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Evaluation of Autonomous Vehicle Applications in Smart Airports using Dombi Bonferroni Operator based CIVL-BWM-TODIM Decision Making Methodology

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Abstract: Recent advancements on autonomous vehicles (AVs) have revolutionized the aviation industry, providing great potential to enhance sustainability for this fuel-intensive industry. Diverse operation types of AVs at airports have emerged (e.g., for baggage/passenger movement). This study aims to provide a guideline on how to switch from the traditional human-driving vehicle operations to AV operations, to help improve the smartness and sustainability of airport operations. Five alternative operation types are evaluated under ten criteria. We propose a new CIVL-BWM-TODIM with Dombi Bonferroni mean operator (DBM) decision framework. The combination of the Continuous Interval-Valued Linguistic tool (CIVL) and the Best Worst Method (BWM) improves the criterial evaluation consistency, and the integration of CIVL and TODIM increases the evaluation accuracy on human language and psychological feelings. Besides, the DBM operator helps effectively integrate information from different experts. Results suggest that applying AVs for both functional activities and scheduled people delivery is the best alternative to build smart and sustainable airports. Sensitivity analyses are conducted to examine the impacts of various parameters on decision making. Moreover, comparative analysis over existing decision-making methods are carried out to validate the merits of the proposed approach.

Keywords: Decision support; Sustainability; Autonomous vehicles, Airport operations; Aviation

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1. Introduction

Owing to the fast development of communication technologies and artificial intelligence technologies, the application of autonomous vehicles (AVs) in the real world is no longer a fiction (Van Brummelen et al., 2018). Giants in AVs like Nvidia have established many real-world application projects in various industries (Pamucar et al., 2022), and the online appendix A lists some of them. Prominently, the usage of AVs at airports has become increasingly important (Deveci et al., 2022). The reasons of the bright future of AVs at airports are multi-facet. First, the transportation at airports is relatively simpler than in public road networks. Second, it has become increasingly challenging for the traditional human-labor based operations to satisfy the rapidly growing air traffic for both passengers and cargo (Choi et al., 2019; Wen et al., 2022). Third, the application of AV shows great potential to improve the smartness and sustainability level of airport operations.

With the assistance of AVs, it is believed that the airport operations can be significantly improved. First of all, as AVs can calculate the optimal speed to make optimized acceleration and deceleration decisions, AVs can decrease energy costs and enhance environmental sustainability by reducing fuel consumption and carbon emissions compared with traditional human-driving cars. Second, AVs facilitate longer working time as they do not need to take rests and day-offs like a human driver. Third, with autonomous technologies, airports are able to cut off much human labor and the related payment costs. Fourth, the human errors widely existing in traditional airport operations could be avoided. Although applying AVs at airports is advantageous in various aspects, and it is true that many airports have started their trial, the optimal operation format of AVs at airports is still unknown. This work studies five potential operation types for AVs at airports based on 10 decision criteria. We approach five experts in the area (i.e., airport manager) to obtain their opinions towards each criterion through face-to-face meetings. Applying the developed CIVL-BWM-TODIM with DBM, we can make recommendations. Moreover, we carry out sensitivity analysis to test the impacts of various parameters on decision making, and further conduct comparative analysis to examine the validity and superiority of the proposed approach over other existing methods. The review of the existing literature is placed in online appendix B.

In terms of methodology, this paper presents a new multi-criteria decision-making framework under the continuous interval-valued linguistic (CIVL) tool, with three main algorithms: (i) the Best Worst Method (BWM) to obtain the weighting of each selection criterion, (ii) the Dombi Bonferroni mean operator (DBM) to integrate information from all experts (Liu et al., 2018) and (iii) the TODIM which is a type of interactive multi-criteria decision making method based on the Prospect theory. The overall decision framework is thus named as CIVL-BWM-TODIM with DBM. The combination of CIVL and BWM improves the ability of the decision framework in dealing with fuzzy linguistic information, which provides a more accurate evaluation methods (instead of a simple number) and a more granular form of assessment between different criteria. Thus, the consistency of the evaluations on criteria is improved. In addition, to improve the agility in decision making as well as to enhance the understanding of the relationships between various elements, the DBM is applied to integrate the information collected from different experts which can also help eliminate the influences of invalid data. Moreover, the integration of CIVL and TODIM improves the calculation precision of the partial dominance degree by using the operator in CIVL (instead of using given numbers as in the traditional TODIM method). Overall, the CIVL-TODIM integrated framework is advantageous in the following aspects: 1) It facilitates more accurate evaluations on human language, while people's subjective psychological feelings could be considered, which can't be achieved by other ranking methods existing in the literature; 2) It effectively reflects human psychological feelings under risks; 3) The attenuation factor of loss can be set by different scenarios which matches the reality.

We summarize the benefits of the proposed CIVL-BWM-TODIM methodology as follows:

- The proposed CIVL-BWM-TODIM with DBM multi-criteria skeleton is the first method which integrates BWM and TODIM under the continuous interval-valued linguistic concept with DBM.
- The reality can be more accurately described by considering evaluation consistency and human psychological behavior.
- The decision model is more flexible, and the relationships between various elements can be better understood.
- Abundant human language expressions can be considered.

