# Optimization and Weighting Analysis of Risk Indicators for Relocated Airports

Longhai Li*, Suyu Mu

School of Transportation Science and Engineering, Civil Aviation University of China Tianjin, China

*5994270@qq.com, caucmsy@163.com

**Abstract.** Airport relocation presents heightened operational safety risks due to environmental changes, system transitions, and managerial complexity. To improve the reliability of risk indicator weighting in such settings, this study proposes a novel fusion model integrating the G1 method, entropy weight method (EWM), and relative entropy optimization. The model first derives subjective weights via expert ranking using G1 and calculates objective weights based on data dispersion through EWM. These weights are then dynamically fused by minimizing their divergence using relative entropy, enabling a data-informed yet expert-sensitive weighting scheme. Unlike conventional hybrid methods with fixed ratios, this approach adjusts adaptively to input consistency. Empirical analysis involving 27 indicators across different airport relocation stages demonstrates that the model aligns well with expert assessments, effectively capturing layered safety risks. The method shows strong potential for supporting operational risk identification, resource allocation, and decision-making in complex airport relocation scenarios.

**Keywords:** Airport relocation; Operational safety; Weighting analysis; G1-EWM combination assignment

## 1 Introduction

As China's civil aviation network grows, many hub airports face airspace and urban development constraints, making relocation vital for improving efficiency and connectivity. However, relocation introduces environmental changes, frequent system adjustments, and higher demands on personnel and management, all of which elevate safety risks. Identifying key risk indicators and assigning proper weights is thus crucial to ensure operational safety during this phase.

Existing airport safety evaluation methods typically adopt either subjective techniques, such as the Analytic Hierarchy Process[1][2] and fuzzy synthesis methods[3]–[5], or objective methods like the entropy weight method[6][7] and the coefficient of variation[8]. Subjective approaches are prone to expert bias, while objective methods often ignore business semantics and indicator ordering, limiting their effectiveness in


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complex systems. In the uncertain context of airport relocation, it is especially necessary to develop a weighting approach that integrates both perspectives.To address this need, this study proposes a fusion model that combines the G1 ordering method[9] and the entropy weight method[10], further refined via a relative entropy-based optimi-zation process[11]. By minimizing the divergence between expert-based and data-driven weights, the model achieves stable and interpretable results under uncertainty, particularly when subjective knowledge and objective data may conflict or be incomplete.

Compared to conventional hybrid methods that use fixed ratios or empirical combinations, the proposed model introduces a dynamic adjustment mechanism based on the statistical alignment of the two sources. Using relative entropy as a fusion criterion ensures mathematical rigor and adaptability to varying information structures. This approach improves robustness and offers a novel application of entropy-guided fusion in evaluating operational risks during airport relocation, contributing both methodological innovation and practical relevance.

## 2 Weighting Analysis of Comprehensive Risk Indicators Based on the Entropy Weighting Method of Ordinal Relationship

In order to scientifically assign the weights of operational safety risk indicators for relocated airports, this paper develops an integrated entropy-based weighting model that combines both subjective expert judgment and objective data characteristics. The model incorporates the G1 method to capture expert preference ordering and the entropy weighting method to reflect data variability, and finally determines an optimal fusion coefficient using relative entropy to enhance the rationality, adaptability, and robustness of the resulting weights.

### 2.1 Sequential Relationship Approach to Determining Subjective Weights

**Table 1.** Relevant Evaluation Criteria and Assignment Table

| $r_k$ | Description of evaluation criteria |
|---|---|
| 1.8 | $X_{k-1}$ More important than $X_k$ |
| 1.6 | $X_{k-1}$ Strongly more important than $X_k$ |
| 1.4 | $X_{k-1}$ Significantly more important than $X_k$ |
| 1.2 | $X_{k-1}$ Slightly more important than $X_k$ |
| 1.0 | $X_{k-1}$ Equally important than $X_k$ |
| 1.7, 1.5, 1.3, 1.1 | $X_{k-1}$ than $X_k$ is between two neighboring judgments |

As a subjective means of assignment, the G1 method constructs a sequence of weight ratios and recursively obtains the weights of each indicator through the expert's judgment of the relative importance of neighboring indicators. With n indicators, the decision maker gives the importance ratio $r_i$ of the $i$-th indicator relative to the $i$+1-th indicator, where the importance ratio standard is shown in Table 1.

