# Fuzzy Logic-Based Model for Predicting Material Removal Rate of Machined Cupola Slag-Reinforced Aluminum Metal Matrix Composite

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## 1 Introduction

The modern era of innovation needs economic new-age materials which have high strength-to-weight ratios and can accommodate tailored properties. Composites can be a great alternative for that fact, although the cost of composite fabrication is very high. The fabrication cost of composites can be reduced by using low-cost fabrication processes like stir casting and using economic reinforcement derived from industrial wastes such as cupola slag. Cupola slag is an industrial waste that can be reused as reinforcement in metal matrix as it contains hard ceramics like $Al_2O_3$, $SiO_2$, CaO, etc. [1]. Aluminum and its alloys are great to be used as matrix materials in composites due to their lightweight and higher conductivity and low melting point. The development of economic composites requires successful fabrication which should be followed by quantitative and qualitative studies of finishing operations such as machining. Machinability can be defined as the ease of machining. One of the most important parameters of machinability is the material removal rate (MRR). Turning is one of the most used machining processes. The MRR analysis in turning requires extensive experimentation and analysis. The experiment should be designed statistically to reduce materials and time loss following techniques such as Taguchi L9 orthogonal array. Taguchi L9 orthogonal array provides the most accurate analysis

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with a minimal number of experiments. Further analysis of MRR requires mathematical modeling. Regression analysis is a simple and well-established mathematical model for MRR prediction. New soft computing-based prediction techniques like fuzzy prediction are believed to provide more accurate predictions. Fuzzy logic-based prediction is based on the principle of human intuition. Fuzzy logic takes various true values between 0 to 1 mimicking human behavior. The crisp input values are converted to linguistic variables which are then passed through pre-defined sets of fuzzy IF–THEN rules to predict the linguistic values of output. These outputs are converted to crisp prediction values.

Attempts have been made to analyze machinability in dry turning of aluminum metal matrix composites (AMCs) in terms of MRR in the present academia. Kesarwani et al. [2] have investigated MRR in hybrid eggshell, boron carbide-reinforced AMCs and concluded that MRR has been improved in presence of a second phase when compared with monolithic alloy. MRR in dry turning of discontinuous $SiC_p$-reinforced Al 7075 matrix has been analyzed by the gray Taguchi approach in the works of Das et al [3]. The MRR was observed to have an increasing trend with increasing cutting speed, feed, weight percentage of reinforcements. Kumar et al. [4] have investigated stir-casted Al/SiC/Mo-reinforced AMCs MRR in dry turning. The results indicate that maximum MRR has been achieved while turning at a high depth of cut, feed and cutting speed. The fuzzy logic-based prediction of MRR in turning has been discussed in the works of Saradhi et al. [5]. The results show valid fuzzy logic prediction with a percentage error of 7.49%. Sharma et al. [6] predicted cutting force in hard turning operations using fuzzy logic and compared it with regression prediction. The authors have concluded that fuzzy prediction is more accurate. The literature survey indicates that MRR analysis in turning of AMCs is adequate, but fabrication and machinability studies on cupola slag-reinforced AMCs are found to be scarce.

In this work, cupola slag-reinforced LM11 matrix composites have been fabricated using the stir casting route. Machinability of cast composites has been analyzed in terms of MRR in dry turning. Spindle speed, feed rate and weight percentage of cupola slag have been chosen as process parameters for turning. The effect of process parameters on MRR has been studied in detail. MRR prediction using regression and fuzzy model has been established and an elaborate comparative study between the models has been presented.

## 2 Materials and Methods

### *2.1 Materials*

Al-4.5-Cu or LM 11 has been chosen as the matrix of the composites due to its lightweight and high strength moreover LM11 has shown great response to solution heat treatment. 99% pure LM 11 has been procured from M/S Kolkata Die Casting,

**Table 1** Chemical composition of LM 11

| Elements | Cu | Mg | Si | Fe | Mn | Ni | Zn | Pb | Sn | Ti | Al |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Wt.% | 4.5 | 0.1 | 0.25 | 0.25 | 0.1 | 0.1 | 0.1 | 0.05 | 0.05 | 0.3 | Bal |

**Table 2** Chemical composition of Cupola slag

| Elements | $SiO_2$ | $Fe_2O_3$ | $Al_2O_3$ | CaO | MnO | MgO | $TiO_2$ | $K_2O$ | $SiO_2$ | $Fe_2O_3$ | Oxides |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Wt.% | 53.1 | 16.1 | 11.1 | 10.7 | 3.33 | 1.94 | 1.22 | 1.05 | 53.1 | 16.1 | Bal |

Liluah, Howrah. The chemical composition of LM 11 as observed using XRF has been shown in Table 1. Composites can be fabricated by using low-cost reinforcement developed from industrial waste cupola slag. Bolder like cupola slag chunks has been fetched from M/s Binoy Udyog Pvt. Ltd., Andul, Howrah. The slag has been ball milled and sieved to an average particle size of 100 μm. The chemical composition of developed cupola slag reinforcement particles has been analyzed using XRF, and the results have been reported in Table 2.

