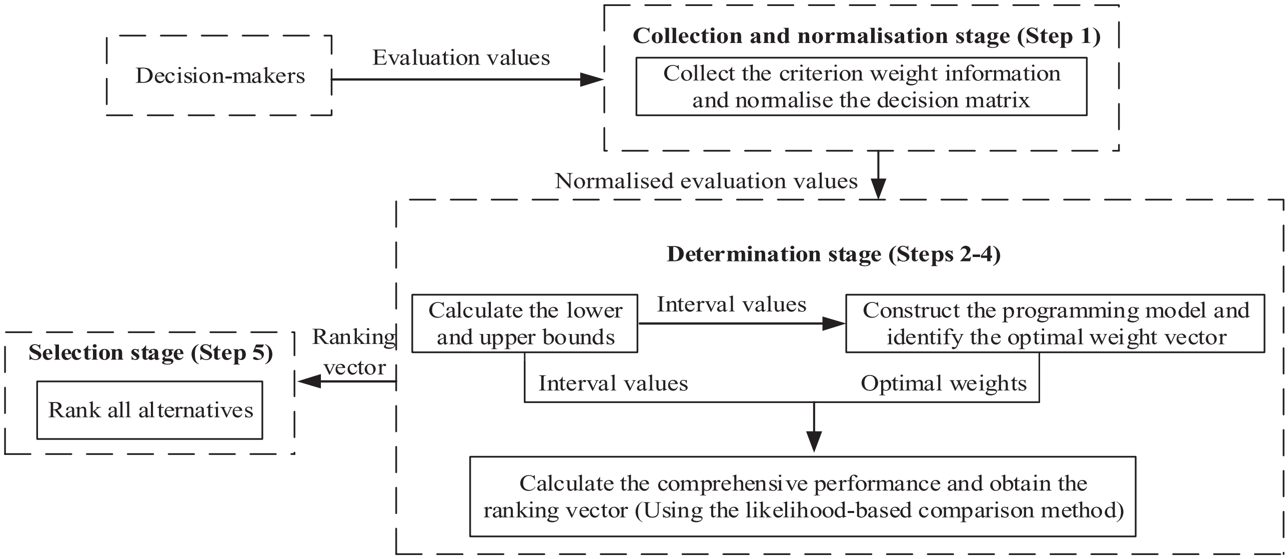

Figure 1. A flow chart of the proposed approach.

Step 1: Normalise the decision matrix.

Use Equation (3) to transform $\tilde{B}$ into $\tilde{R}$. For convenience, the normalised values of $a_i (i = 1, 2, \ldots, m)$ with respect to $c_j (j = 1, 2, \ldots, n)$ are also expressed as $([t_{ij}^L, t_{ij}^U], [i_{ij}^L, i_{ij}^U], [f_{ij}^L, f_{ij}^U])$.

Step 2: Calculate the lower and upper bounds of $\tilde{D}_{ij}$.

Use Equations (8) and (9) to derive the lower bound D_{ij}^L and the upper bound D_{ij}^U, respectively.

Step 3: Identify the optimal weight vector and calculate the preference of each alternative.

Solve Model (M1) or (M2) to identify the optimal weight vector, and calculate the comprehensive performance $\tilde{D}_i (i = 1, 2, \ldots, m)$ by using the operational laws of the interval values in Definition 1.

Step 4: Construct the likelihood matrix and obtain the ranking vector.

Construct the likelihood matrix P by using Equation (11) and obtain the ranking vector $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$ based on Equation (12).

Step 5: Determine the ranking of all alternatives.

Determine the ranking of all alternatives according to the descending order of $\omega_i = (1, 2, \ldots, m)$ and select the optimal one(s).

5. An illustrative example

In this section, the example of an investment appraisal project is used to demonstrate the application of the proposed MCDM approach; then its validity and effectiveness will be tested through a comparative analysis.

The following case is adapted from Wang et al. (2015).

