



**FEASIBILITY ANALYSIS OF DESIGN FOR REMANUFACTURING
IN BEARING USING HYBRID FUZZY-TOPSIS AND TAGUCHI
OPTIMIZATION**

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ABSTRACT

The tremendous advancement in technology, productivity and improved standard of living has come at the cost of environmental deterioration, increased energy and raw material consumption. In this regard, remanufacturing is viable option to reduce energy usage, carbon footprint and raw material usage. In this manuscript, using computational intelligence techniques we try to determine the feasibility of remanufacturing in case of roller bearings. We collected used N308 bearings from 5 different Indian cities. Using Fuzzy-TOPSIS, we found that the roundness, surface roughness and weight play a vital role in design for remanufacturing of roller bearings. Change in diameter, change in thickness and change in width showed minimal influence. We also used Taguchi analysis to reassess the problem. The roundness of inner and outer race was found to be the most influential parameters in deciding the selection of bearing for remanufacturing.



The results suggest the bearing designer to design the bearing in such a way that roundness of both races will be taken care while manufacturing a bearing. However, using Taguchi the weight of the rollers was found to be of least influence. Overall, the predictions of Taguchi analysis were found to be similar to Fuzzy-TOPSIS analysis.

Keywords: Taguchi analysis; Fuzzy-TOPSIS; remanufacturing

1. INTRODUCTION

In earlier day's manufacturers used to ignore the used products and these scraps would eventually pose a landfill problem. However, due to recent stringent environmental rules manufacturer has to consider the end of life strategies for recycling of product (DINDARIAN et al., 2012). Sustainable remanufacturing is a critical tool required to improve the efficiency of a product recovery.

To have the necessary efficient and flexible remanufacturing system, part information and actual condition of product become vital at end of life. For efficient remanufacturing, challenges are the collection of cores, flexibility in process and redistribution of products (LIU, et al., 2016). Selection of components in remanufacturing always have some constraints with a specific objective, again at the time of selection one cannot estimate the consequences of the process accurately (PUROHIT; RAMACHANDRAN, 2015).

Remanufacturing is a systematic process to bring the product back into function. It includes sorting and inspection of components followed by disassembling the components for reprocessing (FEGADE; SHRIVATSAVA; KALE, 2015). Parts disassembled can be replaced if it cannot be repaired or reprocessed to meet the required quality and functionality.

Remanufacturing is beneficial to the environment as it diverts the scrap components from a landfill. It also requires less energy and material as compared to new component manufacturing (KENNE; DEJAX; GHARBI, 2012). Among all end of product life recycling strategies, remanufacturing is perhaps the most potent one as component returned through remanufacturing has specification nearly same as a new one.

Additionally, it saves time, material and energy imparted over the product. Higher quality of product remanufacturing provides longer life extension and viable products. Remanufacturing is a comprehensive industrial process by which a previously sold, worn, or non-functional product or module is returned to a "like-new" or "better than new" condition and warranted in performance level and quality (AYDIN; KWONG; JI, 2015).

Remanufacturing, though still an evolving industry, holds many ecological and economic benefits. Remanufacturing is the complete or partial reconstruction or overhaul of a product to the original stipulation of reusable and repairable parts and replacing some completely worn out parts by new ones (BENKHEROUF; SKOURI; KONSTANTARAS, 2016).

Product recovery is to retrieve a product when the product no longer fulfills desired needs. Product recovery involves recycling, reuse and remanufacturing (HILGER; SAHLING; TEMPELMEIER, 2016). Integration of remanufacturing in closed loop supply chain as a significant end of life product recovery system could potentially generate benefits to both the business and the environment. For any company which manufactures and sell both new and remanufactured products, optimizing the product design is very difficult.

The design decisions taken at early stages have more influence on profits in manufacturing and remanufacturing (RAMACHANDRAN; AGARWAL, 2017). Remanufacturing has environmental benefits as well as significant potential to influence product economy in reverse logistic. Remanufacturing begins with identification and inspection of cores (scrap products) further disassembly, reconditioning, assembly and testing (ZHANG et al., 2011).

Inspections of cores are the critical activity which leads to the effectiveness of the remanufacturing. Remanufacturing is a generic term for technical renovation or engineering activities of waste products. In remanufacturing, a large number of inspections and evaluations of the failure conditions of the parts have to be done, which are uneconomical and inefficient (SUGUMARAN; RAMACHANDRAN, 2007).

After the inspection and selection of the parts, disassembly is the process which gives large impact in any remanufacturing system (FORD; DESPEISSE, 2016). It depends upon the volume of the returned product as volume increases this process becomes more significant because the efficiency of remanufacturing depends upon the effectiveness of the disassembly process (KWAK; KIM, 2015; SUBRAMANIAN; FERGUSON; TOKTAY, 2013).

Selection of the components for remanufacturing is largely affected by the disassembly process. Parameters which influence disassembly of the component are also useful criteria for the selection of the components for remanufacturing (HATCHER; IJOMAH; WINDMILL, 2011).



In this paper, focus is on the selection and optimization of suitable components for remanufacturing. Optimization may be defined as the minimization of unnecessary traits and maximization of necessary ones, to find the most effective and highest attainable performance (SAHARE et al., 2018). In this study, different parameters were considered which affects the viability in remanufacturing as well as impacts the recovery of a product during remanufacturing.

