Selecting an air traffic flow management action to be implemented during airport congestion using a hybrid fuzzy MCDM approach

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Abstract. The issue of flight delays in a growing country like the Philippines is considered very rampant affecting not only an airline's on-time performance but also an airport's operational reputation. In addition to that, unfavorable air travel experience is aggravated, thus, creates unattractiveness of demand for air travel. Ninoy Aquino International Airport (NAIA), being the country's major gateway to both international and domestic air travel, has devised solutions to address this issue guided by the fact that airport congestion is the main cause for such. These solutions are represented by air traffic flow management (ATFM) actions such as ground holding, airborne holding, rerouting, and speed controlling. This paper focuses on selecting the most suitable ATFM action to be applied in the event of airport congestion. An integrated DEMATEL, ANP, and TOPSIS, along with the concepts of fuzzy set theory is used to achieve the objective of this paper. The results revealed that decision-makers in the commercial aviation industry favored to apply rerouting to address airport congestion in a scenario when an aircraft has already taken-off. Furthermore, this preference of ATFM action is based from the belief of decision-makers that aviation safety should be upheld at all times.

Keywords: airport congestion, ANP, DEMATEL, fuzzy set theory, TOPSIS

1. INTRODUCTION

In as early as 1970s, the Philippines has long faced the issue on flight delays along with the continuing growth of demand for air travel at a rate of 11% annually. The country's major airports are prompted to address such issue considering that the entire air transportation system is at stake. Three major entities in the commercial aviation industry, namely airport management, airlines industry, and air traffic service (ATS) providers, are most concerned and affected with the occurrence of flight delays. Aside from credit obligations and huge profit losses, performance metrics represented by on-time schedule reliability, operational reputation, and quality of customer service, are likewise undesirably affected (Bongo & Ocampo, 2016).

According to literature, the causes of flight delays mainly point to both adverse weather and air traffic congestion. This premise is very similar in the local condition in the Philippines which points air traffic congestion as the main cause of flight delays (i.e., air traffic congestion accounts for 40% of flight delays annually). The Aeronautical Information Service under the Philippine Department of Transportation and Communications and Civil Aviation Authority of the Philippines (DOTC-CAAP) recently issued Memorandum Circular No. 15-12 to address air traffic congestion in Ninoy Aquino International Airport (NAIA). In specific, it involves the implementation of an ATFM action (i.e., ground holding, airborne holding, rerouting, and speed controlling) at a given air traffic condition.

A number of optimization models and learning algorithm were developed in domain literature that primarily focus on how each ATFM action should be implemented. For instance, Bertsimas et al. (2011) presented a new integer programming model for large-scale instances of ATFM problems. The model covered all phases of flight and solved for an optimal combination of flow management actions, including ground holding, airborne holding, rerouting, and speed controlling, on a flight-by-flight basis. Clare et al. (2012) contested the model developed because some elements of the demand-capacity balance problem are subject to uncertain variations. Therefore, the deterministic solution generated may be sub-optimal and even infeasible. What Clare et al. (2012) developed as an extension to this model is a deterministic, discrete-decision mixed-integer linear programming (MILP) optimization model. This augments constraints on the chance of sector capacity violations occurring given probabilistic information about the future capacity states. The challenge in implementing this type of scheme lies in defining which sectors should be considered *linked*.

A recent model is developed by Barnhart et al. (2012) to address a scenario when air traffic demand is projected to exceed airport capacity. It comprises two integer programming approaches for coordinating air traffic flow programs that balance the tradeoff between equity (measured by fairness metric according to current industry standards) and efficiency (measured by aggregate system delay). Early model formulation made by Bertsimas et al. (1998) served as a foundation from which Barnhart et al. (2012) described the components of the deterministic, multi resource air traffic flow formulation in their model. Results suggest that this approach could lead to system-wide savings as much as $50 million per year.

These optimization models and algorithms consider only a single criterion (e.g., cost minimization) in addressing air traffic congestion. Although extensive conduct of the study is made, these approaches fail to incorporate the decision process taking into account the multi-criteria nature of the problem in order to model the relationships inherent in the decision structure. With multi-criteria decision-making (MCDM) approach, a decision problem involving evaluation of alternatives (Kuo, 2011) can be illustrated.

