Prioritizing Vehicle Cleanliness (PVC) using Key Green Performance Indicators (KGPI)

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Abstract

This paper aims to develop and support a testing and scoring mechanism, to assess a green vehicle index encompassing all of the relevant criteria affecting consumer choice (e.g. CO2 and polluting emission, energy efficiency, performance, cost). It uses evidential reasoning to develop a new conceptual framework capable of evaluating vehicle cleanliness by identifying and aggregating key green performance indicators (KGPIs). It reviews the latest development of vehicle green technologies and evaluates the importance of assessing vehicle cleanness. To analyse the newest development of emission control technologies for vehicles, a literature review on vehicle emission is undertaken to visualise the natures and objectives of studies of vehicle emission. The review findings reveal that an emerging topic in vehicle emission control is on how to evaluate and prioritise vehicle cleanliness to guide customers to a better choice of greener vehicles. To tackle this emerging issue, this paper firstly describes a full set of KGPIs that appear in the relevant literature on vehicle emission. Secondly, adopts an evidential reasoning approach to develop a new methodology for prioritising vehicle cleanliness. Thirdly, uses a set of real data to demonstrate the feasibility of the newly proposed methodology in a small scale in real world. It makes a scientific contribution on the analysis of state of the art on the vehicle cleanliness/greenness studies, identification of KGPIs influencing cleanliness and customer choice, and the feasible solution to synthesise of KGPIs for prioritising vehicle cleanliness (PVC). It combines the performance scores of different vehicles against the defined KGPIs to demonstrate who is cleaner and better in overall performance. It will aid to reduce emissions from the existing combustion-engine fleet and provide more insights to guide buyers towards the cleanest available vehicles.

Keywords: Transport sustainability, Prioritizing Vehicle Cleanness, Key Green Performance Indicators, Literature Review; Data Analytic

1. Introduction

Despite many efforts on vehicle emission control in the past decade, the air quality situation in the UK still needs to be further improved (Carrington, 2016). Air pollution is threatening the public health, and governments need to do much more including replacing old, dirty diesel vehicles. However, fleet renewal by real zero emission technologies is facing economic limits (Petroff & Riley, 2018) and technical difficulties (Vaughan, 2018). It is too slow to just wait for all vehicles on the road to be replaced by electrified ones. It is therefore essential to address practical solutions to reduce the impact of the existing internal combustion fleet. One answer is to provide incentives to, and at the same time, guide customers who purchase new vehicles

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by making their cleanliness visible. In 2012, there is a discrete choice model on purchasing power and CO2 reduction (Achtnicht, 2012). But, there is not a full picture of customer choice factors, including purchase price, fuel economy and reduction of different pollutions. In 2017, there is an Electric vehicle emissions index (EVEI) established (Dhar, et al., 2017). However, it is not considering the whole private vehicles market. Internal combustion engine vehicles (ICEV) and alternative-fueled vehicle (AFV) are not included in the index framework too. So, it is necessary and beneficial to undergo a study for KGPI to prioritise the vehicle consideration for the whole private vehicle market. This paper aims to develop and support a testing and scoring mechanism, to assess a green vehicle index encompassing all of the relevant Key Green Performance Indicators (KGPIs) affecting consumer choice (e.g., CO2 and polluting emission, energy efficiency, performance, cost). It will serve the purpose of creating competition on who brings to market the cleanest vehicles.

2. Literature Review

In this part, we will introduce the methodology of literature review. Then, we will provide some results, which are related to the KGPIs framework. Distribution by pollutions, distribution of research areas and evaluation of customer choice analysis are the chosen three issues to be further analysed.

