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MULTI-OBJECTIVE GENETIC ALGORITHM OPTIMIZATION TO EXAMINE THE DURABILITY OF CUTTING TOOLS WITH NASA MILLING DATASET

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Abstract. *This work presents an application of multi-objective genetic algorithm (MOGA) optimization to examine the durability of cutting tools using the NASA milling dataset. This dataset encapsulates a variety of cutting tool conditions, including cutting speeds and depths, which were monitored via three sensor types - Acoustic Emission Sensor, Vibration Sensor, and Current Sensor. The primary objective of this research was to develop an optimized method capable of accurately evaluating the durability of cutting tools under different usage conditions. To accomplish this, multi-objective genetic algorithm optimization was utilized, circumventing the drawbacks inherent in traditional optimization techniques, such as direct optimization and response surface optimization. Accordingly, a non-dominated genetic classification algorithm (NSGA-II) was implemented. The data processed through this method presented optimal conditions for various factors. These factors included machining time, spindle vibration, table vibration, spindle current, and spindle acoustic emission, which were all examined as functions of the depth of cut (A_p) and feed (f) variables. As a result, the study was able to reveal all pairs of optimal combinations for the aforementioned objective functions. The study concludes that MOGA is a promising tool for optimizing tool wear and extending tool life by precisely adjusting milling environment variables. By providing a novel approach for optimizing cutting tools in a range of industrial applications, this research could make significant contributions to the enhancement of cutting tool durability across various commercial sectors.*

Keywords: *Artificial Intelligence, Multi-Objective Genetic Algorithm, Cutting tool wear, Milling process, Dataset Analysis*

1. INTRODUCTION

The continuous search for efficiency and quality in the manufacturing industry has led to the adoption of innovative approaches and advanced technologies Anshari and Almunawar (2022). In some cases, a single product needs to go through different types of machining processes to reach its final shape, size, and form Zolpakar *et al.* (2020).

In this context, optimization methods are considered vital tools for improving product and process quality Santhosh *et al.* (2021); Lin *et al.* (2022); Zoghipour *et al.* (2021). As highlighted by Mukherjee and Ray (2006), there are two main categories of optimization techniques for machining processes. The first category comprises conventional optimization techniques such as the Taguchi Method, Response Surface Methodology, and Iterative Mathematical Search Technique. The second category encompasses unconventional techniques such as Heuristic Search Technique and Metaheuristic Search Technique.

Among the unconventional techniques, multi-objective optimization emerges with the purpose of using a set of objectives and operators to optimize solutions Chen *et al.* (2022). The ultimate goal of a multi-objective optimization algorithm is to identify solutions in the optimal Pareto set. A practical approach to multi-objective optimization is to investigate a set of solutions (the most well-known Pareto set) that represents the best possible Pareto optimal set.

This work presents an application of multi-objective genetic algorithm (MOGA) optimization to examine the durability of cutting tools using NASA milling data. The dataset contains cutting conditions of the cutting tool, such as cutting speeds and depths, which can be used to understand the performance of the cutting tool and the influence of tool wear and failure. The dataset was collected from experiments performed with a milling machine under various operating conditions. In particular, tool wear in a regular cutting in-feed and out-feed was measured with the help of three types of sensors - Acoustic Emission Sensor, Vibration Sensor, and Current Sensor - at various positions. An AI algorithm was used to determine the optimal cutting parameters and tool life based on a variety of milling environment variables.

Through this research, significant insights are expected to be provided to the manufacturing industry by offering

optimized strategies to increase the durability of cutting tools and improve the efficiency of machining processes. The obtained results can have a significant impact on reducing production costs, increasing tool life, and overall improving the quality of manufactured products.

The article is structured as follows: Section II presents a literature review on multi-objective genetic algorithms and their application in optimization problems in the machining area; Section III presents the proposed methodology, including problem formulation and parameters of the multi-objective genetic algorithm; Section V discusses the obtained results and compares them with existing approaches; Section VI presents the conclusions and outlines possible future work.

2. LITERATURE REVIEW

First introduced by John Holland in 1975 Jh (1975), the genetic algorithm (GA) is a stochastic search technique that utilizes the combination of two parent states to generate successor states, rather than modifying a single state Russell and Norvig (2013). This process mimics natural selection in biological evolution, but it is applied to sexual reproduction rather than asexual reproduction. In essence, the GA simulates the process of sexual reproduction found in nature to discover optimized solutions for complex problems.

