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Optimization of Cnc Machining Parameters Using Machine Learning Techniques

Dheivendran .R[1], Mostafa Abbas Jabbar[2]
[1]Assistant Professor Department Of Mechanical Engineering
Npr College Of Engineering And Technology,
Npr Nagar, Natham, Dindigul(Dt), Pin Code:624401
Shreedheiva@Gmail.Com
[2]Lecturer Mechanical Engineering Techniques
Nasiriyh Polytechnic College, Southern Technical University, Thi-Qar, Nasiriya 64001, Iraq.
M.Jabbar@Stu.Edu.Iq
Orc Id : 0000-0002-3703-6205

Abstract- Selection of machining parameters in CNC processes has an enormous impact on the resulting surface quality, tool life, and process efficiency. Traditional parameter selection process is mainly driven by operator experience and experimental testing. Such a process takes a lot of time and lacks universality since it can be implemented only in particular situations, taking into account specific material and cutting tool parameters. In this paper, we propose a framework for intelligent machining parameter selection based on integration of machine learning regression techniques with meta-heuristic optimization. The proposed framework uses Random Forest regression model, which is built on the basis of collected machining data. The optimization of machining parameters is performed with the help of Particle Swarm Optimization. The proposed framework is benchmarked against the two baselines, namely response surface methodology and genetic algorithm, in terms of convergence properties, distribution of Pareto front points, and parameter sensitivity rankings. The experiments show that ML-PSO framework explores the space of parameter values more efficiently and finds better surface quality points than traditional techniques.

Key Word: CNC Machining, Machine Learning, Parameter Optimization, Surface Roughness, Particle Swarm Optimization, Surrogate Modeling

I. INTRODUCTION

Computer numerical control (CNC) machining still stands out as an important part of the present-day manufacturing process, allowing the fabrication of high-quality components in aerospace, automotive, and biomedical applications. Machining quality and cost-effectiveness of the process depend on various machining parameters, such as cutting speed, feed rate, depth of cut, and tool geometry. Wrong choice of parameters may result in increased tool wear, poor quality of the machined surface, unnecessary energy expenditure, and decreased accuracy of dimensions. As a result, the issue of machining parameters optimization has been receiving research attention for several decades [3], [10].

The traditional approach to parameter optimization is based on design of experiments (DoE) methods, including Taguchi and response surface methodology (RSM). In this way, the relationship between input parameters and output responses is found using the matrix of experimental designs. Although RSM proved to be effective in many machining cases, it usually presupposes polynomial functional forms that do not allow describing nonlinearity and interactions in cutting processes, especially in case of machining difficult-to-cut materials. Moreover, the application of RSM-based optimization requires performing numerous experimental designs, which are very costly because of the material, tool, and machine time expenses involved [10].

Machine Learning (ML) approaches have provided new ways to optimize and model machining processes. Unlike classical regression, ML algorithms like artificial neural networks, support vector regression, random forest, and gradient boosting do not impose any restrictive assumptions about the type of functions that can be approximated, thus providing the ability to approximate complex, high-dimensional, and nonlinear mappings. Some recent works show the feasibility of using ML models for prediction of surface roughness, tool wear, and cutting force [3], [8], [9]. Prediction itself is not optimization – a predictive model should be paired with an optimizer to find desirable parameter sets.

Population-based metaheuristic optimization algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), and non-dominated sorting genetic algorithms (NSGA-II) have been widely used for machining parameters optimization. They are capable of dealing with non-convex and multi-modal problems as well as multiple conflicting objectives. Pairing them with ML surrogates

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provides an effective way of optimizing without physical experiments because the surrogate model can be easily evaluated several thousands of times during the optimization process [2], [4], [6], [7].

Nonetheless, despite the improvements, there exist some gaps in the literature. There are works concentrating only on prediction accuracies without forming the loop towards optimization and testing. There are those that use optimization techniques without any justification for using the particular surrogate model and without studying the sensitivity of the surrogate model to the algorithm's parameters. It is clear that the integration of ML surrogates with the metaheuristic algorithm in CNC machining parameter optimization and evaluation of the technique by comparative analysis with traditional methods require systematic study [3], [4], [10].