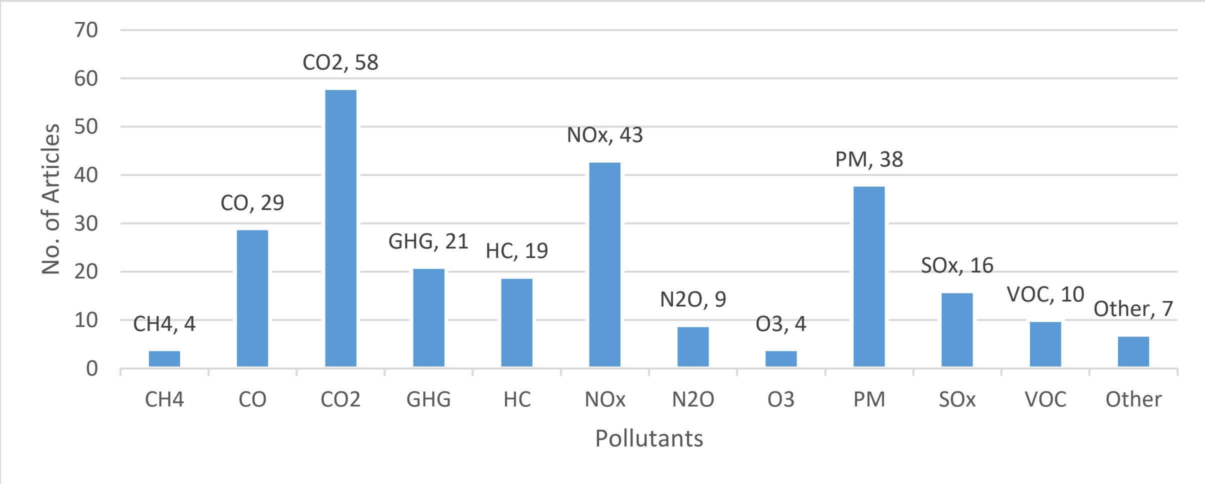
2.1. The methodology of literature review

To carry out a comprehensive literature review of PVC using KGPI, we have set up a systematic analysis for articles searching and selection. Concerning Poo (Poo, et al., 2018), Wan (Wan, et al., 2017), and Luo (Luo & Shin, 2016), we can divide the whole data collection process into three steps: online database searching, article screening and final refining and analysing. Firstly, we collected papers on PVC from all of the peer-reviewed academic journals on Web of Science Core Collection. It is one of the most comprehensive multidisciplinary searching platforms for academic research (Hosseini, et al., 2016; Luo & Shin, 2016; Wan, et al., 2017). We used different strings, such as the combination of the elements from the sets of "Emission (Car or Vehicle or road transport) (Parameter or Indicator or Index or indices or model) (Clean or Cleanliness)", as "Topic" items to perform the searching process. Throughout the searching process, we have used "OR" function to finish the journals collection. The search was completed in February, 2018, covering the period from 2004 to 2018. It covered the whole period of modern EV series production (Baker, 2018). 224 relevant papers were collected. Secondly, we have conducted a two-step scanning process to secure the relevance and quality of the selected articles. The first step is to filter out the peer-reviewed journals by eliminating non-peer-reviewed journals, book chapters, conference proceedings and editorial materials. The peer-reviewed journal papers were chosen for further analysis because it is the most guaranteed type of documents for the acceptance of the scientific community (Bergström, et al., 2015). The number of articles is reduced from 224 to 174. Finally, we carefully conducted the full-text review for the refined 174 articles. As a result, the articles that have no aspect of transportation are also eliminated. After the final refining process, 127 articles remained. The articles are analysed by the distribution of their publishing years, authors, journals, regions, transportation modes and research methods. We found that the research interests and the corresponding trends of different research themes. Furthermore, we analysed the connection of leading authors through their collaborative papers. Finally, we compared all studies to guide the directions of further studies.

2.2. Distribution by pollutions

This section is used to compare the frequencies of pollutants mentioned in papers. As they are easily quoted in articles, contaminants are captured if they are in the analysis or modelling. CO_2, NOx, PM, and CO are the most popular pollutants, and the numbers are 58, 43 and 38 respectively. 22 studies used GHG rather than single pollutants to go through the reviews. HC and N_2O both took place in the certain amount of papers (e.g.19 and 16 respectively). The contaminants mentioned can be analyzed to set KGPI for grading vehicles in the modelling work later.

Figure 1 Distribution by pollutants



2.3. Distribution of research areas

To understand the objectives of the study, regarding research topics, we have identified several different categories: Cleaner technology policy analysis, Congestion/routing analysis, Customer choice analysis, Infrastructure analysis, Life cycle assessment (LCA), Public transport analysis, Regional analysis and Technology analysis.

