Airport Resilience Assessment Using a Novel MCDM Model

Abstract:

Airports are one of the most important facilities in the transportation system of critical infrastructure. In the face of particular disasters, it is difficult to build a risk prediction model based on past statistical data. To strengthen the airport's resilience, it is feasible to develop protection strategies using the expert-based Multiple Criteria Decision Making (MCDM) approach. This study proposes a novel evaluation model that uses the Bayesian Best Worst Method (Bayesian BWM) to determine the optimal group weights for the criteria, and uses the modified Preference Ranking Organization Method for Enrichment Evaluations (modified PROMETHEE) to calculate the difference between each alternative and the aspiration level and then rank it. Taiwan's airports were used to demonstrate the practicality and effectiveness of the model. In addition, the sensitivity analysis and the model comparisons also confirmed the reliability of the proposed model. The research results show that the proposed evaluation system effectively assists policy makers and airport security departments to formulate improvement strategies, thereby enhancing the resilience of airports.

Keywords: Airport resilience, MCDM, Bayesian BWM, modified PROMETHEE

1. Introduction

The reliability of critical infrastructure can significantly affect a country's economic and social development, and both developing and developed countries need to develop a comprehensive set of critical infrastructure protection policies (Palleti et al., 2018). There are numerous cases of human errors, natural disasters, terrorist attacks, etc. that have caused critical infrastructure failures. Therefore, improving the protection capabilities of critical infrastructure is an important issue facing risk management today (Lo et al., 2020). Despite the efforts of governments and security organizations to reduce the damage caused by disasters to critical infrastructure, unprecedented special disasters and intentional human attacks are difficult to predict. However, it is effective to learn from past events as experience to develop relevant protection strategies to enhance the resilience of critical infrastructure

(Labaka et al., 2016; Slivkova et al., 2017).

Critical infrastructure includes transportation systems, communication systems, financial systems, power systems, water systems, medical systems, government agencies, and so on. In view of the steady growth of people's needs to travel abroad, attention has been paid to the aspects such as service quality, security and administrative efficiency. Moreover, the ability of transportation systems to resist interference and adaptability has become increasingly important. Air transport is the fastest and most convenient means of transportation, and the infrastructure of air transport is "airport", which is the center of international transportation. Airport failures can cause serious problems, including restricted entry and exit, flight delays, and passengers' panic. For example, in December 2017, Atlanta's Hartsfield-Jackson airport in the United States, known as the busiest airport in the world, suffered a power outage for nearly 11 hours due to an electrical fire in the tunnel below the airport. In addition to the frustration of airport operations, it also suffered a huge loss of compensation (Sun et al., 2020). Therefore, runway maintenance planning, aircraft ground operation management, and ground emergency response measures are important tasks for airport maintenance.

After the United States suffered a terrorist attack on September 11, 2001, many countries have actively proposed security management policies and counter-terrorism measures for airports (Ito and Lee, 2005). The National Academy of Sciences defines four aspects to reflect the resilience of the system: to plan and prepare for, to absorb, to respond to, and to recover from disasters. In air transport systems, resilience refers to the ability to prevent or mitigate any threat to air traffic operations (Clark et al., 2018). Security risk assessment usually uses cost-benefit analysis (CBA) to estimate the cost and protective benefits of security measures. However, Stewart and Mueller (2014) pointed out that the CBA analysis could not prove that the current estimated airport security costs are reasonable, and they acknowledged that more simulation experiments were needed to explore the interdependence existing in airport security. A reliability evaluation model for the mass transit network in the airport area was proposed by Malandri et al. (2017). Due to the high cost of flight delays caused by late arrivals, pilots may increase navigational risks in order to catch up with expected arrival times. Therefore, there must be multiple airport transportation options to improve this problem. According to Knol et al.'s (2018) literature review of airport security systems, the most common assessment factors are the likelihood, vulnerability, and consequences of the threat. They applied cognitive agent models to analyze the performance of airport security inspections. Skorupski and Uchroński (2017) proposed a model for evaluating the performance of airport security checkpoints based on fuzzy inferences, and inferred airport security performance through expert interviews and questionnaires. Their model takes into account the efficiency of prohibited items detection, the ability of security control and service quality. Bao and Zhang (2018) developed a quantitative framework for large-scale airport resilience assessment to determine how vulnerability and adaptability affect airport system resilience. The results show that the efficiency of emergency handling interacts with airport vulnerability. Even when the airport is extremely vulnerable, it has certain self-regulation and resilience capabilities to reduce the risks. In the development trend of the Internet of Things, a risk assessment model for smart airport network security was proposed by Lykou et al. (2019). The purpose of this research is to actively mitigate malicious attacks and threats to ensure the robustness of the airport network system. In addition, there are many studies related to airport security protection (Yanjun et al., 2019; Zhou et al., 2019; Thompson and Tran, 2019), who have contributed to the safety assessment of global transportation systems.

However, the resilience assessment framework for airports has not been comprehensively discussed. This is a complex and difficult Multiple Criteria Decision Making (MCDM) problem. It is the purpose of MCDM to seek an ideal solution under many constraints. This study defines airport resilience as "the ability of an airport to quickly and effectively absorb hazards and reduce impacts, and quickly return to normal conditions in the event of a crisis." Therefore, this study proposes an MCDM assessment framework for airport resilience. The dimensions are detection capability, resistance capability, rescue capability, and recovery capability, which contain a total of 27 criteria. These four dimensions correspond to the four aspects of the resilience assessment of critical infrastructure, namely "reduced failure probabilities," "reduced consequences from failures," "reduced time to recovery," and "the means of resourcefulness and redundancy" (Bruneau et al., 2003). This study uses the Bayesian Best Worst Method (Bayesian BWM) to determine the optimal group weights for the criteria. Bayesian BWM is a novel group decision analysis technique that overcomes the shortcomings of using conventional arithmetic to integrate experts' opinions with statistical estimation methods (Mohammadi and Rezaei, 2019). Next, the modified Preference Ranking Organization Method for Enrichment Evaluations (modified PROMETHEE) technique is used to assess the resilience performance of the airport. The modified PROMETHEE introduces the concept of aspiration level into conventional PROMETHEE. In the calculation process, the aspiration and the worst levels are considered as alternatives. This approach replaces the conventional concept of "relative satisfaction" with "aspiration level" It can be known how far the alternatives are from the aspiration level for improvement, so that more management information can be obtained in practical applications (Lo et al., 2019). This study provides a more systematic resilience assessment framework for airports and can assist policy makers in developing more appropriate protection strategies.