Currently, in the context of increasingly complex engineering systems and processes, the most effective solutions often rely on trade-offs. From a set of options, the selection of appropriate and preferred decision criteria is required Zolpakar et al. (2016).

In GA optimization, when dealing with multiple objective functions where one function holds more significance than the others, assigning weights to each function is necessary to indicate their relative importance. This approach enables the evaluation of competing solutions without the requirement of determining relative importance weights. In the literature, MOGA has been regarded as superior to other classical algorithms Deb (2011).

The capability of GA to explore various regions of a solution space simultaneously enables the discovery of a diverse set of solutions, even for challenging problems characterized by non-convex, discontinuous, and multimodal solution spaces Konak et al. (2006). Additionally, in multi-objective GAs, there is typically no need for users to prioritize, scale, or assign weights to the objectives. According to Jones et al. Jones et al. (2002), approximately 90% of approaches for multi-objective optimization aim to approximate the true Pareto front of the underlying problem. Among these approaches, a majority utilize metaheuristic techniques, with evolutionary approaches constituting about 70% of all metaheuristic-based methods.

A multi-objective genetic algorithm is a type of genetic algorithm used to solve optimization problems with multiple objectives or criteria. MOGA differs from a standard genetic algorithm because it seeks to find not only a solution that maximizes or minimizes a single objective function, but rather a set of solutions that optimize multiple objectives simultaneously Deb (2011).

In a MOGA, the population of solutions evolves through successive generations, with each individual in the population representing a possible solution to the optimization problem. The fitness of each individual is evaluated based on its performance with respect to multiple objective functions, and the population is then selected, recombined, and mutated to generate the next generation of solutions.

The main challenge in MOGA is balancing the trade-offs between competing objectives. The goal is to find a set of solutions that are not dominated by any other solution in the population, a concept known as Pareto optimization Konak et al. (2006).

MOGA has been successfully applied to a wide range of real-world problems. It has become a popular optimization technique due to its ability to handle complex and multi-objective problems and provide a set of solutions that can be used to make informed decisions based on trade-offs between different objectives.

In recent years, several researchers have used GAs in machining applications to find the optimal surface quality in various traditional and modern machining processes Sekulic et al. (2018); Kumar et al. (2019); Kant and Sangwan (2015); Durairaj and Gowri (2018). In addition to surface roughness, many researchers have used GA optimization to minimize cost and production time Sahali et al. (2015a); An (2021); Ganesan et al. (2011).

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The application of MOGA to solve design and component selection problems requires special considerations during its development. This is because in such problems, there are multiple design variables that must be simultaneously considered, each with different objectives, often conflicting with each other.

Factors that should be analyzed, as listed by Konak et al. Konak et al. (2006), include: Fitness functions (Weighted sum approaches, Altering objective functions, Pareto-ranking approaches); Diversity: fitness assignment, fitness sharing,

and niching (Fitness sharing, Crowding distance, Cell-based density); Elitism (Strategies to maintain elitist solutions in the population, Elitism with external populations); Constraint handling; Parallel and hybrid multi-objective GA.

3. NASA MILLING DATASET

This Dataset containing of cutting tool cutting conditions, such as cutting speeds and depths, which can be used to understand the cutting tool performance and the influence of tool wear and failure. This data has been collected from experiments conducted using a milling machine in different operating conditions. In particular, tool wear in a regular, entry and exit cut has been measured with the help of three types of sensors - Acoustic Emission Sensor, Vibration Sensor, and Current Sensor - at multiple positions, Goebel *et al.* (1996).

The dataset comprises 16 cases, each with a varying number of runs. The number of runs conducted for each case depended on the degree of flank wear observed during the experiments. Measurements of flank wear were taken at irregular intervals, up to a wear limit and sometimes beyond. It's important to note that flank wear measurements were not always recorded, and there may be instances where no measurements were taken, resulting in missing entries in the dataset.