ABC Nonferrous Metals Co. Ltd. is a large state-owned company whose main business is the deep processing of non-ferrous metals. It is also the largest manufacturer of multi-species non-ferrous metals, with the exception of aluminium, in China. To expand its main business, the company regularly engages in overseas investment and a department consisting of executive managers and several experts in the field has been established to make decisions regarding global mineral investment. This overseas investment department recently decided to select a pool of alternatives from several foreign countries based on preliminary surveys. After a thorough investigation, five countries were taken into consideration, denoted by $\{a_1, a_2, \cdots, a_5\}$. There are many factors that affect the investment environment, but four were chosen based on the experience of the department's personnel, namely c_1: resources; c_2 : politics and policy; c_3 : economy; and c_4 : infrastructure.

The members of the overseas investment department have met to determine the evaluation information. Consequently, following a heated discussion, they came to a consensus on the final evaluations which were expressed by INNs shown in Table 1 Moreover, they were only able to provide incomplete information on the weights, that is, $\Gamma = \{0.15 \le w_1 \le 0.3,\ 0.15 \le w_2 \le 0.25,\ 0.25 \le w_3 \le 0.4,\ 0.3 \le w_4 \le 0.45,\ 2.5w_1 \le w_3\}$.

5.1. Illustration of the proposed approach

In the following steps, the main procedures of obtaining the optimal ranking of alternatives are presented.

Step 1: Normalise the decision matrix.

As all the criteria are maximising type, the matrix does not need to be normalised, i.e., $\tilde{R} = \tilde{B}$.

Step 2: Calculate the lower and upper bounds of $\tilde{D}_{ij}$.

Derive the lower bound D_{ij}^L and the upper bound D_{ij}^U by using Equations (8) and,(9), respectively:

$$\left(\tilde{D}_{ij}\right)_{5\times 4} = \begin{bmatrix} [0.5525, 0.7141] & [0.5363, 0.6410] & [0.6130, 0.7571] & [0.6726, 0.7613] \\ [0.4966, 0.7571] & [0.4964, 0.7853] & [0.5363, 0.6429] & [0.5297, 0.6962] \\ [0.5610, 0.7528] & [0.4462, 0.6148] & [0.5525, 0.6753] & [0.4568, 0.5965] \\ [0.3580, 0.4433] & [0.4433, 0.5825] & [0.4350, 0.5525] & [0.6962, 0.8171] \\ [0.4406, 0.5637] & [0.6962, 0.8171] & [0.5873, 0.7141] & [0.4964, 0.6272] \end{bmatrix}.$$

Table 1. The evaluation information.

	c_1	c_2	c_3	c_4
a_1	([0.7,0.8],[0.5,0.7],[0.1,0.2])	([0.6,0.8],[0.4,0.5],[0.3,0.3])	([0.8,0.8],[0.4,0.6],[0.1,0.2])	([0.7,0.9],[0.3,0.4], [0.2,0.2])
a_2	([0.6,0.8],[0.4,0.6],[0.1,0.3])	([0.5,0.7],[0.3,0.5],[0.1,0.3])	([0.6,0.6],[0.2,0.3],[0.4,0.5])	([0.6,0.8],[0.4,0.4], [0.2,0.4])
a_3	([0.4,0.6],[0.2,0.2],[0.2,0.4])	([0.6,0.7],[0.4,0.6],[0.3,0.4])	([0.7,0.8],[0.6,0.7],[0.1,0.2])	([0.5,0.6],[0.5,0.6], [0.2,0.3])
a_4	([0.4,0.5],[0.5,0.6],[0.4,0.4])	([0.5,0.6],[0.3,0.4],[0.4,0.5])	([0.6,0.7],[0.7,0.8],[0.2,0.3])	([0.8,0.9],[0.3,0.4], [0.1,0.2])
a_5	([0.6,0.7],[0.4,0.5],[0.4,0.5])	([0.8,0.9],[0.3,0.4],[0.1,0.2])	([0.7,0.8],[0.5,0.6],[0.1,0.2])	([0.5,0.7],[0.5,0.5], [0.2,0.3])

Step 3: Identify the optimal weight vector and calculate the preference of each alternative.

