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COPRAS Decision Model to Optimize Blind Spot in Heavy Vehicles: A Comparative Perspective

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Abstract

The visibility of a driver is the key phenomenon in the road accidents. Reduction of blind spot improves the area of visibility which leads to reduce the possibility of the accidents. In this paper an effort is taken to reduce the blind spot area through the optimization of design parameters used in the design of rear view mirror in heavy vehicles. This is achieved by using a multi criteria decision making (MCDM) approach called COPRAS (Complex Proportional Assessment of alternatives) technique. The effectiveness of the developed model is proved by a case study conducted in a public transport corporation located in the southern part of India. The weights of the design parameters are calculated using three different approaches such as AHP (Analytical Hierarchy Process), FARE (Factor Relationship) method and Entropy Measurement and the results are compared.

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Keywords: Blind spots; Rear view mirror design; COPRAS; MCDM

1. Introduction

It has been observed that the number of road accidents is increased in line with the raise in the number of vehicles, increasing population and road length. Road Traffic Accidents are one of the major public health concerns throughout the world. The developing countries are showing very little progress towards addressing this problem than the developed countries. The World Health Organization (WHO) estimated that more than 1million deaths occur each year worldwide due to road traffic accidents [1].

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Cho and Han [2] investigated that the vision for the driver as the most critical factor for an unusual driving situation. Statistics revealed that most of the road accidents were happened due to visual problems such as vision of the driver, brightness of the light and glare during night time and the area of blind spot. Among this blind spot is the key attribute. Blind spots exist in a wide range of vehicles such as cars, trucks, motorboats and aircraft. The blind spot in a vehicle is the area around the vehicle that cannot be directly observed by the driver while driving. The heavy vehicle drivers can't see certain areas on the roadway in their front, behind the vehicle and on either sides of the vehicle. Forward visibility of a driver or the front end blind spots are influenced by many design criteria such as vehicle body structure, human anthropometric data, road geometry and the driver seat design [3]. The blind spot in the rear or sides of the heavy vehicle can completely hide a small pedestrian, small motor-cycle or even a full vehicle. Because, blind spots hide the road to verify them before making such maneuvers on roads while turning, reversing, changing lanes, or while overtaking other vehicles. This places the driver in a risky situation resulting sometimes in untoward incidents and accidents.

The area of the blind spot on either sides of the vehicle is depending on the position of the rear view mirror. The positioning of the rear view mirrors with larger viewing area will be helpful in reducing the blind spots. Several factors are affecting the installation of rear view mirrors. Among them the distance of the driver from the pillar or frame structure to the left and right side of the front body structure, driver eye sight height when he is in the driver seat and the height of the centre of the mirror from the ground level are the highly influencing data. In this paper, an attempt is made to find the optimized distance to reduce the blind spot on either sides of the driver while driving is considered.

The reviews the related works, the development of model and the case study are discussed in the remaining part of this paper. Finally the conclusion of the study and some future research directions are also outlined.

2. Literature Review

Burger [4] conducted an extensive review on the rear vision systems in the real world driving conditions. Hwang et al. [5] optimize the parameters to reduce the vibration in the automobile outside rearview mirror system using Taguchi concept. Kouabenan [6] studied the risk perception and causal explanations of road accidents with various kinds of experience and knowledge about traffic and automobile driving. Ayres et al [7] reviewed the safety aspects involved in the use of rear-view mirrors and discussed the research directions. Hughes et al [8] discussed the factors that are motivating the use of electronic vision systems provided in the heavy vehicles in order to reduce the blind zones. Tideman et al. [9] presented the systematic approach when designing a new lane change support system for vehicle using scenarios, virtual reality simulation, and gaming principles. The mock-up system consisted of three flat screens that offer rear view mirror functionality. Kim et al. [10] studied the surface flow and wake structure around an automotive external rear-view mirror and demonstrated that visualizations over the mirror housing surface and the driver side vehicle skin.

