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Optimization of Surface Roughness and Machining Time of Manufacturing for Ankle Foot Orthosis (AFO) with Subtractive Manufacturing using the Taguchi Method and Fuzzy Logic

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Abstract: This research is applied to optimize the manufacturing process of insoles made from EVA foam. This manufacturing process usually produces a molded system insole with the end result typically impersonal and according to the needs of normal users. However, this system is not suitable if applied to people who suffer from foot deformities. An engineering approach is needed to achieve optimization in the process of manufacturing an insole with a subtractive manufacturing technology. This technology requires a lot of data and precision. Of the data required to process the appropriate methods, one that was applied was fuzzy logic to determine the cutting parameters corresponding to the measured responses. A patient with Diabetes Mellitus (DM) had a complaint on the use of footwear. The Taguchi methodology approach was applied to find the lay out parameter (L_{27}). The results of the application of the optimum machining parameter indicate the conditions of the fuzzy level at 0.44 and 0.6 on the left and right legs, respectively of the patient. The optimum combination of this experiment found: raster tool path strategy with 45°, spindle speed at 14,000-14,500 rpm, feed rate at 800-850 mm/min, step over at 0.30 mm, the type of material was EVA rubber foam as AFO, application of setting these parameters yields optimum surface roughness for the second leg of 7.9059 and 7.0082 μm. The optimal machining times were 210.033 and 214.3167 min. The Taguchi methodology and approach to fuzzy logic were very effective to improve the performance and quality of the product that generated the insole.

Key words: EVA rubber foam, custom orthosis, grey fuzzy logic, surface roughness, parameters, diabetes mellitus

INTRODUCTION

The application of optimization techniques that vary in different manufacturing processes is a necessary thing for a process of manufacturing products of the highest quality (surface smoothness, lower processing time and lower production cost). The Taguchi response surface methods experimental design is one of the best methods to control the product quality from the design phase to the production floor in the manufacturing stage. In the industry of manufacturing engineering, e.g., automotive, household appliances, ceramics, footwear and other manufacturing optimizations, the process with machine tools is the most important process and requires a lot of familiarity with the parameter conditions for optimal machining. In modern industry, the manufacturing system is self-employed with CNC machines that have the capability to achieve high-accuracy quality and lower processing times (Benardos and Vosniakos, 2002). Surface milling was the second method (after turning) to cut material, especially for the finishing process of machined parts. Based on theoretical models, the cutting force depends on the area of the chip (feed, step over and depth of cut), the tool path (width of cut and cutting strategy), the characteristics and properties of the cutting tool material and some others were constants during the experimental process (Fu *et al*., 1984).

Montgomery (2013) and Das *et al*. (2014, 2016) had written in their research that the metal cutting process involves the composition and mechanical properties of the cutting tool and the workpiece as well as the other process parameter settings that influence the efficiency of the process and quality of the output. The surface quality of any milled product is mainly responsible for evaluating the productivity of the machine tools used for the production of the product. Hence, a good surface quality

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is essentially required for the functional behavior of the mechanical parts of the product (Benardos and Vosniakos, 2003). Surface roughness influenced resistance to wear and corrosion, the fatigue strength from friction and lubrication of machine parts (Wang and Feng, 2002). Thus, in today's manufacturing industries special attention is given to proper dimensional accuracy and surface finishing of the product. Reddy and Rao (2005) reported that a good surface finish indicates good machining performance.

Diabetic conditions are usually accompanied by neuropathy problems, thus, increasing plantar bone deformities if compared to non-diabetic patients that are usually without foot problems (Yavuz *et al*., 2008). Foot orthoses equipment was used in the prevention of foot ulcers. Chantelau and Haage (1994) conducted research that foot orthoses are available as custom-made equipment and are made from various materials. Custom orthoses are necessary when the patient has a condition such as loss of protective sensation, foot deformities and the condition of a Charcot ulcer (arthropathy or partial foot disability). The custom-made foot orthosis can achieve total contact with the plantar surface of the foot, therefore the patient uses the same total contact in concept as the total number of contacts cast. There are four main types of custom foot orthoses, though not all are indicated for use in patients with diabetic neuropathy (Sinacore and Mueller, 1993; Janisse and Janisse, 2015): rigid, semi-rigid, accommodative and the partial foot prosthesis.

Some research about optimization techniques that use the fuzzy logic approach of Taguchi methods and response surface include Wasfy and Noor (1998) that examined the procedures used to predict dynamic response and evaluate the flexible system with fuzzy parameters. The possibility distribution and the sensitivity coefficients were generated. This coefficient measures the sensitivity of dynamic responses to the variation of material parameters, external forces and geometric systems. In their study, finite element methods, along with fuzzy-based methods were used to assess the effects of uncertainty and variation of system parameters on flexible system responses. Some parameters were written in fuzzy number forms. The effectiveness of the procedures of fuzzy output was shown in numerical examples including an articulated space structure consisting of blocks, shells and joints.

Tamang and Chandrasekaran (2014) aimed to find the optimal parameter that influences performance characteristics using the grey fuzzy approach. Taguchi's orthogonal L_{27} sequence was done in converting the Al-SiCp MMC using a Poly Crystalline Diamond (PCD). The performance measure included Ra as parameters of quality and Material Removal Rate (MRR) for optimized component economic production.

Das *et al*. (2014) also applied traditional Taguchi methods with fuzzy logic for optimization of the Al-5Cu alloy process of the CNC lathe. The cutting parameters were optimized with various Ra characteristics (mean Ra, average maximum Rz height, maximum Rt profile height and maximum local profile distance Sa).

Kumar *et al*. (2015) investigated the cutting forces on a Uni-Directional Glass Fiber Reinforced Plastics (UD-GFRP) composite. Composite materials were used in various engineering applications such as aerospace and the process industries of oil and gas. Process parameters (tool radius, cutting speed, tool angle, feed rate, depth of cut and cutting environment) were investigated using Taguchi's design methodology. The results of the predictions are close to the experimental values.

Palanikumar *et al*. (2006) performed an experiment on turning GFRP composites using a carbide (K10) tool. They considered the fiber orientation angle, cutting speed, feed rate, depth of cut and machining time as input parameters for measuring the material removal rate, tool wear and surface roughness. The Taguchi method with fuzzy logic was used to simultaneously optimize the response and the result concluded that Taguchi with fuzzy logic is a more convenient and useful technique for multi response optimization (Anonymous, 2017).

Krishnamoorthy *et al*. (2012) applied grey fuzzy logic for a multiple response optimization study in the drilling of CFRP composite. They had taken the input, point angle, spindle speed and feed rate input parameters along with the responses of thrust force, torque, entry, exit delamination and delamination eccentricity of the holes. They conclude that a high spindle speed (3000 rpm), low point angle (100°) and low feed rate (100 mm/min) constitute the optimum parameter levels for the drilling of CFRP composites. Palanikumar *et al*. (2012) applied the Taguchi method with grey-fuzzy logic for simultaneous optimization of material removal rate, surface roughness and specific cutting pressure in the machining of a Glass-Fiber Reinforced Plastic (GFRP) composite. Liao (2015) applied two types of fuzzy multi-attribute decision making methods for material selection. Material process selection is important in engineering design. Material selection with applied fuzzy theory has been accepted because capabilities handling measures material properties.

The review of literature reveals that the researchers are mainly focused on optimizing the multi response characteristics of many applications of CNC turning. However, there is yet, no researcher focused on the material of the rubber especially rubber machining with CNC milling. Recently, grey fuzzy logic is self-employed by many researchers in optimizing conventional and nonconventional machining processes such as grinding, turning, milling, drilling, EDM, etc. The aim of this research is to find the optimal cutting parameter conditions of the milling of insole shoe orthotics for diabetic patients using CNC machine based Taguchi Method and Grey Fuzzy Logic (TM-GFL). The six process parameters, i.e., toolpath strategy, spindle speed, feed rate, step over, type of rubber EVA material and type of AFO design were used to investigate two important performance measures: surface roughness and Real Time Machining (RTM). An optimal combination of parameters that minimize Ra and TM is obtained using the grey fuzzy logic approach.

