International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
Article Received: 22 August 2022 Revised: 27 October 2022 Accepted: 19 November 2022

Wear Rate Modelling and Analysis of Limestone Slurry Particulate Composites Using the Fuzzy Method

Dharmana Lokanadham[1], Rakesh Chandmal Sharma[2], Srihari Palli[1,], Sono Bhardawaj[3,*]**
[1]Mech. Engg. Dept., Aditya Institute of Technology and Management, Tekkali, India
[2] Mech. Engg. Dept., Graphic Era (Deemed to be University) Dehradun, *India*
[3] Mech. Engg. Dept., Shivalik College of Engineering, Dehradun, *India*
Corresponding Author Email[*]: sonupanditsharma59@gmail.com
Joint Corresponding Author Email[**]: srihari.palli@gmail.com

Abstract
The present work is aimed at developing an Aluminium metal Matrix Composite (AMC) with an industrial waste Limestone Slurry Particulate (LSP) dust as reinforcement which is available in plenty at no cost. As the stone industry is producing huge amounts of dust as waste, utilization of this waste dust for producing useful materials can reduce its adverse effects on the environment. AMC with reinforced LSP composites are manufactured using stir casting process with varying weight% of LSP (0%, 4%, 8%, 12%, 16%). The particle size of LSP varied from 10-60 µm with an average size of 42 µm. The present work investigates the effect of control parameters on tribological properties (coefficient of friction and wear rate) of AMC reinforced with LSP. The development of suitable wear rate and coefficient of friction models using fuzzy logic is accomplished during this study.

Keywords: Aluminium metal Matrix Composite, Limestone Slurry Particulate, Fuzzy method, Wear rate.

Introduction

Several modern materials have come into existence to meet the challenges of industries in the quest for apt materials for engineering applications. Metal matrix composites have gained importance in engineering over the past couple of decades due to their higher specific strength and wide range of applications. Composites with Aluminium as base metal are more common than that any other base metal due to the abundant availability of Aluminium. To curb the cost and ease of fabrication, aluminium-based composites are now made with fine powders of Al_2O_3/SiC utilizing the stir casting method. However, some hitches are encountered in the fabrication of aluminium-based composites by this process due to the difference between the density of matrix material and reinforcement, variation in melting points, immiscibility and deprived wettability. Many scientists believe that particle retention may be improved by using wetting agents [1, 2 and 6]. Tribology relies on material science, physics, and chemistry concepts, making it a multi-disciplinary field. Since wear accounts for more amount of a loss of machine utilization, it is a huge industrial concern.

Wear occurs whenever two surfaces that are moving relative to one another come into touch with one another, resulting in a progressive loss of material. Researchers [7-10] have established several wear theories, in which the physical and mechanical parameters of the materials are taken into consideration. Reduced wear not only avoids machine failure but also enhances the industrial process.

Wear can be classified based on surface damage into the following categories. The most common types are adhesive and abrasive wear as shown in Figure 1, attributed to Carlos, A. et.al. [11]. Surface fatigue is the type of wear produced when particles are separated from the solid surfaces due to the accumulation of micro-damage in the material. The functioning of the wear mechanism contributes to the development of fractures and voids in the solid surfaces, which are then exacerbated as the cycles continue to be conducted.

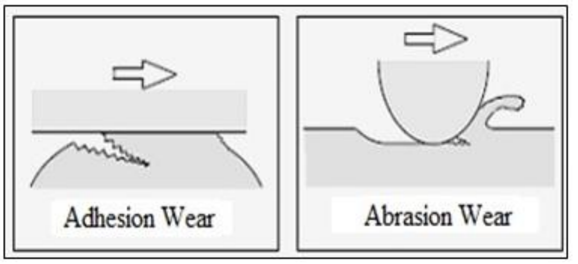

Figure 1. Schematic Descriptions of Adhesive and Abrasive Wear [11]

The purpose of this study is to explore the tribological characteristics of an aluminium metal matrix composite that has been reinforced with limestone slurry particulate. These features include dry sliding wear rate and coefficient of friction (LSP). This work is focused on the development of approximate models for wear rate and coefficient of friction using Fuzzy Logic. To determine the effect of control parameters i.e., load, the weight percentage of LSP, sliding velocity and sliding distance on fuzzy output parameters. It also determines the settings of control parameters that result in the best fuzzy responses [12-19].

1. Review of Literature

Gautam et al., (2022) [20] examined the effects of incorporating slurry waste from the polishing of dimensional limestone into black cotton soil to enhance its geotechnical qualities. Weight-for-weight soil replacement with slurry began at 2.5% and continued until adding more slurry did not affect the soil's quality. The soil's workability, load-bearing capacity, mechanical and durability were all shown to be enhanced when slurry was used as an addition. The swelling behaviour of the soil determined by the free swell index was shown to be reduced when compared to a tidy soil sample. In this laboratory investigation, the use of dimensional limestone slurry waste as an additive was found to improve the characteristics of black cotton soil, making it suitable for use as a subgrade in flexible pavement. Additionally, this provided a sustainable alternative for the disposal of slurry waste created during poising operations.