The structure of this article is described below. Section 2 introduces the proposed evaluation dimensions and criteria, and explains their definitions and references. Section 3 describes the method used and its steps, including Bayesian BWM and modified PROMETHEE. Section 4 uses the international airports in Taiwan as a case to demonstrate the feasibility and effectiveness of the proposed model. Section 5 discusses and illustrates future research directions.

2. The Proposed Airport Resilience Assessment Framework

Due to the particularity of disasters, the methods of risk vulnerability analysis are rarely reflected in operational concepts based on previous disaster data. Even if many disruptive events have been proven to have an impact on airport operations, it is difficult to have a complete study on how to prevent risks. Airport practitioners can obtain defense ability to prevent future uncertain risks by integrating past disaster events and the lessons learned. If these painful experiences and costs can be transformed into valuable knowledge systems, they can provide systematic preventive mechanisms and measures (Clark et al., 2018).

The airport resilience assessment criteria involve many complex factors, and it is feasible to build a knowledge system through past disaster prevention experience. It may be difficult for such a complicated evaluation system to obtain accurate quantitative data. Therefore, an expert-based qualitative research survey was used in the study, with the survey results converted into computable quantitative data through soft calculation methods. And scientific conclusions are obtained for references by the disaster prevention departments (Liou et al., 2007; Lo et al., 2020). Many academic studies on aviation and airport safety have proposed a number of resilience indexes, which have helped to develop an assessment framework for this paper (Yang et al., 2015; Humphries and Lee, 2015; Huizer, 2015; Skorupski and Uchroński, 2016; Chen and Li, 2016; Zhao et al., 2017; Wallace and Webber, 2017; Zhou et al., 2018;

Birgani et al., 2018; Bao and Zhang, 2018; Willemsen and Cadee, 2018; Singh et al., 2019 Ergün and Bülbül, 2019).

The decision-making team was composed of a total of 23 members, including the aviation police station, airport security engineers, and disaster prevention specialists. **Table 1** presents the years of service of all decision-making members, and it shows that they have deep experience working in airports and aviation safety related fields.

Table 1. Background of the experts

	Years of relevant experience	Number of people
International Airport	More than 10 years	5
Maintenance Department	5-10 years	6
	Less than 5 years	2
International Airport Safety	More than 10 years	2
Investigation Agency	5-10 years	1
	Less than 5 years	2
Aviation Police Bureau	More than 10 years	2
	5-10 years	2
	Less than 5 years	1

After reviewing the literature and discussing with the experts, four dimensions were developed to assess the airport's resilience and protection capabilities, including Detection capability before risks (D_1), Resistance capability to risks when they occur (D_2), Emergency measures and Rescue capability (D_3), Recovery capability after risks (D_4). These dimensions can be divided into 27 evaluation criteria, and the description and references of the criteria are presented in **Table 2**. The criteria proposed in this article are so comprehensive that they involve the assessment of airport physical facilities, personnel, equipment and tools, measures and methods, and take into account the complete cycle of risk occurrence (early, middle and late).

Table 2. Proposed dimensions and criteria for airport resilience assessment

Dimensions	Criteria	Reference
Detection Capability (D_1)	Ground crews' safety awareness and risk alertness at work (C_{11}).	Zhao et al. (2017); Singh et al. (2019); Ergün and Bülbül (2019)
	Periodic inspection of airport runways (C_{12}).	Zhao et al. (2017); Humphries and Lee (2015)
	Accuracy of instrument and system testing at	Zhao et al. (2017); Ergün and Bülbül

	security checkpoints (C_{13}).	(2019); Skorupski and Uchroński (2016)
	Safety Management System (SMS) system integrity (C_{14}).	Zhao et al. (2017); Chen and Li (2016); Ergün and Bülbül (2019)
	Early warning accuracy and timeliness of aviation weather service stations (C_{15}).	Zhao et al. (2017); Chen and Li (2016)
	Reliability of the airport's epidemic prevention system (C_{16}).	Huizer et al. (2015)
	Integrity of airport security and surveillance systems (C_{17}).	Zhou et al. (2018); Yang et al. (2015); Ergün and Bülbül (2019)
Resistance capability (D_2)	Emergency procedures when flammables and explosives are found (C_{21}).	Singh et al. (2019)
	Ground crew education and training on airport safety (C_{22}).	Singh et al. (2019); Zhao et al. (2017); Ergün and Bülbül (2019)
	Number of security personnel and aviation police (C_{23}).	Yang et al. (2015); Skorupski and Uchroński (2016)
	Comprehensive physical drainage system (C_{24}).	Birgani et al. (2018)
	Planning and management of tarmacs, number of collisions between vehicles, machinery and aircrafts (C_{25}).	Chen and Li (2016)
	Building structures and earthquake prevention measures for terminals (C_{26}).	Singh et al. (2019)
	Proper isolation measures around the airport (C_{27}).	Willemsen and Cadee (2018)
Rescue capability (D_3)	Adequacy of fire protection resources inside and outside the terminals (C_{31}).	Zhao et al. (2017); Bao and Zhang (2018)
	Stability of communication systems in various departments of the airport (C_{32}).	Zhao et al. (2017); Yang et al. (2015)
	Comprehensive emergency evacuation measures and clear escape instructions (C_{33}).	Bao and Zhang (2018)
	Emergency rescue mechanism for injured patients (C_{34}).	Yang et al. (2015); Wallace and Webber (2017)
	Preparation of emergency plans and relief procedures (C_{35}).	Yang et al. (2015); Bao and Zhang (2018)
	Medical resources surrounding the airport (C_{36}).	Zhou et al. (2018)
Recovery	Morale of all staff at the airport for	Yang et al. (2015); Zhou et al. (2018)

capability (D_4)	post-disaster reconstruction (C_{41}).	
	Cost of maintenance and reinforcement works for terminals (C_{42}).	Yang et al. (2015); Chen and Li (2016)
	Establishment of a recovery command center to coordinate the allocation of people, materials, and resources (C_{43}).	Yang et al. (2015); Wallace and Webber (2017)
	Timeliness of airport runway repair operations (C_{44}).	Humphries and Lee (2015)
	Spare power generation equipment to ensure uninterrupted Information Technology (IT) System (C_{45}).	Yang et al. (2015); Wallace and Webber (2017)
	Spare Management Information System (MIS) (C_{46}).	Yang et al. (2015); Wallace and Webber (2017)
	Comprehensive maintenance equipment to quickly start repairs (C_{47}).	Zhao et al. (2017); Ergün and Bülbül (2019);