In other words, we can observe the solution to reducing pollutants by vehicles or transportation systems. Cleaner technology policy analysis is conducted to assess the outcome of a policy to control vehicle emission. It can be evaluated economically or environmentally. Congestion/routing analysis is using traffic engineering knowledge to reduce congestion as it makes vehicles emitting less pollutants. Customer choice analysis is a kind of studies to observe how the public decides on purchasing a car. Life cycle analysis is to assess the contaminants emitted from vehicles from the cradle to the grave. Public transport analysis is to study how the public transport assists in the emission control. The regional analysis provides an overhead angle to observe the transportation pollutions in one region. Technology analysis is talking about how new technologies, concerning components excluding EV and AFV, can reduce pollutants.

Regional analysis is occupied by 43%, which is the dominating one. Policy analysis is the second largest group by 17% occupancy. And the remaining categories queue as a descending order by occupancy: technology analysis, customer choice analysis, public transport analysis, congestion/routing analysis, infrastructure analysis and LCA. They are 11%, 9%, 6%, 6%, 4%

and 4% respectively. Furthermore, we have divided three periods (2004 – 2008, 2009 – 2013, 2014 – 2018) to understand the trends of different research areas. We can see that cleaner technology policy analysis, regional analysis and LCA had a significant increase in occupancy. Then, public transport analysis and technology analysis decreased in their occupancy. And the remaining research areas did not have apparent trends. We can see that there is still a clear research potential in terms of customer choice analysis, particularly taking into account the need of controlling the existing internal combustion fleet described in the background analysis.

Table 1 Distribution of research areas

Research Area	2004 - 2008	2009 - 2013	2014 - 2018	Total	Occupancy
Cleaner technology policy analysis	3	1	18	22	17%
Congestion/ routing analysis	3	0	4	7	6%
Customer choice analysis	4	3	5	12	9%
Infrastructure analysis	1	2	2	5	4%
Life cycle assessment (LCA)	0	0	5	5	4%
Public transport analysis	3	3	1	7	6%
Regional analysis	7	15	33	55	43%
Technology analysis	2	9	3	14	11%

2.4. Evaluation of customer choice analysis

We have developed a specific focus on and done a comparative analysis of customer choice analysis. We can further split it into questionnaire surveying (Dill, 2004; Achtnicht, 2012; Graham-Rowe, et al., 2012; Okushima, 2015; Hackbarth & Madlener, 2016), simulation modeling (Horne, et al., 2005; Ben Dor & Ford, 2006; Potoglou & Kanaroglou, 2007; Burguillo-Cuesta, et al., 2011; Simmons, et al., 2015; Miotti, et al., 2016) and indicator establishment (Dhar, et al., 2017).

For questionnaire surveying, Dill estimated emissions reductions from accelerated vehicle retirement programs by a trade-off between pollutions and incentives. After that, the following studies included more parameters. In 2012, Graham-Rowe, et al. studied the willingness of German car buyers' on paying for EVs to reduce CO2 emissions (Graham-Rowe, et al., 2012). Okushima simulated social influences on sustainable mobility shifts for heterogeneous agents based on the survey result (Okushima, 2015). In 2016, Hackbarth and Madlener provided stated choice study in Germany for AFVs (Hackbarth & Madlener, 2016).

For simulation modelling, discrete choice studies of personal transportation decisions were used to visualize the possibilities of hybrid energy-economy models (Horne, et al., 2005). In 2006, Ben Dor and Ford simulated a combination of feebates and scrappage incentives to reduce automobile emissions (Ben Dor & Ford, 2006). One year later, Potoglou and Kanaroglou analysed the Household demand and willingness to pay for clean vehicles by nested logit model (Potoglou & Kanaroglou, 2007). In 2011, Burguillo-Cuesta, et al. established the econometric model of simultaneous equations of diesel cars and diesel oil demand (Burguillo-Cuesta, et al., 2011). Simmons, et al. set up a benefit-cost assessment as a sensitivity analysis for fuel economy and new vehicle technologies in the US market (Simmons, et al., 2015). One year later, Moitti et al. evaluated vehicle choices on buyers against climate change mitigation targets (Miotti, et al., 2016).