Among the many methods that characterize MCDM, the following methods are used in the context of air transportation system: (i) simple additive weighting (SAW) and TOPSIS in selecting the preferred alternative/candidate airport for 'building a new runway' as a solution for matching runway airside (runway) system capacity in Europe (Janic, 2015); (ii) fuzzy set theory in evaluating airline service quality (Chang et al., 2002) and further improving such (Kuo, 2011); (iii) a combination of VIKOR (The Serbian name, *VlseKriterijumska Optimizacija I Kompromisno Resenje*) and grey relation analysis (GRA) techniques in evaluating airports service quality under fuzzy environment (Kuo & Liang, 2011); and, (iv) analytic hierarchy process (AHP) assessment for potential multi-airport systems in Africa (Vanderschuren & Zietsman, 2014).

While the use of several MCDM approaches have proven its viability and substance in the previous literature, to the best of the authors' knowledge, air traffic congestion has been addressed using this approach only once. Bongo & Ocampo (2016) attempted to extract the preference of air traffic service providers in relation to the most suitable ATFM action to be applied in the event of destination airport congestion. However, their paper was not able to cover the possibility that an aircraft may already be airborne when the information of destination airport congestion is made known. When this happens, the result of their study involving the application of ground holding may not at all be viable.

As an extension, this paper aims to develop a multi-criteria decision support system using MCDM methods that will select an ATFM action to be implemented during destination airport congestion, sensitive to the general time horizon when air traffic congestion is known. Therefore, the gap advanced is the application of MCDM approach when destination airport is congested and is known after an aircraft's take-off. Lastly, the contribution of this paper in the body of knowledge is that it attempts to address destination airport congestion using hybrid MCDM methods.

1.1 The case of Ninoy Aquino International Airport (NAIA)

NAIA is located in Pasay City, Manila operating for almost 50 years now. It accommodates various types of aircrafts ranging from long-haul international jets to domestic planes, including those for general aviation and military flights. In terms of its physical infrastructure, it has two runways that intersect at a common point, thereby, contributing to congestion and difficult air traffic control.

As demand for air travel grows and air traffic situation aggravates, a new system called ATFM is implemented (Ishida, 2012). It is only in 2012 that ATFM became fully operational in the country with its central unit in Manila area control center (ACC). Its application, however, does not yet cover all the major airports particularly those that are of lower classification (i.e., airports that cater to lesser air travel demand). This is due to the fact that other airports along NAIA's network have not experienced an extreme level of air traffic congestion. Unfortunately, the system only allows key stakeholders (e.g., airport management, airlines industry, ATS) to communicate with one another should any modification be needed during air traffic congestion. It does not take into logical account which criteria are considered essential by one decision-maker to another and the alternatives available for implementation.

The following lists the criteria referred by stakeholders when they need to decide on an ATFM action to be implemented during air traffic congestion (Bongo & Ocampo, 2016). These criteria are believed to have an influence to the final decision made by stakeholders as its impact towards the general operation of the air transportation system can be very substantial.

- Cost of using flight routes
- Landing/Take-off fee
- Fuel cost
- Crew cost
- Passenger cost
- Customer goodwill
- Safety
- Equitable treatment of competing air carriers
- Utilization of runway and terminal
- Environmental value
- Economic value
- Social value

Correspondingly, ATFM actions such as airborne holding, rerouting, and speed controlling, are considered as alternatives in the context of this paper. Recall that resource congestion, in general, is characterized by demand-capacity imbalance (Cavca et al., 2014). There is a growing number of flights per unit of time, while resources like runways and terminals are held constant. These ATFM actions are proven to have addressed flight delays (i.e., being a direct result of air traffic congestion) in various respective scenarios and considerations (Ball et al., 2011; Reynolds, 2014; Bertsimas et al., 2011; Lulli et al., 2015), aside from ground holding which is no longer viable for implementation in this case.

2. THE HYBRID FUZZY MCDM APPROACH

This section aims to highlight the MCDM methods used in this paper. It also discusses the concepts behind these methods.