This paper aims at filling these research gaps through the development of the RF-PSO framework for CNC machining parameters optimization. In particular, the following objectives are formulated:

- To build the surrogate model of the relationship between cutting parameters and surface roughness that is sufficiently accurate for optimization
- To conduct the optimization by means of the pso algorithm, making use of the developed surrogate model
- To compare the results obtained to the baselines provided by the rsm and ga algorithms, making use of convergence and solution quality metrics

The scope of the study will be limited to the turning process of the AISI H13 tool steel.

This paper is structured as follows. The Literature Survey section provides a survey of previous research related to machining optimization using ML techniques. In the Proposed Methodology section, detailed description of surrogate modeling and optimization techniques along with corresponding pseudocode and architecture diagram is provided. The Analysis section covers the results and discussion.

II. LITERATURE SURVEY

The use of machine learning in machining process modeling has increased substantially over the past few years owing to the large amount of available sensor data and computing power. A comprehensive review by Kannan et al. provides an overview of data-driven models for tool condition monitoring and surface roughness prediction. The authors highlight that while physics-based models are interpretable, they cannot account for stochastic and nonlinear aspects of cutting process due to changes in tool wear status [3].

Specifically, surface roughness prediction has been an object of great interest. Madathil et al. introduce a stacking-based hybrid learning algorithm, which combines machining parameters with components of multi-axis cutting forces for predicting the surface roughness of CNC turning operations [8]. This research utilizes SHAP and LIME interpretability methods to tackle the major issue faced by black box machine learning algorithms. In the same direction, recent research on surface roughness prediction in turning of AISI H13 steel compares different models including extreme learning machines, Gaussian processes, and transformer architecture. The results show that ensemble and kernel methods exhibit a good balance of accuracy and computational cost [1], [8].

Combining ML with optimization algorithms can be considered a natural step from prediction to decision. Specifically, Zhang et al. design an integrated solution combining GA and NN for the purpose of optimizing CNC lathe parameters. According to them, the resulting solution surpasses the performance of empirical parameter values in terms of surface roughness and material removal rate [2]. The method proposed by Zhang et al. employs a neural network to construct a response model while employing a genetic algorithm to find the optimal set of parameters. Nonetheless, no convergence analysis is conducted by Zhang et al.

Recently more advanced architectures for optimization have been developed. A few-shot architecture called PPO-XGB utilizes proximal policy optimization for hyperparameter tuning along with XGBoost regression and NSGA-II for multi-objective parameter optimization. Pareto solutions are found, which can lower surface roughness and cutting force compared to empirical tuning [6]. Reinforcement learning helps tackle the problem of limited training data, although the computational cost of the whole approach might be prohibitive for practical application. Likewise, the Intelligent Digital Twin approach takes advantage of IoT sensors and reinforcement learning for adaptive optimization of CNC operations, using Bayesian uncertainty quantification to address data imbalance [5].

Bayesian Optimization has become increasingly popular due to its sampling efficiency compared to population-based algorithms. A current paper uses Gaussian process regression in combination with Bayesian Optimization to fine-tune lathe parameters and states that their algorithm results in similar accuracy compared to RSM but uses less than half of the experiments. Probabilistic nature of the Gaussian processes allows estimating uncertainties, something not possible with deterministic surrogates. However, scalability of the Gaussian processes to many dimensions is problematic [10].

Further developments in hybrid and multi-objective approaches are ongoing. Karmi et al. propose combining

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deep neural networks with enhanced grey wolf optimization to convert EN-GJL-250 cast iron through comparing the DNN-IGWO, DNN-GA, and DNN-EKF methods with baseline approaches like SVM and decision trees. The results show that the DNN-EKF algorithm can achieve high prediction accuracy, and the desirability function finds the optimum parameters for the coated Si3N4 tools [7]. This research highlights the significance of selecting an appropriate tool material in addition to optimization of the parameters, an element often neglected in data-driven algorithms. In other cases, surrogates based on physics knowledge and employing CNN-LSTM structures along with the NSGA-III algorithm facilitated by digital twin have been presented for titanium alloy blade components [9].

