A Combined Fuzzy Approach to Determine Sustainable ELV Strategy

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Abstract: The sustainable End-of-Life Vehicle (ELV) management has emerged as a competitive subject for producers to respond to environmental and economic challenges. There are several ELV strategies such as reuse and remanufacturing which enable companies to reduce environmental impacts and optimize the product life cycle. The selection of the best compromise ELVs management strategy improves the sustainability performance of companies. This study aims at proposing an integrated Fuzzy Multi-Criteria Decision-Making (FMCDM) to evaluate the sustainable ELV strategies with respect to the user's preference orders. Fuzzy Analytic Hierarchy Process (FAHP) is used to determine the relative weights of the assessment sustainable criteria and the extension of the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) is applied to investigate the ELV strategies. The findings indicate the usefulness of the proposed model in evaluating sustainable ELV strategies with human linguistic terms and how it simplifies the decision-making process.

Keywords: End-of-Life Vehicle (ELV), Evaluation, Fuzzy, Multi-Criteria Decision Making, AHP, TOPSIS, Strategy

1 Introduction

Nowadays, the concern for environmental issues has motivated the development of new concepts to decrease the impacts caused by product disposal. Hence, most companies are trying to develop solutions which can aid in the efficient utilization of resources and the reduction of current environmental impacts [1]. In this context, sustainable End-of-Life Vehicle (ELV) management presents strategies such as landfill, incineration, recycle, and repair to reduce environmental impacts and improve economical and social benefits [2].

Using the best sustainable ELV strategy with companies results in reduce the environmental impacts, maintain the minimal regulatory standards for acceptable pollution levels, and decrease the wasteful use of natural resources. In this regard, several models and methods have been used to evaluate sustainable ELV strategies. Dantec [3] assessed the cost of recycling compliance in the automotive sector. Shih et al. [4] suggested an economic model to carry out cost-benefit analysis in recycling. Lee et al. [5] presented a decision model to assess the economics of the remanufacturing and disassembly processes. They considered environmental legislation for this evaluation. Lee et al. [6] and Hula et al. [7] presented a mathematical model to evaluate EoL alternatives by defining objectives such as maximization of net profit or minimization of costs. Similarly, Tan and Kumar [8] and Das and Yedlarajiah [9] suggested a linear programming model and a mixed integer program in order to evaluate EoL options, respectively. Chan and Tong [10] applied grey relational analysis to assess EoL strategies in terms of material selection. A multi-objective procedure has been proposed for product recovery optimization by Jun et al. [11] Ghazalli and Murata [12] proposed an AHP and case-based reasoning method to evaluate EoL options.

According to this subject that the evaluation of ELV strategies and optimal selection of alternatives have multi-level and multi-factor features, so it can be considered as a multiple criteria decision-making (MCDM) problem. It should be noted that using suitable dimensions, criteria, and sub-criteria improve the quality of decision-making in the assessment of sustainable ELV strategies.

In the primitive forms of MCDM methods, experts' comparisons about the criteria, sub-criteria, and alternatives are mentioned in terms of exact numbers. These methods could not obtain correct answers in most practical cases. In fact, the experts' preferences are uncertain and they are reluctant to draw numerical comparisons in many MCDM problems. The fuzzy decision-making methods are presented to tackle aforementioned shortage. These methods are able to use fuzzy and vague data in comparison with classical decision-making methods that work only with exact data. The ability of human for qualitative data processing helps them to make decisions in fuzzy environment. The main objective of this paper is to propose an integrated model of AHP and TOPSIS with a Fuzzy approach to evaluating sustainable ELV strategies. The Fuzzy AHP is applied to determine the importance of weights of evaluation criteria, and the Fuzzy TOPSIS is used to estimate the final ranking of the ELV strategies in linguistic values parameterized with triangular fuzzy numbers.

The reminder of paper is organized as follows. Section two describes the Fuzzy AHP and Fuzzy TOPSIS models. The proposed approach to evaluating sustainable ELV strategies along with a case study is represented in section 3. In the last section, discussion and the extracted conclusions from the suggested model will be presented.