Lokanadham et al., (2021) [21] studied the tribological performance of aluminium composite (Al-MgSi) reinforced with a powder derived from limestone slurry is investigated (LSP). LSP is used to make an AMC (aluminium metal matrix composite) with different weight percentages ranging from 4% wt to 16% wt. A 12%wt LSP. Shows superior wear performance when compared to competing products. The Taguchi method was used in the experiment design (L25). Wear rate (WR- mm3/Nm) and coefficient of friction (CF) are the outcomes of this research, whereas sliding velocity (V), % of LSP (R), sliding distance (D), and load (L) are the input factors. Additionally, grey relation analysis (GRA) simplifies several variables down to a single one. As a result of this transformation, the wear-related responses across several variables may be understood as a single variable, represented by a grey-scale relation grade. A multi-way “analysis of variance (ANOVA)” was carried out to assess the significance of the individual factors and their connections with the design elements. Grey-fuzzy reasoning grade (GFRG) has been shown to increase the performance of wear behaviour features in the tribological process, as shown by experimental data.

Lokanadham et al., (2020) [22] stated that a solid waste called LSP is being employed as a reinforcing material. Al-LSP composites are made with 4, 8, 12, and 16% weight ratios, and are manufactured by double stir casting, to determine the tribological performance of aluminium (Al), magnesium (Mg), and silicon (Si) alloy to improve the mechanical and tribological characteristics of “Aluminum Metal Matrix Composites (AMCs)”. Using the results of tribological tests carried out on a Pin-on-disc Tester, calculations were made to determine the sliding wear rate (WR) and the coefficient of friction (CF). Results show that while load and sliding speed were increased, wear rates were also increased, however, LSP had a mitigating effect. As stress increases, abrasion wear gives way to delamination wear. To analyse the dispersoids phase in sub-surfaces, as well as the worn-out surface, and the distribution of LSP in the base material, a scanning electron microscope (SEM) and an optical microscope are used. The Taguchi Orthogonal Array (L25) is a candidate for use in estimating the best possible response. The effects of sliding distance and working load on WR and CF were shown to be statistically significant by analysis of variance (ANOVA).

Dai et al., (2017) [23] investigated that adding Fenton's reagent and lime allows for deep-dewatering of sludge, however, this process has limited use due to its high price tag. To improve the dewatering ability of sludge, a pre-treatment using Aerobic mesophilic digestion (AMD) and a novel method using Fenton's reagent and lime (F-L) are used. The findings showed that AMD pre-treatment shifted the distributions of EPS fractions in a way that benefited subsequent reconditioning, and that AMD with F-L considerably reduced “specific resistance to filtration (SRF)” by 96.53%. There was a strong correlation between the Tryptophan-like proteins and the Aromatic proteins of the soluble EPS and the dewatering ability of the sludge, which suggested that particle size reduction and surface modification were key contributors to the improvement in dewater ability observed. Further, by using a modifiable pressure filtering system, the combined treatment reduced the moisture of the dewatered sludge cake to around 47 wt%. Moreover, the early economic study indicated that treating AMD with F-L was cost-effective.

Jaworska et al., (2014) [24] analysed that a slurry called limestone slurry is produced during the washing step when processing limestone to make lime. The solid portion is carried by water, while the rest is made up of particles smaller than 2 mm in diameter. The settling tank receives

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
Article Received: 22 August 2022 Revised: 27 October 2022 Accepted: 19 November 2022

the slurry and separates the solid phase from the liquid phase while the transfer system recovers the surplus water for reuse. Tank sludge that has been collected is sent to an on-site landfill for disposal. Because of the resistance, it creates in the pipeline, the rheological qualities of limestone slurry prevent its unimpeded movement farther down the pipeline. Chemical treatment of drilling fluid, the primary goal of which is to provide the slurry with qualities amenable to hydro transport, might be used to ameliorate the current situation. The slurry is treated by adding an appropriate amount of chemical additives. Adding chemical compounds to an aqueous solution to disperse suspended particles is known as deflocculating, thinning, or dispersing. The results shows that the rheological parameters of limestone slurry with and without the inclusion of changed chemicals, which reduces the slurry's viscosity and, hence, the shear stress for the chosen shear rate. To get the outcomes that need, users will need to increase the dispersion of the solid phase inside the carrier liquid. This will allow the liquid to move more smoothly and with less resistance, once it is put under pressure.

1.1 Comparison of reviewed technique

The following study expands on the previous Wear rate Modelling and Analysis of Limestone Slurry Particulate Composites Using the Fuzzy Method; several researchers explain their findings as seen in table 1 below.

Table1. Comparison of reviewed techniques.