For the only study on indicator establishment, Ehar, et al. created electric vehicle emissions index (EVEI) for the quantification of GHG emissions of electric vehicles (EVs) in 2017 (Dhar, et al., 2017).

Table 2 is to identify the most common prospectives on customer choice analysis. Exempted pollutants, fuel economy and purchase price are all crucial concerns affecting buyers' choice of green vehicles. Also, driving power and fuel availability are both apparent factors for choosing cars. Furthermore, maintenance cost, driving range, refuelling/recharging time and Incentives drew considerable attention by private vehicles buyers. We will encouter all these prospectives to obatian a systematic KGPI framework.

Table 2 Distribution of research areas

Journal articles	Purchase option	Fuel economy	Maintenance cost	Pollution	Driving range	Fuel availability	Refueling/ Recharging time	Power	Incentives
(Dill, 2004)				v					v
(Horne, et al., 2005)	v	v						v	
(Ben Dor & Ford, 2006)	v	v		v		v		v	v
(Potoglou & Kanaroglou, 2007)	v	v	v	v				v	v
(Burguillo-Cuesta, et al., 2011)	v	v		v					
(Achtnicht, 2012)	v	v		v		v		v	
(Graham-Rowe, et al., 2012)	v	v	v	v	v	v	v	v	
(Okushima, 2015)	v	v		v					
(Okushima, 2015)		v		v					
(Miotti, et al., 2016)	v	v	v	v					
(Hackbarth & Madlener, 2016)	v	v		v	v	v	v		
(Dhar, et al., 2017)				v					
Total	9	10	3	12	2	4	2	5	3

** The pollution is further breakdown to reflect the particular pollutants in Figure 1.*

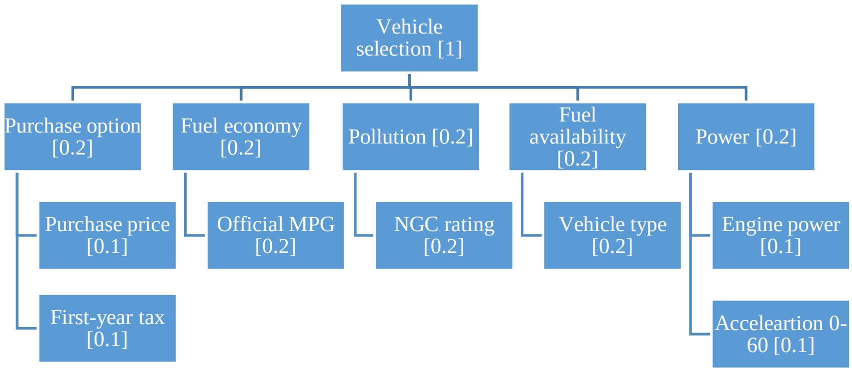
After the literature review, we can observe the research gap in connecting all criteria customer choice and all different kinds of vehicles into one decision-making tool. Besides, we can sort out the most alerted pollutants from the result and take them into the decision-making tool.

3. KGPI Implementation

Based on the thorough literature review, it is well noted that buyers’ choice on green vehicles is one of the critical research areas in the coming years, especially to integrate EV, AFV, and internal combustion vehicles into a single common decision-making model or framework. A significant number of factors associated with their purchase price, fuel economy, maintenance cost, pollution, driving range, fuel availability, refueling/recharging time, power and incentives, affects selection of vehicles, which has been assessed in section 4.4. However, as the difference of nature between different types of private cars, some of the criteria are born to be incomplete in nature such as engine size and battery size. To deal with the characteristic of incompleteness in data, an evidential reasoning (ER) approach, a well-known group multiple criteria decision-making (MCDM) method, is, for the first time, tested within the context of vehicle cleanliness analysis. Based on the study by Yang, et al. (2009), we can split the vehicle selection into steps:

1) Define the problem and construct an analytical hierarchy;

Figure 2 Preliminary KGPI hierarchy



We had constructed a preliminary analytical hierarchy for explaining the meaning of the regime, and it will be furthered described in the following section. It is based on the finding in section 2.3. Five of the most common perspectives in the analysis are chosen for selection criteria. Moreover, NGC rating, which is representing pollutant emission, is explained in section 3.2. We have presented the hierarchy together with the weights in figure 2. The list of the five most common perspectives: Purchase option, Fuel economy, Pollution, Fuel availability and Power. We equally distributed five prospective with the same weight and equally distributed the importance of parameters for the same prospective[2].