Then the weight of the $i$-th indicator can be calculated by the following formula after standardization process $w_g$:

$$w_g = \frac{1}{1+\sum_{k=2}^{m}\prod_{i=k}^{m} r_i} \tag{1}$$

## 2.2 Entropy Weighting Method for Solving Objective Weights

The entropy weight method is a commonly used objective assignment method, and its core idea is to utilize information entropy to measure the degree of data dispersion of each indicator, thus reflecting its importance in the evaluation system. If the data difference of an indicator between different evaluation objects is greater, its information is richer, and the weight given should be higher; on the contrary, it indicates that its differentiation ability is weak, and the weight should be lower. The specific steps of the entropy weight method are as follows.

**Decision-Making Matrix Construction based on Valid Data.**
Assuming that there are $m$ evaluation indicators and $n$ evaluation objects, and noting that $x_{ij}$ is the evaluation value of the $j$-th evaluation object under the $i$-th evaluation indicator, which constitutes the original data matrix:

$$X = \left[x_{ij}\right]_{m\times n} \tag{2}$$

Since indicators vary in scale and direction, the raw data were standardized. For positive indicators, the following normalization formula was applied:

$$p_{ij} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{3}$$

For negative indicators, the following formula is used:

$$p_{ij} = \frac{\max\left(x_j\right) - x_{ij}}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{4}$$

This leads to the normalized matrix, denoted as $P = \left[p_{ij}\right]$, where $p_{ij} \in \left[0,1\right]$.

**Calculation of Entropy Value and Information Utility Value.**
In information theory, information entropy reflects the uncertainty of the system. For the $j$-th indicator, its entropy value $e_j$ is denoted as:

$$e_j = -k\sum_{i=1}^{m} p_{ij}\ln\left(p_{ij}\right) \tag{5}$$

Where $k$ is a normalization factor that takes the value of $1/\ln m$, which is used to ensure a range of entropy values. In order to avoid mathematical singularity of $\ln 0$, if pij is 0, it is specified $p_{ij}\ln\left(p_{ij}\right)=0$. The indicator information utility value measures the amount of effective information about the indicator and is defined as follows: $d_j = 1-e_j$. The smaller the information entropy means the greater the variability of the indicator, the stronger its validity, and the larger $d_j$ is; conversely, if $e_j$ tends to be 1, then $d_j$ tends to be 0, indicating that the indicator contributes less to the evaluation system.

**Calculation and Normalization of Indicator Weights.**

Normalize the information utility value of each indicator to obtain the objective weight of the *j*-th indicator.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

The resulting weight vector $W_j$ satisfies the normalization condition:

$$\sum_{j=1}^{n} w_j = 1 \tag{7}$$

## 2.3 Composite Weight Solution based on Relative Entropy Synthesis Assignment

In multi-indicator evaluations, subjective weighting relies on expert judgment and may introduce bias, while objective methods depend solely on data distribution, potentially overlooking practical relevance. To integrate both sources effectively, this study introduces a relative entropy-based approach that measures the information divergence between subjective and objective weights. A composite weight vector is then constructed by minimizing this divergence to achieve a more balanced and adaptive weighting scheme.

Definition 1: If $x_i, y_i \geq 0$, and $1=\sum_{i=1}^{m} x_i \geq \sum_{i=1}^{m} y_i, i=1,\ldots,n$, then $h(x,y)$ = $\sum_{i=1}^{m} x_i \log(x_i / y_i)$ is chosen to be the entropy of $x$ with respect to $y$, where when $x_i = y_i$, $\sum_{i=1}^{m} x_i \log(x_i / y_i) = 0$.

It can be seen that when the random variables $x_i$ and $y_i$ present discrete probability distributions, the relative entropy can serve as an effective tool to measure the closeness between $x_i$ and $y_i$.

