A review of machine learning methods applied in smart machining

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***Abstract* — The transition to clean (green) production is one of the biggest topics facing the whole world. The manufacturing industry is a major polluter, so any effort to reduce pollution is welcome. Smart sustainable production with minimal pollution and energy consumption is no longer just an idea, but a necessity. Smart production include state-of-the-art technologies such as the Cyber-Physical Systems, Big Data, Cloud Computing, Internet of Things and Artificial Intelligence. The aim of this paper is to find and analyze the application of machine learning methods that are mostly used to optimize manufacturing processes with a greater focus on machining processes, i.e., turning and milling processes. The paper gives a brief overview of machine learning methods that have been identified as the most used in data processing for machining processes optimization.**

I. Introduction

Today, when the environmental protection is one of the burning issues, constant efforts are needed in order to find optimal solutions for achieving green production. The global tendency towards achieving clean and sustainable production raises questions about how to achieve these goals as soon as possible. Reduction of negative environmental impacts can be achieved by optimizing production processes. Optimization of production processes requires the processing of large amounts of data. Large amounts of data and the complexity of optimization problems make it impossible to adequately analyze and solve these problems using standard tools. In addition to information and communication technologies such as cloud computing and the Internet of Things (IoT), an important component of optimization is finding and applying artificial intelligence (AI) methods with an emphasis on machine learning methods. The integration of software, sensors, and machines with the application of machine learning methods is an excellent solution for collecting, analyzing, and monitoring the data necessary for machining process optimization. Machine learning is an area that is constantly evolving. The motivation behind this work is to find the machine learning methods that are most used in data processing in manufacturing.

This paper provides an answer to the question what the most popular machine learning methods in the field of optimization in the last 10 years are. Creating a concise overview of different machine learning methods and systematic analysis of their application in Industry 4.0 enables the growth of the knowledge base of this very popular field today. Identification of machine learning methods can help to choose an adequate method for solving the problem of process optimization in the context of achieving green production. This review paper presents the information collected so far on scientific papers on this topic.

The author of this paper ask the specific question - which machine learning methods would be most suitable for creating a model for optimizing the parameters of the cutting process with minimal consumption of cutting fluid. In addition to the positive effects, cutting fluids have negative effects on the environment and human health. The complexity of this optimization is reflected in the efficient monitoring and control of the cutting process in order to reduce the use of cutting fluid, without compromising machining quality and productivity [1].

II. Literature Review

A large number of methods are used to solve process optimization problems: Adaptive Neuro Fuzzy Inference System (ANFIS), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Artificial Neural Network (ANN), Biogeography Based Optimization (BBO), Differential Evolution (DE), Fuzzy Logic, Genetic Algorithm (GA), Hidden Markov Model (HMM), Particle Swarm Optimization (PSO), Response Surface Methodology (RSM), Simulated Annealing (SA), Support Vector Machine (SVM) and others.

Many researchers use hybrid or combinations of several methods to solve process optimization problems.

Kant and Sangwan [2] have teamed up ANN with GA to predict and optimize machining parameters in order to minimize surface roughness. The results indicate that the developed model surpasses the regression and fuzzy logic models. In combination with GA, ANN leads to a minimum surface roughness value of 0.099 μm, which corresponds to optimal machining parameters of 4.65 m/sec of cutting speed, 0.142 mm/tooth of feed, 0.67 mm/depth of cut and 0.08 mm of flank wear.

A significant number of researchers apply several methods to solve optimization problems and compare the obtained results.

ANN, also known as Neural Network (NN), is used to solve complex nonlinear problems. Many researchers point to the superiority of this method over RSM and others. Mundada and Narala [3] in optimizing the milling process point out that the use of RSM cannot overcome the nonlinearity of the relationship between cutting conditions and output parameters, but that this problem can be overcome by applying ANN, SA or GA.

Some researchers have used methods to optimize the turning and milling process by taking into account the reduction in cutting fluid consumption.

Barnabas and Principal [4] compared DE, PSO and SA to optimize the Minimum Quantity Lubrication (MQL) parameters in the turning process for minimization of cutting zone temperature. The results they obtained indicate that all three methods performed well, but that DE performed relatively better compared to the other two methods. The percentage improvement in S/N value of cutting zone temperature using DE is 3.255% when compared with the maximum experimental S/N value of cutting zone temperature. The percentage improvement in S/N value of cutting zone temperature using PSO is 3.15% and for using SA is 3.209%.

Taking into account cutting fluid consumption and process costs, Jiang et al. [5] used a hybrid GA algorithm for multi-objective optimization of machining parameters, thus managing to reduce cutting fluid consumption by 17%. Cutting fluid consumption and process cost are treated as the two objectives in the optimization model of cylindrical turning process, which are affected by four variables (depth of cut, feed rate, cutting speed and cutting fluid flow). The hybrid GA method identified a depth of cut of 1 mm, cutting speed of 129 m/min, feed rate of 0.31 mm/revolution and cutting fluid flow of 9.85 L/min as optimal machining parameters. This optimal combination of machining parameters achieved optimal objective values for cutting fluid consumption of 36.7 L and process cost of 2.55 $.

Yan and Li [6] based multi-objective optimization of milling parameters on weighted gray relational analysis and RSM in order to estimate trade-offs between sustainability, production rate, and cutting quality. This method identified a spindle speed of 1000 r/min, feed rate of 300 mm/min, depth of cut of 0.4 mm and cut width of 15 mm as optimal combination of milling parameters. This optimal combination of milling parameters was obtained by simultaneously optimizing three objectives (surface roughness, material removal rate and cutting energy). Experimental results, verified trough use of Taguchi design method, indicate that the proposed optimization method is a very useful tool for multi-objective optimization of cutting parameters. The results show that the identified parameters reduce cutting energy consumption by 18.1% compared to traditional objective optimization.

