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# NATURE-INSPIRED METAHEURISTIC ALGORITHMS IN OPTIMIZATION OF MACHINING PARAMETERS

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**Abstract**. *Improving productivity, quality, and efficiency in manufacturing relies heavily on the precise selection of machining parameters. These parameters, such as cutting speed, feed, depth of cut, and tool selection, play a crucial role in achieving optimal results. The optimization of these parameters not only has the potential to reduce costs and minimize waste but also contributes to enhancing product consistency. This paper uses the experimental results from a practical setting and proposes the application of nature-inspired metaheuristics to optimize machining parameters. The main objective is to minimize cutting forces while optimizing the parameters involved in a turning process. The study compares and briefly discusses the optimization results obtained through three nature-inspired metaheuristic algorithms.*

**Key words**: *Machining, Parameters, Optimization, Metaheuristic algorithm, Turning process.*

## 1. INTRODUCTION

Machining parameters are crucial in manufacturing processes that directly influence the efficiency, precision, and quality of material removal operations. These parameters, such as cutting speed, feed, depth of cut, and tool geometry, play a pivotal role in determining factors such as tool wear, surface finish, and overall production cost. Optimal machining parameters enhance productivity by reducing cycle times and contribute to the longevity of cutting tools and machinery. Achieving the right balance in these parameters is essential for meeting specific requirements of different materials and applications. Also, proper parameter selection is integral to minimizing energy consumption and waste, promoting sustainability in manufacturing practices. In essence, the careful control and optimization of machining parameters are fundamental to achieving cost-effective, high-quality production in the ever-evolving landscape of modern manufacturing [1].

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This paper suggests applying nature-inspired metaheuristic algorithms to optimize the machining parameters of a turning process. The paper is organized as follows: Section 1 provides an introduction, followed by an elaboration on the optimization of machining parameters. In Section 2, nature-inspired metaheuristics are briefly described, with a focus on three intelligent algorithms selected for the study. Section 3 introduces the case study on the minimization of cutting forces and discusses the obtained results. Finally, Section 4 concludes the study.

### 1.1 Optimization of machining parameters

The selection and optimization of machining parameters are crucial for achieving desired outcomes such as improved productivity, reduced costs, and enhanced product quality. So far, various methodologies have been employed in optimizing machining parameters, starting from traditional statistical approaches, design of experiments (DOE), Taguchi method, response surface methodology (RSM), and metaheuristic algorithms.

Traditional approaches consider classical statistical techniques that have long been employed to analyze and optimize machining parameters. These methods involve factorial experiments to study the impact of individual parameters and their interactions on the machining process. However, these approaches are often limited by their inability to handle complex, nonlinear relationships between parameters and responses. As manufacturing processes become more intricate, there is a growing need for advanced methodologies [2].

The design of experiments is a systematic and efficient approach aimed at exploring the effects of various factors and their interactions on machining outcomes. By strategically varying parameters according to a well-designed experimental plan, DOE allows researchers to identify the optimal combination of factors leading to improved machining performance. This methodology reduces the number of experiments needed to reach conclusive results, making it a valuable tool for efficient parameter optimization [3].

The Taguchi method, developed by Genichi Taguchi, focuses on achieving robustness in the face of variability. It employs orthogonal arrays to conduct a minimal number of experiments while still capturing the influence of different factors. Taguchi aims to identify parameter settings that are less sensitive to variations, leading to enhanced reliability and quality in machining processes. The method's emphasis on robust design makes it particularly valuable in industries where consistency and reliability are paramount [4].

Response Surface Methodology is another statistical technique used to model and optimize complex processes by creating a mathematical model representing the relationship between input parameters and the response variable. This methodology effectively uncovers the optimal machining parameters within a given range, considering both linear and nonlinear effects. Using regression analysis, RSM provides a comprehensive understanding of the machining process, enabling researchers to fine-tune parameters for optimal results [5].

Recent advancements in optimization have seen the emergence of metaheuristic algorithms that draw inspiration from natural processes, such as evolution and swarm behavior, in order to navigate complex solution spaces [6]. These algorithms excel at exploring large and nonlinear parameter spaces, providing practical solutions to complex optimization problems in machining.

## 2. Nature-inspired metaheuristics

As the popularity of metaheuristic algorithms became more common, there was a need to find ways to organize and classify them. Tsai and Chiang [7] mentioned several classification methods: (1) nature-inspired vs non-nature inspired, (2) dynamic vs static objective functions, (3) one vs various neighborhood structures, (4) memory usage vs memoryless methods, (5) with vs without local search method, and (6) population-based vs single solution based search. It is noteworthy to mention that most metaheuristic algorithms introduced after 2000 belong to population-based algorithms.