MATERIALS AND METHODS

Method and experiment set-up

Design of experiment based on Taguchi method: The experimental design with Taguchi orthogonal arrays used parameters affecting the process and the levels at which they should be varied. The Taguchi method tests pairs of combinations rather than testing all possible combinations in a random manner. This allows for determining the major factors affecting the output with a minimum amount of experimentation. Analysis of the variance in the collected data from the experiments can be used to select new parameter values to optimize the performance (Ross, 1988; Nicolo, 1995). A cause and effect diagram as shown in Fig. 1 for identifying the potential factors that may affect the machining characteristics was constructed.

From the available literature on turning, a total of six input parameter numbers were finally selected. In this study, L_{27} Orthogonal Array (OA) with six control factors, e.g., tool path, spindle speed, feed rate, step over, type of rubber, EVA material and type of AFO design were studied. Signal to noise ratio was obtained using Minitab V17 Software. The Taguchi method used the statistical measure called Signal-to-Noise (S/N) ratio. The S/N ratio considered mean and variance. The S/N is the ratio of the mean (signal) to the standard deviation (noise). The ratio depends on the quality of the characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follow: par is best (NB), Lower-the-Better (LB) and Higher-the-Better (HB). The optimum setting is the parameter combination that has the highest Signal-to-Noise (S/N) ratio. In this study, roughness and surface time machining rate takes "the Lower the Better (LB)" type. The corresponding loss function is expressed as follows by Ross (1988) and Nicolo (1995).

Simultaneous optimization of Ra and TMR: Among various process responses, the optimization of machining parameters for the single objective is not appropriate for the other responses. Therefore, the optimization of multi response characteristics has become important for manufacturing industries. In this research, the simultaneous optimization of the surface roughness ($Ra_{Left\ Foot}$ and $Ra_{Right\ Foot}$) as one of the parameters of product quality and the time machining rate being the economic aspects of the production process of AFO for diabetic patients. These are considered to optimize the process of using a grey fuzzy system with subtractive manufacturing technology on CNC milling machines.

Grey Relational Analysis (GRA): In the GRA, the optimization of multiple response characteristics is converted into a single grey relational grade. The

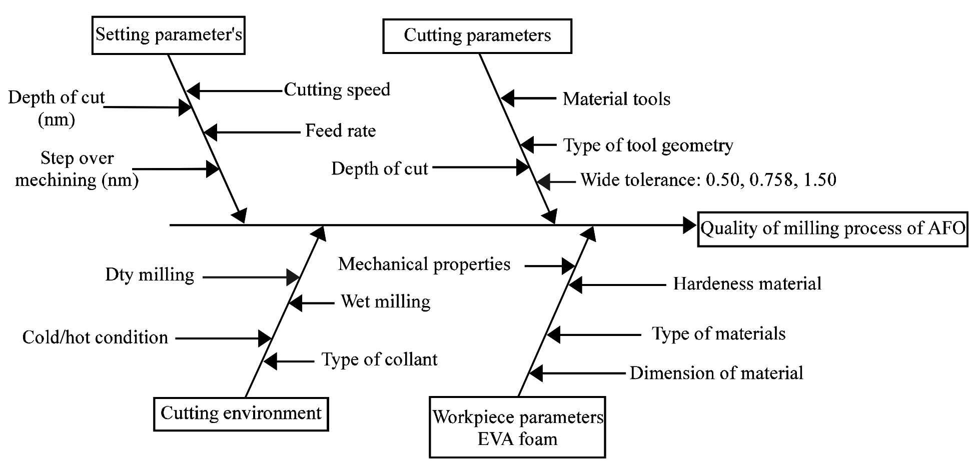

Fig. 1: Ishikawa cause-effect diagram of a milling process

procedure involves: conversion of experimental data into normalized values, performing the experiment, evaluation of grey relational coefficients and process generating the grey relational grading. In this research it was decided to simultaneously optimize $Ra_{Left\ Foot}$, $Ra_{Right\ Foot}$ and TMR. Experimental data sets based on full factorial design 3^3 = 27 data sets are used. The response values are normalized to the Z_{ij} (i.e., $0<Z_{ij}<1$) by using Eq. 1 for the better smaller type:

$$Z_{ij} = \frac{\max(y_{ij}, i = 1, 2, ..., n)-y_{ij}}{\max(y_{ij}, i = 1, 2, ..., n)-\min(y_{ij}, i = 1, 2, ..., n)} \quad (1)$$

where, n = number of replications and y_{ij} = observed response value with i = 1, 2, ..., n and j = 1, 2, ..., k. The grey relation coefficient (ξ) is expressed as the relation between the ideal best and actual normalized experiment values. It's given by Eq. 2:

$$\xi(K) = \frac{\Delta_{min}-\xi\Delta_{max}}{\Delta_{oi}(k)-\xi\Delta_{max}} \quad (2)$$

where, i = 1, 2, 3, ..., n; k = 1, 2, 3, ..., n; $\Delta_{min} = \min_i \min_j \| x_0(k)-x_i(k) \|$; $\Delta_{max} = \max_i \max_j \| x_0(k)-x_i(k) \|$. The grey relation grade (α_i) is determined by averaging the grey relational coefficients as it corresponds to each performance characteristic and it is given by Eq. 3:

$$\alpha_i = \frac{1}{n}\sum_{k=1}^{n}\xi(k) \quad (3)$$

Where:
α_i = The grey relational grade for the ith experiment
k = The number of performance characteristics

Grey fuzzy analysis: The GRG obtained on the basis of the grey relational analysis process allows for some degree of uncertainty in the optimum result obtained and is improved upon by using fuzzy logic. Zadeh (1965) proposed a methodology to deal with uncertainty using a membership value that varies from 0 and 1. The procedure involved a process fuzzification of the input and output parameters, generation of rule base and defuzzification output response.

The set of rules is framed based on "IF-THEN" statements. The two grey relational coefficients (ξ_1 and ξ_2) with one multi response output (η) provide as:

Rule 1: If ξ_1 A_{11} and ξ_2 A_{12}, ... and ξ_n A_{1n} then η is D_1 else
Rule 2: If ξ_1 A_{21} and ξ_2 A_{22} , ... and ξ_n A_{2n} then η is D_2 else
Rule 3: If ξ_1 A_{31} and ξ_2 A_{32} , ... and ξ_n A_{3n} then η is D_3 else
:
:
Rule n: If ξ_1 A_{n1} and ξ_2 is A_{n2} , ... and ξ_n A_{nn} then η is D_1 else

Table 1: Selected levels for cutting

	Levels		
Factors	1	2	3
A	Raster	Raster 45°	Step and shallow
B	14000	14500	15000
C	800	850	900
D	0.20	0.25	0.30
E	20-35	40-50	50-60
F	0.50	0.75	1.00

Here, A_{i1}, A_{i2}, ..., A_{in} and D_i were fuzzy models found by an analysis of corresponding membership function, i.e., μA_{i1}, μA_{i2}, ..., μA_{in} and μD_i. The fuzzy response output is obtained from those rules by applying the max-min interface operation. Finally, the fuzzy response output $\mu_{D0}(\eta)$ must be transferred to a nonfuzzy value, η_0 by the calculation of the centroid defuzzification method using Eq. 4:

$$\eta_0 = \frac{\sum \eta\mu D_0(\eta)}{\sum \mu D_0(\eta)} \quad (4)$$

The non-fuzzy value η_0 is called the Grey Fuzzy Reasoning Grade (GFRG). MATLAB toolbox was used for obtaining the grey fuzzy output. The grey fuzzy reasoning η_0 can handle the optimization of machining multiple complicated responses. Using the value of grey fuzzy reasoning grade η_0, the relational degree between the main and other factors was analyzed for each response characteristic, hence, the higher value of grey fuzzy reasoning grade η_0 indicated that the experimental result was close to the ideally normalized value. Finally, the optimum level of the parameter setting was obtained by performing a response table and a response graph (Table 1-13). The obtained result was verified through a confirmation test.