## 2.2 *Fabrication of Cast Composites*

The stir casting has been performed in vacuum-assisted bottom pouring type stir casting setup supplied by SWYAMEQUIP, Chennai. The weighted amount of LM 11 ingots has been melted in a graphite crucible at 750 °C and at the same time 3% weight percent of developed cupola slag particles (average particle size 100 μm) has been pre-heated to 300 °C in a powder pre-heating furnace. After the complete melting of the LM 11 ingots, mechanical stirrer has been pulled down into the molten metal, and a stirring speed of 500 rpm has been maintained to initiate a vortex in the molten metal. The pre-heated cupola slag particles have been poured into the vortex while stirring. The stirring continues for another 8–10 min with a stirring speed of 600 rpm to ensure homogeneous particle distribution. The spilt-type steel mold has been positioned parallel to the bottom pouring valve after pre-heating to 400 °C to achieve defect less casting. Vacuum pressure has been set to $10^{-2}$ mbar using a vacuum pump. The bottom pouring valve has been opened after the proper mixing of particles. The molten metal has been poured to mold due to gravity and left for solidification for 24 h. Upon solidification, 3wt.% cupola slag-reinforced LM 11 matrix composite has been fabricated. Similar methods have been followed for the fabrication of 5 and 7 wt.% cupola slag-reinforced cast composites.

**Table 3** Input parameters along with their levels [10]

| Parameters | Unit | Low (L) | Medium (M) | High (H) |
|---|---|---|---|---|
| Spindle speed (N) | rpm | 495 | 620 | 800 |
| Feed rate (f) | mm/rev | 0.083 | 0.109 | 0.125 |
| Weight percentage (w) | Wt.% | 3 | 5 | 7 |

## *2.3 Taguchi Experimental Design*

The machinability studies in terms of material removal rate have been performed in dry turning. The process parameters for turning have been chosen as spindle speed (rpm), feed rate (mm/rev) and weight percentage (wt.%) as these are the most effective parameters in turning of cast composites as per established academia [7]. MRR has been chosen as a response parameter as it is one of the most important aspects of machinability. The depth of cut has been deliberately kept constant as 1 mm, in the investigation as the effect of depth of cut on MRR has been found to be nominal in the literature [8, 9].

The experiments have been designed by using 3 factors 3 levels Taguchi L9 orthogonal array. The experimental design and analysis have been performed on Minitab 18 software. The levels of process parameters have been selected as per intuition from academia and pilot experiments and are shown in Table 3 [7–9].

## *2.4 Fuzzy Prediction Modeling*

In this work, experimental investigation has been used to formulate a fuzzy prediction model in MATLAB R2022b. A Mamdani max–min fuzzy interface system has been designed using three inputs, and one output as the Mamdani system is one of the simplest and most accurate processes to predict response [11]. The input variables and output response have been fuzzified by converting the crisp value to linguistic variables of low (L), medium (M) and high (H) as shown in Table 3. The membership functions have been defined as per intuition from the experimental results and literature survey [11]. Triangular membership function has been chosen for all the variables to simplify the prediction model which is given as,

$$\mu_{\text{Triangle}}(x; L, M, H) = \begin{cases} 0, & x \le L \\ \frac{x-L}{M-L}, & L \le x \le M \\ \frac{H-x}{H-M}, & M \le x \le H \\ 0, & H \le x \end{cases}$$
$$= \max\left(\min\left(\frac{x-L}{M-L}, \frac{H-x}{H-M}\right), 0\right) \quad (1)$$

**Table 4** Fuzzy IF–THEN rules

| Rule no. | IF (AND operation between the parameters) | | | THEN |
|---|---|---|---|---|
| | Spindle speed | Feed rate | Weight percentage | MRR |
| 1 | L | L | L | L |
| 2 | L | M | M | M |
| 3 | L | H | H | H |
| 4 | M | L | M | L |
| 5 | M | M | H | M |
| 6 | M | H | L | M |
| 7 | H | L | H | M |
| 8 | H | M | L | H |
| 9 | H | H | M | H |

The fuzzy rules in terms of linguistic variables have been shown in Table 4. In Table 4, parameters under IF are the inputs, and the parameter under THEN column is the output or conclusion.