2. Alternatives and criteria

According to the current practice, we investigate five alternative operation types of AVs at airports (Afonin et al., 2022; Hilgarter & Granig, 2020; Morris et al., 2015) based on 10 evaluation criteria (Pang et al., 2021; Pavlou, 2003; Säther, 2021) as below. The detailed descriptions for the alternatives and criteria are presented in online appendix C.

Alternatives

- A1: AV for functional activities only

- A2: AV for on-demand people delivery only
- A3: AV for scheduled people delivery only
- A4: AV for both functional activities and on-demand people delivery
- A5: AV for both functional activities and scheduled people delivery

Criteria

- (C1) Contribution to airport autonomy level
- (C2) Safety concerns
- (C3) Staff acceptance
- (C4) Management challenge
- (C5) Resource usage
- (C6) Sustainability
- (C7) Operation efficiency
- (C8) Social welfare
- (C9) Losses due to mis-operations
- (C10) Operations costs

3. The proposed CIVL-BWM-TODIM with DBM decision framework

This section describes the main 4 components of the decision framework we develop in this study one by one.

3.1. The CIVLTS

The continuous interval-valued linguistic term set (CIVLTS) is a trendy fuzzy linguistic method that supports ample expressions of linguistic assessments (Liao et al., 2018; Rodriguez et al., 2011).

3.1.1. Definition

Let X be a set of linguistic variables ($x_i \in X(i = 1,2, \dots \dots m)$) and S be a linguistic term set (shorted as LTS)($S = \{S_\alpha | \alpha = -\tau, \dots - 1,0,1, \dots \tau\}$). The CIVLTS on X, as a mathematical form, $\widetilde{H_S}$, can be expressed by formula $\widetilde{H_S} = \{< x_i, \tilde{h}_s(x_i) > |x_i \in X\}$, where x_i is the linguistic variable which represents an evaluation, like "between a little high and high but closer to high with 70% proportion". S is a linguistic term, e.g., $S = \{S_{-3} = \ verylow,\ S_{-2} = low,\ S_{-1} = \ a\ little\ low,\ S_0 = \ medium,\ S_1 = \ a\ little\ high,\ S_2 = high,\ S_3 =$

$veryhigh\}$. Besides, $\tilde{h}_s(x_i)$ is regarded as the subset of the continuous internal-valued form of S and can be expressed as $\tilde{h}_s(x_i) = [S_{L_i}, S_{U_i}]$, where $L_i, U_i \in [-\tau, \tau]$ and $L_i \leq U_i$. Thus, $\tilde{h}_s(x_i)$ can be named as the continuous interval-valued linguistic element (CIVLE), which stands for the possibility of the linguistic variable x_i to S. Besides, S_{L_i} is the lower bound of $\tilde{h}_s(x_i)$ and S_{U_i} is the upper bound of $\tilde{h}_s(x_i)$.

Treating the S above as a linguistic term set, referring to the above example of "between a little high and high but closer to high with 70% proportion", if we use a CIVLE to denote the linguistic variable, it should be $[s_{1.7}, s_2]$. For comparison, if we use the traditional uncertain linguistic variable (Xu, 2004) and the hesitant fuzzy linguistic element (HFLE), the linguistic variable should be $[s_1, s_2]$ and $\{s_1, s_2\}$, respectively. The latter is a discrete set and neither of them shows the percentage description. Thus, compared with traditional uncertain linguistic variables and the HFLTS (i.e., hesitant fuzzy linguistic term set), more detailed and ample expressions of linguistic evaluations can be captured and presented by CIVLTS. For crisp numbers, if we use 1 for "a little high" and 2 for "high", then 2 would be used to represent the above linguistic variable. However, from "between a little high and high but closer to high with 70% proportion", we know that the psychological feeling is actually closer to "2", while this concept can't be represented by simple crisp numbers. Thus, CIVLE is able to grasp richer information from the linguistic expressions of human.

3.1.2. Transformation function

Transformation function translates CIVLE into a reasonable number to ensure that it can be integrated with other multi-criteria decision making methods. In fact, the absolute bias of the contiguous linguistic terms in the same linguistic term set can be sometimes unequal. For instance, the absolute bias between "very low" and "low" could be smaller than the bias between "little high" and "high" for the dominance level of the autonomous vehicle operation types. Thus, an accurate approach to transferring linguistic terms into numeric value is needed.

In the literature, three transformation functions to translate linguistic terms into their semantic have been widely adopted, as described in online appendix D.1 (Wang et al., 2014). Consider the set s_t , $t \in [-\tau, \tau]$ as a linguistic term and φ_t as a numeric value that represents the semantic of s_t. The conversion relationship between s_t and φ_t can be expressed as: $g : s_t \rightarrow \varphi_t$, and g^{-1}: $\varphi_t \rightarrow s_t$, $t \in [-\tau, \tau]$.