2.1 DEMATEL

It is a comprehensive technique designed to construct and analyze a structural model involving cause and effect interrelationships between complex criteria (Uygun, 2015). The DEMATEL method is based on digraphs, which can separate criteria into causal and effect clusters.

The use of DEMATEL can prioritize alternatives based on the type of relationships and severity of influence a criterion brings to another. In other words, alternatives having more effect to another are assumed to have higher priority (i.e., referred to as dispatcher) and those receiving more influence from another are assumed to have lower priority (i.e., referred to as receiver) (Asgharpour et al., 2006). When higher priority is given to an alternative, decision-makers are more likely to focus and give more weight on it, thereby, directly influencing other related alternatives.

2.2 ANP

While ANP is known to be a general form of AHP, this method is chosen in the context of this paper as its applications can display interrelations among criteria; whereas AHP can only provide a unidirectional hierarchical relationship among decision levels (Saaty, 1996). Further, ANP provides measurements to derive ratio scale priorities for the distribution of influence between factors and groups of factors in the decision.

2.3 TOPSIS

According to early definitions of Chen & Hwang (1992), TOPSIS is able to identify solutions from a finite set of alternatives being a multiple criteria method itself. Its manner of defining the optimal solution takes into account both positive ideal solution and negative ideal solution at the same time.

2.4 Fuzzy set theory

The concept of fuzzy set theory integrated to crisp MCDM methods such as of DEMATEL, ANP, and TOPSIS, is applied because it incorporates the vagueness, or technically the fuzziness, of human perception in decision-making (Kuo, 2011). That is, possible fuzzy subjective judgment of decision-makers during the conduct of this research study will be captured and established more objectively. Therefore, in consideration to the ease of using linguistic expressions, the use of fuzzy numbers representing qualitative data is deemed relevant in the case of this paper.

3. METHODOLOGY

A set of criteria denoted as C_n where n is the number of criteria involved, is prepared using fuzzy DEMATEL. These criteria are evaluated by decision-makers according to what they consider to have most impact in mitigating air traffic congestion. In the application of fuzzy DEMATEL, it is expected to obtain an influential network relations map showing the net cause criteria and net effect criteria. Correspondingly, the weights for each criterion is obtained using ANP method. These criteria weights are processed as inputs in the fuzzy TOPSIS method. Next, the same decision-makers are requested to evaluate the alternatives denoted as A_n where n is the number of alternatives involved, with respect to the criteria previously identified. Finally, fuzzy TOPSIS method is conducted to arrive at the final ranking of results for a specific condition. The linguistic expressions used in eliciting judgments in DEMATEL and TOPSIS and its

Table 1: Description of the linguistic expressions for criteria evaluation and its corresponding triangular fuzzy number

Linguistic expression	Description	Triangular fuzzy number
No influence (NI)	Base criterion has no influence to the other criterion	(0.0, 0.1, 0.3)
Very low influence (VLI)	Base criterion has very low influence compared to the other criterion	(0.1, 0.3, 0.5)
Low influence (LI)	Base criterion has low influence compared to the other criterion	(0.3, 0.5, 0.7)
High influence (HI)	Base criterion has high influence compared to the other criterion	(0.5, 0.7, 0.9)
Very high influence (VHI)	Base criterion has very high influence compared to the other criterion	(0.7, 0.9, 1.0)

Table 2: Description of the linguistic expressions for evaluating alternatives with respect to a particular criterion

Linguistic expression	Description	Triangular fuzzy number
Very good (VG)	Performance of such alternative has very huge impact to the criterion	(7, 9, 10)
Good (G)	Performance of such alternative has huge impact to the criterion	(5, 7, 9)
Fair (F)	Performance of such alternative has fair impact to the criterion	(3, 5, 7)
Poor (P)	Performance of such alternative has slight impact to the criterion	(1, 3, 5)
Very poor (VP)	Performance of such alternative has no impact at all to the criterion	(0, 1, 3)

corresponding fuzzy numbers are indicated the Table 1 and Table 2, respectively. Note that the triangular fuzzy numbers indicated in these tables per linguistic expression are adapted from early definitions of Wang & Chang (1995), used by Chen (2000), and recently referred to by Tseng (2011). However, the linguistic expressions are modified to fit the nature of the preference expressed in this paper.