Zavadskas et al. [11] demonstrated a case study for the selection of contractor on the basis of multiple attributes of efficiency with fuzzy inputs applying COPRAS-G method. Podvezko [12] compared SAW (Simple Additive Weighting) method and COPRAS method for multi criteria evaluation models. The COPRAS method outperform by eliminating the drawbacks of the SAW method. Saaty [13] introduced AHP technique to solve complex problem using multiple criteria. Velasquez and Hester [14] analyzed various MCDM tools and concluded that AHP performs better as compared with others. Ginevicius and Podvezko [15] determined the criteria weights by applying FARE method and the alternative solutions of wall insulation or winter proofing of buildings were found. In the first stage, the relationships between the set of criteria and their strength and direction were elicited from experts. Based on the conditions of functioning and the specific features of the complete set of criteria, the relations between each criterion of the set and their direction are determined analytically. Finally the total impact of each particular criterion on other criteria of the set which is nothing but the criteria weights were determined. Lotfi and Fallahnejad [16] used Shannon entropy method to find the weight for each for the imprecise data in the fuzzy data cases. Hung and Chen [17] proposed fuzzy TOPSIS group decision making model using entropy weight for dealing with multiple criteria decision making (MCDM) problems in an intuitionistic fuzzy environment with an investment example. Lee et al [18] used entropy method to determine the weight of evaluation indexes and established multi-level fuzzy evaluation model for enterprise resource planning system selection. Shemshadi et al [19] solved the problem of evaluation and ranking the potential suppliers with the development of intelligent and automated information system. This paper aims to optimize the blind spots for heavy transport vehicles by considering the design parameters used in the design and implementation of rearview mirrors. COPRAS method is proposed to achieve the aim. The weights of the criteria used in the design of rearview mirrors in heavy vehicles are determined by using three different techniques namely AHP, FARE and entropy measurement and the results were compared.

3. Model Development

The framework of the proposed model used in this study is given in the Figure 1. In this work, a decision model based on COPRAS method is proposed.

3.1. COPRAS Method

The procedure consists of the following steps:

3.1.1. Identification and selection of influencing criteria (attributes) and the available alternatives

First the attributes which are influencing the decision in the MCDM problem are identified and the available alternates are selected.

3.1.2. Preparation of decision matrix (Alternatives vs attributes) (X)

The collected data (Alternatives and attributes) are shown in matrix form as shown in equation (1).

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots . x_{1m} \\ x_{21} & x_{22} & \dots . x_{2m} \\ \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & x_{nm} \end{bmatrix} \tag{1}$$

where n= number of alternatives; m = number of attributes

3.1.3. Normalization of decision matrix ($\bar{X}$)

The decision matrix is normalized as shown in equation (2).

$$\bar{X} = \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \dots . \bar{x}_{1m} \\ \bar{x}_{21} & \bar{x}_{22} & \dots . \bar{x}_{2m} \\ \vdots & \vdots & \vdots \\ \bar{x}_{n1} & \bar{x}_{n2} & \bar{x}_{nm} \end{bmatrix} \tag{2}$$

where $\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$; I = 1, 2, …..n; and j = 1, 2, … m

3.1.4. Determination of the weight of the attributes (Wj)

The weights of the attributes are determined by using AHP, FARE and entropy measurement.

3.1.5. Determination of the weighted normalized matrix ($\hat{X}$)

The determined weights are multiplied with the corresponding attribute value of all alternate to get the weighted normalized matrix.

$$(\hat{X}) = \begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \dots . \hat{x}_{1m} \\ \hat{x}_{21} & \hat{x}_{22} & \dots . \hat{x}_{2m} \\ \vdots & \vdots & \vdots \\ \hat{x}_{n1} & \hat{x}_{n2} & \hat{x}_{nm} \end{bmatrix} \tag{3}$$

where $\hat{x}_{ij} = \bar{x}_{ij} * W_j$

3.1.6. Determination of maximizing index (Pj) and minimizing index (Rj)

Based on the qualitative nature of the attribute, the maximizing index (Pj) and minimizing index (Rj) values are calculated. If the maximum value is optimum, for that attribute Pj is determined using equation (4). For others Rj will be calculated using equation (5).

