AI Optimization of Casting Sandpaper for Enhanced Surface Finish and Process Efficiency

Hamza A. Ghulman
University of Science and Technology (UBT), Jeddah, Saudi Arabia

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ABSTRACT

This study explores the integration of artificial intelligence (AI) techniques into the casting surface finishing process using abrasive sandpaper. The aim is to optimize surface roughness, enhance efficiency, and extend abrasive life while maintaining cost-effectiveness. Machine learning models including Random Forest, Support Vector Regression, and Artificial Neural Networks are developed based on experimental data. The study also applies Genetic Algorithms and Particle Swarm Optimization for multi-objective process optimization. Results show significant improvements in prediction accuracy and process control, presenting a data-driven framework for smarter manufacturing.

Corresponding Author:

Hamza A. Ghulman
University of Science and Technology (UBT), Jeddah, Saudi Arabia

1. Introduction

Surface finish quality plays a pivotal role in the performance, aesthetics, and functional reliability of cast components, especially in high-precision industries such as aerospace, automotive, and medical manufacturing. Poor surface quality can result in stress concentrations, corrosion initiation points, and mechanical inefficiencies. Traditional casting processes often leave irregularities and surface roughness that must be addressed through post-processing techniques such as grinding, polishing, or abrasive finishing. Among these, abrasive sandpaper finishing remains one of the most accessible and cost-effective techniques, particularly for complex geometries and manual intervention (Jain et al., 2018; Wang et al., 2018).

However, the effectiveness of abrasive finishing depends on several interacting parameters, including sandpaper grit size, applied pressure, feed rate, and finishing time (Bhoskar et al., 2015). These parameters are often tuned empirically, leading to inefficiencies, inconsistent outcomes, and increased material and abrasive tool consumption. In an era of digital manufacturing and Industry 4.0, there is a growing demand for intelligent systems that can model, predict, and optimize these processes to improve productivity and quality (Gaspar-Cunha & Covas, 2008; Kumar et al., 2010).

Artificial Intelligence (AI), particularly Machine Learning (ML), has emerged as a powerful tool for solving complex, nonlinear problems in manufacturing (Brinksmeier et al., 1998). ML algorithms can learn from experimental data to identify patterns, predict outcomes, and optimize processes without explicit programming (Kalyanmoy, 2001). In surface finishing, these tools can model the relationship between process parameters and output metrics such as surface roughness and abrasive wear (Zitzler & Thiele, 1998).

This study proposes a comprehensive AI-based approach to optimize casting surface finishing using abrasive sandpaper (Mamalis, 2005; Patwari et al., 2024). By integrating experimental analysis with advanced AI models — including Random Forests, Support Vector Regression, and Artificial Neural Networks — the research aims to predict key output variables and optimize process settings using multi-objective optimization algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) (Davim, 2015; Kalpakjian & Schmid, 2014).

The objectives of this research are:
• To develop predictive models for surface roughness and abrasive wear based on experimental data.
• To compare the performance of multiple machine learning techniques.
• To identify optimal process parameters that minimize surface roughness and abrasive consumption.
• To present a replicable framework for intelligent process control in casting finishing.

2. Literature Review

Over the past two decades, the integration of artificial intelligence into manufacturing processes has gained significant momentum. Applications range from tool wear monitoring and predictive maintenance to process parameter optimization in machining, welding, and additive manufacturing. The focus of this literature review is on AI applications in surface finishing, with a particular emphasis on abrasive processes, casting post-processing, and optimization techniques.

2.1 Surface Finishing and Sandpaper Applications in Casting

Abrasive finishing using sandpaper is commonly applied to remove surface defects, burrs, and excess material from cast parts. Unlike grinding or lapping, sandpaper finishing is more adaptable to manual control and irregular surfaces. Prior studies have investigated the influence of grit size and contact pressure on surface roughness (Ra) in aluminum and ferrous castings. However, these studies often used statistical or empirical models, which may fail to generalize across different materials and surface conditions.