2) Set the KGPI grades;

For quantitative factors, a linear distribution function will be used to transform their associated evaluation data to be presented by the pre-defined grades. For example, the assessment grades are given their corresponding values as the set of $\{\alpha_1, \alpha_2, \alpha_3, \alpha_4\} = \{0.2, 0.4, 0.6, 0.8, 1\}$, which can be calculated as {Slightly preferred, Moderately preferred, Average, Preferred, Extremely preferred}. Then, we had separated each criterion into four groups. The assessment grades were defined as {Slightly preferred, Moderately preferred, Average, Preferred, Extremely preferred} based on the nature of parameters. Payment, Emission and NGC rating is better to be lower and the remaining parameters is better to be higher. In addition, the vehicle type grading is defined based on the availability of charging point: Purchase price (£) {50,00, 42,500, 35,000, 27,500, 20,000}, First-year tax (£) {840, 630, 420, 210, 0}, Official MPG (mpg) {35, 70, 105, 140, 175} NGC rating {100, 80, 60, 40, 20}, Vehicle type {AFV, EV, HEV, ICEV}, Engine power (HP) {80, 160, 240, 320, 400}, Acceleration 0-60 (Sec) {12, 10, 8, 6, 4}.

[2] The involved factors and their associated weights are dynamic subject to the investigated scenarios and regions. Therefore, they will be further developed in future studies in which a large-scale survey will be carried out to verify the relationship between the factors in the hierarchy and their relative importance using advanced techniques such as analytic hierarchy process.

3) Evaluate four vehicles using the lowest level KGPIs;

For the case study in section 4.3, we have chosen five vehicles: JAGUAR E-Pace 2.0D I4 150PS FWD, AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic, VW Passat Saloon 2.0 TDI SCR S 150PS BMT, NISSAN LEAF Electric Car Acenta 40kWh Auto, and BMW M2 Coupe M2 Coupe DCT. VW Passat Saloon 2.0 TDI SCR S 150PS BMT and NISSAN LEAF Electric Car Acenta 40kWh Auto by revisiting the NGC Rating Methodology (Next Green Car Limited, 2016). They are from different manufacturers and with three different vehicle types.

4) Transform the evaluation from the lowest level to top level indicator;

Equivalent rules can be implemented to establish relationships between parameters and vehicle selection. In vehicle selection, the grades of different level criteria are not equivalent to 100% degree of belief (DOB). To deal with this problem, DOB can be incorporated to retain the link equivalence between the grades of different criteria to a reasonable extent.

5) Synthesize all assessments using the ER algorithm and its calculation software IDS;
6) Choose the best private vehicle to purchase based on the overall evaluation.

3.1. Evidential reasoning (ER)

One possible and practical way to process the incompleteness and unavailability of data is to integrate different expert judgments based on scientific assessments. Consequently, decision criteria and sub-criteria can have both qualitative and quantitative depending on the sources. To connect all input information and undertake analysis it is necessary to transpose different types of assessments into the same form. MCDM presents a conventional method for analyzing the multi-type of problems. A typical MCDM technique, also as known as ER (Yang & Xu, 2002), requires the conversion from quantitative to qualitative assessments and is appropriate for undertaking PVC problem. The latest ER algorithm can be explained by the following pathway (Yang, et al., 2005) and it is shown in Appendix 1.

3.2. Next Green Car (NGC) Rating

By considering the observation the distribution of pollutants in section 2.2, we can notice that NGC rating is well matched with the most contaminants that we planned to assess. The emissions evaluated in NGC rating included: CO, NOx, HC, PM10, SO2; and the three leading GHG associated with CO2, CH4, and N2O (Next Green Car Limited, 2016). The calculation of NGC rating is to normalize the impact costs to a reduced scale, NGC rating being transposed as a score between 0 and 100, in which higher the score and higher the polluting of vehicles (Next Green Car Limited, 2018).