$$P_j = \sum_{i=1}^{k} \hat{x}_{ij} \quad (4)$$

$$R_j = \sum_{i=k+1}^{m} \hat{x}_{ij} \quad (5)$$

where k = number of attributes which is to be maximized

3.1.7. Determination of relative weights of each alternative (Qj)

Finally, the relative weights of all the attributes will be calculated by using equation(6).

$$Q_j = P_j + \frac{\sum_{j=1}^{n} R_j}{R_j \sum_{j=1}^{n} \frac{1}{R_j}} \quad (6)$$

The alternative with the highest relative weights is considered as the best alternative.

3.2. FARE Method

Ginevicius [15] developed FARE method for determining the weights of the attributes in multi criteria decision making environment. The procedure to determine weights of the attributes is given below:

3.2.1. Determination of the potential impact of the attributes:

First the potential impact of the attributes is determined using equation (7).

$$P = S\,(n - 1) \quad (7)$$

where P – Potential of the system's attribute impact; S – Maximum value of the scale of evaluation used (Table1);

Next the attributes are ranked by the experts based on the importance. Then the relationship between the attributes is determined based on the rank using Table 1. The procedure is as follows: the attribute of a lower rank has the smaller impact on the attributes having higher ranks and, therefore, it should transfer a larger part of its potential impact to them.

3.2.2. Determination of the impact of the attributes on the main attribute:

The impact of the attributes ai on the main criterion is determined and then, this impact is transformed as follows:

$$a1i = S - \tilde{a}1i \quad (8)$$

where,

ai – the impact of ith attribute on the first main attribute; ãi – the part of ith attribute's potential impact transferred to the main attribute.

Table 1. Scale of quantitative evaluation of interrelationship between the system's attributes

Type of the Effect Produced	Rating of the Effect Produced by Interrelationship (in points)
Almost none	1
Very Weak	2
Weak	3
Lower than Average	4
Average	5
Higher than average	6
Strong	7
Very Strong	8
Almost absolute	9
Absolute	10

Table 2. Measurement scale for pair wise comparison

Verbal judgment or preference	Numerical rating
Extremely preferred	9
Very strongly to extremely preferred	8
Very strongly preferred	7
Strongly to very strongly preferred	6
Strongly preferred	5
Moderately to strongly preferred	4
Moderately preferred	3
Equally to moderately preferred	2
Equally preferred	1