Experiment: The experiment was carried out in a Rolland Modella MDX 40R milling CNC manufactured by Roland DGA corporation. The machining was carried out in a dry environment without any cutting fluid. CNC part programs were used for doing the milling operation in the CNC milling machine. The surface roughness parameters were measured with Mark Surf PS1.

Selection of process parameters: Surface roughness depends on several factors such as the geometry of the cutting tool, tool material, workpiece material, machine tool rigidity and several cutting conditions such as cutting speed, feed rate and depth of cut. Factors such as wear of the cutting tool, chip formations and properties of the cutting tool and workpiece material are some of the uncontrollable parameters in actual machining according to Huynh and Fan (1992). Machine tool vibration or

Table 2: Blank orthogonal array L_{27} based Taguchi approach

	L_{27} orthogonal array (factors)					
Exp. No.	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	1	1	1	2	2
3	1	1	1	1	3	3
4	1	2	2	2	1	1
5	1	2	2	2	2	2
6	1	2	2	2	3	3
7	1	3	3	3	1	1
8	1	3	3	3	2	2
9	1	3	3	3	3	3
10	2	1	2	3	1	2
11	2	1	2	3	2	3
12	2	1	2	3	3	1
13	2	2	3	1	1	2
14	2	2	3	1	2	3
15	2	2	3	1	3	1
16	2	3	1	2	1	2
17	2	3	1	2	2	3
18	2	3	1	2	3	1
19	3	1	3	2	1	3
20	3	1	3	2	2	1
21	3	1	3	2	3	2
22	3	2	1	3	1	3
23	3	2	1	3	2	1
24	3	2	1	3	3	2
25	3	3	2	1	1	3
26	3	3	2	1	2	1
27	3	3	2	1	3	2

Table 3: Experimental results for $Ra_{Left foot}$ of diabetic patient

	Factors						Response data (surface roughness)									Time Machining Rate (TMR)	
Exp. No.	A	B	C	D	E	F	Ra_{11}	Ra_{12}	Ra_{13}	Ra_{21}	Ra_{22}	Ra_{23}	Ra_{31}	Ra_{32}	R_{33}	T_{MR} (sec)	T_{MR} (min)
1	1	1	1	1	1	1	7.813	7.517	8.178	7.813	7.517	8.178	8.235	7.882	8.462	20072	334.533
2	1	1	1	1	2	2	9.714	7.421	7.854	9.714	7.421	7.854	9.240	7.266	8.173	21127	352.117
3	1	1	1	1	3	3	6.851	7.953	9.442	6.851	7.953	9.442	7.082	8.261	9.556	21037	350.617
4	1	2	2	2	1	1	8.965	9.446	8.454	8.965	9.446	8.454	8.551	9.501	9.140	16437	273.950
5	1	2	2	2	2	2	9.993	8.746	7.543	9.993	8.746	7.543	9.242	8.991	7.947	17289	288.150
6	1	2	2	2	3	3	8.476	8.437	9.808	8.476	8.437	9.808	8.866	8.345	9.839	17219	286.983
7	1	3	3	3	1	1	8.275	9.577	7.934	8.275	9.577	7.934	8.055	9.279	8.276	12859	214.317
8	1	3	3	3	2	2	9.286	9.152	7.095	9.286	9.152	7.095	9.858	9.496	7.032	14791	246.517
9	1	3	3	3	3	3	8.871	9.994	8.855	8.871	9.994	8.855	8.815	9.140	9.776	14738	245.633
10	2	1	2	3	1	2	6.564	9.242	7.917	6.564	9.242	7.917	6.669	9.718	8.545	15676	261.267
11	2	1	2	3	2	3	9.093	8.948	8.717	9.093	8.948	8.717	9.711	8.814	8.439	15626	260.433
12	2	1	2	3	3	1	6.313	9.717	9.354	6.313	9.717	9.354	6.381	9.229	9.667	12884	214.733
13	2	2	3	1	1	2	9.577	8.162	7.780	9.577	8.162	7.780	9.282	8.160	8.355	19888	331.467
14	2	2	3	1	2	3	8.350	8.729	7.930	8.350	8.729	7.930	8.735	8.438	7.957	19818	330.300
15	2	2	3	1	3	1	7.157	9.643	9.668	7.157	9.643	9.668	7.961	9.706	9.371	20028	333.800
16	2	3	1	2	1	2	9.067	7.846	7.381	9.067	7.846	7.381	9.145	8.368	7.225	18456	307.600
17	2	3	1	2	2	3	7.713	9.584	8.997	7.713	9.584	8.997	8.005	9.156	9.523	18393	306.550
18	2	3	1	2	3	1	6.772	9.816	9.602	6.772	9.816	9.602	6.285	9.373	8.915	16458	274.300
19	3	1	3	2	1	3	8.006	9.879	8.110	8.006	9.879	8.110	8.655	9.101	7.288	18209	303.483
20	3	1	3	2	2	1	8.852	9.535	9.402	8.852	9.535	9.402	9.015	9.973	8.980	16502	275.033
21	3	1	3	2	3	2	7.822	9.739	9.155	7.822	9.739	9.155	8.001	9.784	9.531	18467	307.783
22	3	2	1	3	1	3	6.777	7.706	9.956	6.777	7.706	9.956	7.117	8.032	9.095	18055	300.917
23	3	2	1	3	2	1	8.095	8.953	8.145	8.095	8.953	8.145	8.623	9.324	8.968	16463	274.383
24	3	2	1	3	3	2	7.952	8.562	7.931	7.952	8.562	7.931	8.147	9.126	7.962	18348	305.800
25	3	3	2	1	1	3	8.838	9.198	8.059	8.838	9.198	8.059	8.571	9.007	8.873	21329	355.483
26	3	3	2	1	2	1	9.093	8.948	8.717	9.093	8.948	8.717	9.121	9.202	7.851	20066	334.433
27	3	3	2	1	3	2	7.311	7.908	7.269	7.311	7.908	7.269	7.317	8.038	7.607	21715	361.917

chatter, cutting tool wear, irregular chip formation and work piece material surface defects are responsible for the surface defects during machining operations (Elbestawi and Sagherian, 199; Kline *et al*., 1982), so, it is very difficult to consider all factors that control surface roughness. From the literature, it is clear that