3.1.3. CIVLEs comparison

The transformation function turns the upper and lower bounds of CIVLEs into numbers. In traditional AHP or BWM, we need to allocate a crisp number (absolute figure) to stand for a preference degree of a criterion over another one (usually the larger the number, the higher the preference degree). Thus, if the CIVLE linguistic evaluation method is adopted, we need to set a rule to compare the different CIVLEs. Liao et al. (2018) define the expected function of $\tilde{h}_s$ based on the transformation function as $E(\tilde{h}_s)$. It means that the greater the expectation between different $\tilde{h}_s$, the higher the preference degree. Besides, if the expectations of two $\tilde{h}_s$ are equal, then the reference variance is set as $D(\tilde{h}_s)$ (the smaller the variance, the higher the preference degree). The complete formulas for $E(\tilde{h}_s)$ and $D(\tilde{h}_s)$ are presented in online appendix D.2.

3.2. Combining CIVL-BWM

In this section, the weightings of all criteria are computed by integrating CIVL and BWM, which facilitates the evaluation of abundant information based on the cognitive complicated linguistic information representation tool and the high consistency by using fewer pairwise comparisons (Mou et al., 2017). The mathematical model for obtaining weightings of criteria is shown below. The original BWM and the combining process between CIVL and BWM are described in detail in online appendix D.3.

$$\min \xi$$
$$s.t.\begin{cases} \left|w_B^- - U\left(\tilde{h}_s^{Bj-}\right) * w_j^-\right| \le \xi \\ \left|w_B^+ - U\left(\tilde{h}_s^{Bj+}\right) * w_j^+\right| \le \xi \\ \left|w_j^- - U\left(\tilde{h}_s^{jW-}\right) * w_W^-\right| \le \xi \\ \left|w_j^+ - U\left(\tilde{h}_s^{jW+}\right) * w_W^+\right| \le \xi \\ \sum_{i=1}^{\Omega-j} w_i^+ + w_j^- \ge 1 \\ \sum_{i=1}^{\Omega-j} w_i^- + w_j^+ \le 1 \\ w_j^+ \ge w_j^- \ge 0 \end{cases} \quad j = 1,2,\ldots\ldots n \tag{1}$$

It should be noted that ξ is a slack variable which stands for the deviation degree, and Ω $=\{1,2,\ldots\ldots,n\}$ is the criteria index set. The constraints in the model consist of three parts. The first four constraints regulate that the absolute difference between the ratio of weightings and the utility of evaluation should be smaller than the slack variable ξ. Then, according to Sugihara et al. (2004), the next two constraints (i.e., $\sum_{i=1}^{\Omega-j} w_i^+ + w_j^- \geq 1, \sum_{i=1}^{\Omega-j} w_i^- + w_j^+ \leq 1$) decrease the redundant solution space, which replace the constraint of crisp weightings of $\sum_{j=1}^{n} w_j = 1$. The last constraint (i.e., $w_j^+ \geq w_j^- \geq 0$) indicates the relationship between the upper/lower bounds of uncertain weightings.

If the value of ξ^* is close to 0, it means that the consistency level is high. Using the optimal interval weightings by solving model (1), we can compute the crisp weighting for each criterion. Computation details are shown in online appendix D.3.7.

3.3. Dombi Bonferroni mean operator with CIVLEs

CIVL is a special evaluation language, while Dombi Bonferroni mean operator is a way to integrate different information. Thus, combining the two methods can effectively express the evaluation of the group, making the analyses more complete and rigorous. Following the TrFNDBM (i.e., Dombi Bonferroni mean operator with triangular fuzzy numbers) proposed by Jana et al. (2019), the Continuous Interval-Valued Linguistic Dombi Bonferroni mean operator (CIVLDBM), the interval number Dombi Bonferroni mean operator (INDBM) and the crisp number Dombi Bonferroni mean operator (CNDBM) are presented in online appendix D.4.

3.4. Combining CIVL-TODIM

The steps of conducting ranking are almost the same as the traditional TODIM, except for the operator of partial dominance degree (Nie et al., 2019). The distance formula of CIVLEs $d(\tilde{h}_s^1, \tilde{h}_s^2)$ as a component of the partial dominance operator and the traditional TODIM are shown in online appendix D.5.

The overall CIVL-BWM-TODIM-DBM procedure is briefly described below and the framework is depicted in the online appendix E.

Step 1: Decide the criteria vector $C = \{c_1, c_2, \dots \dots, c_n\}$ and select the proper linguistic term set $S = \{S_\alpha | \alpha = -\tau, \dots - 1,0,1, \dots \tau\}$.

Step 2: Determine the best criterion c_B as well as the worst criterion c_W according to the experience of each decision maker.

Step 3: Make pairwise comparisons between the best criterion c_B and each other criterion, and between each other criterion and the worst criterion c_W under the CIVL. Then, form the CIVL-BO and CIVL-OW preference vector $\tilde{H}_s^B = (\tilde{h}_s^{B1}, \tilde{h}_s^{B2}, \dots \dots, \tilde{h}_s^{Bn})$ and $\tilde{H}_s^W = (\tilde{h}_s^{1W}, \tilde{h}_s^{2W}, \dots \dots, \tilde{h}_s^{nW})^T$ for each expert.

