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Deep Learning Algorithms for Tool Condition Monitoring in Milling: A Review

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Abstract. The 4th Industrial Revolution (Industry 4.0) necessitates implementing the prognostics and health management (PHM) practices in manufacturing processes. The traditional machine learning approach has well assisted the PHM practices within the same data distributions. However, when a high noise environment, versatile operating conditions, and cross-domain machining is considered, it still lacks key steps of generalizing unknown tool faults. In an attempt to address PHM practices under such domains, a generic Deep Learning-based scheme is gaining significant attention. In this paper, an inclusive review is presented in order to provide an insight into the application of DL in tool condition monitoring (TCM), particularly in milling. Commonly used DL algorithms and their applications toward TCM are initially discussed and number of illustrative DL models applied for TCM is presented. Later, emergent DL themes & their computational techniques are summarized with an intention to provide framework for domain generalization. Finally, challenges in further exploration and futuristic trends in TCM are discussed.

1. Introduction

Milling is a generally implemented cutting practice applied to the machining of internal as well as external workpiece for various applications [1]. End mill tools are made out of either cobalt steel alloys (HSS used for both ferrous and nonferrous material), or from tungsten carbide (cobalt lattice: M 42 tool steel). Milling cutter can be made available in 2, 3, 4 or multi flutes as number of flutes, increases the cutting edges increases the space for chip removal becomes narrower [2]. The emerging demands from the customers in industry are time consumed for response should be least, functional reliability should be maximum, manufacturing systems must be updated and enhanced for wide variety of operations which also includes automatic tool control [3], must be more sturdiness, cost for installation should be low, with least calibration one should be able to perform operations, modification in manufacturing should be incorporated with less space requirement [4].



To increase the productivity as well as reliability [5] these demands tool condition monitoring system comes with different approaches [6]. The wearing of milling tool can be of different types. The tool wearing is able to reduce with the system which monitors the condition of tool along with custom of the optimal process parameters in machining process [7, 8]. In cost optimization of machining processes, primary verdict and monitoring of wear progress plays a crucial role [9, 10].

2. TCM System for Milling

The important components engaged in the system are machine tool, sensors, data acquisition system, personal computer etc. [11, 12]. The input data is sensed with different sensors like accelerometer, dynamometer [13]. With the help of FFT analyzer transformation of signals takes place. Suitable features are selected for classification with suitable approach from signals [14]. The methods used for TCM may be based on acoustic emission sensors, cutting force measurement sensors, machine vision sensors, acceleration and vibration measurement, actuator current measurement, stress/ strain measurement, machine learning and prediction based approaches and sensor fusion. The method involving acoustic emission sensors is found to be explored at greater extent [11-19]. Tool condition system consists of following stages a) Sensing data b) feature extraction c) Decision making strategies d) Knowledge learning

CNC milling operations can be divided into two types based on lubrication [15-17] and application [18]. The different kind of sensors can be used depending on which data we are interested into. The single or multi sensors can be used for this purpose [19]. Appropriate data fusion techniques such as IMG and IMDG can be implemented for further drawing out of features. Those drawn features are provided to decision making strategies which may be statistical or distribution free statistical methods [20]. This is used further for to make appropriate decision and for knowledge learning. Manufacturing mechanism have a great capital cost. The cost of tool condition monitoring system desired to be as less as possible to implement in a small scale enterprises. The cost of sensors contributes to a larger extent in building the cost of the TCM system. The sensors may include CCD camera, AE, accelerometer etc. The cost of the system may increase because of use of expensive sensors like dynamometer based on strain gauges to measure cutting force. This problem can be overcome with the use of spindle motor current signals for measurement of cutting forces with removal of electrical and environment noise using proper filters [36,67]. Their efficient use depends on less functioning and repairing costs. Direct and indirect method is the two methods of TCM. Execution of sturdy, trustworthy systems of TCM is one of the fundamental necessities of introducing of Industry 4.0. Strategic steps in TCM are signal separation, tool condition reference value, signal feature choice, decision making process. This task should get done without human intervention [21].

The TCM systems in milling based on force signals are neural network like feed forward back propagation, Fuzzy decision support system, fuzzy inference system, back propagation algorithm, Rumelhart's generalized delta rule and cumulative weight adjustment [22, 23]. A considerably long training time is the main drawback of these methods, which makes it unsuitable in real life. The advantages of Neuro-fuzzy system includes negligible training time as well as there is no need of primary results for the operator [24].

A very fast as well as reliable computer vision based approach for TCM is proposed to detect the condition of all tested tools in drilling which works on the principal of measuring the deviation from linearity metric [25]. A high speed CCD camera and a canny edge detector is used to capture image frames and to extract tool features from the assimilated images respectively [26]. The limitation of this method is that the computation method is to be changed with respect to shape of drill bits [27]. For the manufacturing of T slots in steam turbine rotor with high dimensional accuracy and surface finish TCM to estimate average flank wear is implemented which is based on data fusion technique with ANN [28-30]. The scheme emphasizes on the training of sound emission and vibration so as to relate physical mechanics with tool faults [31]. By means of fusing sound emission and vibration, it is promising to classify tool condition efficiently [32-34]. Tool condition can be identified with more reliably with the combination of sound emission and vibration [35]. The analysis of frequency bands during the milling

operations of steel plates having large thickness as well as size where significant parts and tools are incorporated [36]. This is used to identify condition of tool as well as transition of tool wear conditions [37].

2.1 TCM for Various Types Milling Process

During peripheral milling process energy measurement of the AE signals are required [38]. As cutting parameters increases true mean square (TMS) voltage of AE signal increases [39]. Implementation of mean friction angle and an effective shear angle are accountable for generation of acoustic emission [40]. Fault features can be explained using not only scalogram but also its mean frequency variation [41]. These both are proficient of revealing the features of localized and progressive fault evidently in the presence of strong noise than conventional time and frequency domain analyses. The inclusive average of the mean frequency variation provides a useful indicator the evolution of wear is indicating. Time domain statistics do not give any consistent trend [42].