Powerful and robust computational intelligence techniques like Fuzzy-TOPSIS and Taguchi were used in this research for selection of bearings for remanufacturing. Fuzzy-TOPSIS is a perfect blend of multi-criteria decision methods and fuzzy set theory which handles uncertain and incomplete information (MANICKAM, 2016).

Taguchi method is used to decrease the sensitivity of engineering designs towards ungovernable noise or factors (PANDEY; DUBEY, 2012). Taguchi method uses S/N ratio which shows experimental data quality characteristics for better optimization results.

2. HYBRID FUZZY-TOPSIS & TAGUCHI OPTIMIZATION

Fuzzy refers to the situation whose set of activity boundaries are not well defined. TOPSIS is a widely adopted MCDM technique to solve multiple-criteria decision-making problems in various fields (HAMDAN; SARHAN; HAMDI, 2012). Fuzzy-TOPSIS is domain independent and thus may be applied virtually to any problem. Several research groups like Shiraz, Mirac, Sengul and coworkers (SENGUL et al., 2015; SHIRAZ et al., 2014; BAKIRCI et al. 2014; SENGUL et al., 2016; EREN, 2018; SHIVAKOTI et al., 2017; DIYALEY et al., 2017; DAS et al., 2017; RAGAVENDRAN et al., 2018; AIKHUELE et al., 2017; AIKHUELE et al., 2017; AZIZI et al., 2015) has regularly used Fuzzy-TOPSIS or its variants in a wide range of problems.

Taguchi Analysis is implemented in four steps which are – (i) Design of Experiments (DOE) (ii) selection of model (iii) analysis of responses (iv) desirability function analysis. The traditional experimental design results in a very large number of experiments. DOE endeavors to plan systematic conduction of experiments to acquire data in an intelligent and controlled manner with minimum efforts.

The process can be divided broadly into three parts as System; Input Factors and Responses. The system can be considered as the heart of the process (KIVAK; SAMTACS; CICEK, 2012). Input factors are variable signals which serve as starting mechanisms of the

process. With the help of Fuzzy-TOPSIS, input factors such as various diameters of outer race, inner race and roller diameter combinations were finalized and utilized in Taguchi analysis.

The response is nothing but the performance output of the system. In this case, responses were outer race surface roughness, inner race surface roughness, roller surface roughness, and outer race roundness, inner race roundness, roller roundness, outer race weight, inner race weight and roller weight.

Data obtained from DOE provides the information necessary to establish the relationship between the specified input factors and the responses of the given process. The possible values of input factors are termed as levels. The selection of the input factors, their levels and responses are the most important and critical stage in the analysis. In DOE when all possible combinations of given input factor levels are considered, it is termed as a full factorial design (FFD) (GUNAY; YUCEL, 2013).

However, in this study only existing product combinations of bearings were considered for analysis. An empirical model is selected to establish the relationship that exists between the design input factors and the response. A regression model is selected here and it also referred to as the main effect model. The main effect model needs a smaller number of experiments than its extension. Each experiment corresponds to a set of responses.

The response values acquired from comparatively few experiments enables response prediction for FFD. As this is a multi-response optimization problem, a popular simultaneous optimization approach is employed. The optimal solutions were arranged in the descending order of their combined desirability value. This feature of Taguchi analysis can be used to acquire multiple optimal solutions. In this paper Design-Expert version 11 software was used for implementation of Taguchi Analysis.

3. ROLLER BEARINGS SELECTION

The development of roller bearings and its components has been a research objective for more than five decades (WEINZAPFEL; SADEGHI, 2009). Roller bearings technically comprise of four components namely outer ring, inner ring, roller elements and cage (LU et al., 2013). We selected N308 bearing manufactured by Austin Engineering Company, Gujarat, India for our analysis. We collected two used bearings each from different cities having different climatic conditions namely Mumbai, Delhi, Guwahati, Jaipur and Shimla for understanding the behavior of bearings with climatic conditions. The specifications of N308

bearings are bore diameter (d) 40 mm, outer diameter (D) 90 mm, width (B) 23 mm and weight (g) 662 grams. Fig. 1 shows the different parts of the N308 Bearings.



Figura 1: N308 Bearing Parts

Using Fuzzy-TOPSIS, we observed that the roundness, surface roughness and weight play a vital role for design for remanufacturing of roller bearings. Change in diameter, change in thickness and change in width were the least preference (SELVARAJ; MARAPPAN, 2011; SERVAIS; DUQUENNE; BOZET, 2013).

We carried out roundness test in Carl Zeiss Rondcom 41C. Surface roughness was checked in Carl Zeiss Surfcom S130. The weight was measured using mLabs_SF400C, ASIN: B07B1XKKGW capacity 600g/10mg readability 0.01g/ minimum weight 0.05g, weight balance. We measured inside diameter of outer race and outside diameter of inner race and the roller diameter was taken as a mean of all the rollers diameters in the bearings. We used the three-point technique to measure the diameters with a coordinate measuring machine (GmbH Carl Zeiss Contour G2, Capacity: Size 700 X 700 X 600 mm).

