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Machine learning in cutting processes as enabler for smart sustainable manufacturing

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Abstract

Machine learning is becoming an increasingly popular concept in the modern world since its most common goal is to optimize systems by allowing one to make smarter use of products and services. In the manufacturing industry machine learning can lead to cost savings, time savings, increased quality and waste reduction. At the same time, it enables systems to be designed for managing human behaviour. This research study used a systematic review to investigate the different machine learning algorithms within the sustainable manufacturing context. The study focuses specifically on cutting processes.

Keywords: machine learning; manufacturing; cutting processes

1. Introduction

Manufacturing has been a fundamental aspect to national development and prosperity. It greatly contributes to an individual's quality of life, a nation's growth and the power and position of a country. Machine learning and networking of cyber-physical technologies are on the rise. In the field of sustainable manufacturing, an increasing level of machine learning is used to face the growing production requirements. Smart production systems will integrate the virtual and physical worlds on these Internet of Things (IoT) platforms to ensure resource efficiency and optimized production. In this research study the applications of machine learning techniques in cutting processes were observed to discover machine learning trends in these processes. The different resource efficiency challenges were studied to

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support the discovery of correlations between machine learning applications and smart, sustainable manufacturing problems.

2. Research methodology

The systematic review used, enables the growth of a knowledge base consisting of relevant and useful information, generates information based on research conducted which are of interest and identifies opportunities for further investigation [1]. A systematic review makes use of a pre-specified criteria to collect, evaluate and summarize the collected empirical evidence and research to answer a well-defined research question. The focus of this paper was to review the different machine learning techniques which have been applied in cutting processes. The literature review covers full papers from 2000 to 2017 which are selected according to the criteria provided in Table 1. The modified template was created by [2].

Table 1. The selection criteria for the literature.

Criteria	Desired Value
Contextual Criteria	
Industrial sector of the application	Manufacturing
Specific process	Cutting process
Keywords	Machine learning, artificial intelligence, optimization, cutting process, cutting tools, design, quality, scheduling, sequencing,
Bibliographical criteria	
Date of publication	January 2000 – December 2017

Every paper was further analyzed and the following information about each was extracted: title of the paper, the specific cutting process (for example, drilling) and the machine learning algorithm(s) used.

3. Machine learning techniques

A variety of machine learning techniques have been applied in the research. The most used methods include neural networks, evolutionary algorithms and response surface methodology regression models. Sometimes machine learning algorithms are used in combination with dimension reduction methods, to reduce the computational power and time required to perform the algorithms without reducing the quality of the output. Dimension reduction methods include principal component analysis (PCA), kernel PCA (KPCA), locally linear embedding (LLE), isometric feature mapping (ISOMAP), minimum redundancy maximum relevance (MRMR) [3] and singular spectrum analysis (SSA) [4].

3.1. Neural Networks

A neural network (NN) or artificial neural network (ANN) is an arrangement of statistical algorithms which structure is based on the biological brain patterns found in human brains. NNs are used to identify and create the non-linear relationships between input variables and the output variable(s). A NN consists of an input layer, hidden layer(s) and an output layer. The layers consist of weights and biases and make use of mathematical functions for example tangent hyperbolic activation function, linear activation function [5], sigmoid activation function, logistic activation function [6] and hyperbolic tangent sigmoid activation function. To develop and apply a neural network, three sequential processes occur: training, validation and testing. Various training algorithms exist including the Levenberg–Marquardt algorithm, Conjugate Gradient Descent (CGD), and Bayesian Inference (BI) [6]. Different statistical measures are used to determine the error of the net, for example Mean Absolute Percentage Error (MAPE), mean square error (MSE), Regression (R or R^2) values [6] and maximum/average relative error. Bayesian regularization can be used during the training stage to skip the validation stage [5]. Different NNs are available, including feed-forward NN

(FFNN), back-propagation NN (BPNN), etc. The self-organization feature map (SOM) [7] is based on NNs.

3.2. Evolutionary and swarm intelligence-based algorithms

These algorithms are population-based heuristic optimization algorithms and they are derived from natural biological processes. These algorithms include genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA), particle swarm optimization (PSO), biogeography based optimization algorithm (BBO), firefly algorithm, artificial bee colony (ABC) and Ant Colony Optimization (ACO) [8]. They share common control parameters like population size and number of generations, while each has its own set of algorithm-specific parameters.