3. Proposed Novel MCDM Model

Figure 1 shows a hybrid model architecture for airport resilience assessment. The proposed model consists of two phases. First, according to the dimensions and criteria proposed in Section 2, Bayesian BWM is used to calculate their optimal weights and prioritize the criteria. Subsequently, the modified PROMETHEE technology is used to calculate the performance value of the alternatives (airports), and the management policies to improve airport resilience are proposed. The calculation process of the involved methods will be explained in detail below.

(Figure 1 翻譯完再補上)

3.1 Bayesian BWM technique

BWM was proposed by Rezaei (2015). It overcomes two shortcomings of AHP, namely reducing the number of pairwise comparisons and improving consistency. BWM obtains two sets of vectors (Best-to-Others and Others-to-Worst vectors) through pairwise comparisons. This structured questionnaire design helps decision makers to provide more accurate assessments. However, BWM's way of integrating multiple experts is to use the simplest arithmetic mean. When the opinions of experts are divided, the averaged evaluation value has been distorted. Therefore, Mohammadi and Rezaei (2019) developed a method to optimize BWM, called Bayesian BWM, which uses the concept of probability distribution to integrate group evaluation information to generate a set of optimal criterion group weights. MCDM requires that the sum of weights be 1 and that each weight be greater than or equal to 0. From the concept of probability, the criterion c_j (j = 1, 2,…, n) can be regarded as a random event, and the generation of the weight w_j is the possibility of the criterion c_j occurring. Therefore, it is reasonable to construct a probabilistic model based on BWM. Bayesian BWM has been used in many areas to solve weight problems, including sports tourism (Yang et al., 2020), electrochemical (Guo, 2020), and manufacturing (Man et al., 2020).

In this study, software provided by Mohammadi and Rezaei (2019) was used to perform Bayesian BWM operations. Bayesian BWM's brief steps and instructions are as follows:

Step 1. Establishing evaluation criteria

Discussion with experts through literature review to determine n evaluation criteria $c_j = \{c_1, c_2, \ldots, c_n\}$ for airport resilience.

Step 2. Choosing the most important and least important criteria

The most important (i.e., best, c_B) and least important (i.e., worst, c_W) criteria are chosen from *n* criteria.

Step 3. Comparing the most important criterion with other criteria to obtain a BO vector

Experts assess the importance of the most important criteria to other criteria. The evaluation scale is 1 to 9, and the scale 1 indicates that it is equally important. The scale 9 is far more important. The larger the scale, the greater the relative importance. BO vector is expressed as:

$$A_{Bj} = \left(a_{B1}, a_{B2}, \ldots, a_{Bj}, \ldots, a_{Bn}\right)$$

where a_{Bj} indicates the importance of the most important criterion *B* to criterion *j*.

Step 4. Comparing the other criteria with the least important criterion to obtain the OW vector

This step is similar to Step 3, where experts evaluate the importance of the other criteria and the least important criterion. The OW vector is expressed as:

$$A_{jW} = \left(a_{1W}, a_{2W}, \ldots, a_{jW}, \ldots, a_{nW}\right)^T$$

where a_{jW} indicates the importance of the other criterion *j* to the least important criterion *W*.

Since self-comparison is of equal importance, therefore it is required that $a_{BB} = 1$ and $a_{WW} = 1$.

Step 5. Obtaining the optimal group weights for the criteria

The probability model of the multinomial distribution can be constructed by A_{Bj} and A_{jW}, then the probability function of the multinomial distribution of A_{jW} is shown as **Eq. 1**.

$$P\left(A_{jW} \middle| w_j\right) = \frac{\left(\sum_{j=1}^{n} a_{jW}\right)!}{\prod_{j=1}^{n} a_{jW}!} \prod_{j=1}^{n} w_j^{a_{jW}} \tag{1}$$

where w_j is the probability distribution of weights, which has a proportional relationship with a_{jW}, so **Eq. 2** can be formed. The probability of the weight of the least important criterion w_W is shown in **Eq. 3**. **Eqs. 2** and **3** can be combined to obtain **Eq. 4**.

$$w_j \propto \frac{a_{jW}}{\sum_{j=1}^{n} a_{jW}}, \quad \forall j = 1,2,\ldots,n \tag{2}$$

$$w_W \propto \frac{a_{WW}}{\sum_{j=1}^{n} a_{jW}} = \frac{1}{\sum_{j=1}^{n} a_{jW}} \tag{3}$$

$$\frac{w_j}{w_W} \propto a_{jW}, \quad \forall j = 1,2,\ldots,n \tag{4}$$

Besides, the probability of the weight of the most important criterion w_B is shown in **Eq. 5**.

$$\frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{j=1}^{n} a_{Bj}} = \frac{1}{\sum_{j=1}^{n} a_{Bj}} \Rightarrow \frac{w_B}{w_j} \propto a_{Bj}, \quad \forall j = 1,2,\ldots,n \tag{5}$$

Dirichlet probability distribution is used to construct a model to estimate the optimal weight value w_j, with the probability function shown as **Eq. 6**.

$$Dir\left(w_j \middle| \alpha\right) = \frac{1}{B(\alpha)} \prod_{j=1}^{n} w_j^{\alpha_j - 1} \tag{6}$$

where α is the vector parameter, which is usually set to 1. $w_j \geq 0$ and $\sum w_j = 1$ are required to be in line with the concept of MCDM.