Table 4: Experimental results for Ra $_{Right\ Foot}$ of diabetic patient

	Uncoded values						Response data (surface roughness)									Time Machining Rate (T_{MR})	
Exp. No.	A	B	C	D	E	F	Ra_{11}	Ra_{12}	Ra_{13}	Ra_{21}	Ra_{22}	Ra_{23}	Ra_{31}	Ra_{32}	Ra_{33}	T_{MR} (sec)	T_{MR} (min)
1	1	1	1	1	1	1	8.134	7.937	9.477	8.817	8.056	9.687	8.835	8.277	9.285	19671	327.850
2	1	1	1	1	2	2	9.775	8.574	9.202	9.058	8.639	9.574	9.836	8.677	9.713	20704	345.067
3	1	1	1	1	3	3	6.685	6.937	7.118	7.661	6.102	7.331	6.499	6.780	7.961	20616	343.600
4	1	2	2	2	1	1	9.908	8.23	9.282	9.228	8.610	9.970	9.107	9.005	9.005	16108	268.467
5	1	2	2	2	2	2	8.236	9.688	8.664	8.429	9.316	8.645	8.553	9.608	8.273	16943	282.383
6	1	2	2	2	3	3	9.134	8.481	7.704	9.686	8.698	7.991	8.676	9.050	7.773	16875	281.250
7	1	3	3	3	1	1	9.491	8.633	8.306	9.431	9.045	8.860	9.552	8.430	8.405	12602	210.033
8	1	3	3	3	2	2	8.371	8.551	7.951	8.891	9.490	7.717	8.408	8.915	8.03	14495	241.583
9	1	3	3	3	3	3	9.905	6.435	7.938	9.250	6.990	7.736	9.691	6.413	7.341	14443	240.717
10	2	1	2	3	1	2	7.116	7.784	7.627	7.991	8.011	8.521	7.333	7.218	8.061	15362	256.033
11	2	1	2	3	2	3	8.337	7.093	9.194	8.621	7.248	9.183	7.821	7.096	9.810	15313	255.217
12	2	1	2	3	3	1	6.657	7.391	6.991	6.058	8.105	7.151	6.770	7.563	6.787	12626	210.433
13	2	2	3	1	1	2	6.629	7.242	8.690	6.749	7.311	8.957	6.819	8.123	9.266	19490	324.833
14	2	2	3	1	2	3	9.713	7.222	8.297	9.016	7.742	8.438	9.441	7.739	9.044	19422	323.700
15	2	2	3	1	3	1	7.232	8.280	9.240	7.358	8.874	9.354	7.981	8.151	8.994	19627	327.117
16	2	3	1	2	1	2	6.695	6.288	8.173	6.857	6.181	8.474	6.623	6.551	9.108	18087	301.450
17	2	3	1	2	2	3	7.235	8.154	8.287	7.663	8.437	9.171	7.547	8.654	9.113	18025	300.417
18	2	3	1	2	3	1	8.204	7.902	6.553	8.838	7.862	6.196	8.205	7.311	6.154	16129	268.817
19	3	1	3	2	1	3	8.209	8.079	8.860	8.643	8.864	8.574	8.696	7.745	9.162	17845	297.417
20	3	1	3	2	2	1	8.593	8.622	9.835	9.267	9.552	9.831	9.325	8.014	9.035	16172	269.533
21	3	1	3	2	3	2	8.736	6.979	9.236	9.037	6.605	9.752	8.65	6.386	9.975	18098	301.633
22	3	2	1	3	1	3	8.456	8.515	8.547	8.717	9.111	8.910	8.857	8.461	8.16	17694	294.900
23	3	2	1	3	2	1	8.442	7.602	8.435	8.541	7.749	8.802	8.821	7.419	8.801	16134	268.900
24	3	2	1	3	3	2	7.512	7.368	7.293	8.411	7.995	7.516	8.402	8.065	7.582	17981	299.683
25	3	3	2	1	1	3	8.829	7.982	6.755	8.48	8.021	6.391	9.165	8.059	6.511	20902	348.367
26	3	3	2	1	2	1	8.337	7.093	9.194	8.778	7.687	9.826	8.646	7.549	9.287	19665	327.750
27	3	3	2	1	3	2	9.79	8.969	7.221	9.641	9.035	7.094	9.901	9.097	7.878	21281	354.683

Table 5: Experimental results for the output variables and their S/N ratio

	Surface roughness					
Control factors	Level 1	Level 2	Level 3	SN Ra	Delta	Ranking SN
Ra (ratio (dB) for the Left foot of patient DM)						
(A)	8.319531	8.05258	8.159951	5559.204	0.266951	6
(B)	8.432654	8.123	7.976407	1848.709	0.456247	5
(C)	7.981049	8.00921	8.541802	1004.893	0.560753	3
(D)	8.502309	7.791395	8.238358	776.701	0.710914	2
(E)	7.905889	8.701123	7.925049	487.2832	0.795235	1
(F)	8.116728	8.486481	7.928852	1246.097	0.55763	
SN ratio (dB) for the Right foot of patient DM						
(A)	8.61242	8.523593	8.545	51149.08	0.088827	5
(B)	8.516963	8.600778	8.563272	62358.78	0.083815	6
(C)	8.317802	8.584321	8.778889	2051.434	0.461086	1
(D)	8.368753	8.778235	8.534025	2590.107	0.409481	2
(E)	8.40784	8.71963	8.553543	4516.376	0.31179	4
(F)	8.68158	8.348185	8.651247	3234.201	0.333395	3

Table 6: Comparisons of the results of experiments and predicted values by Taguchi method

Response	Confirmatory experiment result	Calculated values	Confidence Interval (CI)	Difference Ra_{exp}-Ra Ra_{cal}	Optimization
$Ra_{left\ foot}$ (μm)	$Ra_{exp} = 8.158$	$Ra_{cal} = 7.919$	$CI_{Ra} = 0.652$	0.239	0.239<0.652 Successful
$Ra_{right\ foot}$ (μm)	$Ra_{exp} = 8.178$	$Ra_{cal} = 8.621$	$CI_{Ra} = 0.625$	0.443	0.443<0.625 Successful

toolpath strategy machining (Factor "A"), spindle speed (Factor "B"), feed rate (Factor "C"), step over (Factor "D"), type of EVA rubber foam (Factor "E") and type of wide tolerance (Factor "F") are the six primary machining parameters that affect the surface roughness and machining time. Thus, these six parameters are taken into consideration in the present study and are shown in Table 1.

Selection of response parameters: All of the previous studies concentrated on the center line average roughness, Ra but to describe the quality of a multi scale rough surface center line average roughness, Ra is not sufficient. So, in the present investigation, two more roughness parameters were taken into consideration such as $Ra_{Left\ Foot}$ and $Ra_{Right\ Foot}$ as well as Time Machining Rate (TMR).

Table 7: The evaluation of Grey Relation Grade (GRC) for the left foot of patient

	Performance measure		GRC (Grey Relational Coefficient)		
Exp. No.	Ra	T_{MR} (min)	GRC Ra (μm)	GRC Ta (min)	GFRG (Grey Fuzzy Relation Grade) (α)
1	7.9550	334.5333	0.7657	0.1855	0.4756
2	8.2952	352.1167	0.5695	0.0664	0.3180
3	8.1546	350.6167	0.6506	0.0766	0.3636
4	8.9913	273.9500	0.1681	0.5960	0.3820
5	8.7493	288.1500	0.3077	0.4998	0.4037
6	8.9436	286.9833	0.1957	0.5077	0.3517
7	8.5758	214.3167	0.4077	1.0000	0.7039
8	8.6058	246.5167	0.3904	0.7818	0.5861
9	9.2412	245.6333	0.0240	0.7878	0.4059
10	8.0420	261.2667	0.7155	0.6819	0.6987
11	8.9422	260.4333	0.1964	0.6876	0.4420
12	8.4494	214.7333	0.4806	0.9972	0.7389
13	8.5372	331.4667	0.4300	0.2063	0.3181
14	8.3498	330.3000	0.5381	0.2142	0.3761
15	8.8860	333.8000	0.2289	0.1905	0.2097
16	8.1473	307.6000	0.6548	0.3680	0.5114
17	8.8080	306.5500	0.2738	0.3751	0.3245
18	8.5503	274.3000	0.4224	0.5936	0.5080
19	8.5593	303.4833	0.4172	0.3959	0.4066
20	9.2829	275.0333	0.0000	0.5886	0.2943
21	8.9720	307.7833	0.1793	0.3668	0.2730
22	8.1247	300.9167	0.6679	0.4133	0.5406
23	8.5890	274.3833	0.4001	0.5930	0.4966
24	8.2361	305.8000	0.6036	0.3802	0.4919
25	8.7379	355.4833	0.3143	0.0436	0.1789
26	8.8544	334.4333	0.2471	0.1862	0.2166
27	7.5487	361.9167	1.0000	0.0000	0.5000