In this study, emphasis is placed on nature-inspired intelligent algorithms. Fig. 1 shows the classification of metaheuristics according to their source of inspiration.

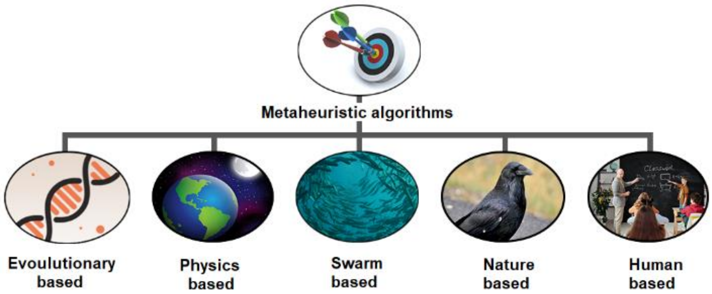



**Fig. 1** Classification of metaheuristic algorithms [8]

Nature-inspired metaheuristics are optimization algorithms that draw inspiration from natural phenomena to solve complex problems. Mimicking the behavior of biological or physical processes, these algorithms emulate the principles observed in nature to efficiently explore solution spaces [9]. Numerous classifications have been proposed so far. Many nature-inspired algorithms include those that belong to the evolutionary, or swarm-based class of algorithms. Therefore, some traditional methods such as genetic algorithms inspired by natural selection, then particle swarm optimization inspired by bird flocking, and ant colony optimization inspired by ant foraging behavior, may belong to the evolutionary and swarm-based class. These metaheuristics demonstrate adaptability and robustness, making them valuable tools for solving optimization problems across various domains, ranging from engineering and logistics to finance and computer science.

Three metaheuristic algorithms, particle swarm optimization, grey wolf optimizer and honey badger algorithm, which are inspired by natural phenomena, are applied in the current study. They are briefly defined in the following sections.

### 2.1 Particle swarm optimization

Particle Swarm Optimization (PSO) is a metaheuristic algorithm inspired by the collective behavior of fish schools or bird flocks to solve optimization problems. It was originally developed in 1995 but was later improved in many ways by the authors [10]. Particles, a population of possible solutions, move through a multidimensional solution space in PSO. Based on its own experiences as well as the best experiences of its neighbors, each particle modifies its position. Particle position and velocity are updated iteratively by the method, which converges to the best possible solutions. Because of its ability to effectively examine expansive and complex solution spaces, PSO is especially well-suited for optimization problems involving nonlinear or discontinuous objective functions.

### 2.2 Grey wolf optimizer

The Grey Wolf Optimizer (GWO) stands as a prominent metaheuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves. Mirjalili [11] developed it in 2014. Introduced as an optimization technique, GWO mimics the collaborative and hierarchical nature of wolf packs in search of optimal solutions within complex problem spaces. It mimics the leadership and cooperation among wolves in a pack to iteratively search for optimal solutions to various mathematical problems. The algorithm utilizes alpha, beta, delta, and omega wolves to represent different roles in the search process, with each wolf adjusting its position to explore and exploit the search space efficiently. So far, GWO has been modified and adapted to various optimization problems in scientific literature.

### 2.3 Honey badger algorithm

The Honey Badger Algorithm (HBA) is the last intelligent algorithm considered in this study. Developed in 2022, it is based on the foraging behaviors of honey badgers [12]. HBA aims to strike a balance between exploitation and exploration in its search for high-quality solutions. This algorithm draws inspiration from the foraging strategies employed by honey badgers, specifically integrating two distinct stages observed in their pursuit of food. The initial phase, termed "the digging stage," involves the honey badger utilizing its smell sensitivity to locate prey. Subsequently, the honey badger traverses the area, identifying an optimal location to excavate before ultimately capturing its prey. The second stage, referred to as "the honey stage," entails the honey badger following a honeyguide bird, which aids in locating beehives. In this context, HBA leverages these dual foraging strategies as foundational principles to inform its optimization approach, contributing to its significance within the domain of swarm intelligence algorithms.

## 3. Case study – Minimization of cutting forces in the turning process

This paper adopts results from a study by Aleksic [13] that investigates the effect of machining parameters on cutting forces in the turning process of CPM 10V steel workpiece. The chemical composition of the CPM 10V steel is shown in Table 1. The size of the workpiece was 80 mm in length and 40 mm in diameter.