## 2.5 *Methodology*

**Setup.** The dry tunning experiments have been carried out in conventional engine lathe in Blue Earth Machine Shop, Jadavpur University, Kolkata. CNMG 120408 coated carbide tool with tool holder DCLNR2020K12 has been used as cutting tool. The cutting length has been taken as 50 mm. The weight of samples before and after machining has been measured using high precision industrial weighing machine Mettler Toledo—BBA236-4A3N.

**Procedure**. The MRR has been measured using weight loss method, the weight of cast composite has been measured before and after machining and the machining time has been noted. Then the MRR has been calculated by,

$$\text{MRR} = \frac{W_i - W_f}{t}\ \text{g/min}, \tag{2}$$

where, $W_i$ is the initial weight, $W_f$ is the final weight and $t$ is machining time.

The measured MRR has been analyzed using Taguchi main effect plots. A regression model has been developed to predict the MRR for same set of data points. Fuzzy prediction model has been applied to predict the same. The comparison between experimental, regression and fuzzy prediction has been investigated. The flow chart of the methodology has been shown in Fig. 1.

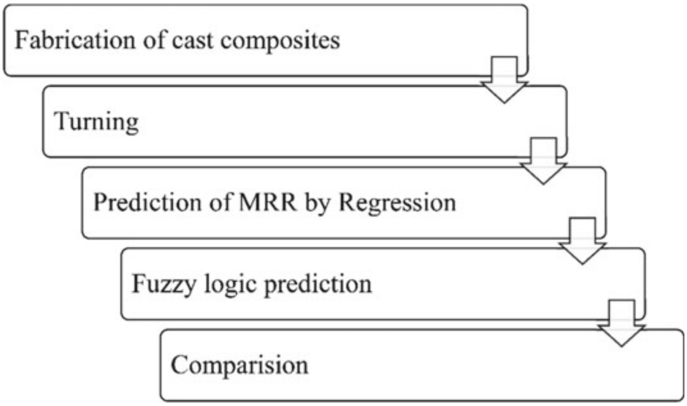


**Fig. 1** Flow chart of experimental investigation

# 3 Results and Discussions

## *3.1 Taguchi Results*

The results of the experimental investigations have been reported in Table 5. It is evident from main effect plot shown in Fig. 2 that with increasing spindle speed, MRR decreases slightly and then increases at highest speed. This is due to the fact that with increasing spindle speed, increases the tool workpiece temperature which initiates strain hardening which reduces the MRR [12]. Further increase in spindle speed increases the interface temperature to an extent, where MRR increases due to thermal softening of the workpiece [13]. The effect of spindle speed on MRR found in agreement with established academia [14]. The MRR observed to be increase with increasing feed rate. This is attributed to the fact that with increasing feed rate, the contact area between cutting tool and work piece increases which results in higher MRR. The similar trend of increasing MRR with feed rate increase has been reported in the works of Yin et al. [15] and Sharma et al. [6]. The MRR has been investigated to increase with an increasing weight percentage of cupola slag. This is due to the fact that an increase in weight percentage increases the presence of cupola slag particles in the matrix. These particles increase porosities and dislocations in the matrix which act as crack generation sites and eases the machining process. This leads to an increase in MRR with an increasing weight percentage.

**Table 5** Experimental results

| Exp no. | Spindle speed | Feed rate | Weight percent | MRR (g/min) | | |
|---|---|---|---|---|---|---|
| | | | | Experimental | Regression | Fuzzy |
| 1 | 495 | 0.083 | 3 | 7.50 | 7.91 | 7.79 |
| 2 | 495 | 0.109 | 5 | 13.85 | 11.86 | 11.7 |
| 3 | 495 | 0.125 | 7 | 15.00 | 14.46 | 14.5 |
| 4 | 620 | 0.083 | 5 | 9.23 | 9.51 | 9.08 |
| 5 | 620 | 0.109 | 7 | 11.54 | 13.46 | 10.7 |
| 6 | 620 | 0.125 | 3 | 13.33 | 14.71 | 13.4 |
| 7 | 800 | 0.083 | 7 | 12.00 | 11.63 | 11.7 |
| 8 | 800 | 0.109 | 3 | 15.00 | 14.22 | 14.9 |
| 9 | 800 | 0.125 | 5 | 17.14 | 16.82 | 16.8 |

