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Optimal Selection of Gear Material by using Distance Based Approach Method

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Abstract: A deterministic quantitative model based on Distance Based Approach (DBA) method has been developed for evaluation, selection and ranking of gear materials, which is a concept hitherto not employed in selection problem of this kind. As a significant development over and above past approaches to gear materials selection, it recognizes the need for, and processes the information about, relative importance of attributes for a given application, without which inter-se-attribute comparison could not be accomplished. It successfully presents the results of this information processing in terms of a merit value which is used to rank the gear materials. In order to demonstrate the aptness of using DBA method as a decision aid, the results so obtained have been compared with other techniques and methods available in the open literature.

Index Terms: DBA method, gear materials, gear material selection parameter.

INTRODUCTION

Gears are used in most types of machines and vehicles for the transmission of power. The design of gears is highly complicated involving the satisfaction of many constraints such as strength, pitting resistance, bending stress, scoring wear, and interference in involutes gears etc. The concentration is focused on spur gear sets which are used to transmit motion between parallel shafts because of the reason that out of the various methods of power transmission, the toothed gear transmission stands unique due to its high efficiency, reliable service, large power transmission, compact layout and simple operation. Gears are toothed members which transmit power / motion between two shafts by meshing without any slip. Hence, gear drives are also called positive drives. In any pair of gears, the smaller one is called pinion and the larger one is called gear immaterial of which is driving the other. When pinion is the driver, it results in step down drive in which the output speed decreases and the torque increases. On the other hand, when the gear is the driver, it results in step up drive in which the output speed increases and the torque decreases. A gear is a wheel with teeth that mesh together with other gears. Gears change the Speed, torque and direction of rotating axles.

Material selection is a task normally carried out by design and materials engineers. For the purpose of material selection, thousands of data would be needed to characterize all the grades of materials. Many selection systems are available to help design engineers to choose the most suitable materials. At the most basic level, design engineers could use tables of material properties in data books. However, data sheets are incomplete and once published, they are difficult to update.
Optimal design of gears requires the consideration of both material and geometrical parameters (Hofmann 1990; Ognjanovic 1996). From a tradeoff point of view, a choice of stronger material parameters may allow the choice of finer geometrical parameters, and vice versa. An important difference among the two types of parameters, however, is that the geometrical parameters are often varied independently (e.g., the face width and diametrical pitch). On the other hand, material parameters can be inherently correlated to each other and may not be varied independently, an example of which being the variation of the bending fatigue limit with the core hardness for some steel materials (Horimoto et al. 2003). If one allows these parameters be varied independently in an optimization problem, it may result in infeasible solutions. That is, the final choice of material may not be possible within available data bases. When gear material and geometrical parameters are optimized simultaneously, it is common to assume empirical formulas approximating a relation between material parameters (e.g. the bending fatigue limit and the ultimate tensile stress as a function of hardness). As such, the variability of material parameters is controlled by one or few parameters (see, e.g., Thompson et al. 2000) and the final choice of material becomes straightforward.

The gear materials used for the manufacture of gears depend upon the strength and service conditions like wear and noise etc. The gears may be manufactured from metallic or non – metallic materials. The cast iron is widely used for the manufacturing of gears due to its good wearing properties, excellent machine ability and ease of producing complicated shapes by casting method. The non – metallic materials like wood, rawhide, compressed paper and plastics like Nylon, Acrylic and Polycarbonate etc are used for gears, especially for reducing weight and noise. Plastic gear are used in watches, toys etc. Weight reduction can be achieved primarily by the introduction of better material, design optimization and better manufacturing processes. The plastic materials have corrosion resistance, low electrical and thermal conductivity, easily formed into complex shapes, wide choices of appearance, colors and transparencies.