Definition 2: set the weight vectors of $m$ evaluation indicators obtained by subjective assignment method ($w_g$) and objective assignment method ($w_e$) are denoted by $\mu_g$ and

$\mu_e$ respectively, then the relative entropy between them can be presented by the following expression:

$$h\left(\mu_g,\mu_e\right)=\sum_{i=1}^{m}\mu_{gi}\log\frac{\mu_{gi}}{\mu_{ei}} \tag{8}$$

The comprehensive weight $d$ under the subjective-objective assignment method can be solved by the following optimization model to realize the organic integration of subjective-objective information and the scientific determination of weights.

$$\begin{cases}\min H(d)=\sum_{j=1}^{2}\sum_{i=1}^{m}d_i\log\frac{d_i}{\mu_{ji}}\\ st.\sum_{i=1}^{m}d_i=1,d_i\geq 0,i-1,2,\cdots,m\end{cases} \tag{9}$$

The formula characterizes the expression that minimizes the relative entropy between the combined weights obtained based on subjective weights, objective weights.

$$d_i=\frac{\prod_{j=1}^{2}(\mu_{ij})^{1/2}}{\sum_{i=1}^{m}\prod_{j=1}^{2}(\mu_{ij})^{1/2}},i=1,2,\cdots,m \tag{10}$$

After the comprehensive weight $d$ is derived through the corresponding calculation process in (10), the degree of fit between the weight coefficients obtained based on the subjective and objective assignment method and this comprehensive weight is further measured based on the principle of relative entropy of the comprehensive weight.

$$h(\mu_j,d)=\sum_{i=1}^{m}\mu_j\log\frac{\mu_{ji}}{d_i} \tag{11}$$

Degree of fit: the extent to which any one of the assignment results plays a role can be reflected by its closeness to the composite weights. Specifically, a higher degree of fit implies that the outcome plays a greater role in the composite assignment, and its corresponding adoptability $a_j$ is also higher.

$$a_j=\frac{h(\mu_j,d)}{\sum_{j=1}^{2}h(\mu_j,d)};j=1,2 \tag{12}$$

The adoptability of the results of the two subjective and objective assignments is calculated from (11) and (12), and the results are brought to the following equation to calculate the composite weight of an indicator:

$$w_k=\sum_{j=1}^{2}a_j\times\mu_{jk};(j=1,2;k=1,2,\cdots,m) \tag{13}$$

# 3 Composite Weighting of Risk Indicators for Relocated Airports Determined

## 3.1 Case Studies

In accordance with the methodology proposed in the previous section, a comprehensive weighting was calculated for the safety indicators of operational risks identified by the experts for the relocated airport, totaling nine primary indicators, including professional competence ($M_A$), resources and monitoring ($M_B$), core equipment reliability ($M_C$), equipment operational efficiency ($M_D$), systems and processes ($M_E$), personnel coordination and training ($M_F$), natural climatic conditions ($M_G$), compliance and innovation ($M_H$), and the physical environment adaptability ($M_I$), and 27 secondary indicators, including Control Personnel Qualification Rate ($M_{A1}$), Fire Fighting Personnel Qualification Rate ($M_{A2}$), Flight Attendant Competence ($M_{A3}$), Emergency Disposal Capability of Operation and Control Personnel ($M_{A4}$), Peak Resource Dispatch Deviation Rate ($M_{B1}$), Real-Time Surveillance System Coverage Rate ($M_{B2}$), Failure Rate of Navigational/Assistant to Navigation Facilities ($M_{C1}$), Baggage System Sorting Efficiency ($M_{C2}$), Aviation Fuel Supply Stability ($M_{C3}$), False Alarm Rate of Security Screening Equipment ($M_{C4}$), Airport Flight Security Regularity ($M_{D1}$) , Aircraft Taxiway Optimization Rate ($M_{D2}$), and so on. Take the primary indicators as an example. Based on the results of the research conducted by experts in the field of airport operation, the order of importance among the primary evaluation indicators is as follows: $M_A > M_E > M_G > M_F > M_C > M_B > M_D > M_H > M_I$. In accordance with the relevant evaluation criteria and the assignment table and formula 5, the relative importance among the primary indicators is $r_{ME} = 1.2$, $r_{MG} = 1.1$, $r_{MF} = 1.2$, $r_{MC} = 1.4$, $r_{MB} = 1.2$, $r_{MD} = 1.1$, $r_{MH} = 1.1$ and $r_{MI} = 1.1$. This results in a subjective weighting of the primary indicators as:

$$w_{MI} = \left[1 + \sum_{\mathrm{k}=2}^{9}\left(\prod_{i=2}^{9} r_k\right)\right]^{-1} = 0.0571 \tag{14}$$