Bayesian BWM is a way of estimating approximate parameters through Bayesian, and considering the survey data of multiple experts to integrate a set of optimal group weights w_j^{agg}. The steps are described as follows:

Step 5.1. Constructing joint probability distribution for the team

The decision-making team has *k* experts *k* = 1,2, ..., *K*, and the individual criterion weight after an expert evaluation is w_j^k, and integrating all of w_j^k can get the group weights as w_j^{agg}. $A_{Bj}^{1:K}$ and $A_{jW}^{1:K}$ represent the BO and OW vectors of the first expert to the K-th expert. These vectors can construct the joint probability distribution of group decision-making as shown in **Eq. 7**.

$$P\left(w_j^{agg}, w_j^{1:K} \middle| A_{Bj}^{1:K}, A_{jW}^{1:K}\right) \tag{7}$$

Step 5.2. Building a Bayesian hierarchy model

Experts' individual optimal weights w_j^k depend on their A_{Bj} and A_{jW} vectors, while the optimal group weights w_j^{agg} depend on w_j^k. The Bayesian hierarchy model is constructed based on the iterative operation method, which means that the A_{Bj} and A_{jW} vectors of the experts will generate w_j^k, and the evaluation data of multiple experts will be added one after another, and the optimal weight w_j^{agg} of the group will be continuously updated. Considering that the conditions among variables are independent, the joint probability of the Bayesian model is shown as **Eq. 8**.

$$P\left(w_j^{agg}, w_j^{1:K} \middle| A_{Bj}^{1:K}, A_{jW}^{1:K}\right) \propto P\left(A_{Bj}^{1:K}, A_{jW}^{1:K} \middle| w_j^{agg}, w_j^{1:K}\right) P\left(w_j^{agg}, w_j^{1:K}\right) \tag{8}$$

Eq. 8 can be further deduced as follows.

$$P\left(A_{Bj}^{1:K}, A_{jW}^{1:K} \middle| w_j^{agg}, w_j^{1:K}\right) P\left(w_j^{agg}, w_j^{1:K}\right) = P\left(w_j^{agg}\right) \prod_{k=1}^{K} P\left(A_{jW}^{k} \middle| w_j^k\right) P\left(A_{Bj}^{k} \middle| w_j^k\right) P\left(w_j^k \middle| w_j^{agg}\right) \tag{9}$$

Eq. 9 shows that by specifying the statistical distribution of each variable, the corresponding probability function can be found. $A_{Bj}^k \middle| w_j^k$ and $A_{jW}^k \middle| w_j^k$ are distributed as **Eq. 10.**

$$A_B^k \left| w_j^k \right. \sim multinomial\left(\frac{1}{w_j^k}\right), \ \forall_k = 1,2,\ldots,K;$$

$$A_{jW}^k \left| w_j^k \right. \sim multinomial\left(w_j^k\right), \ \forall_k = 1,2,\ldots,K \tag{10}$$

And w_j^k under the condition of w_j^{agg} can be constructed as Dirichlet distribution as shown in **Eq. 11**.

$$w_j^k \left| w_j^{agg} \right. \sim Dir\left(\gamma \times w_j^{agg}\right), \ \forall_k = 1,2,\ldots,K \tag{11}$$

where w_j^{agg} is the average value of the Dirichlet distribution, and γ is a non-negative parameter.

The w_j^k must be in the proximity of w_j^{agg} since it is the mean of the distribution, the proximity is determined by the γ parameter, and the distribution of the γ parameter obeys the gamma distribution as shown in **Eq. 12**.

$$\gamma \sim gamma\left(a, b\right) \tag{12}$$

where *a* and *b* are the shape and scale parameters of the gamma distribution.

The optimal group weights w_j^{agg} obey the Dirichlet distribution as shown in **Eq. 13**.

$$w_j^{agg} \sim Dir\left(\alpha\right) \tag{13}$$

Where parameter α is set to 1.

After the construction of probability distribution of all variables is completed, Markov-chain Monte Carlo (MCMC) technology is used to simulate *q* experiments to obtain the optimal group weights w_j^{agg}.

3.2 Modified PROMETHEE technique

PROMETHEE technology is more rigorous than other MCDM performance evaluation methods. It has to perform multiple pairwise comparisons to obtain the integration score of alternatives (net flow). PROMETHEE's concept is to make pairwise comparisons between alternatives based on each criterion. The initial matrix is divided into the leaving flow and entering flow matrix. Although this operation is tedious, we can know the pros and cons of each alternative under each criterion. In this article, we have added the concept of "aspiration level" to PROMETHEE, so we know what is the gap between each alternative and the aspiration level in order to propose more reasonable improvements. Many studies have proven the reliability of PROMETHEE in practice (Bongo et al., 2018). The implementation steps of modified PROMETHEE are explained below.

Step 1. Establishing initial decision matrix

Experts weigh the performance of alternatives according to the established evaluation criteria. Assume that there are *j* criteria and *i* alternatives in the evaluation system, where *j* = 1, 2,..., n;

i = 1,2, ..., m. The experts judge the performance of the alternatives to give evaluation values on a scale of 1 (extremely poor performance) to 10 points (excellent performance). Higher scores indicate better performance. By averaging the evaluation values of all experts, an initial decision matrix ***A*** can be obtained, such as **Eq. 14**.

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}_{m \times n} \tag{14}$$

Step 2. Determining the aspiration and the worst levels for each criterion

Previously, Positive and Negative ideals were formulated based on the maximum and minimum values of the performance of alternatives, as shown in **Eqs. 15 and 16**. In this way, only the ranking of the alternatives can be learned, but no real improvement space can be obtained. Therefore, this paper sets the evaluation scale maximum (10) and minimum (1) as the aspiration and the worst levels, as shown in **Eqs. 17 and 18**. In the execution of PROMETHEE's calculation procedure, the aspiration and the worst levels are not only the basis of normalization, but also considered as alternatives. In this way, each alternative can be determined depending on how much difference it is from the aspiration level, and then the effective improvement measures can be formulated.