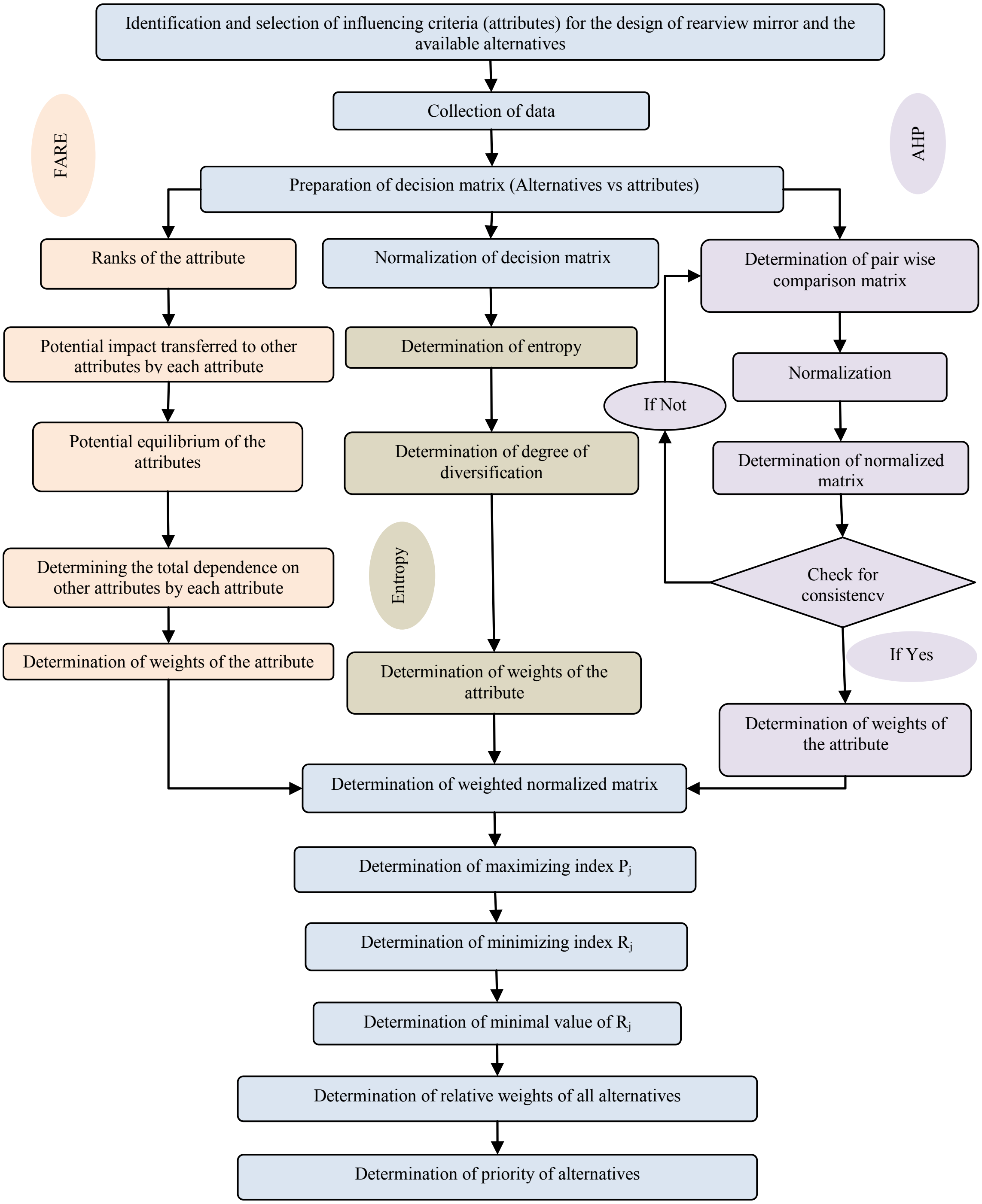

Fig. 1. Proposed Frame work

3.2.3. Determination of the total impact

The total impact of any attribute, as well as the consistency level of a subset may be determined based on the data provided in the form of matrix. The subset considered in the matrix is consistent and stable if the total impact of its attributes with a positive sign is equal to their total impact with a negative sign, i.e. their sum is equal to zero [15]. Next the total impact Pi calculated using equation (9).

$$P_i = \sum_{i=1}^{m} a_{ij},\ j \neq i \tag{9}$$

After that, the total potential, required for determining the attributes weights, will be calculated based on the data presented in the first row of the matrix, thereby making the filling of all other rows of the matrix unnecessary. The following equation (10) is used for determining the total potential.

$$Pi = P1 - n.\ a1i, \tag{10}$$

where Pi – the total impact (dependence) of the ith attribute.

3.2.4. Determination of the weights of the attributes

Finally, the attributes weights can be determined using equation (11).

$$\omega_j = \frac{P_i^f}{P_S} = \frac{P_1 - na_{1i} + S(n-1)}{nS(n-1)} \tag{11}$$

where PS = Total potential of a set of attributes which is found using equation (12) and P_i^f = Actual total impact of the ith attribute of the system which is calculated using equation (13)

$$PS = n.\ P = n.S\ (n - 1) \tag{12}$$

$$P_i^f = P_i + P \tag{13}$$

where Pi = Total impact produced by the ith criterion of the system or its total dependence on other attributes.

