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ANALYSIS OF TRAVEL DEMAND IN DEVELOPING COUNTRIES: A FUZZY MULTIPLE ATTRIBUTE DECISION-MAKING APPROACH

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ABSTRACT

Travel demand analysis is crucial in transport planning process. While developed countries have many choices of approaches in analysing or modelling travel demand that will give the best results, most developing countries are still struggling with elementary problems of the modelling process such as lack of professional work, technical resources and reliable data. Aggregate models that has been criticised as lacking of behavioural basis continue to be used in developing countries. This paper attempts to improve the application of the aggregate model by using fuzzy multiple attribute decision-making. The fuzzy multiple attribute decision-making method is applied to combine the variables affecting travel decision at each step to several single variables. The improvement integrates all the steps and could be considered to giving behavioural basis as well. The application of this approach in modelling the Central Java inter sub-province travel demand improves the statistical significance of the traditional model.

1. INTRODUCTION

Travel demand analysis is crucial in transport planning process. While developed countries have many choices of approaches in analysing or modelling travel demand that will give the best results, most developing countries are still struggling with elementary problems of the modelling process such as lack of technical expertise, technical resources and reliable data. Developing travel demand models sound theoretically strong using disaggregate approaches is then often not a priority, as they are largely data intensive (Wirasinghe and Kumarage, 1998). The models also demand from the analyst a high level of statistical and econometric skill for their use (Ortuzar and Willumsen, 1994).

The models work at aggregate level is mostly developed using statistical modelling techniques, so that it is considered as purely descriptive and have no behavioural basis. The four-steps travel demand model in particular has significant drawbacks, each step in the model has its own behavioural interpretation, and the steps are typically not integrated, for example any change of conditions of routes, modes and destinations cannot be taken into account at trip generation step (Oppenheim, 1995).

In spite of the weaknesses, the aggregate models continue to be used in developing countries (Wirasinghe and Kumarage, 1998). This paper attempts to improve the application of the four steps aggregate model by using fuzzy multiple attribute decision-making. The fuzzy multiple attribute decision-making method is applied to combine the variables affecting travel decision at each step to several single variables. The variables combination could integrates all the steps, so that all variables included at trip distribution, modal split as well as route choice analysis can be taken into account at trip generation model. The improvement is also intended to give behavioural basis and improve the statistical significance of the model.

The next sections of this paper are organised as follow: fuzzy set theory would give introductory concept of fuzzy numbers, fuzzy multiple attribute decision-making explains method to combine variables, and modelling the Cental Java inter sub-province travel demand shows application of the approach and concluding remarks highlight the strengths and the weaknesses of the approach.

2. FUZZY SET THEORY

In the classical sets, the membership of elements in a particular set is restricted to the binary (yes/no) definition of set membership. An element must possess the characteristic of the set to be regarded as a member of the set, if not, then the element does not belong to the set. The membership function of x in a set A is 1 if and only if x is member of A, and 0 if and only if x is not member of A.

In reality, the bound of many sets are not precisely defined. For example if A is a set of "about 40 km distance", then the bound of the set is unclear. Fuzzy set theory, as introduced by Lotfi A. Zadeh (Zimmermann, 1991) is capable of handling it by allowing a graduated definition of membership. In a fuzzy set, each element has a specified degree of membership. A set of elements which is to be analysed by fuzzy means will have the following definition:

$$A = \{(x, \mu_A(x)) \mid x \in X) \qquad (1)$$

A crisp set of X contain of x elements is mapped by a fuzzy set A to a membership space M. The membership function or grade of membership of element x in fuzzy set A is (μ_A (x)).

3. FUZZY MULTIPLE ATTRIBUTE DECISION MAKING

It is common in everyday life that people have to make a decision in selecting an option (out of several alternatives or offer) or have to rank the alternatives based on some criteria. The criteria (attribute) could be, cost, safety, comfort, etc. for a traveller selecting a mode (out of several modes) to work, or could be reputation, facilities, cost, location, etc. for a student selecting university (out of several universities) to study, and still so many others example. The decision-making problems can happen to everyone from an individual level to a whole nation (Chen and Hwang, 1992).

In the decision-making field, the kind of situations above is mostly handled using a method termed multiple attribute decision-making. The method has been widely used and has proven very effective in solving problems with precise data in many fields. For example multiple attribute decision-making method has been used to rank urban transport system projects (Gomes, 1989), and to aid environmental decision-making (Salminen et al., 1998).