A considerable number of optimization methods have been employed in a broad class of engineering applications. For the classic genre, the solving algorithms stress a functional form of the objectives and constraints. On the other hand, engineers are often confronted with the case where obtaining the exact mathematical form of objectives is either impractical or requires extensive work. Despite this, most often it is practical to provide models with a set of experimental data informing optimization algorithms of intrinsic characteristics of objectives and constraints. A common practice of the above situation can be attributed to the context of material selection. From a metallurgical point of view, there are no exact relations available describing the mechanical behavior of materials as a function of all micro-structural and macro-structural characteristics. Nevertheless, the mechanical properties of most of the materials are obtainable through a set of separate engineering tests. Although for a particular design specification, such tests may be adequate, in the case of multiple objectivity (a) the variety of potential alternatives, (b) the multiplicity of criteria to distinguish among the objectives and (c) the absence of a precise formulation correlating the material properties to the objectives, are just a few sources leading the optimal selections to a gray area. In such multi-discipline engineering paradigms, the engineer's experience has typically been associated with iterative performance measurement to choose durable materials. In order to arrive at more concrete solutions, a number of works have been aimed at accommodating Multiple Attribute Decision-Making (MADM) models into engineering decision problems (Sen and Yang 1998). The basic motivation behind this attempt may be two-fold. The MADM models are capable of performing the solution procedure regardless of the functional relationship for the objectives and constraints, and secondly, the number of attributes and alternatives applicable to the model is computationally limitless. Unfortunately, next to these advantages, the MADM models may suffer from two weak points. Firstly, the MADM models are lacking in the delivery of the absolute optimum, however they are capable of deciding over the best options among selected alternatives. Secondly, if not properly assigned, normalization norms within the solution methods (and sometimes the method itself) may fail to reveal true decisions. Recently, it was shown that a similar criticism also applies to multiple objective decision making (MODM) models, where the functional form of objectives and constraints are available (Miettinen and M¨akel¨a 2002).

ATTRIBUTES AND ALTERNATIVES

As might be noted from the previous section of attributes and alternatives are key points. Material properties can be classified as shown in table I this classification consists of two types of properties resulting from (1) the strength of the atomic bonds and (2) the arrangement and packing of the atoms in a solid. The microstructure-insensitive properties are predominantly the physical and chemical properties that do not vary sizably with material imperfections. In contrast, the microstructure-sensitive properties are mainly the mechanical properties that change significantly with material imperfections. It is not always necessary to include all properties within a design selection problem. In certain cases, some properties are independent of the prescribed objective, and therefore should be eliminated. In other cases, a set of (static and moving) weighting factors can be assigned to control the contribution of each property. Indeed, for given design objectives, it is the task of the decision maker (DM) to choose the appropriate failure criteria as well the relevant material parameters.

Table I. Classification of material properties for design of components and structures.

Microstructure insensitive	Microstructure sensitive
Density, ρ	Strength
Modulus of elasticity, E	Ductility
Thermal conductivity, k	Fracture toughness
Coefficient of linear thermal expansions	Fatigue cyclic properties
Melting point	Creep
Glass transition temperature	Impact Hardness

If the choice of material is limited to a list of pre-defined candidates, then two difficulties can be appeared. First, a discrete optimization process should be followed against material parameters. Second, properties of different alternatives materials may not indicate any obvious correlation in the given list. The main goal is to choose material with best characteristic among alternatives. Herein, considering the DBA part, attributes are selected as the following material parameters.

Bending fatigue limit

Surface fatigue limit

Ultimate tensile strength

Surface hardness

Core hardness

Note that these five multiple, potentially conflicting attributes, reflect both benefits and cost features. A higher value with regards to the first four properties is preferred while having relatively low hardness of core is favored to prevent early facture. Proceeding with the alternatives, the great majority of steel power gears are hardened or case-carburized, with a smaller number manufactured from cast iron and from non-metallic materials such as thermoplastic, laminated bonded wood, fabric and paper materials. For high stress and high-speed application, potential gear materials are suggested in table II (A.S.Milani 2005). In the given material domain, the choice seems to be straightforward provided the objective is to optimize one particular property. However, in case of multi-objectivity, the choice is no longer obvious. Attributes weight - The weights of relative importance of attributes may be decided by the decision maker for the considered application either based on the attribute data for various alternatives given in the decision matrix (i.e. objective weights) or based on his/her subjective preferences on the attributes or based on a combination of objective weights and subjective preferences, called as integrated weights.