Table 8: The evaluation of Grey Relation Grade (GRC) for right foot of patient

	Performance measure		GRC (Grey Relational Coefficient)		
Exp. No.	Ra	T_{MR} (min)	GRC Ra (μm)	GRC Ta (min)	GFRG (Grey Fuzzy Relation Grade) (α)
1	8.7228	327.8500	0.2274	0.1855	0.2065
2	9.2276	345.0667	0.0000	0.0665	0.0332
3	7.0082	343.6000	1.0000	0.0766	0.5383
4	9.1494	268.4667	0.0352	0.5960	0.3156
5	8.8236	282.3833	0.1820	0.4998	0.3409
6	8.5770	281.2500	0.2931	0.5077	0.4004
7	8.9059	210.0333	0.1449	1.0000	0.5725
8	8.4804	241.5833	0.3366	0.7819	0.5593
9	7.9666	240.7167	0.5682	0.7879	0.6780
10	7.7402	256.0333	0.6702	0.6820	0.6761
11	8.2670	255.2167	0.4328	0.6876	0.5602
12	7.0526	210.4333	0.9800	0.9972	0.9886
13	7.7540	324.8333	0.6640	0.2064	0.4352
14	8.5169	323.7000	0.3202	0.2142	0.2672
15	8.3849	327.1167	0.3797	0.1906	0.2851
16	7.2167	301.4500	0.9061	0.3680	0.6370
17	8.2512	300.4167	0.4399	0.3752	0.4075
18	7.4694	268.8167	0.7922	0.5936	0.6929
19	8.5369	297.4167	0.3112	0.3959	0.3536
20	9.1193	269.5333	0.0488	0.5887	0.3187
21	8.3729	301.6333	0.3851	0.3667	0.3759
22	8.6371	294.9000	0.2660	0.4133	0.3397
23	8.2902	268.9000	0.4223	0.5930	0.5077
24	7.7938	299.6833	0.6460	0.3802	0.5131
25	7.7992	348.3667	0.6436	0.0437	0.3436
26	8.4886	327.7500	0.3330	0.1862	0.2596
27	8.7362	354.6833	0.2214	0.0000	0.1107

Table 9: The response table for grey relational grade for right foot of patient DM

Levels	A	B	C	D	E	F
1	8.31953	8.43265	8.00921	8.50231	7.92505	**7.92885**
2	**8.05258**	8.12300	**7.98105**	8.23836	8.70112	8.48648
3	8.15995	**7.97641**	8.54180	**8.00921**	**7.90589**	8.11673
Δ = max-min	0.26695	0.45625	0.56075	0.49310	0.79523	0.55763
Rank	6	5	2	4	1	3
Optimal parameters	A_2	B_3	C_2	D_3	E_3	F_1

Bold values are significant

Table 10: The response table for grey relational grade for the left foot of patient DM

Levels	A	B	C	D	E	F
1	8.61242	**8.51696**	**8.31780**	8.53402	**8.36875**	8.68158
2	**8.52359**	8.60078	8.58432	8.77823	8.77823	**8.34819**
3	8.54500	8.56327	8.77889	**8.36875**	8.53402	8.65125
Δ = max-min	0.08883	0.08381	0.46109	0.40948	0.40948	0.33340
Rank	5	6	1	2	2	4
Optimal parameters	A_2	B_1	C_1	D_3	E_1	F_2

Table 11: Grey fuzzy reasoning grades and its order

	Left foot (L)			Right foot (R)		
Exp. No.	GRC	GFRG	Order	GRC	GFRG	Order
1	0.476	0.318	11	0.206	0.143	25
2	0.318	0.217	22	0.033	0.024	27
3	0.364	0.247	18	0.538	0.357	9
4	0.382	0.259	16	0.316	0.216	21
5	0.404	0.273	15	0.341	0.232	18
6	0.352	0.239	19	0.400	0.271	14
7	0.704	0.457	2	0.572	0.378	6
8	0.586	0.386	4	0.559	0.370	8
9	0.406	0.274	14	0.678	0.442	3
10	0.699	0.454	3	0.676	0.440	4
11	0.442	0.297	12	0.560	0.371	7
12	**0.739**	**0.477**	**1**	**0.989**	**0.619**	**1**
13	0.318	0.217	21	0.435	0.293	12
14	0.376	0.255	17	0.267	0.184	23
15	0.210	0.145	26	0.285	0.196	22
16	0.511	0.340	6	0.637	0.417	5
17	0.324	0.221	20	0.408	0.275	13
18	0.508	0.338	7	0.693	0.450	2
19	0.407	0.274	13	0.354	0.240	16
20	0.294	0.202	23	0.319	0.218	20
21	0.273	0.188	24	0.376	0.255	15
22	0.541	0.358	5	0.340	0.231	19
23	0.497	0.331	9	0.508	0.338	11
24	0.492	0.328	10	0.513	0.341	10
25	0.179	0.125	27	0.344	0.234	17
26	0.217	0.150	25	0.260	0.179	24
27	0.500	0.333	8	0.111	0.078	26

Bold values are significant

Table 12: The result of the initial and optimum performance for machining right foot

Setting the level	Initial machining parameters	Predicted ($A_2B_3C_2D_3E_3F_1$)	Experiment ($A_2B_3C_2D_3E_3F_1$)
R_A	9.2829	8.4158	7.9059
T_{MR}	361.9167	288.1167	214.3167
GRG	0.1789	0.6929	0.7389
GFRG	0.1246	0.4503	0.4774

Table 13: The result of the initial and optimal performance for machining left foot

Setting the level	Initial machining parameters	Predicted ($A_2B_1C_1D_3E_1F_2$)	Experiment ($A_2B_1C_1D_3E_1F_2$)
R_A	9.2276	8.1179	7.0082
T_{MR}	282.3583	210.0333	210.0333
GRG	0.0332	0.6929	0.9886
GFRG	0.0236	0.4503	0.6188

Work material: This research used EVA rubber foam sized 250×95°23 mm thickness as the work materials used in this experiment. The specifications of this material according to Nurit *et al*. (2006) are: density 55-65 kg/m^3, nominal size 2000×1000 mm, nominal thickness (split) 3-36 mm, hardness read after 2 sec is 20-60 grade, tensile strength 800 kPa and tear strength is 4.5 kN/m. The hardness of the material is chosen based on the results of the test using shore hardness tester Asker CL-150 range 20-60 H_{RC}. There were three types of EVA foam rubber material, e.g., type of rubber with hardnesses of 20-35, 35-45 and 50-60 H_{RC}. This material can be used in healthcare problem solutions such as exercise mats, insoles, orthopedic shoes and orthotic support shoes.

Cutting tool used: The cutting tool material selected for the machining of this test was the carbide tool for end mill and ballnose cutter milling. The commercial grade of SECO with the specification numbers 93060 F for the end mill cutter and JS533060D1B0Z3-NXT for the Ball Nose cutter was used in this research.

Design of experiment: Three levels of equal spacing within the range of the parameters have been

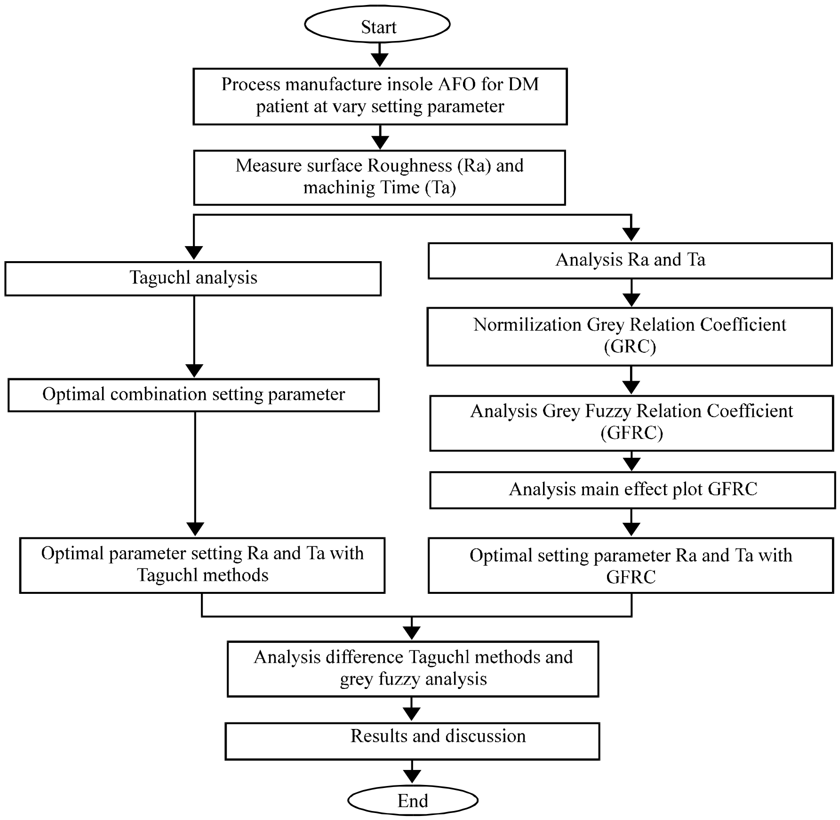

Fig. 2: The stages Taguchi methodology and grey fuzzy logic methodology

selected (Table 1). In the present investigation, L_{27} Taguchi's orthogonal array design has been taken into consideration for the experimentation. The design of the experiment and the measured roughness parameters were listed in Table 2 and 3, respectively. The stage of the experiment with Taguchi methodology and the fuzzy logic approach are shown in Fig. 2.