During face milling tool breakage can be detected through independent component analysis (ICA) and empirical mode decomposition (EMD) by segregating sound signals [43]. To resolve the unknown source separation problem of cutting sound signals in face milling separation of cutting oriented sound signals from background randomness EMD and ICA is performed [44]. ICA can handle higher order statistics. The drawback of the method are minor breakage of cutting tool cannot be investigated and limited quantity of recording distribution of signal available close to Gaussian [45]. EMD is suitable for numerical simulation but not for mathematical framework of TCM and it can evaluate nonlinear and nonstationary signals [41,43]. For multistep form milling a tool condition monitoring system is introduced to make sure inclusive quality of a precision large scale component. For application tree slots of rotor of steam turbine the form milling of a good surface finish as well as great dimensional accuracy is required [46-48].

Tool durability tests using a test piece are carried out for each step to explore the tool deterioration process [49]. By utilizing time series analysis of the spindle motor current based on the S/N ratio η and a two-dimensional diagram that visualizes the transition of multiple sensors ($\Delta\eta$ and AERMS), the features of tool deprivation in multi-step form milling are explained through tool longevity tests [50, 51]. Increased flank wear, crack propagation and severe adhesive wear leads to significant generation in AE during roughing with qualitative mode of inspection for tools [52]. In finishing process AE having large amplitudes occurred which gives the probability of identifying defects with purposefully addition of a package of chips onto a surface [53]. Vibration analysis is the most prevailing technique among thermal imaging, multiple sensor fusion, stator current, acoustic noise [54]. SVM can be used for high dimensional data and suitable if clear margin of separation between the classes is available. It is suitable for both linear as well as nonlinear model and it is memory efficient [55]. Support vector machines (SVM) and Principal Component Analysis (PCA) are used to analyze the data, acquire from them, and make intelligent decisions milling tool condition [55].

In milling various atmospheres are tested. Finest and poorest yield properties of milled powder are obtained using stearic and argon atmosphere without process control agent (PCA) [56]. When steric acid is used as PCA in end milling process amorphization process becomes faster than any other condition investigated [56]. The addition of PCA to mixtures of powders like TIA1-Al₂O₃ reduces the crystallite size of milled powders as compared to those milled without PCA addition. A fairly good generalization capability of three back propagation trained network is proven by testing results. Testing results also gave the correlation between the amount of PCA and a given element size [56, 57]. The yielding of milled powder is determined by PCA in milling. A new PCA content is needed to be chosen for characteristic milling operation [55, 56]. Principal component are the correlated responses which are converted into independent or uncorrelated quality indices. For achieving solution for multi-objective optimization problem PCA constructed on Taguchi method is used during milling process by neglecting the effect of process control parameters [57].

2.2 Data Fusion Technique

An accelerometer and a dynamometer were used in the experiments for collection of data in TCM of milling process. Performance of tool condition monitoring system can be considerably improved by choosing appropriate data fusion technique which works on the principle that the features are extracted from different signals and integrated prior to use as input data. To increase the productivity and reliability of the system the data from multiple sensors are fused together. But it leads to increased dimensions of signals and makes the signal processing more complex [58]. Different methods of data fusion are feature level and decision level. IMG and IMDG are the popular fusion methods used for TCM of CNC milling process [58]. The recital of the tool condition monitoring system can be considerably promoted with appropriate choice of the data fusion method. The domain shift problems involving high noise for unsupervised adaptation approach are addressed with a generalized method [59]. GAN method is used for unsupervised learning approach for combining discriminative modeling as well as for sharing of untied weight [58, 59]. The new adversarial training network is used for adaptation of open data sets. The advantages of this method is that it does not require unknown source labels [59]. The imbalanced data problem with data augmentation can be solved by deep learning approach using generative adversarial method [60]. To transfer data feature between different working conditions one technique called Transfer Component Analysis (TCA) is used for fault diagnosis [61].

Intelligent Sensors, implementation strategies, multisensory approaches, detection of malfunctions makes the system ready for industrial application as well as novel progress in information and signal processing, sensor based process optimization and control increases reliability, productivity, detection of tool wear, reduction of non-productive time, stability of process [62, 63]. Signal segmentation, suitable feature extraction and use of values measured in controlled environments are the challenges in tool condition monitoring systems. The feature extraction and feature selection by a proper technique using a deep learning approach is used. Estimating and predicting remaining useful life plays an important role in TCM. It can be estimated with correlation with desired product quality and tool wear [58-63].

Factors to be considered for model selection:

- a) Accuracy of Classifier: To predict class label
- b) Speed: i) Interval consumed for building the model
ii) Interval to use the model (classification /predicting time)
- c) Robustness : Capability to handle noise and missing values
- d) Scalability: Proficiency in handling disk resident database
- e) Interpretability: Understanding and insight provided by the model

3. Machine Learning Approaches

Adaptive Neuro-Fuzzy Inference System (ANFIS) model contributes better prediction of tool wear condition by mapping the nonlinear association of tool wear and feed force [64]. This proves to be highly active in comparison with of regression trend [65]. The residual useful life of the tool can be found out by using a suitable model which gives true experimental values which describes the deprivation of tool along its complete life [65, 66]. The vibration analysis shows the existence and advancement of fault during end milling process [66, 67]. The development of features of faults was proven using scalogram and its variation in mean frequency. The intensity of wear of tool is function of not only process temperature but also chip properties such as chip size, chip shape, chip color [67, 68]. The wavelet packet decomposition method is used for feature generation accompanied by sound signals for tool condition monitoring of milling process. This method performs with better accuracy than commonly. The wavelet packet decomposition method is used for feature generation accompanied by sound signals for tool condition monitoring of milling process. This method performs with better accuracy than commonly used root mean square method [69, 70]. K NN is used when there is mixture of numerical and categorical features to classify inhomogeneous datasets [71-73].