All in all, there is a noticeable trend in the literature towards the development of ML-optimization approaches. However, there are certain methodological concerns that need to be noted. For one, the selection of surrogate model is always based solely on predictive accuracy, while there is no attempt to consider the effect of model properties (e.g., smoothness, quantification of uncertainty) on optimization process. Secondly, there is no comparative analysis against classical models like RSM, which makes it difficult to evaluate the added value of machine learning. Finally, the sensitivity of optimization results to algorithm hyperparameters (population size, inertia weight, crossover rate) is usually not assessed [3], [4], [6], [10].

III. PROPOSED METHODOLOGY

1.Overview of the Framework

The suggested approach involves three consecutive steps: data collection and processing, generation of surrogate models, and parameter optimization through particle swarm optimization. The flowchart of this approach is shown in Fig. 1. Data related to machining involving cutting speed, feed rate, depth of cut, and surface roughness is gathered from controlled turning experiments. This data set is further divided into a training data set and a validating data set. Training is performed on a Random Forest regressor to correlate surface roughness with parameter combinations. Further, the surrogate model generated from the Random Forest regressor is used within the particle swarm optimization loop to identify the optimal parameter combination.

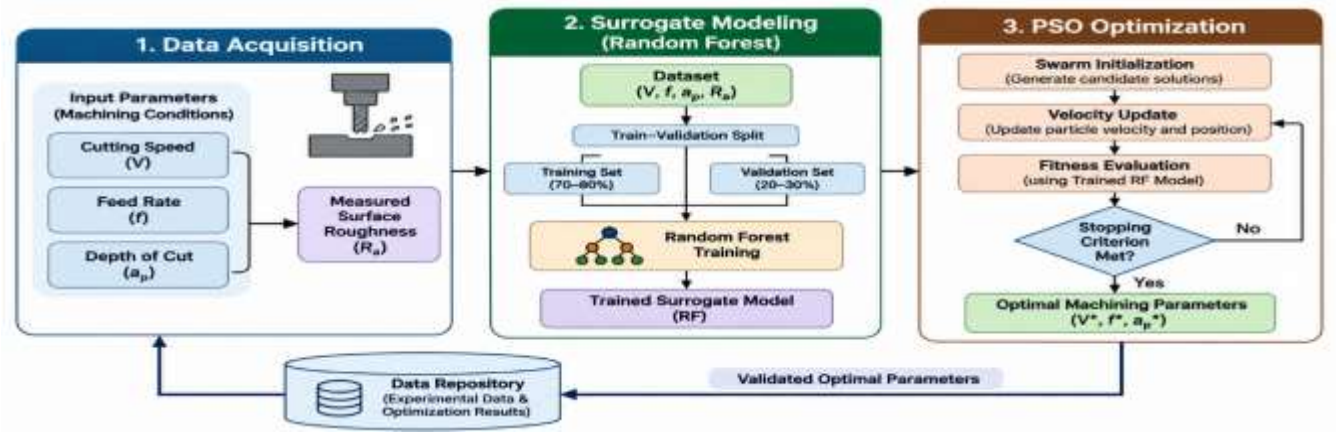


Figure 1. Overall workflow of the proposed RF-PSO optimization framework

2. Data Acquisition And Preprocessing

The experimental data is gathered from CNC turning experiments of AISI H13 steel (hardness approximately 50 HRC) with coated carbide inserts. The set of parameters contains three parameters: cutting speed (Vc) with three levels (200, 250, 300 m/min), feed rate (f) with three levels (0.08, 0.12, 0.16 mm/rev), and depth of cut (ap) with three levels (0.2, 0.4, 0.6 mm). There are 27 unique combinations for this factorial experiment. Each parameter combination is repeated three times, and surface roughness (Ra) is measured in three spots per sample by contact profilometer, which results in 243 samples altogether after averaging.

