

**Morteza YAZDANI\*, PhD**

**E-mail: morteza\_yazdani21@yahoo.com (\*Corresponding author)**

**Department of Business Management, Faculty of Social Sciences**

**Universidad Europea de Madrid, Madrid, 28670, Spain**

**Ali JAHAN, PhD**

**E-mail: iranaliarahan@yahoo.com**

**Department of Industrial Engineering, Semnan Branch**

**Islamic Azad University, Semnan, Iran**

**Professor Edmundas Kazimieras ZAVADSKAS, PhD**

**E-mail: edmundas.zavadskas@vgtu.lt**

**Department of Construction Technology and Management**

**Vilnius Gediminas Technical University, Vilnius, Lithuania**

## **ANALYSIS IN MATERIAL SELECTION: INFLUENCE OF NORMALIZATION TOOLS ON COPRAS-G**

***Abstract.** Multi criteria decision making (MCDM) methods algorithms are influenced by many parameters and variables as orientation of attributes, aggregation attitude, weights and normalization tools. Various MCDM methods find solution for decision problems using different normalization methods. Normalization process has an important role in decision process and can modify the ranking and final decision. Due to uncertainty associated with data in decision making about materials and design, COPRAS method with interval numbers (COPRAS-G) was recognized as a promising approach in this regard. This paper intends to apply COPRAS-G method in several specific material evaluation studies. Normalization tools are positioned in COPRAS method to check the effect of each tool. Two examples of material and design selection projects are recognized suitable for this study. The results show depending on the number of criteria and number of alternatives material, ranking can be changed when a different normalization tools are considered. This help designers and engineers to achieve a compromise on design decision making process, especially when the material properties and design performance criteria are affected from stochastic nature of design and manufacturing parameters.*

***Keywords:** COPRAS-G, interval data, materials selection, MCDM, Normalization tools.*

**JEL Classification: CO2, C44, C61, C63, L6**

## 1 - Introduction

Term multiple criteria decision making is popular and applicable discipline that can be applied for complex decisions when several criteria are involved. Variety of MCDM methods has been proposed in different shapes in numerous kinds of applications as well as in case studies, expanding, and integrating or hybrid models. However, it was observed that different MCDM methods can produce diverse, not always coinciding ranking results. A typical MCDM problem includes features and characteristics as; decision criterion and alternatives, weights of criteria, an algorithmic procedure to reach final solution, orientation of each criterion, aggregation and normalization process and so, clearly final results are affected by each of these features. To begin every MCDM model and to find optimal solution, each alternative should has a performance rating associated to each attribute, and fundamentally performance ratings for different attributes are usually measured by different units. The initial decision matrix in the beginning contains competitive alternatives row-wise, with their performance rating and decision attributes. Normalization process makes these scores conform to or reduced to a norm or standard. For comparison the alternatives on each attribute, the normalized process is usually formed column-wise, and the normalized value will be a positive value between 0 and 1. Thus, computational problems of different measurements in the decision matrix are eliminated. Normalization procedure is a mechanism which is applied in MCDM models to convert the different measurement units of the performance ratings into a comparable (non-dimensional) unit. Many normalization procedures are accessible in literature and MCDM methods generally utilize one of these normalization procedures. But, a question might be raised to state how a normalization tool is suitable or able to affect decision process. Jahan and Edwards (2015) investigated basic and important aspects of normalization methods as capability to remove scales, symmetry in normalization for cost and benefit criteria, rank reversal and handling negative values. In their study, thirty-one normalization methods were identified and categorized in the application of material selection problem.

