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# SELECTION OF BEST MATERIAL FOR DESIGN OF TWO STAGE SPUR GEAR USING MULTI CRITERIA DECISION MAKING TOOL

## Tushar Verma<sup>1</sup>\*, Revendra Kumar Deshmukh<sup>2</sup>

<sup>1</sup>M Tech Scholar, Department of Mechanical Engineering, CSIT Durg, C.G., India. <sup>2</sup>Assistant Professor, Department of Mechanical Engineering, CSIT Durg, C.G., India.

## Abstract

In the competitive scenario, engineering design also require decision to select the shape, material and manufacturing. Thus there are number of materials which can be used for the purpose of designing of two stage reduction gear. But selection of best material is our objective which can be achieved through applying Multi Critetia Decision Making Techniques (MCDM). MCDM is subdivided into Multi Attributed Decision Making (MADM) and Multi Objective Decision Making (MODM). In literature review, we analysed that gear material selection is already being done by Analytical Hierarchy Process (AHP), Technique for Order Preference by Similarly to an Ideal Solution (TOPSIS), Elimination et Choice Translating Reality (ELECTRE), Multi Attribute Utility Theory (MAUT), etc but Normative Prescriptive Approach (NPA), Discrete Choice Analysis (DCA), Nearest Neighbor Search (NNS) was missing. Thus novelty of our research is to provide a material selection framework and to develop new method for performance evaluation of the alternatives by applying the NPA, DCA, and NSS.

The basic material selection is based upon design, utility or belief of decision maker. Thus based upon this above mentioned logic, the material selection is done through advance methodology i.e. NPA, DCA & NSS. DCA is based on observed utility. It is based on MAUT which is a utility value. NPA is based in decision requirement. It generally follows AHP and MAUT. NSS is based on belief. Belief is a function of knowledge and confidence. NSS follows the MADM framework. Findings are compared with available alternative evaluation methods and results of previous works available in literature Review. The Results are consistent with the previous results obtained in literature review. The sensitivity analysis is also conducted by changing the weight criteria and normalizing process for the new methods (NPA ad DCA) only. After comparison it is found that NSS is more sensitive than DCA.

*Keywords:* Material Selection, MCDM, AHP, TOPSIS, ELECTRE, MAUT, TOPSIS, VIKOR, NPA, DCA, NNS. \* *Corresponding author* 

## **1. INTRODUCTION**

One aspect of optimized product design is that of selecting the materials that best meet the needs of the design by maximizing its performance and minimizing its cost. The choice of the best material among a host of alternative

materials might greatly impact the eventual success or failure of a product in the market place. An improper choice can adversely affect productivity and profitability. Like any other decision-making process, material selection can be characterized as the outcomes of (Dieter, 1983):

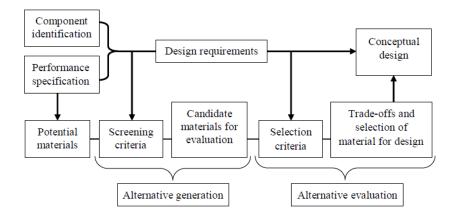


Figure 1. Material Selection Framework of a Product

- Component identification and performance specification: To recognize the component and lay down the possible performance specification in terms of demands and desires from the customer requirements.
- Identify the design and material requirements: To determine the conditions of service and environment that the product must withstand and to translate them into critical material properties or attributes.
- Screening of the candidate materials: To compare the needed properties with large materials property data base to select a few promising materials.
- Evaluation of the candidate materials: To conduct evaluations to determine whether a material does satisfy all the design requirements of the product element under consideration. When there is more than one option of materials, evaluations provide information that will help identify the material with properties that best meet the design requirements, at the lowest cost.

Material selection takes place at the earlier stage of the design process. The above-mentioned material selection steps are shown in Figure 1.1.

