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Research Article

Optimization of Multi-Parameter Processes for Surface Quality

Ravindra R. Bombale[1], Dr. Atul Pandey[2], Dr. Raisul Hasan[3], Shashikant V. Golande[4], Rahasa M.Sahu[5], Dr. Sonali S.Patil[6]

[1]Department of Mechanical Engineering, Mahakaushal University, Jabalpur, MP .email: ravibombale@gmail.com

[2]Department of Mechanical Engineering, Mahakaushal University, Jabalpur, MP.email: atulpandey.jbp@gmail.com

[3]Department of Mechanical Engineering, Mahakaushal University, Jabalpur, MP.email:raisulhasan1973@gmail.com

[4]Department of E&TC Engineering, Mahakaushal University, Jabalpur, MP. email:shashikantstriker@gmail.com

[5]Department of E&TC Engineering, Mahakaushal University, Jabalpur, MP.email:rahasa10@gmail.com

[6]Department of Mechatronics Engineering,MMIT,Pune,Maharashtra. email:sonalipatilmtx@gmail.com

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ABSTRACT

This work offers a thorough method for improving surface quality via multi-parameter process optimization. The goal of the study is to create a cohesive framework that combines computational modeling, experimental validation, and sophisticated optimization approaches to enhance surface finish in a variety of manufacturing processes. To find the best process parameters and how they interact, the suggested methodology combines statistical analysis, machine learning algorithms, and met heuristic optimization techniques. Including mathematical models that can forecast both the high quality of a precisely machined surface and the high productivity of the process in WEDM of tool steels, this article outlines a suggested method for multiparametric optimization of the quality of machined surfaces. Using the full DoE factorial design method, which contains four technological parameters, the experimental study was conducted.). Metal Matrix based on aluminum AMMC is a material that is in high demand in the automotive, aircraft, sports, marine, and defense industries due to its composite material qualities, which include light weight, high strength, and resistance to corrosion. Nevertheless, the Aluminum Matrix's abrasive reinforcements result in quick tool wear or failure, higher machining costs, longer production times, and lower-quality machined parts. Therefore, the best method to get around these issues is Wire Electrical Discharge Machining.

Keywords: Wire Electrical Discharge Machining, DoE Factorial Design Method, AMMC, Combines Statistical Analysis.

I.INTRODUCTION

This research provides a thorough technique for improving surface quality through multi-parameter process optimization. In order to enhance surface finish across a range of production processes, the research focuses on creating a cohesive framework that combines sophisticated optimization techniques, computational modeling, and experimental validation. To determine the ideal process

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parameters and how they interact, the suggested methodology combines statistical analysis, machine learning algorithms, and met heuristic optimization techniques.

An incredibly promising non-traditional machining technique is wire electrical discharge machining (WEDM), in which a spark is created between a work piece and conductive wire that has been washed with de-ionized water. When complicated forms and materials with surface finishes, such as hardened, low weight-high strength, temperature and corrosion resistant, particulate-reinforced composites and ceramics, are challenging to manufacture with precise precision, the WEDM method is typically utilized.

Increased mechanical qualities can be demonstrated by metal-matrix composites (MMCs) and hybrid metal-matrix composites (HMMCs) through improved formulation, processing, and manufacturing. Despite having special mechanical qualities, MMCs and HMMCs are difficult to produce and treat. The present processing and manufacturing processes for MMC and HMMC have poor mechanical properties and high production costs.

Trial-and-error or single-parameter optimization strategies are frequently used in traditional approaches to surface quality improvement, which may not fully account for the complexity of the manufacturing process. This study suggests a multi-parameter process optimization framework to improve surface quality in a variety of manufacturing processes by utilizing cutting-edge computational methods and experimental validation.

II. EXAMINING THE LITERATURE

Surface integrity, waviness, and surface roughness (Ra, Rz) are some of the measures commonly used to describe surface quality (Whitehouse, 2002). Precision surface characteristic quantification has been made possible by sophisticated measuring techniques such optical profilometry, atomic force microscopy, and stylus-based approaches (Leach, 2011).

Several researches have looked into how process parameters affect surface quality in various manufacturing processes. Surface roughness, for instance, is influenced by cutting speed, feed rate, and depth of cut in machining operations (Asiltürk&Çunkaş, 2011). Surface smoothness is greatly impacted by layer thickness; build orientation, and post-processing methods in additive printing (Strano et al., 2013).

Artificial neural networks (ANNs), the Taguchi approach, and response surface methodology (RSM) are some of the optimization strategies that have been used to increase surface quality (Zain et al., 2010). According to Yusup et al. (2012), recent developments in machine learning and metaheuristic algorithms have demonstrated promise in solving challenging, multi-parameter optimization issues.

