FUZZY SIMPLE HIERARCHY ANALYSIS-BASED LINGUISTIC HEDGES IN THE SELECTION OF MIDSIZE LUXURY SPORT UTILITY VEHICLES

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ABSTRACT

The aim of this paper is to propose the use of the Fuzzy Simple Hierarchy Analysis (FSHA) using linguistic weight to deal with an ambiguous or vague multi-criteria datasets environment in the selection process. It focuses on vague multiple datasets evaluated based on fuzzy linguistic approaches. Linguistic hedges were used to cope with this issue during the evaluation process. The applicability and practicality of this proposed method was adopted to the selection of midsize luxury Sport Utility Vehicles (SUVs). Based on the analysis, it was found that this method is highly beneficial for the buyers in the sense that it can distinguish every single judgment made during the selection process clearly. It also offers a unique advantage and has successfully dealt with diversified and ill-defined parameters in terms of input data criterion. Thus, this method can assist potential buyers to make their decision in a simple and systematic manner.

Keywords: Fuzzy Simple Hierarchy Analysis (FSHA); linguistic hedges; luxury SUV selection

ABSTRAK

Penyelidikan ini mencadangkan Fuzzy Mudah Hierarki Analisis (FSHA) dengan menggunakan pemberat linguistik untuk menangani kekaburan atau persekitaran dataset yang samar-samar dari pelbagai kriteria dalam proses pemilihan. Ia memberi tumpuan kepada penilaian pelbagai dataset kabur berdasarkan pendekatan linguistik kabur. Kaedah ini telah dilengkapi dengan lindung nilai linguistik untuk menangani isu ini semasa proses penilaian. Pemilihan kenderaan bersaiz sederhana (SUV) mewah telah digunapakai untuk menunjukkan kesesuaian kaedah yang dicadangkan. Hasil eksperimen telah membuktikan keberkesanan kaedah ini dalam membezakan dengan jelas bagi setiap pertimbangan tunggal yang dibuat semasa proses pemilihan. Ia juga menawarkan kelebihan yang unik dan berjaya berurusan dengan pelbagai parameter yang rumit - ditakrifkan dari segi kriteria data input. Kaedah ini dapat memberi manfaat dan berguna kepada pembeli-pembeli dalam proses pemilihan pembelian kereta mewah bersaiz sederhana.

Kata kunci: *Fuzzy Mudah Hierarki Analisis (FSHA); linguistik hedges; pemilihan kereta mewah SUV*

1. Introduction

Over the years, we have seen a tremendous increase in the number of vehicles on the road especially in Malaysia. Vehicles have become a need; or shall we put it this way, a vehicle is a must-have item and every household must have at least one. Because of this, a potential vehicle purchaser, who is also the decision-maker (DM), considers not only the initial cost of owning a vehicle, but also other parameters such as comfort, performance, running cost and styling, among others. With the increase in the cost of living, customers are aggressively seeking ways to purchase so-called vehicles of high quality which also fall into the appropriate price range. Today's potential buyers also have complicated preferences and expectations of vehicles especially when the vehicles are from the luxury vehicle category (Apak et al., 2012). Since today's manufactured vehicles come with diverse and multifaceted features, this has made decision-making complicated for potential buyers during the vehicle selection process.

Selection is defined as the action or fact of carefully choosing someone or something as being the best or most suitable. According to Markowitz, 1952, the selection process consists of two main stages, namely observation and experiences, and ends with belief on the future performance of the choice. It is crucial for decision-makers (DMs) to make the correct judgment in the selection process. To select something requires consideration from multiple parameters (Ma et al., 2000). Selection is difficult mainly due to vast and ambiguous multi-criteria inputs (Zhang et al., 2005). Many DMs feel the pressure when selecting a vehicle, acknowledging that accurate critical selection involves important attributes such as price, performance delivery, quality, time frame and others (Talluri, 2002). The process is even trickier when there are a number of parameters which is conflicting qualitatively, and are uncertain and inexplicit (Raut et al., 2011). Various methods are applied in order to expedite and ease the process of selection (Humphreys et al., 2003; Raut et al., 2011).

The selection process may apply to any field, for example in the context of maintaining customer-supplier management (Aydin & Kahraman, 2010; Kethley et al., 2002), in raw material selection for construction (Talluri, 2002), in medical or tourism fields (Ngai & Wat, 2003; Song & Li, 2008), in the field of education when selecting students for a programme (Crespo et al., 2005; Zamali et al., 2013), in manufacturing when identifying faulty newly manufactured parts (Catelani & Fort, 2002; Lo et al., 2007), in fault detection based on pattern selection (Dasgupta et al., 2004) and others.