Numerous MCDM methods had been invented and developed and classification of them is somehow related to the number and nature of criterion. In real world application, a single criterion decision problem doesn't exist and decision makers actually are faced to multiple conflicting objectives evaluating a finite set of alternatives in order to find the best one, to rank them from the best to the worst, to group them into predefined homogeneous classes, or to describe how well each alternative meets all the criteria simultaneously (Zavadskas et al. 2009). MCDM methods in one global view are categorized based on actor's information which one sub-category is related to information over criteria. In this sub-category also criteria are defined as cardinal, ordinal and standard level (Roy 2013). The most important

MCDM methods are settled in cardinal criteria area. Methods as simple additive weighting TOPSIS and VIKOR (Yazdani&Payam, 2015), ELECTRE (Figueira et al. 2013), PROMETHEE (Behzadian et al. 2010),and MOORA are part of this area (Brauers and Zavadskas, 2006). Among these techniques, COPRAS (Zavadskas et al. 1994) has achieved increased interest for different application as supply chain, construction and building, marketing, design and engineering. COPRAS get involved with the multi criteria decision making (MCDM) process for its simplicity. It assumes direct and proportional dependences of significance and utility degree of the available alternatives under the presence of mutually conflicting criteria. It considers the performance of the alternatives respecting to defined criteria and the corresponding weights by using an algorithm of ranking and evaluating procedure of the alternatives in terms of utility degree to select the best decision (Brauers and Zavadskas, 2006).The idea of COPRAS-G method comes from real conditions of decision-making and from applications of the Grey systems theory. In this study COPRAS-G measures the performance of different material databases and prioritizes materials according COPRAS index. Each matrix-based prioritization tool should be built by a normalization tool which can enhance quality and effectiveness of ultimate solution.

In part of the literature, research studies were handled to indicate the influence of many normalization methods on decision making results. Since many decades it was investigated as one of the big question of authors (Migilinskas&Ustinovichius, 2007; Ginevicius&Podvezko, 2007)to find optimal normalization strategy for specific MCDM method. For example Zavadskas et al. (2006)employed a new methodology for measuring the accuracy of the relative significance of the alternatives by normalizing attribute values with both non-linear vector and linear normalization in application of TOPSIS. In another study (Milani et al. 2005)examined the affection of normalizations tools through using TOPSIS method to the problem of material selection for power transmission identifying that different normalization procedures produced almost different closeness coefficients. Chakraborty and Yeh (2007)proposed the effect of the four commonly known normalization procedures on SAW method by a simulation process. Zavadskas and Turskis (2008) invented new software LEVI 3.1.and LEVI-4 program to propose a logarithmic normalization method and compared its results with those non-linear normalization methods. Celen (2014) pointed out a research on the suitability of normalization procedure in application of evaluating the financial performances of 13 Turkish deposit banks utilizing fuzzy AHP and TOPSIS. The paper identified fuzzy weights of criteria by fuzzy AHP model and to rank alternative banks TOPSIS with different normalization tools has been captured. However, current study tends to examine usage of five normalization tools for COPRAS-G method. The study and results stability will be proven through some case studies from the proper literature. The five normalization methods are defined and applied as shown in section 2.2. For this aim, applications of

four material selection projects are analyzed and then conclusion is denoted based on some comparison. In order to release an efficient comparison of results, figures are designed by each example. The arrangement of paper can be stated as this; second section will interpret COPRAS method, its anatomy and required normalization tools for this study. Section three will release two examples of previous material selection projects and results of the study, and discussion. Then conclusion will be addressed in section 4.

## **2. Materials and methods**

### **2.1. COPRAS and COPRAS-G review**

Zavadskas invented complex proportional assessment (COPRAS) which assumes direct and proportional dependences of the significance and utility degree of the available alternatives under the presence of mutual conflicting criteria (Zavadskas et al. 2009; Zavadskas et al. 1994). COPRAS takes into account the performance of the alternatives with respect to different criteria and the corresponding weights by using a stepwise ranking and evaluating procedure of the alternatives in terms of their significance and utility degree to select the best decision. Variety of complex decision problem proposes COPRAS to take the benefit of this method in application of construction (Zavadskas et al. 2009; Zavadskas et al. 1994). Practically, different form of COPRAS as fuzzy and grey or interval structures are increasingly applied in research plans related to multiple objective topic to deal with limited or vague information. In competitive market environment, selecting appropriate strategic alliance is a key factor. Rather than fuzzy form of COPRAS, within the literature Sole COPRAS has been approached enormously. Hashemkhani Zolfani and Bahrami (2014) analyzed four high tech industries in Iran including Biomedical Micro Electromechanical Systems (BioMEMS), Nano Technology, Biotechnology, and Biomedical Engineering embedding SWARA and COPRAS techniques. Selection of the most suitable non-conventional machining process (NCMP) for a ceramics machining has been undertaken using WASPAS and COPRAS (Petkovic et al. 2015).