2 The FAHP and FTOPSIS Methodology

2.1 Fuzzy AHP Model

A Fuzzy AHP was developed in terms of AHP to solve the hierarchical fuzzy problems. Many Fuzzy AHP methods are presented by various authors [13, 14]. The fuzzy AHP method which is used in this study is based on methodology steps of Ayag [15]. The performance scores are compared in the first step. Linguistic terms are used to represent the relative strength of each pair of elements in the same hierarchy. Then in the second step, the fuzzy comparison matrices are built. Triangular fuzzy numbers ($\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$) are applied to display the relative strength of each pair of elements in the same hierarchy. The fuzzy judgment matrix, $\tilde{A}$ via pair wise comparison is constructed as given below:

$$\tilde{A}=\begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{12} & \cdots & \cdots & 1 \end{bmatrix} \quad (1)$$

Where $\tilde{a}_{ij}$ = 1, if *i* is equal *j*, and $\tilde{a}_{ij} = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}$, $\tilde{9}$ or $\tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}$, if *i* is not equal *j*. In the third step, the fuzzy eigenvalues are calculated. A fuzzy eigenvalue, $\tilde{\lambda}$, is a fuzzy number solution to:

$$\tilde{A}\tilde{x}=\tilde{\lambda}\tilde{x} \quad (2)$$

Where $\tilde{\lambda}_{max}$ is the largest eigenvalue of $\tilde{A}$ and $\tilde{x}$ is a non-zero n × 1, fuzzy vector containing fuzzy number $\tilde{x}_i$. To compute fuzzy multiplications and additions by using the interval arithmetic and α-cut, the equation $\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x}$ is equivalent to:

$$[a_{i1l}^{\alpha}x_{1l}^{\alpha},\ a_{i1u}^{\alpha}x_{1u}^{\alpha}] \oplus \ldots \oplus [a_{inl}^{\alpha}x_{nl}^{\alpha},\ a_{inu}^{\alpha}x_{nu}^{\alpha}] = [\lambda x_{il}^{\alpha}, \lambda x_{iu}^{\alpha}]$$

where,

$$\tilde{A} = [a_{ij}^{\alpha}],\ \tilde{x}^{t} = (\tilde{x}_1, \ldots \tilde{x}_n),$$
$$\tilde{a}_{ij}^{\alpha} = [a_{ijl}^{\alpha}, a_{iju}^{\alpha}],\ \tilde{x}_{ij}^{\alpha} = [x_{il}^{\alpha}, xj_{1u}^{\alpha}],$$
$$\tilde{\lambda}^{\alpha} = [\lambda_l^{\alpha}, \lambda_u^{\alpha}] \quad (3)$$

for $0 < \alpha \leq 1$ and all i, j, where i = 1, 2, . . . , n, j = 1, 2 . . . , n.

The α-cut is famous to contain the experts or decision maker confidence over his/her preferences. The degree of satisfaction for the judgment matrix $\tilde{A}$ is calculated by the index of optimism μ. A larger value of the index μ shows a higher degree of optimism. The index of optimism is a linear convex combination defined as:

$$\tilde{a}_{ij}^{\alpha} = \mu\tilde{a}_{ijl}^{\alpha} + (1-\mu)\,\tilde{a}_{ijl}^{\alpha},\ \forall\alpha\epsilon[0,1] \quad (4)$$

When α is fixed, the following matrix can be obtained by setting the index of optimism, μ, in order to estimate the degree of satisfaction:

$$\tilde{A}=\begin{bmatrix} 1 & \tilde{a}_{12}^{\alpha} & \cdots & \cdots & \tilde{a}_{1n}^{\alpha} \\ \tilde{a}_{21}^{\alpha} & 1 & \cdots & \cdots & \tilde{a}_{2n}^{\alpha} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{n1}^{\alpha} & \tilde{a}_{n2}^{\alpha} & \cdots & \cdots & 1 \end{bmatrix} \quad (5)$$

After constructing all required pairwise judgment matrices between criteria/sub-criteria levels, for each, the consistency ratio (CR) should be calculated. The deviation from consistency, the measure of inconsistency is named the consistency index (CI) and computed using the following equation:

$$CI=\lambda_{max}-1/n-1 \quad (6)$$

where *n* is matrix size.

The CR is applied to calculate directly the consistency of pairwise comparisons, and computed by dividing the CI by a value obtained from a table of random consistency index (RI) (Table 1), the average index for randomly generated weights (Saaty, 1980), as shown in the following equation:

$$CR=\frac{CI}{RI} \quad (7)$$

If the CR less than 10%, the comparisons are acceptable, otherwise not. In the fifth and the last step, the priority weight of each alternative can be computed by multiplying the matrix of evaluation ratings by the vector of attribute weights and summing over all attributes.