This gives $w_{MA} = 0.1996$, $w_{ME} = 0.1667$, $w_{MG} = 0.1522$, $w_{MF} = 0.126$, $w_{MC} = 0.0895$, $w_{MB} = 0.0766$, $w_{MD} = 0.069$, $w_{MH} = 0.0633$. This study collected data on aviation accidents and incidents attributable to airport-related factors in China from 2020 to 2023. Through comprehensive statistical analysis employing nine primary evaluation indicators, the resultant dataset is systematically presented in Figure 1.Based on the above data, the original data matrix can be obtained, and the entropy value and information utility value of each primary indicator can be calculated through normalization. The objective weight values of the nine prioritized primary indicators were determined through the aforementioned methodology $w_{MA} = 0.379$, $w_{MB} = 0.1149$, $w_{MC} = 0.1609$, $w_{MD} = 0.092$, $w_{ME} = 0.1035$, $w_{MF} = 0.1034$, $w_{MG} = 0.1264$, $w_{MH} = 0.0806$, $w_{MI} = 0.0804$.

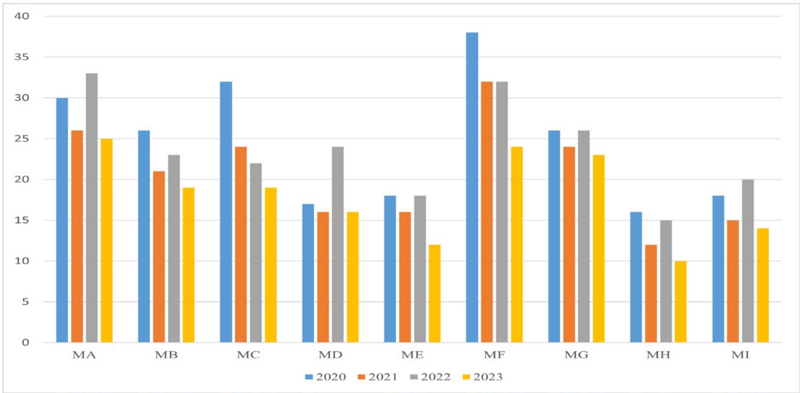


**Fig. 1.** Aviation accidents or accident symptoms based on airport factors during the period 2020-23.

**Table 2.** Combined weights of operational safety risk indicators for relocated airports

| Primary indicators | Combined weights | Secondary indicators | Combined weights |
|---|---|---|---|
| $M_A$ | 0.16641 | $M_{A1}$ | 0.314 |
| | | $M_{A2}$ | 0.163 |
| | | $M_{A3}$ | 0.27 |
| | | $M_{A4}$ | 0.253 |
| $M_B$ | 0.08548 | $M_{B1}$ | 0.426 |
| | | $M_{B2}$ | 0.574 |
| $M_C$ | 0.12733 | $M_{C1}$ | 0.318 |
| | | $M_{C2}$ | 0.214 |
| | | $M_{C3}$ | 0.193 |
| | | $M_{C4}$ | 0.275 |
| $M_D$ | 0.07486 | $M_{D1}$ | 0.243 |
| | | $M_{D2}$ | 0.254 |
| | | $M_{D3}$ | 0.298 |
| | | $M_{D4}$ | 0.205 |
| $M_E$ | 0.14854 | $M_{E1}$ | 0.448 |
| | | $M_{E2}$ | 0.552 |
| $M_F$ | 0.12094 | $M_{F1}$ | 0.495 |
| | | $M_{F2}$ | 0.505 |
| $M_G$ | 0.14546 | $M_{G1}$ | 0.286 |
| | | $M_{G2}$ | 0.107 |
| | | $M_{G3}$ | 0.187 |
| | | $M_{G4}$ | 0.175 |
| | | $M_{G5}$ | 0.245 |
| $M_H$ | 0.06803 | $M_{H1}$ | 0.524 |
| | | $M_{H2}$ | 0.476 |
| $M_I$ | 0.06295 | $M_{I1}$ | 0.558 |
| | | $M_{I2}$ | 0.442 |

The subjective and objective weights of the primary indicators obtained above are integrated through the weight vector matrix, and the set weights, degree of fit and credibility of each indicator can be obtained according to the above formula, and the comprehensive weights of each indicator can be obtained from (14), and the comprehensive weights of the 9 primary indicators and the 27 secondary indicators obtained from the preference of the preceding sequence are shown in Table 2.