Grey or interval model of COPRAS is named COPRAS-G. Application of COPRAS-G model is surrounded by vast area as project selection, social media evaluation, supplier selection and etc. Tavana et al. (2013) reported a hybrid model of fuzzy ANP for weight determination and COPRAS-G to demonstrate the most suitable social media platform by a case study. Fuzzy ANP and COPRAS-G have been combined to select machine tools with consideration of the interactions of the attribute (Nguyen et al. 2014). To deal with the problem of water shortage, DEMATEL, AHP and COPRAS-G were joined to grasp the most conclusive adaptive policy response and to reveal root sources of water shortage in Yazd province, Iran

(Azarnivand&Chitsaz 2015). Maity et al. (2012) also in application of cutting tool material selection introduced COPRAS-G model to show applicability and comparability of MCDM methods. As explained, COPRAS-G is fascinating academic researchers undoubtedly and thus its contribution is undeniable. The procedure of COPRAS-G method is followed by these steps;

1. Choose the most relevant attributes which describe decision alternatives for specific decision problem
2. If  $x_{ij}$  is the performance rating of  $j^{th}$  alternative ( $j=1,2,\dots,m$ )  $A_1, A_2, \dots, A_m$ , respecting to the  $i^{th}$  criterion ( $i=1,2,\dots,n$ )  $C_1, C_2, \dots, C_n$ , then interval scale of variables in an unknown situation would be defined as  $x'_{ij}$  for the minimum values or lower level and  $x''_{ij}$  for maximum or upper values. So, to form the interval decision matrix  $X$  and weight of each criterion following table and variables should be considered;

$$X = [x'_{ij}, x''_{ij}] = \begin{bmatrix} [x'_{11}, x''_{11}] & [x'_{12}, x''_{12}] & \dots & [x'_{1n}, x''_{1n}] \\ [x'_{21}, x''_{21}] & [x'_{22}, x''_{22}] & \dots & [x'_{2n}, x''_{2n}] \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ [x'_{m1}, x''_{m1}] & [x'_{m2}, x''_{m2}] & \dots & [x'_{mn}, x''_{mn}] \end{bmatrix}, W = [w_1, w_2, \dots, w_n] \quad (1)$$

For ( $i=1,2,\dots,n$ ) and ( $j=1,2,\dots,m$ )

3. Normalize the decision matrix as  $\bar{x}$ . The normalization process is accomplished through following equations;

$$\bar{x}'_{ij} = \frac{x'_{ij}}{\frac{1}{2} \left( \sum_{j=1}^m x'_{ij} + \sum_{j=1}^m x''_{ij} \right)} = \frac{2x'_{ij}}{\sum_{j=1}^m (x'_{ij} + x''_{ij})} \quad (2)$$

$$\bar{x}''_{ij} = \frac{x''_{ij}}{\frac{1}{2} \left( \sum_{j=1}^m x'_{ij} + \sum_{j=1}^m x''_{ij} \right)} = \frac{2x''_{ij}}{\sum_{j=1}^m (x'_{ij} + x''_{ij})} \quad (3)$$

In this way normalized decision-making matrix is shown as;

$$\bar{X} = \begin{bmatrix} [\bar{x}'_{11}, \bar{x}''_{11}] & [\bar{x}'_{12}, \bar{x}''_{12}] & \dots & [\bar{x}'_{1n}, \bar{x}''_{1n}] \\ [\bar{x}'_{21}, \bar{x}''_{21}] & [\bar{x}'_{22}, \bar{x}''_{22}] & \dots & [\bar{x}'_{2n}, \bar{x}''_{2n}] \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ [\bar{x}'_{m1}, \bar{x}''_{m1}] & [\bar{x}'_{m2}, \bar{x}''_{m2}] & \dots & [\bar{x}'_{mn}, \bar{x}''_{mn}] \end{bmatrix} \quad (4)$$