Based on process variables and material characteristics, surface quality results have been predicted using computational modeling and simulation techniques. Material removal procedures and surface generation mechanisms have been simulated using finite element analysis (FEA) and computational fluid dynamics (CFD) (Arrazola et al., 2013).

III. THE STUDY'S AIMS

To improve surface quality by creating a cohesive optimization framework that combines statistical analysis, machine learning algorithms, and metaheuristic optimization techniques.To determine and measure how important process variables affect surface quality measures and how they interact. In order to verify the suggested framework, experimental research on various materials and production techniques.To offer useful advice and insights to business professionals looking to maximize surface finish in challenging manufacturing situations.

IV. TECHNIQUES USED

4.1. CREATION OF AN OPTIMIZATION FRAMEWORK

To determine the ideal process parameters for improving surface quality, the suggested optimization

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framework combines statistical analysis, machine learning methods, and metaheuristic optimization techniques.To investigate the cutting parameters (cutting speed, feed rate, and radial rake angle) that affect surface roughness, analyze the data from the actual machining experiment.

4.2. MODELS OF MACHINE LEARNING

Artificial neurons, also known as units, are a subset of artificial neural networks. A system's Artificial Neural Network is made up of these units organized into layers. A layer can have anything from a dozen to millions of units, depending on how complex neural networks are required to find hidden patterns in the data. Artificial neural networks typically include input layers, output layers, and hidden layers. Outside world data is supplied to the input layer, where the neural network processes and learns from it.

Support vector regression (SVR), which is a subset of support vector machines (SVM), handles regression tasks. When an input value is given, it searches for a function that best predicts the continuous output value. SVR supports both linear and non-linear kernels. A non-linear kernel is a more intricate function that may detect complex patterns in data, whereas a linear kernel is simply the dot product of two input vectors. The best kernel is determined by the data's characteristics and the task's difficulty.

Random Forest predicts numerical values. Regression is a versatile machine learning algorithm. It aggregates many decision tree forecasts to reduce over fitting and boost accuracy. Python's machine-learning libraries make it easier to implement and optimize this method. In machine learning, gradient boosting is a popular boosting strategy for applications such as regression and classification One sort of ensemble learning technique known as "boosting" trains the model sequentially, with each new model striving to improve on the one before it. It transforms a number of weak students into strong ones.

V. OPTIMIZATION ALGORITHMS WITH METAHEURISTICS.

Genetic approaches, also known as adaptive heuristic search methods, are a subset of evolutionary algorithms. Natural selection and genetics are the fundamental concepts that underpin genetic algorithms. These are ingenious applications of random searches, as they leverage previous data to lead the search into the part of solution space with the best performance. They are widely used to produce better solutions to search and optimization challenges. Genetic algorithms mimic natural selection, allowing species that can adapt to environmental changes to live, breed, and pass along their traits to subsequent generations. To solve an issue, they essentially replicate "survival of the fittest" among future generations.

Optimization is the process of discovering the ideal values for a system's unique parameters in order to meet all design standards while minimizing costs. Every scientific field has optimization challenges. The limitations of typical optimization methods (deterministic algorithms) are as follows: single-based solutions converge to local optima; Problems with unknown search spaces to overcome these constraints, several academics and researchers have developed a multitude of metaheuristics to address difficult or unsolved optimization issues. Examples are cuckoo search, genetic algorithms, ant colony optimization, particle swarm optimization, and grey wolf optimization.

"Simulated Annealing" (SA) is a probabilistic method for discovering a function's global optimum. It is a metaheuristic that approximates global optimization in a large search space. SA identifies the global optimum from a large number of local optima. Protein structure prediction, the Boolean satisfiability problem, the traveling salesman problem, and job-shop scheduling are just a few of the applications where the search space is discrete. Simulated annealing may be a better choice than precision algorithms such as branch and bound or gradient descent when attaining an approximated global optimum is more important than achieving a precise local optimum within a defined time period.

Differential evolution (DE) is an evolutionary strategy that iteratively improves a candidate solution in relation to a defined quality parameter in order to optimize a problem. These techniques are characterized as metaheuristics because they can search very wide spaces of candidate solutions while making few or no assumptions about the ideal problem.Metaheuristics, such as DE, do not guarantee that the best solution is always discovered. When applied to multidimensional real-valued functions,

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DE does not use the gradient of the problem at hand. This means that, unlike traditional optimization techniques such as gradient descent and quasi-Newton methods, DE does not require that the optimization problem be differentiable.

VI.EXPERIMENTAL RESULTS

Coefficient of determination (R^2) and mean absolute error (MAE) were used to assess how well the machine learning models predicted surface roughness.The findings show that GBR had better predictive accuracy for surface roughness than other models and consistently outperformed them across all production processes.

