria GDM methodology is applied to the Brandon Emergency Support Team. 

### Table 3
Criteria weights determined by three different approaches.

<table>
<thead>
<tr>
<th>DM</th>
<th>Criterion</th>
<th>Variation coefficient method</th>
<th>Entropy-based method</th>
<th>Distance-based method</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>$\phi_i$ $w_f$</td>
<td>$\phi_i$ $w_f$</td>
<td>$\phi_i$ $w_f$</td>
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<td>0.4651 0.4222</td>
<td>0.0476 0.4712</td>
<td>0.2627 0.2014</td>
</tr>
<tr>
<td></td>
<td>$C_3$</td>
<td>0.2533 0.2299</td>
<td>0.0160 0.1586</td>
<td>0.5182 0.3973</td>
</tr>
</tbody>
</table>

### Table 4
Decision scores of standard MCDM process from decision-makers’ perspective.

<table>
<thead>
<tr>
<th>Criteria weight method</th>
<th>DM</th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$A_3$</th>
<th>$A_4$</th>
<th>$A_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variation coefficient method</td>
<td>$DM_1$</td>
<td>0.3109</td>
<td>0.3246</td>
<td>0.3206</td>
<td>0.3573</td>
<td>0.3137</td>
</tr>
<tr>
<td></td>
<td>$DM_2$</td>
<td>0.2926</td>
<td>0.2972</td>
<td>0.3011</td>
<td>0.3403</td>
<td>0.3097</td>
</tr>
<tr>
<td></td>
<td>$DM_3$</td>
<td>0.2938</td>
<td>0.2937</td>
<td>0.3417</td>
<td>0.3097</td>
<td>0.3164</td>
</tr>
<tr>
<td>Entropy-based method</td>
<td>$DM_1$</td>
<td>0.2902</td>
<td>0.3170</td>
<td>0.3088</td>
<td>0.3773</td>
<td>0.2954</td>
</tr>
<tr>
<td></td>
<td>$DM_2$</td>
<td>0.2685</td>
<td>0.2707</td>
<td>0.2854</td>
<td>0.3509</td>
<td>0.3023</td>
</tr>
<tr>
<td></td>
<td>$DM_3$</td>
<td>0.2653</td>
<td>0.2678</td>
<td>0.3448</td>
<td>0.2952</td>
<td>0.3080</td>
</tr>
<tr>
<td>Distance-based method</td>
<td>$DM_1$</td>
<td>0.3165</td>
<td>0.3301</td>
<td>0.3235</td>
<td>0.3369</td>
<td>0.3167</td>
</tr>
<tr>
<td></td>
<td>$DM_2$</td>
<td>0.3379</td>
<td>0.3455</td>
<td>0.3319</td>
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<td>0.3259</td>
</tr>
<tr>
<td></td>
<td>$DM_3$</td>
<td>0.3509</td>
<td>0.3671</td>
<td>0.3120</td>
<td>0.3595</td>
<td>0.3638</td>
</tr>
</tbody>
</table>

### Table 5
Decision scores of standard MCDM process from the methodology perspective.

<table>
<thead>
<tr>
<th>Decision-maker</th>
<th>Criteria weight method</th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$A_3$</th>
<th>$A_4$</th>
<th>$A_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$DM_1$</td>
<td>Variation coefficient method</td>
<td>0.3109</td>
<td>0.3246</td>
<td>0.3206</td>
<td>0.3573</td>
<td>0.3137</td>
</tr>
<tr>
<td></td>
<td>Entropy-based method</td>
<td>0.2902</td>
<td>0.3170</td>
<td>0.3088</td>
<td>0.3773</td>
<td>0.2954</td>
</tr>
<tr>
<td>$DM_2$</td>
<td>Variation coefficient method</td>
<td>0.2926</td>
<td>0.2972</td>
<td>0.3011</td>
<td>0.3403</td>
<td>0.3097</td>
</tr>
<tr>
<td></td>
<td>Entropy-based method</td>
<td>0.2685</td>
<td>0.2707</td>
<td>0.2854</td>
<td>0.3509</td>
<td>0.3023</td>
</tr>
<tr>
<td>$DM_3$</td>
<td>Variation coefficient method</td>
<td>0.2938</td>
<td>0.2937</td>
<td>0.3417</td>
<td>0.3097</td>
<td>0.3164</td>
</tr>
<tr>
<td></td>
<td>Entropy-based method</td>
<td>0.2653</td>
<td>0.2678</td>
<td>0.3448</td>
<td>0.2952</td>
<td>0.3080</td>
</tr>
</tbody>
</table>

### Table 6
Aggregation of different evaluation results based on different methods.

<table>
<thead>
<tr>
<th>Decision-maker</th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$A_3$</th>
<th>$A_4$</th>
<th>$A_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$DM_1$</td>
<td>0.3058</td>
<td>0.3239</td>
<td>0.3176</td>
<td>0.3573</td>
<td>0.3083</td>
</tr>
<tr>
<td>$DM_2$</td>
<td>0.2983</td>
<td>0.3030</td>
<td>0.3052</td>
<td>0.3385</td>
<td>0.3122</td>
</tr>
<tr>
<td>$DM_3$</td>
<td>0.3009</td>
<td>0.3066</td>
<td>0.3338</td>
<td>0.3196</td>
<td>0.3277</td>
</tr>
</tbody>
</table>