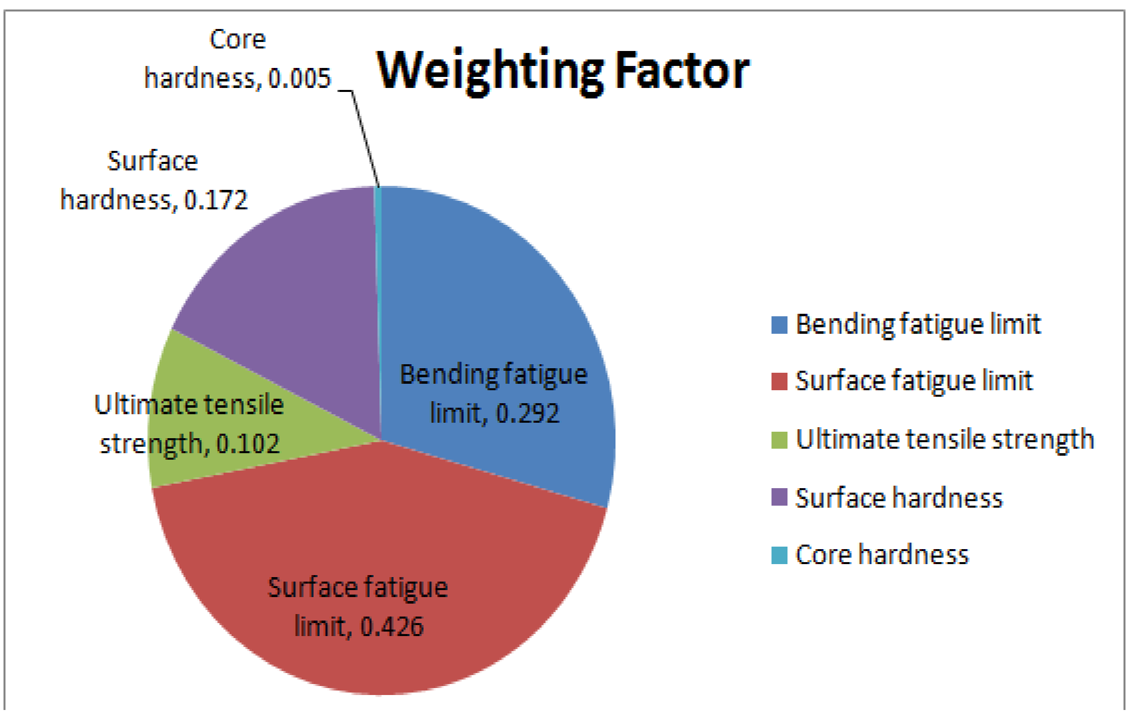

Fig 1 weighting factor

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Material type	Typical Specification	Hardness Surface	core	Surface fatigue limit (N/mm^2)	Bending fatigue limit (N/mm^2)	UTS(N/mm^2)	Material ID
cast iron	DIN 1691	As Core	200HB	330	100	380	B1
ductile iron	DIN1692	As Core	220HB	460	360	880	B2
S.G. iron	DIN1692	As core	180-300HB	480-620	240-440	590-1100	B3
Cast alloy steel	BS3100	As core	220-320HB	560-700	420-450	590-1100	B4
Through hardened alloy steel	34CrMo4	As core	220-320HB	600-740	500-580	800-1580	B5
surface hardened alloy steel	34CrMo4	560-610HV	200-280HV	1160	680	1580	B6
Caburised steels	15CrNi6	650-750HV	270-360HV	1500	920	2300	B7
Nitrided steels	14CrMoV6.9	700-800HV	270-360HV	1250	760	1250	B8
Through hardened carbon steel	St50	As core	160-210HV	450-550	440-420	560-710	B9