ANN algorithm with Edge worth Pareto method which is prepared in MATLAB forecasts the surface finish and least MRR in the course of CNC face milling operation within experimental speed, feed and

depth of cut ranges which leads reduction in production cost and increased in accuracy [74]. Genetic Algorithm based ANN hybrid forecasting model is trained for forecasting surface roughness and tool wear [73, 74]. The dominant parameters are cutting speed, feed velocity, lubricant flow rate and depth of cut in end milling process [74]. For multi-objective optimization, Grey Relational Analysis (GRA), Principal component analysis (PCA), and Taguchi method can be used for obtaining optimum machining parameters [72-74]. GRA is used for decision making multi features model and establish relation between discrete data sets. Higher design complexity, lack of experimentally resulting design procedures, discrepancies in technology and terminology are some shortcomings of GRA method [72-74]. Taguchi method is used to determine best level of control factors. But it is can not be used for zero degrees of freedom if all possible factors are used [72-74].

Prediction of Optimum cutting conditions and tool geometry is achieved with ANN and simulated algorithms by formulating mathematical model with response surface methodology [75, 76]. The methodology of prediction can be made use of in Computer Aided Manufacturing (CAM) through a stage of Computer Aided Process Planning (CAPP). The dry machining has some advantages over wet machining [77,78]. Hilbert and Hilbert-Huang transformation (HHT), Wavelet transformation Fast Fourier transformation (FFT) techniques show forthcoming for application of processing of AE signal and investigation in various machining applications [79]. In dry as well as MQL cutting during progressive tool wear signals collected by fracture and plastic deformation are proportional to visual basic (VB). Therefore, linear fitting AE energy scatter points at different VB can used to compute the tool flank wear [75-79].

3.1 Shortcomings of Machine Learning Approaches

- a) Data acquisition (DAQ): ML method for huge data sets for training on and these would be inclusive, impartial and of good quality. There may also be times where waiting for new data sets to be generated gets indispensable.
- b) Times and needed Resources: ML needs abundant time to let the algorithms learn and develop enough to accomplish their purpose with a substantial amount of correctness and relevancy. It also needs huge resources to function. This can mean surplus requirement of computer power for us.
- c) Interpretation of results: The ability to interpret accurately results generated by the algorithms is one of the major challenges. The algorithms for anticipated purpose must be selected carefully.
- d) High error susceptibility: There may be high susceptibility of error for the machine learning approaches.
- e) Feature extraction: Feature extraction for the complex problems with classical machine learning approach is one of the big challenges.

Deep learning (DL) based approaches are thus becoming considerably popular to serve these demands to achieve an improved performance at flexible operating conditions and noisy environments [77-79].

4. Deep Learning Algorithms for TCM

Various process monitoring techniques like melt pool monitoring or off axis infrared monitoring have been projected for finding of defects [80]. This technique is a blend of deep learning-based neural network and thermographic off-axis imaging as data source [80]. Even though less powerful hardware is available it works in actual time as network is very small and has less computing costs. The runtime performance of model is not estimated. [80]. Bagavathiappan S et al have performed monitoring with more accurate, more reliable and cost effective technique where temperature is measured in real time using non-contact type of sensor [81]. Neural network is basis of deep learning. Huge amount of generated data is available in deep learning [82]. Monitoring of flank wear and breakage in milling with sensor fusion technique. It is independent of cutting conditions used but requires little more computation time. Deep learning techniques have powerful and enhanced computational capability. Tool condition monitoring of milling can be conducted using deep learning techniques likewise convolutional neural

network (CNN), Auto-encoder (AE), deep belief network (DBN), recurrent neural network (RNN), generative adversarial network (GAN) [80-82]. For all computation the derivation of gradients which are needed to know can be found out by CNTK. This is counted as one of the important advantage of CNTK. The type of network, the source of input data, and the suitable technique to optimize parameters can be specified by their networks in CNTK. CNTK eliminates copied computations in forward as well as backward travel. It uses least memory and reduces memory reallocation by reusing them. CNTK is written in C++ in proficient way. Theano easier to express and train different architectures of deep learning models, such as Pylearn2, Lasagne, and Keras. Many software packages developed a higher level user interface on top of Theano. Developers are permitted to train a wide variety of deep neural network model with flexible network of tensor flow and it is used for deploying machine learning systems into production for different Tensor Flow uses different APIs of quite a few languages such as Python, C++, and Java for constructing and executing a graph (Python API is the most complete and the easiest to use) [83]. Google engineer Chollet founded Keras which was one of the part of research project ONEIROS (Open-ended neuro-Electronic Intelligent Robot Operating System). Keras is the library developed by python. It is an open source library. It works on the upper of CNTK. Table 1 shows the property wise comparison of different software that can prove helpful for one to choose appropriate software

Table 1: List of software and hardware involved in deep learning

Deep Learning Software	Deep Learning Hardware
Google-Tensorflow	GPUs with high number of CUDA Cores
Facebook-Pytorch	RAM preferably more than 16 GB DDR4
Keras	SSD or HDD > 1 TB for handling big datasets easily
Theano	-
Math works-MATLAB	-

4.1 Convolutional Neural Network (CNN)

Neural networks typically used in deep learning are computing systems inspired from structure and function of a human brain. It is used for those methods for which algorithmic method is expensive or does not exist. Neural network learns by examples so we do not need to program it in depth. Neural Network takes input data and train themselves to recognize pattern and then predict output for a new set of data [84]. The neural network controls average cutting force with minimization of counter error. It is also applicable for any random parts [84, 85]. Convolutional Neural Network: Convolutional neural network is a kind of deep neural network designed for automatic feature extractor and classifier. It is also applicable for one dimensional data also. With the help of CNN it is easier to train the data and have many rarer parameters than fully connected networks with the same number of hidden units. Convolution is the first layer to extract features from an input image/ data. For extraction of features from input data in the form of images convolution is used. Two inputs namely image matrix and filter/kernel can be taken in the form of a mathematical equation [86-88].