4. TESTING PARAMETERS SELECTION

We used Fuzzy-TOPSIS analysis for testing parameter selection. Linguistic variables R1, R2, R3, R4, R5, R6 were assigned to various impacts of testing, like remanufacture ability, quality, level of integration, cost saving, End of life condition and durability. Similarly, P1, P2, P3, P4, P5, and P6 were assigned for the testing parameters. The linguistic variables and testing parameters are reported in Table 1.

Table 1: Linguistic variables and testing parameters

Requirements	Description	Parameters	Description
R1	Remanufacture ability	P1	Surface Roughness
R2	quality	P2	change in Diameter
R3	Level of Integration	P3	change in Thickness
R4	Cost saving	P4	Change in Width
R5	EOL condition	P5	Weight

R6	Durability	P6	Roundness
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Table 2: Fuzzy number allotment for Requirements and Testing’s parameters

Requirements for Design of Remanufacturing			Testing’s parameters		
	Notation	Fuzzy No		Notation	Fuzzy No
Not important	A	(0,0, 0.1)	Very poor	P	(0,0,0.1)
Less important	B	(0,0.1,0.3)	Medium poor	Q	(0,0.1,0.3)
Medium Less important	C	(0.1,0.3,0.5)	Poor	R	(0.1,0.3,0.5)
Medium important	D	(0.3,0.5,0.7)	Fair	S	(0.3,0.5,0.7)
Medium high important	E	(0.5,0.7,0.9)	Good	T	(0.5,0.7,0.9)
High important	F	(0.7,0.9,1)	Very Good	U	(0.7,0.9,1)
Very high important	G	(0.9,1,1)	Excellent	V	(0.9,1,1)

The results are classified as very poor, medium poor, poor, fair, good, very good and excellent (Table 2). The notation and the fuzzy number of each of the six grades for both requirements for the design of remanufacturing and testing's parameters were made with respect to triangular membership function.

Table 3 highlights the opinions given by three decision makers (DM1, DM2, DM3) on requirements for the design of remanufacturing. We took DM as design engineers from bearing manufacturing industries. The same decision maker's opinion regarding the requirements for the design of remanufacturing with respect to testing’s parameters was taken in order to enhance the design for remanufacturing (Table 4). Based on the aggregate fuzzy numbers obtained, fuzzy numbers are assigned to the linguistic variables suggested by the decision maker. The values of normalized fuzzy decision matrix are weighted by multiplying them with the relevant aggregated fuzzy number (Table 5).

Table 3: Design makers opinion

Requirements for design of remanufacturing	DM1	DM2	DM3	Aggregate Fuzzy No.
R1	G	F	G	(0.84,0.97,1)
R2	E	G	F	(0.7,0.87,0.97)
R3	E	F	C	(0.44,0.64,0.8)
R4	F	D	E	(0.5,0.7,0.87)
R5	C	E	F	(0.44,0.64,0.8)
R6	G	F	F	(0.76,0.93,1)

Table 4: Decision maker’s opinion about requirements for design of remanufacturing with respect to testing’s parameters

	R1	R2	R3	R4	R5	R6
P1	T	T	T	P	R	S
P2	V	S	U	R	U	S
P3	U	T	U	Q	S	S
P4	V	S	U	T	Q	R
P5	T	U	U	R	T	T
P6	V	V	V	V	U	U

Table 5: Weighed normalized fuzzy decision matrix

	R1	R2	R3	R4	R5	R6
P1	(0.58,0.87,1)	(0.35,0.60,0.60)	(0.22,0.44,0.72)	(0.45,0.7,0.87)	(0.04,0.19,0.4)	(0.22,0.46,0.7)
P2	(0.75,0.97,1)	(0.21,0.43,0.67)	(0.30,0.57,0.8)	(0.05,0.21,0.43)	(0.30,0.57,0.8)	(0.22,0.46,0.7)
P3	(0.58,0.87,1)	(0.35,0.60,0.60)	(0.30,0.57,0.8)	(0,0.07,0.26)	(0.13,0.32,0.56)	(0.22,0.46,0.7)
P4	(0.75,0.97,1)	(0.21,0.43,0.67)	(0.30,0.57,0.8)	(0.25,0.49,0.78)	(0,0.06,0.24)	(0.07,0.27,0.5)
P5	(0.42,0.67,0.9)	(0.49,0.78,0.97)	(0.30,0.57,0.8)	(0.05,0.21,0.43)	(0.22,0.44,0.72)	(0.38,0.65,0.9)
P6	(0.75,0.87,1)	(0.63,0.87,0.97)	(0.39,0.64,0.8)	(0.45,0.7,0.87)	(0.30,0.57,0.8)	(0.53,0.83,1)

Next, the ranking of the testing parameters was obtained using the relations below.

D* represents the Fuzzy Positive Ideal Solutions (FPIS D*).

$$D^* = \sum \frac{1}{2} [\max (|1st - 1|; |3rd - 1|) + (2nd - 1)]$$

Here, the values |1st - 1| and |3rd - 1| from weighed normalized decision matrix are compared. The greater of the 2 values is added to (2nd - 1).