Distance Based Approach (DBA) Method

The development of the Distance Based Approach (DBA) method begins with defining the optimal state of the overall objective, and specifies the ideally good values of attributes involved in the process. In this study, the optimal state of the objective is represented by the optimum gear materials, the optimal. The vector OP(x1,x2,…,xn) is the set of optimum simultaneous attributes values. In an n-dimensional space, the vector OP is called the optimal point. For practical purposes the optimal good value for attribute is defined as the best values which exist within the range of values of attributes. The Optimal, then, is simply the gear materials that has all the best values of attributes. It may happen that a certain gear materials has the best values for all attributes, which is very unlikely. Instead a variety of alternatives may be used as simulate the optimal state. For this reason, in this study, the Optimal has not to be considered as feasible alternatives, but it is used only as reference to which other alternatives are quantitatively com- pared. The numerical difference resulting from comparison represents the effectiveness of alternatives to achieve the optimal state of objective. The smaller numerical differences, the closer the alternative resembles the optimal state, and vice versa. Hence, here, the decision problem is to find a feasible solution which is as close as possible to the optimal point. The objective function for finding such a solution can be formulated as

Minimize δ[Alt(x),Optimal]

Subject to xςX

Where {Alt(x)} and δ represent a gear material alternative in the n-dimensional space and the distance from the optimal point, respectively. Thus the problem, and its solutions depend on the choice of optimal point, OPTIMAL, and the distance metric,δ, used in the model. In two dimensional spaces, this solution function can be illustrated as in Fig.1, where H is feasible region and OP is the optimal point.

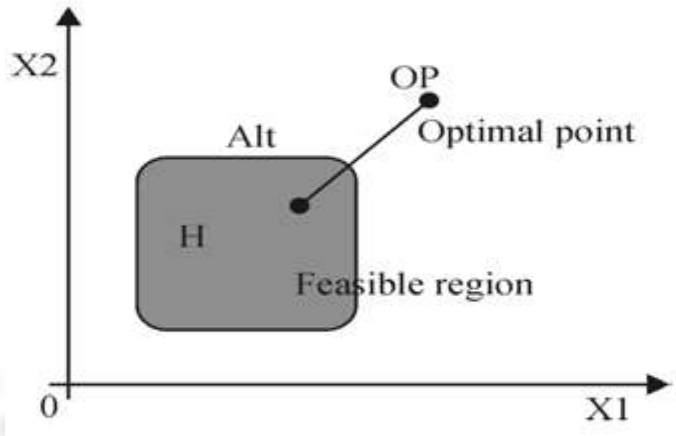

Fig. 2 Solution Function in 2 - Dimensional Space

The DBA method determines the point in the H region which is "the closest" to the optimal point, and is graphically explained in Fig. 2 for two dimensional cases. Note that the lines (Alt-OP)X1, and (Alt-OP)X2 are parallel to the X1 and X2 axis respectively. Therefore, (Alt-OP)X1 = |OP X1-Alt X1| and (Alt-OP)X2 = |OP X2-Alt X2| based on Pythagoras theorem in two dimensional, δ is
δ = [(OPx1-Altx1)2 + (OPx2-Altx2)2]

in two dimensional space. In general terms, the ''distanced'' can be formulated as:
$\delta = [\sum(OPij - Altij)^2]$

Where i = 1, 2, 3, ..., n = alternate gear material(s),
and j=1, 2, 3,... ,m = selection parameter.