CNN is implemented for to extract deep features when time series signal is provided as input and BiLSTM network with CABLSTM mechanism is constructed to learn times series information between the feature vectors with accuracy around 97%. Generally Softmax classifier is used as classifier to classify tool wear state. To train the network delamination of critical defect as well as uncritical defect splatter were selected for one geometrical shape. The network can use output heatmap for detection of type and position of error. This model is appropriate for detection of defect during L-PBF processes and can be easily implemented to other types of defects, material systems, as well as geometric shapes. It is easy to adopt not only other types of defects and materials this model is solitary based on a single source of data, there is no requirement to carry out additional evaluations using costly and slow methods such as CT or X-ray. For detection of defects such as splatter and delamination CNN can be used. The cracks, pores and unused powder in laser welding are not evaluated by CNN [88].

4.2 Probabilistic Neural Network (PNN)

The blend of AE and cutting power signal can increase the performance of PNN. The sensitivity of AE signal increases complexity of problem is the challenge for the analysis [89]. The methods of connecting sensor signals from cutting process which are used in enrichment of tool conditioning monitoring system to indicate the changes in monitoring [90]. Cutting forces that may be static as well as dynamic and acceleration in terms of vibration are reflected to be the most commonly associated parameters [90, 91]. Computer simulation centered on the relationship between certain harmonics and flank wear in process of milling can be implemented for online monitoring method. [89-91]

4.3 Deep Belief Network (DBN)

DBN (Deep Belief Network) is built on the fundamental features to learn high level deep features. Finally a supervised learning algorithm named back propagation neural network is used to model the relationships between extracted features and mill level. A DBN can be used to generatively Pre train a DNN can be generated by using the learned DBN weights as the primary DNN weights. For fine tuning of these weights Back propagation or other discriminative algorithms can then be pragmatic. A deep belief network is a probabilistic, reproductive model built with multiple layers of hidden units. A configuration of simple learning components that mark up each layer [92].

4.4 Recurrent Neural Network (RNN)

The prediction of next output is not possible using feedforward networks. This challenge can be overcome with help of RNN. RNN is designed to recognize pattern in sequence of data or numerical time series data emanating from sensors [93]. Gradient i.e., rate of change of error with respect to weight De/dw is very small then change in weight is small. So old w is approximately equal to new w . whereas when gradient is very large then new w is completely different than old one then there is no updating so no learning is possible. To overcome this challenge using exploding gradients: Truncated BTT: Instead of starting back-propagation at the least time stramps, we can choose a smaller time stamp like 10 (we will lose the temporal context after 10 time stramps). Clip gradients at threshold: clip the gradient when it goes higher than threshold. RMSprop is used to adjust learning rate [93]. To overcome this challenge using fading gradients: ReLU activation function: We can use activation functions like ReLU, which gives output one while calculating gradient. RMS prop: Pin the gradient as it crosses threshold. LSTM, GRU: Diverse network architectures that have been specially designed can be used to combat this problem.

A data driven recurrent neural networks can be used for time dependent industrial process. Multiobjective optimization can be achieved establishing the trade of between overfitting and aspect of accuracy under noisy conditions in milling. Cultured features of input signal and complex methods of processing data gained from multi sensors is the main challenge in modelling of milling process. Zoom in zoom out (ZIZO) method helps RN to quickly find asset of appropriate dataset. Maintaining the minimum size of RL layers and simultaneously improving prediction accuracy. RNN trained with recursive least square training algorithm is able to acquire functional correlation among steady state average resulting force and feed rate for getting aware of cutting force during end milling operation [92, 93]. Long Short term memory neural network (LSTM) can be used to enrich the generality in milling. Compared to model based approach LSTM has less root mean square error. They are capable of earning long term dependencies [93].

4.5 Generative Adversarial Networks (GAN)

There are two models generator and discriminator which compete with each other to analyze, capture and copy variations within dataset. Generator network takes a sample and generates a sample of data. If data is generated or it is taken from real values is decided by Discriminator Network with a binary classification problem by using a sigmoid function whose output ranges between 0-1. GAN gives a new approach towards smart manufacturing by presenting milling tool conditions using acoustic by

identifying anomalies in the time-frequency domain with around 90 percent accuracy. There is no necessity of generating data similar to that from a rebellious tool in order to train the network [94,95].

4.6 Comparative Study of Neural Networks

The different neural network is to be implemented for a specific type of input and desired output conditions. Table 2 summarizes description of different neural network with their characteristics.

Table 2: Description of different deep learning algorithms

Sr. No.	Name of algorithm and characteristics	Pros. and Cons.
1	Artificial Neural Network <ul style="list-style-type: none"> Learning rate is from 10^{-5} to 10^{-1} fully connected layer size : 2^4 to 2^8 Regularization constant is ranging between 10^{-5} to 10^{-1} 	Pros: <ul style="list-style-type: none"> Able to handle missing values and noise in the data to be trained. Even if the data to be trained contains error it will not affect final output. It is used where the quick valuation of the known target function required. The training time is function of number of weights associated in the network and the number of samples to be trained. It stands for lengthy training times Cons: <ul style="list-style-type: none"> Unexplained functioning of the network Assurance of proper network structure The duration of the network is unknown Problems have to be translated into numerical values before being introduced to ANN. This is dependent on uses ability.
2	Convolutional Neural Network <ul style="list-style-type: none"> Used for image recognition Learning rate is from 10^{-5} to 10^{-1} Filter size is from 3 to 7 Pooling size is 2 to 7 Dropout rate is 0.5 to 0.9 Fully connected layer size : 2^4 to 2^8 	Pros: <ul style="list-style-type: none"> Higher performance (GPU) Improved accuracy Less time of classification BUT Requires a tons of data Cons: <ul style="list-style-type: none"> Data requirements leads to over fitting & under fitting, Parameter-to-memory requirements Non-expressive learning and logics Tuning requirements, Computationally expensive
3	Deep Belief Network <ul style="list-style-type: none"> Speech recognition Motion capture data Video sequences Image recognition 	Pros: <ul style="list-style-type: none"> Particularly available when restricted data to be trained is existing These pre trained weights are closer to the optimal weights. Proficient usage of unseen layers (developed performance achievement by adding layers compared to Multilayer perceptron)

