

A data-to-decision framework for selecting turning conditions of C3604 brass

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ABSTRACT

This study presents a data-to-decision workflow that combines surrogate modeling, multi-objective optimization, and decision-making in a single procedure. Four surrogate models, including Kolmogorov–Arnold Networks (KAN), CatBoost (CAT), Gradient Boosting Regressor (GBR), and LightGBM (LGB), were trained under a unified preprocessing and Bayesian tuning scheme and evaluated on held-out data. The retained models were then embedded in NSGA-III to generate the Pareto front for the trade-off between surface roughness (Ra) and material removal rate (MRR). To move from the Pareto set to a single operating condition, the candidate solutions were further assessed using multiple MCDA methods under different objective weighting schemes, and the resulting rankings were combined through rank aggregation (Borda, Copeland, Kemeny–Young, Robust Rank Aggregation). A turning case study on C3604 free-cutting brass, using cutting speed, feed, depth of cut, nose radius, and coolant condition as inputs, showed that the final recommendation remained stable across different weighting and ranking settings. Experimental verification at selected Pareto points agreed well with the predicted values, with relative errors of about 5 % for both Ra and MRR . The results show that the proposed workflow provides a practical and consistent route from limited machining data to a final operating decision.

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