Modelling Centrifugal Disc Finishing Process Using the Fuzzy Rule-Based Method

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Abstract.
Mass Finishing (MF) is a mechanical process extensively utilized to achieve the desired surface finish on a considerable volume of small parts or small batches of parts with complex geometrical feature. The adoption of MF technology is increasing as it meets the growing requirements for surface finish and quality, particularly in critical operations for super-finishing components in biomedical, auto-sport and aerospace engineering. However, understanding how to effectively modify or refine operations to achieve desirable outcomes for diverse parts and target criteria remains a challenge. This challenge stems from the considerable numbers of process variables that necessitate control, encompassing abrasive media type, processing time, workpiece materials and machine speed. In this paper, a feasible study has been conducted to optimize surface finishing processes on a centrifugal machine. A fuzzy rule-based system has been proposed, which involves defining the input and output parameters, creating fuzzy sets and membership functions, and defining rules that describe the relationship between the input and output parameters. The fuzzy logic model is implemented through the utilization of MATLAB software. The results indicate the effectiveness of the proposed method in modelling surface finishing processes and achieving consistent outcomes.

Introduction

Mass finishing (MF), also referred to as loose abrasive finishing, is a mechanical process used for burnishing, deburring, clearing, polishing, and other surface finishing operations on engineering components, ranging from small batches to large quantities. In recent decades, interest in this technology has rapidly accelerated across various sectors, driven by the need for cost-effective, consistent quality and precise finishing. Among the most widely used MF processes, the centrifugal disc finishing presents a high-energy approach that offers a compelling alternative to traditional vibratory processing methods. This type machining operates by immersing workpieces in a bowl filled with abrasive particles. The bottom disk of the bowl rotates, generating a rolling motion that propels the workpieces and media to flow in a helical path around the bowl. The resulting high pressure and relative movement between the workpieces and media produce an intensive grinding action. However, the centrifugal disc machine process lacks control due to its free motion manner, resulting in only specific areas of the samples being exposed to the finishing media. Consequently, this can lead to uneven treatment of the sample surface [1, 2]. Furthermore, this media-based finishing process is complex and often requires more energy. To enable centrifugal disc finishing as an effective and efficient operation, it is crucial to establish predictability so as to replace the commonly used traditional approach (trial-and-error) in process design. This is necessary to avoid the energy loss and waste of resources during the finishing process.

Artificial intelligence (AI) refers to the simulation of human intelligence processes, incorporating computer science and comprehensive datasets to facilitate decision-making and problem-solving. The rapid progress of AI has resulted in the creation and utilization of potent computing tools across diverse real-world industrial domains. A notable example is the application of AI in abrasive surface finishing processes (AFM), where predictive modeling and optimization play a significant role. Previous studies have employed various AI approaches for performance prediction, such as Artificial Neural Network (ANN), Fuzzy logic (FL), and Genetic algorithm (GA), among others [3-7]. One of the earliest studies focusing on the optimization of surface finishing processes was conducted by Lam and Smith [3], who employed ANN to model the abrasive flow machining of automotive engine intake manifolds. The study considered multiple input variables, including samples, AFM machining settings, media conditions, and ambient conditions, while the output parameter of interest was the total air flow. The results obtained from their preliminary ANN model indicated its capability to make predictions. Similarly, Petri et al. [4] developed a predictive process modeling system utilizing ANN to forecast surface finish and dimensional changes in an abrasive flow machining process, which was validated and confirmed to be reliable. Jain et al. [5] proposed a straightforward predictive model for the abrasive flow machining process, employing a back-propagation neural network. The model was designed based on conducted experiments, and the results demonstrated a notable agreement between the predictive model and both experimental and theoretical outcomes (with an error of only 0.25% up to 8.95%).