Table 3 and 4 show the experimental results for Ra parameters ($Ra_{Left\ Foot}$, $Ra_{Right\ Foot}$ and T_{MR}) and S/N ratio values that were analyzed with experimental research combinations (Table 5). These four different performance characteristics in the Taguchi method and the the S/N ratios corresponding to the surface roughness parameters are proposed by the fuzzy logic unit.

RESULTS AND DISCUSSION

The final analysis of the Taguchi method was a verified optimization parameter by confirmation experiments after determining the variable levels that gave the optimum results. The confirmation experiment results were performed at the optimum variable levels for surface Roughness (Ra). The determined optimal levels in Fig. 3 as $A_2B_1C_1D_3E_1F_2$ and $A_2B_3C_2D_3E_3F_1$ and their levels were used for the calculation of the predicted optimal surface Roughness Ra for patient DM in this research. Equation is given for the predicted optimal Ra_{pred} is as follows:

$$Ra_{pred} = T_{Ra\_exp} + \left(\bar{A}_2 - T_{Ra\_exp}\right) + \left(\bar{B}_2 - T_{Ra\_exp}\right) + \left(\bar{C}_1 - T_{Ra\_exp}\right) + \left(\bar{D}_2 - T_{Ra\_exp}\right) + \left(\bar{E}_1 - T_{Ra\_exp}\right) + \left(\bar{F}_2 - T_{Ra\_exp}\right) \quad (5)$$

Where:

$\bar{T}_{Ra\_exp}$ = 8.158
$\bar{A}_2$ = 8.053
$\bar{B}_2$ = 7.977
$\bar{C}_2$ = 7.981
$\bar{D}_2$ = 8.009
$\bar{E}_2$ = 7.906
$\bar{F}_2$ = 7.929

Hence, Ra_{pred} for the left foot of patient = 8.158+(8.053-8.158)+(7.977-8.158)+(7.981-8.158)+(8.009-8.158)+(7.906-8.158)+(7.929-8.158) = 7.919 μm:

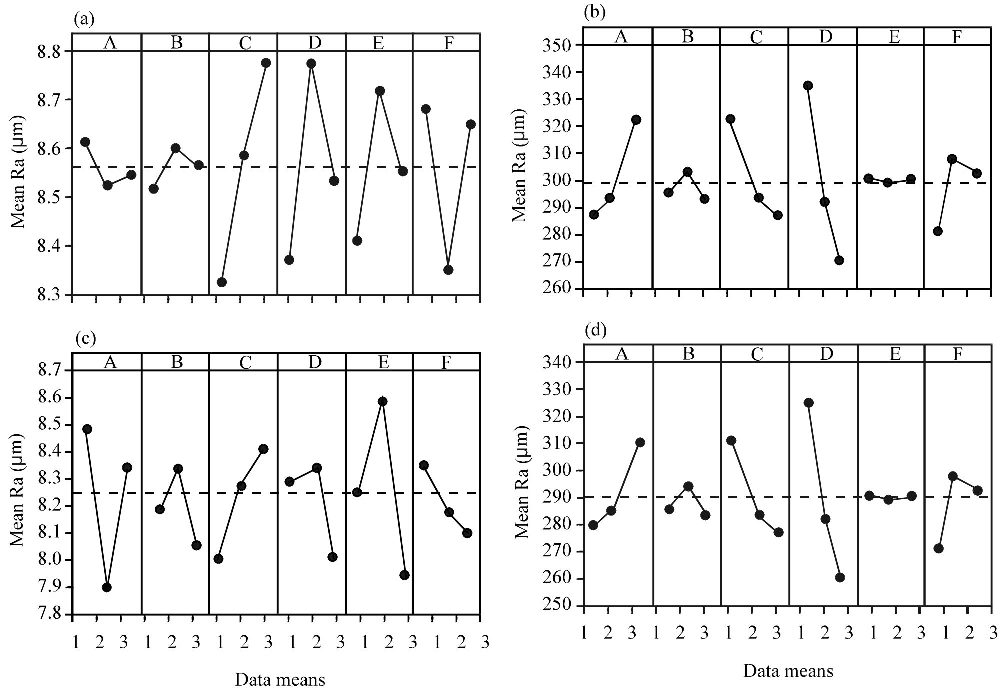

Fig. 3: Main effects plots of patient: a) Effects of control factors surface Roughness Ra (Main effects plot for surface Roughness Ra average (left foot)); b) Effects of control factors Machining Time (TM) (Main effects plot for Machining Time TM (left foot); c) (Main effects plot for surface Roughness Ra average (right foot)) and d) (Main effects plot for Machining Time TM (right foot)

$$Ra_{pred} = T_{Ra\_exp} + \left(\bar{A}_2 - T_{Ra\_exp}\right) + \left(\bar{B}_3 - T_{Ra\_exp}\right) + \left(\bar{C}_1 - T_{Ra\_exp}\right) + \left(\bar{D}_2 - T_{Ra\_exp}\right) + \left(\bar{E}_1 - T_{Ra\_exp}\right) + \left(\bar{F}_2 - T_{Ra\_exp}\right) \quad (6)$$

Where:

T_{Ra_exp} = 8.178
$\bar{A}_2$ = 8.524
$\bar{B}_2$ = 8.517
$\bar{C}_2$ = 8.318
$\bar{D}_2$ = 8.369
$\bar{E}_2$ = 8.369
$\bar{F}_2$ = 8.348

Hence, Ra_{pred} for the right foot of patient = 8.178+(8.178-8.524)+(8.517-8.178)+(8.318-8.178)+(8.318-8.178)+(8.348-8.178) = 8.621 µm.

The Confidence Interval (CI) is the self procedure that verifies the characteristics of quality resulting from the experiment. The confidence interval was the step to predicted optimal values that were calculated using the following equations (Roy, 1990):

$$CI = \sqrt{F_{\alpha,\, do\int V_{error}} V_{error} x \left(\frac{1}{n_{eff}}\right)} \quad (7)$$

$$n_{eff} = \frac{\text{Number of experiment}}{1+\text{total dof in items in used in estimate}} \quad (8)$$

The confidence interval for surface roughness Ra_{pred} for the left foot of the patient is as follows: $F_{0.05;1.26}$(tabulated), V_{erorr} = 0.2259 (Table 5) and N_{eff}= 2.25. The CI_{Ra} = ±0.652 µm. The predictive mean of Ra is Ra_{pred} = 7.119 µm, $|Ra_{pred}-CI|<Ra_{pred}<|Ra_{prede}+CI|$ ie., 7.919-0.652 µm<7.919 µm<7.919+0.652 µm, 7.267 µm<Ra_{pred}<8.571 µm. The confidence interval for the surface roughness Ra_{pred} for the right foot of patient 1 is as follows: $F_{0.05;\ 1.26}$ (tabulated), V_{erorr} = 0.208 (Table 5) and N_{eff} = 2.25. Thus, CI_{Ra} = 0.625 µm. The predictive mean of Ra_{pred} = 8.621 µm $|Ra_{pred}-CI|<Ra_{pred}<|Ra_{pred}+CI|$, ie., 8.621-0.625 µm<8.621 µm<8.621+0.625 µm, 7.996 µm<Ra_{pred}<9.246 µm.