Authors[Ref.]	Technique	Outcome
Gautam et al., (2022) [20]	Dimensional limestone slurry waste	In this laboratory investigation, the use of dimensional limestone slurry waste as an additive was found to improve the characteristics of black cotton soil, making it suitable for use as a subgrade in flexible pavement.
Lokanadham et al., (2021) [21]	GFRG	Grey-fuzzy reasoning grade has been shown to increase the performance of wear behaviour features in the tribological process, as shown by experimental data.
Lokanadham et al., (2020) [22]	SEM	The effects of sliding distance and working load on WR and CF were shown to be statistically significant by analysis of variance (ANOVA).
Dai et al., (2017) [23]	AMD	The combined treatment reduced the moisture of the dewatered sludge cake to around 47 wt% by using a modifiable pressure filtering system.
Jaworska et al., (2014) [24]	Chemical treatment	The results shows that the rheological parameters of limestone slurry with and without the inclusion of changed chemicals, which reduces the slurry's viscosity.

2. Materials and Methods

- **Matrix**

The composite used in the current work uses Al-Si-Mg alloy as matrix metal and Limestone particulates as reinforcement material to fabricate the Al-LSP composites. Due to decent properties such as low density, moderate strength, superior corrosion resistance, and good castability Al-Si-Mg alloys are utilized as matrix material in the preparation of the composites. These properties make them a good choice for automotive applications like brake drums, cylinder liners, and connecting rod bearings of internal combustion engines. Table 2 depicts the chemical components that make up the matrix material.

Table 2: Chemical Composition of Al-Si-Mg Alloy

Si	Mg	Cu	Zn	Fe	Mn	Al
0.85%	0.35%	0.1%	0.1%	0.08%	0.05%	>98%

- **Reinforcement**

In the preparation of granite and marble which is predominantly used in the building of domestic and industrial infrastructure, the stone processing industry plays a key role. These industries produce large amounts of residue with different particle sizes. Recycling this stone dust waste is a significant factor in sustainable development,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
***Article Received**: 22 August 2022 **Revised**: 27 October 2022 **Accepted**: 19 November 2022*

---

thus the adverse effect of this residual waste on the environment would be minimized.

The reinforcing LSP in its wet condition was obtained from a stone-cutting factory located close to Tekkali, Andhra Pradesh, and goes by the name Siva Sai Granites. To remove the moisture content in the wet slurry, it is dried for 15 days followed by preheating for 3 hours (up to 300°C). The dry slurry is shifted to a ball mill for making fine particulates monitored by screening with 90 BSS mesh (≤ 60 µm). The fine LSP particulates have been utilized as reinforcement to fabricate AMCs. The detailed sequence of operations to prepare LSP is shown in Figure 2.

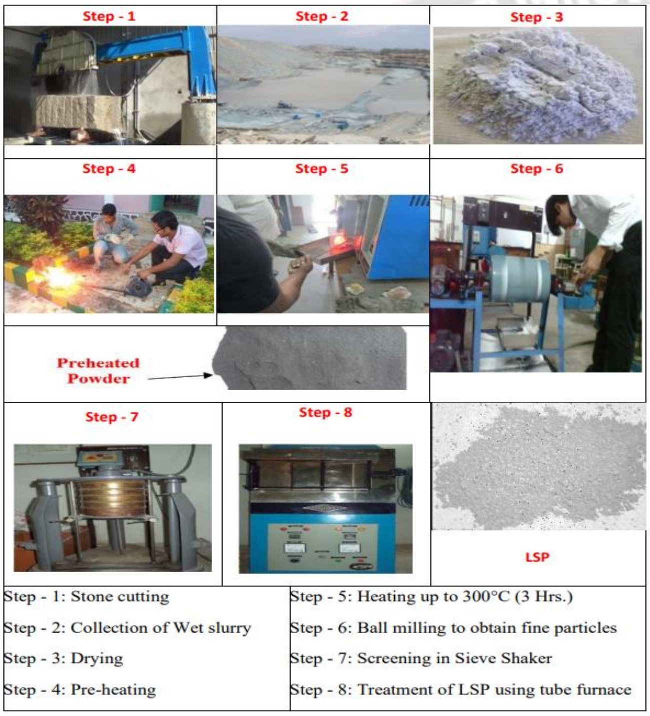

Figure 2. Stepwise Procedure to produce LSP.

- **Composite Preparation**

After examining the LSP through the standard scanning electronic microscope and Xray Diffractometer for various phases, then it is forwarded to fabricate the composite along with matrix material. The matrix material Al-Si-Mg alloy is cut into tiny pieces and then preheated to a temperature of 300ºC for 1 hour. The preheated material is transported to a vertical furnace maintained at 800ºC. The melting process is carried out in an inert (Argon) environment to prevent oxidation. The furnace is equipped with a speed regulating (PID controller) stirrer. The vortex is created by gradually lowering the spindle into the liquid pool. Simultaneously, the LSP (preheated up to 950°C) particles are dropped into the vortex. The spindle is gently agitated to ensure the even distribution of LSP particles in the molten liquid.

To retain the fine powder in the liquid pool, it is necessary to have a higher viscosity of the molten liquid. This is achieved by gradually lowering the temperature of the liquid pool from 800ºC to 750ºC. The above-molten liquid is then poured into a steel mould (100 × 20 × 40 mm^3) maintained at 400°C. Four Al-LSP composites are prepared by varying the weight percentage of LSP from 4 to 16 in steps of 4%.