The genetic algorithm (GA) is an evolutionary algorithm based on the theory of natural selection. At the start a population consisting of chromosomes (feasible solutions) is generated. Three primary genetic operations occur to create the next generation or population: reproduction, crossover and mutation [9]. During reproduction parent chromosomes are randomly selected to create offspring. Crossover is the process where genetic material is exchanged between the two parents by randomly selecting a crossover point and swapping their 'genes' to create two offspring which are different from the parents. Single-point or multi-point crossover can occur. During mutation a random chromosome and random mutation point on the chromosome is selected [10]. The value of the selected 'gene' is then altered or in the case of binary 'genes' a 1 becomes a 0 and vice versa. The elitist members of the current population, the non-dominated chromosomes, are selected and added, together with the offspring (some are mutated), to the next population. GA parameters include mutation probabilities, mutation rate, crossover point probabilities, crossover rate [11] and elitism number (number of good solutions in current population which are transferred to the next population) [10].

3.3. Response surface methodology

Response surface methodology (RSM) creates empirical models which approximates the true functional relationship between the response surface (dependent variable(s)) and a set of experimental input parameters (independent variables). Various methods are available to help determine the constant terms of a RSM model. The Box-Behnken design, which is specifically developed for RSM [12] [13], and design of experiments (DOE), like Taguchi, Central Composite Design (CCD) [14] and full factorial design [15], can be used to design experiments in such a way that the cause and effect relationship between the input and output parameters can easily be identified with minimized number of experiments. ANOVA analysis can be performed next to determine the degree of influence the various input parameters have on the output parameter(s) as well as the interactions between the input parameters [15]. Grey relational analysis or weighted grey relational analysis [16] can also be used to determine the interrelationships between multiple responses by calculating the grey relational coefficients (weight factors) of multiple responses in a multi-objective problem and based on that, calculating the grey relational grades which is the input of the RSM [17]. Next, RSM is employed. The RSM models can be validated by the ANOVA analysis (specifically the R2 and p values), F-ratio test [18] and the maximum deviation between the experimental results and the RSM model.

4. Machine learning applications in cutting processes

Traditionally process parameters are determined by the operator's experience, the conservative technological data provided by the machining equipment manufacturers and trial-and-error operations. This leads to inconsistent machining performance since operator's experience is limited and subjective while the manufacturer data is based on safety-conscious principles and it only includes applications on certain machining materials [19]. Trail-and-error operations employ post-process techniques to inspect the quality of the finished product. This methodology includes a range of disadvantages: it is costly, time-consuming and it leads to numerous defective and useless products which are only discovered once the process has been completed [4]. Machine learning addresses these resource efficiency challenges by determining the optimal process parameters given an objective(s). Machine learning also increases sustainability since it leads to the permanent availability of uniform, objective cutting process knowledge (manufacturers do not have to hire costly consultants repeatedly), it enables manufacturers to optimally benefit from their machining equipment without the acquisition of new costly, carbon-footprint related equipment and it reduces the usage of valuable resources including time, money, energy and natural resources. Machine learning also enables employee safety as well as product safety, since it can be used proactively to allow one to view the cutting parameters before application. Thus, harmful parameters can be identified before the process started.

Machine learning algorithms have been applied to a variety of cutting processes including cutting, turning, milling, drilling, boring, grinding, broaching [20], coroning [19], electric discharge machining (EDM), ultrasonic-assisted EDM (US/EDM) [21], wire EDM (WEDM), abrasive water jet machining (AWJM) [8], laser cutting process [11], electro- chemical machining (ECM) [11] and focused ion beam (FIB) micro- milling. Table A in Appendix A provides a detailed summary of the different cutting processes and the different machine learning algorithms applied in these processes, according to the review.

There are complex interrelationships between cutting parameters, process output, economic factors and environmental factors. The cutting parameters directly affect the production efficiency, production cost, quality of the product, tool life, processing time, power energy consumption and the carbon emissions [22]. All the machine learning applications considered during the systematic review investigated one or combinations of these sustainability-related relationships. Fig. 1. (a) illustrates the cutting processes supported by machine learning applications. It is evident that turning and milling are the fields in which the most applications have been applied, followed by EDM and drilling. Fig. 1. (b). illustrates the different types of machine learning algorithms which have been applied in cutting processes. ANNs are the most common application, followed by GA, RSM and PSO.