Table 6 gives the comparison of the results of the confirmation experiment that were conducted according to the optimum levels of the variables and the values calculated using Eq. 5-8. Additionally, according to Eq. 7-8, the Confidence Interval (CI) is calculated as 0.652 and 0.625 µm for $Ra_{Left\ Foot}$ and $Ra_{Right\ Foot}$ of patient DM. It can be seen from Table 6 that the result values of the confirmation test conducted for the responses are obtained in the confidence interval with a 95% confidence level. Thus, the system optimization for surface Roughness (Ra) was achieved using the Taguchi method at a significance level of 0.05.

The values of grey relational coefficients and grey relational grades for different experimental runs are presented in Table 7 and 8. The optimal combination level and its factor are obtained by separating out the effects of each machining parameter on the grey relational grade at different levels. It was evaluated as the mean of the grey relational grade for the tool path strategy (A) at levels 1-3 is obtained by averaging the grey relational grade for the experiments 1-9, 10-18 and 19-27, respectively. Similarly the mean of the grey relational grade for B-F are also evaluated. Table 9 summarizes the result. The GRG at all levels of A-F are obtained using the smaller the better relationship. The GRG among the highest levels of each parameter decides the optimum parameter combination.

In the present case the optimum combination is A_2-B_3-C_2-D_3-E_3-F_1 which corresponds to the highest value of GRG 8.05258, 7.97641, 7.98105, 8.00921, 7.90589 and 7.92885 for the right foot and A_2-B_1-C_1-D_3-E_1-F_2, which corresponds to the highest value of GRG 8.52359, 8.51696, 8.31780, 8.36875, 8.36875 and 8.34819 for the left foot, respectively, for A-F (Table 9 and 10). The experimental result of the optimum parameter combination is compared with the predicted value. The rank of the parameter gives important information among the others. The parameter having the highest delta (Max-Min) has the top priority and so on. However, there is still some degree of uncertainty in the obtained optimal result. The theory of fuzzy logic is used for representing uncertainties associated with imprecision, vagueness and lack of information in the problem.

In this research a triangular membership function was used to fuzzyify the input and output values (Fig. 4). The fuzzy grey relation of $Ra_{Left\ Foot}$, $Ra_{Right\ Foot}$ and TMR was fuzzified into three sets; Low, medium and high. The output of the grey fuzzy reasoning grade was fuzzified into eight sets from very very low until very very high.

Table 11 shows the obtained grey fuzzy reasoning grade from the predicted values of Fuzzy Inference System (FIS) and its order.

Based on Eq. 4, Table 11 and Fig. 5, the optimal Grey Fuzzy Reasoning Grade (GFRG) coming in at order 1 in experiment number 12 is at the value 0.477 for the left foot and 0.619 for the right foot.

The optimal combination of the parameters are determined from the highest level of each response maintained at level 1 for factors B, C and E, level 2 for factors A and F and level 3 for factor D as shown in the response graph for left foot (Fig. 6). Thus, the optimal parameter combination for Ra's left foot is $A_2B_1C_1D_3E_1F_2$ which implies a raster toolpath strategy at 45°, spindle speed at 14,000 rpm, feed rate at 800 mm/min, step over of 0.30 mm, type A with rubber EVA material hardness H_{RC} 20-35 and type wide tolerance of the design of AFO is 0.75 mm. The optimal parameter combination for Ra's right foot is $A_2B_3C_2D_3E_3F_1$ which implies a raster toolpath strategy at 45°, spindle speed at 14.500 rpm, feed rate at

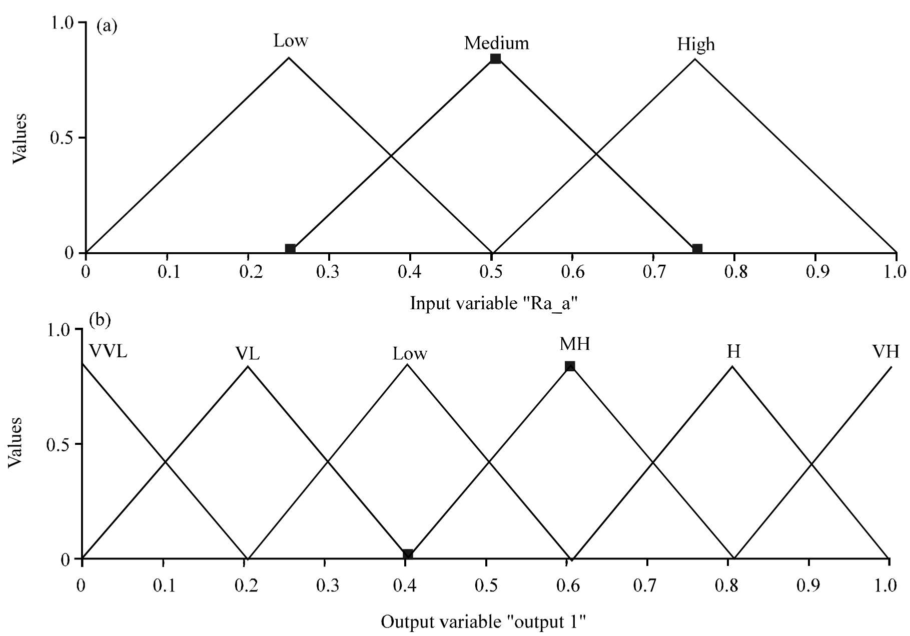

Fig. 4: a, b) Fuzzification of inputs and outputs

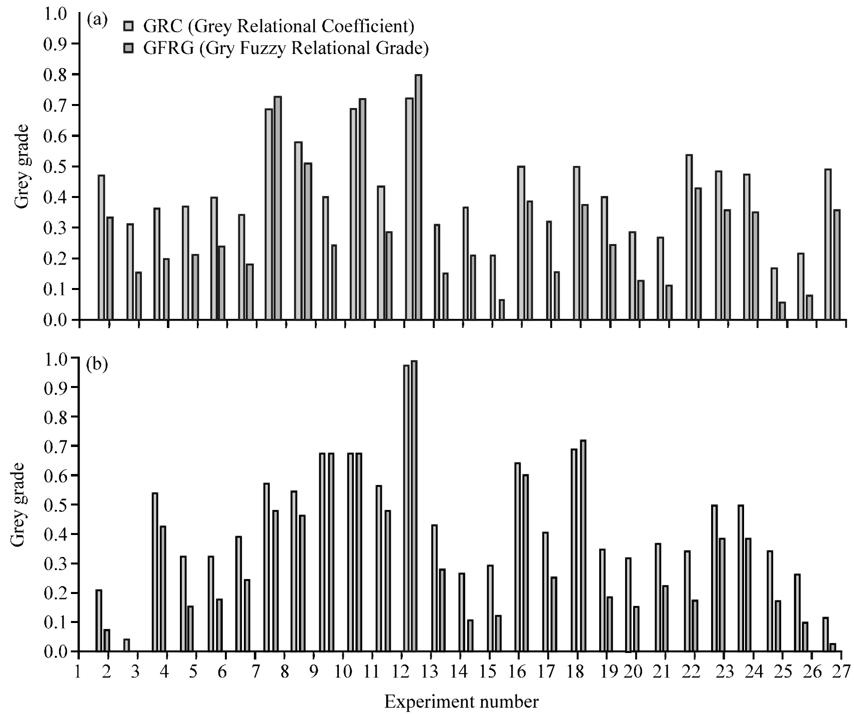

Fig. 5: Comparisons of GRG and GFRG: a) Comparisons graph GRC and GFRG (left foot) and b) Comparisons graph GRC and GFRG (right foot)