- **Tests on Composite Specimens**

These Al-LSP composite specimens are subjected to various tests to study the mechanical properties related to their strength and toughness. Accordingly, the wear tests which are of interest in the current study are performed under dry sliding conditions on a pin-on-disc machine.

The diameter and length of the test samples are 6 mm and 27 mm, respectively, following ASTM G 99-95 specifications. Each sample is polished with 240 grit, followed by 320 grit, and finally 600 grit of silicon carbide emery paper before being tested. All of the tests are performed on a 50 mm circular track. Acetone was used to clean the test samples. The wear test experiment on Al-LSP composites along with the working principle is shown in Figures 3 and 4.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
***Article Received**: 22 August 2022 **Revised**: 27 October 2022 **Accepted**: 19 November 2022*

Figure 3. Specimens

Figure 4. Pin-On-Disc Apparatus

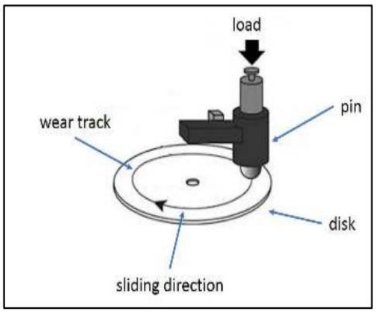

Figure 5. Working Principle

The weight loss is estimated by taking the difference of measured weights of test samples before and after each test by using an electronic balance. The wear rate is obtained by taking the ratio of volume loss to sliding distance. The frictional force divided by the normal load unit is used in the calculation of the average coefficient of friction. The wear rate is computed using the Equation,

$$\mathbf{W.R.} = \frac{\Delta \mathbf{m}/\rho}{\mathbf{v.t}} \qquad (1)$$

Where $\boldsymbol{\Delta m}$ is the mass loss of the alloy composite during the wear test in (g), **W.R**. is the wear rate in (mm^3/m), **V** is the sliding velocity (m/s), **ρ**is the density of the composite (g/cm^3), and **t** is the test duration (s).

- **Wear Rate Modelling**

In this research, the Fuzzy Logic Toolbox of MATLAB R2021b is used for fuzzy logic modelling. It is experiential that wear rate depends significantly on sliding distance (70.9%, $p = 0.000 < 0.05$), and then on load (19.9%, $p = 0.001 < 0.05$). Wear rate depends on sliding velocity only to a very small extent (5.5%, $p = 0.034 < 0.05$). To keep the fuzzy logic model simple enough, only the top 2 significant inputs are taken while modelling the responses. As the number of input variables grows, the number of membership rules to be written increases exponentially and this requires a lot of experience or information about the dependence of the response variables in terms of its input variables. Generally, such information is not available, and thus it is advisable to keep the fuzzy logic model simple. Thus, Fuzzy Wear Rate is assumed to be dependent on load and sliding distance only in the present work.

Fuzzy Wear Rate (F_WR) = f (Load, Sliding Distance)

Figure 6 shows that the Fuzzy Wear Rate depends on 2 inputs viz., load and sliding distance.

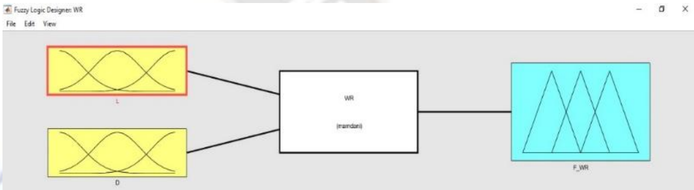

Figure 6.Fuzzy Interface System of Wear Rate.

- **Input and Output Membership Functions of Fuzzy Wear Rate**

In this research, Gaussian fuzzifiersare used as membership functions to fuzzify input control parameters load and sliding distance, along with the response wear rate. To better depict the smoothness of the transitions in the input and output variables from one zone to the next zone, Gaussian membership functions were chosen over the more frequent triangle and trapezoidal membership functions (without sharp function endings). In nature too, transitions from one zone to its adjacent zone are closer to the smoother Gaussian functions.

3 linguistic membership functions viz., Low (L), Medium (M), and High (H) are used for input parameters load and sliding distance. The Matlab Fuzzy Logic Toolbox's input variable load's Gaussian membership functions are detailed in Table 3. Figure 7 shows graphically the three Gaussian membership functions of the load input variable.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
***Article Received**: 22 August 2022 **Revised**: 27 October 2022 **Accepted**: 19 November 2022*

Table 3. Membership Function Specification of Load

Level	Symbol	Type of Function	Coded			
			Lower Limit	Upper Limit	Value1	Value2
Low	L	Zmf	0	1	0.00 Starting Point	0.4 Ending Point
Medium	M	gaussmf	0	1	0.15 Standard Deviation	0.5 Mean
High	H	Smf	0	1	0.60 Starting Point	1.0 Ending Point
Level	**Symbol**	**Type of Function**	**Actual**			
			Lower Limit	**Upper Limit**	**Value1**	**Value2**
Low	L	Zmf	10	50	10 Starting Point	26 Ending Point
Medium	M	gaussmf	10	50	6 Standard Deviation	30 Mean
High	H	Smf	10	50	34 Starting Point	50 Ending Point