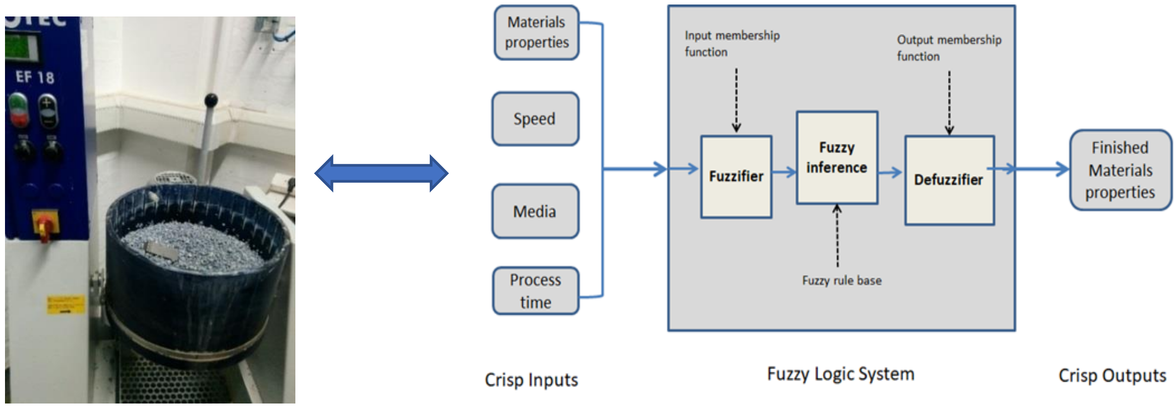
However, in the realm of mass finishing processes, there has been limited research conducted on the application of AI modeling. To the best of the author's knowledge, Vijayaraghavan and Castagen [6] have made some relevant contributions in this area. They investigated power consumption and material removal rate in a mass finishing process utilizing a vibration machine. Their analysis involved two distinct approaches: Gene Expression Programming (GEP) and ANN to analyse the process. The findings of their study highlight the importance of effectively controlling the media factor to achieve an environmentally friendly mass finishing process. Furthermore, they developed a predictive model for surface roughness using a combined GEP–ANFIS approach in their subsequent studies, which yielded similar conclusions [7]. However, there was no optimization work has been conducted in their studies.

This paper aims to address the existing research gap by developing a comprehensive predictive model for mass finishing processes, with a specific focus on centrifugal disc finishing. Additionally, it seeks to investigate and optimize the process parameters, including media, machine speed, processing time and sample material, to achieve the desired surface finish. The integration of predictive modeling in this study will significantly contribute to advancing the understanding of mass finishing processes and provide practical guidance for achieving enhanced surface finish in industrial applications.

Experimental Details

In this study, all tests were conducted using an OTEC – CF18 element series centrifugal disc finishing machine (Fig.1 (a)). The machine comprises an open-top bowl with a diameter of 330 mm, a control unit, and a manual separating unit. The workpieces used in the study were rectangular-shaped black mild steel, bright steel, stainless steel and additive manufactured steel, each measuring 50 mm × 20 mm × 5 mm. Conical-shaped plastic media and pyramid-shaped ceramic media were utilized for the tests. Prior to conducting the experiments, all workpieces underwent thorough cleaning, drying, and measuring. Surface roughness and hardness measurements were carried out using Taylor Hobson - Series 1 and Mitutoyo Rockwell machines, respectively. Each measurement was repeated three times for every individual workpiece. For the experimental setup, the centrifugal disc finishing machine was filled with 18 liters of media, and the workpieces were carefully positioned within the finishing bowl in conjunction with the media. After finishing, the workpieces were removed from the machine and cleaned in an ultrasonic bath to remove any impurities that could affect the measurements.

The selection of input and output variables for this study is summarized in Table 1. Four input parameters were considered: workpiece material, media type, machine speed and process time. These variables were chosen to investigate their influence on the desired outcomes. The output parameters measured in the study were surface roughness (Ra). These variables were selected as indicators of the quality and characteristics of the finished workpieces. Prior to constructing the predictive model, it is essential to perform preprocessing and analysis on the collected raw data. The initial step involves identifying and rectifying any inconsistencies or faults present in the dataset. Subsequently, a correlation analysis is conducted to examine the relationship between the input and output parameters. To assess this correlation, the Pearson correlation coefficient and p-value are used.