In any decision-making process, it is also common that one or more criteria or attribute are imprecise in which those may come from unquantifiable information (e.g. safety, comfort, etc.), incomplete information (e.g. speed, such as “about 100 km/h”, etc.), unobtainable information (e.g. a very secret information, high cost data, etc.), and partial ignorance (e.g. only knows part of the facts) (Chen and Hwang, 1992). Since the application of fuzzy set theory to multicriteria analysis, it is now possible to include the imprecise, subjective and qualitative criteria in the decision-making process. There also have been many application of fuzzy multicriteria analysis, for instance to evaluate attack helicopters (Cheng et al., 1999), to evaluate performance of bus companies (Yeh et al., 2000), and to evaluate environmental impacts of road traffic (Klungboonkrong and Taylor, 1999).

The multipla attribute decision-making problem can be expressed in a matrix format namely decision matrix. For instance an individual H has to make a decision, then a matrix H is formed where there must be alternatives/options A_i (i=1, 2, 3,…,m) in y axis and criteria X_j (j=1, 2, 3,…,n) in x axis. The matrix contains x_{ij} values, which are the rating of alternative A_i with respect to criteria X_j.

H =

	X_1	X_2	…	X_n
A_1	x_{11}	x_{12}	…	x_{1n}
A_2	x_{21}	x_{22}	…	x_{2n}
…	…	…	…	…
A_m	x_{m1}	x_{m2}	…	x_{mn}

There are many methods in the multiple attribute decision-making fields in order to select or rank the alternatives. Hwang and Yoon (1981) gave the most famous classical method such as the dominance method, the maximin method, the maximax method, the conjunctive method, the disjunctive method, the lexicography method, the simple additive weighting method, ELECTRE, TOPSIS, the analytic hierarchical process (AHP) method, the weighted product method, and the distance from target method. The inclusion of fuzzy number to represent some or all attributes and attribute weights in the classical method has expanded the classical methods to be fuzzy multiple attribute decision-making (FMADM).

Before developing decision matrix, there are some steps need to be prepared before valuing each alternative based on attributes selected (Ai), those are: determining the attributes and fuzzy attributes (Xj), and determining attribute weights.

In term of transport, the attributes could consist of the transport system’s level of service and the socio-economic conditions of travellers as listed in the model structure above. It is also possible that an attribute has several sub-attributes, for instance the level of service of routes as an attribute of selecting destination usually consist of length of the route, road geometry, etc.

In dealing with fuzzy attributes, there are two steps: converting linguistic terms to fuzzy number and assigning crisp score to fuzzy number.

Eight conversion scales are provided in Chen and Hwang (1992) to convert linguistic terms into fuzzy numbers, in which the use of each scale depend on the total number of linguistic terms to be converted. If the decision maker is familiar with the decision problem, they pointed that a detailed conversion is very much suggested.

The fuzzy numbers are assigned to crisp values using Chen and Hwang method (Chen and Hwang, 1992), which is based on assumption that a crisp score of a fuzzy number can be obtained by maximising set ($\mu_{max}(x)$) and minimising set ($\mu_{min}(x)$) technique. The membership functions of these sets are defined as:

$$\mu_{max}(x) = \begin{cases} x\,, 0 \le x \le 1 \\ 0\,, \textit{otherwise} \end{cases} \quad (2)$$

$$\mu_{min}(x) = \begin{cases} 1 - x\,, 0 \le x \le 1 \\ 0\,, \textit{otherwise} \end{cases} \quad (3)$$

The total score of a fuzzy number A ($\mu_T(A)$) is calculated by the following formulae:

$$\mu_T(A) = (\mu_R(A) + 1 - \mu_L(A))/2 \quad (4)$$

where $\mu_R(A)$, the right score, and ($\mu_L(A)$, the left score are defined as

$$\mu_R(A) = \max_x [\min (\mu_A(x), \mu_{max}(x))] \quad (5)$$

$$\mu_L(A) = \max_x [\min (\mu_A(x), \mu_{min}(x))] \quad (6)$$

After this step, the decision-making can be performed using any of the multiple attribute decision-making methods, as the decision matrix will contain only crisp data. A detailed explanation of Chen and Hwang method is provided in the application of the model at sub-section 4.3.