**Table 1** Chemical composition of the CPM 10V steel [14]

| Steel | C | Mn | Si | Cr | V | Mo | S |
|---|---|---|---|---|---|---|---|
| 10V | 2.45% | 0.5% | 0.9% | 5.25% | 9.75% | 1.3% | 0.07% |

Employing a methodological approach, the authors implemented the design of experiments and analysis of variance to accurately present the significance of the models and parameters under consideration. The primary objective of the experimental study was to analyze the machining parameters, precisely the depth of cut $a_p$, feed $f_n$, and cutting speed $v_c$, and investigate their influence on cutting forces—main cutting force ($F_c$), radial force ($F_p$), and feed force ($F_f$). For the 3-factor, 3-level design of experiments, the authors performed an analysis of variance and determined the significance of the model. Response surface regression equations were obtained for all three cutting force components, which are given as follows:

$$F_v = 335 - 300 \cdot a_p + 648 \cdot f_n + 0.284 \cdot v_c + \\ +176.6 \cdot a_p^2 + 4450 \cdot a_p \cdot f_n - 2.873 \cdot f_n \cdot v_c \quad (1)$$

$$F_p = 37 + 9.7 \cdot a_p - 0.0157 \cdot v_c + 36.42 \cdot a_p^2 + 0.0384 \cdot a_p \cdot v_c \quad (2)$$

$$F_f = 343.4 - 228 \cdot a_p + 649 \cdot f_n + 0.153 \cdot v_c + 22.5 \cdot a_p^2 + \\ +414 \cdot a_p \cdot f_n + 0.1974 \cdot a_p \cdot v_c - 1.267 \cdot f_n \cdot v_c \quad (3)$$

According to the results of the experimental study in [13], the effects of machining parameters on each force are graphically presented, and their influence is ranked. R squared values of the significance of the model suggest that the model is adequate to predict the influence of these parameters on cutting forces.

After determining the significance of parameters using the ANOVA, the next logical step is to find the best set of machining parameters that will minimize the cutting forces. An effective approach to address these challenges is the adoption of a metaheuristic strategy [15, 16]. In that sense, three different nature-inspired metaheuristic algorithms, PSO, GWO, and HBA, are applied to optimize the machining parameters. Three regression equations shown above are used as objective functions. Single-objective optimization is performed, where each cutting force represented by the regression Eq. 1-3 is optimized separately. PSO, GWO, and HBA source codes are freely available online. These algorithms are implemented using a Matlab programming environment to find the optimal machining parameters for the main cutting force, radial force, and feed force. The input parameters for optimization are bounded to lower and upper values according to the recommendations given in the experimental study [12]:

- Depth of cut ($a_p$): 0.8 mm –1.6 mm
- Feed ($f_n$): 0.18 mm/rev – 0.26 mm/rev
- Cutting speed ($v_c$): 300 m/min – 600 m/min

All algorithms are executed 20 times for each objective in order to achieve average results. Also, they share the same number of iterations (100) and the number of search agents (20). As far as the other parameters are considered, in HBA constant C is set to 1.5 and parameter beta is set to 4. In the PSO algorithm the following parameters are considered: $c_1 = 2$, $c_0 = 2$, and weight coefficient linearly decreases from 0.8 to 0.2. The optimization results are given in Tables 2 to 4.

Firstly, a short discussion will be made regarding the optimal results. As can be noticed, all three nature-inspired metaheuristics found identical minimal values of cutting forces, including the set of optimal machining parameters. This simple optimization task proved to be a slight challenge for these intelligent algorithms. Secondly, execution time is a valuable measure since various optimization problems express different levels of complexity. Therefore, some particular tasks can be very demanding in terms of time and space complexity and present a more challenging task for many optimizers. Here, the focus was on a simple optimization problem with no constraints except for the upper and lower bounds. In that sense, small values of execution times are obtained. One thing worth emphasizing is that PSO required slightly more execution time than GWO and HBA. One reason is that the mathematical model of PSO is slightly more complex than the models of the other two metaheuristics. GWO and HBA do not require the local best positions of their individuals in every iteration.

**Table 2** Optimal results obtained by PSO algorithm

| Output | Results | Optimal machining parameters | | | Average execution time [s] |
|---|---|---|---|---|---|
| | | Depth of cut, $a_p$ [mm] | Feed, $f_n$ [mm/rev] | Cutting speed, $v_c$ [m/min] | |
| Main cutting force, $F_c$ [N] | 825.58 | 0.8 | 0.18 | 600 | 0.1116283 |
| Radial force, $F_p$ [N] | 344.486 | 1.6 | 0.18 | 300 | 0.1241837 |
| Feed force, $F_f$ [N] | 72.5748 | 0.8 | 0.18 | 300 | 0.1184612 |