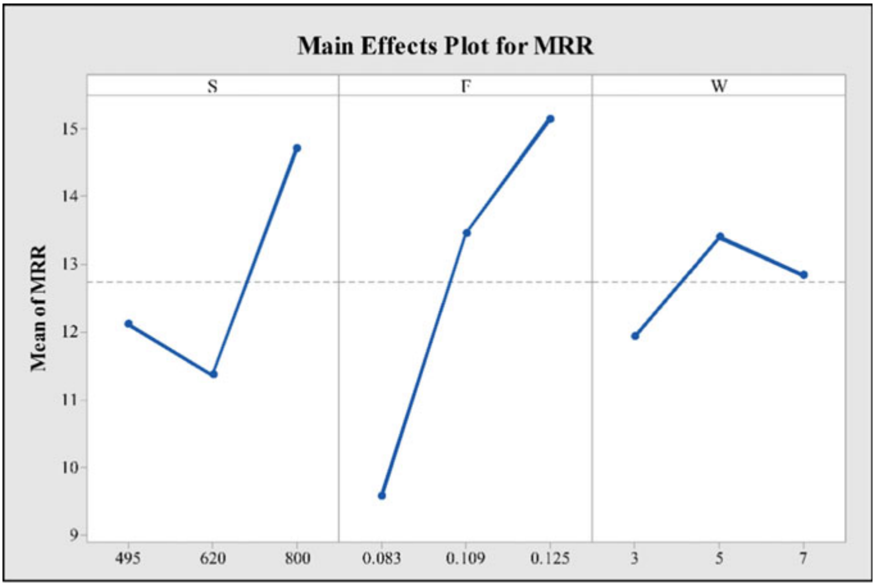


**Fig. 2** Main effect plots of MRR

### 3.2 Regression Results

The results of regression analysis have been shown in Table 5. The linear regression has been adopted for finding the regression equation. The regression equation has been given as,

$$\mathrm{MRR} = -8.50 + 0.00923S + 134.5F + 0.225W, \tag{3}$$

where $S$, $F$ and $W$ are spindle speed, feed rate and weight percentage, respectively. The value predicted from the regression equation has been presented in Table 5.

### 3.3 Fuzzy Logic Prediction

The prediction using fuzzy logic has been reported in Table 5. The predictions have been observed using rule viewer in MATLAB and reported in Table 5. Table 5 indicates prediction to be valid as the predicted data is maps with the experimental results.

### 3.4 Comparison

The comparison of fuzzy and regression prediction has been analyzed based on root mean squared error (RMSE). The comparison table along with residual and RMSE values has been shown in Table 6. The RMSE value found to be less in case of fuzzy prediction. Figure 3a shows the prediction plot for regression and fuzzy. It is evident from Fig. 3a that fuzzy logic prediction results are nearer to the experimental results. Residual plots of regression and fuzzy prediction have been shown in Fig. 3b for better comparison. Figure 3b indicates that the residuals for regression model are larger when compared with residuals of fuzzy prediction. Figure 3b also shows that the residuals for both fuzzy prediction and regressions are random which indicates that the models are free from inherent error thus can be treated as valid. The similar results in comparison of fuzzy logic prediction and regression prediction have been found in the works of Sharma et al. [6] and Amir et al. [11]. Comparison of predictions along with experimental values has yield error of 1.10% and 0.81% for regression and fuzzy-based model, respectively, as per Table 6. The fuzzy-based model yields more accurate result due to the fact that fuzzy logic is soft computing-based method in which model learns the trends of output by intuition from the experimentation thus yields more accurate results [6].

**Table 6** Comparison between experimental, regression and fuzzy prediction in terms of residual and RMSE

| Exp no | MRR | | | Residuals | | Residual squared | |
|---|---|---|---|---|---|---|---|
| | Exp | Regression | Fuzzy | Regression | Fuzzy | Regression | Fuzzy |
| 1 | 7.50 | 7.91 | 7.79 | −0.41 | −0.29 | 0.17 | 0.08 |
| 2 | 13.85 | 11.86 | 11.7 | 1.99 | 2.15 | 3.95 | 4.61 |
| 3 | 15.00 | 14.46 | 14.5 | 0.54 | 0.50 | 0.29 | 0.25 |
| 4 | 9.23 | 9.51 | 9.08 | −0.28 | 0.15 | 0.08 | 0.02 |
| 5 | 11.54 | 13.46 | 10.7 | −1.92 | 0.84 | 3.70 | 0.70 |
| 6 | 13.33 | 14.71 | 13.4 | −1.38 | −0.07 | 1.90 | 0.00 |
| 7 | 12.00 | 11.63 | 11.7 | 0.37 | 0.30 | 0.14 | 0.09 |
| 8 | 15.00 | 14.22 | 14.9 | 0.78 | 0.10 | 0.61 | 0.01 |
| 9 | 17.14 | 16.82 | 16.8 | 0.32 | 0.34 | 0.10 | 0.12 |
| RMSE (%) | | | | | | 1.10 | 0.81 |