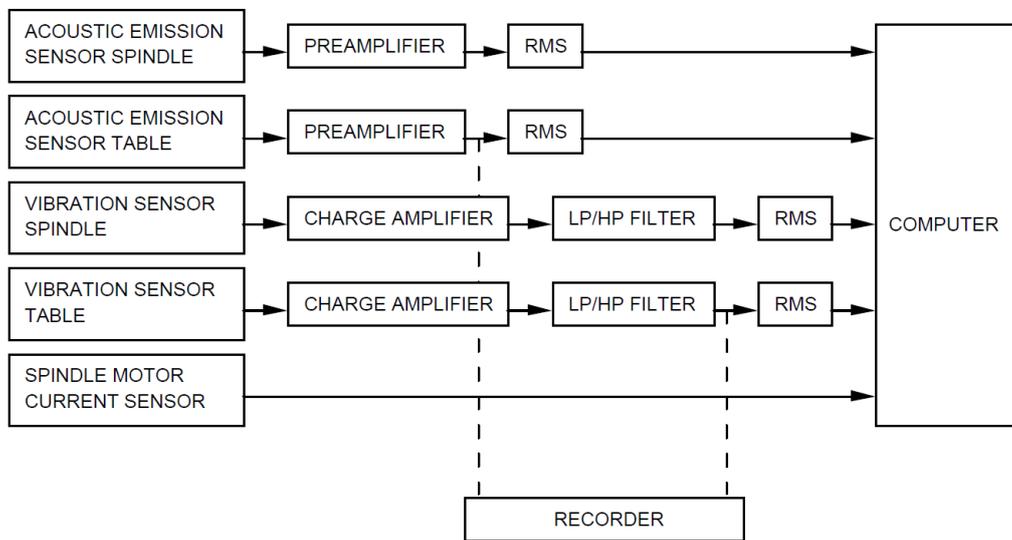The experimental configuration that the data were acquired is described in Fig. (1).

Figure 1. Experimental Setup NASA Dataset. Adapted from Goebel *et al.* (1996)

This NASA milling dataset had the experimental setup involved a Matsuura machining center MC-510V, consisting of a spindle and a table. The experimental parameters were chosen based on industrial applicability and recommended manufacturer's settings. The cutting speed was set at $200m/min$, and two different depths of cut ($1.5mm$ and $0.75mm$) and two feeds ($0.5mm/rev$ and $0.25mm/rev$) were selected. Two types of materials, cast iron and stainless steel $J45$, were used, along with inserts of type $KC710$. This resulted in eight different experimental settings. Each experiment was conducted twice, using a second set of inserts. The workpieces had dimensions of $483mm \times 178mm \times 51mm$, Goebel *et al.* (1996).

The methodology employed for the experimental design utilizes a full factorial design approach, consisting of a minimum of two replications, implemented across two distinct levels and incorporating two factors. The factors subjected to analysis within this context are denoted as the tool feed, represented by f, and the depth of cut, symbolized by A_p. The dataset makes available the Root Mean Square (RMS) values corresponding to each executed test.

Given the intricacies involved in the machining process, it was deemed pertinent to isolate one material from the dataset for analysis. The material chosen for this focus was cast iron. This strategy has been adopted in the anticipation that it would foster greater clarity and precision in the elucidation of the phenomena under study, thereby providing more reliable and applicable insights for the field of machining.

3.1 Multiple linear regression

A Multiple Linear Regression and Design of Experiments are commonly used in combination to build predictive models (Sahali *et al.*, 2015b), Eq. (1).

$$y_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \epsilon_i \tag{1}$$

where ϵ_i is the error term expressing or summarizing the missing information in the linear regression of the y_i values. $X_{i1}, \cdots, X_{ij}$ and $\beta_0, \cdots, \beta_j$ are the coefficients of the parameters to be estimated.

This approach can lead to a highly accurate theoretical predictive model of observed or measured values.

4. PROPOSED MODEL FOR OPTIMIZATION

Utilizing the data procured from the inquiries, both linear regression and variance analysis were applied to ascertain the empirical models, and to identify the key variables impacting each output $(Time, Vib_{spindle}, Vib_{table}, smcDC, AE_{spindle})$. These outputs are evaluated as functions of the input parameters (A_p, f). In this study, the objective was to maximize the machining time and minimize the other parameters, according to Eq. (2)

$$\begin{cases} Time(f, A_p) \\ Vib_{spinde}(f, A_p) \\ Vib_{table}(f, A_p) \\ smcDC(f, A_p) \\ AE_{spindle}(f, A_p) \end{cases} \tag{2}$$