		<ul style="list-style-type: none"> • Capability of handling noise and missing values in terms of size, position, color, view angle etc.
	Cons:	<ul style="list-style-type: none"> • Various training parameters such as the size, the learning rate and initial weights are to be considered with a DNN. • Feasibility with respect to cost, time and computational resources is difficult for optimal parameters.
4	Recurrent Neural Network	
	<ul style="list-style-type: none"> • Used for speech recognition • Learning rate is from 10^{-5} to 10^{-1} • Layer sizes ranges are from 2^4 to 2^8 • Dropout rate 0.5 to 0.9 	Pros: <ul style="list-style-type: none"> • Learn sequential events • Able to model time dependent model • Many variation such as LSTM, BLSTM, MDLSTM, HLSTM • Provide accuracies recognition in speech, recognition in character and various tasks related to Natural Language Processing.
	Cons:	<ul style="list-style-type: none"> • Some issues may arise due to vanishing gradient and requirement of huge datasets.
5	Generative adversarial networks	
	<ul style="list-style-type: none"> • There are two models generator and discriminator which compete with each other to evaluate, seize and duplicate variations in the interior of dataset. • If data is generated or it is taken from real values is decided by Discriminator Network with a binary classification problem by using a sigmoid function whose output ranges between 0 to 1 	Pros: <ul style="list-style-type: none"> • Used for unsupervised learning approach • It uses only input data to train the model. • Accuracy is around 90 percent • Able to work on time and frequency domain
	Cons:	<ul style="list-style-type: none"> • Problem of stability between generator and discriminator • Problem to determine positioning of the objects • Problem in understanding the perspective • Problem in understanding global objects

5. Conclusion

As size of data increases the performance of models using classical artificial intelligence increases. There are many machine learning approaches available for tool condition monitoring for milling process. The shortcomings of machine learning are accuracy, speed, robustness etc. These are overcome with deep learning approach. The comparative study of different deep learning techniques are rigorously discussed. ANN is used for training of numeric data. CNN is used for image and text data processing. RNN is used for recommendation in tool condition monitoring process. Depending of the nature of signals one can select appropriate technique for tool condition monitoring. The software and hardware are listed for deep learning. The comparison of different software used for deep learning is discussed. The comprehensive review shows that to meet emergent demands to successfully implement industry 4.0 deep learning approach plays an important role which overcomes the shortcomings offered by machine learning approach at some extent.

References

- [1] Abhishek Dhananjay Patange a,b,*, Jegadeeshwaran R. 2020, A machine learning approach for vibration-based multipoint tool insert health prediction on vertical machining centre (VMC), measurement 0263-2241, <https://doi.org/10.1016/j.measurement.2020.108649>
- [2] Yang K, Liang Y-c, Zheng K-n, Bai Q-s, Chen W-q. Tool edge radius effect on cutting temperature in micro-end-milling process. Int J Adv Manuf Technol 2011;52:905–12.
- [3] Jemielniak, Krzysztof. (2019). Contemporary challenges in tool condition monitoring Journal of Machine Engineering. 19. 48-61. 10.5604/01.3001.0013.0448
- [4] Nalavade SP, Patange AD, Prabhune CL, Mulik SS, Shewale MS. Development of 12 Channel Temperature Acquisition System for Heat Exchanger Using MAX6675 and Arduino Interface. Lecture Notes in Mechanical Engineering, Springer, Singapore 2019
- [5] Byrne, G. Tool Condition Monitoring (TCM) - The Status of Research and Industrial Application, CIRP Annals – Manufacturing Technology, 1995, Volume 44, Issue 2, Pages 541-567
- [6] G. Byrne D. Dornfeld , I. Inasaki , G. Ketteler, W. Konig, and R. Teti. Tool Condition monitoring (TCM) - The Status of and Industrial Application, Annals of the CIRP Vol.44/2/1995
- [7] Li X, Li HX, Guan XP, Du R. Fuzzy estimation of feed-cutting force from current measurement -a case study on intelligent tool wear condition monitoring. IEEE Trans Syst Man Cybernet C 2004;34:506–12.
- [8] la Fé-Perdomo I, Beruvides G, Quiza R, Haber R, Rivas M. Automatic selection of optimal parameters based on simple soft-computing methods: a case study of micromilling processes. IEEE Trans Ind Inf 2018;15:800–11.
- [9] Abhishek Patange, Suhas Deshmukh, Sharad Mulik, Mahesh Shewale, 2017/8, Review of Vibration Monitoring Techniques Using Low Cost Sensors and Microcontrollers, Journal of Mechatronics and Automation, Volume 4, Issue 2, pages 8
- [10] T. Mohanraj, S. Shankar, R. Rajasekar, N.R. Sakthivel, A. Pramanik. 2020, Tool condition monitoring techniques in milling process — a review, Journal of Materials Research and Technology, 2020, vol. 9, pp. 1032 – 1042
- [11] Zhang D. An adaptive procedure for tool life prediction in face milling. Proc Inst Mech Eng J J Eng Tribol 2011, 1350650111414332.
- [12] Balazinski M, Czogala E, Jemielniak K, Leski J. Tool condition monitoring using artificial intelligence methods. Eng Appl Artif Intell 2002;15:73–80.
- [13] Mahesh S. Shewale, Sharad S. Mulik, Suhas P. Deshmukh, Abhishek D. Patange, Hrishikesh B. Zambare and Advait P. Sundare et al , 2019, Novel Machine Health Monitoring System, Proceedings of the 2nd International Conference on Data Engineering and Communication Technology, Advances in Intelligent Systems and Computing 828
- [14] Krishnakumar P, Rameshkumar K, Ramachandran K. Feature level fusion of vibration and acoustic emission signals in tool condition monitoring using machine learning classifiers. Int J Progn Health Manag 2018;9:1–15.
- [15] Chengdong Wang, Zhenlin Bao, Peiqiang Zhang, Weiwei Ming, Ming Chen, Tool wear evaluation under minimum quantity lubrication by clustering energy of acoustic emission burst signals, Measurement, Volume 138, 2019, Pages 256-265
- [17] Chandrasekhar U., Yang LJ., Gowthaman S. Innovative Design, Analysis and Development Practices in Aerospace and Automotive Engineering (I-DAD 2018). Lecture Notes in Mechanical Engineering, Springer, Singapore 2019
- [18] Xu G, Chen J, Zhou H. A tool breakage monitoring method for end milling based on the indirect electric data of CNC system. Int J Adv Manuf Technol 2019;101:419–34.
- [19] Cho, S., Binsaeid, S. & Asfour, S. *Design of multisensor fusion-based tool condition monitoring system in end milling*. Int J Adv Manuf Technol 46, 681–694 (2010).