## 1.1 Introduction of MADM

When there is a set of alternatives, tangible or not, subject to restrictions and limitations, and when it is necessary to perform a selection and ranking, i.e. when there is a complex choice, it is convenient to solve the problem by applying a set of sequential procedures in MADM framework. MADM methods are generally sub- domain of multiple-criteria decision analysis (MCDA) where the alternatives are described in terms of evaluative criteria. MCDA methods can be categorized as:

- Multi-attributed decision making (MADM) where the decision space is explicitly known and discrete.
- Multi-objective decision making (MODM) where the decision space is continuous.
- MADM processes are becoming popular due to its user-friendly nature to select the best material from that finite number of alternatives. MADM approaches are more likely to be modeled with uncertain values for

the attributes (Shahinur et al., 2017; Wallenius et al., 2008). The most rational approach to select the best alternative is about its utility. In MODM there is usually no attempt to capture the alternatives utilities. Some of the popular MADM models in material selection point of view are:

- Scoring Model that selects an alternative which deserves the maximum score, such as, MAUT (Hatush & Skitmore, 1998; Yuan-pei et al., 2010), SAW (Kahraman et al., 2008), FUZZY logic (Girubha & Vinodh, 2012; Chan et al., 2008) and AHP (Mujgan et al., 2004; Chan, 2003).
- Compromising Model that skims off an alternative which is closest to the ideal solution, such as, TOPSIS (Gupta, 2011; Thakker et al., 2008) and VIKOR (Opricovic & Tzeng, 2004; Bahraminasab & Jahan, 2011).
- Outranking Model that arranges a set of performance relations among alternatives to acquire information on the best alternative, such as, ELECTRE (Shanian, 2008) and PROMETHEE (Peng & Xiao, 2013).
- Material selection is an integral part of the engineering design process and rather uncertainty takes place in material attributes and design formulation. Engineering design is a decision-making process where the decision should be formulized under risk and uncertainty. More specifically the above-mentioned scoring models under MADM in the domain of risk and uncertainty are dichotomized as (Howard, 1992):
- Descriptive Model that deals with human behaviour of real-life choice under certain heuristics (availability, representativeness, and anchoring and adjustment). One of the most prominent descriptive models under uncertainty is the Prospect Theory model of Kahneman and Tversky (1979).
- Normative Model that is built on some basic assumptions (cancellation, transitivity, dominance, and invariance) and focuses a rational choice. Most inspirational normative models are expected utility model of von Neumann and Morgenstern (1947) and subjective expected utility model of Savage (1954).
- Prescriptive Model is the assemblage of theoretical and operational assumption that helps the people to make better decision. Many prescriptive applications of expected utility theory have been carried out to capture the risk and uncertainty especially for problems that have multiple attributes e.g. MAUT (Keeney and Raiffa (1976)) and AHP (Satty, 1980).

## 1.2 Objective of the Project

The existence of a designer depends on the satisfaction of a customer and a designer and a customer both are in the same situation of 'which alternative' is to choose from a set of alternatives under uncertainty. The objective of the project is to:-

- 1. Understanding the need, scope and concept of new MADM Techniques.
- 2. Summarize the current knowledge regarding MCDA process which has been applied in material selection and to identify the major shortcomings in the existing MCDA process.
- 3. Analysis of Various MADM Techniques for selection of material in Two Stage Spur Gear Design.

- 4. Development of the notion is to suggest the ways to improve the conventional decision-making process used in material selection by overcoming the shortcomings in the existing methods.
- 5. Implementation of the notion is to apply the suggested ways in some practical cases and investigate the suitability of the suggested ways.
- 6. Compare the Results of Ranking for Selection of material in Two Stage Spur Gear Design.
- Synthesizes the Results obtained by Various MADM techniques for selection of material in Two Stage Spur Gear Design.

#### 2. METHODOLOGY

#### 2.1 Decision Making Alternative

Engineering design encompasses a wide range of activities whose goal is to determine all attributes of a product before it is manufactured. A strong capability to engineer industrial and consumer products is needed by any nation to stay competitive in an increasingly global economy. Good engineering design know-how results in lower time to market, better quality, lower cost, lower use of energy and natural resources, and minimization of adverse effects on the environment. Engineering decision making theory recognizes that the ranking produced by using a criterion has to be consistent with the engineer's objectives and preferences. The theory offers a rich collection of techniques and procedures to reveal preferences and in this research work, it has been tried to introduce them into the proposed models of decision-making in Materials selection by evaluating their performance. Material selection framework and two new methods for performance evaluation of the alternatives is explained. One of them is newly developed method and all the approaches with overcoming the previous are termed as:

- 1. Normative-prescriptive approach (NPA)
- 2. Discrete choice analysis (DCA)
- 3. Nearest neighbour search (NNS)

#### 2.2 Normative-prescriptive approach (NPA)

Hazelrigg (1998), proposed a framework known as Decision-Based Design (DBD) to select an alternative among the set of alternatives by assigning utility function to each alternative (Mastron & Mistree, 1998). It is a normative approach based on Neumann-Morgenstern (1947) utility axioms to ensure a rational choice that are explicitly considered. von Neumann and Morgenstern (1947) axiomatized expected utility theory by showing that, if a set of apparently normatively appealing axioms hold, alternative actions can be ranked by their expected utilities. The expected utility of an alternative action is the weighted average of the utilities of the possible outcomes where the weights are the objective probabilities of each outcome. Objective probability is decided through observations. it is too costly, time consuming, or technologically infeasible to make the observations, or in principle because that quantity in which we are interested, such as the probability of a rare event or condition occurring in the future, cannot be observed. Savage (1954) proposed Bayesian view of probability in which probability describes an individual's "degree of belief." This is also known as subjective probability. Savage's (1954) subjective expected utility model allows the derivation of a decision maker's own subjective probabilities for events, which are then used to compute the subjective expected utility of each alternative.

#### 2.3 Discrete choice analysis (DCA)

The above-discussed method is a deterministic approach considering only the observed performance ratings or utilities of the alternatives. In the choice analysis, unobserved attributes, unobserved taste variation, and variability in observed utilities should be considered (Wassenaar and Chen 2003). Discrete Choice Analysis (DCA) platform accommodates these unobserved factors or random disturbance along with the deterministic part. In this section, the Conditional Logit (CLGT) under DCA platform is introduced that addresses the acceptance of an alternative in terms of choice probability under risk and uncertainty.

#### 2.4 Nearest neighbor search (NNS)

Nearest neighbor search is the finding of a point (a) in a given set which is nearer to a reference point or query point (q) in multi-dimensional Euclidean space. In the above mentioned TOPSIS-based methods, the closeness or nearness between two points is decided by a ratio lies in between 0 and 1 where the higher value dictates the close proximity.

## **3. RESULTS AND DISCUSSION**

#### 3.1 Normative-prescriptive approach (NPA)

| Alternative $(a_i)$   |                    | <i>e</i> <sub>1</sub> (max) |                        | $e_2 (max)$     |                 | $e_3$ (min)     |                 | $e_4$ (min)     |                 |          |      |
|-----------------------|--------------------|-----------------------------|------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------|------|
|                       |                    | $w_1 = 0.47$                |                        | $w_2 = 0.33$    |                 | $w_3 = 0.08$    |                 | $w_4 = 0.12$    |                 | $U(a_i)$ | Rank |
|                       |                    | $d_{i1}$                    | <i>u</i> <sub>i1</sub> | d <sub>i2</sub> | u <sub>i2</sub> | d <sub>i3</sub> | u <sub>i3</sub> | d <sub>i4</sub> | u <sub>i4</sub> |          |      |
| <i>a</i> <sub>1</sub> | AISI 1040          | 515                         | 0.687                  | 149             | 0.014           | 7.84            | 0.013           | 1.3             | 1               | 0.449    | 4    |
| $a_2$                 | AISI 4130          | 560                         | 1                      | 156             | 0.065           | 7.85            | 0               | 2               | 0.741           | 0.58     | 2    |
| <i>a</i> <sub>3</sub> | AISI 304           | 515                         | 0.687                  | 147             | 0               | 7.8             | 0.067           | 2.85            | 0.426           | 0.379    | 5    |
| $a_4$                 | AISI 405           | 448                         | 0.222                  | 150             | 0.021           | 7.8             | 0.067           | 3.5             | 0.185           | 0.139    | 7    |
| a <sub>5</sub>        | ASTM<br>class 60   | 431                         | 0.104                  | 285             | 1               | 7.3             | 0.733           | 3.3             | 0.259           | 0.469    | 3    |
| a <sub>6</sub>        | Grade 60-<br>40-18 | 416                         | 0                      | 167             | <b>0.14</b> 5   | 7.1             | 1               | 4               | 0               | 0.128    | 8    |
| a <sub>7</sub>        | Grade 65-<br>45-12 | 464                         | 0.333                  | 167             | 0.145           | 7.1             | 1               | 4               | 0               | 0.284    | 6    |
| a <sub>8</sub>        | Grade 80-<br>55-06 | 559                         | 0.993                  | 192             | 0.326           | 7.1             | 1               | 4               | 0               | 0.654    | 1    |