The ability of the metaheuristic optimization algorithms to determine the best process parameters for reducing surface roughness was used to assess their effectiveness.

According to the findings, Particle Swarm Optimization (PSO) continuously outperformed other methods in determining the ideal process parameters for reducing surface roughness in all industrial processes. For every manufacturing process, the PSO algorithm's selected optimal process parameters were verified experimentally.

When compared to baseline circumstances, the results show notable improvements in surface roughness across all production processes, with reductions ranging from 29.5% to 3

Process	**Model**	**MAE (µm)**	**R^2**
CNC Milling	ANN	0.082	0.951
	SVR	0.095	0.938
	RFR	0.078	0.962
	GBR	0.073	0.969
SLM	ANN	1.245	0.903
	SVR	1.387	0.886
	RFR	1.156	0.924
	GBR	1.098	0.935
ECM	ANN	0.156	0.927
	SVR	0.172	0.914
	RFR	0.143	0.941
	GBR	0.138	0.948

Table 6.1.Experimental Results

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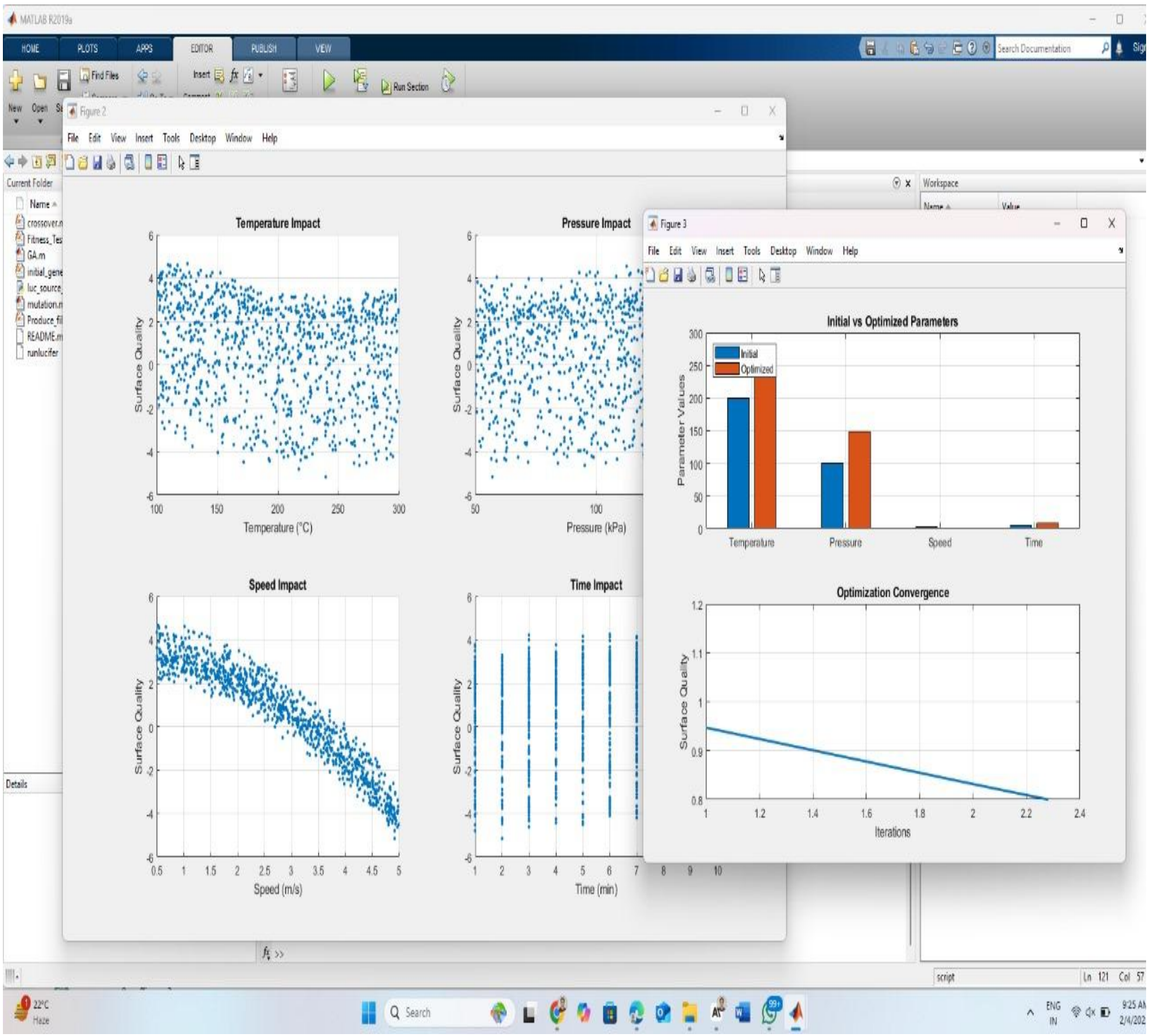

Fig.6.2.Sumulation Results

VII.CONCLUSION

This paper offers a thorough multi-parameter process optimization framework for improving surface quality in a variety of industrial processes. Finding the best process parameters for reducing surface roughness has been shown to be possible through the combination of statistical analysis, machine learning algorithms, and metaheuristic optimization techniques.