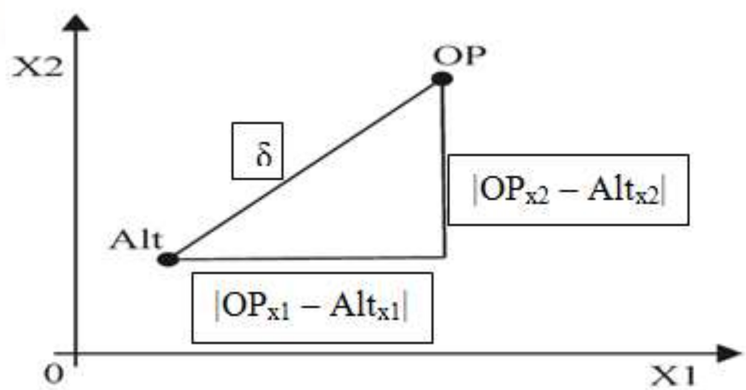

Fig. 3 Distances of Real Vector in 2 - Dimensional Space

To implement the above approach, let us assume that we have 'n' alternate gear materials and 'm' selection parameter corresponding to each alternate gear material e.g. Alt1 (X11,X12…..,X1m), Alt2 (X21,X22…..,X1m), Altn (rn1,rn2…..,rnm), and the OPTIMAL (Xb1,Xb2…..,Xbm) , where Xbm = the best value of the parameter 'm'. It is observed that the best numerical value of some parameter is smaller than that of the worst level of the other parameter. To avoid confusion and difficulties in performing the analysis, those values have been adjusted using following two cases:

Case - I: When smaller value of the parameter represents fitting well to the actual data i.e. is the best value:

Parameter Adjusted Value = Parameter Maximum Value in the database – Parameter Value.

Case - II: When bigger value of the Parameter represents fitting well to the actual data i.e. is the best value:

Parameter Adjusted Value = Parameter Value -Parameter Minimum value in the database.

Thus, the whole set of alternatives can be represented using the adjusted values of the parameter by the matrix

$$[r] = \begin{pmatrix} X_{11} & X_{12} & \vdots & X_{1m} \\ X_{21} & X_{22} & \vdots & X_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & \vdots & X_{nm} \\ X_{b1} & X_{b2} & \vdots & X_{bm} \end{pmatrix}$$

Thus, in this matrix, a vector in an m-dimensional space represents every alternate gear material. To ease the process, and to eliminate the influence of different units of measurement, the matrix is standardized using

$$Z_{ij} = (X_{ij} - \overline{X}_j)/S_j$$

$$\overline{X}_j = 1/n \, \Sigma \, X_{ij}$$

$$S_j = [1/n \, \Sigma \, (X_{ij} - \overline{X}_j)^{1/2}]$$

Where i=1,2,3,4,…,n

m=Number of different gear materials attributes
n=Number of gear materials
Xij=Indicator value for alternative gear materials i for attribute j Sj=Standard deviation of attribute of j.

$$\boxed{[Z_{std}] =} \begin{pmatrix} Z_{11} & Z_{12} & \dots & Z_{1m} \\ Z_{21} & Z_{22} & \dots & Z_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ Z_{n1} & Z_{n2} & \dots & Z_{nm} \\ Z_{OP1} & Z_{OP2} & \dots & Z_{OPm} \end{pmatrix}$$

The next step is to obtain the difference of each alternate gear material to the reference point, the OPTIMAL, by subtracting each element of the optimal set by a corresponding element in the alternate set. This result in another interim matrix namely distance matrix and is given as:

$$\boxed{[Z_{dis}] =} \begin{pmatrix} Z_{OP1} - Z_{11} & Z_{OP2} - Z_{12} & \dots & Z_{OPm} - Z_{1m} \\ Z_{OP1} - Z_{21} & Z_{OP2} - Z_{22} & \dots & Z_{OPm} - Z_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ Z_{OP1} - Z_{n1} & Z_{OP2} - Z_{n2} & \dots & Z_{OPm} - Z_{nm} \end{pmatrix}$$