- [20] Marek Balazinski, Ernest Czogala, Krzysztof Jemielniak, Jacek Leski, Tool condition monitoring using artificial intelligence methods, *Engineering Applications of Artificial Intelligence*, Volume 15, Issue 1, 2002: 73-80
- [21] Chen, Xie, Yuan, Huang, Li. *Research on a Real-Time Monitoring Method for the Wear State of a Tool Based on a Convolutional Bidirectional LSTM Model*, *Symmetry*, 11(10), 1233
- [22] Marek Balazinski, Ernest Czogala, Krzysztof Jemielniak, Jacek Leski. Tool condition monitoring using artificial intelligence methods, *Engineering Applications of Artificial Intelligence*, 15 (2002) 73–80
- [23] Dutta S, Pal SK, Sen R. On-machine tool prediction of flank wear from machined surface images using texture analyses and support vector regression. *Precis Eng* 2016;43:34–42.
- [24] Li X, Li HX, Guan XP, Du R. Fuzzy estimation of feed-cutting force from current measurement-a case study on intelligent tool wear condition monitoring. *IEEE Trans Syst Man Cybernet C* 2004;34:506–12.
- [25] Wo Jae Lee, Gamini P. Mendis, John W. Sutherland. Development of an Intelligent Tool Condition Monitoring System to Identify Manufacturing Tradeoffs and Optimal Machining Conditions, *Procedia Manufacturing*, Volume 33, Pages 256-263
- [26] Yoshimitsu S, Iwashita D, Shimana K, Kobaru Y, Yamashita, Monitoring of cutting state in end-milling based on measurement of tool behavior using CCD image. *Int J Autom Technol* 2019;13:133–40.
- [27] Atli, A. V. & Urhan, Oguzhan & Erturk, Sarp & Sönmez, M. A computer vision-based fast approach to drilling tool condition monitoring. *Proceedings of The Institution of Mechanical Engineers Part B-journal of Engineering Manufacture - PROC INST MECH ENG B-J ENG MA*. 220. 1409-1415. 10.1243/09544054JEM412
- [28] S.C. Lin, R.J. Lin, Tool wear monitoring in face milling using force signals, *Wear*, Volume 198, Issues 1–2, 1996, Pages 136-142
- [29] Tansel I, Arkan T, Bao WY, Mahendrakar N, Shisler B, Smith D, McCool M. Tool wear estimation in micro-machining.: Part I: tool usage–cutting force relationship. *Int J Mach Tools Manuf* 2000;40:599–608.
- [30] Chen S-L, Jen Y. Data fusion neural network for tool condition monitoring in CNC milling machining. *Int J Mach Tools Manuf* 2000;40:381–400
- [31] Kishawy HA, Hegab H, Umer U, Mohany A. Application of acoustic emissions in machining processes: analysis and critical review. *Int J Adv Manuf Technol* 2018;98:1391–407.
- [32] Jemielniak K, Otman O. Tool failure detection based on analysis of acoustic emission signals. *J Mater Process Technol* 1998;76:192–7.
- [33] Alonso F, Salgado D. Analysis of the structure of vibration signals for tool wear detection. *Mech Syst Signal Process* 2008;22:735–48.
- [34] Fang N, Pai PS, Edwards N. A method of using Hoelder exponents to monitor tool-edge wear in high-speed finish machining. *Int J Adv Manuf Technol* 2014;72:1593–601
- [35] Lopes da Silva, Rodrigo & Bacci Da Silva, Marcio & Hassui, Amauri. A probabilistic neural network applied in monitoring tool wear in the end milling operation via acoustic emission and cutting power signals. *Machining Science and Technology*. 20. 386-405.
- [36] Masahiro Uekita, Yasuhiro Takaya, 2016, Tool condition monitoring for form milling of large parts by combining spindle motor current and acoustic emission signals", *The International Journal of Advanced Manufacturing Technology*, 89, pages65–75
- [37] Uekita, M., Takaya, Y. Tool condition monitoring for form milling of large parts by combining spindle emission signals. *Int J Adv Manuf Technol* 89, 65–75 (2017).
- [38] Liu, M.1991, Analytical modeling of acoustic emission for monitoring of peripheral milling process, *International Journal of Machine Tools & Manufacture*, Volume 31, Issue 4, Pages 589-606
- [39] Jemielniak K, Arrazola PJ. Application of AE and cutting force signals in tool condition monitoring in micro-milling. *CIRP J Manuf Sci Technol* 2008;1:97–102.