Campatelli et al. [7] also used RSM to evaluate and optimize the milling process parameters with goal to minimize power consumption under dry lubrication conditions to eliminate the environmental impact of the cutting fluid without significantly affecting energy consumption.

Beatrice et al. [8] applied ANN to automated hard turning of AISI H13 steel with minimal application of cutting fluid. They tested the ability of ANN to predict surface roughness. In doing so, they came to the conclusion that ANN can be very useful in fixing the cutting parameters in order to achieve the desired surface finish with minimal use of cutting fluid.

Vukelic et al. [9] used a GA algorithm for multi-objective optimization of steel AISI 1040 turning in dry environment. The basic idea was to obtain multiple combinations of optimal input process parameters depending on the importance of each output process parameter. Based on the results, optimal surface roughness is in the range of 0.315–5.808 μm, optimal flank wear is in the range of 0.150–0.218 mm and optimal material removal rate is in the range of 1088.384–8228.571 mm^3/s. Optimal ranges of machining parameters are 307–384 mm/min, 0.10–0.40 mm/rev, 2.04–3 mm for cutting speed, feed and depth of cut, respectively. They calculated a mean percentage error (MPE) of 1.478% for flank wear and 1.146% for arithmetical mean roughness. This is considered to be highly acceptable for practical application of multi-objective optimization based on genetic algorithm.

Dambhare et al. [10] used RSM for optimization of AISI 1040 carbon steel turning from power consumption point of view. The experiment was performed on three lathes with different capacity and motor power using three types of tools (Brazed ceramic tool, Insert with Titanium Nitride (TiN) Coating and Insert with Titanium Aluminum Nitride (TiAlN) coating) in dry, wet and MQL machining environment. The objective was to optimize the most influential turning parameters in order to minimize power consumption and surface roughness while maximizing material removal rate. The RSM method identified a cutting speed of 50.55 m/min, feed rate of 0.2107 mm/rev and depth of cut of 1 mm as optimal turning parameters in dry environment conditions with TiAIN coated tool. ANOVA and Taguchi analyses were used for ranking and determining the significance of turning parameters that affect the response. From the aspect of environmental protection, it has been determined that the cutting fluid consumption, i.e. the cutting environment, affects energy consumption and to a large extent the surface roughness.

Sarıkaya and Güllü [11] based the optimization of turning parameters of AISI 1050 steel on RSM, Taguchi design and desirability function. Experiments were performed under dry, wet and MQL environment conditions. ANOVA analysis was used to determine the significance of turning parameters on surface roughness, which showed that the biggest significance is that of cooling condition and feed rate. The RSM method identified a cutting speed of 200 m/min, feed rate of 0.07 mm/rev, depth of cut of 1.2 mm and cooling condition of MQL at 120 mL/h flow rate as optimal turning parameters.

Nouioua et al. [12] used ANN-based GWO (gray wolf optimizer) algorithm in multi-objective optimization for high machining performance with MQL. They examined the performance of MQL compared to dry and wet cooling methods during X210Cr12 steel turning using coated carbide insert with various nose radius. This ANN-MOGWO method identified a depth of cut of 0.16 mm, cutting speed of 190 m/min, feed rate of 0.12 mm/rev and nose radius of 1.2 mm as optimal turning parameters. This optimal combination of turning parameters achieved optimal outputs for surface roughness of 0.561 μm and cutting force of 86.878 N.

Canh Nguyen et al. [13] used support vector regression and Non-dominated Sorting GA (NSGA) for multi-objective optimization in milling of S50C carbon steel under MQL condition. SVM was used to generate the regression model. Following this, NSGA2 was performed to optimize surface roughness, specific cutting energy and production rate. This hybrid SVM-NSGA2 method identified a depth of cut of 0.899 mm, cutting speed of 298.735 m/min, feed rate of 0.094 mm/tooth, lubricant flow rate of 149.122 ml/h and air pressure of 2.0077 MPa as optimal cutting and lubrication parameters under MQL condition.

Hernández-González et al. [14] analyzed the effects of cutting speed and various cutting tools, regarding the materials they are made of, on cutting forces and specific energy consumption during dry high-speed turning of AISI 1045 steel using ANN.

Hsiao et al. [15] used RSM and NSGA for modeling and optimization of machining parameters (cutting speed, feed per tooth, depth of cut and corner radius of cutting tool) in milling of INCONEL-800 super alloy. They used NSGA-II to solve the multi-objective optimization problems in terms of energy, productivity and quality of the machining process. The optimal results show that the specific cutting energy and energy consumption can be reduced up to 20.2% and 6.4%, respectively. They compared two cutting conditions (nanofluid MQL and pure MQL) in terms of energy efficiency and environmental protection. One of the goals was to demonstrate superiority of multi-walled carbon nanotube (MWCNT) for MQL lubrication. The results indicated that nanofluid MQL with MWCNT is better than pure MQL because it increases tribology and in that way reduces the cutting force in specific cutting energy (below 0.93 J/mm^3). It not only protects the environment, but also can reduce surface roughness by 8.4%, specific cutting energy by 6.1% and cutting power by 10.5%.

III. CONCLUSIONS

Review and analysis of the application of machine learning methods in optimization are based on papers published since 2012. The summarized information of these research papers provides a basis and assistance for further research to a large number of researchers working in this field. The most used methods so far for turning and milling process optimization problems are ANN, GA and RSM. This review showed that machine learning methods can deal with process optimization problems. With their help, cost and time can be saved through increased productivity. Through process optimization, the use of cutting fluid and energy consumption can be reduced in the context of achieving cleaner production, without compromising the machining quality.

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