Similarly, in the selection process during vehicle purchasing, potential buyers place multiple parameters as input to assist them in making a decision. Some may want to ponder on the safety features (Hellinga et al., 2007; Zhan & Vrkljan, 2011), price (Whitehead et al., 2014), fuel economy (Bhat & Sen, 2006; Caulfield et al., 2010), quality and reliability (Binder et al.,, 2014) and others. Research has provided simple definitions for the customer preference criterion for luxury cars. Even though these are defined, these preference criteria are very subjective and vague, depending on one's point of view (Belgiawan et al. 2013), which contributes to the complexity in making a decision before a purchase is made.

The goal of this research is to implement the Fuzzy Simple Hierarchy Analysis (FSHA) using linguistic weight in the selection process and to focus on the linguistic hedges for DMs to make their verdict for weighting purposes. We believe that this method is a suitable approach to assist the DMs in the selection process using both qualitative and quantitative criteria (Ahmed et al., 2002; Aydin & Kahraman, 2010) and that it is flexible in dealing with ill-structured and complex problems. The approach used in this paper engaged the haziness multi-criteria datasets environment during the selection process. It was applied to the selection of midsize luxury Sport Utility Vehicle (SUV). A numerical example is presented in this paper by adopting from the equation [see section 4 below] to show the applicability and practicality of the proposed method. Thus, this method aims to assist potential customers in their vehicle selection by evaluating vague multiple datasets. The result of this work indicates that the approach manages to identify the best midsize luxury SUV for the potential buyers (i.e.,DMs). The proposed method has proven to be helpful because it reduces the time spent in the selection process and skips the tricky evaluation process.

The remainder of this paper is presented as follows: Problem identification is presented in Section 2 while Section 3 depicts the theoretical concept of the fuzzy set theory and the proposed methodology. Section 4 describes the implementation of the proposed method with a numerical example, portraying the application before the conclusion made in Section 5.

2. Problem Identification

Based on literature, decision-making during the selection process is not favoured by anyone and can be risky when it is not done correctly. Though there are plenty of methods designed to assist in the selection process, there is no distinct method available yet on assisting buyers in decision-making during the selection process when it comes to purchasing a midsize luxury SUV. Similar to the purchasing process in other situations, midsize luxury SUV buyers cannot skip the decision-making part and have to consider multiple vague datasets (i.e., comfort, fuel, styling, handling) which also makes the process a tedious and complicated one. In this research, the researchers are proposing a FSHA-based linguistic hedges concept, which is able to minimise ambiguous elements during the selection process. This method is able to assist potential buyers in making a better and more accurate purchase.

3. The Theoretical Concept and Proposed Methodology

3.1. *Preliminaries*

In this sub-section, the basic definitions and the theoretical concept are briefly elaborated for reference purposes.

Definition 1 A fuzzy set A in a universe of discourse X is characterised by a membership function $\mu_A(x)$ that takes the values in the interval of [0,1]. It can be denoted as follows:

$$A = \{(\mu_A(x)/x); x \in X\} \quad (1)$$

Definition 2 A fuzzy number A is a fuzzy subset in the universe of a real number $\boldsymbol{R}$ that is both convex and normal.

Definition 3 A linguistic hedge or a modifier is an operation that modifies the meaning of a term more generally, of a fuzzy set. If $\tilde{A}$ is a fuzzy set then the modifier k generates the (composite) term $\tilde{B} = k\left(\tilde{A}\right)$.

The modifier is defined as:

$$\mu_{con(\tilde{A})}(a) = \left[\mu_{\tilde{A}}(a)\right]^{\alpha}$$

Concentration , where $\alpha > 1$ (2)

$$\mu_{dil(\tilde{A})}(a) = \left[\mu_{\tilde{A}}(a)\right]^{1/\alpha}$$

Dilation , where $\alpha > 1$ (3)

Definition 4 The linguistic hedges and their approximate meanings are specifically classified as shown in Table 1.

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Table 1: The hedge values of the specific *concentration*

Linguistic hedges	*Extremely Important (EI)*	*Very Important (VI)*	*Fairly important (FI)*	*Somewhat important (SI)*	*Less important (LI)*	*Between linguistic hedges*
Meaning	Intensify a fuzzy region	Contrast intensification	-	Contrast difussion	Dilate a fuzzy region	Intensify contrast dilate
Hedge values (α)	$[\mu_{EI}(x)]^3$	$[\mu_{VI}(x)]^2$	$[\mu_{FI}(x)]^1$	$[\mu_{FI}(x)]^{1.2}$	$[\mu_{FI}(x)]^{1.4}$	Between two hedges value range

3.2. *Simple Hierarchy Analysis-Based Linguistic Hedges*

The idea of introducing the Simple Hierarchy Analysis, which is a simplification method, is based on the Analytic Hierarchy Process (AHP) introduced by Saaty in 1980. In this study, the mean of fuzzy numbers was utilised for the hierarchical process stage to represent the crisp values. In addition, we equipped the linguistic hedge to derive the importance of the relative weights for each criterion in the selection process. Obviously, words such as '*extremely comfortable*', '*very comfortable*', '*slightly comfortable*', etc. have been used for rating purposes after the potential buyers had test driven a latest AUDI Sport Utility Vehicle (SUV) Q3 model. Thus, words such as '*extremely*', '*very*', '*slightly*' are called linguistic hedges.