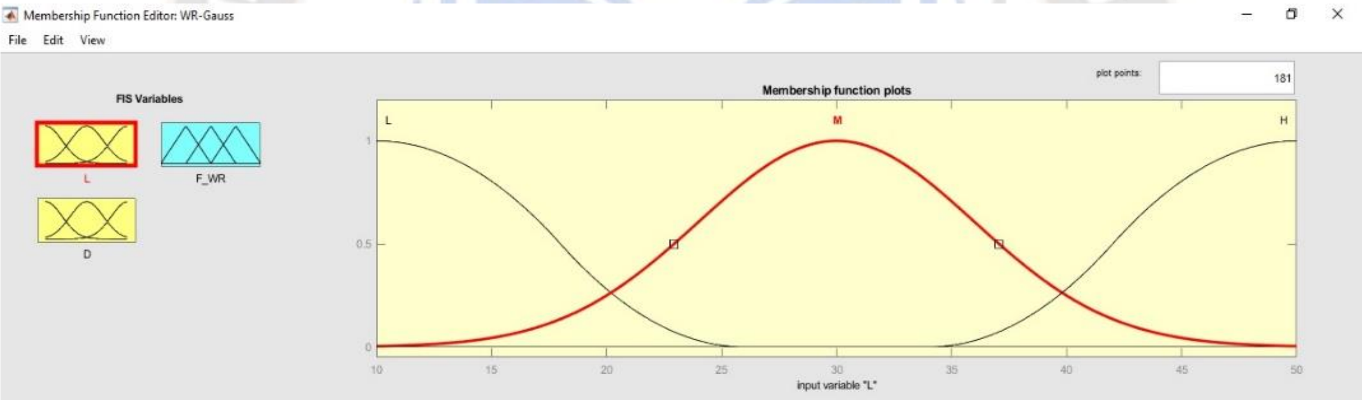

Figure 7 Membership Function of Load

Table 4 shows the specifications of Gaussian membership functions of input variable sliding distance.

Table 4. Membership Functions Specification of Sliding Distance.

Level	Symbol	Type of Function	Coded			
			Lower Limit	Upper Limit	Value1	Value2
Low	L	Zmf	0	1	0.00Starting Point	0.4Ending Point
Medium	M	Gaussmf	0	1	0.15Standard Deviation	0.5 Mean
High	H	Smf	0	1	0.60Starting Point	1.0Ending Point
Level	**Symbol**	**Type of Function**	**Actual**			
			Lower Limit	**Upper Limit**	**Value1**	**Value2**

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
***Article Received**: 22 August 2022 **Revised**: 27 October 2022 **Accepted**: 19 November 2022*

Low	L	Zmf	500	2500	500Starting Point	1300Ending Point
Medium	M	Gaussmf	500	2500	300Standard Deviation	1500 Mean
High	H	Smf	500	2500	1700Starting Point	2500Ending Point

Figure 8 shows graphically the 3 Gaussian membership functions of the sliding distance input variable.

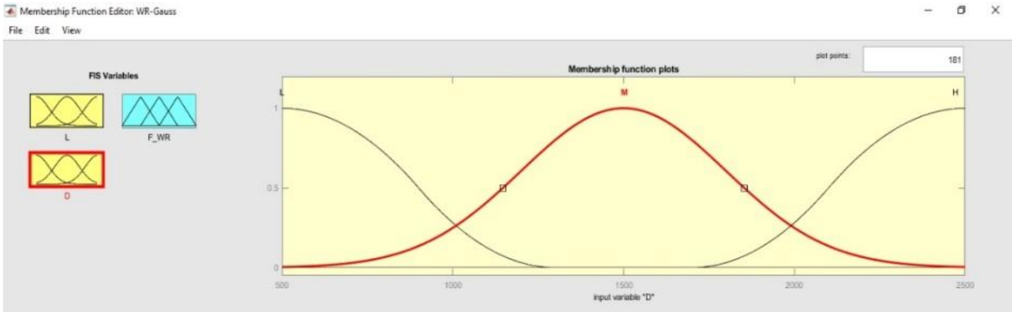

Figure 8 Membership Functions of Sliding Distance

5 linguistic membership functions viz., Low (L), Small-Medium (SM), Medium (M), High-Medium (HM), and High (H) are used for output response wear rate. For the output variable fuzzy wear rate, Table 8.3 details the requirements for the Gaussian membership functions.

Table 5 shows the specification of the 5 Gaussian membership functions used for output variable fuzzy wear rate.

Table 5. Membership FunctionsSpecification of fuzzy Wear Rate.