The detailed description of the hybrid MCDM method is discussed in the following:

Step 1: *Aggregate linguistic values from the decision-maker's evaluation according to Tseng (2011).*

The evaluation made by decision-makers is aggregated by means of synthetic value notation as in Equation (1):

$$\widetilde{w}_j = \frac{1}{k}\left(\widetilde{w}_j^1 + \widetilde{w}_j^2 + \widetilde{w}_j^3 + \cdots + \widetilde{w}_j^k\right) \qquad (1)$$

Step 2: *Defuzzify corresponding linguistic values based on signed distance method.*

For this paper, signed distance of triangular fuzzy numbers is used in order to compute for its corresponding crisp value. Equation (2) presents the formula for calculating such.

$$d(\tilde{A}, 0) = \frac{l+2m+u}{4} \qquad (2)$$

Step 3: *Apply DEMATEL and ANP methods according to Tzeng et al. (2013) by calculating the direct-influence matrix* $\boldsymbol{G}$ *by scores.*

Using the linguistic rating scale shown in Table 1 with triangular fuzzy scores represented by natural language, the direct-influence matrix can be obtained based from the evaluation made by decision-makers. When criterion i is believed to have an influence on criterion j, this is indicated by g^{ij}. Thus, the matrix $\boldsymbol{G} = [g^{ij}]_{n\times n}$ of direct relationships.

Step 4: *Normalize the direct-influence matrix* $\boldsymbol{G}$.

The direct-influence matrix $\boldsymbol{G}$ calculated from the previous step is normalized using Equation (3). The diagonals of this matrix is zero, and the maximum sum of rows or columns is one. The normalized direct-influence matrix is labeled as matrix $\boldsymbol{X}$.

$$\boldsymbol{X} = v\boldsymbol{G} \qquad (3)$$

where

$$v = min_{i,j}\left\{\frac{1}{\max\limits_{i}\sum_{j=1}^{n} g_c^{ij}}, \frac{1}{\max\limits_{j}\sum_{i=1}^{n} g_c^{ij}}\right\} \qquad i,j, \in \{1,2,\dots,n\}$$

Step 5: *Attain a total-influential matrix* $\boldsymbol{T_c}$.

Matrix $\boldsymbol{T_c}$ can be calculated by using Equation (4), where $\boldsymbol{X}$ denotes the normalized direct-influence matrix and $\boldsymbol{I}$ as the identity matrix.

$$\boldsymbol{T_c} = \boldsymbol{X}(I - \boldsymbol{X})^{-1}, \text{when } \lim_{\ell\to\infty} X^{\ell} = [0]_{n\times n} \qquad (4)$$

Step 6: *Analyze the results.*

The matrix components of matrix $\boldsymbol{T_c}$ are expressed as vectors $\boldsymbol{r}$ and $\boldsymbol{s}$, respectively, using Equations (5) and (6). A criterion is considered under causal cluster when $(r_i - s_i)$ is positive. Otherwise, it is part of effect cluster. An influential network relations map can be created by mapping the data set $(r_i + s_i,\ r_i - s_i)$.

$$\boldsymbol{T_c} = \left[t_c^{ij}\right]_{n\times n}, \quad i,j\ \epsilon\{1,2,\dots,n\}$$

$$r = \left[\textstyle\sum_{j=1}^{n} t_c^{ij}\right]_{n\times 1} = [t_c^i]_{n\times 1} = (r_1,\dots,r_i,\dots,r_n)' \qquad (5)$$

$$s = \left[\textstyle\sum_{i=1}^{n} t_c^{ij}\right]'_{1\times n} = \left[t_c^j\right]_{n\times 1} = (s_1,\dots,s_i,\dots,s_n)' \qquad (6)$$

where vector r and vector s are the sum of the rows and the sum of the columns from the total-influential matrix, respectively, and the superscript $'$ denotes transpose of a matrix.

Step 7: *Find the normalized total-influential matrix* $\boldsymbol{T_c^{nor}}$.