(a) **(b)**

Fig.1. (a) Diagram of a centrifugal disk finishing machine, (b) modelling of the finishing process using a fuzzy rule-based method

Table 1 Input Variables for centrifugal disc finishing machine experiments

Materials	Medias	Speed (rpm)	Process time (mins)
Black Mild Steel	Plastic (conical shape)	150	0
Bright Steel	Ceramic (pyramid shape)	190	20
Stainless Steel		230	40
Additive Manufactured Steel		270	60
			80
			100
			120
			180

Fuzzy rule-based systems (FRBSs) Model Development

In this study, a data-driven modeling method is employed, utilizing fuzzy rule-based systems (FRBSs) to facilitate mapping and generalization capabilities as shown in Fig.1 (b). FRBSs are adept at learning from data and predicting complex relationships, while requiring minimal or no prior knowledge about the system being studied [8]. Fuzzy rule-based systems (FRBSs) offer a higher level of transparency and interpretability compared to many other black-box modeling techniques. This attribute stems from the utilization of linguistic descriptive "If-Then" rules within FRBSs, allowing for direct interpretation by human experts. Given the context of the present study, where the available dataset is relatively small, FRBSs emerge as a suitable modeling approach. An example of IF-Then statement is given below (Eq.1):

$$\textbf{IF } X_1 \text{ is } A_1, X_2 \text{ is } A_2 \ldots \text{ and } X_n \text{ is } A_n \textbf{ THEN } Y \text{ is } B \quad (1)$$

where X_1, X_2 ,..., X_n and Y are input and outputs linguistic variables, respectively. A_1, A_2 ,..., A_n is antecedent fuzzy sets and B is consequent fuzzy set.

A conventional approach to constructing fuzzy rule-based models involves generating fuzzy membership functions and fuzzy rules based on knowledge acquired from field experts. However, the availability of experts may be limited, and their knowledge may lack accuracy, consistency, and completeness. With the increasing availability of data, data-driven modeling has become feasible and practical. In data-driven fuzzy modeling methods, various learning, and optimization techniques, such as evolutionary computation and multi-objective optimization, have been demonstrated to effectively enhance both the structure and parameters of FRBSs [9]. This study employs two sequential and iterative learning mechanisms to iteratively refine the structure and parameters of the fuzzy models. Specifically, the Reduced Space Searching Algorithm (RSSA) is used to optimize the model parameters, aiming to improve the models' overall accuracy. Furthermore, the Multi-Objective Reduced Space Searching Algorithm (MO-RSSA) is employed to enhance the model structure, with the primary objectives of achieving enhanced interpretability and reduced complexity [10]. In the process of modeling, an initial FRBS comprising 15 fuzzy rules was constructed using a data-driven approach. Fig. 2 presents examples of 4 fuzzy rules used in the surface roughness model. This FRBS serves the purpose of predicting the surface roughness of diverse materials subjected to varying media and processing conditions. The model incorporates the four input variables as shown in Table 1. For materials, type numbers 1- 4 represent stainless steel, black mild steel, bright steel and additive manufactured steel, respectively. For media, type numbers 1 and 2 represent ceramic and plastic respectively. 70% of the collected data was used for training and 30% of the data was used for testing. The Root Mean Square Error (RMSE) of training and testing for the surface roughness model are 0.3496 and 0.3664 μm, respectively.