4. Determine weighted normalized decision matrix;

$$\hat{x}'_{ij} = \bar{x}'_{ij} * w_i \quad (5)$$

$$\hat{x}''_{ij} = \bar{x}''_{ij} * w_i \quad (6)$$

In this equation  $w_i$  is the weight of criterion  $C_i$

Therefore the weighted normalized decision matrix could be formed as;

$$\hat{X} = \begin{bmatrix} [\hat{x}'_{11}, \hat{x}''_{11}] & [\hat{x}'_{12}, \hat{x}''_{12}] & \dots & [\hat{x}'_{1n}, \hat{x}''_{1n}] \\ [\hat{x}'_{21}, \hat{x}''_{21}] & [\hat{x}'_{22}, \hat{x}''_{22}] & \dots & [\hat{x}'_{2n}, \hat{x}''_{2n}] \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ [\hat{x}'_{m1}, \hat{x}''_{m1}] & [\hat{x}'_{m2}, \hat{x}''_{m2}] & \dots & [\hat{x}'_{mn}, \hat{x}''_{mn}] \end{bmatrix} \quad (7)$$

5. Identify the  $P_j$  value for all the criteria which should be maximized (For benefit criteria)

$$P_j = \frac{1}{2} \sum_{i=1}^k (\hat{x}'_{ij} + \hat{x}''_{ij}) \quad (8)$$

Where in this formula,  $k$  is number of criteria which have the benefit optimization direction

6. Identify the  $R_j$  value for all the cost criteria (The criteria which their minimum value is preferred)

$$R_j = \frac{1}{2} \sum_{i=k+1}^n (\hat{x}'_{ij} + \hat{x}''_{ij}) \quad (9)$$

Thus, it can be noted that  $n-k$  is number of criteria which have cost optimization direction (the criteria which

7. Calculate the relative weight of each alternative as  $Q_j$ ;

$$Q_j = P_j + \frac{\sum_{j=1}^m R_j}{R_j \sum_{j=1}^m \frac{1}{R_j}} \quad (10)$$

8. Determine the optimality criterion  $T$ ;

$$T = \max_j Q_j, \quad j = 1, 2, \dots, m \quad (11)$$

9. Identify the priority of alternatives. The higher value of  $Q_j$  as relative weight of alternatives indicates better rank of the alternative. Actually,  $Q_j$  expresses the satisfaction degree of decision making participants. In this way,  $Q_{\max}$  shows the satisfaction degree is in the highest quantity.

10. Compute the utility degree of each alternative. This task is done by comparing the analyzed alternatives with the best one. The utility degree which is introduced by  $N_j$  is computed as

$$N_j = \frac{Q_j}{Q_{\max}} \times 100\% \quad (12)$$

## 2. 2. Normalization instruments

Jahan and Edwards (2015) categorized normalization techniques in several classes as the sum-based dimensionless; linear ratio-based normalization methods, linear max–min dimensionless methods and other dimensionless methods. This part depicts all the five norm procedures with variables and parameters. First norm (Norm.1) is called vector normalization. By this norm the ratio of the values remains constant for this type of normalization in the interval [0,1]. Equations below show vector norm for both benefit and non-benefit criteria;

$$N_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}^2} \quad \text{For benefit criteria} \quad (13)$$

$$N_{ij} = 1 - \frac{r_{ij}}{\sum_{i=1}^m r_{ij}^2} \quad \text{For non-benefit criteria} \quad (14)$$

Next norm as Norm.2 is a new logarithmic method developed by Zavadskas&Turskis (2008) by inventing software LEVI 3.1 as the following equations;

$$N_{ij} = \frac{\ln(r_{ij})}{\ln\left(\prod_{i=1}^m r_{ij}\right)} \quad \text{For benefit criteria} \quad (15)$$

$$N_{ij} = \frac{1 - \frac{\ln(r_{ij})}{\ln\left(\prod_{i=1}^m r_{ij}\right)}}{m-1} \quad \text{For non-benefit criteria} \quad (16)$$