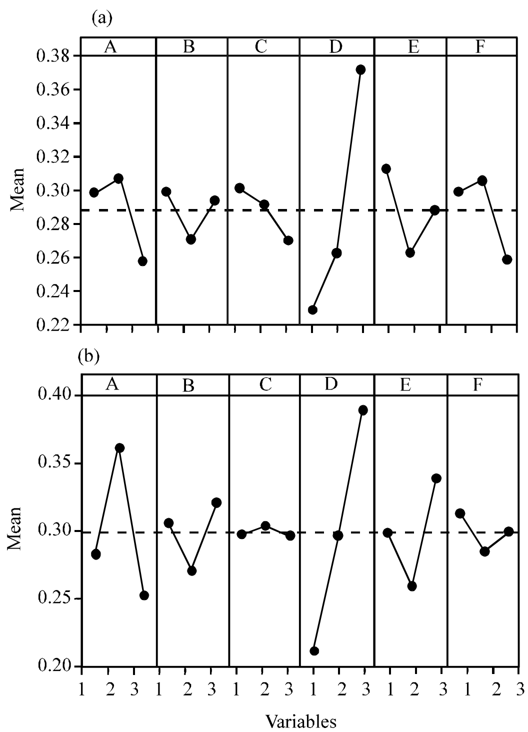

Fig. 6: Response graph for grey fuzzy reasoning grade: a) Responce Graph Grey Fuzzy (GFRG) (left foot) data means and b) Responce Graph Grey Fuzzy (GFRG) (right foot) data means

850 mm/min, step over of 0.30 mm, type E with EVA rubber hardness 50-60 H_{RC} and type wide tolerance of design of AFO is 0.75 mm. The larger the mean of the grey fuzzy reasoning to grade the better is based on the last multiple performance.

While comparing the output response of the optimal parameter level setting of A_2-B_3-C_2-D_3-E_3-F_1 and A_2-B_1-C_1-D_3-E_1-F_2 with the initial setting of the level of machining parameters, surface roughness decreases from 9.2829-8.4158 μm (right foot), 9.2276-8.1179 μm (left foot) and the time machining rate decreases from 361.9167-288.1167 min (right foot) and 282.3583-210.0333 min for the left foot. Table 12 and 13 show the results obtained. This improves productivity as well as the quality of the components produced. The predicted responses are close to experimental results with the maximum% of error of 5.4%. Also, it is seen that, the grey fuzzy reasoning grade is higher than grey relational grade in all cases. This shows the proposed method of grey fuzzy optimization is advantageous in optimizing multiple performance characteristics of the milling operation of shoe orthotic insoles for diabetic patients.

Analysis of Variance (ANOVA) found significance of the parameters that affect the response process. The GRFG obtained used the analysis gained by using ANOVA. This process was done by separating the variability GRG that was measured by the sum of the

Table 14: ANOVA for grey-fuzzy reasoning grade for left foot

Sources	Sq	v	Mq	F-ratio	Sq′	Rho (%)
A	0.162	2	0.081	0.142	0.122	2.78
B	0.488	2	0.244	0.427	0.366	8.36
C	0.898	2	0.449	0.786	0.673	15.37
D	1.162	2	0.581	1.017	0.871	19.89
E	1.853	2	0.926	1.620	1.388	31.71
F	0.724	2	0.362	0.634	0.543	12.40
e	0.428	5	0.086	0.150	0.416	9.49
St	5.717	10	0.572			
Mean	0.572	27				
ST	0	27		4.378	100.00	

Table 15: ANOVA for grey-fuzzy reasoning grade for left foot

Sources	Sq	v	Mq	F-ratio	Sq′	Rho (%)
A	1.221	2	0.611	1.068	0.915	34.29
B	0.202	2	0.101	0.176	0.151	5.67
C	0.329	2	0.164	0.287	0.246	9.22
D	0.161	2	0.081	0.141	0.121	4.53
E	1.035	2	0.517	0.905	0.775	29.05
F	0.120	2	0.060	0.105	0.090	3.38
e	0.380	5	0.076	0.133	0.370	13.85
St	3.448	10	0.345			
mean	0.345	27				
ST	0.000	27	2.6686	100.00		

Table 16: Comparison of optimum and predicted result

	Ra					
	Optimal		Predicted		Absolute error (%)	
Optimization technique	Left foot	Right foot	Left foot	Right foot	Left foot	Right foot
Taguchi approach	8.1580	8.1780	7.9190	8.6210	2.93	5.14
Grey fuzzy approach	7.0082	7.9059	8.1179	8.4158	13.67	6.06
improvement (%)	14.09	3.33	-	-		

squared deviations from the mean of the total GRFG into contributions by each turning process parameter and the error. Results of ANOVA that are presented in Table 14 and 15 indicate that the E factor of the left and right foot is highly influential, contributing 31.71%, followed by factor D 19.89%. Factor A had a very small contribution of 2.78% for the left foot. As for the right foot, factor A is highly influential contributing 34.29%, followed by E factor 29.05% and factor F has a very small contribution of 3.38%. The equation relation GFRC to each factor setting parameter is shown in Eq. 9 and 10:

$$\text{GRFG left foot} = 0.05682+0.0068\ A+0.0021\ B-0.00180\ C+0.0017\ D-0.00142E-0.00137\ F+0.2355\ A^2+0.0255\ B^2-0.0125\ C^2+0.0255\ AC \quad (9)$$

$$\text{GRFG right foot} = 0.013221+0.0052\ A+0.0017\ B-0.0235\ C+0.0567D-0.00142E+0.0079\ F-0+0.2355\ A^2+0.0255\ B^2-0.06020\ D^2+0.0255\ BC \quad (10)$$

The optimal results obtained by different optimization techniques (TM and grey fuzzy approach) were compared and found a significant improvement in surface finish with a hybrid approach. The predicted and comparative analysis at optimal condition has been summarized in Table 16. It has been observed (Table 16) that the hybrid optimization technique of the grey fuzzy approach gives a 14.09 and 3.33% better surface finish as compared to optimal results obtained from the Taguchi approach. It has also been observed that the prediction capability of the developed model is significant with 13.67 and 6.06% error for both feet at the optimal condition obtained by the hybrid approach.

CONCLUSION

In this research, Taguchi's array of orthogonal experiments L_{27} was performed for optimizing the process parameters in the milling of shoe orthotic insoles with three types of EVA rubber foam. Two important performance measures, surface Roughness (Ra) and Time Machining Rate (T_{MR}) were simultaneously optimized using the grey fuzzy logic approach. The different parameters include toolpath strategy, spindle speed, feed rate, step over, type of rubber and EVA type of wide tolerance of insole shoe orthotic, each at three different levels, contribute to the mean grey relational grade. Grey relational analysis is self-employed for obtaining an optimal machining parameters setting. The grade is improved by employing fuzzy logic by minimizing the uncertainty in GRG.

The combinations of parameters with the larger value of grey fuzzy reasoning grades of 0.44 and 0.6 provide $A_2B_1C_1D_3E_1F_2$ (left foot) and $A_2B_3C_2D_3E_3F_1$ (right foot). It implies a raster toolpath strategy at 45°, spindle speed at 14.000 rpm, feed rate at 800 mm/min, step over of 0.30 mm, EVA rubber material type A with hardness H_{RC} 20-35 and type wide tolerance of design of AFO is 0.75 mm for optimal machining parameter of the left foot. As for the right foot condition, the optimal cutting parameters exist on toolpath strategy with 45° raster, spindle speed at 14,500 rpm, feed rate at 850 mm/min, step over of 0.30 mm, type E with EVA rubber hardness 50-60 H_{Rc} and type wide tolerance of design of AFO is 0.75 mm. Both of the combinations will result in the optimum position on the Ra values of 7.9059 μm (right foot) and 7.0082 μm (left foot). The T_{MR} for optimum insole workmanship is 210.033 for the left foot with 214.3167 min to minute for the right foot.

ANOVA statistics revealed that the feed is the most influential parameter contributing 31.71-34.29% in achieving good results. The proposed optimization procedure is found more effective for evaluating the multiple performance characteristics and significantly improves the economic production of quality components in milling shoe orthotic insoles for diabetic patients.

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