Step 4: Calculate the crisp weightings and consistency indicators based on the proposed mathematical models and INDBM as in online appendix D.

Step 5: Use the same linguistic term set as in step 1 to obtain the combined evaluation values for all experts in terms of each alternative under different criteria in CIVL based on CIVL-DBM.

Step 6: Obtain the alternative ranking by TODIM (following the TODIM steps as discussed in online appendix D). By far, we should have obtained the crisp weighting of each criterion and the evaluation matrix in CIVL. Using the TODIM method, what we need to pay attention to is that each element of the evaluation matrix is a CIVLE (this is different from the traditional TODIM method in which a fixed number is used). Thus, we shall apply the distances between CIVLEs instead of the gap between the real numbers.

4.Experiment results

This section carries out numerical experiments to test the results obtained by the developed CIVL-BWM-TODIM with DBM decision-making framework, examine the impacts of various parameters on decision making, as well as compare with existing methods. The values of parameters p, q, ρ in the three operators CIVLDBM, INDBM and CNDBM are all set as 1.

4.1 Criteria weighting calculation

The process of obtaining the weighting of each criterion is shown below:

Step1: Decide the criteria vector and linguistic term set. Recall that in Section 2, ten criteria for the AV operation types are determined. Then, the expert sets a linguistic term set $S = \{S_{-4} = verylow,\ S_{-3} = low,\ S_{-2} = moderately\ low, S_{-1} = a\ little\ low,\ S_0 = medium,\ S_1 = a\ little\ high, S_2 = moderately\ high,\ S_3 = high,\ S_4 = \ veryhigh\}$.

Step2: Select the best and worst criterion for each expert. For instance, Safety concerns (C2) and Losses due to mis-operations (C9) are set as the best and worst criterion by the first expert, respectively.

Step 3: Make pairwise comparisons of CIVL-BO and CIVL-OW for each expert. For example, the first expert is suggested to conduct the comparisons between the best criterion (C2) with each other criterion (i.e., CIVL-BO), and between each other criterion with the worst criteria (C9) (i.e., CIVL-OW) with linguistic assessment according to the linguistic term set S.

Besides, the value of best/worst is also given by the expert, which is 9. Thus, based on Step1, the value of parameter a can be obtained as $\sqrt[2\tau]{\frac{best}{worst}} = \sqrt[8]{9}$.

Step4: Obtain the interval weighting and the maximum bias between the fully consistent preference degree and the actual evaluation degree for each expert.

The interval weighting vector of all criteria and ξ^* can be obtained by solving the mathematical models in appendix D. The interval weighting vector can thus be acquired as: w^*= ([0.096,0.114], [0.158,0.163], [0.120,0.130], [0.073,0.086], [0.091,0.102], [0.066,0.066], [0.079,0.086], [0.055,0.086], [0.043,0.043], [0.055,0.079]). Besides, the value of ξ^* is 0.033. The interval weightings and maximum deviation values for each expert are shown in Table 1 as below.

Table 1. The interval weightings and maximum deviation

expert	interval weighting	ξ^*
1	([0.096,0.114], [0.158,0.163], [0.120,0.130], [0.073,0.086], [0.091,0.102], [0.066,0.066], [0.079,0.086], [0.055,0.086], [0.043,0.043], [0.055,0.079])	0.033
2	([0.089,0.112], [0.146,0.163], [0.121,0.128], [0.068,0.085], [0.084,0.100], [0.054,0.064], [0.079,0.085], [0.064,0.085], [0.051,0.051], [0.064,0.078])	0.030
3	([0.094,0.111], [0.153,0.168], [0.098,0.128], [0.073,0.085], [0.074,0.100], [0.048,0.048], [0.065,0.085], [0.078,0.085], [0.059,0.064], [0.063,0.078])	0.024
4	([0.114,0.114], [0.151,0.161], [0.115,0.131], [0.053,0.087], [0.087,0.102], [0.066,0.066], [0.058,0.087], [0.066,0.087], [0.063,0.066], [0.050,0.050])	0.037
5	([0.096,0.111], [0.157,0.171], [0.104,0.127], [0.073,0.084], [0.093,0.099], [0.059,0.064], [0.079,0.084], [0.060,0.084], [0.050,0.050], [0.060,0.077])	0.021

Based on the INDBM, the interval weightings of five experts are combined into an integrated interval weighting vector, which is presented in Figure 1.

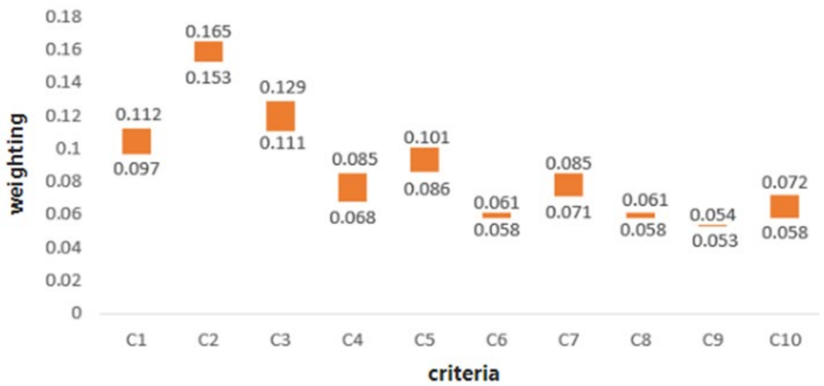

Figure 1. The chart of combined interval weighting

Then, the combined crisp weighting of each criterion is obtained which is (0.119, 0.180, 0.136, 0.086, 0.105, 0.067, 0.089, 0.084, 0.060, 0.073).