The third norm (Norm.3) is linear normalization sum-based method involving the following formulas;

$$N_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \quad \text{For benefit criteria} \quad (17)$$

$$N_{ij} = \frac{1/r_{ij}}{\sum_{i=1}^m 1/r_{ij}} \quad \text{For cost criteria} \quad (18)$$

The other norm (Norm.4) that has been considered for this work is the linear normalization supposed by Jahan and Edwards (2015).

$$N_{ij} = \frac{r_{ij}}{r_{ij}^{\max}} \quad \text{For benefit criteria} \quad (19)$$

$$N_{ij} = 1 - \frac{r_{ij} - r_{ij}^{\min}}{r_{ij}^{\max}} \quad \text{For cost criteria} \quad (20)$$

The final norm for this study is the non-linear normalization approach Turskis et al. (2009) which is computed here (Norm.5):

$$N_{ij} = \left( \frac{r_{ij}}{r_{ij}^{\max}} \right)^2 \quad \text{For benefit criteria} \quad (21)$$



$$N_{ij} = \left( \frac{r_{ij}^{\min}}{r_{ij}} \right)^3 \quad \text{For non-benefit criteria} \quad (22)$$

### 3 - Result and discussion

To figure out the influence of the aforementioned normalization tools four different material selection applications which already have been done successfully are acquired. In case studies MCDM with interval model solved the decision problem and the order preference of materials has been reported successfully with regard to design specifications and properties. Case 1 gets involved with selection nine different material families used for a gear which solved material problem using VIKOR and interval data (Jahan, Edwards, 2013; Milani et al. 2005). Case 2 is a light weight design selection problem (Rezvani, Jahan 2015). Totally the paper is accomplished to apply different normalization methods in COPRAS-G and compare results to increase quality and reliability of decision making in material and design selection process.

#### 3.1. Case 1

This case is going to sort best gear materials specific application. Due to various types of gear materials for designers several studies are concentrated on that. For this case six material criteria including surface hardness, core hardness, surface fatigue limit, bending fatigue limit, and ultimate tensile stress have been taken into consideration. Among these criteria core hardness is non-benefit attribute and clearly rest of them have benefit orientation which higher values are favorite for design. There are nine potential materials that cast iron, ductile iron, cast alloy steel, Nitrided steel are part of them. The weights of material attributes are stated like 0.172, 0.005, 0.426, 0.292 and 0.102. Table 1 exhibits the material information, weights of each attributes and also orientation of each material criterion.

To show the arrangement of material based on their priority, COPRAS-G model is employed which section 2.1 indicates the equations and stepwise algorithm. Firstly normalized decision matrixes and then weighted normalized matrix are computed and ranking of material is obtained. Table 2 illustrates the ranking of materials including COPRAS-G original method and applying five normalization tools. It is observed that ranking of materials using all norms is the same as COPRAS-G original algorithm. In this case there is agreement over ranking of materials. It declares normalization tools have no influence on algorithm of COPRAS in this condition. In this case, carburized steel and Nitrided steel are the best materials and cast iron is the worst one for application of gear material selection. Figure 1 pictures illustrative form of different ranking score for this case.

**Table 1 - Interval material properties for gear material selection (case 1)**

Material items	C <sub>1</sub>		C <sub>2</sub>		C <sub>3</sub>		C <sub>4</sub>		C <sub>5</sub>	
	W <sub>1</sub> = 0.172		W <sub>2</sub> = 0.005		W <sub>3</sub> = 0.426		W <sub>4</sub> = 0.292		W <sub>5</sub> = 0.102	
	Max	Min	Max	Min	Max	Min	Max	Max	Min	Max
M <sub>1</sub>	200	200	200	200	330	330	100	100	380	380
M <sub>2</sub>	220	220	220	220	460	460	360	360	880	880
M <sub>3</sub>	180	300	180	300	480	620	240	440	590	1100
M <sub>4</sub>	220	320	220	320	560	700	420	450	590	1000
M <sub>5</sub>	220	320	220	320	600	740	500	580	800	1580
M <sub>6</sub>	560	610	200	280	1160	1160	680	680	1580	1580
M <sub>7</sub>	650	750	270	360	1500	1500	920	920	2300	2300
M <sub>8</sub>	700	800	270	360	1250	1250	760	760	1250	1250
M <sub>9</sub>	160	210	160	210	450	550	420	440	560	710