The total-influential matrix is normalized and presented as in Equation (7). For the case of this paper, the normalized total-influential matrix $\boldsymbol{T_c^{nor}}$ also represents the weighted supermatrix W_C^*.

$$W = [w_{ij}]_{nxn} \text{ where } w_{ij} = {t^{ij}}/{t^j}\ ,\ t^j = \textstyle\sum_{i=1}^{n} t^{ij} \quad (7)$$

Step 8: *Obtain the DEMATEL-ANP supermatrix.*

Limit the weighted supermatrix W_C^* by raising it to a sufficiently large power φ until it converges and becomes a long-term stable supermatrix to obtain global priority vector, which defines the influential weights $w = (w_1, \dots, w_j, \dots, w_n)$ from $\lim_{\varphi\to}(W_C^*)^{\varphi}$ for the criteria.

Step 9: *Find the aggregated fuzzy weight (Chen, 2000).*

The same set of decision-makers are requested to evaluate the performance of each alternative with respect to each criterion using linguistic rating scale shown in Table 2. Then, results are aggregated using the same method presented in Equation (1).

Step 10: *Construct the fuzzy decision matrix and the normalized fuzzy decision matrix.*

Linear scale transformation represented by Equations (8) through (10) is used to calculate the normalized fuzzy decision matrix. This is done in order to convert the different units into comparable ones.

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right); \quad u_j^+ = \max_i u_{ij}^+; \quad \forall j^+ \quad (8)$$

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right); \quad l_j^- = \min_i l_{ij}^+; \quad \forall j^- \quad (9)$$

The variables l, m, and u are the smallest possible value, the most promising value, and the largest possible value, respectively. For benefit criteria, the larger $\tilde{r}_{ij}$ has the greater preference; while for the cost criteria, the smaller $\tilde{r}_{ij}$ has the greater preference.

$$\tilde{R} = [\tilde{r}_{ij}]_{n\times m} \quad (10)$$

where,

$\tilde{r}_{ij}$ is the normalized value of $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$

Step 11: *Construct the weighted normalized fuzzy decision matrix.*

In order to carry out this step, the weighted normalized value $\tilde{v}_{ij}$ is calculated by multiplying the weights (w_j) of criteria with the normalized fuzzy decision matrix $\tilde{r}_{ij}$. Recall that the weights referred to is from the global priority vector described in the fuzzy DEMATEL and ANP methods. The weighted normalized decision matrix $\boldsymbol{\tilde{V}}$ for each criterion is expressed as in Equation (11).

$$\boldsymbol{\tilde{V}} = [w_j \tilde{r}_{ij}] = [\tilde{v}_{ij}]_{n\times j} \quad i = 1,2,\dots,m \quad j = 1,2,\dots,n \quad (11)$$

In matrix $\boldsymbol{\tilde{V}}$, each element $\tilde{v}_{ij}$ is a fuzzy normalized number within the closed interval [0, 1].

Step 12: *Determine fuzzy positive ideal solution and fuzzy negative ideal solution.*

The fuzzy positive ideal solution (A^+) and fuzzy negative ideal solution (A^-) are calculated using Equations (12) and (13), respectively:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \tilde{v}_3^+, \dots, \tilde{v}_n^+) = \left\{\max_i v_{ij} | (i = 1,2,\dots,m; j = 1,2,\dots,n)\right\} \quad (12)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \tilde{v}_3^-, \dots, \tilde{v}_n^-) = \left\{\min_i v_{ij} | (i = 1,2,\dots,m; j = 1,2,\dots,n)\right\} \quad (13)$$

Step 13: *Calculate the distance of each alternative from fuzzy positive ideal solution and fuzzy negative ideal solution, respectively.*

The distance of each alternative from A^+ and A^- is obtained by using Equations (14) and (15),

$$d_i^+ = \textstyle\sum_{j=1}^{n} (\tilde{v}_{ij}, \tilde{v}_j^+) \quad (14)$$

$$d_i^- = \textstyle\sum_{j=1}^{n} (\tilde{v}_{ij}, \tilde{v}_j^-) \quad (15)$$

where, d_i^+ and d_i^- are the primary and secondary distant measures, respectively. The distance measurement between two triangular fuzzy numbers of (l_1, m_1, u_1) and (l_2, m_2, u_2), is calculated by the vertex method as in Equation (16):

$$d_v(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]} \quad (16)$$

Step 14: *Calculate the closeness coefficient* (C_c) *of each alternative and rank order of alternatives.*

The relative C_c index of each alternative with respect to both fuzzy positive ideal solution and fuzzy negative ideal solution is obtained as:

$$C_c = \frac{d_i^-}{(d_i^+ + d_i^-)} \tag{17}$$

Each alternative is ranked according to its C_c index. The larger the index value, the better the performance of the alternatives with respect to each criterion, thus, is more preferred by decision-makers.