The next step is to introduce the aggregated preference weights for each selection criteria i.e. .attribute. If the aggregated preference weight for any selection criteria j is denoted by Wj then this will result in another interim matrix as given

$$\begin{pmatrix} (Z_{OP1} - Z_{11})W_1 & (Z_{OP2} - Z_{12})W_2 & \dots & (Z_{OPm} - Z_{1m})W_m \\ (Z_{OP1} - Z_{21})W_1 & (Z_{OP2} - Z_{22})W_2 & \dots & (Z_{OPm} - Z_{2m})W_m \\ \vdots & \vdots \quad \vdots & & \vdots \\ (Z_{OP1} - Z_{n1})W_1 & (Z_{OP2} - Z_{n2})W_2 & \dots & (Z_{OPm} - Z_{nm})W_m \end{pmatrix}$$

Finally the Euclidean composite distance, CD, between each alternative gear materials to the optimal state OPTIMAL, is derived from the following formula:

$CDOPAlt = [\Sigma \{(ZOP - Zij)Wj\}^2]$ ½

Within any given set of alternate gear material, this distance of each alternate to every other is obviously a composite distance. In other words, it can be referred to as the mathematical expression of several distances on each selection parameter for which the gear material are evaluated and ranked. The lowest value of composite distance ranked first and so far.

Table 3. Ranking of gear material by DBA method with composite distance

MATERIAL ID	COMPOSITE DISTANCE	RANK
B1	5.296	9
B2	4.2257	5
B3	4.8168	7
B4	4.2735	6
B5	3.9376	4
B6	1.895	3
B7	0.2117	1
B8	1.7632	2
B9	4.6904	8

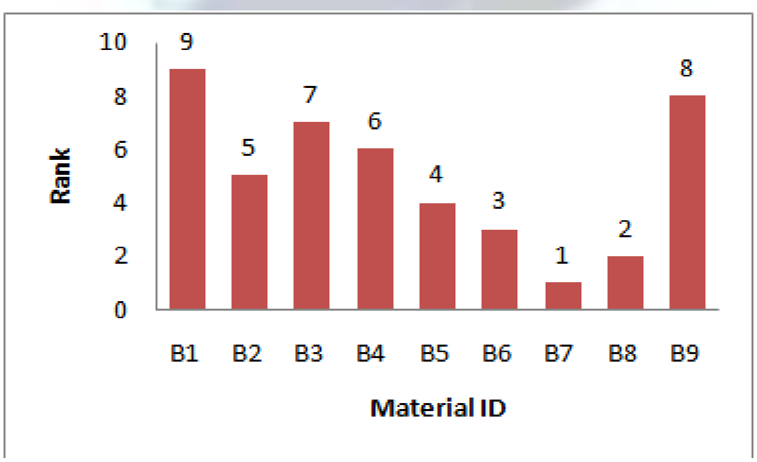

Fig 4 Results of gear material selection using DBA method

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Technique for Order Preference By Similarity To Ideal Solution (TOPSIS)

In this method two artificial alternatives are hypothesized. Ideal alternative is the one which has the best level for all attributes considered. Negative ideal alternative is the one which has the worst attribute values. TOPSIS selects the alternative that is the closest to the ideal solution and farthest from negative ideal alternative. The ranking order of table no. 2 given by A.S. Milani, A. Shanian, R. Madoliat & J.A. Nemes (2005) using a TOPSIS was

Table 4. Ranking of gear material by TOPSIS method

MATERIAL ID	C*	RANK
B_1	0.008	9
B_2	0.1821	8
B_3	0.2015	7
B_4	0.3014	5
B_5	0.3653	4
B_6	0.7063	3
B_7	0.9490	1
B_8	0.7824	2
B_9	0.2394	6