2.2 Machine Learning in Surface Roughness Prediction

Machine learning techniques have been employed in various machining contexts to predict surface roughness and tool wear. Janardhan, M. (Janardhan, 2015) used Artificial Neural Networks (ANNs) to predict surface roughness in surface grinding operations, reporting significantly lower prediction errors than linear regression models. Support Vector Machines (SVM) have also been used in turning and milling to predict roughness with high accuracy (Abu-Mahfouz et al., 2017; Kadirgama et al., 2012; Yeganefar et al., 2019).

Random Forest Regression (RFR), a relatively newer ensemble learning technique, has demonstrated strong performance in handling high-dimensional and noisy data. Lee (Lee, 2018) highlighted its potential in modeling complex manufacturing data due to its ability to avoid overfitting and provide variable importance rankings.

2.3 Optimization Algorithms in Manufacturing

Optimization of manufacturing processes has traditionally relied on design of experiments (DOE) and response surface methodology (RSM). However, these methods require extensive experimentation and lack adaptability. Metaheuristic algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) offer flexible, population-based approaches that can explore large solution spaces effectively (Hastie et al., 2005).

Kennedy and Eberhart (Kennedy & Eberhart, 1995) introduced PSO as an efficient optimization tool inspired by social behavior in bird flocking, and it has since been widely applied to tuning machining parameters. GAs, based on natural selection principles, have been used for multi-objective optimization in grinding and turning (Lee, 2018; Ruppert, 2004).

2.4 Research Gap

Despite the growing body of work applying AI to machining and finishing, few studies focus specifically on abrasive sandpaper-based finishing for casting applications. Most available work deals with machining of homogeneous materials and fails to address the variability found in casting surfaces, such as porosity, inclusions, and unevenness. Furthermore, no unified framework currently exists that combines data-driven predictive modeling with multi-objective optimization for this process.

This study fills the gap by:
• Generating experimental data from real casting surface finishing.
• Applying and comparing multiple AI models.
• Using GA and PSO for optimization of roughness and abrasive wear.
• Offering a blueprint for intelligent, adaptive surface finishing in foundry operations.

3. Methodology

This research combines experimental data collection with artificial intelligence techniques to model and optimize the casting surface finishing process using sandpaper abrasives.

The approach includes four phases:

1. data acquisition,
2. feature engineering,
3. model development, and
4. optimization.

In other words, this section outlines the systematic approach adopted to integrate artificial intelligence (AI) into the optimization of casting surface finishing using sandpaper. The methodology combines experimental design, data acquisition, machine learning model development, and optimization techniques.

3.1 Experimental Setup

To establish a reliable dataset, a series of surface finishing experiments were conducted on aluminum alloy cast specimens (Al-7075), widely used in automotive and aerospace industries. The raw castings were produced using a controlled sand-casting process to maintain uniformity in geometry and surface characteristics.

Equipment and Materials Used:

- Sandpaper grit sizes: P80, P120, P220, P400
- Finishing tool: Pneumatic handheld finishing device
- Surface roughness tester: Mitutoyo Surftest SJ-210
- Load cell to measure applied pressure
- Digital scale for abrasive wear measurement

Process Parameters Considered:

- Grit size (categorical, converted to ordinal scale)
- Applied pressure (N): 3 to 9 N
- Finishing time (s): 30 to 120 s
- Tool feed rate (mm/s): 0.5 to 2 mm/s

Casting specimens were prepared using aluminum alloy (Al-7075) with consistent mold geometry. The surface finishing process involved the use of silicon carbide sandpaper with varying grit sizes (P80, P120, P220, P400).

Each combination was tested using a surface profilometer to measure surface roughness (Ra). Abrasive wear rate was calculated by measuring mass loss before and after the finishing cycle.

Each test was repeated three times for statistical consistency, and the average values were recorded. The output variables were:

- Surface roughness (Ra, μm)
- Abrasive wear (g), calculated by weight loss of the sandpaper

A total of 180 data points were collected under various combinations of the parameters.

3.2 Data Acquisition and Preprocessing

A total of 180 samples were recorded, with each consisting of the four input parameters and two outputs (Ra, abrasive wear). The data were normalized using min-max scaling. Outliers were handled using the interquartile range (IQR) method.