Positive ideal: $a_i^* = \max_i a_{ij} \,\middle|\, i = 1,\ 2, \ldots,\ m;\ j = 1,\ 2, \ldots,\ n.$ (15)

Negative ideal: $a_i^- = \min_i a_{ij} \,\middle|\, i = 1,\ 2, \ldots,\ m;\ j = 1,\ 2, \ldots,\ n.$ (16)

After introducing the aspiration level concept to the PROMETHEE technology, the Positive and Negative ideals are changed from **Eqs. 15** and **16** to **Eqs. 17** and **18.**

The aspiration levels: $a_j^{asprie} = \left(a_1^{asprie},\ a_2^{asprie}, \ldots,\ a_n^{asprie}\right) = 10$ (17)

The worst levels: $a_j^{worst} = \left(a_1^{worst},\ a_2^{worst}, \ldots,\ a_n^{worst}\right) = 1$ (18)

Step 3. Calculating the normalized decision matrix

PROMETHEE has six basic preference functions, proposed by Brans and Vincke (1985). This study uses Type V's preference function "Criterion with Linear Preference and

Indifference Area" as the normalized formula (called "Degree of Preference for All Alternatives for Each Criterion" in the PROMETHEE terminology). Through normalization, the range of all evaluation values can be converged between 0 and 1, and the unit of the criteria is unified. **Eq. 19** is the normalization decision matrix, and the normalization formula used is **Eq. 20.**

$$\boldsymbol{F} = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix}_{m\times n} \tag{19}$$

where $\boldsymbol{F} = \left[f_{ij} \right]_{m\times n}$.

$$f_{ij} = \left(a_{ij} - a_j^{worst}\right) \Big/ \left(a_j^{aspire} - a_j^{worst}\right) \tag{20}$$

Step 4. Calculating the preference functions of the alternatives under each criterion

We define a preference function $S_j\left(u,\ v\right)$ to indicate the degree to which alternative u is better than alternative v under criterion j, as shown in **Eq. 21.**

$$S_j\left(u,\ v\right) = \begin{cases} 0 & ,\ f_{uj} - f_{vj} \le f_j^{worst} \\ f_{uj} - f_{vj} & ,\ f_j^{worst} < f_{uj} - f_{vj} \le f_j^{aspire} \\ 1 & ,\ \text{otherwise} \end{cases} \tag{21}$$

where $f_j^{aspire}=1$ and $f_j^{worst}=0$.

Step 5. Generating multi-criteria preference index for each alternative

Because there are quite a few of evaluation criteria and they are not equally important, this step combines the optimal weight w_j of Bayesian BWM with the preference function $S_j(u, v)$ obtained in Step 4 to obtain a multi-criteria preference index $\pi(u, v)$. Where $\pi(u, v)$ index indicates the degree to which alternative u is superior to alternative v in overall performance, as shown in **Eq. 22**.

$$\pi(u, v) = \sum_{j=1}^{n} w_j \pi_j(u, v) \tag{22}$$

Step 6. Obtaining net flow for all alternatives

The pros and cons of all alternatives can be identified according to the multi-criteria preference index. We can calculate the three flows of the alternatives in order to rank, including leaving flow, entering flow, and net flow, which are shown in **Eqs. 23–25.**

The leaving flow: $$\theta^{+}(u) = \sum_{v=1}^{z} \pi(u, v) \tag{23}$$

The entering flow: $$\theta^{-}(u) = \sum_{v=1}^{z} \pi(v, u) \tag{24}$$

The net flow: $$\theta(u) = \theta^{+}(u) - \theta^{-}(u) \tag{25}$$

where z represents the total number of times that alternative u is compared with alternative v. Assume there are 3 alternatives, z is 2(n-1) times. The larger the net flow of the alternative, the better, because it means that the alternative has a better performance than the others.

4. Empirical Research on Airport Resilience Evaluation

4.1 Case description

This study uses Taiwan as a case, evaluating Taiwan's airports' ability to respond to and recover from disasters when it faces them. The decision-making team reviewed the risk events that damaged the operations of Taiwan's airports in the past ten years, including floods, malfunctions of machinery and equipment, terrorist attacks, epidemics, and strikes. Taiwan's geographical position is special, for it is an island surrounded by the sea. There are earthquakes all year round and typhoons frequently coming in summer. Most people enter and leave the country relying on the air transport system (Lo et al., 2020). In Section 2, we have established a framework for airport resilience assessment, which includes dimensions of detection capability (D_1), resistance capability (D_2), rescue capability (D_3), and recovery capability (D_4), as well as 27 criteria (C_{11} to C_{47}) that are classified under them. First, experts must think carefully about how important these criteria are to airport resilience assessment, that is, weight determination. Then, the experts evaluated the performance of alternatives according to the definition of the criteria, and then obtained the ranking and the management implications for improvement planning.

Based on the Taiwan government's classification standards for airports, the decision-making team decided to evaluate the alternatives for Class A+ and Class A airports, including Taipei Airport (A_1), Taoyuan Airport (A_2), and Kaohsiung Airport (A_3). (Class A+ airport: more than 10 million passengers or more than 50,000 flights per year. Class A airport: more than 4 million passengers or more than 40,000 flights per year.) Relevant information for each alternative is shown in **Table 3**.

Table 3. Basic information of three international airports in Taiwan

Airport	IATA code	ICAO code	City	Class	Passenger flow in 2019
Taipei International Airport (A_1)	TSA	RCSS	Taipei	Class A	6,350,353 passengers
Taoyuan International Airport (A_2)	TPE	RCTP	Taoyuan	Class A+	48,689,372 passengers
Kaohsiung International Airport (A_3)	KHH	RCKH	Kaohsiung	Class A	7,506,753 passengers

According to **Table 3**, the alternatives are Taiwan's three major airports. They urgently need to have resilience to maintain the stability of people's entry and exit. It is hoped that by constructing a disaster resilience assessment method suitable for Taiwan, it will serve as a guide and thus assist other airports in improving resilience research. Next, the actual survey data and its calculation procedures are introduced.

4.2. Calculating criteria group weights with Bayesian BWM

Each expert performs 5 Bayesian BWM calculations, including the dimensions themselves and the criteria under the 4 dimensions. In terms of dimensions, experts were asked to compare the most important dimensions they judged with other dimensions to obtain BO vectors, as shown in **Table A1**. For example, Expert 1 believes that the most important dimension is D_1, which is about three times more important than D_2. And the other dimensions can also be evaluated in the same way. Similarly, the evaluation values of other dimensions compared to the least important dimension can constitute OW vectors, as shown in **Table A2**. **Tables A1** and **A2** include the evaluation information of the 23 experts. According to the calculation procedure introduced in Section 3.1, the optimal criteria group weights can be obtained, as shown in **Table 4**.