3.3. AHP

The concept of AHP was introduced by Thomas L. Saaty in 1980. It is one of the human judgment based tool used to determine the weights of the attributes in the MCDM problems. The weights of the attributes using AHP are determined by the following steps:

3.3.1. Pairwise comparison of attributes

Each attribute is compared with other attributes in a natural, pairwise mode. The fundamental scale that captures individual preferences with respect to quantitative and qualitative data [13] is shown in Table 2. It converts individual preferences into a linear additive weight for each alternative. The pair wise comparison matrix is also called original matrix which is given by matrix Xatt as shown in equation (14).

All the cell values are assigned based on the importance of the attributes received from the experts.

$$X_{att} = [a_{ij}];\ 1 \leq i,j \leq n \tag{14}$$

where, aij = Pair wise comparison of ith and jth attribute; n = the number of alternatives

$$X_{att} = \begin{bmatrix} a_{11} & a_{12} & \dots.a_{1n} \\ a_{21} & a_{22} & \dots.a_{2n} \\ \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix}$$

3.3.2. Normalization

Then the pairwise comparison matrix is normalized using the equation (15) and the normalized matrix Natt is obtained.

$$N_{ij} = \frac{a_{ij}}{T_j} \tag{15}$$

where $T_j = \sum_{i=1}^{n} a_{ij},\ 1 \leq j \leq n$

$$N_{att} = \begin{bmatrix} N_{11} & N_{12} & \dots.N_{1n} \\ N_{21} & N_{22} & \dots.N_{2n} \\ \vdots & \vdots & \vdots \\ N_{n1} & N_{n2} & N_{nn} \end{bmatrix}$$

3.3.3. Computation of weights

After the normalization, the weights Wj are computed from the normalized matrix using equation (16).

$$w_j = \frac{\sum_{j=1}^{n} N_{ij}}{n} \tag{16}$$

From the weights of the attributes Watt matrix will be formulated as shown in equation (17)

$$W_{att} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ :: \\ :: \\ w_n \end{bmatrix} \tag{17}$$

3.3.3. Consistency checking

The consistency of the proposed pairwise comparison was checked using the equation (18).

Consistency Ratio CR = CI/RI (18)

where CI = Consistency Index and RI = Random indices.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{19}$$

where $\lambda_{\max}$ = Max of B or n;

$$B = \left(\frac{\frac{A_1}{w_1} + \frac{A_2}{w_2} + \frac{A_3}{w_3} + \cdots + \frac{A_m}{w_m}}{m} \right) \tag{20}$$

where m=Number of criteria and A1, A2 ….. Am are calculated using the equation (22).

$$[X_{att}] * [W_{att}] = [A] \tag{21}$$

$$\begin{bmatrix} a_{11} & a_{12} & \dots a_{1n} \\ a_{21} & a_{22} & \dots a_{2n} \\ \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix} * \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{bmatrix} \tag{22}$$

Random indexes (RI) for various number of variables ‘n’ have been approximated by Saaty (1980) as shown in Table 3.

Table 3. Random indices

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

If the CR < 0.10 the decision maker's pairwise comparison matrix is acceptable (Saaty, 1980).

3.4. Entropy Measurement

The concept of "entropy" was introduced by Claude E. Shannon in 1948. The entropy is a measure of the uncertainty associated with a random variable of the expected information content of a certain message and the uncertainty is represented by a discrete probability distribution [20]. Shannon [21] determined the weights of attributes using the following steps:

3.4.1.Determination of Entropy (Ej)

The entropy Ej of the set of alternatives for attribute j from the normalized decision matrix $(\overline{X})$ is determined by using the equation (23).

$$E_j = \frac{1}{ln(m)} \sum_{i=1}^{m} \bar{X} * ln(\bar{X}) \tag{23}$$

3.4.2. Determination of Degree of Diversification

The degree of diversification of the information provided by the outcomes of the attribute j is determined using the equation (24).

$$D_j = 1 - E_j \tag{24}$$

3.4.3. Determination of Weights of Criteria

Finally the weights of each attribute were calculated by the following equation (25).