### 3.2. Case 2

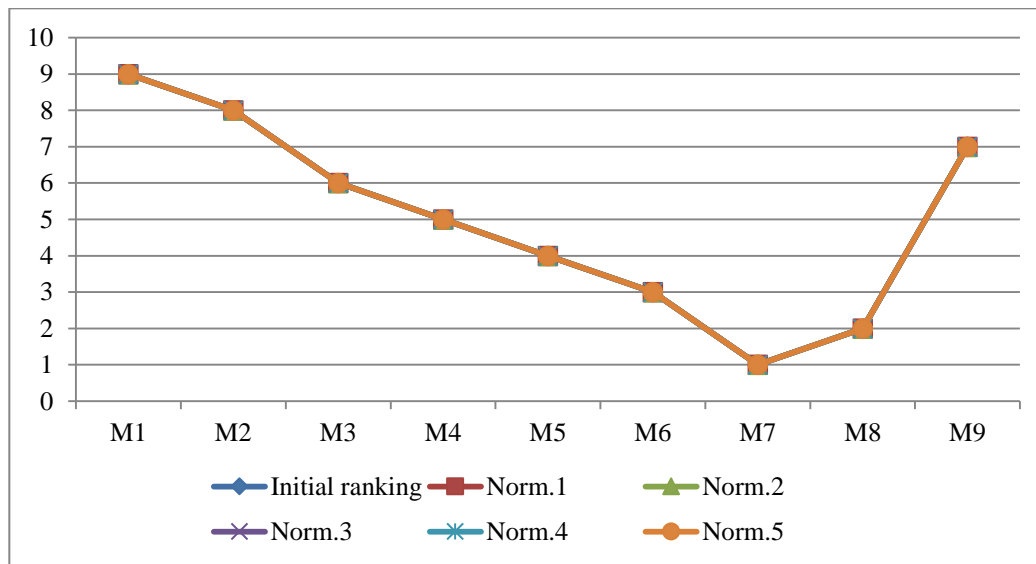
This case is a design selection problem that evaluates crashworthiness characteristics of thin-walled round aluminum tubes under axial loadings, with and without initiator, as well as different number of rings, and different densities of rigid PU foam for filling the tubes (Rezvani, Jahan, 2015). The energy absorption capacity of thin-walled tubes is significantly influenced by the material properties and the geometry. List of materials and weights of three material criteria are represented in Table 3. In order to achieve the best crashworthiness as well as light weight design, different criteria must be satisfied simultaneously. Eight designs of thin-walled cylindrical tubes compared concerning to three criteria with the same importance. The criteria are mass of structure (C<sub>1</sub>), energy absorption (C<sub>2</sub>), and crush force efficiency (C<sub>3</sub>). Performance rating measured with both real experiments and computer simulation analysis. Due to stochastic nature of production systems, usually there are differences between simulation and experimental outputs. Initial ranking of COPRAS delivers 217-C-6R-1I (M<sub>4</sub>) as the best material. Similar results are derived by Norm.3, 4 and 5 for best option. However, the highest similarity is seen between initial ranking and Norm 2 based on correlation coefficient of 0.98. In addition most of the rankings approve that 174-C-4R-1I (M<sub>5</sub>) is the most undesirable material. Therefore, for this case this material can be recommended to designers as  $M_4 = M_2 > M_8 > M_1 > M_3 > M_7 > M_6 > M_5$ . As presented in table 4, in such situations, using interval data might be a

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logical approach for developing design decision making matrix. Figure 2 illustrates the trend of ranking scores for this case.