Multiple linear regressions were performed using the statsmodels library in Python. The 'ols' (Ordinary Least Squares) function from this library was utilized, feeding in the respective formula and data for each model. Upon model creation, they were then fitted to the data employing the 'fit' method. This action effectively executes linear regression and calculates regression coefficients to minimize the sum of squares of the residuals. Upon applying Eq. (1) to the dataset, it is found that the obtained objective functions are described in Eq. (3).

$$\begin{cases} Time & = & 85.6555 - 41.8880A_p - 81.2420f + 55.7300(A_pf) \\ Vib_{spindle} & = & 0.3015 - 0.0159A_p - 0.1135f + 0.1018(A_pf) \\ Vib_{table} & = & 0.1647 - 0.0364A_p - 0.1680f + 0.0598(A_pf) \\ smcDC & = & 1.3106 + 0.1575A_p + 0.2732f - 0.6398(A_pf) \\ AE_{spindle} & = & 0.1565 - 0.0052A_p - 0.0078f + 0.0152(A_pf) \end{cases} \tag{3}$$

4.1 Restrictions associated with dataset

Through dataset analysis, empirical models can be determined, as indicated in Eq(3). Moreover, it allows for the identification of certain constraints suitable for implementation within the genetic algorithm. The inclusion of these restrictions in the NSGA-II algorithm is crucial as they guide the search towards feasible and optimal solutions, reducing computational time and effort. The constraints adopted in this case are as follows:

- Restriction on advancement : $0, 25 \leq f \leq 0, 5$.

- Cutting depth restriction : $0, 75 \leq Ap \leq 1, 50$.

- Machining time restriction : $0 \leq Time \leq 150$.

- Spindle vibration restriction : $0 \leq Vib_{spindle} \leq 0, 50$.

- Table vibration restriction : $0 \leq Vib_{table} \leq 0, 50$.

- Spindle current restriction : $0 \leq smcDC \leq 2, 00$.

- Spindle acoustic emission restriction - $0 \leq AE_{spindle} \leq 0, 20$.

5. MULTI-OBJECTIVE GENETIC ALGORITHM OPTIMIZATION - MOGA

This segment discusses the algorithm utilized to generate a collection of points on the Pareto front. The method employed is a controlled, elitist genetic algorithm (Non-dominated Sorting Genetic Algorithm II – NSGA-II) Kalyanmoy (2001). This algorithm places emphasis on favoring individuals with superior fitness values or ranks, adopting an elitist perspective.

An elitist genetic algorithm promotes individuals that demonstrate higher fitness values or ranks within the population. This ensures that the algorithm continually progresses towards better solutions. However, the multi-objective genetic algorithm (MOGA) employs a controlled elitist GA, which not only prioritizes higher fitness values but also gives importance to individuals that contribute to enhancing the diversity of the population, even if they possess lower fitness values. This strategy allows the algorithm to navigate the multi-objective optimization problem landscape effectively, uncovering a diverse set of points on the Pareto front.

In the context of a genetic algorithm, several key parameters must be set prior to executing the algorithm. The tuning of these parameters can significantly influence the performance of the algorithm, affecting its efficiency and the quality of the solutions it generates. Careful consideration and understanding of each parameter is, therefore, crucial for the successful application of a genetic algorithm. The specific parameters employed and their corresponding roles in the process are defined as follows:

- *Dimension of population:* This parameter defines the total number of individuals in a population for a given generation of the genetic algorithm. A larger population size provides a wider search space, increasing the probability of finding a solution that meets the specified criteria. However, it also increases the computational complexity of the algorithm.

- *Rate of crossover:* This parameter represents the probability with which the crossover operation is performed on a pair of parent individuals. A higher crossover rate leads to a greater exploration of the solution space, facilitating the discovery of new regions of potential solutions. Conversely, a lower crossover rate promotes exploitation of the current search region, refining existing solutions.

- *Rate of mutation:* This parameter signifies the probability that a mutation operation occurs on a given individual. The mutation rate directly influences the diversity of the population. A higher mutation rate ensures a wider exploration of the search space, while a lower mutation rate maintains the stability of the population and prevents drastic changes in the solutions.

- *Number of generations:* This parameter specifies the total number of iterations or cycles the genetic algorithm performs. Each generation consists of the selection, crossover, mutation, and evaluation operations. The number of generations indirectly influences the convergence of the algorithm, with a larger number of generations typically leading to better solutions.