- [40] Man Liu, Steven Y. Liang. Analytical modeling of acoustic emission for monitoring of peripheral milling process, *International Journal of Machine Tools and Manufacture*, Volume 31, Issue 4, 1991
- [41] Shi, X., R. Wang, Q. Chen, and H. Shao. 2015, Cutting sound signal processing for tool breakage detection in face milling based on empirical mode decomposition and independent component analysis, *Journal of Vibration and Control*, 2015 , 96, pages, 2509–2523
- [42] Datta A, Dutta S, Pal SK, Sen R. Progressive cutting tool wear detection from machined surface images using Voronoi tessellation method. *J Mater Process Technol* 2013;213:2339–49.
- [43] Xinhua Shi, Ran Wang, Quntao Chen, Hua Shao. 2014 Cutting sound signal processing for tool breakage detection in face milling based on empirical mode decomposition and independent component analysis, *Journal of Vibration and Control*, Volume 21 Issue 16, pp. 3348–3358
- [44] Chuangwen X, Hualing C. Fractal analysis of vibration signals for monitoring the condition of milling tool wear. *Proc Inst Mech Eng J J Eng Tribol* 2009;223:909–18.
- [45] Shi X, Wang R, Chen Q, Shao H. Cutting sound signal processing for tool breakage detection in face decomposition and independent component analysis. *Journal of Vibration and Control*. 2015;21(16):3348
- [46] Dutta S, Pal SK, Sen R. Progressive tool condition monitoring of end milling from machined surface images. *Proc Inst Mech Eng B J Eng Manuf* 2018, 0954405416640417.
- [47] Atli AV, Urhan O, Ertürk S, Sönmez M. A computer vision-based fast approach to drilling tool condition monitoring. *Proc Inst Mech Eng B J Eng Manuf* 2006; 220:1409–15.
- [48] Krishnakumar P, Rameshkumar K, Ramachandran K. Machine learning based tool condition classification using acoustic emission and vibration data in high speed milling process using wavelet features. *Intell Decis Technol* 2018; 12:265–82.
- [49] Zhu K, Zhang Y. A generic tool wear model and its application to force modeling and wear monitoring in high speed milling. *Mech Syst Signal Process* 2019;115:147–61.
- [50] Kim S, Klamecki B. Milling cutter wear monitoring using spindle shaft vibration. *J Manuf Sci Eng* 1997;119:118–9.
- [51] Kakade S, Vijayaraghavan L, Krishnamurthy R. In-process tool wear and chip-form monitoring in face milling operation using acoustic emission. *J Mater Process Technol* 1994;44:207–14.
- [52] Tahir NH, Muhammad R, Ghani JA, Nuawi MZ, Haron CH. Monitoring the flank wear using piezoelectric of rotating tool of main cutting force in end milling. *J Teknol* 2016;78:45–51.
- [53] P. Krishnakumar, K. Rameshkumar, K. I. Ramachandran. 2018, Acoustic Emission-Based Tool Condition Classification in a Precision High- Speed Machining of Titanium Alloy: A Machine Learning Approach, *International Journal of Computational Intelligence and Applications*, Vol. 17, No. 03, 1850017
- [54] Kishawy HA, Hegab H, Umer U, Application of acoustic emissions in machining processes: analysis and critical review. *Int J Adv Manuf Technol* 2018;98:1391–407.
- [55] A D Patangel*, Jegadeeshwaran R1 and N C Dhobale1. Milling cutter condition monitoring using machine learning Approach, 1st International Conference on Mechanical Power Transmission IOP Conf. Series: Materials Science and Engineering 624 (2019) 012030
- [56] Y.F. Zhang, L. Lu, S.M. Yap. 1999, Prediction of the amount of PCA for mechanical milling, *Journal of Materials Processing Technology*, 89±90 (1999) 260±265
- [57] Wang G, Zhang Y, Liu C, Xie Q, Xu Y. A new tool wear monitoring method based on multi-scale PCA. *J Intell Manuf* 2019;30:113–22.
- [58] Clayton Cooper, Jianjing Zhang, Robert X. Gao, Peng Wang, Ihab Ragai. 2020, Anomaly detection in milling tools using acoustic signals and generative adversarial networks, *Procedia Manufacturing*, Volume 48, 2020, Pages 372-378.