D# represents the Fuzzy Negative Ideal Solutions (FNIS D#).

$$D^\# = \sum \frac{1}{2} [\max (|1st - b; - 0|, |3rd - 0|) + |2nd - 0|]$$

Here, the values |1st-0| and |3rd-0| from weighed normalized decision matrix are compared. The greater of the 2 values is added to (2nd-0).

$$\text{Relative closeness coefficient of strategies}(C^*) = D^\# / (D^* + D^\#)$$

Table 6: Ranking of Testing's Parameters

Piston	D*	D#	C* = D-/(D*+D#)	RANK
P1	3.44	3.695	0.518	2
P2	3.48	3.805	0.522	4
P3	3.765	3.405	0.474	5
P4	3.815	3.39	0.470	6
P5	3.41	4.02	0.541	3
P6	2.235	4.76	0.680	1

From the Fuzzy-TOPSIS analysis, we found that roundness ranks first followed by surface roughness, weight, change in diameter, change in thickness, and change in width. The rankings and relative closeness coefficient are reported in Table 6.

5. TAGUCHI OPTIMIZATION ANALYSIS

The surface roughness of outer race measured from inside face and inner race measured from outside face. Values obtained from the testing are reported in Table 7. For this experiment, we used the following notations— outer race diameter (F1); inner race diameter (F2); roller diameter (F3); outer race surface roughness (R1); inner race surface roughness (R2); roller surface roughness (R3); outer race roundness (R4); inner race roundness (R5); roller roundness

(R6); outer race weight (R7); inner race weight (R8) and roller weight (R9). The data of 11 bearings were considered for analyses. The signal to noise ratio is calculated using the difference between the minimum and maximum response value and the standard deviation. Signal-to-Noise ratio was set as per data in Table 8. An optimized design is made by determining the parameters and their values. The data was feed in the software where the parameters were specified with their respective values as shown in Table 9.

Table 7: Testing results for selected bearings

Bearing no	F 1	F 2	F 3	R 1	R 2	R3	R4	R5	R 6	R 7	R 8	R 9
1	77.5247	53.5025	12.0071	0.131	0.079	0.106	3.5	6	0.001	283.203	207.141	11.2844
2	77.5398	53.4566	12.0007	0.341	0.234	0.213	13	12.4	0.003	275.365	208.407	10.3439
3	77.5083	53.5937	11.9957	0.267	0.658	1.156	4.7	9	0.0026	276.641	206.576	10.4011
4	77.5183	53.4100	12.0134	0.293	0.155	0.332	8	251	0.0017	279.293	204.695	10.4361
5	77.5458	53.4308	11.9583	1.381	0.675	1.45	120	30	0.0068	270.579	199.621	10.2388
6	77.5039	53.5413	11.9655	0.837	0.814	1.422	13	63	0.0024	276.919	201.181	10.415
7	77.5438	53.4570	11.8234	0.238	0.224	0.589	41	18	0.0068	282.843	199.934	9.8912
8	77.5596	53.4617	12.0431	0.809	0.255	0.129	15	17	0.0021	276.158	207.732	10.4629
9	77.5192	53.5189	12.0145	0.145	0.25	0.38	15.9	9	0.002	273.587	203.041	10.3922
10	77.5086	53.3786	12.0041	0.554	0.307	0.711	17	18	0.0036	273.912	206.006	10.1073
11	77.4961	53.4869	12.0081	1.409	0.509	0.347	68	9	0.0027	277.053	209.666	10.3417

Table 8: S/N ratio for all responses

Response	Minimum	Maximum	Mean	Std. Dev.	S/N Ratio
R1	0.131	1.409	0.5823	0.4683	10.76
R2	0.079	0.814	0.3782	0.2437	10.30
R3	0.106	1.45	0.6214	0.5015	13.68
R4	3.5	120	29.01	35.57	34.29
R5	6	251	40.22	71.73	41.83
R6	0.001	0.0068	0.0032	0.0019	6.80
R7	270.579	283.203	276.87	3.79	1.05
R8	199.621	209.666	204.91	3.49	1.05
R9	9.8912	11.2844	10.39	0.3412	1.14

Table 9: Constraints used for optimization analysis

Name	Goal	Lower Limit	Upper Limit
R1	minimize	0.361939	1.18701
R2	minimize	0.281069	0.902219
R3	minimize	0.325576	1.20416
R4	minimize	1.87083	10.9545
R5	minimize	2.44949	15.843
R6	minimize	0.001	0.0068
R7	maximize	270.579	283.203
R8	maximize	199.621	209.666
R9	maximize	9.8912	11.2844

Table 10: Ranking of bearings

Bearing No	R1	R2	R3	R4	R5	R6	R7	R8	R9	Desirability
1(new)	0.131	0.079	0.106	3.500	6.	0.001	283.203	207.141	11.284	0.968
2	0.341	0.234	0.213	13.000	12.4	0.003	275.365	208.407	10.344	0.654
8	0.809	0.255	0.129	15.000	17.	0.002	276.158	207.732	10.463	0.637
9	0.145	0.250	0.380	15.900	9.	0.002	273.587	203.041	10.392	0.581
3	0.267	0.658	1.156	4.700	9.	0.003	276.641	206.576	10.401	0.483
10	0.554	0.307	0.711	17.000	18.	0.004	273.912	206.006	10.107	0.472
6	0.837	0.814	1.422	13.000	63.	0.002	276.919	201.181	10.415	0.006

Table 10 shows the best seven bearings which were selected for remanufacturing by Taguchi analysis having a positive desirability ratio ranging from 0.006 to 0.968. Bearing no. 1 is a new bearing taken for reference purposes. This shows Taguchi analysis provided the significant results in the selection of bearings for remanufacturing and correspondingly all the bearing were graded as per the degradation of the bearing and four bearings we rejected due to excessive degradation over the lifetime. However, 60% of the old bearings were selected for remanufacturing by the analysis directly without doing any modification.