Table 1. The random consistency index (RI)

Size (n)	1	2	3	4	5
RI	0	0	0.52	0.89	1.11
Size (n)	6	7	8	9	10
RI	1.25	1.35	1.40	1.45	1.51

2.2 Fuzzy TOPSIS Model

The fuzzy TOPSIS method is an integrated model that is applied to solve real life application problems under a fuzzy environment [16]. The steps of Fuzzy TOPSIS method are presented as follows:

Step 1: Finding the linguistic rating values for the alternative with respect to criteria

There are m possible alternatives called A = {A_1,A_2. . .A_m} which are to be calculated against the criteria, C = {C_1,C_2 ,. .C_n} The criteria weights are indicated by w_j (j = 1,2,. . .,n). The performance ratings of each expert D_k (k = 1,2,. . .K) for each alternative A_i (i = 1,2,. . .m) with respect to criteria C_j(j = 1,2,. . .n) are indicated by $\tilde{R}_k = \tilde{x}_{ijk}$ (i= 1; 2; . . .m; j= 1; 2; . . . n; k= 1; 2 . . . K) membership function $\mu\tilde{R}K(x)$. The scale used for solutions rating is given in Table 2.

Table 2. Linguistic variables for solutions ratings

Linguistic variables	Corresponding TFN
Very low	(1, 1, 2)
Low	(2, 3, 4)
Medium	(4, 5, 6)
High	(6, 7, 8)
Very high	(8, 9, 10)

Step 2: Compute aggregate fuzzy ratings for the alternatives

If the fuzzy ratings of all experts are displayed as TFN $\tilde{R}_k$= (ak, bk, ck), k = 1,2,. . .K then the aggregated fuzzy rating is represented by $\tilde{R}$= (a,b,c) k = 1,2,. . .K where

a= min {a_k}, b = $\frac{1}{K}\sum_{k=1}^{k} b_k$, c = max {c_k}, (8)

If the fuzzy rating of the kth decision maker are $\tilde{X}_{ijk}$ = (a_{ijk} , b_{ijk}, c_{ijk}), i= 1, 2, ….. m; j = 1, 2, …..n, then the aggregated fuzzy ratings $\tilde{X}_{ij}$ alternatives with respect to each criteria are given by $\tilde{X}_{ij}$ (a_{ij} , b_{ij}, c_{ij}) , where:

a_{ij}= min {a_{ijk}}, b = $\frac{1}{K}\sum_{k=1}^{k} b_{ijk}$, c = max {c_{ijk}}, (9)

Step 3: Construct the fuzzy decision matrix

The fuzzy decision matrix for the alternatives ($\tilde{D}$) is built as follows:

$C_1C_2C_n$

$$\tilde{A} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad i= 1, 2, \ldots m ;$$

j= 1, 2, …….,n (10)

Step 4: Build the Normalize fuzzy decision matrix

In this step by applying linear scale transformation, the raw data are normalized to bring the various criteria scales into a comparable scale. The normalized fuzzy decision matrix $\tilde{R}$ is given by:

$\tilde{R} = [r_{ij}]_{m\times n}$, i= 1, 2,..m ; j= 1, 2, ..,n (11)

Where

$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right)$ and c_j^* = max c_{ij} (benefit criteria) (12)

$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right)$ and a_j^- = min a_{ij} (benefit criteria) (13)

Step 5: Build the weighted normalized matrix

The weighted normalized matrix $\tilde{v}$ for criteria is calculated by multiplying the weights (W_j) of evaluation criteria with the normalized fuzzy decision matrix $\tilde{r}_{ij}$.

$\tilde{V} = [\tilde{v}_{ij}]_{m\times n}$, i= 1, 2, …..m ; j= 1, 2, …….,n where $\tilde{v}_{ij} = \tilde{r}_{ij} W_j$ (14)

Step 6: Determine the fuzzy ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

The FPIS and FNIS of the alternatives are calculated as follows:

A^* = ($\tilde{v}_1^*$, $\tilde{v}_2^*$, …… $\tilde{v}_n^*$) where $\tilde{v}_j^*$ = ($\tilde{c}_j^*$, $\tilde{c}_j^*$, $\tilde{c}_j^*$) and $\tilde{c}_j^*$= max {$\tilde{c}_{ij}$ } (15)

A^- = ($\tilde{v}_1^-$, $\tilde{v}_2^-$, …… $\tilde{v}_n^-$) where $\tilde{v}_j^-$ = (a_j^-, $\tilde{a}_j^-$, $\tilde{a}_j^-$) and $\tilde{a}_j^-$= min {$\tilde{a}_{ij}$ } (16)