## 4 Conclusions

The objective of this experimental work is to successfully fabricate cupola slag-reinforced LM11 metal matrix composite along with machineability studies in terms of MRR. The regression and fuzzy-based prediction model have been developed and validated. The experimental investigation can be concluded as:

- Successful fabrication of 3, 5, 7 wt.% cupola slag-reinforced LM11 composites has been achieved using stir casting route.
- The MRR has been observed to have increasing trend with increasing spindle speed, feed and weight percentage.
- The regression and fuzzy-based prediction model have been compared with experimental results and has an RMSE error of 1.10% and 0.81%, respectively.
- The fuzzy prediction model observed to have better prediction when compared with regression model.

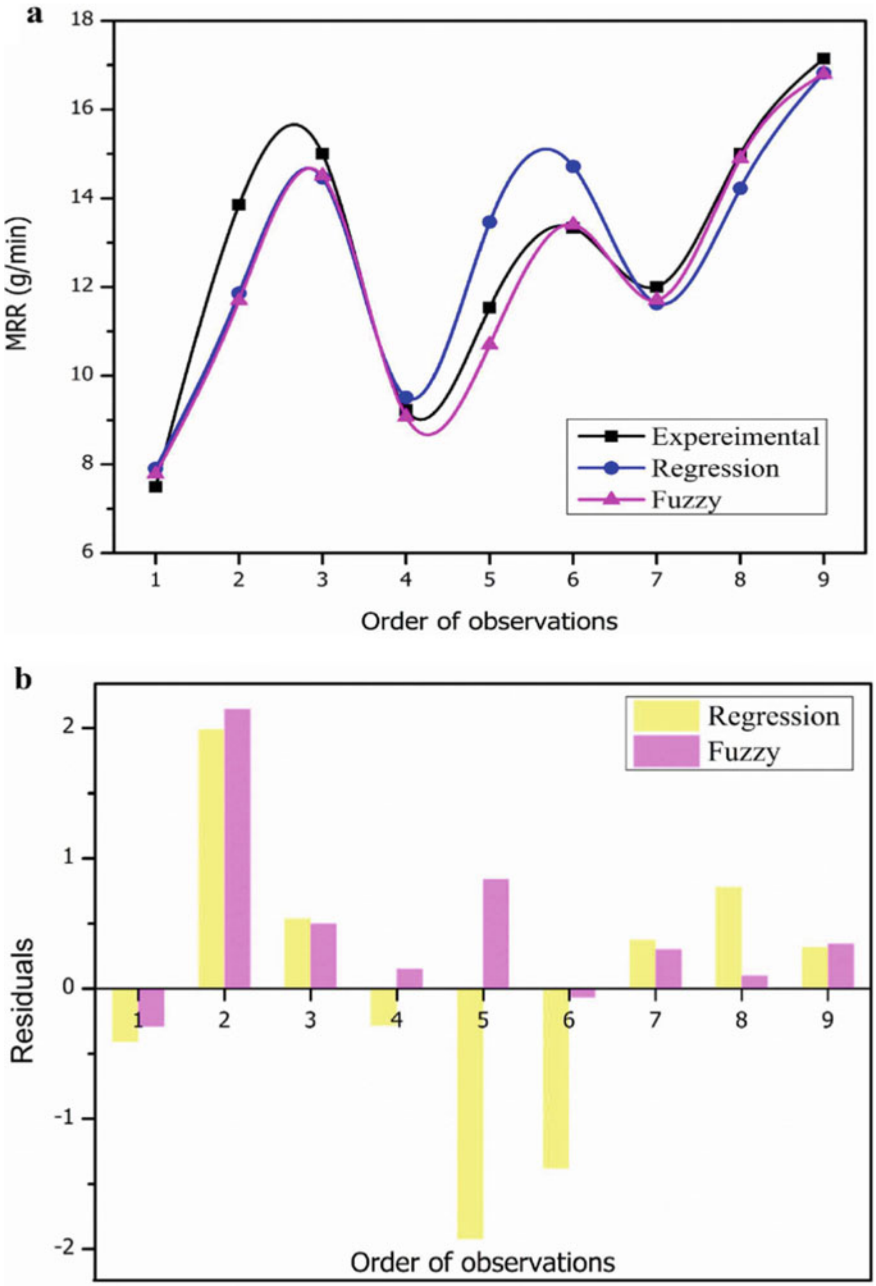


**Fig. 3** **a** Prediction plot for regression and fuzzy logic, **b** residual plot for regression and fuzzy

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