4.2 Operation type alternatives ranking

The process of ranking the types for the application of AVs at airports is presented below:

Step 5: Obtain combined CIVL evaluation for different alternatives against each other criterion. The linguistic assessments of all experts are transformed into CIVL evaluations. Then, the combined CIVL assessment matrix is obtained based on CIVLDBM, which is shown in Table 2.

Table 2. combined CIVL evaluations for different alternatives against each other criterion

alternatives criteria	A1	A2	A3	A4	A5
C1	$[s_{0.7},s_{1.4}]$	$[s_{1.3},s_{1.7}]$	$[s_{2.8},s_{3}]$	$[s_{2.9},s_{3.3}]$	$[s_{2.3},s_{2.7}]$
C2	$[s_{1.8},s_{2.3}]$	$[s_{-0.9},s_{-0.6}]$	$[s_{-0.7},s_{-0.2}]$	$[s_{-2},s_{-1.8}]$	$[s_{-1.9},s_{-1.6}]$
C3	$[s_{2.2},s_{2.6}]$	$[s_{0.1},s_{0.9}]$	$[s_{0.9},s_{1.1}]$	$[s_{0.2},s_{0.2}]$	$[s_{0.9},s_{1.2}]$
C4	$[s_{2.5},s_{2.9}]$	$[s_{-1.3},s_{-1.1}]$	$[s_{0.1},s_{0.3}]$	$[s_{-2.0},s_{-1.1}]$	$[s_{-1.5},s_{-1.0}]$
C5	$[s_{2.2},s_{2.5}]$	$[s_{3},s_{3.3}]$	$[s_{2.8},s_{3.1}]$	$[s_{3.1},s_{3.7}]$	$[s_{3.3},s_{3.8}]$
C6	$[s_{2.2},s_{3.0}]$	$[s_{3},s_{3.5}]$	$[s_{3.1},s_{3.4}]$	$[s_{2.1},s_{2.7}]$	$[s_{3.0},s_{3.4}]$
C7	$[s_{2.6},s_{3.0}]$	$[s_{2.4},s_{3.0}]$	$[s_{3.5},s_{4}]$	$[s_{3.0},s_{3.2}]$	$[s_{3.3},s_{3.9}]$
C8	$[s_{-1.9},s_{-1.5}]$	$[s_{-0.7},s_{0}]$	$[s_{-1},s_{-0.4}]$	$[s_{-2.0},s_{-1.5}]$	$[s_{-2.1},s_{-1.9}]$
C9	$[s_{3.0},s_{3.2}]$	$[s_{0.3},s_{0.6}]$	$[s_{1.0},s_{1.9}]$	$[s_{2.9},s_{3.2}]$	$[s_{3.4},s_{3.9}]$
C10	$[s_{2.1},s_{2.3}]$	$[s_{3.3},s_{4.3}]$	$[s_{3.0},s_{3.5}]$	$[s_{3.5},s_{3.7}]$	$[s_{3.7},s_{4.0}]$

Step 6: Rank the alternatives. In this step, the value of the attenuation factor of loss (i.e., θ) is set as 1. The global dominance of each alternative is computed by the CIVL-TODIM method, which is (0.254, 0.027, 0.936, 0, 1). Thus, the priorities of alternatives are arranged from the largest to the smallest as A5 $>$ A3 $>$ A1 $>$ A2 $>$ A4.

4.3 Sensitivity analysis

In this section, we carry out the sensitivity analysis from two aspects. The first is to test the influence of parameters p, q and ρ on determining weightings, and the second is to test the impact of parameter θ on the ranking process.

In the process of obtaining the weightings of criteria, the INDBM is used to integrate the interval weightings of experts. In this paper, the values of parameters p, q and ρ are initially set as 1. The influence of altering the values of these parameters can be observed in four scenarios which are shown in Figure 2 and Figure 3. Under the first scenario(S1), the value of parameter p varies from 1 to 50 while the values of q and ρ remain as 1. Under the second scenario(S2), the value of parameter q changes from 1 to 50 whilst the other two parameters are kept as 1. It is noted that the trend of crisp weighting value of each criterion should be the same as the S1 since p and q are symmetric in INDBM. Similar to the two instances above, the value of parameter ρ is altered but others keep the same under the third scenario(S3). For the last scenario(S4), the values of all parameters are varied simultaneously from 1 to 50. It is obvious that the order of criteria keeps in line with the ranking in section 4.1 for all scenarios. For the crisp weighting value, the changes in S3 and S4 are more significant than the changes in S1 and S2, since parameter ρ is in the form of an exponential function which better reflects the differences when ρ increases. Although the biases exist, the largest difference for the four scenarios is 0.00592 which does not alter the final ranking. However, in this experiment, when we are using CIVLDBM to integrate expert evaluation information, a slight change in the value of ρ leads to a different ranking result, which is caused by the excessive difference in the evaluation value of different alternatives under different criteria by individual experts. Thus, the values of these parameters are suggested to be 1 to ensure that the experiment takes into account the internal connections between the different factors.