### Table 7
Final decision results by aggregation of different decision-makers’ evaluation results.

<table>
<thead>
<tr>
<th>Final decision</th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$A_3$</th>
<th>$A_4$</th>
<th>$A_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregated results</td>
<td>0.3016</td>
<td>0.3110</td>
<td>0.3188</td>
<td>0.3384</td>
<td>0.3161</td>
</tr>
<tr>
<td>Rank</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

3.2. A practical emergency decision simulation for chemical spill emergency management

In order to verify effectiveness of the proposed multi-criteria GDM model, a practical chemical spill emergency decision example is presented. For comparison purpose, all data are obtained from Levy and Taji. That is, the proposed distance-based multi-criteria GDM methodology is applied to the Brandon Emergency Support Team (BEST) “Community Contact” Emergency Exercise, which was held on Wednesday, June 21, 2006 in Brandon, Manitoba. In this example, four key decision-makers were first identified, including Brandon Police Service ($DM_1$), Brandon Fire Division ($DM_2$), Western Manitoba Hazardous Materials Technical Team ($DM_3$), and Brandon School Division ($DM_4$) to formulate a GDM framework. Mathematically, these four decision-makers $DM_k (k = 1, …, 4)$ are required to evaluate six emergency response alternatives $A_j (j = 1, …, 6)$ under the three criteria $C_i (i = 1, 2, 3)$, where $C_1$ represents physiological discomfort, $C_2$ represents emergency cost, and $C_3$ represents the safety criterion (in terms of expected number of lives saved). During the release of hazardous airborne material, the “shelter-in-place alternative” ($A_1$) is the practice of staying inside (or going indoors as quickly as possible) and moving to an area of maximum safety. Time permitting, it is recommended to shut and lock all windows and doors (locking a door may improve the seal against chemicals). On the other hand, “evacuation” involves transporting the victims to a nearby destination ($A_2$) or the more distant Brandon Keystone Center ($A_3$). $A_1$, followed by $A_2$, gives rise to the fourth alternative of sheltering in place followed by
evacuation to a nearby location (A4). Similarly, A1 followed by A3 produces the fifth alternative of sheltering-in-place followed by evacuation to the Keystone Center (A5). Finally, alternative A6 is "do-nothing" [13]. Accordingly, evaluation results of each decision-maker are provided in Table 8 in terms of different criteria. Note that Table 8 illustrates the utility scores provided by the four emergency decision-makers for the six alternatives. DM₁ evaluates alternatives A₂ and A₃ (only) for all three criteria, while DM₂ evaluates all the alternatives under all the criteria. For all criteria, DM₂ evaluates half of the alternatives (A₁, A₂ and A₃), while DM₄ evaluates every alternative (for all criteria) except alternatives A₁ and A₆. In addition, C₁ and C₂ are negative criteria and C₃ is the positive criterion.

Using the proposed procedure presented in Section 2.4 and the standard MCDM process, we can easily obtain decision results based on the distance-based multi-criteria GDM methodology and distance-based MCDM method, as shown in Table 9. Note that the second column in Table 9 is the group consensus, and others are decision results of four individual DMs.

Two interesting results can be found by comparing results in Table 9 with Table 3 in Levy and Taji (Table 10 in this paper, for direct comparison) [13]. On the one hand, decision results of the distance-based MCDM method for DM₁ and DM₃ are basically consistent with results of Levy and Taji [13], though numerical values of evaluation results are different. This implies that the distance-based MCDM method is an alternative solution to the multi-criteria decision-making problem. On the other hand, group decision results from the proposed distance-based multi-criteria GDM method and the Group Analytic Network Process (GANP) approach presented in the paper of Levy and Taji [13] are different. The main reason is that different criteria weight determination methods and different decision-makers weight determination approaches are used in the two different methodologies. However, the decision results of the proposed distance-based multi-criteria GDM methodology are more suitable for practical situations than the GANP approach presented in Levy and Taji [13] because the proposed distance-based multi-criteria GDM methodology can provide more suitable alternatives than the GANP approach.
In this paper, a distance-based multi-criteria GDM methodology is proposed for multi-person emergency decision support. In terms of experimental results, it is easy to find that across different models and three different evaluation criteria, for the test cases of numerical and practical examples, the proposed distance-based multi-criteria GDM methodology can effectively solve the multi-person multi-criteria decision-making (MCDM) problems. In the presented practical cases, decision results of the proposed distance-based multi-criteria GDM methodology can provide the most suitable decision results, indicating that the proposed distance-based multi-criteria GDM methodology can be used as a promising tool for multi-person multi-criteria emergency decision-making problems. This implies that the proposed distance-based multi-criteria GDM methodology has great potential for application to other MCDM problems.

4. Concluding remarks

In this paper, a distance-based multi-criteria GDM methodology is proposed for multi-person emergency decision support. In terms of experimental results, it is easy to find that across different models and three different evaluation criteria, for the test cases of numerical and practical examples, the proposed distance-based multi-criteria GDM methodology can effectively solve the multi-person multi-criteria decision-making (MCDM) problems. In the presented practical cases, decision results of the proposed distance-based multi-criteria GDM methodology can provide the most suitable decision results, indicating that the proposed distance-based multi-criteria GDM methodology can be used as a promising tool for multi-person multi-criteria emergency decision-making problems. This implies that the proposed distance-based multi-criteria GDM methodology has great potential for application to other MCDM problems.

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