$$W_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{25}$$

4. Case Study

The developed model is tested by a case study which is conducted in a public transport division located in the southern part of India with four different types of vehicle bodies. One of the body of the vehicles is built in the same organization (IS) and other three are outsourced (OS -1, OS – 2 & OS – 3) bodies. The design and implementation of rear view mirror in heavy vehicle is highly influenced by the following variables such as the distance between the driver and the right side of the body pillar or frame structure (A), the distance between the driver and the left side of the body pillar or frame structure (B), the distance of driver's eye right height from the platform (C) and the distance between the centre of the rear view mirror and the ground level (D). The data set collected through the case study is given in Table 4. The data set is called decision matrix.

Then the decision matrix is normalized using equation (2) and shown in Table 5. After that, the weighted normalized decision matrix is determined using equation (3). To compute the weighted normalized decision matrix, the weights of the attributes are calculated. In this paper the weights of the attributes are determined by FARE, AHP and Entropy measurement.

Table 4. Data set

Types of Vehicle	A (cm)	B (cm)	C (cm)	D (cm)
IS	36	178	122	242
OS – 1	34	181	123	240
OS – 2	34	182	123	224
OS - 3	34	177	119	204

Table 5. Normalized decision matrix

Types of Vehicle	A	B	C	D
IS	0.261	0.248	0.251	0.266
OS – 1	0.246	0.252	0.253	0.264
OS – 2	0.246	0.253	0.253	0.246
OS - 3	0.246	0.247	0.244	0.224

4.1. Determination of weights of the attributes by FARE

First the potential impact of the attributes is determined using equation (7). The potential impact of the attributes for this work is 30. Next the attributes are ranked by the experts based on the importance. As per the experts opinion the order of attributes are A, B, D and C. The interrelationships between the system's attributes (Table 6) based on their ranks are quantified by using Table 1.

Table 6. Inter relationship between the attributes

Attributes	A	B	C	D
A		2	6	4
B	-2		4	2
C	-6	-4		-2
D	-4	-2	2	

Table 7. Potential impact transferred to the first main criterion

Attributes	A	B	C	D	Sum
A		8	4	6	18
B	-8		6	8	6
C	-4	-6		-8	-18
D	-6	-8	8		-6

Finally the weights of the attributes are determined by using the equations (9) to (11) and tabulated in the Table 8.

Table 8. Actual impact (P_i^f) and weights of the criteria

Attributes	P_i^f	Weight
A	48	0.4
B	36	0.3
C	12	0.1
D	24	0.2

4.2. Determination of weights of the attributes by AHP

The pair wise comparison matrix for this study is shown in Table 9. For the quantification, Table 2 is used.

Table 9. Pair wise comparison matrix

Attributes	A	B	C	D
A	1	2	5	3
B	0.5	1	4	2
C	0.2	0.25	1	0.2
D	0.333	0.5	5	1

Table 10. Normalized matrix

Attributes	A	B	C	D
A	0.492	0.533	0.333	0.484
B	0.246	0.267	0.267	0.323
C	0.098	0.067	0.067	0.032
D	0.164	0.133	0.333	0.161

Then the normalized matrix (Table 10) is computed using equation (15). Next the consistency of the proposed pairwise comparison was checked using the equation (18) and found as 0.057 which is less than 0.1. Hence the used pairwise comparison is acceptable.

Table 11 Weights of the attributes using AHP

Attributes	Weights
A	0.461
B	0.275
C	0.066
D	0.198

The weights are computed from the normalized matrix using equation (16) and shown in Table 11.

4.3. Determination of weights of the attributes by Entropy measurement

First the entropy of the data set is determined by using the equation (23). Then the degree of diversification is determined using the equation (24). Finally the weights of attributes are calculated by using equation (25).