The table (1) outlines the specified parameters for the multi-objective genetic algorithm optimization. In this context, the 'Dimension of population' refers to the number of potential solutions that the algorithm operates upon in each generation. The 'Rate of crossover' and 'Rate of mutation' are the probabilities of these respective operations occurring during the reproduction phase, serving to introduce variability and diversity in the population. The 'Number of generations' denotes the number of iterations the algorithm will execute, dictating the extent of solution refinement.

Table 1. Parameters of multi-objective genetic algorithm optimization

Parameter	Value
Dimension of population	200
Rate of crossover	0.80
Rate of mutation	0.10
Number of generation	200

6. IMPLEMENTATION RESULTS

As depicted in Fig. (2), the Pareto fronts offer a visual representation of all possible combinations among five objective functions: Machining Time, Spindle Vibration, Table Vibration, Spindle Current, and Spindle Acoustic Emission. Each subplot within the figure corresponds to a distinct pairing of these objective functions, showcasing the dispersion of outcomes derived from the MOGA (Multi-Objective Genetic Algorithm). The intention behind this representation is to enable a comprehensive understanding of relationships and interactions between different pairs of objectives, thereby facilitating the analysis of trade-offs and the identification of optimal Pareto solutions. This comprehensive approach enables the recognition of potential correlations or dependencies, playing an integral role in the decision-making process within the context of multi-objective optimization problems.

Employing the implemented algorithm allows for the determination of optimal solutions for varying combinations of five objectives in a Multi-Objective Genetic Algorithm (MOGA) optimization problem, utilizing the Pareto front technique. This approach enables the identification of the most suitable solution for each pair of objectives resulting from the multi-objective optimization. Table (2) delineates the parameters of the multi-objective genetic algorithm optimization for a variety of objective function combinations, such as time, spindle vibration, table vibration, spindle current, and acoustic emission. These values offer insightful revelations regarding the performance of the derived solutions and significantly enhance decision-making in complex multi-objective optimization problems.

The experiments conducted in this study are fully replicable. The datasets used, as well as the multi-objective optimization algorithm, are publicly accessible. Moreover, the computational implementation was developed and is hosted
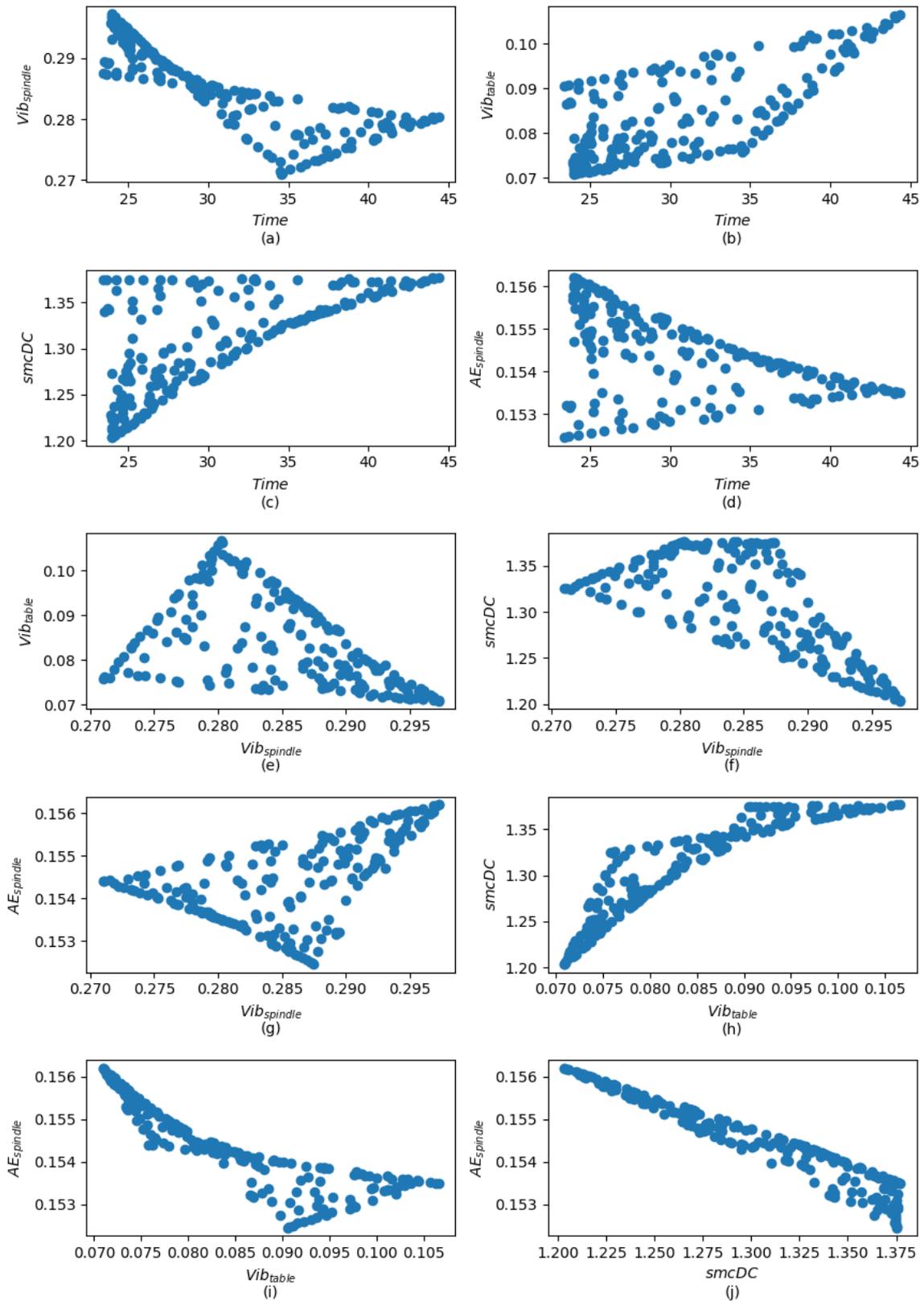
Figure 2. Pareto fronts showing scatter plots of all possible pairs of objective functions: Machining Time, Spindle Vibration, Table Vibration, Spindle Current, and Spindle Acoustic Emission.