Because no inconsistent weight information exists in the evaluation, Model (M1) can be applied to identify the optimal weight vector:

$$\max D = 2.8198w_1 + 3.0295w_2 + 3.033w_3 + 3.175w_4$$
$$\text{s.t.}\begin{cases} 0.15 \le w_1 \le 0.3 \\ 0.15 \le w_2 \le 0.24 \\ 0.25 \le w_3 \le 0.4 \\ 0.3 \le w_4 \le 0.45 \\ 2.5w_1 \le w_3 \\ \sum_{j=1}^{4} w_j = 1 \end{cases}$$

The optimal weight vector can be obtained as $w = (0.15, 0.15, 0.375, 0.325)$. Then, $\tilde{D}_i\ (i = 1, 2, \cdots, 5)$ can be calculated by referring to the operational laws of interval values in Definition 1:

$$\tilde{D}_1 = [0.6118, 0.7346],\ \tilde{D}_2 = [0.5222, 0.6987],$$
$$\tilde{D}_3 = [0.5067, 0.6522],$$

$$\tilde{D}_4 = [0.5096, 0.6266] \quad \text{and} \quad \tilde{D}_5 = [0.5521, 0.6788].$$

Step 4: Construct the likelihood matrix and obtain the ranking vector.

Use Equation (11) to construct the likelihood matrix P and obtain the ranking vector $\omega = (\omega_1, \omega_2, \ldots, \omega_5)$ based on Equation (12):

$$P = (p_{ij})_{5\times 5} = \begin{bmatrix} 0.5 & 0.7096 & 0.8493 & 0.9384 & 0.7316 \\ 0.2904 & 0.5 & 0.5962 & 0.6444 & 0.4836 \\ 0.1507 & 0.4038 & 0.5 & 0.5434 & 0.3679 \\ 0.0616 & 0.3556 & 0.4566 & 0.5 & 0.3057 \\ 0.2684 & 0.5164 & 0.6321 & 0.6943 & 0.5 \end{bmatrix},$$
$$\omega_1 = 0.2614,\ \omega_2 = 0.2007,\ \omega_3 = 0.1733,$$
$$\omega_4 = 0.1590 \quad \text{and} \quad \omega_5 = 0.2056.$$

Step 5: Determine the ranking of all alternatives.

According to the descending order of $\omega_i = (1, 2, \ldots, 5)$, the ranking of all alternatives is $a_1 \succ a_5 \succ a_2 \succ a_3 \succ a_4$ and the best one is a_1.

5.2. Comparative analysis and discussion

In order to further verify the feasibility and effectiveness of the proposed approach, a comparative analysis is now conducted using six existing methods with the analysis being based on the same illustrative example.

(1) Chi and Liu's method (2013) contains two major phases (criterion weights determination and ranking obtainment with TOPSIS). First, the maximising deviation method is developed to determine the criterion weights and then an extended TOPSIS method is employed to rank the alternatives.

(2) In Ye's method (2014b), the distance-based similarity measures are employed, which involves aggregating the weighted similarity measures between each alternative and the PIS.

(3) In Zhang et al.'s methods (2014), first, the comprehensive INNs are aggregated by using the INNWA or INNWG operators, and then the ranking vectors can be obtained by constructing the likelihood matrices based on the score function. Moreover, Zhang et al. (2015b) developed an outranking method for MCDM on the basis of the score function constructing the outranking relation matrix. Since Zhang et al.'s method (2015b) does not take the criterion weights into consideration but the illustrative example does, it is necessary to construct the outranking relation matrix after calculating the weighted evaluation values.

