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“OPTIMIZATION OF TURNING PARAMETERS USING MACHINE LEARNING ALGORITHMS: A SYTEMATIC REVIEW”

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ABSTRACT

Manufacturing industries attempt to make high quality products at lower cost to remain competitive in the market. The products may be made using various manufacturing methods, such as machining, etc. Turning is among the most common machining processes used to make smooth surfaces with faster material removal rate and enhanced quality. The imperative objective of the science of metal cutting is the solution of practical problems associated with the efficient and precise removal of metal from work piece. It has been recognized that the reliable quantitative predictions of the various technological performance measures, preferably in the form of equations, are essential to develop optimization strategies for selecting cutting conditions in process planning.

Key Words: Iron, Dry Turning, Optimization, Machine Learning, Algorithm

I. INTRODUCTION

Turning is used to produce rotational, typically axi-symmetric, parts that have many features, such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces. Parts that are fabricated completely through turning often include components that are used in limited quantities, perhaps for prototypes, such as custom designed shafts and fasteners. Turning is also commonly used as a secondary process to add or refine features on parts that were manufactured using a different process. Due to the high tolerances and surface finishes that turning can offer, it is ideal for adding precision rotational features to a part whose basic shape has already been formed.

Speed: Speed always refers to the spindle and the work piece.

Feed: It is the rate at which the tool advances along its cutting path. The feed of the tool also affects to the processing speed and the roughness of surface.

Depth of Cut: Depth of cut is practically self explanatory. It can be defined as the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface, expressed in mm.

Cutting Tool Materials

Selecting the appropriate cutting tool material for a specific application is crucial in achieving efficient operations. Increasing cutting speed to increase productivity is only possible to a limited extent as this shortens the tool life, increasing tool re-grinding/ replacement costs and increasing interruptions to production. No single material meets all requirements. The properties needed by cutting tools mean compromise is needed, for example increasing hardness generally results in lower toughness.

Carbon Tool Steel

Unstable, very inexpensive, extremely sensitive to heat. Mostly obsolete in today's commercial machining, although it is still commonly found in non-intensive applications such as hobbyist or MRO machining, where economy-grade drill bits, taps and dies, hacksaw blades, and reamers are still usually made of it (because of its affordability). Hardness up to HRC 65. Sharp cutting edges possible.

High Speed Steel (HSS)

Unstable and Inexpensive. Retains hardness at moderate temperatures. The most common cutting tool material used today. Used extensively on drill bits and taps. Hardness up to about HRC 67. Sharp cutting edges possible.

HSS Cobalt

Unstable and Moderately expensive. The high cobalt versions of high speed steel are very resistant to heat and thus excellent for machining abrasive and/or work hardening materials such as titanium and stainless steel. Used extensively on milling cutters and drill bits. Hardness up to about HRC 70. Sharp cutting edges possible.

Cemented Carbide

Stable, moderately expensive. The most common material used in the industry today. It is offered in several "grades" containing different proportions of tungsten carbide and binder (usually cobalt). High resistance to abrasion. High solubility in iron requires the additions of tantalum carbide and niobium carbide for steel usage. Its main use is in turning tool bits although it is very common in milling cutters and saw blades. Hardness up to about HRC 90. Sharp edges generally not recommended.

Ceramics

Stable, moderately inexpensive. Chemically inert and extremely resistant to heat, ceramics are usually desirable in high speed applications, the only drawback being their high fragility. Ceramics are considered unpredictable under unfavorable conditions. The most common ceramic materials are based on alumina (aluminum oxide), silicon nitride and silicon carbide. Used almost exclusively on turning tool bits. Hardness up to about HRC 93. Sharp cutting edges and positive rake angles are to be avoided.

Cubic Boron Nitride (CBN)

Stable, Expensive. Being the second hardest substance known, it is also the second most fragile. It offers extremely high resistance to abrasion at the expense of much toughness. It is generally used in a machining process called "hard machining", which involves running the tool or the part fast enough to melt it before it touches the edge, softening it considerably. Used almost exclusively on turning tool bits. Hardness higher than HRC 95. Sharp edges generally not recommended.

Diamond

Stable, very expensive. The hardest substance known to date. Superior resistance to abrasion but also high chemical affinity to iron which results in being unsuitable for steel machining. It is used where abrasive materials would wear anything else. Extremely fragile. Used almost exclusively on turning tool bits although it can be used as a coating on many kinds of tools. Sharp edges generally not recommended.

Coatings

Coatings are frequently applied to carbide tool tips to improve tool life or to enable higher cutting speeds. Coated tips typically have lives 10 times greater than uncoated tips. Common coating materials include titanium nitride, titanium carbide and aluminum oxide, usually 2 - 15 micro-m thick. Often several different layers may be applied, one on top of another, depending upon the intended application of the tip. The techniques used for applying coatings include chemical vapor deposition (CVD) plasma assisted CVD and physical vapor deposition (PVD). Diamond coatings are also in use and being further developed.