The attribute weight, a numerical measure to the relative importance of the criterion in valuing a set of alternatives, is an important part of fuzzy multiple attribute decision-making analysis. It could be calculated by several methods like entropy maximisation or the use of pairwise comparison of the Analytical Hierarchy Process (AHP). If the decision maker is familiar with the decision problem, then it can be given directly (Chen and Hwang, 1992). In a case that an attribute has sub-attributes, the weight of the sub-attributes must also be determined, so that the value of the attribute can be calculated.

I use coefficient of correlation (r) between attributes and observed travel demand divided by total (r) as attribute weight. This is done to ensure that the total attribute weight is 1. As coefficient of correlation (r) indicates the closeness of two variables, so the higher correlation coefficient (r) the higher the weight of attribute in the decision matrix.

$$w_j = r_j \Big/ \sum_{j=1}^{n} r_j \quad (7)$$

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

To calculate the numerical values of each alternative with respect to all attributes in the decision matrix (to combine variables affecting travel decision), I use the following formula:

$$A_i = \sum_{j=1}^{n}\left(\left(\frac{x_{ij}}{\max x_{ij}}\right)^{w_j}\right) \qquad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n \qquad (8)$$

In this formula the attributes chosen in a decision matrix is first normalised by maximum value (max x_{ij}) of each attribute (so that they will be in a single dimension comparable units). These values are then powered by their attribute weights. In case the attribute has negative correlation, then it must be kept positive in calculating formula (8) but in calculating formula (9) the result of formula (8) is transformed back to negative. For example the r's are –0.2, 0.3 and 0.3, then attribute weights are –0.25, 0.375 and 0.375.

4. MODELLING THE CENTRAL JAVA INTER SUB-PROVINCE PASSANGER TRAVEL DEMAND

4.1. TRADITIONAL TRIP GENERATION MODEL

The problems of aggregate models are not in theoretical aspects only as described in introduction section. In many cases the applications of the four- steps model in developing countries are also faced with condition where available variables that intuitively affect travel decisions perform low correlations with observed travel demand data. Sjafruddin et al. (1999) reported that they found very low coefficient of determination when modelling regional road transport freight demand in Java Island. This condition leads to a deficient model.

For example the application of the four-steps approach in modelling inter sub-province passenger travel demand in Central Java (Indonesia) shows unsatisfactory results. The coefficient of correlations between observed travel demand (trip generation per day (TG)) and other zonal based variables (gross domestic regional product (GDRP), population density (PD), Population (Pop), Income (Inc) and number of productive people (age 15-64)) are very insignificant (the data are taken from the 1996 national origin destination survey (MOCRI, 1997) and Central Java in figures 1997 (Central Java Statistic Office, 1997).

Tabel 1. Coefficient of Correlations (Trip Generation and Other Variables)

	t_i	GDRP	PD	Population	Income
t_i	1	.475	.379	.230	.407
GDRP	.475	1	-.044	.488	.754
PD	.379	-.044	1	-.454	.342
Population	.230	.488	-.454	1	-.109
Income	.407	.754	.342	-.109	1

To represent all socio-economic variables and based on the coefficient of correlations above, then trip generation model should include GDRP and PD. From regression analysis the trip generation model (T_i) is given by

$$T_i = 12445.789 + 4.996(PD) + 0.0134(GDRP) \qquad (9)$$

Although, statistically the t-values are significant, the coefficient of determination (R^2) of 0.386 is very low.

4.2. THE STRUCTURE OF THE FMADM APPROACH MODEL

The main idea of this paper is to use the first theoretical basis of decision-making process of the second-generation models. The difference is that the decision making-process is performed mainly by the modeller and use aggregate data.