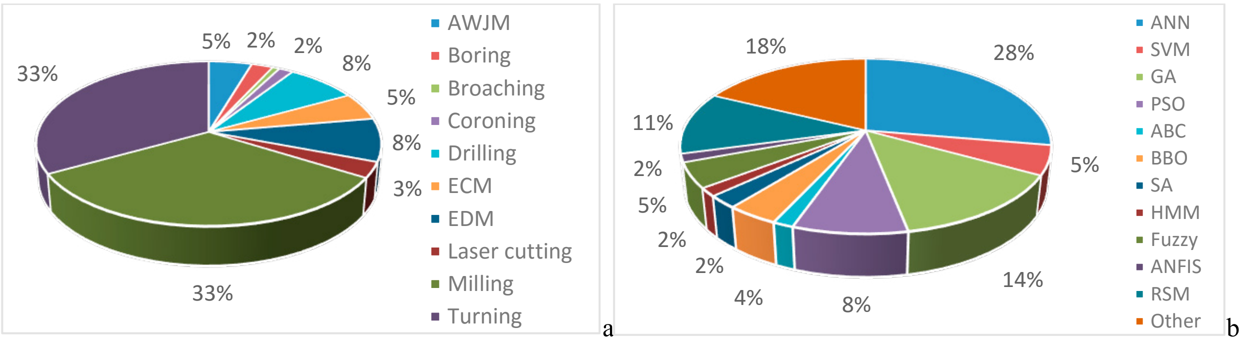

Fig. 1. (a). Cutting processes supported with machine learning applications; (b) The different types of machine learning applications applied in cutting processes.

5. Conclusions

In the manufacturing industry, machine learning can lead to cost savings, time savings, increased quality and waste reduction. At the same time, it enables systems to be designed for managing human behavior. From the systematic review, the author learned of the different machine learning techniques which have been applied to cutting processes, the process of applying machine learning techniques in cutting processes and the machine learning trends in these manufacturing processes.

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Appendix A. Different cutting processes versus different machine learning algorithms

An 'H' superscript indicates that the study is a hybrid or combination of machine learning algorithms, while an '&' superscript indicates that various algorithms were compared in the study.

Table A. Different cutting processes versus different machine learning algorithms.

Machine learning method	ANN	SVM	GA	PSO	ABC	BBO	SA	HMM	Fuzzy	ANFIS	RSM	Other
AWJM			[8]&,	[8]&,	[8]&,	[8]&,	[8]&,					[8]&,
Boring	[23], [24]H,			[24]H,								
Broaching		[20]										
Coroning								[21]H,				[21]H,
Drilling	[25], [6], [26], [27]H, [28]H, [29]H,		[27]H, [29]H,						[28]H,			[29]H,
ECM	[30], [31]H,		[11]&,	[11]&,		[11]&,						[11]&, [31]H,
EDM	[19]H, [5]&, [32]		[19]H, [11]&,	[11]&,		[11]&,	[5]&,		[33]			[11]&,
Laser cutting			[11]&,	[11]&,		[11]&,						[11]&,
Milling	[34]H, [35], [36], [7], [12]&, [37], [13]&, [38], [39]H, [40], [41], [42], [43]H,	[3], [44]	[11]&, [34]H, [45]H, [22], [46]H,	[11]&, [34]H, [47]		[11]&,			[48], [49],	[34]H, [45]H,	[12]&, [13]&, [39]H, [16]H, [46]H, [17]H,	[50], [11]&, [51], [16]H, [52], [53]H, [43]H, [17]H,
Turning	[14]&, [54], [55]H, [56], [57]H, [58]&, [59], [60], [61]H, [62]&,	[63], [64], [65], [66]&,	[67]&, [68], [55]H, [57]H, [69]H, [70]	[57]H, [71]H,	[72]&,		[61]H,	[73]	[69]H,		[14]&, [67]&, [4], [15], [71]H, [58]&,	[66]&, [62]&, [72]&,