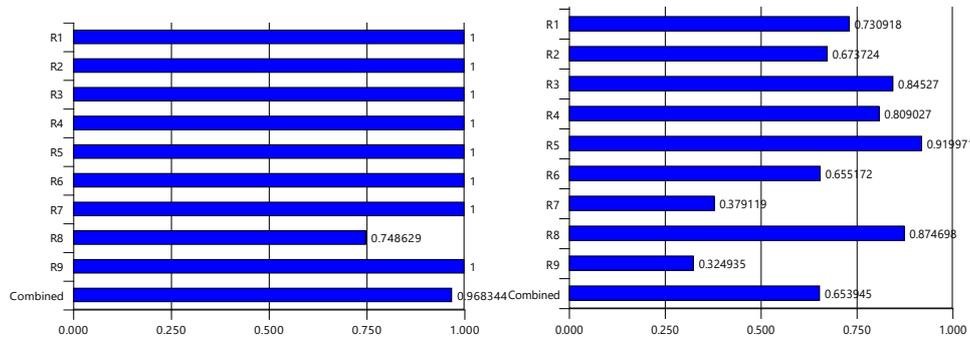


Figure 2: (a) Desirability curve for bearing no. 1(new) (b) Desirability curve for bearing no. 2

Figure 2(a) shows the new bearing desirability curve and for that, we achieved a combined desirability value of 0.968. This shows even the new bearing having a slight variation from the optimized values. The desirability of all the testing parameters was achieved 100% except for the inner race weight which has a desirability of 0.74. This decrease in desirability is due to the manufacturing tolerance range set by the original equipment manufacturer which is acceptable.

Figure 2(b) shows the desirability curve for old used bearing no. 2. A combined desirability value of 0.635 was obtained for this case. The highest desirability value was for the inner race roundness and the lowest was inner race weight. The result shows that the inner race parameters are having both the lowest and highest desirability value but both are in the acceptable range.

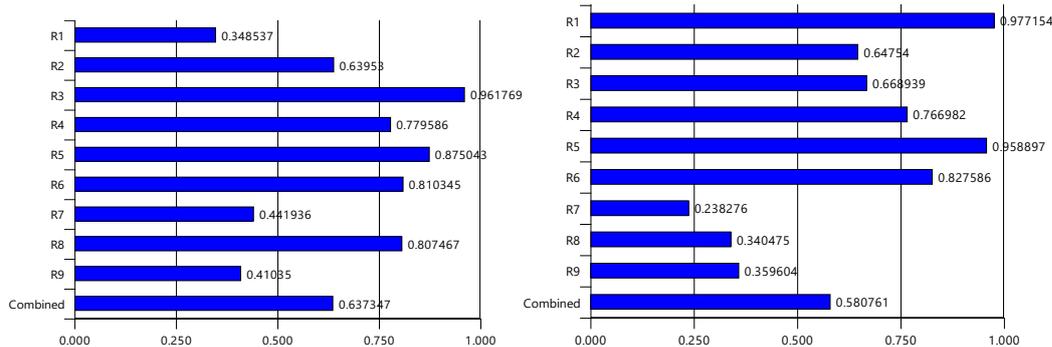


Figure 3: (a) Desirability curve for bearing no. 8, (b) Desirability curve for bearing no. 9

Figure 3(a) shows the desirability curve for old used bearing no. 8 and for that, a combined desirability value of 0.637 was achieved. The highest desirability value was for the roller surface roughness and the lowest was inner race weight. The result shows that the inner race parameters are having lowest desirability value and second highest desirability value but both are in the acceptable range.

Figure 3(b) shows the desirability curve for old used bearing no. 9 having a combined desirability value of 0.580. The highest desirability value was for the outer race roundness and the lowest was outer race weight. The result shows that the outer race parameters are having both the lowest and highest desirability value but both are in the acceptable range.