Considering the criterion weights obtained using the proposed programming model, the results obtained by different methods are summarised in Table 2.

It can be seen that there are some differences between them. The reasons for the inconsistency of the rankings are explained as follows.

(1) The difference in the ranking results of the proposed approach and that of Chi and Liu (2013) is the sequence

Table 2. The ranking results of the different methods.

Methods	Ranking results
Chi and Liu's method (2013)	$a_1 \succ a_5 \succ a_2 \succ a_4 \succ a_3$
Ye's methods (2014b)	
Similarity measure based on the Hamming distance	$a_1 \succ a_5 \succ a_2 \succ a_4 \succ a_3$
Similarity measure based on the Euclidean distance	$a_1 \succ a_5 \succ a_2 \succ a_3 \succ a_4$
Zhang et al.'s methods (2014)	
Method based on the INNWA operator	$a_1 \succ a_5 \succ a_2 \succ a_4 \succ a_3$
Method based on the INNWG operator	$a_1 \succ a_5 \succ a_2 \succ a_3 \succ a_4$
Zhang et al.'s method (2015b) ($p = 0.2$ and $q = 0.1$)	$a_1 \succ a_2 \succ \{a_3, a_4, a_5\}$
The proposed approach	$a_1 \succ a_5 \succ a_2 \succ a_3 \succ a_4$

Table 3. The ranking results obtained by revising the methods of Ye (2014b).

Methods	Ranking results
Similarity measure based on the Hamming distance	$a_1 \succ a_5 \succ a_2 \succ a_3 \succ a_4$
Similarity measure based on the Euclidean distance	$a_1 \succ a_5 \succ a_2 \succ a_3 \succ a_4$

of a_3 and a_4. In Chi and Liu's method (2013), the relative closeness coefficients (performance of each alternative) are conducted based on the relative ideal solutions, which have certain drawbacks. First, it is not easy to choose the appropriate PIS and NIS with INNs because each INN has three interval elements. Second, the PIS and NIS are closely related to the number of alternatives as well as the evaluation values. Thus, they may vary as the original information changes. Third, the relative closeness coefficients are in the form of crisp real numbers, which may cause information loss and affect the ranking results. Finally, suppose that there are m alternatives and n criteria to be evaluated. In order to determine the criterion weights, Chi and Liu's method (2013) needs to derive $m \times m \times n$ distance measures, whereas the proposed approach only needs to calculate $m \times n$ cross-entropy measures. Thus, it takes less time than that of Chi and Liu (2013).

(2) Similarly, the order of a_3 and a_4 is the only difference between the proposed approach and the first method of Ye (2014b). This is because the comparison methods in Ye (2014b) only consider the weighted similarity measures between each alternative and the PIS. If only the PIS is taken into account and the NIS is ignored, the ranking of alternatives may be incorrectly reversed and this may be amplified in the final results. However, the ranking result in this method will be identical to that of the proposed approach in a situation where, simultaneously, the PIS is replaced with the absolute one and the absolute NIS is not ignored; moreover, the closeness coefficient would have to be utilised to determine the ranking of alternatives. The updated results are shown in Table 3. Therefore, the methods in Ye (2014b) are not reliable enough.

(3) The positions of a_3 and a_4 obtained by the method based on the INNWA operator (Zhang et al., 2014) are not consistent with either those obtained by the method based on the INNWG operator (Zhang et al., 2014) or the proposed approach. This may be caused by the inherent characteristics of aggregation operators, as the INNWA operator focuses on the impact of the overall criterion values, while the INNWG operator emphasises the impact of a single item. Additionally, the outranking method of Zhang et al. (2015b) can only yield partial orders of alternatives, in which a_3, a_4 and a_5 are indistinguishable. This method has to convert the INNs into real numbers and artificially set both the threshold p and indifference threshold q before constructing the dominance relations. It is by nature inappropriate to replace the INNs with real numbers, and it may lead to information loss in the transformation process. Furthermore, when manually providing the parameters p and q, it is difficult to avoid subjective randomness. Therefore, the result obtained by the outranking method is not always reliable.