4. RESULTS AND DISCUSSION

This paper intends to address air traffic congestion that specifically occurs during a condition when an airport destination is congested known after an aircraft's take-off. With the application of MCDM methods such as fuzzy DEMATEL, ANP, and fuzzy TOPSIS, a multi-criteria decision support system is developed. That is, to select the most preferred ATFM action to be implemented during such air traffic congestion condition. The key results obtained with the aid of Microsoft Excel© 2016 are presented in the following sub-sections.

Table 3: Cluster classification of each criterion and its rank according to influential weight

Criteria	$(r+s)$	$(r-s)$	Clusters	Weights	Rank
C1	5.78	0.77	*causal*	0.096	*2*
C2	4.05	-0.08	*effect*	0.058	*12*
C3	4.89	0.14	*causal*	0.074	*9*
C4	4.97	0.08	*causal*	0.074	*10*
C5	5.18	0.12	*causal*	0.078	*8*
C6	5.73	0.13	*causal*	0.086	*7*
C7	7.21	0.22	*causal*	0.108	*1*
C8	6.27	-0.37	*effect*	0.087	*6*
C9	6.36	-0.40	*effect*	0.087	*5*
C10	5.32	-0.29	*effect*	0.074	*11*
C11	6.18	-0.04	*effect*	0.090	*3*
C12	6.25	-0.27	*effect*	0.088	*4*

Note: *The code for each criterion corresponds to the following: C1 for cost of using flight routes, C2 for landing/take-off fee, C3 for fuel cost, C4 for crew cost, C5 for passenger cost, C6 for customer goodwill, C7 for safety, C8 for equitable treatment of competing air carriers, C9 for utilization of runway and terminal, C10 for environmental value, C11 for economic value, and C12 for social value.*

Key results generated from fuzzy DEMATEL and ANP method is summarized in Table 3. It can be noted that among the 12 criteria, 5 of which fall under causal cluster (i.e., cost of using flight routes, fuel cost, crew cost, passenger cost, customer goodwill, and safety). These causal criteria influence other criteria in one way or another. For instance, one decision-maker emphasized that more fuel costs incurred translate to an increase in fuel consumption, thereby, not only increasing fuel burn but also aggravating noise pollution – both essential to preserving a region's environmental value as represented by C10 (environmental value). A prior paper conducted by Babić et al. (2014) verified that, indeed, there are issues related to environmental impact when fuel consumption is increased significantly, let alone, when aircrafts fly in less efficient trajectories. On the other hand, when the overall safety of flights is considered, decision-makers believe that it further affects other criteria such as increase in customer goodwill (e.g., as air passengers are more likely to patronize an air carrier that upholds safe operation of flights).

The remaining 7 criteria are classified as effect criteria (i.e., landing/take-off fee, equitable treatment of competing air carriers, utilization of runway and terminal, environmental value, economic vale, and social value). These criteria receive the consequences brought about by criteria that fall under causal cluster.

Notice that in terms of influential weights given by decision-makers, C7 (safety) ranks first with 10.80%. In real-life applications of mitigating air traffic congestion, decision-makers have asserted that overall aviation safety should at all times be kept and held to maximum. It is further believed that in keeping safe operations of flights, other related criteria such as customer goodwill, environmental value, and passenger costs, to name a few, are favorably influenced (Vanderschuren & Zietsman, 2014). This result is expectedly in line with the objective of all three decision-makers where safe, orderly, and expeditious flow of air traffic is observed. Earlier studies conducted by Chang et al. (2002), Kou (2011), and Kou & Liang (2011) also obtained results similar to this paper by using other MCDM methods.

