Chapter 3
A Novel Approach for Optimizing Wire Electric Discharge Machining of Mg–Cu–RE–Zr Alloy Using Machine Learning Algorithm

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ABSTRACT

This study focuses on the optimisation of the wire electric discharge machining (WEDM) process for WE43 alloy using machine learning methods. The alloy, made of magnesium (Mg), copper (Cu), rare earth (RE) elements, and zirconium (Zr), is extensively employed in aerospace and automotive sectors for its lightweight and high-strength features. The research applies three machine learning models—artificial

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neural networks (ANN), random forest (RF), and decision trees (DT)—to optimize the important process parameters, including current (A), pulse on (P On), and pulse off (P Off). A full experimental design based on the Taguchi L27 array is undertaken, methodically altering each parameter at three levels. Material removal rate (MRR) is chosen as the response variable for optimisation. The process parameters are adjusted by the use of machine learning techniques, with ANN emerging as the most accurate predictor, obtaining an accuracy of 96.7%.

INTRODUCTION

WEDM is a commonly used precision machining technology for sculpting complicated geometries in electrically conductive materials (Chinta et al., 2023; Natrayan, 2023). The evolution of machine learning methods has provided new opportunities for improving WEDM procedures and forecasting Material Removal Rates (MRR) correctly (Lakshmaiya, 2023b; Velumayil et al., 2023). This literature review intends to give a complete analysis on the optimization of WEDM of WE43 alloy using machine learning (Chehelgerdi et al., 2023; Saadh et al., 2023; Ugle et al., 2023). The emphasis is on process parameter adjustment and MRR prediction (Anjankar et al., 2023; Chennai Viswanathan et al., 2023; Thakre et al., 2023).

WE43 alloy, a magnesium-based alloy, has outstanding mechanical qualities and is extensively applied in aerospace and automotive applications (Biradar et al., 2023; Sai et al., 2023; M. Vijayakumar et al., 2023). However, because to its low machinability, obtaining high machining efficiency and precision is problematic (Konduri et al., 2023; Mahat et al., 2023; Siddiqui et al., 2023). Traditional optimization approaches need large experimental trials, which are time-consuming and expensive (Mehta et al., 2023). Machine learning technologies provide an alternate answer by exploiting past data to construct prediction models and enhance process parameters (Prabagar et al., 2023). Process parameter tweaking plays a significant role in WEDM optimization (Ragumadhavan et al., 2023; Sasi et al., 2023). Parameters such as pulse on-time, pulse off-time, and current substantially impact the machining performance (Arul Arumugam et al., 2023). Several research have employed machine learning methods, such as ANN, support vector regression (SVR), and RF, to improve these parameters (Kiruba Sandou et al., 2023). These algorithms can capture intricate interactions between process parameters and MRR, allowing the determination of optimum parameter combinations for enhanced machining results (Lakshmaiya, 2023h; Natrayan & Richard, 2023a; Sukumaran et al., 2023).

In recent years, several optimization strategies have been utilised to boost the performance of machine learning models in WEDM. Genetic algorithms (GA), particle swarm optimization (PSO), and simulated annealing (SA) are regularly

A Fuzzy Simulated Evolution Algorithm for Hard Problems

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