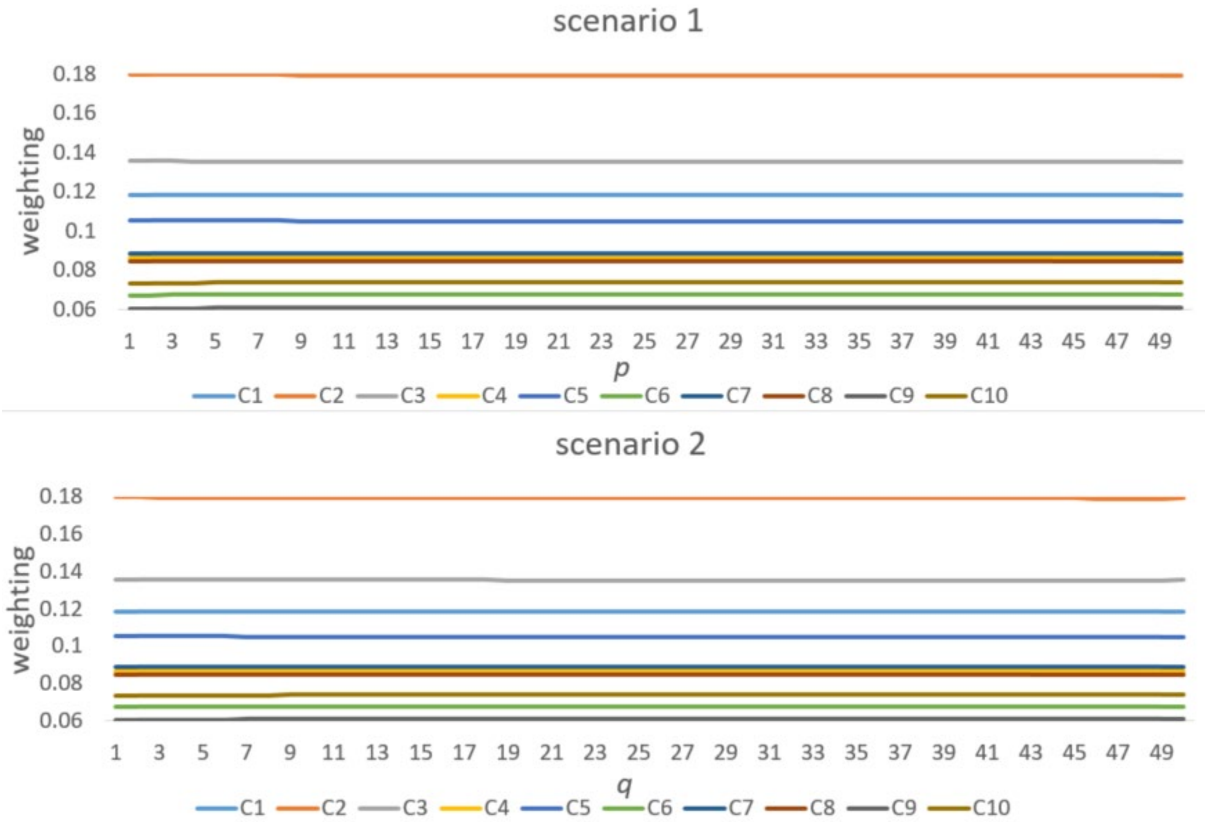

Figure 2. Weightings obtained when varying the values of p and q

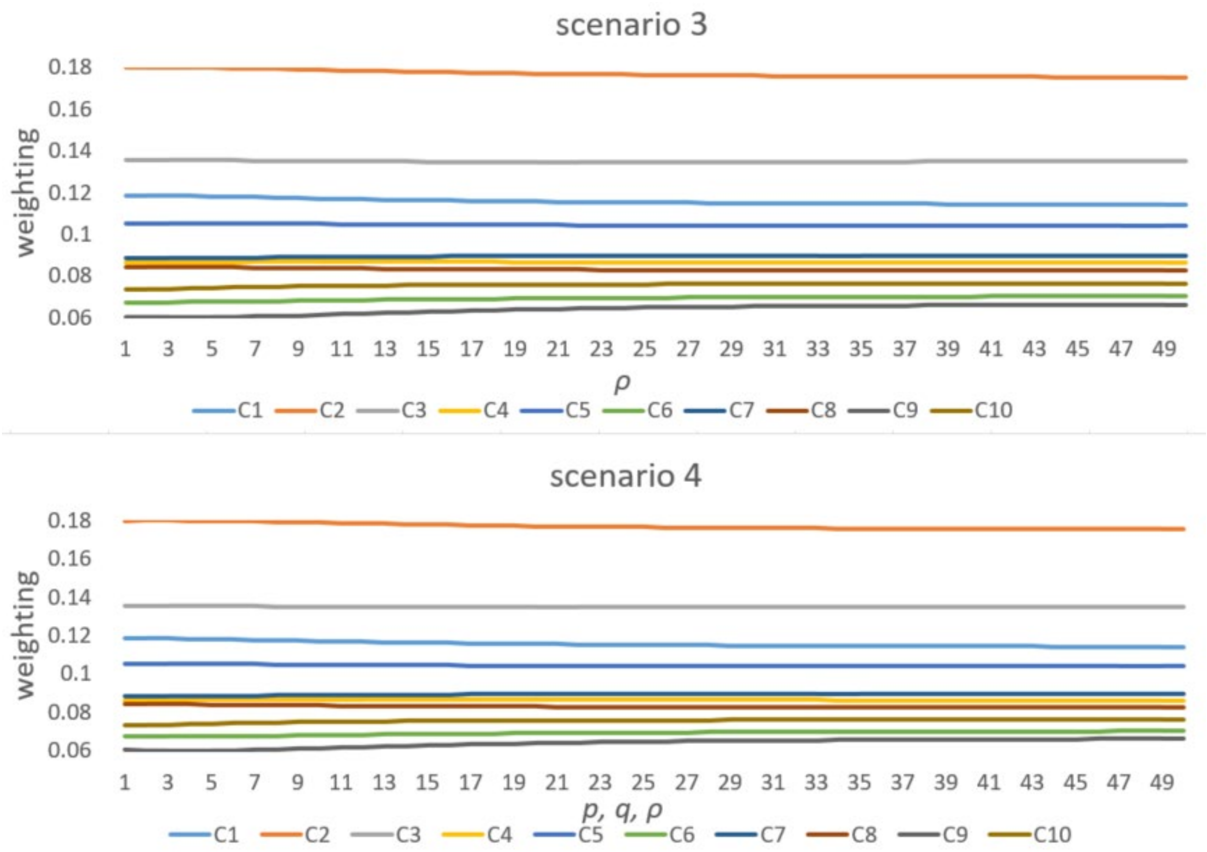

Figure 3. Weightings obtained when varying the values of ρ and p, q, and ρ

For the attenuation factor of loss (i.e., θ in TODIM), we initially set its value as 1. In order to analyze the impact of θ on the global dominance degree and the final ranking, the value of θ is varied from 0.1 to 5 and the result is illustrated in Figure 4. It indicates that, if $\theta \leqslant 2.5$, the ranking result of all alternatives is consistent with the ranking in section 4.2. The global dominance degrees of A1, A2 and A3 increase gradually as θ grows. When $\theta > 2.5$, the order of A3 and A5 is changed because the sensitivity of losses for the decision makers is reduced to a certain level. To be specific, for A3, because of the increase of θ, the losses for the global dominance degree caused