Table 2. Parameters of multi-objective genetic algorithm optimization

Objective functions	A_p	f
$Time$ and $Vib_{spindle}$	1.50	0.25
$Time$ and Vib_{table}	1.50	0.25
$Time$ and $smcDC$	1.50	0.25
$Time$ and $AE_{spindle}$	1.50	0.25
$Vib_{spindle}$ and Vib_{table}	0.75	0.50
$Vib_{spindle}$ and $smcDC$	1.50	0.50
$Vib_{spindle}$ and $AE_{spindle}$	0.75	0.50
Vib_{table} and $smcDC$	1.50	0.50
Vib_{table} and $AE_{spindle}$	1.50	0.50
$smcDC$ and $AE_{spindle}$	1.50	0.50

on the Google Colaboratory platform. This transparency ensures the rigor and integrity of our results, contributing to the scientific robustness of our research. To access the datasets, the algorithm, and the computational implementation, please follow the link: `https://colab.research.google.com/drive/1jO7gmZLr3bC1haiXSuPNn8Yvpd-2rQyM?usp=sharing`. To further assist in understanding the implemented code, a video explanation has been created and uploaded on YouTube. It can be accessed via the following link: `https://www.youtube.com/watch?v=QtEerjs2VgU`.

7. CONCLUSIONS

The application of a multi-objective genetic algorithm optimization (MOGA) in this study facilitated the simultaneous consideration of several objective functions. This approach aimed to achieve an optimal balance among these objectives. Linear regression models were formulated using the NASA milling dataset, providing functional mappings between input machining parameters (depths of cut and feed rate) and output response variables.

The incorporation of empirical models, derived from the dataset analysis, was instrumental in establishing realistic constraints within the NSGA-II algorithm. These restrictions proved effective in guiding the algorithm towards feasible and superior solutions, significantly reducing computational time and effort.

The results, as presented through the Pareto fronts, provided extensive insights into the interactions and trade-offs among different objective functions. These results illuminated correlations or dependencies between pairs of objectives, which are crucial for informed decision-making in complex multi-objective optimization problems.

This work represents a significant advancement towards understanding and optimizing machining parameters using a sophisticated multi-objective genetic algorithm approach. The methodologies and insights generated could be valuable in decision-making processes within the manufacturing industry, paving the way for enhanced efficiency, cost-effectiveness, and quality control.

8. ACKNOWLEDGMENTS

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10. RESPONSIBILITY NOTICE

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