The NGC rating takes into account of both direct and indirect emissions. Direct emission means the pollutants generated during the operation of cars and the indirect emission means the pollutants produced during the production of fuel, and the vehicle manufacturing and vehicle disposal. The methodology of NGC rating includes a partial LCA. It is accumulated by direct emission, feedstock production, feedstock transport, fuel production and fuel distribution. The data sources are from the UK Vehicle Certification Agency (VCA) (UK Vehicle Certification Agency, 2018), Department for Environment Food &Rural Affairs (Defra) (Department for Environment Food & Rural Affairs, 2018), the European Joint Research Centre (JRC) (European Comission, 2014) and GREET LCA tool (Argonne National Laboratory, 2017).

3.3. Case Study with an analytical hierarchy for KGPI

To test the feasibility of using ER on PVC, we have simplified this illustrative scenario by constraining the hierarchy (in figure 2) to a single sub-criteria for one criterion, and each criterion represents the same weight of importance to the whole selection[3]. We can notice that AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic, which has scored 0.7735, is the best choice upon the five alternative cars. However, NISSAN LEAF Electric Car Acenta 40kWh Auto information is incomplete. After surveying with expertise, we can assess different degrees of belief to criteria at the different level to each level. It will be expanded to a full assessment to complete the KGPI evaluation to tackle the incompleteness of the information.

Table 3 Preliminary KGPI Evaluation

	Purchase cost [0.2]		**Fuel economy [0.2]**	**Pollution [0.2]**	**Fuel availability [0.2]**	**Power [0.2]**		
Sampling vehicles	**Purchase price (£) [0.1]**	**First-year tax (£) [0.1]**	**Official MPG (mpg) [0.2]**	**NGC rating [0.2]**	**Vehicle type [0.2]**	**Engine Power (HP) [0.1]**	**Acceleration 0 – 60 (mph) [0.1]**	**Total Score**
JAGUAR E-Pace 2.0D I4 150PS FWD	30,750	205	60	58	ICEV	148	9.5	0.6174
AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic	33,965	0	166	32	HEV	148	7.6	0.7735
VW Passat Saloon 2.0 TDI SCR S 150PS BMT	25,105	205	68	39	ICEV	148	8.7	0.6906
NISSAN LEAF Electric Car Acenta 40kWh Auto	24,290	0	N/A	24	EV	148	8.6	0.6495
BMW M2 Coupe M2 Coupe DCT	48,975	830	37	80	ICEV	370	4.3	0.6034

4. Recommendation for future studies

Customer choice analysis, through a well established KGPI hierarchy, is essential for vehicle emission reduction. While the new technologies, like EVs and AFVs, make contributions to reducing vehicle emission, new PVC index will be useful to guide customers' choice on relatively greener cars from the existing internal combustion fleet. It is because we can foresee that the diversity of vehicles will extend in the market in the coming years. Also, KGPI is vital because new technology vehicles are providing some other kinds of pollutants (Ingenito, et al., 2015) and a full ER data analytic is essential to analyse the result. Furthermore, more infrastructure investment analyses should be done for driving range, charging availability and recharging time are also important factors for customer choices. By the integration of findings into KGPI framework, we can have a more comprehensive decision-making model by KGPI for all kinds of vehicles.

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[3] The involved factors and their associated weights are dynamic subject to the investigated scenarios and regions. Therefore, they will be further developed in future studies in which a large-scale survey will be carried out to verify the relationship between the factors in the hierarchy and their relative importance using advanced techniques such as analytic hierarchy process.