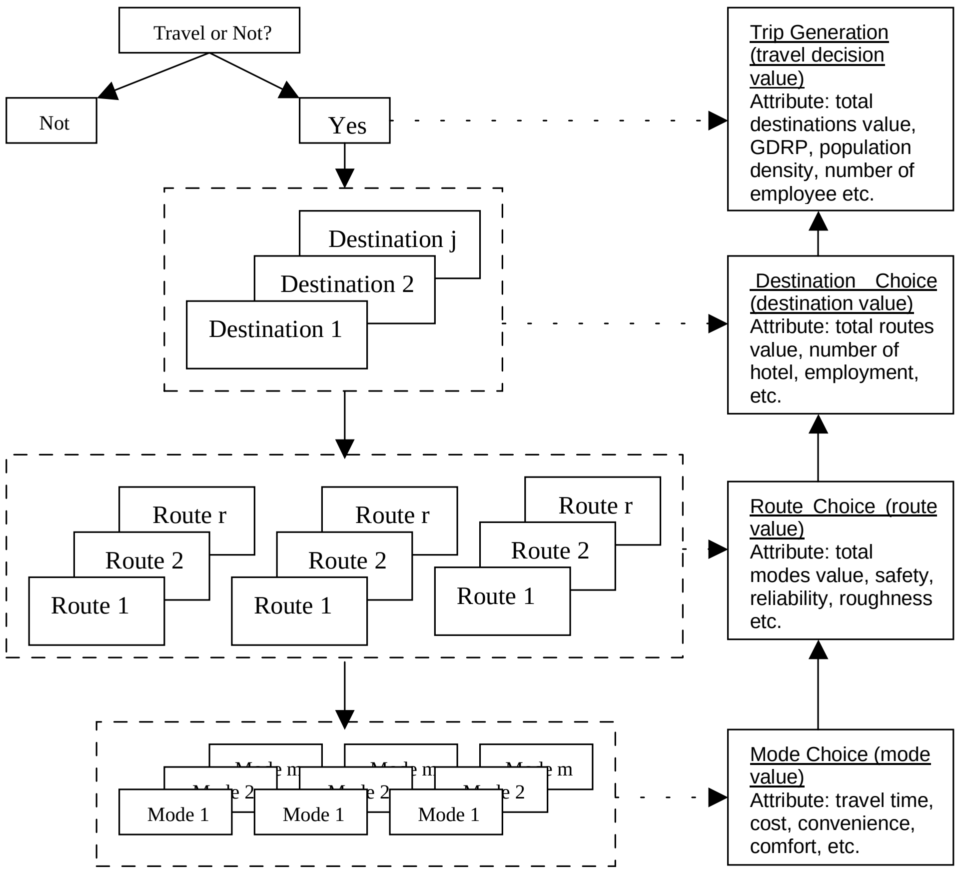
The idea is based on assumptions that the aggregate zonal data represent characteristics of all individuals in a particular zone, the travellers has perfect capability to value each alternative, each alternative has attributes as well as its weights, and the number of travellers choose an alternative is based on the total value of attributes representing the alternative.

The problem is then how to select criteria, how to determine the attribute weights and how to calculate the value of each alternative. This paper attempts to apply fuzzy multiple attribute decision-making explained in the previous section to do so by combining all attributes (variables) in all steps of traditional model.

Before valuing the alternatives, we need to determine the alternatives and their hierarchy. In travel decision, the alternatives and the hierarchy may be as follows: making travel or not, destinations, modes, and routes. The value of an alternative could be an attribute of higher hierarchy of alternatives. For instance the performance of modes serving a study area could be an attribute of destinations.

In this paper, I consider the hierarchy of the alternatives of passenger travel decision using road transport as follow: making travel or not, destinations, routes and modes. The reason is that it can be used to calculate the route performance with respect to all modes. Figure 1 shows the alternatives hierarchy.

Figure 1. The Hierarchy of Alternatives



The figure above can be explained as follow:

- The value of each available mode is calculated for each available route connecting a particular origin and a destination. The attributes could be travel time (walking time, waiting/transfer time, in vehicle travel time), cost, convenience, comfort, etc.
- The total value of all modes on a particular route must be one of attributes of each route connecting a particular origin and a destination. The other attributes may be safety, reliability, roughness, road geometry, etc.
- The total value of all routes connecting a particular origin and a destination must be one of attributes of each destination. The other attributes may be income, population, number of hotel room, number of school, number of employment, etc.
- The total value of all destinations available for an origin zone must be one of attributes of travel decision of people in the origin zone. The other attributes may be income, car ownership, population, number of employee, etc.

Given the travel decision value of each origin zone (TV_i), then the trip generated by a particular zone is simply the function of the travel decision value. Meanwhile the trip distribution, route choice and mode choice could be calculated using multinomial logit model.

$$T_i = f(TV_i) \tag{10}$$

From the figure above it can be seen that all the steps are connected, any changes of attributes at a step can be taken into account at other steps. For instance any damages or improvements of road connecting an origin and a destination can be taken into account at trip generation, which also means this structure could be used to determine induced travel. This cannot be done by traditional four-steps model. This approach can also take into account all modes performance as well as all routes characteristics in travel impedance calculation.