According to the comparative analysis, the following advantages over the other methods can be outlined.

(1) The calculations required for the proposed approach are relatively straightforward and time-saving, and the burden of computation can be greatly decreased with the help of the proven mathematical derivation.

(2) In the proposed approach, the interval closeness coefficients are conducted to rank alternatives. In this way, the fuzziness of the original information can be maintained and fully utilised. Therefore, the proposed approach is more competent in interval neutrosophic MCDM than the other methods considered.

(3) In the proposed approach, the transformation operator is employed to convert INNs into SNNs, which can avoid various kinds of aggregation operators processing directly with INNs. Furthermore, the parameters of the transformation operator are determined through mathematical derivation and not artificially produced. Thereby, the final ranking obtained by the proposed approach is more conclusive than those produced by the other methods, and it is evident that the proposed approach is accurate and reliable.

6. Conclusions

INSs are flexible at expressing the uncertain, imprecise, incomplete and inconsistent information that is very common in scientific and engineering situations; therefore, the study of MCDM methods with INSs is highly significant. In this paper, a transformation operator and cross-entropy were defined. Consequently, an MCDM method was established based on cross-entropy and TOPSIS, which calculated the cross-entropy after transforming INNs into SNNs on the basis of the transformation operator. Furthermore, it aggregated the performances of alternatives into interval numbers, from which two mathematical programming models were constructed to identify the criterion weights. Finally, a ranking result was obtained by comparing these weighted interval numbers with a possibility degree method.

The advantages of this study are that the approach is both simple and convenient to compute and effective at decreasing the loss of evaluation information. The feasibility and validity of the proposed approach have been verified through the illustrative example and comparative analysis. The comparison results demonstrated that the proposed approach can provide more reliable and precise outcomes than other methods. Therefore, this approach has great application potential in solving MCDM problems in an interval neutrosophic environment, in which criterion values with respect to alternatives are evaluated by the form of INNs and the criterion weights are incomplete.

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Notes on contributors

Zhang-peng Tian received his BS degree in electronic commerce from Tianjin Chengjian University, Tianjin, China, in 2012. He is currently working towards the MS degree with the Business School, Central South University, Changsha, China.

Hong-yu Zhang received her MS degree in computer software and theory and PhD degree in management science and engineering from Central South University, Changsha, China, in 2005 and 2009, respectively. She is currently an associate professor with the Business School, Central South University. Her research interests include information management and its applications in production operations. Her current research focuses on remanufacturing production management and decision-making theory.

Jing Wang received her MSc degree in information engineering from the University of Osnabrueck, Osnabrueck, Germany, in 2006. She is currently working towards the PhD degree with the Business School, Central South University, Changsha, China. She is also a lecturer with International College, Central South University of Forestry and Technology. Her current research interests include decision-making theory and application, risk management and control, and information management.

Jian-qiang Wang received his PhD degree in management science and engineering from Central South University, Changsha, China, in 2005. He is currently a professor with the Business School, Central South University. His current research interests include decision-making theory and application, risk management and control, and information management.

Xiao-hong Chen received her PhD degree in management from the Tokyo University of Technology, Tokyo, Japan, in 1999. She is currently a professor with the Business School, Central South University, Changsha, China. Her current research interests include decision theory and methods, decision support systems, resource-saving, and the environment-friendly society. She has published academic papers in many journals, including *Decision Support System* and *Expert Systems with Applications*.

ORCID

Zhang-peng Tian http://orcid.org/0000-0002-0825-9194
Hong-yu Zhang http://orcid.org/0000-0001-5142-5277
Jing Wang http://orcid.org/0000-0002-2407-5985
Jian-qiang Wang http://orcid.org/0000-0001-7668-4881
Xiao-hong Chen http://orcid.org/0000-0003-3919-5215

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