**Table 2 - Ranking of materials for case 1 using different norms**

COPRAS-G material ranking						
Material list	Initial ranking	Norm.1	Norm.2	Norm.3	Norm.4	Norm.5
M <sub>1</sub>	9	9	9	9	9	9
M <sub>2</sub>	8	8	8	8	8	8
M <sub>3</sub>	6	6	6	6	6	6
M <sub>4</sub>	5	5	5	5	5	5
M <sub>5</sub>	4	4	4	4	4	4
M <sub>6</sub>	3	3	3	3	3	3
M <sub>7</sub>	1	1	1	1	1	1
M <sub>8</sub>	2	2	2	2	2	2
M <sub>9</sub>	7	7	7	7	7	7



**Figure 1 - Ranking of different norms applied for COPRAS-G model (case 1)**

**Table 3 - Information of design scenarios for case 2**

Material	C <sub>1</sub>		C <sub>2</sub>		C <sub>3</sub>	
	W <sub>1</sub> =0.333	0.43	W <sub>2</sub> =0.333	1917	W <sub>3</sub> =0.333	56
217-C-4R-1I (M <sub>1</sub> )	0.43	0.43	1917	1963	56	56
217-C-5R-0I (M <sub>2</sub> )	0.13	0.13	1698	1781	59	59
217-C-5R-1I (M <sub>3</sub> )	0.44	0.44	2069	2129	49	49
217-C-6R-1I (M <sub>4</sub> )	0.45	0.45	2011	20129	50	51
174-C-4R-1I (M <sub>5</sub> )	0.42	0.42	1678	1768	43	43
174-C-5R-1I (M <sub>6</sub> )	0.43	0.43	1818	1915	45	46
174-C-6R-1I (M <sub>7</sub> )	0.44	0.44	1582	1684	51	52
174-C-6R-2I (M <sub>8</sub> )	0.53	0.53	2636	2656	61	62

**Table 4 - COPRAS-G ranking index using different normalization (case 2)**

COPRAS-G material ranking (case 2)						
Material	Initial ranking	Norm.1	Norm.2	Norm.3	Norm.4	Norm.5
M <sub>1</sub>	4	6	4	3	3	3
M <sub>2</sub>	2	8	1	8	7	4
M <sub>3</sub>	5	4	5	4	4	5
M <sub>4</sub>	1	2	2	1	1	1
M <sub>5</sub>	8	7	8	7	8	8
M <sub>6</sub>	7	5	7	6	6	7
M <sub>7</sub>	6	3	6	5	5	6
M <sub>8</sub>	3	1	3	2	2	2