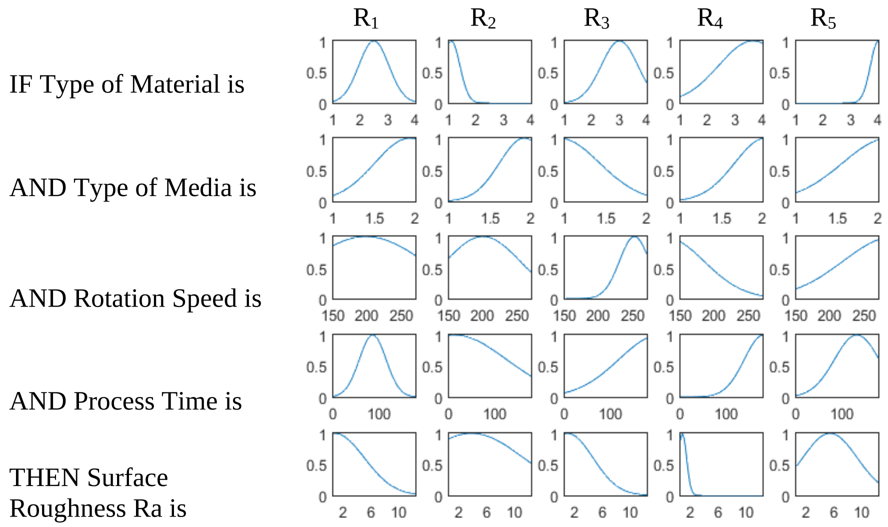


Fig.2. An example of the fuzzy rules of the surface roughness model

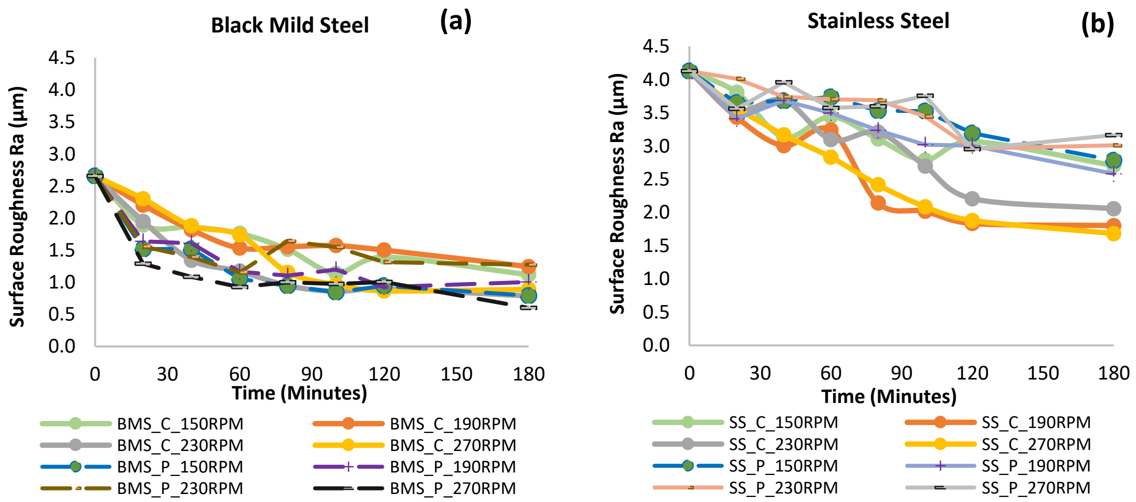


Fig.3. Examples of the surface roughness Ra obtained using ceramic and plastic media with varying durations for the following materials: (a) black mild steel and (b) stainless steel**.**

Fig. 3 illustrates the relationship between surface roughness Ra and process time for black mild steel and stainless steel. The data clearly indicate a consistent decrease in the surface roughness Ra for both materials as the process time increases. This observation aligns well with the calculated Pearson correlation coefficient, which approximately equals 0.83, indicating a strong positive correlation between Ra and the process time. Moreover, it has been observed that the choice of media has a substantial impact on the surface finishing performance, particularly in the case of stainless steel. Notably, the use of ceramic media results in a more distinct reduction in surface roughness Ra compared to plastic media.