Level	Symbol	Type of Function	Coded			
			Lower Limit	**Upper Limit**	**Value1**	**Value2**
Low	L	zmf	0	1	0.000	0.25
Small-Medium	SM	gaussmf	0	1	0.078	0.25
Medium	M	gaussmf	0	1	0.078	0.50
High-Medium	HM	gaussmf	0	1	0.078	0.75
High	H	smf	0	1	0.750	1.00
Level	**Symbol**	**Type of Function**	**Actual**			
			Lower Limit	**Upper Limit**	**Value1**	**Value2**
Low	L	zmf	1	10	1.00 Starting Point	3.25 Ending Point
Small-Medium	SM	gaussmf	1	10	0.70 Standard Deviation	3.25 Mean
Medium	M	gaussmf	1	10	0.70 Standard Deviation	5.50 Mean
High-Medium	HM	gaussmf	1	10	0.70 Standard Deviation	7.75 Mean

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
***Article Received**: 22 August 2022 **Revised**: 27 October 2022 **Accepted**: 19 November 2022*

High	H	smf	1	10	7.75 Starting Point	10.00 Ending Point

Figure 9 shows graphically the 5 Gaussian membership functions of the fuzzy wear rate output variable.

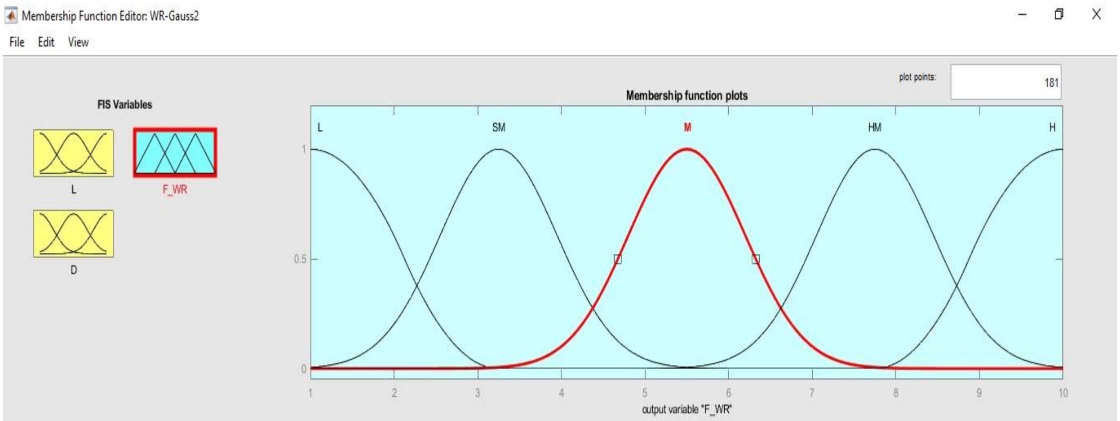

Figure 9. Membership Function of Fuzzy Wear Rate

- **Membership Function Rules for Fuzzy Coefficient of Friction**

Total of 9 fuzzy rules are developed for two input control parameters load, weight% of LSP and one output (coefficient of friction) using IF and THEN conditions (Table 6 & Figure 10) from the results obtained from L_{25} Taguchi experimental runs.

Table 6. Membership Rules for Fuzzy Coefficient of Friction (Load and weight%LSP)

L\R	L	M	H
L	SM	L	L
M	HM	M	SM
H	H	H	HM

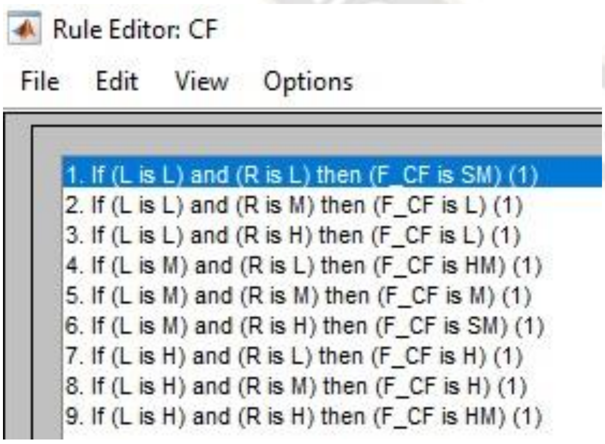

Figure 10. If/Then Conditions of Fuzzy Coefficient of Friction (Load and weight%LSP)

MATLAB allows viewing all the membership rules in a graphical surface format (Rules Surface). Figure 11 shows the Rules Surface for the Fuzzy Coefficient of friction.

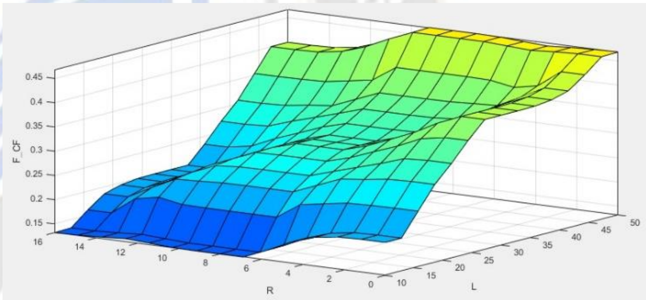

Figure 11. Rules Surface of Fuzzy Coefficient of Friction (Load and weight%LSP)