$\forall i$= 1, 2,……,m and j= 1,2,…….,n

Step 7: Calculate the distance of each alternative from FPIS and FNIS

The distance (d_i^+, d_i^-) of each weighted alternative i = 1,2,. . .,m from the FPIS and the FNIS is computed as follows:

$d_i^+ = \sum_{j=1}^{n} dv(\tilde{v}_{ij}, \tilde{v}_j^*)$ i= 1, 2, ….m (17)

$d_i^- = \sum_{j=1}^{n} dv(\tilde{v}_{ij}, \tilde{v}_j^-)$ i= 1, 2, …..m (18)

Step 8: Calculate the closeness coefficient (CCi) of each alternative

The closeness coefficient CC_i displays the distances to the fuzzy positive ideal solution (A^*) and the fuzzy negative ideal solution (A^-) simultaneously. The closeness coefficient of each alternative is estimated as:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{19}$$

Step 9: Rank the alternatives

In step 9, the different alternatives are prioritized according to the closeness coefficient (CC_i) in decreasing order.

3 Proposed Approach

The importance of ELV strategy selection has forced companies to use different methods to evaluate these strategies. While this problem is taken into consideration as a multi-criteria problem but most studies have applied one criterion, economic dimension, to investigate End-of-Life strategies. Conventional MCDM models are not able to effectively resolve problems with such imprecise data. For this reason, Fuzzy set theory which is introduced by Zadeh is recommended to resolve this shortcoming. In this study, AHP and TOPSIS models are applied in the Fuzzy environment to investigate ELV strategies. At first, weights of sustainable criteria are determined by Fuzzy AHP. Then Fuzzy TOPSIS is applied for the evaluation of strategies considering sustainable criteria. Schematic diagram of the proposed model is shown in Fig. 1. The proposed approach is applied to select the best ELV strategy for one component of automobile part in a company. The methodology is detailed in following steps.

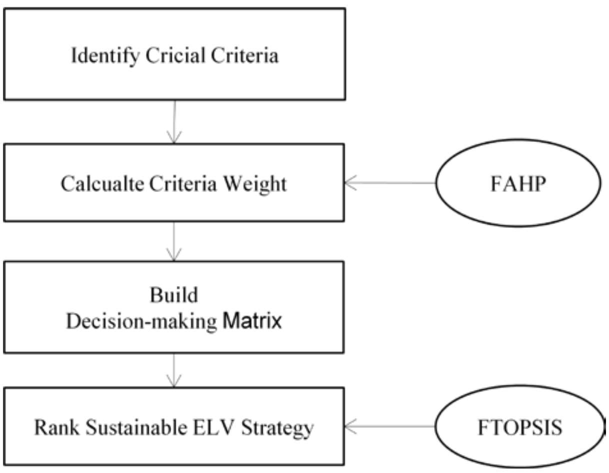

Fig.1. Schematic diagram of the proposed model

Step 1: Define criteria and build hierarchal framework

In the first step, sustainable ELV management criteria are identified and tried to build the hierarchical structure. The hierarchy structure is formed such that the objective is at the first level, criteria at the second level, and sustainable ELV management Alternatives at the third level. In this research, the decision group is consisting of the 5 expert panels which comprising three managers of the considered company and two experts from academic domain. It should be mentioned, all information are collected with questionnaires.

Step 2: Calculate the weights of criteria with Fuzzy AHP

After forming a decision hierarchy, the weights of the criteria are calculated by Fuzzy AHP. Pair-wise comparison matrixes of experts' evaluations are made to calculate weights of criteria by using the scale in Table 3. By computing the arithmetic mean of the values gotten from their evaluation, the final evaluation matrix will be made. From this matrix, the weight of the criteria will be evaluated as presented in Fuzzy AHP section. Results are given in Table 4-6.

Table 1. The Scale of relative importance used in the pairwise comparison matrix.

Intensity of importance	Fuzzy Number	Judgment or preference	Function
1	$\tilde{1}$	Equally important	(1, 1, 2)
3	$\tilde{3}$	Moderately more important	(2, 3, 4)
5	$\tilde{5}$	Strongly more important	(4, 5, 6)
7	$\tilde{7}$	Very strongly more important	(6, 7, 8)
9	$\tilde{9}$	Extremely more important	(8, 9, 10)

Table 4. Fuzzy comparison matrix of the criteria using triangular fuzzy numbers

	Economic	Social	Environmental	Technology
Economic	1			
Social		1		
Environmental	$\tilde{9}$		1	
Technology				1

Table 5. α-Cuts fuzzy comparison matrix for the criteria (α = 0.5, μ = 0.5)