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6. Appendix 1: Formulation of ER Algorithm

Let *A* be the set with three linguistic expressions (L_1, L_2, L_3, L_4, L_5), which have been connected to two subsets A_1 and A_2 based on two sub-criteria, where each α represents degrees of belief attached to linguistic terms. Then, A, A1 and A2 can be expressed separately by:

$$A = \{\alpha_1 L_1, \alpha_2 L_2, \alpha_3 L_3, \alpha_4 L_4, \alpha_5 L_5\} \quad ,where \ \sum_{m=1}^{5} \alpha_m \le 1 \tag{1}$$

$$A_n = \{\alpha_{1,n} L_1, \alpha_{2,n} L_2, \alpha_{3,n} L_3, \alpha_{4,n} L_4, \alpha_{5,n} L_5\}, \ where \ \sum_{m=1}^{5} \alpha_{m,n} \le 1 \ and \ n = 1, 2 \tag{2}$$

Let the relative normalized weights of two sub-criteria in the evaluation are stated be ω_1 and ω_2 where $\omega_1 + \omega_2 = 1$ and ω_1 and ω_2 can be calculated by using established methods such as simple rating methods or more systematic methods based on pair-wise comparisons (Yang, et al., 2005).

$$M_{m,n} = \omega_n \alpha_{m,n}, \ where \ m = 1, 2, 3, 4, 5 \ and \ n = 1, 2 \tag{3}$$

Let H_1 and H_2 be the individual remaining belief values unassigned for $M_{m,1}$ and $M_{m,2}$. Then, H_1 and H_2 can be understood as follows (Yang and Xu, 2002):

$$H_n = \bar{H}_n + \tilde{H}_n, \ where \ n = 1, 2 \tag{4}$$

Let $\bar{H}_n$ (n = 1 or 2) represents the degree to sub-criteria that can play a role in the analysis and let $\tilde{H}_n$ (n = 1 or 2) exists because of the possible incompleteness in the subsets A_1 and A_2, can be described as follows:

$$\bar{H}_n = 1 - \omega_n = \omega_o, \ where \ n = 1, 2, \ o = 1, 2 \ and \ n \neq o \tag{5}$$

$$\tilde{H}_n = \omega_n \left(1 - \sum_{m=1}^{5} a_{m,n}\right), \ where \ m = 1, 2, 3, 4, 5 \ and \ n = 1, 2 \tag{6}$$

Let $a_m^{'}$ be the non-normalized degree to which the synthesized evaluation is confirmed to the four linguistic expressions as a result of the synthesis of the judgments produced by sub-criteria 1 and 2. Let $H_U^{'}$ be the non-normalized remaining belief unassigned after the commitment of belief to the four linguistic expressions as a result of the synthesis of the judgments related to sub-criteria. The ER algorithm can be stated as follows:

$$a_m^{'} = K\left(M_{m,1} M_{m,2} + M_{m,1} H_2 + H_1 M_{m,2}\right), \ where \ m = 1, 2, 3, 4, 5 \tag{7}$$

$$\bar{H}_U^{'} = K\left(\bar{H}_1 \bar{H}_2\right) \tag{8}$$

$$\tilde{H}_U^{'} = K\left(\tilde{H}_1 \tilde{H}_2 + \tilde{H}_1 H_2 + H_1 \tilde{H}_2\right) \tag{9}$$

$$K = \left[1 - \sum_{t=1}^{5} \sum_{r=1, t \neq r}^{5} M_{t,1} M_{r,2} \right]^{-1} \quad (10)$$

Let H_U be the remaining normalized belief unassigned in the synthesized group. After the above aggregation, let a_m be the combined degrees of belief by assigning $\bar{H}_U^{'}$ back to the four expressions using the following normalization process:

$$a_m = a_m^{'} \Big/ \left(1 - \bar{H}_U^{'} \right), \textit{ where } m = 1, 2, 3, 4, 5 \quad (11)$$

$$H_U = \tilde{H}_U^{'} \Big/ (1 - \bar{H}_U^{'}) \quad (12)$$

The above gives the process of combining two sub-criteria based on four linguistic variables. If three sub-criteria with more (or less) linguistic expressions are required to be consolidated, the result obtained from the combination of any two sets can be further synthesized with the third one using the above algorithm. Similarly, multiple group from the evaluations of more sub-criteria or the judgements from numerous persons can also be combined. However, the application of the approach requires the assumption that all assessments are assessed or obtained by the same linguistic expressions (one common utility space), which is often not the case in decision making. Therefore, the evaluations of both upper-level criteria and lower-level sub-criteria need to be transformed before being aggregated using a belief distribution based utility mapping technique.