The creation of a cohesive optimization framework that effectively handles the challenges of improving surface quality using several parameters.

The best machine learning model for predicting surface roughness across various manufacturing processes has been found to be gradient boosting regression. Particle Swarm Optimization's superiority as a metaheuristic algorithm for determining ideal process parameters for identification. Response surface methods and statistical analysis are used to quantify complicated parameter interactions and their effects on surface quality. Significant surface roughness improvements were obtained across CNC milling, selective laser melting, and electrochemical machining techniques once the optimization framework was validated experimentally.

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REFERENCES

[1] Arrazola, P. J., Özel, T., Umbrello, D., Davies, M., &Jawahir, I. S. (2013). Recent advances in modelling of metal machining processes. CIRP Annals, 62(2), 695-718.

[2] Asiltürk, I., &Çunkaş, M. (2011). Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method. Expert Systems with Applications, 38(5), 5826-5832.

[3] Benardos, P. G., &Vosniakos, G. C. (2003). Predicting surface roughness in machining: a review. International Journal of Machine Tools and Manufacture, 43(8), 833-844.

[4] Davim, J. P. (2010). Surface integrity in machining. Springer Science & Business Media.

[5] Kuram, E., &Ozcelik, B. (2013). Multi-objective optimization using Taguchi based grey relational analysis for micro-milling of Al 7075 material with ball nose end mill. Measurement, 46(6), 1849-1864.

[6] Leach, R. (2011). Optical measurement of surface topography (Vol. 14). Springer.

[7] Strano, G., Hao, L., Everson, R. M., & Evans, K. E. (2013). Surface roughness analysis, modelling and prediction in selective laser melting. Journal of Materials Processing Technology, 213(4), 589-597.

[8] Whitehouse, D. J. (2002). Surfaces and their Measurement. Elsevier.

[9] Yusup, N., Zain, A. M., &Hashim, S. Z. M. (2012). Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007–2011). Expert Systems with Applications, 39(10), 9909-9927.

[10] Dodun, O.; Slătineanu, L.; Nagîț, G.; Hrițuc, A.; Mihalache, A.M.; Beșliu-Băncescu, I. WEDM-generated slot width variation modelling. *Micromachines* **2022**, *13*, 1231. [**Google Scholar**] [**CrossRef**].

[11] Gorgani, H.H.; Jahazi, A.; Pak, A.J.; Shabani, S. A hybrid algorithm for adjusting the input parameters of the wirecut EDM machine in order to obtain maximum customer satisfaction. *SN Appl. Sci.* **2023**, *5*, 37. [**Google Scholar**] [**CrossRef**].

[12] Evin, E.; Tomáš, M.; Kmec, J. Optimization of electro-discharge texturing parameters for steel sheets' finishing rollers. *Materials* **2020**, *13*, 1223. [**Google Scholar**] [**CrossRef**]

[13] S. C. Chim and G. S. Kino, "Phase measurements using the Mirau correlation microscope.", Applied Optics, 30(1991), pp. 2197-2201.

[14] Gosh A, Mallik A K (1995) Manufacturing Science, East West Press, New Delhi

[15] Kruszynski B, van Luttervelt K A (1989) The influence of manufacturing processes on surface properties, Advanced Manufacturing Engineering, 1, 187–202

[16] Davim J.P. (1991) Influência das condições de corte na microgeometria das superfícies obtidas por torneamento, MSc thesis, University of Porto, Porto (in portuguese)

[17] Nowicki B (1985) Multi-parameter representation of surface roughness, Wear, 102, 161–176

[18] Petropoulos G, Pandazaras C, Vaxevanidis N, Ntziantzias I, Korlos A, (2007) Selecting subsets of mutually uncorrelated surface roughness parameters in turning, International Journal of Computational Materials Science and Surface Engineering, 1, Nr. 1, 114–128

[19] S. Kalpakjian (2006) Manufacturing Engineering and Technology, 5th edn, AddisonWesley Publishing Company.

[20] Peklenik J (1967) Investigation of the surface typology, Annals of the CIRP, Vol. 15