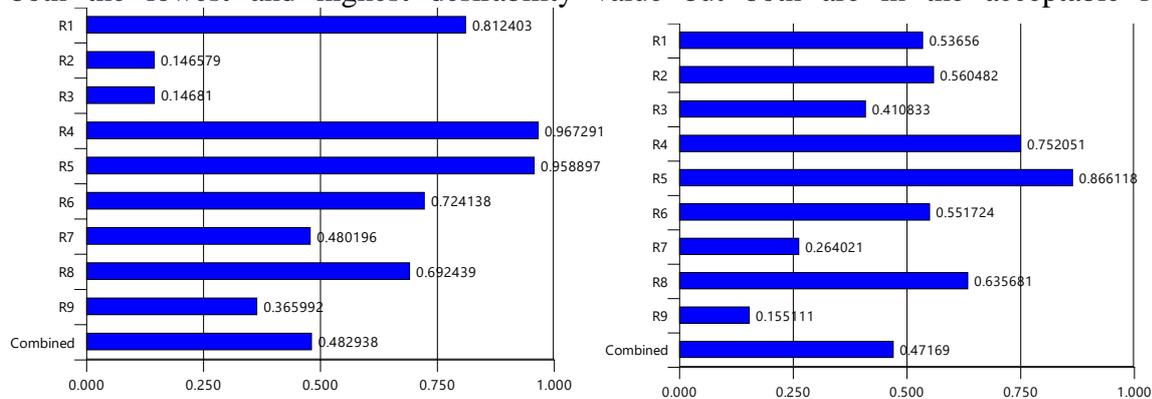


Figure 4: (a) Desirability curve for bearing no. 3 (b) Desirability curve for bearing no. 10

Figure 4(a) shows the desirability curve for old used bearing no. 3 with a combined desirability value of 0.483. The highest desirability value was for the outer race roundness and the lowest was inner race surface roughness. The desirability curve for bearing no. 10 was reported in Figure 4(b) and has a combined desirability value of 0.471. The highest desirability value was for the inner race roundness and the lowest was roller weight.

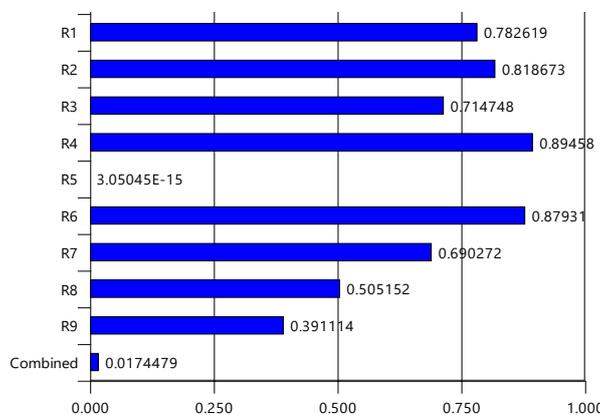


Figure 5: Desirability curve for bearing no. 6

Figure 5 shows the desirability curve for old used bearing no. 6 and for that, we achieved a combined desirability value of 0.0174. The highest desirability value was for the outer race roundness and the lowest was inner race roundness. From the overall desirability values, it has

been observed that both inner race and outer race roundness have not changed from the original dimensions. However the roller weight was getting reduced in most of the old bearings. This phenomenon is due to wear. This study reveals that the failure of the roller is usually because of the outer race roundness.

6. CONCLUSION

Using advanced computational intelligence techniques like Fuzzy-TOPSIS and Taguchi analysis, we tried to understand the feasibility of roller bearing for design for remanufacturing. In our study, we achieved a combined desirability of 0.968 giving maximum importance to all the testing parameters and compromising slightly in inner race weight with the individual desirability of 0.748 on a scale of 1.

Overall in bearings which were selected by Taguchi analysis, the roundness of inner race and outer race were found to be the most influential parameters in deciding the selection of bearing for remanufacturing. The results suggest the bearing designers to design the bearing in such a way that the roundness of both races will be taken care off while manufacturing a bearing. The weight of the rollers was found to be the least influential parameter in deciding the selection of bearing for remanufacturing.

The result obtained from Taguchi analysis was seen to be similar to Fuzzy-TOPSIS analysis which infuses further confidence in the findings. As expected in the analysis, the bearing ranking one was the new one, this shows that roller bearing selection using Taguchi desirability analysis is a significant one. The study successfully highlighted the potential of remanufacturing of bearing strategy in Indian region since more than 50% of the bearings used in the analysis were selected for remanufacturing.

REFERENCES

- AIKHUELE, D. O.; FAIZ, M. T.; ODOFIN, S. M.; ANSAH, R. H. (2017) Interval-Valued Intuitionistic Fuzzy Topsis-Based Model For Troubleshooting Marine Diesel Engine Auxiliary System. **International Journal Maritime Engineering**, v. 159, p. 107-114. DOI: <http://umpir.ump.edu.my/id/eprint/16772>
- AIKHUELE, D. O.; SOROOSHIAN, S.; ANSAH, R. H.; TURAN, F. M. (2017) Application of Intuitionistic Fuzzy Topsis Model for Troubleshooting an Offshore Patrol Boat Engine. **Polish Maritime Research**, n. 24, p. 68-76. DOI: <https://doi.org/10.1515/pomr-2017-0051>
- AYDIN, R.; KWONG, C. K.; JI, P. (2015) A novel methodology for simultaneous consideration of remanufactured and new products in product line design. **International journal of production economics**, n. 169, p. 127-140. DOI: <https://doi.org/10.1016/j.ijpe.2015.07.022>
- AZIZI, A.; AIKHUELE, D. O.; SOULEMAN, F. S. (2015) A Fuzzy TOPSIS Model to Rank

Automotive Suppliers. **Procedia Manufacturing**, n. 2, p. 159-164. DOI:
<https://doi.org/10.1016/j.promfg.2015.07.028>

BAKIRCI, F.; SHIRAZ, S. E.; SATTARY, A. (2014) BIST'da Demir, Celik Metal Ana Sanayii Sektorunde Faaliyet Gosteren Isletmelerin Finansal Performans Analizi: VZA Super Etkinlik ve TOPSIS Uygulamasi/Financial Performance Analysis of Iron, Steel Metal Industry Sector Companies in The Borsa Istanbul: DEA Super Efficiency and TOPSIS Methods. **Ege Akademik Bakis**, 14, 9.