Criteria that are practically categorized under the general welfare of the entire air transportation system immediately follow safety's rank in order of decision-makers' preference. These criteria are C1 (cost of using flight routes) C8 (equitable treatment of competing air carriers), C9 (utilization of runway and terminal), C11 (economic value), and C12 (social value). Once safe operation of flights is secured, these criteria are then considered closely. This suggests that while airlines management and airport management are concerned with its own auxiliary goals including cost-related and reputation-wise aspects, they, along with ATS, converge on the idea that the general betterment of air transportation system should be given due considerations.

Lastly, criteria that represent both tangible and intangible congestion costs attributable to the airlines industry have garnered lower influential weights. These criteria are C2 (landing/take-off fee), C3 (fuel cost), C4 (crew cost), C5 (passenger cost), C6 (customer goodwill), and C10 (environmental value). This can be due to the fact that only the airlines industry is faced with the consequences of paying for such costs as a direct consequence of air traffic congestion.

Table 4: Rank of alternatives in order of preference

Alternatives	d_i^+	d_i^-	C_c	Rank
A1	3.374	0.810	0.1937	3
A2	3.365	0.851	0.2020	1
A3	3.366	0.845	0.2006	2

Note: *The code for each alternative corresponds to the following: A1 for airborne holding, A2 for rerouting, and A3 for speed controlling.*

When the destination airport is congested known after an aircraft's take-off, the ranking in order of preference is rerouting, speed controlling, and airborne holding as shown in Table 4. As indicated in this table, A2 (rerouting) has the highest C_c value, thus, most preferred by decision-makers. They believe that under this condition, it is best to reroute an aircraft in order to cover with the anticipated destination airport congestion. This result coincides with the belief of Agustín et al. (2012) that rerouting is favored and is considered efficient being a mode of manipulating flight operational plans and strategies for the enhancements of flight operations. Although, one strict limitation is found when rerouting an aircraft under such condition. That is, the information of congestion should be transmitted to the pilot within a considerable amount of flight time and aeronautical mile such that an alternate flight route can still be traversed with the least deviation from the original route established. Otherwise, additional resources will be needed further to take on another route.

Based from the results, speed controlling ranks next to rerouting and is observed to be as efficient as it is. Loosely, speed controlling and rerouting are statistically tied and both viable to be carried out. A more detailed situational analysis of this condition can aid decision-makers in choosing between rerouting or speed controlling. For instance, even when the first choice of ATFM action should have been rerouting, in cases when the alternate flight route is no longer accessible due to navigational restrictions, controlling the speed of aircrafts can be considered as a better option.

Airborne holding is least preferred to be implemented during this condition because decision-makers believe that aircrafts will require additional resources (e.g., fuel supply) to execute this action. Also, since the description of airborne holding for this paper is focused on the arrival holding stacks only, there is least possibility for this action to be taken first, or even second. This is because the holding stacks are located a few aeronautical miles near the destination airport already.

4. CONCLUSIONS

In this paper, a hybrid fuzzy MCDM approach based from the concepts of DEMATEL, ANP, TOPSIS, and fuzzy set theory, is used in order to address air traffic congestion in a specific condition when the destination airport is known to be congested after an aircraft's take-off. This condition serves as an extension to a prior study which has not tackled on the possibility that an aircraft may already be airborne when the information of destination airport congestion is known. Based from the multi-criteria decision support system developed in this paper, it suggests to implement rerouting of flights when such condition occurs. Note that there are various criteria considered in arriving at a final decision of which ATFM action should be applied during air traffic congestion. Among these criteria, safety of flights has earned the highest influential weight. In comparison to the other two ATFM actions (i.e., airborne holding and speed controlling) presented, rerouting of flights is believed to deliver flights the safest. It is also interesting to emphasize that coming in with a very close margin to rerouting is speed controlling. This implies that still depending on the situation, any of these two ATFM actions can be applied alternatively based on the preference of decision-makers.

The authors suggest to investigate how each decision-maker's views affect the others considering that they are independent entities of various auxiliary concerns. By having one decision-maker's views practically significant (i.e., of higher weight) to be considered than the others', a shift of the ranking of alternatives may be evident.

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