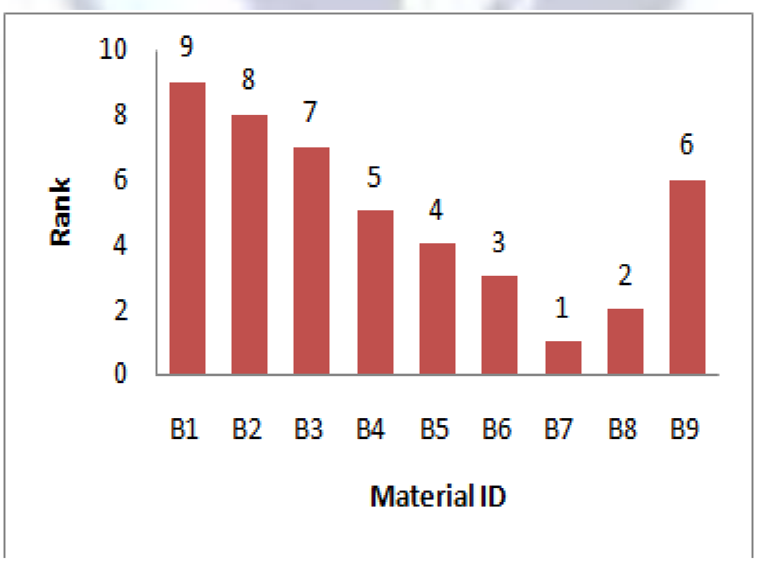

Fig 5 Results of gear material selection using TOPSIS method

Results Comparison of DBA & TOPSIS

The ranking order obtained using DBA method is:

B7 > B8 > B6 > B5 > B2 > B4 > B3 > B9 > B1

The ranking order given by A.S.Milani et al. (2005) using a TOPSIS method was:

B7 > B8 > B6 > B5 > B4 > B9 > B3 > B2 > B1

Table 5. Comparison of Ranking by DBA & TOPSIS method

MATERIAL ID	RANK BY DBA	RANK BY TOPSIS
B1	9	9
B2	5	8
B3	7	7
B4	6	5
B5	4	4
B6	3	3
B7	1	1
B8	2	2
B9	8	6

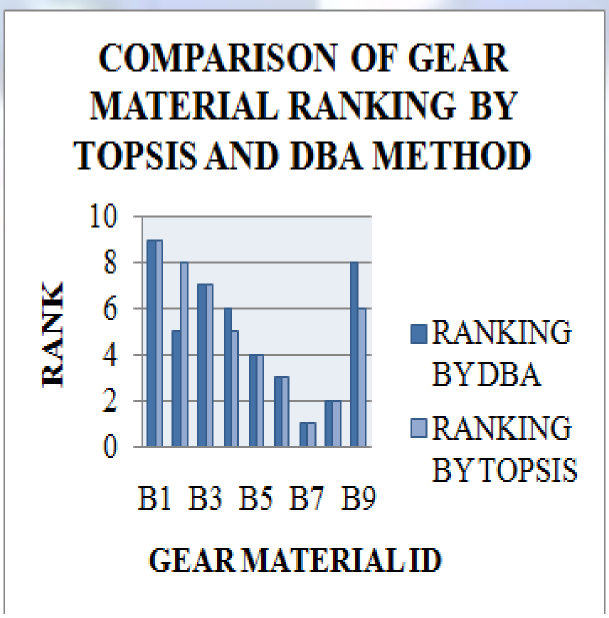

Fig 6. Comparison of gear material ranking by TOPSIS & DBA method

CONCLUSIONS

Selecting a best alternative is very important problem in manufacturing environment considering various multiple performance attributes. The proposed MADM method, the distance based approach (DBA) are help in selection of a suitable material from amongst a large number of alternative gear materials for manufacturing a given gear. Distance Based Approach method is based on matrix operations which can be easily computed using MATLAB. The Distance Based Approach methodology considers gear material and parameters, which gives the first rank accordingly to lowest magnitude value of composite distance and hence more preferred. The alternative with highest magnitude value of composite distance has last rank and hence least preferred. This methodology has no limits for number of parameters and number of alternatives and is capable of solving complex multi-attributes decision problems, incorporating both quantitative and qualitative parameters. The DBA method is validated by comparing the results of ranking with TOPSIS method, and is found consistent.

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