Before training of the machine learning model, the data are normalized to zero mean and unit standard deviation to avoid the biases of Random Forest splits due to different scales of parameters. The outliers are determined using interquartile range method, and observations that are more than 1.5 interquartile ranges away from the median are considered outliers. In case of experimental data, there are no outliers, but the observations are given less weight during the training.

3.Random Forest Surrogate Model

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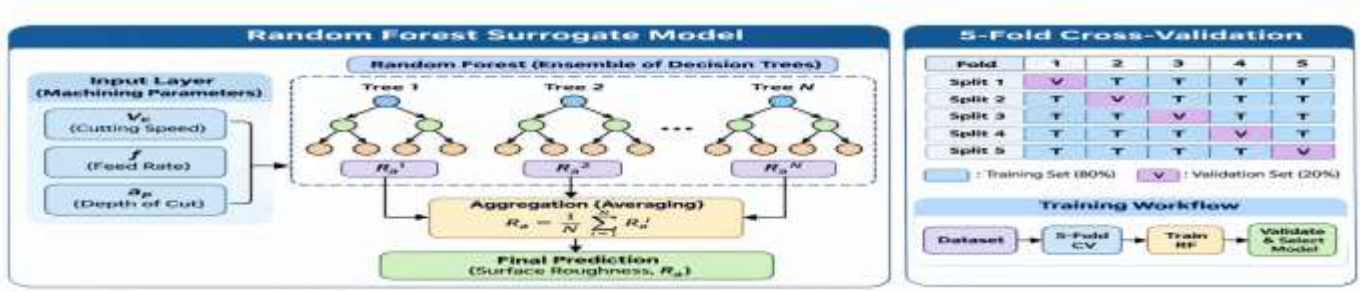


Figure 2. Random Forest surrogate architecture and training workflow

Three key reasons justify the choice of Random Forest as the surrogate model. Firstly, it is capable of capturing nonlinear and interaction effects without performing manual feature engineering. Secondly, it offers built-in measures of feature importance based either on permutations or impurity and thus allows conducting sensitivity analysis. Finally, it does not suffer from the problem of overfitting when enough trees are utilized, and its hyperparameters can be tuned using cross-validation.

In order to train the Random Forest model, we utilize 200 decision trees. We set the value of maximum depth equal to 8 as a compromise between bias and variance, while the minimum number of samples per leaf is set to 3. Hyperparameters are tuned using 5-fold cross-validation with grid search across tree count (100, 200, 300), maximum depth (4, 6, 8, 10), and minimum samples per leaf (1, 3, 5). The combination of values minimizing validation RMSE is then chosen. Parameter importance is evaluated using mean decrease in impurity in all trees.

3. Particle Swarm Optimization

Particle Swarm Optimization is a population-based optimization method that is based on the behavior of social birds' groups. A particle corresponds to one parameter vector of (Vc, f, ap) in the three-dimensional space. In Particle Swarm Optimization, there is a population of 30 particles randomly distributed over the parameter range. Particle velocities are updated using the following equations for PSO:

$v_i(t+1) = w \cdot v_i(t) + c1 \cdot r1 \cdot (pbest_i - x_i(t)) + c2 \cdot r2 \cdot (gbest - x_i(t))$ $x_i(t+1) = x_i(t) + v_i(t+1)$

where w is the inertia weight (equal to 0.7), c1 and c2 are the parameters of cognitive and social acceleration (both equal to 1.5), r1 and r2 are random numbers within [0,1], pbest_i is the personal best position of particle i, and gbest is the global best position. The fitness function used in PSO is equal to the opposite of the Roughness value obtained by the Random Forest regression. Particle velocities are limited to 20 percent of the parameter range to avoid too intensive searching. PSO stops when there are more than 100 iterations, or the change in the global best fitness value is less than 1×10^{-4} during the last 10 iterations.