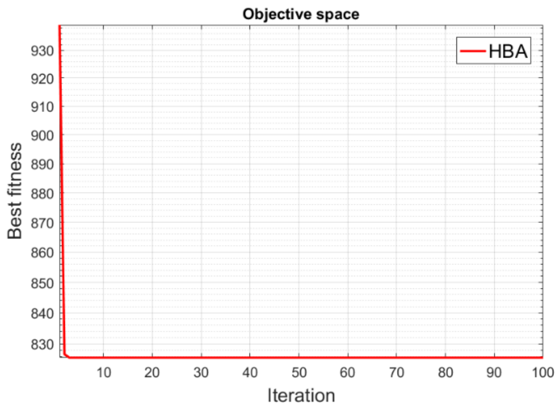
**Table 3** Optimal results obtained by GWO algorithm

| Output | Results | Optimal machining parameters | | | Average execution time [s] |
|---|---|---|---|---|---|
| | | Depth of cut, $a_p$ [mm] | Feed, fn [mm/rev] | Cutting speed, $v_c$ [m/min] | |
| Main cutting force, $F_c$ [N] | 825.58 | 0.8 | 0.18 | 600 | 0.013365 |
| Radial force, $F_p$ [N] | 344.486 | 1.6 | 0.18 | 300 | 0.0148384 |
| Feed force, $F_f$ [N] | 72.5748 | 0.8 | 0.18 | 300 | 0.0124783 |

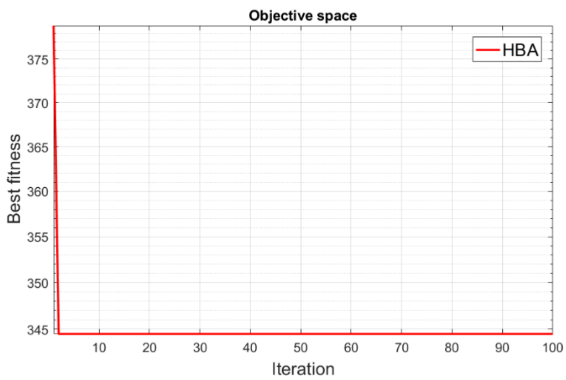
**Table 4** Optimal results obtained by HBA algorithm

| Output | Results | Optimal machining parameters | | | Average execution time [s] |
|---|---|---|---|---|---|
| | | Depth of cut, $a_p$ [mm] | Feed, fn [mm/rev] | Cutting speed, $v_c$ [m/min] | |
| Main cutting force, $F_c$ [N] | 825.58 | 0.8 | 0.18 | 600 | 0.0148838 |
| Radial force, $F_p$ [N] | 344.486 | 1.6 | 0.18 | 300 | 0.0156324 |
| Feed force, $F_f$ [N] | 72.5748 | 0.8 | 0.18 | 300 | 0.0165448 |

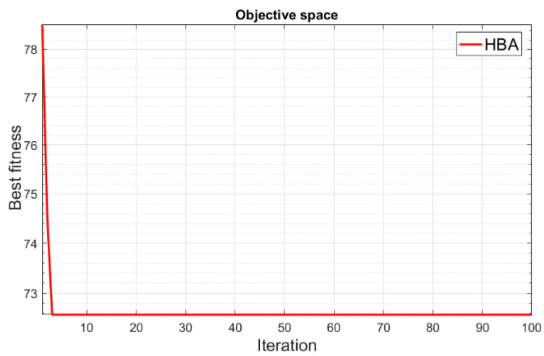
Since this problem of minimizing the cutting force using regression equations as objective functions required a few iterations to find optimal solutions, convergence curves are almost identical for each optimization task. Fig. 2 shows convergence curves for optimization of main force $F_c$, radial force $F_p$ and feed force $F_f$, respectively.




a) Main cutting force, $F_c$




b) Radial force, $F_p$




c) Feed force, $F_f$

**Fig. 2** Convergence curve of HBA algorithm

## 4. CONCLUSIONS

This study aimed to demonstrate the effectiveness of nature-inspired metaheuristic algorithms, specifically PSO, GWO, and HBA, in optimizing machining parameters for the turning process to minimize cutting forces. The optimization task in this paper was based on a recent experimental study from literature. All three algorithms proved highly efficient in solving this simple optimization problem. In 20 runs, HBA and GWO exhibited shorter execution times compared to PSO. Despite this difference, all metaheuristics identified the same optimal values for the main cutting force, radial force, and feed force. The machining parameters, including depth of cut, feed, and cutting speed, were also consistent across the algorithms. This approach can be applied in other experimental studies involving more factors and variation levels. Additionally, future studies may explore the adaptive weighted sum method for multi-objective optimization.

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