Table 1. Overall Performance of the Gear Material following the NPA

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## 3.2 Discrete choice analysis (DCA)

Here we will directly proceed from the ranking or evaluation process using the equations and results are tabulated in Table 2.

|                       |                       | <i>e</i> <sub>1</sub> (max) |              |                 | $e_2$ (max)     |                 |                 | $e_3$ (min)            |                 |                 | $e_4$ (min)     |                 |                 |            |   |
|-----------------------|-----------------------|-----------------------------|--------------|-----------------|-----------------|-----------------|-----------------|------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|------------|---|
|                       | Alternative           |                             | $w_1 = 0.47$ |                 | $w_2 = 0.33$    |                 | $w_3 = 0.08$    |                        | $w_4 = 0.12$    |                 |                 | $P(a_i)$        | Rank            |            |   |
| $(a_i)$               |                       | d <sub>i1</sub>             | $r_{i1}$     | P <sub>i1</sub> | d <sub>i2</sub> | r <sub>i2</sub> | P <sub>i2</sub> | <i>d</i> <sub>i3</sub> | r <sub>i3</sub> | P <sub>i3</sub> | d <sub>i4</sub> | r <sub>i4</sub> | P <sub>i4</sub> | - (        |   |
| <i>a</i> <sub>1</sub> | AISI<br>1040          | 515                         | 0.371        | 0.127           | 149             | 0.29            | 0.118           | 7.84                   | 0.37            | 0.123           | 1.3             | 0.141           | 0.151           | 0.126<br>8 | 4 |
| a2                    | AISI<br>4130          | 560                         | 0.403        | 0.132           | 156             | 0.303           | 0.12            | 7.85                   | 0.37            | 0.123           | 2               | 0.217           | 0.14            | 0.128      | 2 |
| a3                    | AISI<br>304           | 515                         | 0.371        | 0.127           | 147             | 0.286           | 0.118           | 7.8                    | 0.368           | 0.123           | 2.85            | 0.309           | 0.128           | 0.123<br>8 | 5 |
| a4                    | AISI<br>405           | 448                         | 0.322        | 0.121           | 150             | 0.292           | 0.118           | 7.8                    | 0.368           | 0.123           | 3.5             | 0.38            | 0.119           | 0.120<br>2 | 7 |
| a <sub>5</sub>        | ASTM<br>class<br>60   | 431                         | 0.31         | 0.12            | 285             | 0.554           | 0.154           | 7.3                    | 0.344           | 0.126           | 3.3             | 0.358           | 0.122           | 0.131<br>8 | 1 |
| a <sub>6</sub>        | Grade<br>60-40-<br>18 | 416                         | 0.299        | 0.119           | 167             | 0.325           | 0.122           | 7.1                    | 0.335           | 0.127           | 4               | 0.434           | 0.113           | 0.119<br>8 | 8 |
| a <sub>7</sub>        | Grade<br>65-45-<br>12 | 464                         | 0.334        | 0.123           | 167             | 0.325           | 0.122           | 7.1                    | 0.335           | 0.127           | 4               | 0.434           | 0.113           | 0.121<br>8 | 6 |
| a <sub>8</sub>        | Grade<br>80-55-<br>06 | 55 <b>9</b>                 | 0.402        | 0.131           | 192             | 0.373           | 0.128           | 7.1                    | 0.335           | 0.127           | 4               | 0.434           | 0.113           | 0.127<br>8 | 3 |

## 3.3 Nearest neighbor search (NNS)

The overall performances of the alternatives are evaluated through the equations and the results are tabulated in Table 3.