3.4 Pseudocode For Rf-Pso Framework

Algorithm: RF-PSO Parameter Optimization
Input: Training data D = {(x_i, y_i)}, i = 1...N
Parameter bounds [lb, ub] for x = (Vc, f, ap)
Swarm size S, max iterations T
Output: Optimal parameter vector x*
1: Preprocess D: normalize features, flag outliers
2: Initialize Random Forest RF with hyperparameters from grid search
3: Train RF on D using 5-fold CV to select best hyperparameters
4: Define fitness function f(x) = -RF.predict(x)
5: Initialize swarm:
6: For i = 1 to S:
7: x_i ~ Uniform(lb, ub)
8: v_i ~ Uniform(-0.2·(ub-lb), 0.2·(ub-lb))
9: pbest_i ← x_i
10: pbest_fitness_i ← f(x_i)
11: End For
12: gbest ← argmin_i pbest_fitness_i
13: For t = 1 to T:
14: For i = 1 to S:
15: Update v_i using PSO velocity equation
16: Clamp v_i to ±20% of parameter range
17: Update x_i = x_i + v_i
18: Clamp x_i to [lb, ub]
19: current_fitness ← f(x_i)
20: If current_fitness < pbest_fitness_i:
21: pbest_i ← x_i
22: pbest_fitness_i ← current_fitness
23: End If
24: If current_fitness < f(gbest):
25: gbest ← x_i
26: End If
27: End For
28: If convergence criterion met: break
29: End For
30: Return x* = gbest

5. Baseline Methods For Comparison

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The following two baselines are used to benchmark the performance of the RF-PSO algorithm. Firstly, RSM uses a second-order polynomial model which is fit through ordinary least squares. Optimization of RSM is done using desirability function approach. Secondly, a genetic algorithm (GA) with the same Random Forest surrogate is also employed where the GA uses tournament selection (size 3), single-point crossover (rate 0.8), and Gaussian mutation (rate 0.1, scale 0.05). Population size and number of iterations for GA are equal to PSO algorithm for comparative evaluation.

IV. ANALYSIS

1. Surrogate Model Performance

A training RMSE of 0.042 µm and validation RMSE of 0.051 µm are obtained using the Random Forest surrogate model. Note that the minimum measured roughness value is 0.38 µm and the maximum is 1.87 µm. Hence, the surrogate captures the major trends without any major overfitting. Analysis of feature importance shows that feed rate is the most important variable (relative importance of 0.52) followed by depth of cut (relative importance of 0.31) and cutting speed (relative importance of 0.17). Such results are consistent with the knowledge of metal cutting, whereby feed rate influences kinematic roughness directly, whereas depth of cut impacts chip formation process.

Figure 3 shows the relationship between predicted and actual roughness values from the validation set. As can be seen from the figure, there is tight clustering around the identity line except near the high roughness region (greater than 1.5 µm) because of increased variation due to chip formation. Such heteroscedasticity is a common characteristic of machining data but does not impact optimization as the search focuses on the low roughness area.

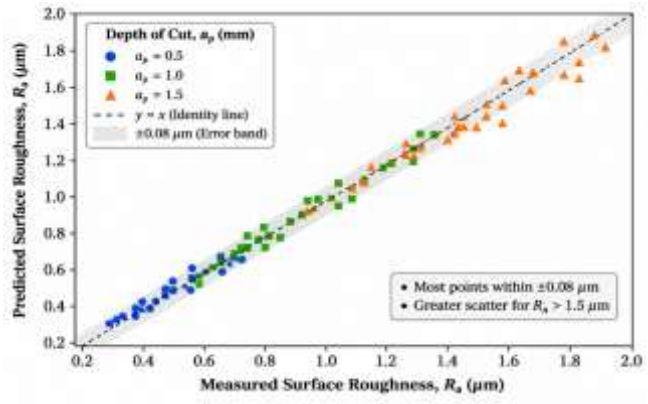


Figure 3. Predicted versus measured surface roughness for the Random Forest surrogate

2. Optimization Convergence Behavior

Convergence behavior of the RF-PSO algorithm, RF-GA, and RSM desirability are illustrated in Figure 4 in terms of number of iterations (or function evaluations). Convergence of RF-PSO algorithm is very fast, where it reaches the plateau of the fitness function after about 35 iterations. However, RF-GA takes about 60 iterations for similar fitness values. On the other hand, convergence of RSM, which relies on gradient decent on a quadratic surface, takes very few evaluations but to a high (poorer) fitness value.