4.3. CREATING TRAVEL IMPEDANCE DATA USING FUZZY SETS THEORY

The developed approach is applied mainly to improve the inter sub-province (*kabupaten*) travel demand model in the Central Java Province presented in sub-section 4.1 above, in which the available data are very limited and the statistical performance is very low.

Based on the data, the model structure started with travel impedance calculation in order to determine routes value (only one route available for travelling from any origins to any destinations (all-or-nothing assignment)), the total of routes value is then one of the attributes of destinations value, and finally the total of destinations value is one of the attributes of travel decisions value for trip generation model.

The travel demand data (origin-destination matrix) are in total passenger per year (not divided by mode), meanwhile the socio-economic data are the total and aggregate of each sub-province. The distance between cities is the only data available for travel impedance calculation.

Based on Highway Development and Management version 4 (HDM-4) model (Bennett and Paterson, 2000), beside the distance there is other variables considered affecting road user cost namely road geometry and ride quality. These three variables are then should be included in creating travel impedance data.

In this paper, the travel impedance between an origin *i* to a destination *j* (C_{ij}) is simply a result of multiplication of distance (d_{ij}) with road geometry (rg_{ij}) and ride quality (rq_{ij}). The C_{ij} is determined using the all-or-nothing assignment method.

$$C_{ij} = d_{ij} \times rg_{ij} \times rq_{ij} \tag{11}$$

As there is no data on road geometry and ride quality, these data are then created using qualitative judgment of modeller. The judgment is based on available maps and the knowledge of modeller on conditions of the Central Java inter-city road network. The road geometry is determined from a map showing topographic condition of the Central Java province as well as the road network. The ride quality is determined from a map showing roughness level, road width and road function. The fuzzy set theory is applied to quantify these qualitative judgments.

The distance is also considered fuzzy due to following reason: most travellers would not know the exact distance between origins and destinations and in fact each traveller starts to travel from different points within an origin zone to different points in the destination zone, so the fuzzy distance could represent these conditions. It also means that the fuzzy distance can overcome the drawback of models that assume the origin and destination of travel must be from and to a node, such as in a gravity model. The use of fuzzy distance also enables the approach to take account of external trips. The distances are converted into 11 fuzzy numbers, such as less than 40 km, about 40 km, about 80 km, and the last one is more than 360 km.

Beside the reason of unavailable data, the qualitative judgment of the road geometry and ride quality might also representing the reality that the travellers do not know the exact condition of these two sub-attributes. The conversions to fuzzy numbers (qualitative judgments) of these two sub-attributes are based on data aggregation provided by the HDM-4 model.

The road geometry is converted to 6 fuzzy numbers namely A (straight and level), B (mostly straight and gently undulating or bendy and generally level), C (bendy and gently undulating), D (bendy and severely undulating), E (winding and gently undulating) and F (winding and severely undulating). The ride quality is converted to 4 fuzzy numbers namely good, fair, poor and bad. The membership functions of those fuzzy numbers are shown below, in which the diagonal broken line represents the maximising set ($\mu_{max}(x)$) and diagonal solid line represents minimising set ($\mu_{min}(x)$). The membership functions of those fuzzy numbers are shown in figure 1, 2 and 3.

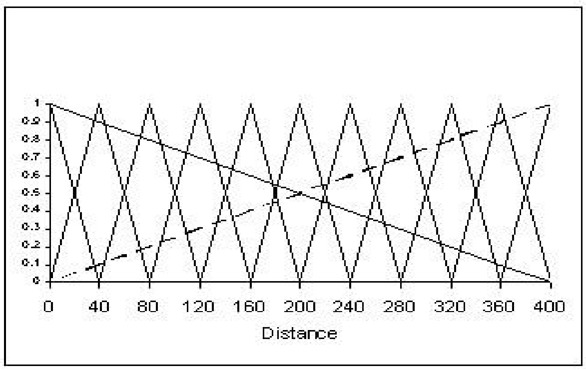


Figure 1. Membership Functions of Fuzzy Numbers less than 40, about 40, about 80,…, and more than 360.