	Economic	Social	Environmental	Technology
Economic	1	[1/8,1/6]	[1/10,1/8]	[1/4,1/2]
Social	[6,8]	1	[1/4,1/2]	[4,6]
Environmental	[8,10]	[2,4]	1	[6,8]
Technology	[2,4]	[1/6,1/4]	[1/8,1/6]	1

Table 6. Eigenvector for comparison matrix of the criteria (CR = 0.065)

	Economic	Social	Environmental	Technology	e-vector
Economic	1	0.146	0.113	0.375	0.04
Social	7	1	0.375	5	0.30
Environmental	9	3	1	7	0.58
Technology	3	0.21	0.146	1	0.09

Step 3: Prioritize Sustainable ELV strategies with Fuzzy TOPSIS

In the last step, ELV strategies are ranked according to sustainability criteria by using fuzzy TOPSIS. The experts were asked to compare strategies under each of the criteria separately by using linguistic variables presented in Table 2. Ranking of ELV strategies is finalized according to CCi values calculated by Fuzzy TOPSIS in descending order.

Table 7. Fuzzy TOPSIS result

Strategy			CC_i	Rank
Used Vehicle Export	3.77	2.251	0.374	3
Resale/Reuse	3.87	2.121	0.354	4
Recycling	3.55	2.312	0.394	2
Remanufacturing Parts	3.93	2.051	0.343	5
Remanufacturing Finished Product	3.95	2.011	0.337	6
Recondition/Repair	3.18	2.718	0.461	1

As it can be seen from Table 7, recondition/repair strategy was ranked first. It means this strategy has the best performance in terms of economic, environmental, social, and technology criteria for the considered component. Also, it can be inferred from Table 7 that remanufacturing finished product strategy is not suitable for end-of-life of this component. Recycling strategy was recognized as the best strategy after recondition strategy. The used vehicle export, resale, remanufacturing part strategies ranked third, fourth, and the fifth strategy, respectively.

4 Discussion & Conclusions

The selection of the best sustainable ELV strategy is recognized as one of the most important activities covering vital decisions for the survival of a company. If companies can effectively manage the required activities for end-of-life of their products they will be able to change threats to opportunities. Therefore, the decision-making process for sustainable ELV strategy should be timed and effective if a company wants to reach optimum results. The process of ELV strategy evaluation considering several criteria, leading to a large set of subjective or ambiguous data. For this reason, an integrated Fuzzy MCDM model was proposed to assess these strategies.

The Fuzzy AHP was applied to assign weights to the sustainable criteria to be employed in ELV strategy evaluation, while fuzzy TOPSIS was used to prioritize alternatives. The weights extracted from fuzzy AHP are included in the decision-making process by employing them in fuzzy TOPSIS calculations and the ELV strategy priorities were determined based on these weights. The empirical case study was presented to demonstrate the applicability of the presented model. According to obtained results, environmental dimension is the most important criteria to evaluate ELV strategies. The considerable point that should be mentioned is, the economic criterion was not taken into consideration as an important factor. The social and technology criteria were ranked second and third according to experts' opinions of this company. The findings of this paper also represent that recondition/repair strategy is the best alternative to manage the end-of-life of the considered component in this case study.

The several managerial implications for managers of companies can be drawn from the suggested model in this study. This model enables companies to analyze available sustainable ELV strategies for managing their products. In fact, managers can determine which EOL strategy should be applied for components of their products. Also, the proposed model helps to recycling organizations to determine which sustainable dimension is important in accomplishing strategic aims and improve the sustainable performance in managing ELV. Companies should take a comprehensive approach to evaluating the sustainable ELV strategies which include a set of criteria rather than focusing on any single factor if they want to achieve useful results. The proposed model was done with four main sustainability dimensions namely economic, environmental, social, and technology which are easily adaptable to add other factors to model.

Like other studies, the proposed model in this study has its own limitations and drawbacks. In this study, four main sustainable criteria were applied to evaluate sustainable ELV strategies while other crucial criteria and sub-criteria could be added to this model. It should be mentioned that this study was limited to only one component of one industry, and therefore, the findings could not be generalized to other types of industries and components. The results of such approaches are dependent upon experts' conceptual opinions. This is considered as other limitation for the proposed model. For this reason, it is so important that experts who make the comparisons be familiar with the sustainable criteria and ELV strategies. Sustainable ELV collection in the reverse supply chain can be the future research direction for researchers. Also, the results of this study could be compared with that of other fuzzy multi-criteria techniques such as fuzzy ELECTRE, fuzzy PROMETHEE, or fuzzy VIKOR.

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