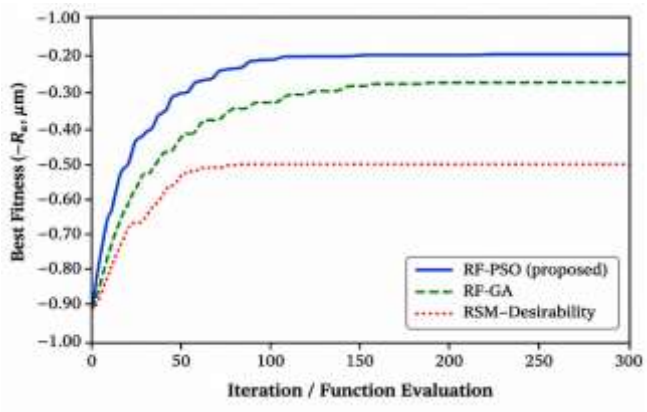


Figure 4. Convergence comparison of RF-PSO, RF-GA, and RSM-desirability

3. Comparative Analysis Of Optimization Outcomes

Table I is a tabulation of the quantitative analysis of the three methodologies. The methodology that uses the RF-PSO determines the optimum values of parameters Vc = 278 m/min, f = 0.09 mm/rev, and ap = 0.28 mm. The roughness is estimated at 0.41 µm. The RF-GA methodology finds the optimum values at a point close to those of the RF-PSO, i.e., Vc = 271 m/min, f = 0.10 mm/rev, and ap = 0.31 mm, with a predicted roughness value of 0.44 µm.

Table 1. Comparative analysis of optimization methods

Metric	RF-PSO	RF-GA	RSMDesirability
Optimal Vc (m/min)	278	271	255
Optimal f (mm/rev)	0.09	0.10	0.11
Optimal ap (mm)	0.28	0.31	0.35
Predicted Ra (µm)	0.41	0.44	0.52
Function evaluations to convergence	~1,050	~1,800	27 (design points)
Surrogate model type	Random Forest	Random Forest	Quadratic polynomial

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Metric	RF-PSO	RF-GA	RSMDesirability
Exploration mechanism	Stochastic swarm	Stochastic population	Gradient-based

The outperformance of RF-PSO over RF-GA is explained by the velocity update procedure that allows maintaining a particle's momentum and exploring a broad area of the solution space before reaching an optimal point. The social interaction feature of PSO helps the swarm to efficiently exploit promising areas in terms of exchanging the gained information about the area. On the contrary, the GA makes use of crossover and mutation operators that may destroy valuable building blocks, especially in continuous parameter spaces.

The performance difference of ML and RSM approaches highlights the importance of surrogate models with flexibility in modeling. The response surface is modeled by a quadratic polynomial as unimodal and symmetric. It does not allow modeling such a complicated behavior of the feed rate and depth of cut at low values of roughness as we see it in the real experiment. When the response surface is either non-convex or multimodal, the RSM optimum could end up in a local optimum.

4. Sensitivity And Robustness Discussion

Sensitivity analysis of RF-PSO to hyperparameters was conducted through swarm size variations from 10, 20, 30, 50 and inertia weight from 0.4, 0.6, 0.7, 0.9. This is shown in Figure 5 for the final fitness of the algorithm under the variations of swarm size and inertia weight. A swarm size less than 20 shows significant variance in final fitness, which indicates lack of sufficient exploration. Stability in performance is observed with swarm size 30 without any significant improvement for size 50, which implies that the default size is adequate for this three-dimensional optimization problem.