BENKHEROUF, L.; SKOURI, K.; KONSTANTARAS, I. (2016) Optimal control of production, remanufacturing and refurbishing activities in a finite planning horizon inventory system. **Journal of Optimization Theory and Applications**, n. 168, p. 677-698. DOI:
<https://doi.org/10.1007/s10957-015-0741-9>

DAS, P. P.; GUPTA, P.; GHADAI, R. K.; RAMACHANDRAN, M.; KALITA, K. (2017) Optimization of turning process parameters by Taguchi-based Six Sigma. **Mechanics and Mechanical Engineering**, n. 21, p. 649-656.

DINDARIAN, A.; GIBSON, A. A.; QUARIGUASI-FROTA-NETO, J. (2012) Electronic product returns and potential reuse opportunities: a microwave case study in the United Kingdom. **Journal of Cleaner Production**, n. 32, p. 22-31. DOI:
<https://doi.org/10.1016/j.jclepro.2012.03.015>

DIYALEY, S.; SHILAL, P.; SHIVAKOTI, I.; GHADAI, R. K.; KALITA, K. (2017) PSI and TOPSIS Based Selection of Process Parameters in WEDM. *Periodica Polytechnica Mechanical Engineering*, n. 61, p. 255-260. DOI: <https://doi.org/10.3311/PPme.10431>

EREN, M. (2018) forecasting of the fuzzy univariate time series by the optimal lagged regression structure determined based on the genetic algorithm. **Economic Computation & Economic Cybernetics Studies & Research**, v. 52, n. 2

FEGADE, V.; SHRIVATSAVA, R. L.; KALE, A. V. (2015) Design for Remanufacturing: Methods and their Approaches. **Materials Today: Proceedings**, n. 2, p. 1849-1858. DOI:
<https://doi.org/10.1016/j.matpr.2015.07.130>

FORD, S.; DESPEISSE, M. (2016) Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. **Journal of Cleaner Production**, n. 137, p. 1573-1587. DOI: <https://doi.org/10.1016/j.jclepro.2016.04.150>

GUNAY, M.; YUCEL, E. (2013) Application of Taguchi method for determining optimum surface roughness in turning of high-alloy white cast iron. **Measurement**, n. 46, p. 913-919. DOI: <https://doi.org/10.1016/j.measurement.2012.10.013>

HAMDAN, A.; SARHAN, A. A.; HAMDI, M. (2012) An optimization method of the machining parameters in high-speed machining of stainless steel using coated carbide tool for best surface finish. **The International Journal of Advanced Manufacturing Technology**, n. 58, p. 81-91. DOI: <https://doi.org/10.1007/s00170-011-3392-5>

HATCHER, G. D.; IJOMAH, W. L.; WINDMILL, J. F. (2011) Design for remanufacture: a literature review and future research needs. **Journal of Cleaner Production**, n. 19, p. 2004-2014. DOI: <https://doi.org/10.1016/j.jclepro.2011.06.019>

HILGER, T.; SAHLING, F.; TEMPELMEIER, H. (2016) Capacitated dynamic production and remanufacturing planning under demand and return uncertainty. **OR spectrum**, n. 38, p. 849-876. DOI: <https://doi.org/10.1007/s00291-016-0441-3>

KENNE, J.-P.; DEJAX, P.; GHARBI, A. (2012) Production planning of a hybrid

manufacturing--remanufacturing system under uncertainty within a closed-loop supply chain. **International Journal of Production Economics**, n. 135, p. 81-93. DOI: <https://doi.org/10.1016/j.ijpe.2010.10.026>

KIVAK, T.; SAMTACS, G.; CICEK, A. (2012) Taguchi method based optimisation of drilling parameters in drilling of AISI 316 steel with PVD monolayer and multilayer coated HSS drills. **Measurement**, n. 45, p. 1547-1557. DOI: <https://doi.org/10.1016/j.measurement.2012.02.022>

KWAK, M.; KIM, H. (2015) Design for life-cycle profit with simultaneous consideration of initial manufacturing and end-of-life remanufacturing. **Engineering Optimization**, n. 47, p. 18-35. DOI: <https://doi.org/10.1080/0305215X.2013.868450>

LIU, M.; LIU, C.; XING, L.; LIU, Z.; LI, X.; LIN, L. (2016) Assembly process control method for remanufactured parts with variable quality grades. **The International Journal of Advanced Manufacturing Technology**, n. 85, p. 1471-1481. DOI: <https://doi.org/10.1007/s00170-015-8026-x>