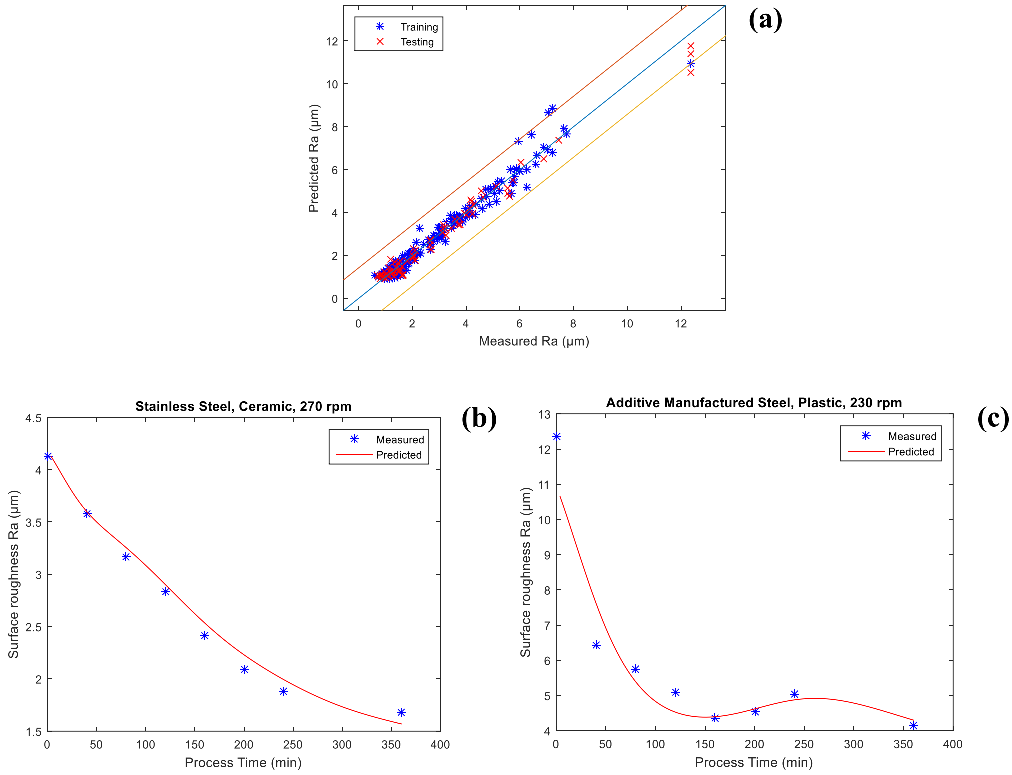


Fig.4. (a) Predicted vs measured surface roughness Ra (μm) on both training and testing data, (b) the predicted surface roughness for the case of stainless steel using ceramic media with machining speed 270 rpm and (c) for the predicted surface roughness the case of additive manufactured steel using plastic media with machining speed 230 rpm.

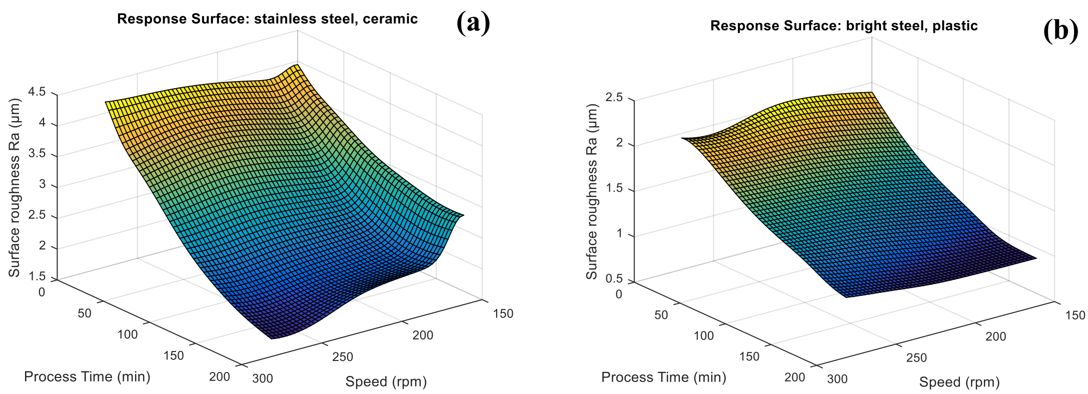


Fig.5. Response surfaces of the developed FRBS: (a) for the case of stainless steel using ceramic media and (b) for the case of bright steel using media plastic.

Fig.4 (a) presents the predictive performance evaluation of the developed model. The analysis reveals a close proximity between the predicted outputs and the measured outputs, with a majority of the predictions falling within the 10% error band. The error bands are calculated as the central values ± 10% of the output value range, which represents the discrepancy between the maximum and minimum values of the measured output. Two specific instances where the model is utilized to forecast the surface roughness for particular processes are shown in Fig.4 (b) and (c). These examples demonstrate the model's significant accuracy and ability to generalize effectively.

The effects of process time and machine speed on the surface roughness are plotted using response surfaces of the developed FRBS in Fig. 5. Fig. 5 (a) focuses on the case of stainless steel with ceramic media, and the model reveals an inverse relationship between the process time and the surface roughness. Furthermore, higher machine speeds are observed to yield improved surface finish. However, in the case of bright steel with plastic media, machine speed does not seem to have a significant impact on the process performance (Fig. 5 (b)). These findings are consistent with the expert knowledge and domain expertise of professionals in the field.

Conclusion

The present study employed a fuzzy rule-based systems approach to model and predicts surface roughness in a centrifugal disc finishing machine. The developed model demonstrated reliable performance, with predictions falling within a 10% error margin. Extensive analysis of process variables revealed material-dependent effects on finishing performance. The models indicated that longer process times led to significant reductions in surface roughness, while no significant relationship was observed between machine speed and surface roughness. These findings offer valuable insights into the intricate dynamics between process variables and surface roughness in centrifugal disc finishing. Furthermore, the presented models enable the determination of optimal process parameter settings for different materials, facilitating the attainment of desired surface finishes. This optimization contributes to improved environmental performance by minimizing material waste and energy consumption.

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