- **Defuzzification and Fuzzy Coefficient of Friction Calculation**

Using the centroid de-fuzzification technique, the defuzzifier transforms the fuzzy value into a clear result. Fuzzy Coefficient of friction is calculated for each of the Taguchi L_{25} data points by inputting the corresponding load and sliding distance values in the Rules Viewer Screen of MATLAB. Figure 12, shows the determination of the Fuzzy Coefficient of friction for the minimum coefficient of friction point where L = 10 N and R = 16% LSP.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5818
***Article Received**: 22 August 2022 **Revised**: 27 October 2022 **Accepted**: 19 November 2022*

Figure 12 Rule Viewer at Minimum Fuzzy Coefficient of Friction Point

- **Comparing the Fuzzy Coefficient of Friction with the Experimental Coefficient of Friction**

Table 7 shows the actual experimental coefficient of friction values obtained from Taguchi L_{25} along with the predicted Fuzzy Coefficient of friction values using the Fuzzy Logic model developed in this research. The error percentages vary from +15% to -35%. Thus the error percentages indicate that the developed fuzzy logic model for the fuzzy coefficient of friction with such limited input information is a reasonably good approximate model. Compared with the Fuzzy Wear Rate model, the Fuzzy Coefficient of Friction model is more accurate as it has a lesser error% when compared to experimental Taguchi L_{25} data.

Table 7. Comparison of Coefficient of Friction and Fuzzy Coefficient of Friction

Exp.No	L	R	D	V	CF	F_CF	%Error
1	10	0	500	0.500	0.311	0.202	-35%
2	10	4	1000	0.875	0.230	0.190	-17%
3	10	8	1500	1.250	0.182	0.131	-28%
4	10	12	2000	1.625	0.168	0.143	-15%
5	10	16	2500	2.000	0.186	0.130	-30%
6	20	0	1000	1.250	0.363	0.295	-19%
7	20	4	1500	1.625	0.267	0.281	5%
8	20	8	2000	2.000	0.205	0.234	14%
9	20	12	2500	0.500	0.259	0.223	-14%
10	20	16	500	0.875	0.200	0.180	-10%
11	30	0	1500	2.000	0.412	0.400	-3%
12	30	4	2000	0.500	0.397	0.357	-10%
13	30	8	2500	0.875	0.294	0.300	2%
14	30	12	500	1.250	0.229	0.243	6%
15	30	16	1000	1.625	0.267	0.200	-25%
16	40	0	2000	0.875	0.540	0.420	-22%
17	40	4	2500	1.250	0.389	0.377	-3%
18	40	8	500	1.625	0.317	0.366	15%
19	40	12	1000	2.000	0.308	0.319	4%
20	40	16	1500	0.500	0.398	0.305	-23%
21	50	0	2500	1.625	0.543	0.470	-13%
22	50	4	500	2.000	0.466	0.457	-2%
23	50	8	1000	0.500	0.487	0.469	-4%
24	50	12	1500	0.875	0.436	0.410	-6%
25	50	16	2000	1.250	0.418	0.398	-5%

3. Conclusions

Based on the results of the fuzzy analysis, it can be shown that the fuzzy values for wear rate, coefficient of friction, and grey relational grade are all in line with their classical counterparts. This suggests that the fuzzy logic model developed for predicting fuzzy wear rate and fuzzy coefficient of friction is reasonably accurate enough to be used for prediction purposes. However, whenever actual experimental data is available, always it should be used because fuzzy is an approximate model and never be better than actual experimental model results.

References

[1]. Pasha, Mudasar BA, and Mohammed Kaleemulla. "Processing and characterization of aluminium metal matrix composites: an overview." Reviews on Advanced Materials Science 56, no. 1 (2018): 79-90.

[2]. Hassan, S. B., and V. S. Aigbodion. "Effects of eggshell on the microstructures and properties of Al–Cu–Mg/eggshell particulate composites." Journal of King Saud University-Engineering Sciences 27, no. 1 (2015): 49-56.

[3]. Alaneme, Kenneth Kanayo, and Bethel Jeremiah Bamike. "Characterization of mechanical and wear properties of aluminium based composites reinforced with quarry dust and silicon carbide." Ain Shams Engineering Journal 9, no. 4 (2018): 2815-2821.

[4]. Alhawari, K. S., M. Z. Omar, Mariyam J. Ghazali, M. S. Salleh, and M. N. Mohammed. "Evaluation of the microstructure and dry sliding wear behaviour of thixoformed A319 aluminium alloy." Materials & Design 76 (2015): 169-180.

[5]. Singh, Jaswinder. "Fabrication characteristics and tribological behaviour of Al/SiC/Gr hybrid aluminium matrix composites: A review." Friction 4, no. 3 (2016): 191-207.

[6]. Altinkok, N., I. Özsert, and F. Findik. "Dry Sliding Wear Behavior of Al 2 O 3/SiC Particle Reinforced Aluminium Based MMCs Fabricated by Stir Casting Method." Acta Physica Polonica, A. 124, no. 1 (2013).

[7]. Yu, Kang, Yitian Peng, Haojie Lang, Shuyang Ding, and Yao Huang. "Material transfer mechanism for fabrication of superlubricity interface by reciprocating rubbing on graphite under high contact stress." Carbon 188 (2022): 420-430.