| Candidate Material    |                    | <del>∂a</del> 1 | oq    | $\overrightarrow{oa_1}.\overrightarrow{oq}$ | $\cos \theta_i$ | $\sin\theta_i$ | $\overline{a_i b_i}$ | $\overline{b_i q}$ | $d_M(a_i,q)$ | Rank |
|-----------------------|--------------------|-----------------|-------|---|-----------------|----------------|----------------------|--------------------|--------------|------|
| <i>a</i> <sub>1</sub> | AISI<br>1040       | 0.2016          | 0.265 | 0.0515                                      | 0.964           | 0.2658         | 0.0879               | 0.0121             | 0.0999       | 5    |
| a2                    | AISI<br>4130       | 0.2178          | 0.265 | 0.0554                                      | 0.959           | 0.2835         | 0.0833               | 0.004              | 0.0873       | 3    |
| <i>a</i> <sub>3</sub> | AISI 304           | 0.2037          | 0.265 | 0.0516                                      | 0.9562          | 0.2928         | 0.0919               | 0.0075             | 0.0994       | 4    |
| a4                    | AISI 405           | 0.1875          | 0.265 | 0.0478                                      | 0.9623          | 0.2721         | 0.0959               | 0.0237             | 0.1196       | 7    |
| a <sub>5</sub>        | ASTM<br>class 60   | 0.2394          | 0.265 | 0.0625                                      | 0.9851          | 0.1718         | 0.0497               | 0.0084             | 0.0582       | 1    |
| a <sub>6</sub>        | Grade 60-<br>40-18 | 0.1863          | 0.265 | 0.0478                                      | 0.9684          | 0.2495         | 0.0927               | 0.027              | 0.1196       | 8    |
| a <sub>7</sub>        | Grade 65-<br>45-12 | 0.1988          | 0.265 | 0.0509                                      | 0.9655          | 0.2603         | 0.0882               | 0.015              | 0.1033       | 6    |
| a <sub>8</sub>        | Grade 80-<br>55-06 | 0.2331          | 0.265 | 0.0599                                      | 0.9693          | 0.2458         | 0.0681               | 0.0129             | 0.081        | 2    |

Table 3. Overall performance evaluation of Gear Material following the NNS

## 3.4 Rank Comparison

Carburized Steel is well-known gear material but it is not new to choose it as a gear material. Ultimate selection of gear material depends on functional requirements i.e. forces acting on it as well as the required factor of safety and the analysis directs us towards the grey cast iron or ductile cast iron. Ductile cast iron as a gear material is becoming very popular in automotive industries specially austempered ductile iron (ADI) due to its high strength to weight ratio, good damping quality and recyclability.

| Can                   | didate Material | NPA | DCA | NSS | Pahl &<br>Beitz | TOPSIS | VIKOR | ELECTRE     |
|-----------------------|-----------------|-----|-----|-----|-----------------|--------|-------|-------------|
| <i>a</i> <sub>1</sub> | AISI 1040       | 4   | 4   | 5   | 4               | 4      | 3     | 4           |
| a <sub>2</sub>        | AISI 4130       | 2   | 2   | 3   | 2               | 3      | 2     | 1 or 2 or 3 |
| <i>a</i> <sub>3</sub> | AISI 304        | 5   | 5   | 4   | 5               | 5      | 4     | 5           |
| <i>a</i> <sub>4</sub> | AISI 405        | 7   | 7   | 7   | 7               | 8      | 7     | 8           |
| <i>a</i> <sub>5</sub> | ASTM class 60   | 3   | 1   | 1   | 3               | 1      | 6     | 1 or 2 or 3 |
| <i>a</i> <sub>6</sub> | Grade 60-40-18  | 8   | 8   | 8   | 8               | 7      | 8     | 7           |
| <b>a</b> <sub>7</sub> | Grade 65-45-12  | 6   | 6   | 6   | 6               | 6      | 5     | 6           |
| <b>a</b> 8            | Grade 80-55-06  | 1   | 3   | 2   | 1               | 2      | 1     | 1 or 2 or 3 |

In Table 4, the proposed methods (DCA and NNS) give consistent results with TOPSIS (Jahan et al., 2012). ELECTRE raises the most dominating alternatives ASTM class 60 (*a5*), Grade 80-55-06 (*a8*), and AISI 4130 (*a2*)

## 3.5 Discussions

The design is a sequential decision-making process. Decision-making is the process by which the decision makers skim off an alternative and belief that will meet the destined objective function. It is the versatility of the MADM approaches blended with mathematics and cognitions that different decision-making methods yield different rankings considering the same input data. Whatever the methods, if the methods have definite logic, the fittest materials will always survive, but there should have some consistency among the rankings inside a particular method. The methodology gives an entire picture but we have to take the right decision from this picture. The following observations have been noted in the case studies.