Table 2: The mean of fuzzy numbers

Linguistic variables	Mean of fuzzy numbers
Very poor (*VP*)	0
Poor (*P*)	0.17
Medium poor (*MP*)	0.33
Fair (*F*)	0.50
Medium good (*MG*)	0.67
Good (*G*)	0.84
Very good (*VG*)	1

3.3. *The proposed methodology*

In order to clarify our proposed method, we present the step-by-step procedures as follows:
Step 1: Decompose the actual problem in the hierarchy structure for criteria and its definition.
Step 2: Assign each criteria based on the DMs' evaluation with regard to each alternative using mean of fuzzy numbers in Table 2. The performance scores $(\tilde{PS}_{ALL})$ can be obtained as

$$(\tilde{PS}_{ALL}) = \begin{array}{c} \\ M_1 \\ M_2 \\ \cdots \\ M_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_3 \end{array} \\ \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{a}_{m1} & \tilde{a}_{m2} & \cdots & \tilde{a}_{mn} \end{bmatrix} \end{array}, \tag{4}$$

where, C_i $(i = 1,2,3,\ldots, n)$ is the number of the criterion, and
$M_i (i = 1,2,3, \ldots, n)$ is the number of an alternative (i.e., SUV)

Step 3: Assign the power of *dilation* and/or *concentration* for each criterion based on potential buyers' (i.e., DMs) opinion and aggregate it as

$$\tilde{FD}_{\alpha} = \left[\begin{pmatrix} \mu_{11}(a) \\ \mu_{12}(a) \\ \cdots\cdots \\ \mu_{1n}(a) \end{pmatrix}^{\alpha_1} \begin{pmatrix} \mu_{12}(a) \\ \mu_{22}(a) \\ \cdots\cdots \\ \mu_{2n}(a) \end{pmatrix}^{\alpha_2} \begin{pmatrix} \cdots\cdots \\ \cdots\cdots \\ \cdots\cdots \\ \cdots\cdots \end{pmatrix}^{\alpha_{n-1}} \begin{pmatrix} \mu_{1n}(a) \\ \mu_{2n}(a) \\ \cdots\cdots \\ \mu_{m\times n}(a) \end{pmatrix}^{\alpha_n} \right], \tag{5}$$

where, α_i (i = 1,2,3,…, n)

Step 4: Identify the best alternative by maximising the minimum membership value for overall criteria in descending order given by the following operator,

$$\mu_{\tilde{FD}_{\alpha}}(a_i) = \max_i \left(\min_j \mu_{ij}^{\alpha_j} \right), \tag{6}$$

4. Implementation

For illustration, a case study from Apak et al. (2012) was adopted. The evaluation was carried out based on 7 criteria; C_1= price, C_2 = technology, C_3 = quality, C_4 = performance, C_5 = reliability, C_6 = brand image, and C_7 = flexibility. For calculation purposes, say that four potential buyers (i.e., DMs) have considered buying one of three equivalent midsize luxury SUV model; $M_1 \approx$ model Q3 Audi, $M_2 \approx$ model GLA 200 Mercedes Benz, and $M_3 \approx$ model X1 BMW. Next, all four DMs evaluate the seven criteria based on his/her opinion (see Table 4) as a raw input dataset using mean of fuzzy numbers in Table 2.

Table 4: The raw input dataset of seven criteria

Model	M_1	M_2	M_3
C_1	*G*	*G*	*MG*
C_2	*G*	*VG*	*G*
C_3	*VG*	*VG*	*VG*
C_4	*G*	*G*	*G*
C_5	*MG*	*MG*	*G*
C_6	*G*	*VG*	*G*
C_7	*MG*	*G*	*MG*

Thus, the information depicted in Table 5 is a summary of the identified 7 criteria and their definitions.