Although this study focuses on Chinese relocated airports, similar relocation practices have been observed internationally. For instance, Munich Airport in Germany and Kansai International Airport in Japan experienced extensive environmental transitions, operational reconfiguration, and safety management challenges during relocation. These scenarios share structural similarities with the cases analyzed in this study. The proposed model, which integrates subjective expertise and objective data through entropy-based fusion, is theoretically adaptable to such contexts. Future work will consider extending the method to international cases to further validate its generalizability and support cross-regional airport risk assessment.

### 3.2 Validation of the Validity of Composite Weights

In order to verify the practical validity of the constructed relocated airport operation safety evaluation index system and the relative entropy comprehensive assignment results, this paper selects several airport relocation typical case scenario data, combines the 27 secondary indexes constructed in this paper and the calculated comprehensive weights, carries out the sample scoring and sorting analysis, and determines whether the results of the weight assignment have the differentiation degree and application value.Based on the combined weights $w_j$ obtained in the previous section, the sample risk evaluation score model is constructed as follows:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij} \tag{15}$$

Where $S_i$ is the comprehensive risk score of the ith relocated airport sample; $w_j$ is the comprehensive weight of the $j$-th secondary indicator; $x_{ij}$ is the normalized score of the sample under the $j$-th indicator. In this paper, the evaluation data matrix is obtained after processing the actual data results of the three domestic relocated airport samples, and its comprehensive score is calculated for ranking, and the ranking results are shown in Figure 2.

To validate the proposed weighting approach, we analyzed both the distribution of raw indicator scores and the final evaluation results. As shown in Figure 2, the three relocated airports exhibit distinct performance patterns across 27 safety indicators. Airport A excels in execution-oriented metrics like emergency response, Airport B performs well in system-level areas, and Airport C shows consistent strength in management, oversight, and adaptability. While the radar chart reveals structural differences, it lacks insight into indicator importance. By applying the fused weights, we calculated composite scores: Airport C ranked highest (22.26), followed by B (21.07) and A

(20.94). This demonstrates the model's ability to emphasize high-weight indicators and enable clearer differentiation, explaining Airport A's lower score due to weaker performance in governance-related areas.

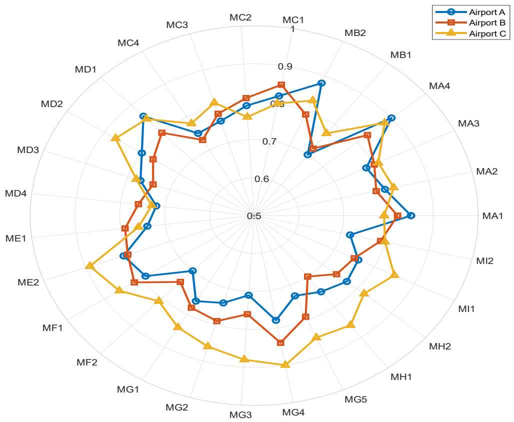


**Fig. 2.** Radar chart of operational risk indicators for relocated airports.

Overall, the comparison between the radar charts and the weighted rankings clearly demonstrates that the model effectively captures not only surface-level variations but also deeper structural priorities within the indicator system. By thoughtfully integrating expert judgment with robust data-driven insights, the proposed method significantly outperforms traditional equal-weight or single-source approaches, providing a more credible, interpretable, and actionable framework for risk assessment in the complex context of airport relocation.