All BWM questionnaires must conduct a consistent test to ensure the logic and rationality of the experts in the process of filling out the questionnaires. The consistency ratio (CR) for any questionnaire is less than 0.03, and the average CR of the 23 questionnaires is 0.0118, indicating that the result of the questionnaires is reliable (Rezaei, 2015). According to the results in Table 4, the weight of resistance capability (D_2) is 0.377, so it is the most important dimension. In addition, Periodic inspection of airport runways (C_{12}), Proper isolation measures around the airport (C_{27}), Preparation of emergency plans and relief procedures (C_{35}), and Establishment of a recovery command center to coordinate the allocation of people, materials, and resources (C_{43}) are the most important criteria in each dimension. In terms of the overall system, the top five criteria are Proper isolation measures around the airport (C_{27}) $\succ$ Preparation of emergency plans and relief procedures (C_{35}) $\succ$ Number of security personnel and aviation police (C_{23}) $\succ$ Ground crew education and training on airport safety (C_{22}) $\succ$ Emergency procedures when flammables and explosives are found (C_{21}).

Table 4. Weighted results of Bayesian BWM calculation

Dimensions	Local weight	Ranking	Criteria	Local weight	Ranking	Global weight	Ranking
D_1	0.258	2	C_{11}	0.178	3	0.046	9
			C_{12}	0.180	1	0.046	6
			C_{13}	0.151	4	0.039	12
			C_{14}	0.179	2	0.046	7
			C_{15}	0.107	6	0.028	18
			C_{16}	0.088	7	0.023	21
			C_{17}	0.117	5	0.030	16
D_2	0.377	1	C_{21}	0.157	4	0.059	5

			C_{22}	0.159	3	0.060	4
			C_{23}	0.165	2	0.062	3
			C_{24}	0.109	7	0.041	11
			C_{25}	0.121	6	0.046	10
			C_{26}	0.122	5	0.046	8
			C_{27}	0.169	1	0.064	1
D_3	0.204	3	C_{31}	0.180	2	0.037	13
			C_{32}	0.146	4	0.030	17
			C_{33}	0.153	3	0.031	15
			C_{34}	0.101	6	0.021	23
			C_{35}	0.311	1	0.064	2
			C_{36}	0.109	5	0.022	22
D_4	0.161	4	C_{41}	0.143	3	0.023	20
			C_{42}	0.118	7	0.019	27
			C_{43}	0.216	1	0.035	14
			C_{44}	0.127	4	0.020	24
			C_{45}	0.151	2	0.024	19
			C_{46}	0.123	5	0.020	25
			C_{47}	0.122	6	0.020	26

In order to check whether the optimal group weights obtained and their ranking are reliable, Bayesian BWM provides a confidence test for ranking. Taking dimensions as an example, as shown in **Figure 2**, there is 90.87% of confidence that D_1 is more important than D_3. The average ranking confidence of the overall evaluation system is 87.58%, indicating that the criteria ranking has a high degree of confidence. Next, we apply modified PROMETHEE to integrate the performance values of the alternatives.

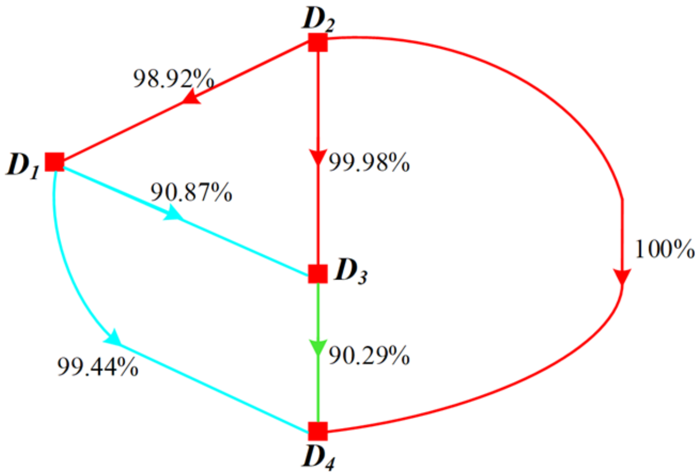

Figure 2. Confidence in ranking dimensions

4.3. Using modified PROMETHEE to calculate airport resilience performance

Assessing airport resilience is a complex and difficult task. In the face of unpredictable risks, it is difficult to establish perfect protection measures. Improvement strategies can only be formulated through past failure experiences. This research is a qualitative survey based on expert knowledge. The interview results are converted into computable data. PROMETHEE is effective in processing this type of data. **Table A3** presents the average survey opinion of 23 experts. For example, the performance of Taipei International Airport (A_1) in criterion C_{11} (ground staff's safety awareness and risk alertness at work) is rated 5.739. In the table, Planning and management of tarmacs, number of collisions between vehicles, machinery and aircrafts (C_{25}) and Cost of maintenance and reinforcement works for terminals (C_{42}) are "expected to be small" indicators (the smaller the evaluation values, the better), then the aspiration level is 1. By substituting the data of **Table A3** into the modified PROMETHEE calculation procedure introduced in Section 3.2, the leaving, entering and net flows of each alternative can be obtained. The preference function of the alternative solution can be found in **Table 5**. For example, the multi-criteria preference index of A_1 toward A_2 is 0.010, which is expressed as $\pi\left(A_1, A_2\right)=0.010$. All alternatives are unlikely to be better than the aspiration level, then $\pi\left(u, A^{aspire}\right)=0$, and conversely, the worst level is also not better than any alternative, then $\pi\left(A^{worst}, v\right)=0$. The rows and columns of the multi-criteria preference index $\pi(u,\ v)$ are summed separately to obtain the leaving flow $\theta^{+}(u)$ and the entering flow $\theta^{-}(u)$ of the alternative. With the same concept, the aspiration level will not have the entering flow, therefore, $\theta^{-}\left(A^{aspire}\right)=0$. On the contrary, the worst level will not have the leaving flow, therefore, $\theta^{+}\left(A^{worst}\right)=0$.