by the negative partial dominance degree reduced and the gains caused by the positive partial dominance were equal. Besides, the loss of A5 is not as sensitive as the loss of A3. Thus, A3 replaced A5, and becomes the best alternative. Furthermore, when θ is set as 100 and 1000, the sorting results for these two scenarios are the same, which means that all losses can be ignored if θ is large enough. The above analysis is consistent with the prospect theory, so that the feasibility of our proposed method is validated.

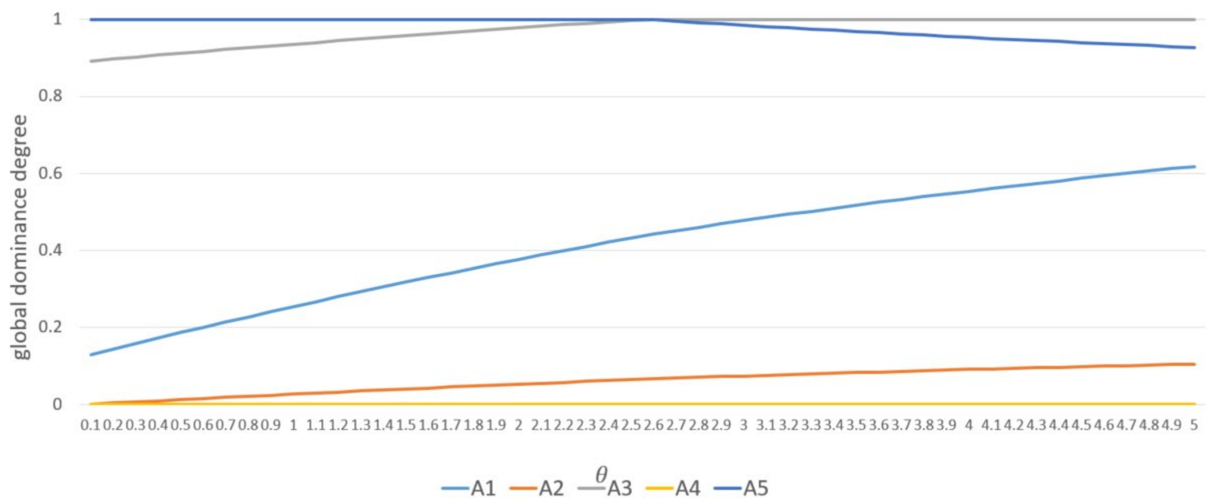

Figure 4. Global dominance degree for varying value of θ

4.4 Comparative analysis

We carry out comparative analysis against BWM-TODIM and CIVL-TODIM, which demonstrates the merits of our proposed approach. The results of the above two methods and CIVL-BWM-TODIM with DBM are summarized as below. The detailed description of BWM-TODIM and CIVL-TODIM are presented in appendix F.