[8]. Baradeswaran, A., S. C. Vettel, A. Elaya Perumal, N. Selvakumar, and R. Franklin Issac. "Experimental investigation on mechanical behaviour, modelling and optimization of wear parameters of B4C and graphite reinforced aluminium hybrid composites." Materials & Design 63 (2014): 620-632.

[9]. Baradeswaran, A., and A. Elaya Perumal. "Wear and mechanical characteristics of Al 7075/graphite composites." Composites Part B: Engineering 56 (2014): 472-476.

[10]. Basavarajappa, S., G. Chandramohan, Arjun Mahadevan, Mukundan Thangavelu, R. Subramanian, and P. Gopalakrishnan. "Influence of sliding speed on the dry sliding wear behaviour and the subsurface deformation on hybrid metal matrix composite." Wear 262, no. 7-8 (2007): 1007-1012.

[11]. Gonçalves, Aparecido Carlos, Daniel Fabiano Lago, and Maria da Consolação Fonseca de Albuquerque. "Maintenance of Reducers with an Unbalanced Load Through Vibration and Oil Analysis Predictive Techniques." Recent Advances in Vibrations Analysis. InTech, on line (2011): 81-102.

[12]. Sharma, Rakesh Chandmal, Sakshi Sharma, Sunil Kumar Sharma, Neeraj Sharma, and Gurpreet Singh. "Analysis of a bio-dynamic model of seated human subject and optimization of the passenger ride comfort for a three-wheel vehicle using random search technique." Proceedings of the Institution of Mechanical Engineers, Part K: Journal of Multi-body Dynamics 235, no. 1 (2021): 106-121.

[13]. Bhardwaj, Sono, Rakesh Chandmal Sharma, and Sunil Kumar Sharma. "Development of multibody dynamical using MR damper based semi-active bio-inspired chaotic fruit fly and fuzzy logic hybrid suspension control for a rail vehicle system." Proceedings of the institution of mechanical engineers, Part K: journal of multi-body dynamics 234, no. 4 (2020): 723-744.

[14]. Gopala Rao, L. V. V., Rakesh Chandmal Sharma, V. S. V. Satyanarayana, and Srihari Palli. "Stochastic optimal preview control response of a quarter-car nonlinear suspension model using spectral decomposition method." Noise & Vibration Worldwide (2022): 09574565221093234.

[15]. Sharma, Rakesh Chandmal, Srihari Palli, M. Avesh, and Neeraj Sharma. "Vibration Isolation of Railway Vehicle Car body using Semi-active Suspension." International Journal of Vehicle Structures & Systems (IJVSS) 13, no. 4 (2021).

[16]. Palli, Srihari, Raghuveer Dontikurti, Rakesh Chandmal Sharma, and Neeraj Sharma. "Analysis of Dynamic Response of a Railway Locomotive Using ANSYS." International Journal of Vehicle Structures & Systems (IJVSS) 13, no. 2 (2021).

[17]. Sharma, Rakesh Chandmal, Srihari Palli, and Ramji Koona. "Stress and vibrational analysis of an Indian railway RCF bogie." International Journal of Vehicle Structures & Systems 9, no. 5 (2017): 296-302.

[18]. Sharma, Rakesh Chandmal. "Ride, eigenvalue and stability analysis of three-wheel vehicle using Lagrangian dynamics." International Journal of Vehicle Noise and Vibration 13, no. 1 (2017): 13-25.

[19]. Palli, Srihari, Rakesh Chandmal Sharma, and P. P. Rao. "Dynamic Behaviour of a 7 DoF Passenger Car Model." International Journal of Vehicle Structures & Systems (IJVSS) 9, no. 1 (2017).

[20]. Gautam, Pradeep Kumar, Pravesh Saini, Pawan Kalla, Ajay Singh Jethro, and Harshwardhan Singh Chouhan.

"Performance Analysis of Black Cotton Soil Treated with Dimensional Limestone (Kota Stone) Slurry Waste." In *Proceedings of the Fifth International Conference of Transportation Research Group of India*, pp. 179-192. Springer, Singapore, 2022.

[21]. Lokanadham, D., and K. Venkata Subbaiah. "Estimation of tribological performance of Al-LSP composites using grey–fuzzy reasoning approach." In *IOP Conference Series: Materials Science and Engineering*, vol. 1070, no. 1, p. 012120. IOP Publishing, 2021.

[22]. Lokanadham, D., and K. V. Subbaiah. "Estimation of wear behavioural response of al-limestone slurry composite using Taguchi orthogonal array." *Tribology in Industry* 42, no. 3 (2020): 419.

[23]. Dai, Yongkang, Shaosong Huang, Jialin Liang, Siwei Zhang, Shuiyu Sun, Bing Tang, and Qizhi Xu. "Role of organic compounds from different EPS fractions and their effect on sludge dewaterability by combining anaerobically mesophilic digestion pre-treatment and Fenton's reagent/lime." *Chemical Engineering Journal* 321 (2017): 123-138.

[24]. Jaworska, Beata, and Artur Bartosik. "The influence of additives on rheological properties of limestone slurry." In *Journal of Physics: Conference Series*, vol. 530, no. 1, p. 012052. IOP Publishing, 2014.