- [59] Saglam H, Unuvar A. Tool condition monitoring in milling based on cutting forces by a neural network. *Int J Prod Res* 2003;41:1519–32
- [60] Aykut S, , Bageci E, Kentli A, Yazıcıoğlu O. Experimental observation of tool wear, cutting forces and chip morphology in face milling of cobalt based super-alloy with physical vapour deposition coated and uncoated tool. *Mater Des* 2007;28:1880–8
- [61] Torabi AJ, Er MJ, Li X, Lim BS, Peen GO. Application of clustering methods for online tool condition monitoring and fault diagnosis in high-speed milling processes. *IEEE Syst J* 2015;10:721–32
- [62] Lin SC, Lin RJ. Tool wear monitoring in face milling using force signals. *Wear* 1996;198:136–42.
- [63] Da Silva RHL, da Silva MB, Hassui A. A probabilistic neural network applied in monitoring tool wear in the end milling operation via acoustic emission and cutting power signals. *Mach Sci Technol* 2016;20:386–405
- [64] Bagavathiappan S, Lahiri B, Suresh S, Philip J, Jayakumar T. Online monitoring of cutting tool temperature during micro-end milling using infrared thermography. *Insight Non Destr Test Cond Monit* 2015;57:9–17.
- [65] Li W, Liu T. Time varying and condition adaptive hidden Markov model for tool wear state estimation and remaining useful life prediction in micro-milling. *Mech Syst Signal Process* 2019;131:689–702
- [66] Yesilyurt I, Ozturk H. Tool condition monitoring in milling using vibration analysis. *Int J Prod Res* 2007;45:1013–28
- [67] Li H, Zeng H, Chen X. An experimental study of tool wear and cutting force variation in the end milling of Inconel 718 with coated carbide inserts. *J Mater Process Technol* 2006;180:296–304
- [68] Özel T, Altan T. Process simulation using finite element method — prediction of cutting forces, tool stresses and temperatures in high-speed flat end milling. *Int J Mach Tools Manuf* 2000;40:713–38.
- [69] Hong G, Rahman M, Zhou Q. Using neural network for tool condition monitoring based on wavelet decomposition. *Int J Mach Tools Manuf* 1996;36:551–66..
- [70] Ong P, Lee WK, Lau RJH. Tool condition monitoring in CNC end milling using wavelet neural network based on machine vision. *Int J Adv Manuf Technol* 2019;104:1369–79
- [71] Ghosh N, Ravi Y, Patra A, Mukhopadhyay S, Paul S, Mohanty AR, Chattopadhyay AB. Estimation of tool wear during CNC milling using neural network-based sensor fusion. *Mech Syst Signal Process* 2007;21:466–79.
- [72] Olufayo O, Abou-El-Hossein K. Tool life estimation based on acoustic emission monitoring in end-milling of H13
- [73] Wang M, Wang J. CHMM for tool condition monitoring and remaining useful life prediction. *Int J Adv Manuf Technol* 2012;59:463–71
- [74] Zhang JZ, Chen JC. Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. *Int J Adv Manuf Technol* 2008;39:118–28.
- [75] Giriraj B, Raja VP, Gandhinadhan R, Prediction of tool wear in high speed machining using acoustic emission technique & neural network. *Indian J Eng Mater Sci* 2006;13:275
- [76] Nouri M, Fussell BK, Ziniti BL, Linder E. Real-time tool wear monitoring in milling using a cutting condition independent method. *Int J Mach Tools Manuf* 2015;89:1–13.
- [77] Rohitha. B. Kurdikeri, A. B. Raju. et al. Comparative Study of Short-Term Wind Speed Forecasting Techniques Using Artificial Neural Networks, *International Conference on Current Trends towards Converging Technologies* , 89:65–75
- [78] Shankar S, Mohanraj T, Rajasekar R. Prediction of cutting tool wear during milling process using artificial intelligence techniques. *Int J Comput Integr*

- [79] Antonio J, Oscar Victor M, Hirose S. Ultrasonic imaging of concrete by synthetic aperture focusing technique based on hilbert-huang transform of time domain data. *Mater Trans* 2012;53:621–6
- [80] Hermann Baumgartl, Josef Tomas, Ricardo Buettner, Markus Merkel. "A deep learning based model for defect detection in laser powder bed fusion using in-situ thermographic monitoring", *Progress in Additive Manufacturing*, 2020, 5:277–285
- [81] Bagavathiappan S, Lahiri B, Saravanan T, Philip J, Jayakumar T. Infrared thermography for condition monitoring—a review. *Infrared Phys Technol* 2013;60:35–55.
- [82] Rangwala S, Dornfeld D. Sensor integration using neural networks for intelligent tool condition monitoring. *J Eng Ind* 1990;112:219–28.
- [83] Soheil Bahrapour, Naveen Ramakrishnan, Lukas Schott, Mohak Shah Research and Technology Center, Robert Bosch LLC, 2016, Comparative Study of Deep Learning Software Frameworks, , arXiv:1511.06435v3 [cs.LG] 30 Mar 2016
- [84] Wang W, Hong G, Wong Y, Zhu K. Sensor fusion for online tool condition monitoring in milling. *Int J Prod Res* 2007;45:5095–116.
- [85] Aliustaoglu C, Ertunc HM, Ocak H. 2009, Tool wear condition monitoring using a sensor fusion model based on fuzzy inference system. *Mech Syst Signal Process* ;23:539–46.
- [86] Jemielniak K. Commercial tool condition monitoring systems. *Int J Adv Manuf Technol* 1999;15:711–21.
- [87] Ambhore N, Kamble D, Chinchani S, Wayal V. Tool condition monitoring system: a review. *Mater Today Proc* 2015;2:3419–28.
- [88] Chen G, Ren C, Zhang P, Cui K, Li Y. Measurement and finite element simulation of micro-cutting temperatures of tool tip and workpiece. *Int J Mach Tools Manuf* 2013;75: 16–26.
- [89] Dimla, Eric. Sensor signals for tool-wear monitoring in metal cutting operations—A review of methods. *International Journal of Machine Tools and Manufacture*. 40. 1073-1098. 10.1016/S0890-6955(99)00122-4.
- [90] Kuljanic E, Sortino M. TWEM, a method based on cutting forces—monitoring tool wear in face milling. *Int J Mach Tools Manuf* 2005;45:29–34.
- [91] Lu, Muchao, Yan Kang, Xiaoming Han, and Gaowei Yan. Soft sensor modeling of mill level based on Deep Belief Network, The 26th Chinese Control and Decision Conference (2014 CCDC),
- [92] Chitra A. Dhawale, Krtika Dhawale. 2020, chapter 3, Current Trends in Deep Learning Frameworks With Opportunities and Future Prospectus, IGI Global :63-77
- [93] Choudhury, S.K. & Rath, Subhashree. In-process tool wear estimation in milling using cutting force model. *Journal of Materials Processing Technology - J MATER PROCESS TECHNOL*. 99. 113-119. 10.1016/S0924-0136(99)00396-9.
- [94] Elbestawi M, Papazafiriou T, Du R. In-process monitoring of tool wear in milling using cutting force signature. *Int J Mach Tools Manuf* 1991;31:55–73.
- [95] Haber RE, Jiménez JE, Peres CR, Alique JR. An investigation of tool-wear monitoring in a high-speed machining process. *Sens Actuators A Phys* 2004;116:539–45