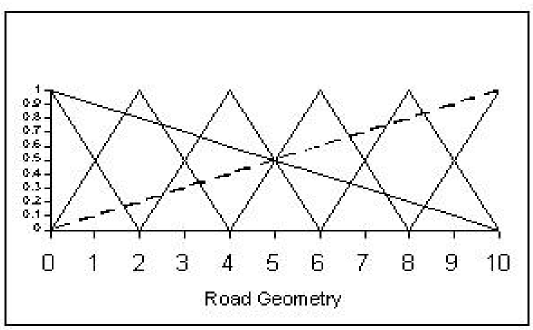


Figure 2. Membership Functions of Fuzzy Numbers A, B, C, D, E and F.

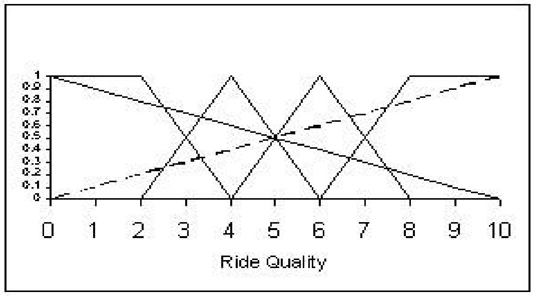


Figure 3. Membership Functions of Fuzzy Numbers good, fair, poor and bad.

Based on the formula 6, the left score ($\mu_L(A)$) is basically the intersection points between the minimising set ($\mu_{min}(x)$) and left side of the fuzzy numbers. Similarly, based on the formula 5, the right score ($\mu_R(A)$) is the intersection points between the maximising set ($\mu_{max}(x)$) and right side of fuzzy numbers. The following tables are the total score ($\mu_T(A)$) of each fuzzy number calculated using formula 4.

Table 2. The Left Score, The Right Score and The Total Score of Fuzzy Numbers Less Than 40, About 40, etc.

Fuzzy Number I	The left score (I)	The right score (I)	The total score (I)
Less than 40	1.00	0.09	0.05
About 40	0.91	0.18	0.14
About 80	0.82	0.27	0.23
About 120	0.73	0.36	0.32
About 160	0.64	0.45	0.41
About 200	0.55	0.55	0.50
About 240	0.45	0.64	0.59
About 280	0.36	0.73	0.68
About 320	0.27	0.82	0.77
About 360	0.18	0.91	0.86
More than 360	0.09	1.00	0.95

Table 3. The Left Score, The Right Score and The Total Score of Fuzzy Numbers A, B, C, D, E, and F.

Fuzzy Number I	The left score (I)	The right score (I)	The total score (I)
A	1.00	0.17	0.08
B	0.83	0.33	0.25
C	0.67	0.50	0.42
D	0.50	0.67	0.58
E	0.33	0.83	0.75
F	0.17	1.00	0.92

Table 4. The Left Score, The Right Score and The Total Score of Fuzzy Numbers Good, Fair, Poor, and Bad.

Fuzzy Number I	The left score (I)	The right score (I)	The total score (I)
Good	1.00	0.33	0.17
Fair	0.67	0.50	0.42
Poor	0.50	0.67	0.58
Bad	0.33	1.00	0.83

The C_{ij} is calculated after assigning crisp score to the fuzzy numbers (defuzzification), where it is usually done before defuzzification using fuzzy arithmetic method. This new approach is preferred to fuzzy arithmetic following the experience of Cheng et al. (1997) who found an interesting result from their study, that the application of fuzzy arithmetic will cause some information loss or more fuzziness and may thus lead to mistakes in decision-making.

4.4. THE FMADM APPROACH TRAVEL DEMAND MODEL

The travel impedance between origin destination pairs (routes value) is then one of the attributes of destinations value, and finally the total destinations value is one of the attributes of travel decisions value for trip generation model.

4.4.1. Calculating Destination Value

The first decision-making problem in this case is to determine the value of the preference that travellers in a zone origin i attaches to all available destinations (destinations value). Other attributes available for destinations value calculation are number of hotel room (HR), number of industry (NI), number of bed in hospital (NBH), and number of market (NM). The coefficient of correlations of those attributes as well as the route values (total travel impedance (Cij)) of each destination with observed trip attraction data (TA) is presented in the following table.