- Throughout the case studies, the material properties are considered as discrete and average, but these are rather variable in nature. The true value cannot be known precisely (aleatory uncertainty). As the material selection is initiated at the conceptual stage of the design process, there is a further scope to analyse the suitability of the chosen material at the embodiment stage.
- In the above case studies, the proposed conditional logit (CLGT) method under DCA gives more consistent results when compared with the other MADM approaches. MADM is based on the observed attribute with certainty, but CLGT is based on both the observed and unobserved attributes that give us confidence under risk and uncertainty.

- Material selection takes place at the earliest stage of the design process when there is a lack of information and variability in the available information in the decision space. Under these circumstances, the proposed NNS gives a confidence in visualizing (geometrical) point of view and courage in ranking consistency point of view as compared with other rankings.
- This project basically proposes two methods, Conditional Logit (CLGT) under Discrete Choice Analysis (DCA) and Nearest Neighbor Search (NNS) in the Decision- Based Design (DBD) framework. CLGT was developed to solve the socio demographic problems.
- One of the limitations of the proposed approach CLGT is associated with the IID assumption, i.e., the unobserved factors are not correlated over alternatives and also have the same variance for all alternatives.

# 4. CONCLUSION

- Engineering design is the judicious trade-off among shape, materials, and manufacturing that requires a wide range of decisions. Decision-making in engineering design allocates all the resources optimally while fulfilling the design objectives within economic constraints, quality constraints, safety constraints, environmental constraints etc under uncertainty.
- The intention in this thesis is to develop a strategy for supporting a designer to choose a preeminent material in the context of product design. Several comprehensive and flexible procedures for performance evaluation of the engineering materials in engineering design have been defined and analysed in this thesis and many practical applications have been described.
- A structured rational decision-making framework based on DBD framework (decision-based design) is suggested to ensure a ration choice where the alternatives are evaluated by the traditional MAUT method under uncertainty. The entire approach is termed as Normative-prescriptive approach (NPA). In this approach, the alternatives are evaluated by their observed utility but, it has also unobserved utility that should be considered.
- At every stage of the design, a designer is supposed to make a rational decision. The rationality in the design is mapping the customer requirements to the useful design requirements precisely from the available information, but rather this information is incomplete. Therefore, the decision problem is inductive in nature that requires an inductive logic. To consider the above-mentioned unobserved utility, this thesis proposes the Conditional Logit from the domain of discrete choice analysis (DCA) in rational decision-making framework that assigns the probability to the alternatives. Probabilistic choice addresses the risk and uncertainty associated with unobserved taste variation and unobserved attribute.
- The advantage of using conditional logit is its closed-form formulation, i.e. no computer simulation is required. Decision making is the process to choose an appropriate alternative based on the belief of the decision maker. Belief is the function of knowledge and confidence. The above-mentioned proposed approaches are modelled with structured knowledge but, the knowledge is always covered with aleatory and

epistemic uncertainty. Therefore, a decision model should be structured in cognitive way to get the confidence under these uncertainties.

- A new method is developed in this thesis based on nearest neighbour search (NNS) which is a spatial approach in the Cartesian plane. If the points (alternatives) with multidimension (attributes) are mapped in the 2-dimensional plane and the nearness is compared with a reference or query point, then we can easily visualize the comparison of these points with the query point. In this proposed method, a spatial relationship is introduced to make the belief as a justified belief. A designer rather enjoys the spatial relationship which gives a confidence and courage to select a preeminent alternative under uncertainty.
- In this research work, DCA is first applied in MADM framework to select the preeminent material in design. Discrete choice analysis (DCA) gives the good result but, nearest neighbour search (NNS) gives the confidence and courage under uncertainty in the geometrical point of view.

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