### 3.3 Sensitivity Analysis

To verify the stability and robustness of the proposed relative entropy fusion assignment model under uncertainty, a sensitivity analysis experiment was designed. It simulates slight perturbations in subjective weights and objective data to assess the model's sensitivity to input errors and the stability of output results. Two perturbation scenarios were set: applying ±10% changes to some subjective weight indices to simulate expert cognitive bias, and adding ±5% changes to the original data for entropy weighting to reflect potential data collection errors. Each scenario was repeated 20 times to recalculate fusion weights and compare index ranking consistency. The analysis used the Top-5 retention rate and Kendall rank correlation coefficient as evaluation metrics. The former reflects the consistency of the top five indicators before and after perturbation, while the latter measures overall ranking agreement, with values closer to 1 indicating higher consistency. Results are presented in Table 3.

**Table 3.** Results of sensitivity analysis

| Metric | Mean |
|---|---|
| Subjective weight Top-5 stability | 1.000 |
| Subjective weight Kendall's Tau | 0.961 |
| Objective weight Top-5 stability | 1.000 |
| Objective weight Kendall's Tau | 0.964 |

As shown in Table 3, under subjective weight perturbation, the top five indicators remain fully consistent across all trials, with a Kendall coefficient of 0.961, indicating minimal impact from expert input variation. Similarly, with objective data perturbation, Top-5 stability stays at 100%, and Kendall's coefficient reaches 0.964, showing high ranking consistency. These results confirm that the proposed fusion model is robust and resistant to input uncertainty, making it suitable for complex decision-making scenarios like airport operational risk assessment, where data may be imprecise or incomplete.

## 4 Conclusions

This study proposes a relative entropy-based fusion weighting model that integrates the G1 method and entropy weight method to address subjectivity and imbalance in evaluating operational safety risks at relocated airports. By combining expert rankings and accident data, the model optimally balances subjective and objective weights. Empirical validation using 27 indicators shows that the resulting weights are well-structured and capable of differentiating risk characteristics across airport samples. The model demonstrates strong explanatory power and robustness, offering a practical tool for risk assessment, resource allocation, and operational control in the context of airport relocation.

## References

1. Sennaroglu B, Celebi G V. A military airport location selection by AHP integrated PROMETHEE and VIKOR methods[J]. Transportation Research Part D: Transport and Environment, 2018, 59: 160-173.
2. Dožić S, Babić D, Kalić M, et al. An AHP approach to airport choice by freight forwarder[J]. Sustainable Futures, 2023, 5: 100106.
3. Wan L, Peng Q, Wang J, et al. Evaluation of airport sustainability by the synthetic evaluation method: A case study of Guangzhou Baiyun international airport, China, from 2008 to 2017[J]. Sustainability, 2020, 12(8): 3334.
4. Loh H S, Yuen K F, Wang X, et al. Airport selection criteria of low-cost carriers: A fuzzy analytical hierarchy process[J]. Journal of Air Transport Management, 2020, 83: 101759.
5. Wang X, Brownlee A E I, Weiszer M, et al. An interval type-2 fuzzy logic-based map matching algorithm for airport ground movements[J]. IEEE Transactions on Fuzzy Systems, 2022, 31(2): 582-595.
6. Żak J, Gołda P, Cur K, et al. Assessment of airside aerodrome infrastructure by SAW method with weights from Shannon's interval entropy[J]. Archives of Transport, 2021, 60(4).

7. Zhang Z, Cheng S, Xu H, et al. Research on airport leading goods selection based on maximum entropy principle[C]//2018 International Workshop on Education Reform and Social Sciences (ERSS 2018). Atlantis Press, 2019: 480-486.
8. Niu Y, Yu X, Zhu H, et al. Research on estimation method for airport runway friction coefficient based on numerical analysis[J]. IEEE Access, 2024.
9. Ali H, Guleria Y, Alam S, et al. A passenger-centric model for reducing missed connections at low cost airports with gates reassignment[J]. IEEE Access, 2019, 7: 179429-179444.
10. Mizrak F, Polat L, Tasar S A. Applying Entropy Weighting and 2-Tuple Linguistic T-Spherical Fuzzy MCDM: A Case Study of Developing a Strategic Sustainability Plan for Istanbul Airport[J]. Sustainability, 2024, 16(24): 11104.
11. Ren G. Robustness analysis of air route network based on topology potential and relative entropy methods[J]. Journal of Advanced Transportation, 2021, 2021(1): 5527423.