Table 5. Coefficient of Correlations (Trips Attraction and Other Variables)

	t_j	NHR	No. of market	No. of industry	Total Cij
t_j	1	.800	-.055	-.289	-.827
NHR	.800	1	.035	-.140	-.637
No. of market	-.055	.035	1	.295	.106
No. of industry	-.289	-.140	.295	1	.319
Total Cij	-.827	-.637	.106	.319	1

Based on table 2, the combination of attributes could be included in the decision-making problem are total C_{ij} and HR, total C_{ij} and NBH, or between total C_{ij}, HR and NBH. As there are 35 zones, so there are also 35 decision-making matrices must be made, in which each matrix contains of 34 alternatives of destination zones.

A combination of attributes is taken when the fuzzy multiple attribute decision-making gives the highest total sum of coefficient of correlation with observed travel demand. The combination between total C_{ij} and HR is taken, in which it gives the total of 25.55 (the average of *r* is 0.73 (25.55/35)).

Given the coefficient of correlations above (table 2) and formula 7, the weight of total C_{ij} is 0.51 (0.83/1.63) and the weight of HR is 0.49 (0.80/1.63). The value of the preference that travellers in a zone origin i attaches to destination j (destination value) is given by

$$DV_{ij} = (\frac{C_{ij}}{\max C_{ij}})^{-0.51} + (\frac{HR_j}{\max HR_j})^{0.49} \tag{12}$$

and the total of destinations value (DV_i) is given by

$$DV_i = \sum_{j=1}^{n} DV_{ij} \tag{13}$$

4.4.2. Calculating Travel Decision Value (Trip Generation Model)

The second decision-making problem is in determining the power of peoples in origin zone i to travel (travel decision value (TV_i)), in which the total destination value must be one of attributes. Based on table 1, the other attributes may be included decision matrix are GRDP and PD. The decision matrix could contain of DV_i and GRDP, DV_i and PD, or DV_i, GRDP and PD. The combination gives the highest correlation with trips generation must be taken to calculate travel decision value. Those three combinations of attributes give the coefficient of correlation as follow: 0.56, 0.52 and 0.70, so that the combination of DV_i, GRDP and PD is then taken, with the attributes weight as follow: 0.43 (0.65/1.51), 0.31(0.47/1.51), and 0.26 (0.38/1.51). The (TV_i) is calculated by formula as follow:

$$TV_i = (\frac{DV_i}{\max DV_i})^{0.43} + (\frac{GDRP_i}{\max GDRP_i})^{0.31} + (\frac{PD_i}{\max PD_i})^{0.26} \tag{14}$$

To ease in understanding the process of variables combination using the fuzzy multiple attribute decision-making, the following table might help