Table 5: The criteria and its definition

Criteria	Definition
Price (C_1)	The price appropriateness of that brand when compared with those of other alternative brand models from the same market segment
Technology (C_2)	The technology, comfort and environmental (social) responsibility level offered by that brand
Quality (C_3)	After-sales service quality such as parts and maintenance support
Performance (C_4)	The quality and reliability of the required (brand) model delivery time
Reliability (C_5)	The reliability of the products produced by that brand
Brand image (C_6)	Brand perception of the car
Flexibility (C_7)	Customisation varieties of the required brand model and its delivery time or order accessibility.

Source: Apak et al., 2012

Here, from the previous section we provide the step-by-step procedure as follows:
Step 1: Decompose the actual problem in the hierarchy structure as defined in Table 5.

Step 2: Assign each criteria based on DMs' evaluation with regard to each model using Table 2. Here, we obtain the overall performance scores from (3) as,

$$\tilde{PS}_{ALL} = \begin{bmatrix} 0.84 & 0.84 & 1.0 & 0.84 & 0.67 & 0.84 & 0.67 \\ 0.84 & 1.0 & 1.0 & 0.84 & 0.67 & 1.0 & 0.84 \\ 0.67 & 0.84 & 1.0 & 0.84 & 0.84 & 0.84 & 0.67 \end{bmatrix},$$

Table 6: The hedges (dilation and concentration) from all DMs with respect to seven criteria

DMs	C_1	C_2	C_3	C_4	C_5	C_6	C_7
DM_1	*EI*	*VI*	*VI*	*FI*	*FI*	*VI*	*FI*
DM_2	*EI*	*EI*	*VI*	*VI*	*FI*	*FI*	*VI*
DM_3	*VI*	*EI*	*VI*	*FI*	*VI*	*FI*	*FI*
DM_4	*VI*	*VI*	*VI*	*VI*	*FI*	*EI*	*VI*

Step 3: Assign the power of *concentration* and/or *dilation* for each criterion ($\tilde{FD}_\alpha$) and aggregate the DMs' evaluated values.

Assuming that all DMs have different judgment/opinion for each criterion as given in Table 6 and the average aggregated power of *concentration* and *dilation* for each criterion were obtained. Hence, from (5) we have

$$\tilde{FD}_\alpha = \begin{bmatrix} \begin{pmatrix} 0.84 \\ 0.84 \\ 0.67 \end{pmatrix}^{5/2} & \begin{pmatrix} 0.84 \\ 1.0 \\ 0.84 \end{pmatrix}^{5/2} & \begin{pmatrix} 1.0 \\ 1.0 \\ 1.0 \end{pmatrix}^{2} & \begin{pmatrix} 0.84 \\ 0.84 \\ 0.84 \end{pmatrix}^{3/2} & \begin{pmatrix} 0.67 \\ 0.67 \\ 0.84 \end{pmatrix}^{5/4} & \begin{pmatrix} 0.84 \\ 1.0 \\ 0.84 \end{pmatrix}^{7/4} & \begin{pmatrix} 0.67 \\ 0.84 \\ 0.67 \end{pmatrix}^{3/2} \end{bmatrix}$$

$$= \begin{bmatrix} 0.6467 & 0.6467 & 1.0 & 0.7699 & 0.6062 & 0.7370 & 0.5484 \\ 0.6467 & 1.0 & 1.0 & 0.7699 & 0.6062 & 1.0 & 0.7699 \\ 0.3674 & 0.6467 & 1.0 & 0.7699 & 0.8042 & 0.7370 & 0.5484 \end{bmatrix}$$

Step 4: We can easily identify the best midsize luxury SUV and rank them in descending order. By using (6) the $M_2 = 0.6062$ has the maximum membership values, followed by $M_1 = 0.5484$, and the last is $M_3 = 0.3674$. Apparently we can write as $M_2 > M_1 > M_3$, where M_2 is the best in terms of its overall performance scores compared to other similar models. The symbol '>' means 'is superior or preferred to'.

5. Conclusions

By using FSHA based on linguistic hedges, the best midsize luxury SUV can be identified easily by potential buyers. The method is quite simple and equips the power of *dilation* and *concentration* for each criterion in the evaluation process. It is clearly seen that the proposed method is highly beneficial to avoid the complexity of the evaluation process and at the same time, can reduce the time consumed during the analysis stage. Although the numerical results may be relevant only for this case study, we can expect similar outcomes for other real cases. Next, the proposed method has unique advantages in the sense that it can distinguish clearly for every single judgment made from potential buyers' perspective. The method also provides a

systematic procedure and successfully deals with ill-defined input criterion. Thus, it can help potential buyers to make their decision in a simple and systematic manner. Our next effort is to equip the method with sensitivity analysis (SA) to ensure the results obtained are robust enough for DMs to make their decision with regard to any small disturbance in terms of input parameters. This initiative is left to our future research work.

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