Table 3. The results of CIVL-BWM-TODIM, BWM-TODIM and CIVL-TODIM with DBM

method (with DBM)	**crisp weighting of criterion**	**global dominance degree/weight score of alternative**	**ranking**	ξ^*
CIVL-BWM-TODIM	[0.119,0.180,0.136, 0.086,0.105,0.067, 0.089,0.084,0.060, 0.073]	[0.254,0.028,0.936,0,1]	A5 A3 A1 A2 A4	(0.033 0.030 0.024 0.037 0.021)
BWM-TODIM	[0.132,0.229,0.163, 0.075,0.086,0.043, 0.078,0.060,0.033, 0.045]	[0,0.374,0.841,0.246,1]	A5 A3 A4 A2 A1	(0.090 0.067 0.052 0.066 0.065)
CIVL-BWM	[0.119,0.180,0.136, 0.086,0.105,0.067, 0.089,0.084,0.060, 0.073]	[0.208,0.191,0.210,0.178,0.215]	A5 A3 A1 A2	(0.033 0.030 0.024 0.037

		A4	0.021)

Since all three methods use DBM, we focus on the differences between these methods. The advantages of CIVL-BWM-TODIM are reflected in three aspects. First, the CIVL-BWM-TODIM is shown to be effective by comparing the rankings of alternatives obtained by the three methods (as shown in Table 3). It is clear that the rankings of alternatives obtained from CIVL-BWM-TODIM and CIVL-BWM are the same. However, there are small differences in the ranking of alternatives obtained from CIVL-BWM-TODIM and BWM-TODIM. In CIVL-BWM-TODIM, A4 ranks the last and A1 ranks the third. Differently, A4 ranks the third and A1 ranks the last in BWM-TODIM. Besides, A2, A3 and A5 get the same ranking positions in CIVL-BWM-TODIM and BWM-TODIM. Thus, the CIVL-BWM-TODIM is shown to be valid.

Second, the indicators of the consistency of the comparisons (i.e., ξ^*) in getting weightings are not the same from CIVL-BWM-TODIM and BWM-TODIM. It is obvious that, for each expert, the ξ^* in CIVL-BWM-TODIM (i.e., 0.033, 0.030, 0.024, 0.037, 0.021) is smaller than the ξ^* in BWM-TODIM (i.e., 0.090, 0.067, 0.052, 0.066, 0.065). Thus, instead of evaluating criteria in crisp numbers, using CIVLEs to represent the cognitive linguistic assessments leads to higher consistency of pairwise comparisons.

Last, even though the same ranking is suggested by CIVL-BWM-TODIM and CIVL-BWM, the former needs fewer pairwise comparisons. In CIVL-BWM, after the crisp weightings of criteria are obtained, for each criterion, the expert needs to choose the best and worst alternatives, make pairwise comparisons in CIVL, and then establish an optimization model for solution. Based on the above steps, the score of each alternative against different criteria can be obtained. Then, the weight scores are calculated to deduce the ranking of all alternatives. Thus, CIVL-BWM needs more steps compared with CIVL-BWM-TODIM, which also validates the merits of the proposed CIVL-BWM-TODIM.

5. Discussions

Through the analysis based on the proposed decision-making framework, we see that A5 (for both functional activities and scheduled people delivery) is mostly recommended, followed by A3 (for scheduled people delivery only). We could see that applying AVs for scheduled people delivery is much more preferred than on-demand people delivery. It is reasonable as managing on-demand vehicle routing is much more challenging compared with managing scheduled activities. Thus, at the early development stage of smart airport development, experts would suggest to start from scheduled people delivery. Moreover, as human factors are the main reasons for previous operations errors, using AV for functional activities is thus highly recommended.

6. Conclusions

Nowadays, AVs are increasingly applied in various aspects of airports. The introduction of AVs helps enhance the operations efficiency and sustainability level of airports. However, it also brings challenges (e.g., people's safety concerns and technology acceptance level). Even though the application of AVs has come into reality, little is known on what is the best operation type at airports. This paper makes evaluations on five alternative operation types of AVs at airports under ten criteria. A multi-criteria decision making framework, CIVL-BWM-TODIM, is proposed. Results suggest that applying AVs for both functional activities and scheduled people delivery is the best alternative. However, if there are too many criteria to be considered, the linguistic terms set chosen in this paper can only be applied to evaluate criteria in a relatively small range, and therefore the gap between different criteria cannot be well represented by CIVLE. Thus, we propose to combine CIVL with other methods for calculating weights (e.g., a new algorithm based on the fuzzy logarithmic function) to overcome the shortcoming of the existing method in the future.

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