Table 12 Entropy measurement calculations

	A	B	C	D
Entropy	0.999775	0.999952	0.999934	0.998355
Degree of diversification	0.000225	0.000048	0.000066	0.001645
Weights of attributes	0.113527	0.023992	0.03312	0.829361

4.4. Ranking by COPRAS

The weights are multiplied with the corresponding attributes to get the weighted normalized matrix. The weighted normalized decision matrix is shown in Table 13. Then the maximizing index (Pj) and minimizing index (Rj) values are calculated using equation (4) and equation (5). From these indexes, the relative weights (Qj) of all the attributes will be calculated by using equation (6). The relative weights of all the attributes are shown in Table 14 and Figure 2.

Table 13 Weighted normalized decision matrix

Types of Vehicle	**FARE**				**AHP**				Entropy measurement			
	A	**B**	**C**	**D**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
IS	0.104	0.074	0.025	0.053	0.120	0.068	0.017	0.053	0.030	0.006	0.008	0.221
OS – 1	0.099	0.076	0.025	0.053	0.114	0.069	0.017	0.052	0.028	0.006	0.008	0.219
OS – 2	0.099	0.076	0.025	0.049	0.114	0.070	0.017	0.049	0.028	0.006	0.008	0.204
OS - 3	0.099	0.074	0.024	0.045	0.114	0.068	0.016	0.044	0.028	0.006	0.008	0.186

Table 14 Relative weights of the attributes

Types of Vehicle	**FARE**				**AHP**				**Entropy measurement**			
	P_j	R_j	$1/R_j$	Q_j	P_j	R_j	$1/R_j$	Q_j	P_j	R_j	$1/R_j$	Q_j
IS	0.179	0.078	12.781	0.250	0.188	0.069	14.453	0.251	0.036	0.229	4.370	0.238
OS–1	0.174	0.078	12.820	0.246	0.183	0.069	14.516	0.246	0.034	0.227	4.403	0.238

OS–2	0.175	0.074	13.425	0.250	0.183	0.065	15.289	0.250	0.034	0.213	4.706	0.252
OS-3	0.173	0.069	14.436	**0.254**	0.181	0.061	16.525	**0.253**	0.034	0.194	5.154	**0.272**

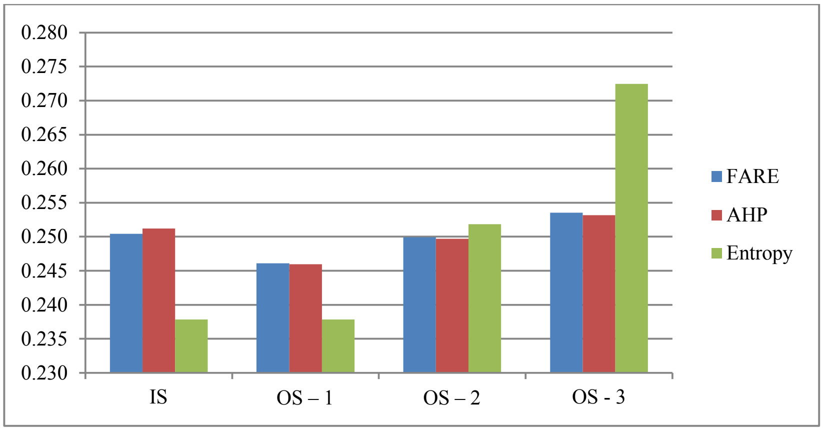

Figure 2 Relative weights of the attributes

The alternative with the highest relative weights is considered as the best alternative. From Table 14, OS - 3 vehicle has the higher relative weights and hence the body built by OS-3 is having less area of blind spot.

5. Conclusion

In this paper COPRAS based MCDM approach was proposed to reduce the area of blind spots in the sides and rear side of the heavy vehicle using the design parameters of rear view mirror. The human judgment based techniques (FARE and AHP) and mathematical approaches (Entropy measurement) were used to compute the weights of the attributes and those weights were used in COPRAS model. All approaches provide the same result and so a decision maker is able to make concrete decision. The model was also proved by a case study. It is an important study in the vehicle safety area and it can be extended to optimize the blind spot in the other area around the vehicle.

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