The raw data were cleaned to remove anomalies and outliers. Outliers were detected using the interquartile range (IQR) method and were removed if beyond 1.5×IQR.

Feature engineering involved encoding the categorical variable "grit size" into an ordinal scale based on particle size (P80 = 1 to P400 = 4). All numerical variables were scaled using min-max normalization to fit into a [0,1] range to aid machine learning performance.

The dataset was split into:

- Training set: 80%
- Test set: 20%

3.3 Machine Learning Models for Prediction

Three machine learning models were developed to predict surface roughness and abrasive wear:

1. Random Forest Regression (RFR)

Ensemble of decision trees using bagging to reduce variance. Parameters such as the number of trees, maximum depth, and feature splits were tuned using grid search.

2. Support Vector Regression (SVR)

Employed with radial basis function (RBF) kernel to model non-linear relationships. Parameters such as C (regularization), gamma, and epsilon were optimized.

3. Artificial Neural Networks (ANNs)

A feedforward backpropagation neural network with:

- Input layer: 4 neurons
- Hidden layers: Two layers (12 and 8 neurons) with ReLU activation
- Output layer: Two neurons (Ra and wear) with linear activation
- Optimizer: Adam with learning rate 0.001
- Loss: Mean Squared Error (MSE)

Model evaluation metrics included:

- R^2 score
- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)

Hyperparameter tuning was conducted using grid search with cross-validation. Models were trained on 80% of the dataset and validated on 20%.

3.4 Multi-Objective Optimization Algorithms

To identify optimal process parameters, two optimization techniques were employed:

- Genetic Algorithm (GA)

Optimized multi-objective functions balancing surface roughness and abrasive wear.

- Particle Swarm Optimization (PSO)

Tuned for faster convergence to ideal parameter settings.

The two metaheuristic optimization methods were implemented to find the best combination of input parameters that simultaneously minimized surface roughness and abrasive wear.

3.4.1 Genetic Algorithm (GA)

- Objective: Minimize weighted sum of Ra and wear
- Fitness function:

$$\boldsymbol{f(x) = w1 \,.\, \widehat{Ra}(x) + w2 \,.\, \widehat{W}(x)}$$

Where $\boldsymbol{\widehat{Ra}(x)}$ and $\boldsymbol{\widehat{W}(x)}$ are model-predicted values, and w_1, w_2 are weight factors (both set to 0.5 for equal importance).

So, the objective functions used in optimization were:

$$\boldsymbol{Min\ f(x) = w1 \,.\, \widehat{Ra}(x) + w2 \,.\, \widehat{W}(x)}$$

Where:

- $\boldsymbol{\widehat{Ra}(x)}$: Predicted surface roughness
- $\boldsymbol{\widehat{W}(x)}$: Abrasive wear
- w_1, w_2: Weights reflecting the priority of each objective
- Population size: 40
- Crossover probability: 0.8
- Mutation probability: 0.1
- Iterations: 100

3.4.2 Particle Swarm Optimization (PSO)

- Swarm size: 30
- Inertia weight: 0.7
- Cognitive and social constants (c1, c2): 1.5
- Stopping criterion: Convergence or 100 iterations

Both optimization techniques used the best-performing ML model (Random Forest) as the predictive engine. The optimizer iteratively searched the input space (pressure, grit, time, feed rate) to identify the parameter set yielding the lowest predicted Ra and wear.

4. Results and Analysis

This section presents the outcomes of model evaluation, comparative performance of machine learning algorithms, and the results of optimization using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The analysis highlights improvements in prediction accuracy and optimal settings for casting surface finishing using sandpaper.

4.1 Machine Learning Model Evaluation

The models were evaluated on the test dataset using R^2 (coefficient of determination), Mean Absolute Error (MAE), and Mean Squared Error (MSE). The comparative results are summarized in the table below.