Table 5. Multi-criteria preference index for each alternative

	A_1	A_2	A_3	A^{aspire}	A^{worst}	Leaving flow
A_1	-	0.010	0.010	0	0.550	0.571
A_2	0.022	-	0.025	0	0.562	0.609
A_3	0.004	0.007	-	0	0.544	0.554
Aspire	0.450	0.438	0.456	-	1.000	2.344
Worst	0	0	0	0	-	0
Entering flow	0.475	0.455	0.491	0	2.656	

Table 6 presents the net flow and the ranking of all alternatives, A2 $\succ$ A1 $\succ$ A3. It is worth noting that the leaving flow of all alternatives is equal to the entering flow of all alternatives. It can be seen here that the performance of the three airports is better than the average ($\theta(u)>0$). Conventional PROMETHEE can only help understand the relative difference among the alternatives, but cannot advance effective suggestions for improvement. Through the modified PROMETHEE the gap between each airport and the aspiration level is known. Even though A_2 is the first-ranked airport, the overall evaluation performance is still 2.19 (2.344-0.154 = 2.19) units behind the aspiration level, indicating that there is still much room for improvement. Conventional PROMETHEE will consider A_2 as the expected value, and such a concept will cause decision makers to think that A_2 does not need improvement. The model proposed in this paper can overcome the above disadvantages and provide more reliable management implications.

Table 6. Analysis results of PROMETHEE

	A_1	A_2	A_3	A^{aspire}	A^{worst}

Leaving flow	0.571	0.609	0.554	2.344	0.000
Entering flow	0.475	0.455	0.491	0.000	2.657
Net flow	0.096	0.154	0.063	2.344	-2.657
Ranking	2	1	3		

4.4 Management implications and discussion

All the countries invest huge sums of money to strengthen risk management capabilities for critical infrastructure. However, air transport is the most important transportation system for Taiwanese people to enter and exit, and its resilience assessment is an important and difficult task. In order to improve the protection ability against unknown disasters, many airport resilience assessment models have been continuously proposed. We propose an MCDM model based on expert knowledge and use some soft calculation tools to transform qualitative surveys into quantifiable data that can be calculated.

After interviewing 23 professional aviation safety experts, Bayesian BWM and modified PROMETHEE were used to analyze and discuss the implications of management, as described below:

(i) First, the results of Bayesian BWM's analysis echo many studies. Proper isolation around the airport (C_{27}) is the most important criterion. In order to ensure the safety of the airport area, many airports are equipped with electronic equipment to support the outside fence to fully grasp the movements of people, vehicles and aircrafts in the control area. In addition, boarding corridors are equipped with thermal cameras to monitor and identify images within 3 kilometers. Today's security protection technology should be combined with electronic technology to replace manual patrolling and surveillance at any time to improve security protection efficiency (Willemsen and Cadee, 2018).

(ii) Second, Preparation of emergency plans and relief procedures (C_{35}) is the second most important criterion. Standard operating procedures (SOPs) for prioritizing incidents and disasters must be properly established to reduce the lead time for emergency response. The planning of this standard must be formulated in conjunction with relevant authorities such as the Airport Operation Control Center, the Airscle management department, and the Aviation Police Bureau (Yang et al., 2015; Bao and Zhang, 2018). In addition, the resistance capability at the time when airport risks occur has always been the concern of Taiwan’s disaster prevention departments. Manpower establishment, education and training planning, and special skills training are all key items for resilience assessment. These all reflect the importance of criteria C_{21}, C_{22} and C_{23}. (Skorupski and Uchroński, 2016; Zhao et al., 2017; Ergün and Bülbül, 2019; Singh et al. 2019).

(iii) Finally, according to the results of **Table 6**'s modified PROMETHEE, Taoyuan International Airport ($\boldsymbol{A_2}$) is a more resilient airport in Taiwan. With the development trend of intelligence and automation, Taoyuan Airport has proposed many safety system update plans, including the integration of new and old equipment, the improvement of monitoring equipment, and the introduction of the Internet of Things. For Taipei International Airport (A_1) and Kaohsiung International Airport (A_3), Taoyuan International Airport (A_2) is their benchmark. For all the alternatives, how much room there is for improvement can be known based on their distance from the aspiration levels, and further improvements towards the aspiration levels can be achieved.

More management implications can also be explored based on the analysis results of this study, and each alternative should be improved sequentially in accordance with the criteria with the greatest weight. The improvement suggestions put forward are not limited to Taiwan and can be used as a reference for all the international airports around the world to develop a more suitable resilience assessment model.

5. Sensitivity Analysis and Model Comparison

Sensitivity analysis can be used to understand whether the results of the assessment will differ due to changes in a certain variable. In MCDM, criterion weight is a conditional variable for the evaluation of the system. According to the weight results presented in Section 4.2, D_2 has the highest weight, and 4 criteria (C_{21}, C_{22}, C_{23} and C_{27}) under this dimension are included in the top 5 rankings. Therefore, we need to understand whether changes in D_2 will significantly affect the results of the overall analysis. The weight of D_2 was adjusted from 0.1 to 0.9, and the other dimensions were adjusted in equal proportions. The total weight of each run is required to be equal to 1, as shown in **Table 7**. The sensitivity analysis of the modified PROMETHEE was performed 9 runs by the weight combination of **Table 7**, and the ranking results of the alternatives are shown in **Table 8**. The alternatives for Run 1 to Run 9 remain $A_2 \succ A_1 \succ A_3$. Obviously, although D_2 is determined as an important dimension, it will not affect the ranking because of its weight change, indicating that the proposed hybrid model is robust.

Table 7. Dimensional weight allocation for 9 runs of sensitivity analyses

	Bayesian BWM	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9
D_1	0.258	0.373	0.331	0.290	0.248	0.207	0.166	0.124	0.083	0.041
D_2	0.377	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
D_3	0.204	0.295	0.262	0.230	0.197	0.164	0.131	0.098	0.066	0.033
D_4	0.161	0.232	0.206	0.181	0.155	0.129	0.103	0.077	0.052	0.026

Table 8. Ranking results after 9 runs of sensitivity analysis

	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9
A_1	2	2	2	2	2	2	2	2	2
A_2	1	1	1	1	1	1	1	1	1
A_3	3	3	3	3	3	3	3	3	3

Furthermore, this study also compares Bayesian BWM with other MCDM methods, including Simple Additive Weighting (SAW), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), VIsekriterijumska optimizacija i KOmpromisno Resenje (VIKOR) , Weighted Aggregated Sum Product Assessment (WASPAS) and Complex

Proportional Assessment (COPRAS). These methodologies are popular methods for MCDM integration alternative performance and ranking. The results of the model comparisons are shown in **Table 9**, and our proposed hybrid model is consistent with the alternative ranking results obtained by other models. However, the modified PROMETHEE calculation procedure is more rigorous. It makes alternative comparisons under each criterion making pairwise comparisons in order to obtain the overall net flows and learn about the gap from the aspiration level.