LU, D.; ZHAO, W.; LU, B.; ZHANG, J. (2013) Cage speed of hydrodynamic rolling hybrid bearings. **Tribology Letters**, n. 51, p. 303-309. DOI: <https://doi.org/10.1007/s11249-013-0154-6>

MANICKAM, R. (2016) Back propagation neural network for prediction of some shell moulding parameters. **Periodica Polytechnica Mechanical Engineering**, n. 60, p. 203-208. DOI: <https://doi.org/10.3311/PPme.8684>

PANDEY, A. K.; DUBEY, A. K. (2012) Taguchi based fuzzy logic optimization of multiple quality characteristics in laser cutting of Duralumin sheet. **Optics and Lasers in Engineering**, n. 50, p. 328-335. DOI: <https://doi.org/10.1016/j.optlaseng.2011.11.005>

PUROHIT, P.; RAMACHANDRAN, M. (2015) Selection of Flywheel Material using Multicriteria Decision Making Fuzzy Topsis. **Indian Journal of Science and Technology**, 8.33. DOI: <https://doi.org/10.17485/ijst/2015/v8i33/80028>

RAGAVENDRAN, U.; GHADAI, R. K.; BHOI, A.; RAMACHANDRAN, M.; KALITA, K. A. (2018) Sensitivity Analysis and Optimization of EDM Process Parameters. **Transactions of the Canadian Society for Mechanical Engineering**. DOI: <https://doi.org/10.1139/tcsme-2018-0021>

RAMACHANDRAN, M.; AGARWAL, N. (2017) Identification of Most Affected Parameter for Design for Remanufacturing of Scrap Piston by Taguchi Desirability Function Analysis. **International Conference on Man--Machine Interactions**, p. 320-329. DOI: https://doi.org/10.1007/978-3-319-67792-7_32

SAHARE, S. B.; UNTAWALE, S. P.; CHAUDHARI, S. S.; SHRIVASTAVA, R. L.; KAMBLE, P. D. (2018) Optimization of End Milling Process for Al2024-T4 Aluminum by Combined Taguchi and Artificial Neural Network Process. **In Soft Computing: Theories and Applications**, p. 525-535. Springer. DOI: https://doi.org/10.1007/978-981-10-5699-4_49

SELVARAJ, A.; MARAPPAN, R. (2011) Experimental analysis of factors influencing the cage slip in cylindrical roller bearing. **The International Journal of Advanced Manufacturing Technology**, n. 53, p. 635-644. DOI: <https://doi.org/10.1007/s00170-010-2854-5>

SENGUL, U.; EREN, M. (2016) Selection of digital marketing tools using fuzzy AHP-fuzzy TOPSIS. **In Fuzzy Optimization and Multi-Criteria Decision Making in Digital**

Marketing, p. 97-126. DOI: <https://doi.org/10.4018/978-1-4666-8808-7.ch005>

SENGUL, U.; EREN, M.; SHIRAZ, S. E.; GEZDER, V.; SENGUL, A. B. (2015) Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. **Renewable Energy**, n. 75, p. 617-625. DOI: <https://doi.org/10.1016/j.renene.2014.10.045>

SERVAIS, C.; DUQUENNE, M.; BOZET, J.-L. (2013) Influence of tribology of cage material on ball bearing cage instability. **15th European Space Mechanism and Tribology Symposium (ESMATS)**, p. 71-78.

SHIRAZ, S. E.; SENGUL, U.; EREN, M. (2014) Determination of extended fuzzy TOPSIS method of criteria leading to supplier selection for industries. **Asian Social Science**, n. 10, p. 183. DOI: <https://doi.org/10.1007/s13369-017-2673-1>

SHIVAKOTI, I.; PRADHAN, B. B.; DIYALEY, S.; GHADAI, R. K.; KALITA, K. (2017) Fuzzy TOPSIS-Based Selection of Laser Beam Micro-marking Process Parameters. **Arabian Journal for Science and Engineering**, n. 42, p. 4825-4831. DOI: <https://doi.org/10.1007/s13369-017-2673-1>

SUBRAMANIAN, R.; FERGUSON, M. E.; BERIL TOKTAY, L. (2013) Remanufacturing and the component commonality decision. **Production and Operations Management**, n. 22, p. 36-53. DOI: <https://doi.org/10.1111/j.1937-5956.2012.01350.x>

SUGUMARAN, V.; RAMACHANDRAN, K. I. (2007) Automatic rule learning using decision tree for fuzzy classifier in fault diagnosis of roller bearing. **Mechanical Systems and Signal Processing**, n. 21, p. 2237-2247. DOI: <https://doi.org/10.1016/j.ymssp.2006.09.007>

WEINZAPFEL, N.; SADEGHI, F. (2009) A discrete element approach for modeling cage flexibility in ball bearing dynamics simulations. **Journal of Tribology**, n. 131, p. 021-102. DOI: <https://doi.org/10.1115/1.3063817>

ZHANG, T.; CHU, J.; WANG, X.; LIU, X.; CUI, P. (2011) Development pattern and enhancing system of automotive components remanufacturing industry in China. **Resources, Conservation and Recycling**, n. 55, p. 613-622. DOI: <https://doi.org/10.1016/j.resconrec.2010.09.015>