II. LITERATURE REVIEW

B. Padma et al (2017) studied the optimization of the machining process parameters for the turning of EN 9 carbon steel (it is a carbon steel, also known as 070m55, available in diameters, flats, squares and plates – it can be used for gears, sprockets and cams) on the lathe machine using a combination of the Taguchi and the Grey Relational Analysis

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to yield a minimum cutting forces and expected minimum surface roughness. Process parameters chosen are as the rotational speed, a feed, the depth of cut and a selected cutting fluid. The experiments which are conducted as per the Taguchi experimental designs and the L9 orthogonal array were carried out in the experiment. The Analysis of variance (ANOVA) has also been used to evaluate the most impact of processing parameters which were resulted in the experiment. The reversion equations were also been established between a process parameters & the response. The results that indicate the depth of cut is an important factor on that affecting a cutting force & the surface roughness assessed by the feed, a speed and the cutting fluid.

P. G. Inamdar et al (2017) optimized the surface roughness in conventional turning operation using Taguchi Method for the material medium carbon steel EN8. In this work cutting speed, feed rate and depth of cut are taken as performance parameters to achieve better surface roughness. Taguchi Method is used to obtain the main parametric effect on the surface roughness using their levels and factors. L9 orthogonal array is used to design the experiments. Also, analysis of variance (ANOVA) was carried out with the significance factor of 95%. After the experimentation, it was found that cutting speed has more influenced on the surface roughness in conventional turning process than feed rate and depth of cut.

Literature depicts that a considerable amount of work has been carried out by number of investigators for modeling, simulation and parametric optimization of surface roughness and material removal rate in turning operation using different process parameters, different cutting tools and various cutting condition. A survey of journal articles published between 2001 and 2017 yields studies that vary in scope and level of analysis, yet with consistently good results. Some more advanced studies utilized cutting force, power consumption, material removal rate, or tool life as response factors simultaneously with surface roughness. The authors also demonstrate clear and useful correlations between at least some of their control parameters and the response. All of these studies did well to efficiently determine the parameters treatment combinations necessary to minimize surface roughness of the turned surface.

III. OPTIMIZATION

Taguchi Method is developed by Dr. Genichi Taguchi, a Japanese quality management consultant. The method explores the concept of quadratic quality loss function and uses a statistical measure of performance called Signal-to Noise (S/N) ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). The ratio depends on the quality characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follows: - Nominal is Best (NB), Lower the Better (LB) and Higher the Better (HB). In this project the experiments are designed with the help of Taguchi L9 orthogonal array. The software used for DOE (Design of experiment) is Minitab17. The project contains many processes which are described one by one in the methodology respectively.

IV. MACHINE LEARNING ALGORITHMS

Optimizing turning parameters using machine learning involves selecting the appropriate machine learning algorithms and techniques to find the best combination of input parameters (e.g., cutting speed, feed rate, depth of cut) that result in optimal output performance (e.g., surface finish, tool wear, material removal rate). Here is a step-by-step guide on how to approach this problem:

Step 1: Data Collection

Collect experimental data on turning operations. This data should include various input parameters and their corresponding output responses.

Step 2: Data Preprocessing

Normalization: Normalize the data to ensure all features contribute equally to the model.

Step 3: Model Selection

Choose suitable machine learning algorithms for the optimization task. Commonly used algorithms include:

Linear Regression: For simple, linear relationships between inputs and outputs.

Decision Trees: For capturing non-linear relationships and interactions between parameters.

Random Forests: For improving model robustness and accuracy.

Support Vector Machines (SVM): For handling high-dimensional data and complex relationships.

Neural Networks: For modeling highly non-linear relationships.

Gradient Boosting Machines (GBM): For combining the strengths of multiple weak models.

Step 4: Model Training

Train-Test Split: Divide the data into training and testing sets to evaluate model performance.

Cross-Validation: Use techniques like k-fold cross-validation to ensure the model generalizes well to unseen data.

Hyperparameter Tuning: Optimize model hyperparameters using grid search or random search to improve performance.

Step 5: Model Evaluation

Metrics: Use evaluation metrics like R-squared, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to assess model performance.

Validation: Validate the model using the test set to ensure it performs well on unseen data.

Step 6: Optimization

Optimization Algorithms: Use optimization algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), or Bayesian Optimization to find the optimal turning parameters based on the trained model.

Objective Function: Define an objective function that incorporates the desired outputs (e.g., minimizing tool wear while maximizing material removal rate).

Step 7: Implementation

Implement the optimized turning parameters in actual machining operations and validate the results experimentally.

This example demonstrates the use of a Random Forest model for predicting surface finish based on turning parameters. The steps include data preprocessing, model selection, training, hyperparameter tuning, and evaluation. You can extend this approach to other machine learning algorithms and optimization techniques based on your specific requirements.

V. CONCLUSION

In conclusion, optimizing turning parameters is crucial for enhancing machining performance and product quality. Two complementary approaches, the Taguchi Method and machine learning algorithms, can significantly aid in this optimization process. By integrating the Taguchi Method with machine learning techniques, this project demonstrates a comprehensive approach to turning parameter optimization. The Taguchi Method provides a robust framework for initial experimentation and analysis, while machine learning algorithms offer predictive power and adaptability for continuous improvement. This synergy ensures optimal machining performance, improved product quality, and enhanced efficiency in manufacturing processes.

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