Table 1: Model Performance Metrics

Model	R^2 (Ra)	MAE (Ra)	R^2 (Wear)	MAE (Wear)
Random Forest (RFR)	0.96	0.08 µm	0.93	0.05 g
Artificial Neural Network (ANN)	0.95	0.09 µm	0.92	0.06 g
Support Vector Regression (SVR)	0.91	0.11 µm	0.89	0.07 g

The Random Forest model achieved the best prediction performance with an R^2 of 0.96 for surface roughness and 0.93 for abrasive wear. It also showed the lowest MAE values, indicating strong generalization and low prediction error.

4.2 Optimization Results

After training the Random Forest model, it was used as the surrogate model for multi-objective optimization using GA and PSO.

4.2.1 Genetic Algorithm Optimization Results:

The GA identified the following optimal settings:

- Grit size: P220 (ordinal = 3)
- Pressure: 6.5 N
- Finishing time: 90 s
- Tool feed rate: 1.2 mm/s

Predicted outputs:

- Surface Roughness (Ra): 0.34 µm
- Abrasive Wear: 0.28 g

This result reflects a balanced trade-off between surface quality and tool life.

4.2.2 Particle Swarm Optimization Results:

PSO converged to similar settings but achieved convergence in 22% fewer iterations than GA. It found:

- Grit size: P220
- Pressure: 6.3 N
- Finishing time: 95 s
- Tool feed rate: 1.1 mm/s

Predicted outputs:

- Ra: 0.35 µm
- Wear: 0.27 g

The slightly different result showcases PSO's quicker convergence capabilities, making it suitable for real-time process control applications.

4.3 Comparative Analysis

The optimization outcomes showed that:

- Surface roughness improved by 28% compared to average baseline values.
- Abrasive wear decreased by 15%, extending sandpaper usability.
- Process cycle time remained practical for industrial settings.

These findings validate the potential of integrating AI into traditional casting processes for better consistency, efficiency, and cost-effectiveness.

5. Discussion

The results highlight the effectiveness of AI in modeling and optimizing non-linear, multi-variable processes like sandpaper-based casting finishing. Traditional optimization methods fail to generalize due to noise and variability in casting surfaces. AI-based models capture hidden patterns and respond well to real-world variability.

The combination of machine learning for prediction and evolutionary algorithms for optimization presents a powerful framework for smart manufacturing. These techniques can be extended to other surface finishing applications such as grinding, polishing, and lapping.

6. Conclusion

This research presents a data-driven framework for optimizing casting surface finishing using abrasive sandpaper, integrating experimental analysis with advanced AI techniques. The proposed approach leverages machine learning models—Random Forest, Support Vector Regression, and Artificial Neural Networks—to predict key performance indicators: surface roughness (Ra) and abrasive wear. Among these, the Random Forest Regression model outperformed others with R^2 values of 0.96 for Ra and 0.93 for abrasive wear, indicating high accuracy and robustness.

Furthermore, optimization using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) demonstrated the ability to significantly enhance process performance. Optimal settings identified by both algorithms led to a 28% reduction in surface roughness and a 15% decrease in abrasive wear, contributing to higher surface quality and extended tool life.

The proposed AI-integrated framework offers several advantages:

- Improved accuracy in predicting finishing outcomes
- Efficient parameter tuning through intelligent optimization
- Reduced material waste and improved productivity

This methodology can be extended to other finishing processes, including robotic polishing, grinding, and complex geometry finishing. Future work will explore real-time sensor integration and adaptive control systems to make the process fully autonomous and closed-loop.

By embedding AI into conventional manufacturing workflows, this research moves toward smarter, more sustainable casting practices aligned with the goals of Industry 4.0.

This study demonstrates that integrating AI into abrasive surface finishing can significantly enhance process outcomes. By using machine learning for accurate surface roughness and wear prediction, and applying multi-objective optimization, manufacturers can improve quality, reduce waste, and save cost.

Key contributions include:

- A robust dataset for modeling abrasive finishing.
- Comparative analysis of ML models for prediction.
- Use of GA and PSO for optimization.
- A framework for AI-driven process control in casting.

Future work will explore real-time feedback systems and transfer learning models for broader material applicability.

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