Table 5. The Calculation of Travel Decision Value

No	Kabupaten	DV_i	$GRDP_i$	PD_i	($4/M\ DV_i$) ^0.43	($5/M\ GRDP_i$) ^0.31	($6/M\ PD_i$) ^0.26	TV_i (7+8+9)
1	2	4	5	6	7	8	9	10
1	Cilacap	60.91	5460300.17	718	0.90	1.00	0.50	2.40
2	Banyumas	61.46	1133012.53	1041	0.91	0.61	0.54	2.06
3	Purbalingga	61.74	672547.45	964	0.91	0.52	0.53	1.96
4	Banjarnegara	63.70	902865.99	753	0.92	0.57	0.50	1.99
5	Kebumen	60.88	1102241.95	888	0.90	0.60	0.52	2.03
6	Purworejo	60.54	713052.01	678	0.90	0.53	0.49	1.92
7	Wonosobo	56.81	499167.88	695	0.88	0.47	0.49	1.84
8	Magelang	63.13	1160191.28	951	0.92	0.61	0.53	2.06
9	Boyolali	66.64	1054323.63	842	0.94	0.60	0.52	2.05
10	Klaten	65.45	1322775.61	1637	0.93	0.64	0.61	2.18
11	Sukoharjo	66.75	1080160.57	1519	0.94	0.60	0.60	2.14
12	Wonogiri	62.66	827986.73	533	0.91	0.55	0.46	1.93
13	Karanganyar	66.18	1268087.41	949	0.94	0.63	0.53	2.10
14	Sragen	65.84	791606.30	886	0.93	0.54	0.52	2.00
15	Grobogan	71.41	878581.41	605	0.97	0.56	0.48	2.01
16	Blora	61.84	746076.31	438	0.91	0.53	0.44	1.88
17	Rembang	66.96	568009.59	532	0.94	0.49	0.46	1.89
18	Pati	72.87	1103002.31	728	0.98	0.60	0.50	2.08
19	Kudus	71.42	3788307.22	1537	0.97	0.89	0.60	2.46
20	Jepara	65.95	1014846.61	876	0.93	0.59	0.52	2.05
21	Demak	70.75	828275.74	992	0.96	0.55	0.54	2.05
22	Semarang	76.64	1001814.01	855	1.00	0.59	0.52	2.10
23	Temanggung	63.97	745383.35	728	0.92	0.53	0.50	1.95
24	Kendal	62.07	1703101.92	832	0.91	0.69	0.51	2.12
25	Batang	62.20	818413.05	774	0.91	0.55	0.51	1.97
26	Pekalongan	63.46	926733.65	859	0.92	0.57	0.52	2.01
27	Pemalang	62.72	1042708.71	1170	0.91	0.59	0.56	2.07
28	Tegal	65.98	978775.12	1459	0.93	0.58	0.59	2.11
29	Brebes	65.03	1322522.03	986	0.93	0.64	0.54	2.11
30	Magelang City	62.86	320149.21	6749	0.92	0.41	0.87	2.20
31	Surakarta City	71.05	1314774.75	11734	0.97	0.64	1.00	2.60
32	Salatiga City	66.69	262641.29	1937	0.94	0.39	0.64	1.96
33	Semarang City	77.11	5307686.22	3610	1.00	0.99	0.74	2.74
34	Pekalongan City	64.50	453735.97	7213	0.93	0.46	0.89	2.27
35	Tegal City	65.47	358772.84	8609	0.93	0.42	0.93	2.28
	Maximum Value (M)	77.11	5460300.17	11734				
	r (between trip and attributes)	0.65	0.47	0.38				0.70
	Total r	1.51						
	(r/total r)	0.43	0.31	0.26				

Finally using analysis of regression the trip generation model can be performed and is given by

$$T_i = 29397.110 + 0.038(TV_i)^{15} \qquad (15)$$

The *t-values* are significant and the R^2 is 0.61. Although the R^2 is still quite low, this new approach is 1.58 times (0.61/0.386) better than the traditional model above (formula 9). If the available data for travel decision value have better correlation with observed trip generation data, this approach could give satisfactory results.

4.4.3. Trip Distribution

As this approach gives the trips produced by each zone and the value of all destinations (aggregate utility), then the logit model (production constraint gravity model) can be applied to calculate trips from i to j (T_{ij}/trips distribution).

$$T_{ij} = T_i \times \left(\frac{e^{bDV_{ij}}}{\sum_{i=1}^{n} e^{bDV_{ij}}}\right) \tag{16}$$

The diversion parameter (β) could be determined using Hyman's method (Hyman, 1969), which is usually used for calibrating gravity model parameter. The parameter is determined once the mean modelled trip cost (c_m) is sufficiently close to mean observed trip cost (c_o). The method gives the calibration parameter (β) of 1.092, where the difference between the mean modelled trip cost (c_m) and the mean observed trip cost (c_o) is zero.

$$c_m = \frac{\sum_{ij} T_{ij} DV_{ij}}{\sum_{ij} T_{ij}} \tag{17a}$$

$$c_0 = \frac{\sum_{ij} t_{ij} DV_{ij}}{\sum_{ij} t_{ij}} \tag{17b}$$

$$\sum_j T_{ij} = \sum_j t_{ij} \tag{17c}$$

5. CONCLUDING REMARKS

This approach produces quite good results, where it increases the traditional model performance in modelling trip generation 1.58 times. The application of fuzzy multiple attribute decision-making to combine variables affecting travel decision enable to connect the separated steps of the traditional four-steps travel demand model, so that all variables can be taken into account in the trip generation model (elastic).

As the alternatives are chosen based on decision-making problems, then this approach may be considered give behavioural basis to the traditional model. The use of fuzzy distance especially could overcome the weakness of models that the origins and destinations of trips are centroid of zones.

This approach could be extended to improve the structure and policy sensitivity of traffic count based models assuming a prior OD matrix is unavailable. Overall the main weakness of this approach is that it does not take into account aggregation biases and ecological correlation in the model. It is as for other aggregate models, where the model is estimated using average zonal variables.

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