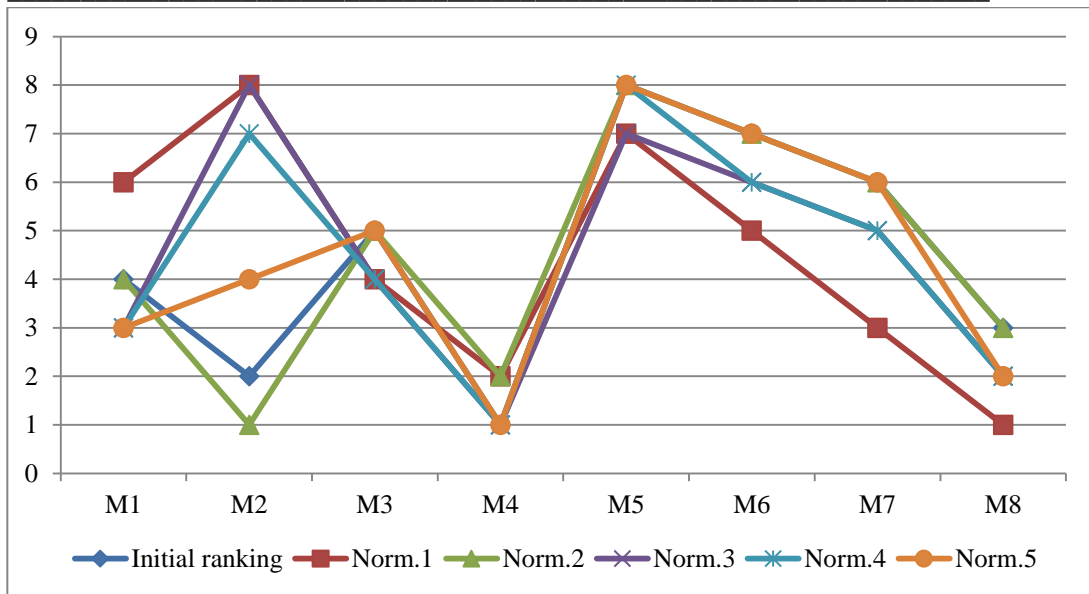


Figure 2 - Ranking of norms applied for COPRAS-G model for case 2

### 3.5. Discussion

It is clear each MCDM method like TOPSIS, VIKOR, SAW, ELECTRE etc. acts differently in various subjects and applications due to their functionality and uniqueness. However, modifying anatomy of a special method as COPRAS-G through putting new normalization equation can be interesting to discuss and it is worthy to investigate on behavior of normalization tools in above examples. First case was composed *nine materials* and five criteria. This case releases all the normalization tools produced exact similar ranking and it has been shown there is very good correlation between all norms and original ranking of COPRAS-G. *Eight materials* and three material criteria was structure of case 2. Norm.2 ranking values was the highest among others and after that Norm.5 delivered higher ranking than other normalization tools. Also and most errors have been achieved using Norm.1 and Norm.3. To be precise and based on our experiments, when material decision matrix has smaller dimensions and includes lower alternatives, Norm.2 is a very good option and can be used in optimization problems. Additionally, in general talking, Norm.5 reflected acceptable behavior as in three cases its function was close to original COPRAS method. To recognize highest errors and far ranking to original method, Norm.1 and 3 can be mentioned. It seems the normalization equations of these two norms function totally different from the existing norm of COPRAS method.

All in all, COPRAS-G method comes from real condition of decision making and application of grey system theory. It is a compensatory and rank-problem approach, its operational approach is preference priority, and the results are totally preordered. The complexity of a decision-making problem can be judged by the number of alternatives, number of the criteria, type of the criteria (qualitative or quantitative, deterministic, interval or fuzzy), type of normalization tool is being used etc. In cases solutions are similar, while in other cases very different results are achieved. Given that the ranking orders of normalization tools compared with the original COPRAS rather than the methods used initially for the case studies, the contribution of this study is to help material engineers and experts to establish different normalization tool getting optimal material and further effective design objectives.

#### **4 - Conclusion**

Material evaluation and selection is always deal with the complexity and uncertainty that exists in product development process which requires systematic formation and standard formulation to overcome the difficulty of design parameters and elements. In order to evaluate the overall ranking of alternatives it is a critical task to identify selection attributes, to assess information relating to these attributes, and to develop methods for evaluating the attributes to meet the decision maker's (designers or experts) needs. MCDM techniques are concerned with the situation in which a decision-maker has to choose among several alternatives by considering a common set of attributes. This work intended to enhance quality and reliability of multi-criteria decision analysis in application of material selection through utilizing applied normalization tools. For this objective, five normalization tools are examined by COPRAS-G method using four material and design selection problems with different amount of alternatives and criteria. The cases were assigned to evaluate and choose: 1) best gear materials, and 2) crashworthiness characteristics of thin-walled structures. COPRAS-G method algorithm with integration of normalization tools was employed to report ranking of materials. It was shown that by taking to account application of validated normalization tools to COPRAS-G method, as a simple and efficient technique, some reliable ranking orders for alternatives will be generated. This helps designers and engineers to achieve a compromise on design decision making process.

Designers usually select the best alternative based on the ranking orders of a selected MCDM technique. But different often generates different outcomes for ranking a set of alternative decisions, especially when options are very similar. Sensitivity analysis is an instrument to test validity of the results and so important stage in ranking problems. Although researcher takes to account this by changing importance of material criteria, applying different fitting normalization methods, as a new tool for sensitivity analysis, can increase quality of final decision making for

complex problems. For any research objective in area of material selection accompanying MCDM, practicing the treatment of other methods as MOORA, WASPAS, and VIKOR can be recommended. Another suggestion is comparison of MCDM methods in terms of analyzing affection of normalization tools on them.

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