Table 9. Ranking results of the other five methods

	SAW	TOPSIS	VIKOR	WASPAS	COPRAS	Our method
A_1	2	2	2	2	2	2
A_2	1	1	1	1	1	1
A_3	3	3	3	3	3	3

5. Conclusions

This study proposes a novel MCDM model to implement airport risk protection and analysis, which overcomes the limitations of CBA, which previously only took cost into consideration. However, the occurrence of each risk is unique, and it is difficult to infer future disaster occurrences based on past statistics. The experience brought by past accidents or disasters can be transformed into valuable knowledge, which is often recorded as an expert's experience and documentation. Therefore, the methodology proposed in this study can systematically analyze experts' opinions. We have shown that Bayesian BWM can effectively determine criterion weights, especially useful in a multi-expert decision-making environment. The method also provides a test of the confidence of the criterion ranking to determine that the weights generated are reliable. Conventional PROMETHEE takes the existing relatively good performance value as the ideal solution, ignoring the potential for improvement. The modified PROMETHEE technology incorporates the concept of aspiration level to obtain the gap between alternatives and benchmarks, and prioritizes each airport. In addition, the sensitivity analysis and comparison of the models show that the proposed model is robust and practical.

The four dimensions, detection capability before the risk, resistance capability when risks occur, emergency measures and rescue capability for the risks, and recovery capability after the risk, constitute the airport resilience assessment system. The framework is novel and comprehensive, and it echoes the four dimensions of critical infrastructure resilience. We used the top three airports in Taiwan to demonstrate the analysis process, and the results of the analysis were submitted to the relevant airport security departments. They demonstrates that not only this study met their expectations, but also they gained more potential knowledge and information, which would help formulate a more useful improvement strategies in the future.

Although this study has made innovations and contributions to airport resilience assessment, there are other studies that can be extended. For example, combining the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique to consider the mutual influential relationships among the criteria, and combining fuzzy theory to adapt to the uncertainty of the evaluation environment.

Appendix A.

Table A1 BO vectors

	Best	D_1	D_2	D_3	D_4
Expert 1	D_1	1	3	5	7
Expert 2	D_1	1	5	2	3
Expert 3	D_3	5	8	1	5
Expert 4	D_1	1	2	3	6
Expert 5	D_4	7	9	5	1
Expert 6	D_2	9	1	3	6
Expert 7	D_2	5	1	2	4
Expert 8	D_2	2	1	5	3
Expert 9	D_2	4	1	3	7
Expert 10	D_2	7	1	9	8
Expert 11	D_2	9	1	5	7
Expert 12	D_2	4	1	8	6
Expert 13	D_2	2	1	1	2
Expert 14	D_2	4	1	9	5
Expert 15	D_2	2	1	3	4
Expert 16	D_1	1	5	7	9

	Best	D_1	D_2	D_3	D_4
Expert 17	D_2	5	1	7	9
Expert 18	D_2	3	1	2	4
Expert 19	D_1	1	2	5	7
Expert 20	D_2	3	1	4	8
Expert 21	D_1	1	2	3	9
Expert 22	D_1	1	3	5	7
Expert 23	D_2	5	1	7	3

Table A2. OW vectors after transposition

OW	Worst	D_1	D_2	D_3	D_4
Expert 1	D_4	7	3	2	1
Expert 2	D_2	5	1	3	2
Expert 3	D_2	2	1	8	2
Expert 4	D_4	6	5	3	1
Expert 5	D_2	2	1	2	9
Expert 6	D_1	1	9	5	2
Expert 7	D_1	1	5	4	2
Expert 8	D_3	4	5	1	3
Expert 9	D_4	2	7	3	1
Expert 10	D_3	2	9	1	1
Expert 11	D_1	1	9	3	2
Expert 12	D_3	3	8	1	2
Expert 13	D_4	1	2	2	1
Expert 14	D_3	3	9	1	2
Expert 15	D_4	3	4	2	1
Expert 16	D_4	9	3	2	1
Expert 17	D_4	2	9	2	1
Expert 18	D_4	2	4	3	1
Expert 19	D_4	7	4	2	1
Expert 20	D_4	3	8	2	1
Expert 21	D_4	9	5	4	1
Expert 22	D_4	7	4	2	1
Expert 23	D_3	2	7	1	3

Table A3. Average decision matrix for 23 experts

	A_1	A_2	A_3	Aspiration Level	Worst Level
C_{11}	5.739	5.522	5.391	10	1
C_{12}	5.870	5.739	6.000	10	1
C_{13}	5.565	5.826	5.696	10	1
C_{14}	5.696	5.913	5.478	10	1
C_{15}	6.391	6.435	6.217	10	1
C_{16}	5.913	6.609	5.913	10	1
C_{17}	5.957	6.391	5.783	10	1
C_{21}	5.565	5.956	5.609	10	1
C_{22}	5.609	5.522	5.609	10	1
C_{23}	5.522	5.696	5.522	10	1
C_{24}	6.391	6.044	6.000	10	1
C_{25}	3.174	4.174	3.304	1	10
C_{26}	6.000	6.261	6.174	10	1
C_{27}	5.826	5.826	5.739	10	1
C_{31}	6.000	6.609	5.957	10	1
C_{32}	5.565	5.652	5.565	10	1
C_{33}	5.783	6.174	5.956	10	1
C_{34}	5.783	6.000	5.957	10	1
C_{35}	5.957	6.261	5.913	10	1
C_{36}	6.261	6.348	5.913	10	1
C_{41}	5.957	5.913	5.783	10	1
C_{42}	4.130	2.652	4.087	1	10
C_{43}	6.000	5.870	5.957	10	1
C_{44}	6.043	5.826	5.913	10	1
C_{45}	5.870	5.913	5.652	10	1
C_{46}	5.783	5.957	5.783	10	1
C_{47}	5.913	6.130	5.870	10	1

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