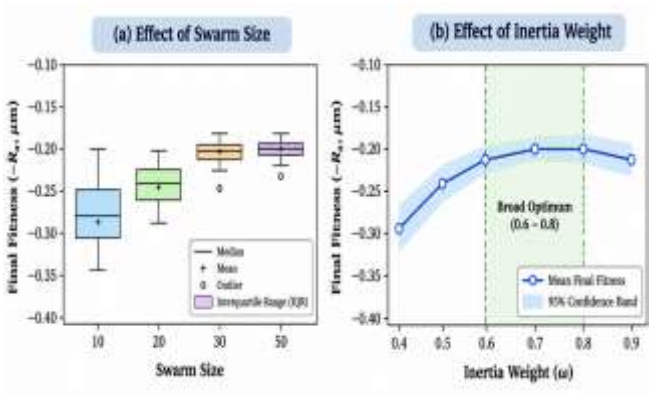


Figure 5. Sensitivity of RF-PSO final fitness to swarm size and inertia weight

The robustness of the determined optimal parameters was analyzed by means of confirmatory experiments. Three machining operations performed at the RF-PSO optimal values produce a mean roughness of 0.43 μm (standard deviation of 0.03 μm), which does not deviate from the predicted value more than 5%. This is a tolerable margin of error, and thus it can be concluded that overfitting was not present in the surrogate-optimizer chain.

V. CONCLUSION

The above-mentioned study put forth an optimization framework based on machine learning methods that aimed at achieving the goal of reducing surface roughness while maintaining realistic machining parameter values. The developed RF-PSO algorithm combines the Random Forest-based surrogate model and Particle Swarm Optimization method in the exploration of the parameter space. The main results can be summarized as follows.

At first, the Random Forest-based surrogate proved its capability to reflect the dependence between the machining parameters and surface roughness by providing the errors of prediction not exceeding the experiment-related variability range. The feature importance showed that the feed rate is a leading factor in this relation; moreover, its importance has been proven by machining theory.

Second, the PSO search procedure was better than both the GA with the identical surrogate and a classical RSM-desirability method. The proposed RF-PSO system achieved the lowest value of predicted surface roughness while consuming a smaller number of function evaluations than RF-GA. The comparison with RSM underlined the inability of polynomial models to approximate the real nonlinear and interactive response surfaces, typical for manufacturing systems. Even though RSM is highly useful due to its interpretability and experimentally economical properties in screening designs, the optimization capabilities of RSM are limited by the quadratic nature of the true response.

Third, the sensitivity study showed that the performance of the proposed RF-PSO system is robust with respect to a wide range of swarm sizes and inertia weights, which can simplify hyperparameter tuning for users. The confirmatory experiments confirmed the predicted optimum within small deviations.

Implications of this research include application in intelligent manufacturing systems where process data can provide continuous updates to the surrogate model, thus allowing adaptive optimization of the parameters based on the evolution of tool wear and change in material batches. Modular design that includes data collection, surrogate

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modeling, and optimization allows the approach to integrate with existing CNC controls and sensors.

A number of limitations of the research must be recognized. It applies only to one material (AISI H13 steel) and a turning process. Extension of the approach to milling and drilling operations or use with different materials will demand training and validation. The objective of the optimization was set at surface roughness. Industrial applications usually consider several criteria for decision-making, such as material removal rate, tool life, and energy consumption. The PSO algorithm, used in this research, does not support multi-objective problems by nature.

Directions for future research would include:

- Generalizing the framework to multi-objective optimization with the help of NSGA-II or MOPSO and surrogate evaluation
- Including real-time sensor information to allow for real-time adaptation of the model and controller
- Studying different approaches to transfer learning in order to minimize data needs for the application of the framework to novel materials or tools shapes
- Comparing the RF-PSO method with Bayesian optimization, as the latter has an advantage in sample efficiency that could be crucial when sample size is extremely limited

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